# Essays on the Nexus between Capital Market and Macroeconomic Activity

Tutsirai Sakutukwa,

Ph.D Economics

A thesis submitted for the degree of Doctor of Philosophy at

Monash University in 2015

Department of Economics, Monash University

Melbourne, Victoria

Australia

## Copyright notice



Tutsirai Sakutukwa

Date: 11/09/2015

## Abstract

This dissertation consists of three essays focusing on linking the capital market with the macroeconomy, and use this knowledge in forecasting some macroeconomic variables.

The first essay analyses whether implied stock market volatility could be used to forecast both stock market returns and future output. While addressing the potential issues of autocorrelation and heteroskedasticity due to overlapping data, we examined the forecasting information in implied stock market volatility for seven developed economies (Belgium, France, Germany, Japan, the Netherlands, the UK, and the US). In-sample results showed that implied stock market volatility had forecasting power for stock returns and output, however the forecasting power of the information content differed by country. By splitting the sample, as dictated by structural break tests, we showed that the output forecasting information content in implied stock market volatility was stronger in recent years than earlier years. We further explored the out-of-sample forecasting properties of implied stock market volatility for Germany and the US, and showed that the forecasting information was stronger for Germany. However, the out-of-sample predicting power of output by holding period stock returns performed relatively better for the US than for Germany. In addition, combined forecasts out-performed any single predictor alone.

The second essay tests the in-sample and out-of-sample forecasting of output growth rates using the composite leading business cycle indicator (CLI) for South Africa, and then compares the results to the traditional yield curve approach. Compared to both the yield curve and the benchmark model (lagged output growth), the CLI contained more in-sample forecasting information. Using squared forecasting error ratios of the benchmark, the yield curve, and the CLI models, together with an econometric approach that addressed the upward bias present in a nested model (overlapping models), we found evidence that the CLI outperformed both the yield curve and the benchmark model in the out-of-sample forecasting. In addition, as shown by the diagnostic plots, the CLI was more consistent and stable in out-of-sample forecasting than the yield curve. However, compared to the benchmark model, the yield curve's forecasting ability was more accurate.

In the third essay, the main objectives are to evaluate the intra-relationship between the volatility of financial variables and to investigate their link with macroeconomic volatility for six industrialised countries (Belgium, France, Germany, Japan, the UK, and the US). The results of the analysis indicated that implied stock market volatility (VIX) led both the

Treasury bill rate volatility (TB) and term structure volatility (TS). Even though TB led TS, this link was relatively weak. On the relationship between finance and the macroeconomy, our empirical results were positioned between the findings of Schwert (1989) and Diebold and Yilmaz (2008). The relationship between VIX and inflation was statistically significant in all countries but the UK and France. In addition, uncertainty in an economy measured by real output growth volatility and inflation rate volatility could be predicted by VIX. The results showed that there was a statistically significant relationship between TB and the volatilities of real GDP growth rate for all countries, except for Japan and the US. Conversely, the relationship between TB and inflation rate volatility was weak for all countries.

## Declaration

This thesis contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

**Signed:** [redacted]

**Date:** 11/09/2015

## Acknowledgements

I owe a sincere debt of gratitude to my supervisors Ratbek Dzhumashev, Hee-Seung Yang, Siew Ling Yew and Philip Inyeob Ji (former) for their invaluable research guidance, support and mentoring. They showed strong interest in my research and worked tirelessly to guide me throughout this process. I drew a lot of encouragement from their constant patience and willingness to help. As the main supervisor, Ratbek's prompt responses to working drafts of my chapters, constructive comments and deadlines helped to keep me focused, and contributed immensely to the quality of the study, for that I am greatly indebted to him. I would also like to thank Evan Hannah for his assistance with proof reading my thesis.

From time of application for the program through the early stages of my dissertation, Stephen Miller has always been ready and willing to help me succeed. In addition, his valuable insights and contributions during the critical early stages of my research helped me with that needed springboard to see the completion of my research. I also appreciate the useful comments and suggestions from Gaurav Datt and Lata Gangadharan. In addition, I will forever be thankful to Monash University and the faculty of Business and Economics for the financial support they extended during my PhD journey. I would also like to express my gratitude to all my fellow PhD students; especially, Luke, Miriam and Joe.

Finally, this thesis is dedicated to my wife Sekai Adella Mushaniga and son Ayden Sakutukwa for putting up with the discomfort of me continuously working and for their encouragement and support to see this project a success. To Arthur and Evelyn Mushandi, I would like to say thank you for your inspiration and helping when I needed you the most. I would like to extend my great appreciation to my family, friends and loved ones. I am deeply indebted to my parents, France Sakutukwa and Joyce Sakutukwa, and to my siblings, for their patience, unwavering support and firm belief in my abilities.

Contents

**List of Tables**

# Chapter 1: Introduction

This thesis is comprised of three essays that link finance to macroeconomic activity and attempts to use this knowledge in forecasting some macroeconomic variables. In the wake of the recent global financial crises (the GFC), macroeconomic predictors, and particularly output growth forecasters, are increasingly gaining interest from academics and practitioners because output forecasting has far reaching implications for policymakers. For example, policymakers strive to forecast and counter any undesirable slowdowns in output growth, because the welfare cost of a recession is profound. In particular, the GFC has taught us that the Keynesian ideas of using fiscal and monetary instruments may still be an important basis for economic policy. Blanchard, Dell'Ariccia, and Mauro (2010) assert that the policy instruments help in smoothing out output fluctuations. In light of this rationale, the main objective of all three essays is to analyse links between different financial and macroeconomic variables, and then to propose better macroeconomic predictors.

In the first essay, we analyse how the information contained in implied stock market volatility helps to improving forecasts of stock returns and output growth for seven industrialised countries: Belgium, France, Germany, Japan, the Netherlands, the UK, and the US. The choice of countries is dictated by the availability of the VIX data. We first explore, using linear regression, how the recently-developed implied stock market volatility measure could be used to forecast stock returns. In turn, we examine the in-sample information content of the implied stock market volatility in forecasting output growth for the aforementioned countries.

We conduct simulated output out-of-sample forecasting using the implied stock market volatility for Germany and the US only, as the data series of other countries in our sample are too short for such an exercise. To carry out the out-of-sample forecasting, we first define a direct univariate forecasting of the output growth by adopting an autoregressive model as the benchmark model. Three other forecasting models are identified: One model containing only stock returns with lagged output growth, a model using implied stock market volatility with lagged output growth, and finally a model containing both stock returns and implied stock market volatility with lagged output growth. To test the information content of each model, real-time simulated out-of-sample estimation is conducted and evaluated using the ratio of the mean squared forecasting errors, together with the recent econometric technique developed by Clark and West (2007). Also, we examine whether a combination of implied stock market volatility and stock returns improves forecasting accuracy. Since the definition of the dependent variable implies overlapping data, the contemporaneous variance of the error term can be correlated with the regressors. To circumvent this problem, all inferences are based on heteroskedastic and autocorrelation consistent (HAC) standard errors.

The results on stock returns forecasting show that current implied stock market volatility contains forecasting information about the future stock returns for Belgium, Germany, Japan and the US. With regards to output forecasting, we first test the forecasting strength of our candidate variables (stock returns and implied stock market volatility) by running each independently in an in-sample forecasting framework at forecasting horizons of one, two and four quarters to predict output. The in-sample results indicate that both variables independently carry output forecasting information. It is demonstrated that after combining the variables together in predicting output, the forecasting significance improved, and the overall performance of the model measured by the adjusted R-Squared increased.

For the out-of-sample forecasting, the results show that even though all models could be used in forecasting output, the model that includes both the stock returns and implied stock market volatility increases forecasting precision more than any other model. In addition, we show that the forecasting information content in implied stock market volatility has increased in recent years compared to earlier years. This is achieved by breaking the sample into two using a structural break test suggested by Bai and Perron (1998). These overall results suggest that implied stock market volatility and stock returns complement each other in forecasting output, and it appears that implied stock market volatility is gaining more forecasting power.

The second essay is motivated by the later discovery by Binswanger (2000) and Estrella (2005) that indicates that financial variables are losing their output forecasting information power, together with the findings of Eickmeier and Ziegler (2008) who show that dynamic factor models perform better than single variable models. In view of this, we first analyse if the traditional term structure contains output growth forecasting information for an emerging economy such as South Africa, and compare it to an index called the composite leading business cycle indicator (CLI), constructed by the Reserve Bank of South Africa from 10 different economic indicators. Furthermore, we test the out-of-sample output forecasting properties of these predictors. This is conducted using recent techniques that address the noise bias present in nested models, and taking into account autocorrelation and heteroscedasticity due to overlapping data. In addition, we investigate the stability of the CLI and the term structure models.

In-sample results show that both the composite leading business cycle indicator and the term structure of interest rates contains output growth predicting information. Simulated out-of-sample results demonstrate that even though both the yield curve and the composite leading business cycle indicator contain some output growth forecasting information for up to eight quarters ahead, the composite leading business cycle indicator contains relatively more output growth forecasting information. Both the ratio of the mean squared forecasting errors and Clark and West (2007) econometric specifications confirm this finding. In estimations of the test statistics, we employed the rolling regression approach. To check robustness, we conducted the same test using regressive regressions and obtain similar results to that of rolling regressions.

To test the stability and consistence of the two forecasting models, we used the diagnostic approach proposed by Welch and Goyal (2008). If the candidate model is stable and consistent, the difference between the adjusted accumulated forecast errors from the benchmark model (containing only lagged output growth) and the candidate model should continuously increase over time. The results show that prior to 1993 both models perform significantly better than the benchmark model, with the term structure of interest rate having a steeper slope at the two quarter and four quarter forecasting horizons. However, in the post-1993 period, the CLI is more reliable and consistent as a forecasting tool, at all forecasting horizons, compared with the term structure of interest rate. The important implication of these findings is that they provide additional information for policy development. The results suggest that South African policymakers may wish to adopt the composite leading indicator considered in our study in forecasting output, as it increases forecasting accuracy compared with the traditional forecasting tools such as the yield curve.

Finally, the third essay draws from the point highlighted by Diebold and Yilmaz (2008) that little is known between the second moments of the financial sector and the macroeconomy. This relationship is important because high volatility in the variables of financial sector and macro-economy can be interpreted as an increase in uncertainty in an economy, and this could lead to a fall in output growth. Empirical evidence suggests that there is a negative relationship between macroeconomic volatility and economic growth rates

(Imbs, 2007). In light of this, the factors that are associated with output volatility, or could be used to forecast volatility, become important in developing forecasting models.

Through the use of reduced-form vector auto regression, we analyse the relationship between intra-financial sector volatility and link it with macroeconomic volatility for six industrialised countries: Belgium, France, Germany, Japan, the UK, and the US (the choice of countries is dictated by the availability of data). By exploiting the impulse response functions, variance decomposition, and the Granger causality test, we test the relationship between the volatilities of the financial sector, namely short-term interest rates (three-month Treasury bills), the term structure of interest rate (the difference between 10-year government bonds with the three-month Treasury bills rate), and implied stock market volatilities. To understand the effect of these variables on the macro economy, we investigated the relationship between these financial volatilities with macroeconomic volatilities, being output growth and inflation.

The results on the intra-financial sector volatility are mixed. Specifically, the impulse response functions for Belgium, the UK, France, and Germany suggest that a one standard deviation innovation in short-term interest rates imposes a statistically significant impact on the term spread of interest rate. This suggests that short-term interest rates could be used as a potential predictor for the term spread of interest rate. Inferences from the three statistical tests – impulse response, variance decomposition, and the Granger causality tests – indicate that implied stock market volatility leads both the Treasury bill rate volatility and term structure volatility for Germany and the US. However, the effect of short-term interest rate volatility on term spread of interest rate volatility is weak.

On the relationship between finance and the macroeconomic volatility, empirical results show that implied stock market volatility leads inflation for all countries except the UK and France. In addition, the relationship between implied stock market volatilities and real GDP is statistically significant for four countries, except for Belgium and the UK. This implies that the uncertainty in an economy measured by real output growth volatility could be predicted by implied stock market volatilities. The results show that there is a statistically significant relationship between the volatility of the Treasury bill rate and the volatilities of real GDP growth rate for all countries, except for Japan and the US. These results suggest that fixed income managers should use implied stock market volatility to forecast changes in interest rates and interest rate volatility, and accordingly change their portfolio allocations. To forecast the uncertainty captured by output growth volatility, forecasters should use implied stock market volatility and Treasury bill rate volatility. However implied stock market volatility should be used to forecast inflation volatility in Belgium, Germany, Japan, and the US, as the other two factors are weak as leading indicators of inflation volatility.

# Chapter 2: On Predicting Future Output: Does Implied Stock Market Volatility Contain Predicting Information?

## Abstract

This chapter investigates whether implied stock market volatility contains any forecasting information. In-sample results show that implied stock market volatility has forecasting power for stock returns and output, however, the degree of forecasting information content differs by country. For out-of-sample results, the forecasting properties of implied stock market volatility for Germany and the US show that the forecasting information is stronger for Germany. However, the out-of-sample predicting power of output by holding period stock returns performs relatively better for the US than Germany. In addition, combined forecasts out-perform any single predictor alone.

## 1 Introduction

The role asset prices play in explaining future output fluctuations has received renewed interest, particularly after the recent global financial crisis. A number of asset prices, including but not limited to stock returns, interest rates, and interest rate spreads, have been identified to contain some information about the future output. However, the nexus between output and stock market volatility is not well documented, with some economists suggesting that high volatility precedes a reduction in future economic activity. This begs the question of whether implied stock market volatility contains output forecasting information. The answer to this question has far-reaching policy implications both at a national level, and at a local level such as corporate decision-making. Inspired by this potential, this chapter aims to investigate if implied volatility anticipates any future developments in the real activity.

Since the downfall of traditional forecasting tools such as broad money supply during and after the 1973-4 recessions, the birth of alternative forecasting tools emerged during the 1980s. The most prominent forecasting instruments proposed and tested were short-term interest rate, yield curve, stock returns, and stock market volatility. There are mixed empirical results on the extent to which these variables can be used for output prediction. For example Fama (1990) finds evidence that stock returns lead economic recession for the period 1953-1987, while Binswanger (2000) utilises the same equations Fama (1990) ran and shows that the relationship falls for the later period 1984-1995 for the case of the US. On the other hand, the relationship between future output and the yield curve has been weakening too. In addition, Estrella, Rodrigues, and Schich (2003) attribute this weakening to the possibility of the existence of structural breaks. The structural break are suspected to be driven by globalisation and inflation rate targeting. These two elements have an effect of diluting leading indicator information, and reducing the variability of macroeconomic variables respectively. However, after the inclusion of various financial forecasting tools, Stock and Watson (2003) show that there is a relationship between stock returns and future output, yield curve, and future output. Even though the relationship is not constant over time for within-country analysis, and varies across countries, they find evidence that a combination of forecasting instruments increases the forecasting accuracy.

With Stock and Watson (2003) pointing toward the synthesis of information from different arrays of financial variables to foster forecasting accuracy, the properties of the recently-developed measure of implied stock market volatility, seems to contain some leading indicator information. This variable, implied stock market volatility (VIX), is a measure of the expectations of stock returns volatility over the next 30 calendar days, and is calculated as 100 times the square root of the expected 30-day variance of the stock rate of return. The VIX is constructed on an intraday basis by taking the weighted average of the implied volatility of both calls and puts options. The VIX is weighted to reflect the implied volatility of 30 calendar day options. Because of the forward-looking nature of VIX, the level of implied volatility contains the best information regarding the remaining life of an option, and for that reason, it has been called the “investor fear gauge” (Whaley, 2000). When the VIX index is relatively high, it implies a greater fear in the economy, and vice versa. This implied volatility gives an assessment of the expected volatility of the respectively stock index over the remaining life of the option (Whaley, 2000).

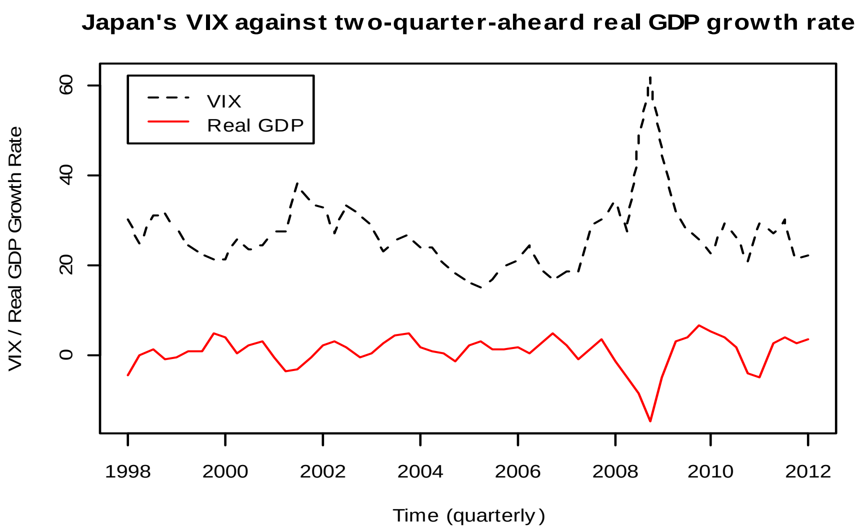
On the other hand, a number of authors have investigated the link between realised stock market volatility and future stock returns, and show that realised stock volatility contains some forecasting information.[1] Additionally, Verhofer, Ammann, and Skovmand (2009) find evidence that link current implied volatility with future stock market volatility.[2] Even though historical data (realised stock market volatility) contains some information about future stock market volatility, Blair, Poon, and Taylor (2010) show that the historical

1 See French, Schwert, and Stambaugh (1987), among others
2 See Bluhm and Yu (2001); Nishina, Maghrebi, and Kim (2006); Yang and Liu (2012) and He and Yau (2007); among others

prices do not give any additional information beyond that contained in the VIX. Moreover, the VIX is superior on out-of-sample performance. Nonetheless, inconclusive evidence exists on the relationship between implied stock market volatility and future stock returns (Banerjee, Doran, & Peterson, 2007; Driessen, Lin, & Lu, 2012).

In addition, there is empirical evidence linking realised stock market volatility with future output. For example, Guo (2002) shows that historical stock market volatility contains some output forecasting information, but realised volatility does not give any further information beyond that contained in stock returns. The recent economic recession caused by the global financial crisis triggered the search for additional forecasting tools. The background of this search, and the preceding discussion, together with evidence by Stock and Watson (2003) that a combination of forecasting tools increases forecasting accuracy, provide the major thrust of this paper to test the forecasting power of a new variable, implied stock market volatility captured by VIX in forecasting future output. Given its forward-looking nature, VIX is likely not only to contain forecasting information that could complement asset returns in predicting at a longer time horizon. This argument stems from the fact that if VIX can successfully forecast future stock returns, and in turn future stock returns contain information to forecast output, hence VIX should be able to forecast output at a longer horizon.

The graph below shows an inverse relationship between implied stock market volatility measured by the VIX index and two-quarters-ahead output growth rate in the case of Japan.



As depicted on the graph, there is a conspicuous negative relationship between the VIX and future output (two-quarters-ahead) and clearly, the negative relationship is much stronger in recent years. This holds true for all other nations under study. There is a negative relationship between output growth rate and the implied stock market volatility and the graphs shows that the relationship is stronger in recent times compared to earlier time. (for relevant graphs, please refer to Appendix 2 at the end of the chapter).

The construction of the VIX index is a relatively new idea, and as such does not have long time series. However, the US has a relatively longer series available, and as a result, the empirical testing of the relationship between VIX and future stock return has been limited to the case of the US only. By analysing the forecasting content of implied stock market volatility, we extend existing literature in three major ways. First, we lengthen the span of the investigation of the in-sample link between implied stock market volatility and future stock returns beyond the US to include six other developed countries: Belgium, France, Germany, Japan, the Netherlands, and the UK. The in-sample results confirm that implied stock market volatility contains forecasting information. Second, we explore the previously unknown in-sample relationship between implied stock market volatility and future output at a quarterly, bi-quarterly, and yearly forecasting horizon for all countries in our sample. We find that implied stock volatility has strong in-sample forecasting information for future output. Lastly, in practice, what is more important is to carry out real future output forecasts, so we conduct simulated out-of-sample forecasts. Due to the length of time series data, this analysis is limited only to the cases of Germany and the US. Results show that the use of VIX significantly reduces forecasting errors compared with the baseline model.

The rest of the chapter is organised as follows: The next section proceeds with a brief review of related literature. Methodology is presented in section 3. Section 4 reports the empirical results, and section 5 discusses results and gives the conclusion.

## 2 Review of related literature

This section gives a review of related literature and is in three parts. First, we begin by reviewing the literature between stock market volatility and expected stock returns, then we proceed to the literature on stock market returns and future output, and finally we discuss studies on the relationship between stock market volatility and future output.

## 2.1 Stock market volatility and expected stock returns

Theory states that economic agents are risk averse, and they seek compensation for assuming risk. For any bet, a higher risk should be matched by a correspondingly higher return. The capital asset pricing model (CAPM) predicts that there is a positive relationship between market risk and market return. Given this background, an increase in volatility, which can be interpreted as an increase in risk, should be accompanied by an increase in expected return. In this case, today's stock market volatility should contain information about the future stock returns.

Fama and MacBeth (1973) tested the predictions of the CAPM, that is, that there is a positive relationship between risk and stock returns. They found that the stock market's own volatility (measured by variance) is not an important variable in itself, rather that the variables related to the stock market's variance have an influence on stock returns. Building on the idea of Fama and MacBeth (1973), Cutler, Poterba, and Summers (1989) use the variance of excess returns for individual stocks each month, and found that cross-sectional volatility affects returns. An increase in diversifiable risk positively affects stock returns, but the effect is only contemporaneous. On the other hand, non-diversifiable risk negatively affects current stock returns, and leads to an increase in long-term stock returns. Even though most economists agree that the predictable part of stock market volatility affects stock returns, not all agree on the direction of the unpredictable elements. French, Schwert and Stambaugh (1987) found that there was a positive relationship between predictable volatility and excess return. However, there existed a strong negative relationship between the unpredictable stock market volatility and excess holding period returns.

A different result emerges in the literature regarding implied stock market volatility (VIX) and stock returns vis-à-vis realised volatility and stock returns. Verhofer et al. (2009) used US equity options and found a strong relationship between realised stock market returns volatility and lagged implied volatility, and conversely, that there was no relationship with lagged historical volatility. Banerjee et al. (2007), showed that implied volatility together with innovations affected future returns. The relationship was even stronger for high beta portfolios. Since VIX is a relatively new variable, this chapter seeks to extend prior work by including more developed countries where the data are available.

For a sample running from 1947 to 2000, in the case of the US, Guo (2002) found that the predicting information embodied in conditional stock market variance was statistically significant in forecasting stock market returns. The relationship was more economically significant for the period 1963 through 1997. As predicted by theory, the contemporaneous volatility has a negative effect on current returns, and lagged realised volatility has a positive impact on returns. Our methodology is closely related to Guo (2002). However, we use VIX as our predictor instead of realised stock market volatility. This choice is also supported by the work of Driessen et al. (2012), who directly incorporated implied stock market volatility, but the their analysis was limited only to the US economy. They investigated the ability of implied volatility to forecast stock returns for the case of the US, given earnings and analyst-related news, and found that implied volatility significantly predicted earnings surprises, analyst recommendations changes, and analyst forecasting revisions. Moreover, they found that the predictability more than doubles around earnings and/or analyst-related events.

### 2.2 Stock market returns and future output

This section explores the literature on the relationship between stock returns and future output. There is almost a unanimous agreement in the literature that, prior to 1980s, stock returns contained some degree of forecasting information for future output.[3] However, results are mixed especially during the Great Moderation period since mid-1980s. We review the literature and show the role of new and alternative forecasting tools.

The dismal failure of monetary aggregates as predictors of future output and inflation in the 1970s and early 1980s invited testing of alternative predicting tools. The most prominent was the use of asset prices as a predictor of future real activities. Early in this literature, Fama (1981) documented that stock returns contained forecasting information for predicting future trends of output and inflation. His findings triggered much research in this field (Barro, 1990; Harvey, 1989; Lee, 1992).

Theoretically, the link between asset prices and future output is captured in broad theories such as real business cycles. The specific theoretical link between stock prices and future output is derived through Consumption Capital Asset Pricing Model (CCAPM). The CCAPM incorporates the dynamic changes in consumers' marginal utility with some component of uncertainty. This approach is illustrated in Harvey (1989, 1997), who applied

[3] See Barro(1990); Schwert (1989)

the result to the US and Canadian economies. The results showed the link between asset prices and economic activity. By adopting constant elasticity of substitution and applying it to CCAPM, Epstein and Zin (1991) showed that a combination of asset prices helped in explaining changes in future consumption.

Empirically, Fischer and Merton (1984) strongly supported the important role the stock market plays in predicting the business cycles and gross national product. They documented that even if the stock market was assigned a small weight in macroeconomics, primarily due to its high volatility, it was a good predictor of future macro variables. Furthermore, they ruled out the possibility of neglecting the high fluctuation by managers as a non-possibility in real practice, as managers tended to take into account the information they get from the stock market in their decision-making. Regardless of the theoretical supposition of high volatility of the stock market, they concluded that such a proposition is not empirically conclusive. Reinforcing the role of the stock market on the real sector, Barro (1990) argued that the stock market was imperative in investment decision-making. In the long term, the stock market contained substantial explanatory power about future investment in the case of the US. However, in the case of Canada, the US stock market contained more information for Canadian investment than the Canadian stock market itself. Even though the stock market's prediction precision fell a little bit off since the 1987 crash, the errors were not statistically significant.

The evidence for the stock returns forecasting ability was significant for the case of the US. Fama (1990) showed that stock returns had great forecasting power for the period 1953-1987. By extending the Fama (1990) data set to more than a century of data, and by comparing two measures of industrial production, Schwert (1990) ran the same equation and concluded that there was a significant relationship between the expected stock returns and future real sector. On the same note, by utilising data from 17 countries, together with a nonlinear panel data model, in particular by adopting a switching regression approach, Henry, Olekalns, and Thong (2004) concluded that stock returns were very powerful in predicting future output when the economy is in recession.

In line with Harvey (1997), and Peña and Rodríguez (2007), Grabowski (2009) used the CCAPM framework to examine the possibility of using financial markets in forecasting future real economic activity for an emerging economy, Poland. He argued that it was not only possible to exploit the financial market expectation in general to predict future economic activities, but also the data about a financial system can be employed to forecast the future flow of real activity. Grabowski (2009) showed that for the case of small and open economy such as Poland, asset prices are an integral forecasting tool. His results were robust in the use of times series and the Probit model approach. Furthermore, the out-of-sample properties confirm the forecasting power of asset prices.

Since there is overwhelming evidence that the banking sector is important in stirring economic growth, Cole, Moshirian, and Wu (2008) analysed the relevance of the banking sector stock returns in forecasting future economic growth. To have a robust result, they extended their analysis to 18 developing and 18 developed countries. They also documented that country-specific and other institutional characteristics affected the path of growth through the banking stock returns.

Subsequent studies explore issues of non-linearity of the relationship between asset prices and future output. By evaluating linear and nonlinear forecasting methods using out-of-sample forecasting performance, together with multivariate nearest-neighbour regression models, Jaditz, Riddick, and Sayers (1998) explored the use of optimally-combined forecasts. They concluded that non-parametric methods alone did not yield a significant improvement on forecasts, even when nonlinearity is not persistent. However, the optimal combination of parametric and non-parametric models led to improvements in the forecasting power of the model, even though the improvement in the mean forecast error was small. Non-parametric tests, however, seemed to yield the results consistent with the findings from parametric tests. Hassapis (2003) conducted a non-parametric test in the cases of the US and Canada to establish if stock prices, interest rates, interest rate spreads, and monetary aggregates had any predictive power over the future real activity. His findings were in line with what has been previously documented using parametric tests, which is that these variables contain valuable information for the prediction of future real activity. However, this is contrary to the findings of Swanson and White (1997). In their empirical analysis, they found that linear forecast performed better for a series of the US variables. Reinforcing this argument is Galbraith and Tkacz (2000); by utilising international data, they did not find any strong evidence of the superiority of non-linear form over linear of the asset price-output relationship.  Based on these results, we use linear regression in our econometrics tests of the relationship between stock prices and output.

Furthermore, Harvey (1989) documented that compared to the stock returns, there was even more evidence of the forecasting information in the bond prices. Particularly for the period 1957-1989, the yield curve measures explained 30% of the variations in the future GNP, compared with 5% from the stock market variable. By exploiting the VAR approach, Lee (1992) showed that stock returns Granger-caused future real activity. However, by adding interest rates into the system of equations, the ability of stock returns to forecast the real sector was reduced. Further, trying to use inflation itself to forecast real activity proved to be of limited scope. However, these papers moved toward a general conclusion that asset returns help in forecasting real activity, although the forecasting information is limited.

In a more later turn of events, Binswanger (2000) adopted the regression equations of Fama (1990), but with later data sets, and concluded that the stock returns have ceased to lead real activity for the US. In particular, Binswanger (2000) found that the relationship was non-existent for the period 1984-1995, however, the relationship for the sub-period 1953-1965 was strong. Nevertheless, he cautioned that it was still premature to make a solid conclusion on the later breakdown of the relationship, because the sample period considered was too short for such a firm assertion. This comes in light of a century of evidence for the same methodology by Schwert (1990). In an attempt to reconcile this structural shift in the relationship between stock returns and real activity, Binswanger (2000) attributed the shift to the existence of 'bubbles', however, it was difficult to distinguish bubbles from some unobservable factors. Monetary policy and increasing globalisation were also cited as possible explanations.

The findings by Madsen, Dzhumashev, and Yao (2013), extended some support to the Binswanger (2000) results. They investigated the long-run relationship between stock returns and per capita output growth in the context of the stochastic general equilibrium model for 20 Organisation for Economic Co-operation and Development countries by using a century of data. In support of those who attribute the weakening of the stock returns-output relationship to the Great Moderation, they found empirical evidence that the long-run positive relationship only existed during the period 1916–1951, when extraordinary per capita output volatility was observed. However, they recognised the possibility of the existence of a short-run relationship, since their model eliminates business cycle components from the data.

Inspired by Binswanger (2000), Mao and Wu (2007) conducted empirical investigation on the forecasting ability of Australia's stock market for future real sector.

Unlike the Binswanger (2000) results, the stock market leads the industrial sector and GDP during Australia's high growth periods. However, the connection disintegrates during the low growth of 1974-1983. They attributed this breakdown to an increase in globalisation of the financial system. It was highly anticipated that the expected dividends should explain the future output, or at least be highly correlated with the future flow of output. However, a study by Campbell (1999) revealed that the role of dividend to price ratio in forecasting the future real sector was limited.

**2.2 Volatility and Future output**

This section reviews the literature on the link between realised volatility and future output, and shows that there is general consensus that an increase in realised stock market volatility leads to a slowdown in economic activity. Given that implied stock market volatility, captured by VIX, forecasts future stock market volatility, then VIX itself should contain forecasting information about future economic activity.

Share prices fluctuate due to either new firm-specific information or to the change in general expectations of the future course of the economy, with stock market volatility capturing the uncertainty around the future cash flows and discounting factors (Raunig & Scharler, 2010). Volatility tends to be countercyclical with future real sector; this is to say, when volatility goes up, future output goes down. In addition to the evidence that stock market volatility helps in predicting industrial production growth rates, Chauvet, Senyuz, and Yoldas (2010) show that stock market volatility is an effective indicator of the turning points of business cycles. This remarkable pinpointing of the turning point of business cycles was initially conducted for the in-sample data, with the same result holding for the out-of-sample. This was achieved by estimating both the Probit model and the Markov switching dynamic factor models. By exploiting the aggregated information content embodied in realised volatility, they showed that volatility outperformed other popular financial variables in forecasting, especially at short horizons, and came to the conclusion that volatility consistently leads the business cycle.

The stock market volatility index, among other variables, captures the level of uncertainty in an economy. There are different perspectives on the extent to which uncertainty feeds into the real economy. In the case of the US, Schwert (1989) documented that stock market volatility increased after stock price falls, increased during recession, and it rose around major financial crises. He concluded that stock market volatility was significantly higher for all recorded 19th century financial crises, during the early 1930s (post World War 1), during the Great Depression and during the 1973-1974 OPEC recession. Alexopoulos and Cohen (2009) showed that an unanticipated increase in uncertainty reflected by stock market volatility, among other factors, can result in sharp and short-lived recessions. In the real sector, industrial production levels fall, unemployment increases, consumption decreases, and productivity and investment went down. The result of this uncertainty is to decrease the future output and create “business cycles”. In other words, if historical data on volatility captures future flows of output, would it not imply that stock market volatility can produce more accurate forecast figures? This is what previous literature seems to have failed to capture, which we wish to address in this study.

By adopting the variance of stock returns rather than stock returns themselves, Campbell, Lettau, Malkiel, and Xu (2001) showed that, for the in-sample prediction, high volatility in the current quarter signalled a low flow of output in the next quarter. This was explained by the fact that high volatility signals high uncertainty about the future, and hence economic agents become sceptical about investing in the real sector. Nevertheless, Guo (2002) extended the analysis to test out-of-sample performance, and concluded that the forecasting content significantly weakened. Nonetheless, the predictive content was stronger in some periods than others, implying it was not consistent over time.

Stock market volatility can be treated as speculative asset. Most speculative assets receive and process new economic information at a faster rate than real economic indicators. This is to say, the real economic activity indicators, such as real GDP growth rate, tend to react at a lag to economic information realised today. Supporting this notion is Schwert (1989) who documented evidence that financial volatility strongly helped in predicting future macroeconomic volatility. Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) examined – theoretically and empirically – the effect of increased uncertainty on the decision-making of a firm, and concluded that stock-returns volatility increased the “cautionary” behaviour in undertaking investment activities. They documented that an increase in uncertainty induced by major economic shocks could even weaken subsequent monetary and fiscal policies. The analysis was also inferred for the labour market, with an increase in uncertainty leading to more caution in employment responses. Particularly for the short-term investment dynamics for the large manufacturing firms under study, an increase in uncertainty reduced the demand for investment.

With some authors proposing that an increase in volatility and uncertainty only signifies a decrease in future output, Gilchrist, Sim, and Zakrajsek (2010) tested causality issues. They documented that an increase in uncertainty increased the cost of capital, which would, in turn, lead to a decline in total factor productivity through an increase in inefficient allocation of resources. The decline in total factor productivity would then lead to a fall in economic activity. If economic agents perceived and interpreted an increase in stock market volatility as an increase in the general uncertainty of the economy, then investment would fall, with output following. By employing firm-level and aggregated time-series data, Gilchrist et al. (2010) showed that uncertainty shock and financial friction can lead to fluctuations in real economic activity. On the other hand, Poterba (2000) argued that an increase in stock market volatility influenced future output via consumption; in particular, an increase in a stock value by a dollar would lead to an increase in consumption, after about a year, by between one and two cents. This line of analysis falls on the same footing with Romer (1990), who developed a model in which stock market volatility was associated with uncertainty about future real economic activities, and impacted the economy through a decrease in consumption and investment. Even though there seem to be different channels through which future output is influenced by today's stock prices, economists agree on their final impact on future output.

Unlike Poterba (2000), Romer (1990) did not limit the analysis to the asset holders only, but extended the analysis to non-stock asset holders. If the non-asset holders perceived the high volatility as a signal for uncertainty, they would reduce their consumption and investment levels. Likewise, if both the asset holders and the non-asset holder viewed lower stock market volatility as a sign of stability, then consumption and investment increased. We would expect the VIX, now deemed the "investors' fear barometer", to disseminate similar information, both to assets and non-asset holders. In a US empirical analysis for the period 1949-1986, Romer (1990) showed that twice as much increase in stock market volatility reduced durable consumer goods demand by about 6%, while the effect on non-durable goods was insignificant. Jansen and Nahuis (2003) confirmed the existence of this mechanism by analysing the relationship between stock returns and consumer sentiments. In their study, they found that stock returns and consumer sentiments moved in the same direction, and that causality ran from stock returns to consumer sentiments, and not vice versa.

In line with Romer (1990), Raunig and Scharler (2011) used the post-war US data to analyse the relationship between realised stock market volatility and the real sector. They found that high levels of realised stock market volatility exert a negative impact on the growth rate of durable consumption and investment. However, there was a limited effect on non-durable consumption. Moreover, Choudhry (2003) found a similar result by analysing the stock market volatility and GDP and GDP components. In an error-correction framework, he found that stock market volatility had adverse effects on consumption and investment. Since the consumption of durable goods and investment tend to be of lump-sum nature in acquisitions, and is usually irreversible or very costly to undo, high levels of uncertainty will drive away economic agents from embarking on these irreversible expenditures.

There is both theoretical and empirical evidence suggesting that the stock market receives and processes information at a quicker rate than the real sector. Driven by this ability of the stock market, different variables have been identified, as discussed above, and some have been shown to carry information to forecast output. However in recent years, the ability of these variables to carry information has gone down, and as such there is need to come up with new forecasting tools while still maintaining the relevance of the stock market in forecasting. This chapter proposes such a tool by introducing a new forward-looking variable in VIX to forecast output, and compares the forecasting information to the traditional stock returns.

# 3 Methodology

This section begins by laying out the theoretical and empirical nexus between uncertainty and future economic activity, and this will be followed by empirical analysis that is presented in three stages. Firstly, the chapter examines the in-sample relationship between implied volatility and stock returns. Secondly, it investigates the in-sample contributions of stock returns and implied volatility in forecasting output at different horizons. Lastly, for those countries with long enough data series (Germany and the US), the study explores the out-of-sample properties of these predictors. To begin, we explore the theoretical connection between these variables in the next subsection.

## 3.1 Theoretical Link: Uncertainty and the real sector

This section outlines different theories that point towards the negative relationship between uncertainty and growth rates. We describe the mechanisms through which uncertainty affects the economic activity, which will be used as a basis for our empirical models. We begin by exploring the theoretical postulate of Song (2003), and later incorporate other theoretical formulations on irreversible investment and the option value of waiting. Song (2003) develops two models based on the model of Black and Scholes (1973), and shows that an increase in uncertainty has a negative impact on output. The first model has an indirect effect via the human capital channel, while the second model shows the impact of uncertainty directly on the production function.

#### 3.1.1 First model

The first model considers that all consumers have an identical utility function given as:

$$E_0 \sum_{t=0}^{\infty} \beta^t (\ln c_t + \alpha \ln d_t) , \tag{1}$$

where $c_t$ and $d_t$ are consumption and leisure in period *t* respectively. $\beta$ and $\alpha$ are time preference parameter and elasticity of substitution between consumption and leisure respectively.

The production function of each individual firm is given by:

$$y_t = h_t l_t , \tag{2}$$

where $y_t$ is output and $h_t$ and $l_t$ are human capital level, and a fraction of time allocated to production in period *t* respectively. The shock is assumed to hit the human capital accumulation technology. The human capital accumulation technology is given by:

$$h_{t+1} - h_t = (\gamma u_t + \varepsilon_{t+1}) h_t \tag{3}$$

where $u_t$ is the proportion of time devoted to learning, $\varepsilon_{t+1}$ is an i.i.d. shock realised at the beginning of period *t+1* and is only one source of fluctuation in this economy, with its variance an increasing function of $u_t$. The functional form of the relationship between $\varepsilon_{t+1}$ and $u_t$ is represented by the equation:

$$\varepsilon_{t+1} = \sigma \tilde{\varepsilon}_{t+1} u_t , \tag{4}$$

where $\tilde{\varepsilon}_{t+1}$ is i.i.d. shock realised at the beginning of period *t+1*, which takes a value on a small interval around zero with mean zero and finite variance. A parameter to allow mean preserving spread is given by $\sigma$ and is incorporated to capture the impact of an increase in uncertainty on the choice of $u_t$ and hence on the growth rate. Specifically the variance is given by:

$$Var\,(\tilde{\varepsilon}_{t+1}) = \Omega(u_t) = \sigma^2 \xi u_t^2, \tag{5}$$

where $\xi$ is the variance of $\tilde{\varepsilon}_{t+1}$ .

Through the use of the Bellman equation, Song (2003) shows that the solution reduces to:

$$\frac{1+\alpha}{1-u} = \frac{\beta}{1-\beta}\int\left(\frac{\gamma+\sigma\varepsilon}{\gamma u+\sigma\varepsilon u+1}\right)f(\varepsilon)d\varepsilon \tag{6}$$

The first differential of the function above with respect to the shock $\varepsilon$ is less than zero for $\sigma > 0$, implying an increase in uncertainty in the investment technology of human capital results in a decrease in the investment, and as a result growth rate decreases.

Since VIX captures uncertainty as it is a variant of variances, but with unique characteristics, its information can be harnessed to establish the relationship between external shocks emanating from the volatility, captured by VIX, to future changes in real sector. As put forward by Whaley (2000), VIX acts as an "investor fear gauge", given this and the prior argument, we propose that:

- An increase in volatility (captured by VIX) will bring about a decrease in future output.
- Since VIX is forward-looking, it forecasts output more efficiently than any other volatility measure.

#### 3.1.2 Second model

The second model takes a similar approach to the first model, but the impact of the uncertainty shock hits the production technology directly.

Song (2003) assumes a production function of the form:

$$y_t = (A_t + A)h_t l_t, \tag{7}$$

where $A_t + A$ is total factor productivity (TFP) in period $t$, while $A$ is a constant.

Human capital accumulation is given as:

$$h_{t+1} - h_t = \gamma u_t h_t \tag{8}$$

Technology shock affects TFP as:

$$A_{t+1} = \varepsilon_{t+1}, \tag{9}$$

where $\varepsilon_{t+1}$ is an i.i.d. shock with mean zero realised at the beginning of period *t+1*.

It is further assumed that the impact of the shock takes the form:

$$\varepsilon_{t+1} = \sigma \tilde{\varepsilon}_{t+1}(1 - q_t) \tag{10}$$

$q_t$ is a proportion of time devoted to controlling the impact of the shock.

Using Bellman's equation, Song (2003) shows that solution to the objective function reduces to:

$$\frac{(\alpha + (1-\beta)\gamma\alpha)}{(1-\beta)(1+\gamma(1-q))} = -\beta \int \left( \frac{\sigma}{\sigma\varepsilon(1-q) + A} \right) \varepsilon f(\varepsilon) d\varepsilon \tag{11}$$

To analyse the impact of an increase in shock on output, he differentiates this function with respect to $\sigma$. An increase in $\sigma$ leads to an increase in the function above and that $(1 - q)$ goes down. This implies the value of $q$ increases with equilibrium value of $u$ deceasing. The value of $q$ is then given by:

$$(1 - q) = D + (1 + \gamma D)u \,, \tag{12}$$

where $D = \{(1 - \beta)(1 + \alpha)\} / \{\beta\gamma\}$

So, when uncertainty increases, people channel more resources into an activity that reduces its impact, and in turn reduces growth rates, and vice versa. This model shows a negative relationship between uncertainty and growth rate. Since VIX captures uncertainty, an increase in the value of VIX implies a decrease in future economic activity.

### 3.1.3 Other theoretical link

Fornari and Mele (2013) develop a theoretical model in which a firm makes its decision to produce given a signal derived from the economy. The model is built on the assumptions that the firm is a monopoly, operates in two periods, produces in the first period and sells in the second period. The firm faces an inverse demand function of the following specification;

$$D^{-1}(Q) \equiv a + \tilde{v} - \lambda Q \tag{13}$$

where $a$ and $\lambda$ are constants, $Q$ is total demand, and $\tilde{v}$ is a demand shock which is assumed to be normal with mean zero and constant variance. The firm's decision to produce is subject to observing signal $s$ on $\tilde{v}$, where $s = \tilde{v} + \varepsilon$ and $\varepsilon \sim N(0, \sigma^2)$. This signal $s$ represents the information firms can observe today having an impact in the future. Since firms are uncertain about the future, this signal ameliorates some of the uncertainty, for example, near-constant exchange rate, favourable monetary policy, stable political climate etc.

To show the impact of uncertainty on production, the analysis is based on three assumptions:

1) The firm managers are risk neutral and maximise the value of the firm.
2) The firm's cost is linear and takes the form, $C(Q) = zQ$, $z$ is a constant.
3) The interest rate is zero.

Fornari and Mele (2013) show that production only takes place if the signal on $s$ reaches a certain cut-off value, $\hat{s} \equiv -\frac{a - z}{\phi}$, where $\phi = \frac{n-1}{n}$ and $n$ is defined as the signal-to-noise ratio. With these conditions fulfilled, the stock price $P$, production $Q$, and the volatility of the returns $Vol$, are all functions of the current signal $s$ and equal;

$$P(s) = \frac{\phi^2}{4\lambda}(s - \hat{s}), \quad Q(s) = \frac{\phi^2}{2\lambda}(s - \hat{s}), \quad Vol = \frac{2\sigma\sqrt{1-\phi}}{\phi(s - \hat{s})} \text{ and for all, } s > \hat{s} \tag{14}$$

As shown above, production growth is positively, linearly, related to signal $s$. Since $s$ captures the information a firm observes before making a decision on production, this implies stock market volatility (VIX) can be used to capture such information. In particular, $s = (vix)^{-1}$, where *vix* is the implied stock market volatility. As noted by Whaley (2000), VIX acts as an “investor fear gauge”, hence the information given by VIX gives a signal to the firm about the state of the economy. Since implied volatility is inversely related to signal *s*, as signal on future demand worsens, realised volatility increases severely. This implies VIX, captured as a signal to the firm, can be used as a tool to predict stock prices, stock market volatility, and output.

The first theoretical outline suggests that an increase in volatility will cause a decrease in output through the labour market. The second suggests a direct effect of uncertainty, induced by an increase in volatility, on future output. Both propositions give a strong theoretical link between volatility and output. The third theoretical formulation ties down the stock market returns, realised stock market volatility, and future output, in light of uncertainty. Firms observe the state of the economy (the level of uncertainty) before making a production decision. It can be summarised that all theoretical propositions point towards the important role uncertainty plays in an economy.

In this context, the important question is how to measure uncertainty. We recall that an increase in implied stock market volatility reflects an increase in uncertainty over the future developments of the economy. This may not only signal reduced economic activities, but may actually cause a decrease in economic activities. Through the financial accelerator hypothesis, an increase in implied stock market volatility makes the future value of collateral more uncertain, thereby inducing financial intermediaries to reduce the volume of funds supplied to the real sector (Borio, Furfine, & Lowe, 2001). Overall, the theory behind uncertainty entails that implied stock market volatility can be used to forecast realised stock market volatility, stock returns, and output.

## 3.2 Empirical specification and procedures: Stock returns, implied volatility and future output

The empirical specification and procedures include two elements. Namely, we consider the relationship between stock returns and implied volatility, and their combined effect on output. Below, we describe these empirical models and their estimation.

### 3.2.1 Implied volatility and stock returns

This section provides a theoretical and empirical link between stock market volatility and stock returns. Following Merton (1980), Schwert (1989) and Guo (2002), among others, we assume a positive and linear relationship between stock returns and implied volatility of the form:

$$E_t e_{t+1} = \gamma E_t \sigma^2_{t+1} \tag{15}$$

where $E_t e_{t+1}$ is stock returns variable, $E_t \sigma^2_{t+1}$ is implied volatility, and $\gamma > 0$ is a measure of relative risk aversion.

In line with the existing literature, we model the implied volatility as an AR(1) process of the form:

$$\sigma^2_{t+1} = \alpha + \beta\sigma^2_t + \varepsilon_{t+1} \tag{16}$$

As shown in Guo and Whitelaw (2000) and Guo (2002), by assuming a log-linear relationship, equations (15) and (16) imply:

$$e_{t+1} \approx \gamma\alpha + \gamma\beta\sigma^2_t - \frac{\gamma\rho\beta}{1-\rho\beta}\varepsilon_{t+1} + \eta_{d,t+1} \tag{17}$$

where $\rho$ is a constant slightly less than 1, and $\eta_{d,t+1}$ is the shock to expected future dividend growth.

Equation (17) shows that current implied volatility can be used to forecast future stock returns. Furthermore, Guo (2002) shows that, by rearranging terms in equation (17), equation (18) can be derived and takes the form,

$$e_{t+1} \approx \frac{\gamma\alpha}{1-\rho\beta} + \frac{\gamma\beta\sigma^2_t}{1-\rho\beta} - \frac{\gamma\rho\beta}{1-\rho\beta}\sigma^2_{t+1} + \eta_{d,t+1} \tag{18}$$

Equation (18) shows that current volatility has a positive effect on future stock market return, while future volatility is negatively related to future stock market return. This is because of the volatility feedback effect, which is explained by the serial correlation in variance (more information on the derivation in Appendix 1).

### 3.2.2 Output and implied stock market volatility and stock returns: In-sample analysis

To analyse the contributions of implied stock market volatility and stock returns on forecasting output, we follow the standard models in the literature.[4] Firstly, we make the in-sample forecasting based only on lagged GDP growth rate, hereafter called the "benchmark model", as specified below:

$$y_{t+k} = \beta_0 + \sum_{i=1}^{4} \alpha_i y_{t-i} + \varepsilon_{t+k} \qquad (19)$$

where $y_{t+k} = \frac{400}{k} \ln(\frac{y_{t+k}}{y_t})$ is the annualised $k$ quarters ahead growth rate, $y_{t-i} = 400 \ln(\frac{y_{t-i+1}}{y_{t-i}})$ is the output growth rate lagged $i$ times and $\varepsilon_{t+k}$ is an error term (a factor of 400 standardises the growth rates into annual percentage growth). In literature, for data based on quarterly data, permitting an autoregressive component of four lags is sufficient to capture the output autocorrelation (Baltzer & Kling, 2007; Bordo & Haubrich, 2008; Poke & Wells, 2009). This framework is proposed because as with most time series, the variable, $y_{t+k}$ is serially correlated, implying its own past values contain forecasting information.

To analyse if a candidate variable, $X_t$, is useful for predicting output, a relatively straightforward method is to include a candidate variable in equation (19). One way of assessing the forecasting impact of variable $X_t$ (for example, the current implied stock market volatility) on future output, $y_{t+k}$, is to test the hypothesis that $X_t$'s parameter is zero against the alternative that it is different from zero. If the coefficient is statistically different from zero, then today's value of a candidate variable can be adopted in forecasting output, as it contains information over and above that embodied in the past values of the dependent variable.

Primarily, the economic assessment of the predictive ability is hinged upon the value of $R^2$ and variance of the regression. This relatively straightforward way is prone to some hiccups. Since the definition of the dependent variable implies overlapping data, the

[4] For example Harvey (1997), Stock and Watson (2003), Poke and Wells (2009) and Schrimpf and Wang (2010)

contemporaneous variance of the error term can be correlated with the regressor $X_t$ (heteroskedastic) and might also be the case that the error term itself is correlated with its previous values (autocorrelation). Adopting standard errors from this regression for inference purposes may be misleading. To circumvent this problem, all inferences should use heteroskedastic and autocorrelation consistent (HAC) standard errors – we therefore use the Newey and West (1986) correction for heteroskedasticity and autocorrelation.

The first model to forecast output will only contain stock returns as a candidate forecasting variable hereafter called the "*model 1*". This is done essentially for comparative purposes. The basic forecasting equation is given by:

$$y_{t+k} = \beta_0 + \beta_1 sr_t + \sum_{i=1}^{4} \alpha_i y_{t-i} + \varepsilon_{t+k} \qquad (20)$$

where $y_{t+k}$, is the cumulative output growth rate over the next *k* quarters, $sr_t$ is the holding period stock returns in period[5] *t*, $y_{t-i}$ is the lagged growth rate, $\beta_0, \beta_1$ and $\alpha_i$ are unknown parameters, and $\varepsilon_t$ is a contemporaneous error term.

The variable to forecast is denoted $y_{t+k}$; this is the output growth rate at different forecasting horizons, *k*, and this equation will be used to quantify the in-sample forecasting relationship between output and stock returns.

The analysis will continue by investigating the output forecasting information contained in the implied stock market volatility variable, VIX, hereafter called the "*model 2*". The econometric equation takes the form:

$$y_{t+k} = \beta_0 + \beta_2 {\sigma^2}_t + \sum_{i=1}^{4} \alpha_i y_{t-i} + \varepsilon_{t+k} \qquad (21)$$

[5] HPR is preferred because we are looking at uncertainty and return, it is important we take into account the holding period of the stock. The holding period turns to affect the risk on return of a stock. For example, McEnally (1985) finds that the standard deviation of annual stock returns decreases as the holding period increases.

where $\sigma^2{}_t$ is the implied stock market volatility in period *t*, and , $\beta_0, \beta_2$ and $\alpha_i$ are unknown parameters.

The final step in the in-sample analysis is to compare the impact of the two explanatory variables by combining the explanatory variables into one equation, hereafter called the "*model 3*", which takes the form:

$$y_{t+k} = \beta_0 + \beta_3 sr_t + \beta_4 \sigma^2{}_t + \sum_{i=1}^{4} \alpha_i y_{t-i} + \varepsilon_{t+k} \tag{22}$$

where $y_{t+k}$ , is the cumulative output growth rate over the next *k* quarters, $sr_t$ is the stock returns in period *t*, $\sigma_t$ is the implied stock market volatility in period *t*, $y_{t-i}$ is the lagged growth rate, and $\varepsilon_t$ is an error term.

#### 3.2.3 Output and implied stock market volatility and stock returns: Out-of-Sample Analysis

The out-of-sample analysis is based on pseudo out-of-sample evaluation, and is based on *rolling regressions* and robustness check is conducted using *recursive regressions*. Rolling regressions only consider data available prior to making the forecast. For example, assuming we have quarterly data for the period 1990:1 to 2012:1, we start by selecting a window, *m*, and say 1990:1-2000:1. By only utilising data available to the end of sample *m*, we make a forecast for the period *m+1*, that is 2000:2, as if we were actually in 2000:1, and compare this forecast with the actual realisation of the period *m+1* values. The next step is to drop the 1990:1 data point as we add the 2000:2 data point and make *m+1* forecast. This is repeated each quarter ahead up to the end of the sample. This is different to recursive regressions that do not drop earlier data points as successive data points are added at each forecast. To analyse the performance of the candidate forecast, we compare the mean squared forecast error (MSFE) of the benchmark model (the one that only uses lagged GDP growth rates as an explanatory variable) with the MSFE of the candidate forecast. Specifically, the comparative equation of the MSFEs is given by;

$$[n^{-1} \sum_{t=m+1}^{T-k} (y_{t+k} - \hat{y}_{1t+k})^2] / [n^{-1} \sum_{t=m+1}^{T-k} (y_{t+k} - \hat{y}_{st+k})^2] \tag{23}$$

where $\hat{y}_{1t+k}$ is output forecast value for period $t+k$ from the benchmark model and $\hat{y}_{st+k}$ represents the output forecasting value for period $t+k$ for each of models 1, 2 and $3, m+1$ and $T-k$ are, respectively, the first and last day of the pseudo out-of-sample forecast period. If the relative MSFE is greater than one, then the candidate forecasting equation is considered to contain more forecasting information than the benchmark model. However, there is a need to formally test this hypothesis. Since the analysis involves nested models, Diebold and Mariano (1995) will not be appropriate; instead we use the Clark and West (2007) method. This methodology tests the null hypothesis that the difference between squared forecasting errors (SFE) from the benchmark and forecasting models (equation 21, or 22), after correcting for the noise from nested models, is not statistically different from zero against the alternative.

Specifically, to test the significance of the difference between the two SFE, we run the variable $\hat{f}_{t+k}$, defined below, on a constant and test the significance of the constant.

$$\hat{f}_{t+k} = (y_{t+k} - \hat{y}_{1t,t+k})^2 - [(y_{t+k} - \hat{y}_{st,t+k})^2 - (\hat{y}_{1t,t+k} - \hat{y}_{st,t+k})^2] \tag{24}$$

If the test rejects the zero coefficient of the constant, then the forecasting equation is superior to the benchmark model.

# 4 Empirical Results

This section first presents the full in-sample empirical results, and then proceeds to give the split “two in-sample” results before giving out-of-sample results.

## 4.1 In-Sample results

### 4.1.1 Stationarity and Structural break tests

Before performing the regression, we subjected the data to unit root tests and augmented Dickey–Fuller tests. The results of these tests indicates that all other variables were stationary except for VIX. The VIX variable was non-stationary for France and the Netherlands. For robustness purposes, we used the Clemao unit root test in the presence of structural break (Clemente, Montañes, & Reyes, 1998), and the tests suggested that, for the case of Germany, there was one structural break point (1998), and for the US there were two structural break points (1998 and 2008). For the data that contains unit roots, appropriate differencing was undertaken to correct for non-stationarity.

#### 4.1.2 Stock Returns Forecasting

As suggested by Banerjee et al. (2007) and Yan (2011), the growth rate of lagged implied stock market volatility may contain stock returns forecasting information. In light of this proposition, we estimate equation 18 including the growth rate of lagged VIX variable as a predictor.

The table below reports the regression results of stock returns on implied stock market volatility ( $sr_{t+1} = \beta_0 + \beta_1\sigma_t^2 + \beta_2\Delta\sigma_t^2 - \beta_3\sigma_{t+1}^2 + \varepsilon_{t+k}$ ). As shown in Table 1, the regression results returned the correct coefficient signs as predicted by theory; that is, current implied stock market volatility had a negative relationship with stock returns, lagged, and the growth rate of lagged implied stock market volatility had a positive impact on stock returns.

**Table 1: VIX-Stock Returns forecast**

| *Country:* | Belgium | UK | France | Germany | Japan | Netherlands | US |
|---|---|---|---|---|---|---|---|
| *Variable* | | | | | | | |
| $\sigma^2_{t+1}$ | -10.31*** | -3.92 | -3.08 | -4.39*** | -4.79*** | -2.66 | -3.83*** |
| | (0.00) | (0.16) | (0.39) | (0.00) | (0.01) | (0.74) | (0.01) |
| $\sigma^2_t$ | 9.57*** | 3.66 | 2.88 | 3.97** | 4.51*** | 2.57 | 3.79*** |
| | (0.00) | (0.20) | (0.42) | (0.00) | (0.01) | (0.42) | (0.01) |
| $\Delta\sigma^2_t$ | 0.33*** | 0.18 | 0.09 | 0.20* | 0.19 | 0.0.03 | 0.19** |
| | (0.01) | (0.24) | (0.66) | (0.06) | (0.17) | (0.44) | (0.02) |
| R-Sq | 0.33 | 0.10 | 0.11 | 0.09 | 0.15 | 0.15 | 0.08 |

**Note:** $\sigma^2_{t+1}$, $\sigma^2_t$ and $\Delta\sigma^2_t$ are current, lagged, and lagged growth rate of implied stock market volatility and R-Sq is R squared. P-value is reported in parenthesis and *, **, and *** denote significance at 1%, 5% and 10% levels.

Of the seven countries under investigation, Belgium, Germany, and the US had a significant relationship between stock returns and all the implied volatility variables, while for Japan, current and lagged stock market volatility were both significant, however the innovation element was insignificant. Nevertheless, for the UK, France, and the Netherlands, the results suggested the instantaneous, lagged growth rate, and lagged implied volatility did not contain statistically significant stock returns relationship.

#### 4.1.3 Output Forecasting Results

Table 2 report results on the output predicting power of stock returns for three different forecasting horizons for seven developed countries. For brevity, in all subsequent output tables, the constant and four coefficients of the lagged real GDP growth rate results are not reported, but available upon request.

For all the countries, stock returns contained forecasting information for one-quarter-ahead output, with results statistically significant at the 10% level, but the relationship was weaker for the UK, Germany and Japan. At a two-quarter-ahead forecasting, stock returns statistical significance for Germany improved, with the UK losing significance. For all subsequent forecasting horizons, the UK's stock returns forecasting power was statistically insignificant, while all other countries' forecasting power was statistically significant, at least at the 10% level. Even though economic significance is debatable, stock returns contained some forecasting information, at least for the sample period under review.

**Table 2: Stock returns: GDP growth forecast (Equation 22 without VIX, Model 1)**

| *Country:* | Belgium | UK | France | Germany | Japan | Netherlands | US |
|---|---|---|---|---|---|---|---|
| *Forecasting horizon* | | | | | | | |
| Q1 $sr_t$ | 0.03*** | 0.02* | 0.02*** | 0.01* | 0.03* | 0.02*** | 0.04*** |
| | (0.00) | (0.09) | (0.01) | (0.07) | (0.07) | (0.00) | (0.00) |
| Adj-R-Sq | 0.61 | 0.65 | 0.44 | 0.07 | 0.20 | 0.41 | 0.39 |
| Q2 $sr_t$ | 0.04*** | 0.02 | 0.03*** | 0.03** | 0.04* | 0.04*** | 0.04*** |
| | (000) | (0.11) | (0.00) | (0.03) | (0.08) | (0.00) | (0.00) |
| Adj-R-Sq | 0.58 | 0.53 | 0.63 | 0.17 | 0.25 | 0.57 | 0.51 |
| Q4 $sr_t$ | 0.03*** | 0.001 | 0.03*** | 0.03*** | 0.03*** | 0.03*** | 0.04*** |
| | (0.00) | (0.78) | (0.00) | (0.01) | 0.00) | (0.01) | (0.00) |
| Adj-R-Sq | 0.50 | 0.43 | 0.42 | 0.25 | 0.24 | 0.35 | 0.45 |

**Note:** Q1, Q2 and Q4 are one-quarter-ahead through four quarter-ahead-forecasting horizons, and Adj-R-Sq is adjusted R squared. P-value is reported in parenthesis and *, **, and *** denote significance at 1%, 5% and 10% levels.

The above analysis tested the forecasting relationship between stock returns and future output; we extended the analysis to implied stock market volatility (VIX) and output. As shown in Table 3, for all countries the relationship between current VIX and future output took the correct sign as suggested by literature. Of all the seven countries, it was only the UK and the US that rejected the null hypothesis that current VIX contains forecasting information for one, two, and four-quarter-ahead forecasts, with other countries confirming the existence of forecasting information. However, the relationship tended to weaken as the forecasting horizon was extended.[6] Comparing Table 2 and 3, stock returns performs better for Belgium, UK and the US while VIX does better for France, Germany, Japan and the Netherlands.

**Table 3: (VIX)-GDP growth forecast (Equation 22, without sr, Model 2)**

| *Country:* | Belgium | UK | France | Germany | Japan | Netherlands | US |
|---|---|---|---|---|---|---|---|
| *Forecasting horizon* | | | | | | | |
| Q1 $\sigma_t^2$ | -0.16*** | -0.03 | -0.10*** | -0.13** | -0.34*** | -0.18*** | -0.09 |
| | (0.01) | (0.46) | (0.01) | (0.02) | (0.01) | (0.00) | (0.13) |
| Adj-R-Sq | 0.50 | 0.63 | 0.39 | 0.19 | 0.36 | 0.52 | 0.28 |
| Q 2 $\sigma_t^2$ | -0.16** | -0.03 | -0.11*** | -0.14** | -0.26*** | -0.18** | -0.07 |
| | (0.03) | (0.62) | (0.01) | (0.03) | (0.00) | (0.02) | (0.14) |
| Adj-R-Sq | 0.33 | 0.50 | 0.41 | 0.25 | 0.31 | 0.40 | 0.27 |
| Q4 $\sigma_t^2$ | -0.14* | -0.01 | -0.08*** | -0.08*** | -0.19*** | -0.11*** | -0.03 |
| | (0.06) | (0.87) | (0.00) | (0.01) | (0.00) | (0.00) | (0.32) |
| Adj-R-Sq | 0.19 | 0.19 | 0.16 | 0.14 | 0.27 | 0.11 | 0.14 |

**Note:** Q1, Q2 and Q4 are one-quarter-ahead through four-quarter-ahead forecasting horizons, and Adj-R-Sq is adjusted R is squared. P-value is reported in parenthesis and *, **, and *** denote significance at 1%, 5% and 10% levels.

The next step was to regress both the stock returns and implied volatility on different levels of future output horizon. The correlation between VIX and stock returns was less than 0.27 for all countries, except for the Netherlands with 0.33, which kept the possibility of multicollinearity at bay. In addition, variance inflation factors for all countries were less than 4, implying multicollinearity was not a problem.

As Table 4 shows, the forecasting information contained in implied stock market volatility was statistically significant for all countries under review at a one-quarter-ahead output forecast. However, the prediction of stock returns for the UK, German and Japan became statistically insignificant. For these countries (UK, German and Japan), the relationship between stock returns and future output for the equation that contains only stock returns was weak. Implying the stock return did not provide any further forecasting information beyond what is contained in VIX index.

The results for two-quarter-ahead forecasting of output by stock returns and implied stock market volatility showed that both covariates were statistically significant for all countries except the UK and Japan. Both variables were statistically insignificant for the UK; however, for the case of Japan, it was only implied stock

[6] See e.g., Eickmeier and Ziegler (2008)

market volatility that was significant. The UK output forecasting has always been weaker compared to other countries, this is consistent with the findings of Eickmeier and Ziegler (2008) who, using meta-analytic approach, show that output forecasting for UK is weaker compared to the US. This may be attributed to heterogeneity difference across countries, for example, difference in perceived risk, risk tolerance and the relative importance attached to financial data by economic agents. Since stock returns were significant before the addition of the VIX variable, this means the information content of the VIX encompassed that of stock market for the first and second forecasting horizons for Japan.

**Table 4: Stock returns and (VIX)-GDP growth forecast (Equation 22, Model 3)**

| | *Country:* | Belgium | UK | France | Germany | Japan | Netherlands | US |
|---|---|---|---|---|---|---|---|---|
| *Forecasting horizon* | | | | | | | | |
| Q1 | SR | 0.03***<br>(0.00) | 0.02<br>(0.11) | 0.02**<br>(0.02) | 0.01<br>(0.35) | 0.02<br>(0.21) | 0.01***<br>(0.00) | 0.04***<br>(0.00) |
| | VX | -0.08**<br>(0.04) | -0.02<br>(0.58) | -0.08***<br>(0.01) | -0.13**<br>(0.04) | -0.31***<br>(0.01) | -0.15***<br>(0.00) | -0.09*<br>(0.06) |
| Adj-R-Sq | | 0.63 | 0.65 | 0.59 | 0.17 | 0.36 | 0.54 | 0.43 |
| Q2 | SR | 0.03***<br>(0.00) | 0.02<br>(0.12) | 0.03***<br>(0.00) | 0.02**<br>(0.04) | 0.03<br>(0.15) | 0.03***<br>(0.00) | 0.04***<br>(0.00) |
| | VIX | -0.06**<br>(0.03) | -0.02<br>(0.77) | -0.07***<br>(0.00) | -0.12**<br>(0.03) | -0.22***<br>(0.00) | -0.10***<br>(0.03) | -0.06**<br>(0.03) |
| Adj-R-Sq | | 0.59 | 0.52 | 0.68 | 0.30 | 0.37 | 0.63 | 0.54 |
| Q4 | SR | 0.03***<br>(0.00) | 0.002<br>(0.75) | 0.03***<br>(0.00) | 0.02**<br>(0.02) | 0.02**<br>(0.02) | 0.03***<br>(0.00) | 0.04***<br>(0.00) |
| | VX | -0.05<br>(0.19) | 0.01<br>(0.92) | -0.04*<br>(0.09) | -0.06**<br>(0.02) | -0.15***<br>(0.01) | -0.04<br>(0.12) | -0.02<br>(0.24) |
| Adj-R-Sq | | 0.51 | 0.21 | 0.42 | 0.30 | 0.33 | 0.34 | 0.45 |

**Note:** SR and VIX are stock returns and implied volatility respectively. Q1, Q2 and Q4 are one-quarter-ahead through four-quarter-ahead forecasting horizons, and Adj-R-Sq is adjusted R squared. P-value is reported in parenthesis and *, **, and *** denote significance at 1%, 5% and 10% levels.

Extending the forecasting horizon to four quarters saw the statistical forecasting significance of VIX for Belgium, the Netherlands, and the US losing significance. Even though all other countries had a statistically significant four-quarter-ahead VIX-output forecasting, the magnitude of the VIX coefficient decreased. For Japan, VIX and stock returns complemented each other in forecasting, as the stock returns variable was significant.

With every country confirming the existence of stock return forecasting information for GDP at a four quarter forecasting period, while implied stock market volatility lost significance for others, this implies that the VIX was more powerful in forecasting at short horizons compared to stock returns, and vice versa.

### 4.2 The two sample regression

The structural break identified by the Clemao test may suggest the structural shift on the perception of VIX as a fear factor in recent years compared to earlier years (Clemente, Montañes, & Reyes, 1998). The VIX index may have become more important recently due to the 1997 Asian financial crises and the 1998 Russian financial crisis – the "Ruble Crises" (Desai, 2000; Goldstein, 1998). The financial crises in Asia and the fall of the long-term capital management in Russia had a ripple effect on the global futures and options trading, and hence affected the VIX.

Advancements in technology in the financial sector running up to the new millennium–for example algorithmic trading and high-frequency trading – saw an increase in the processing and disseminating of financial information. As pointed out by Stoll (2006), electronic trading has increased efficiency in the financial sector by increasing the speed and lowering the cost of transmitting information, and increased accuracy of price signalling. Furthermore, the creation of many derivatives and an increase in retail investing created a new class of online traders, providing even more avenues to disseminate information. All these factors gave rise to capturing and disseminating information as reflected in the VIX index.

To test if the above-mentioned elements have increased the way VIX captures and disseminates information, we used the Bai and Perron (1998) structural break test. For the US, three breaks were identified; 1997Q3, 2003Q2, and 2007Q3. A Chow test, however, dismissed the 2003 break point. In the case of Germany, only 1997Q3 was identified and was confirmed by Chow test. In light of this, the sample was split into two, sample one (up to 1997Q3) and two (from 1997Q3) for both the US and Germany. We then ran the in-sample forecasting relationship at one, two and four quarter forecasting horizons for each sample.

Table 5 shows the in-sample prediction of output at a one quarter, two quarter and four quarter horizon for Germany and the US, for each sample. Beside the *pre-crisis* relationship having a wrong sign for both countries as predicted by theory, the sample's results were insignificant for the case of the US, and had a relatively smaller coefficient compared to sample 2. For both countries, the *post-crisis* sample assumed the right sign and was statistically significant for the US's one-quarter-ahead forecast, and for all quarters for Germany.

**Table 5: Two sample – Implied stock market volatility and output for Germany and the US**

| *Country* <br> *Horizon* | Sample <br> (*pre-crisis*) | Germany | US |
|---|---|---|---|
| Q1, $\sigma_t^2$ | | 0.17 | 0.08 |
| | | (0.02)** | (0.17) |
| Q2, $\sigma_t^2$ | | 0.24 | 0.04 |
| | | (0.01)*** | (0.46) |
| Q4, $\sigma_t^2$ | | 0.05 | 0.04 |
| | | (0.31) | (0.43) |
| | (*post-crisis*) | | |
| Q1, $\sigma_t^2$ | | -0.17 | -0.13 |
| | | (0.02)** | (0.05)** |
| Q2, $\sigma_t^2$ | | -0.19 | -0.08 |
| | | (0.02)** | (0.13) |
| Q4, $\sigma_t^2$ | | -0.11 | -0.02 |
| | | (0.00)*** | (0.58) |

**Note:** Q1, Q2, and Q4 are one-quarter-ahead through four-quarter-ahead forecasting horizons. P-value is reported in parenthesis and ** and *** denote significance at 5% and 10% levels.

In light of earlier discussion, this shows that implied stock market volatility measured by VIX was gaining more and more forecasting information with time for these two countries under review, with the relationship becoming much stronger and statistically significant in recent years. This implies that this forecasting variable forms a good grounding as a future forecasting tool.

### 4.3 The out-of-sample analysis

We began by analysing the out-of-sample results generated from rolling regressions, and then proceeded to conduct some robust tests by carrying out recursive estimates. As mentioned earlier, due to data limitation, this analysis was limited to the cases of Germany and the US.

### 4.3.1 The out-of-sample analysis – Rolling regression

This subsection discusses the out-of-sample results. We limited the out-of-sample analysis to Germany and the US because other countries did not have sufficient number of observations. We began by running the rolling estimation for the two countries, with the US having a rolling window of 12 years (**48 quarters**), and Germany of 11 years (**44 quarters**). There was no statistical inferences used on window selection, but we selected the window so that there were enough observations and degrees of freedom to run the tests proposed by Clark and West (2007).

**Table 6: Ratio of mean squared forecasting error (MSFE) (Equation 23)**

| *Horizon* | Quarter 1 | Quarter 2 | Quarter 4 |
|---|---|---|---|
| *Country* | | | |
| **Germany** | | | |
| *Model 1* | 1.08* | 1.29* | 1.45* |
| *Model 2* | 1.34* | 1.50* | 1.14* |
| *Model 3* | 1.40* | 1.88* | 1.59* |
| **US** | | | |
| *Model 1* | 1.34* | 1.80* | 1.55* |
| *Model 2* | 1.18* | 1.06* | 1.00 |
| *Model 3* | 1.74* | 2.10* | 1.57* |

**Note:** Quarter 1, Quarter 2, and Quarter 4 are one-quarter-ahead through four quarter-ahead-forecasting, and (*) shows that the MSFE of the candidate model outperforms the benchmark model.

To assess the performance of each candidate model, mean squared forecasting errors (MSFE) were divided by the MSFE of the benchmark model (containing only lagged real GDP growth rates). Table 6 reports the ratio of the (MSFE) of three models; for the case of Germany, all three models outperformed the benchmark model as indicated by greater than 1 MSFE ratios. The MSFE ratios for *model 1* were relatively small to other models over the first and second quarters, implying stock returns carry less out-of-sample forecasting information. However, stock returns did better in the fourth quarter than the VIX model (*model 2)* in forecasting. It is important to note that the combined information of stock returns and VIX significantly outperformed any of the models containing individual variables. On the other hand, for the case of the US, *model 2* did better than the benchmark model for the first and second quarters, nevertheless, at a four quarter forecasting horizon, it did not outperform the benchmark model. Nonetheless, the model containing stock returns alone made less forecasting errors as the MSFE ratios were all greater than 1. However, the forecasting accuracy of *model 3* increased drastically when both variables were utilised in one equation (VIX and stock returns).

To ascertain the statistical significance of the MSFE, we ran the tests proposed by Clark and West (2007) (equation 24) and the results are presented in Table 7 below. Even though the MSFE ratio was greater than 1 for the US's *model 2*, after accounting for the noise factor originating from nested models, the simulated out-of-sample performance for the US was not statistically significant. However, for all three forecasting horizons in the case of Germany, *model 2* showed that the forecasting information in VIX was statistically significant and was stronger at short horizons.

**Table 7: Out-of-sample performance – rolling regressions**

| *Horizon* | Quarter 1 | Quarter 2 | Quarter 4 |
|---|---|---|---|
| *Country* | | | |
| Germany | | | |
| *Model 1* | 0.91(0.19) | 2.45 (0.06)* | 2.64 (0.02)** |
| *Model 2* | 3.1 (0.04)** | 3.6 (0.09)* | 1.1 (0.06)* |
| *Model 3* | 3.5 (0.04)** | 3.8 (0.09)* | 3.2 (0.00)* |
| US | | | |
| *Model 1* | 2.16 (0.03)** | 2.99 (0.04)** | 2.25 (0.03)** |
| *Model 2* | 1.1 (0.32) | 0.41(0.42) | 0.28 (0.61) |
| *Model 3* | 3.03 (0.06)* | 0.41(0.03)** | 2.2 (0.02)** |

**Note:** Quarter 1, Quarter 2, and Quarter 4 are one-quarter-ahead through four quarter-ahead-forecasting. P-value is reported in parenthesis and *, **, and *** denote significance at 1%, 5% and 10% levels.

For *Model 1,* stock returns did a relatively better job in forecasting output in the case of the US than for Germany. After adjusting for the noise emanating from nested models, the stock returns ability to forecast was statistically insignificant for Germany in the first quarter. However, the model that contained both stock returns and implied volatility (*Model 3)* did better for both Germany and the US for all quarters, and the relationship was statistically significant. In addition, this model had a higher forecasting accuracy than any of the models that contained either stock returns or VIX alone. For the US, the relationship was more statistically significant at the two and four-quarter-ahead forecasting horizons than at a one-quarter-ahead forecast.

#### 4.3.2 Robustness Analysis: Out-of-Sample – Recursive regression

To ascertain the robustness of our findings obtained above, we ran recursive regression with the same initial window of 44 and 48 observations for Germany and the US, respectively. We then compared the results thereof to those from rolling regression.

Table 8 reports the MSFEs generated from recursive regression for *models 1* through *model 3*, for both Germany and the US. The results were similar to those obtained using rolling regression except for Germany's second quarter, where *model 2* outperformed *model 3*. The US's *model 2*, fourth quarter, became statistically significant. It is worth noting that, overall, the MSFE ratios generated by recursive forecasting were relatively larger compared with those generated by rolling regression.

**Table 8: Ratio of mean squared forecasting error (MSFE) (Equation 23)**

| *Horizon* | Quarter 1 | Quarter 2 | Quarter 4 |
|---|---|---|---|
| *Country* | | | |
| Germany | | | |
| *Model 1* | 1.08* | 1.22* | 1.35* |
| *Model 2* | 1.27* | 1.42* | 1.16* |
| *Model 3* | 1.30* | 1.41* | 1.48* |
| US | | | |
| *Model 1* | 1.43* | 2.11* | 1.68* |
| *Model 2* | 1.28* | 1.16* | 1.05* |
| *Model 3* | 1.82* | 2.33* | 1.72* |

**Note:** Quarter 1, Quarter 2, and Quarter 4 are one-quarter-ahead through four quarter-ahead-forecasting, and (*) shows that the MSFE of the candidate model outperforms the benchmark model.

To assess the validity of the ratios of MSFE, we corrected for the noise factor present in nested models by performing Clark and West (2007) regressions, and the results are reported in tables below.

**Table 9: Out-of-sample performance – recursive regressions**

| *Horizon* | Quarter 1 | Quarter 2 | Quarter 4 |
|---|---|---|---|
| *Country* | | | |
| Germany | | | |
| *Model 1* | 1.04 (0.10)* | 2.04 (0.13) | 2.24 (0.05)** |
| *Model 2* | 2.8 (0.05)** | 3.3 (0.14) | 1.2 (0.09)** |
| *Model 3* | 3.1 (0.05)** | 3.2 (0.07)* | 2.9 (0.03)* |
| US | | | |
| *Model 1* | 2.52 (0.06)* | 3.99(0.07)* | 3.06 (0.04)** |
| *Model 2* | 1.4 (0.33) | 0.83(0.35) | 0.26 (0.32) |
| *Model 3* | 3.4 (0.11) | 3.9(0.06)* | 3.1 (0.04)** |

**Note:** Quarter 1, Quarter 2, and Quarter 4 are one-quarter-ahead through four quarter-ahead-forecasting. P-value is reported in parenthesis and *, **, and *** denote significance at 1%, 5% and 10% levels.

As shown in Table 9, the recursive regression results on *model 1* gave results which were similar to those generated by rolling regression, except that the result for Germany's second quarter lost statistical significance, with the first quarter becoming insignificant at the

0.1 level. Likewise, the squared forecasting errors for *model 2* were similar to rolling regressions, except for Germany's second quarter result, which became statistically insignificant with a p-value of 0.14. The results for *model 3* were in the same line, with the only difference being the case of the US's first quarter, which became statistically insignificant with a p-value of 0.11. Besides these minor deviations, the results from recursive regressions were similar to the rolling regressions results.

Even though these results were similar, the results from recursive regressions were, on average, slightly weaker than rolling regression. This has a simple interpretation: rolling regression attaches more weight to recent values, while recursive regressions spread the weights to distant past values. This implies that even though the overall picture of the results is the same, using rolling regression brings about slightly improved forecasting accuracy. This is important given the results in Table 5 that indicate that VIX has become more relevant to output changes in recent times than earlier times.

## 5 Conclusion

In this chapter, we show that the newly-constructed index that captures uncertainty in an economy, the VIX index, contained in-sample forecasting information for future stock returns. Extending the analysis to output forecasting for seven countries, it has been demonstrated that VIX had predicting power for five out of the seven countries. Furthermore, its forecasting power was more concentrated at a shorter forecasting horizon than at further horizons. Due to the limited time series data, the out-of-sample analysis was conducted for Germany and the US. For both countries, the mean squared forecast errors of the benchmark model to candidate model was greater than 1, indicating that the VIX may contain forecasting information. Econometrics analysis reveals that the out-of-sample relationship was stronger for Germany, while insignificant for the US. This may be driven by weak forecasting information content of VIX on output for earlier years in the sample. However, as evidenced by splitting the sample into two, the VIX variable has gained more power for Germany and weakly for the US. Using both stock returns and VIX as forecasting variables improved forecasting accuracy, suggesting that both VIX and stock returns complement each other in forecasting. We have shown that VIX contains forecasting information, and as pointed out by Stock and Watson (2003), a combination of VIX with other traditional forecasting tools is likely to result in a significant improvement in forecasting accuracy.

# Appendix 1

## A1. Data

The data was collected for seven developed countries from two different sources. The VIX index and stock prices data were collected from DataStream at a daily level. Arithmetic mean was taken to convert the data from daily frequencies to quarterly. This was done to match the data with the gross domestic product (GDP), which was measured at a quarterly level. The real GDP was used to represent real activities, and was collected from the International Financial Statistics (IMF). Quarterly data spanning different periods depending on the length of the countries' VIX index was used, namely, Belgium and the UK 2000Q1-2012Q1, France 2000Q1-2012Q1, Germany 1992Q1-2011Q4, Japan 1998Q1-2012Q2, the Netherlands 2000Q1-2011Q3 and the US 1990Q1-2012Q1. The choice of the countries was dictated by the availability of data. For the US the VIX index used was the S&P 500. The quarterly annualised holding period (*HPR*) return was computed as follows:

$$HPR_t = \left(1 + \frac{SMI_t - SMI_{t-1}}{SMI_{t-1}}\right)^4 - 1 \qquad 1$$

where SMI is the stock market index for the country in question, and the factor of 4 is to annualise the holding period return.

Realised stock market volatility is calculated as follows:

$$RV_t = 100 * \sqrt{\left(\frac{252}{n} * \sum_{i=1}^{n} R_{t+i}^2\right)} \qquad 2$$

where *RV* is realised stock market volatility, *252* is an annualising factor, which is a constant representing the approximate number of trading days in a year, *n* is the number of trading days in the measurement time frame which is a quarter, and *R* is defined as follows:

$$R_t = \ln\left(\frac{S_t}{S_{t-1}}\right) \qquad 3$$

where $S_t$ is the daily stock market index at time *t* for each respective country.

## A2: Theoretical framework

Following Log linearization method of Campbell et al. (1997) Guo shows

$$E_t sr_{t+1} \cong \gamma E_t \sigma_{t+1}^2 - (E_{t-1} - E_t)[\sum_{j=1}^{\infty} \rho^j \sigma_{m,t+1+j}^2] + \eta_{d,t+1} + \eta_{f,t+1} \quad \text{i}$$

Substituting equation 16 into the equation above16 gives:

$$sr_{t+1} \approx \gamma\alpha + \gamma\beta\sigma_t^2 - \frac{\gamma\rho\beta}{1-\rho\beta}\varepsilon_{t+1} + \eta_{d,t+1} + \eta_{f,t+1} \tag{17}$$

Also equation 16 can be written as:

$$\varepsilon_{t+1} = \sigma_{t+1}^2 - \alpha - \beta\sigma_t^2 \tag{16'}$$

Substituting iii into ii gives:

$$sr_{t+1} \approx \frac{\gamma\alpha}{1-\rho\beta} + \frac{\gamma\beta\sigma_t^2}{1-\rho\beta} - \frac{\gamma\rho\beta}{1-\rho\beta}\sigma_{t+1}^2 + \eta_{d,t+1} \tag{18}$$

**A3. Realized Stock Market Volatility and Output**

For comparison purposes we computed realized stock market volatility (details on calculations in Appendix) and analyse the relationship with output. The below table reports the results of the output forecasting information content of realized stock market volatility. Even though, realized stocked market volatility is statistically significant, implied stock market volatility carries more information.

**Table 1: Realized stock market volatility - GDP growth forecast**

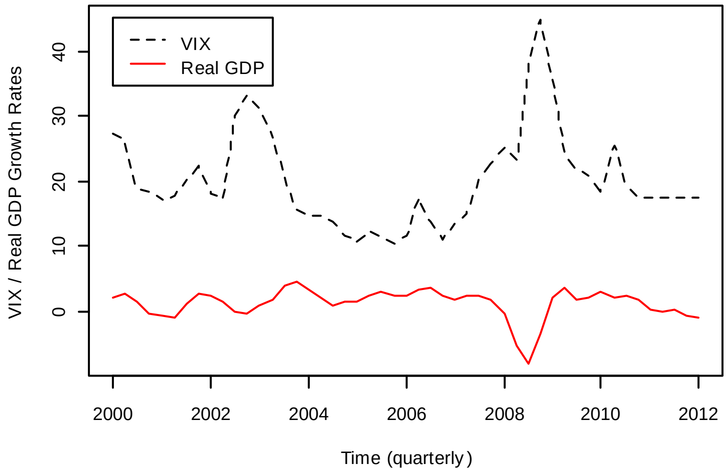
| *Country:* *Forecasting horizon* | Belgium | UK | France | Germany | Japan | Netherlands | US |
|---|---|---|---|---|---|---|---|
| Q1 | -0.10*** | -0.04 | -0.10*** | -0.13** | -0.27*** | -0.10*** | -0.03 |
| | (0.01) | (0.33) | (0.01) | (0.03) | (0.00) | (0.00) | (0.19) |
| Adj-R-Sq | 0.48 | 0.63 | 0.47 | 0.18 | 0.34 | 0.47 | 0.23 |
| Q2 | -0.10*** | -0.03 | -0.06*** | -0.08*** | -0.13*** | -0.10*** | -0.02 |
| | (0.00) | (0.53) | (0.00) | (0.00) | (0.00) | (0.00) | (0.26) |
| Adj-R-Sq | 0.30 | 0.50 | 0.40 | 0.13 | 0.18 | 0.33 | 0.23 |
| Q4 | -0.08** | -0.01 | -0.05*** | -0.06*** | -0.11*** | -0.05*** | -0.004 |
| | (0.02) | (0.83) | (0.00) | (0.00) | (0.01) | (0.01) | (0.89) |
| Adj-R-Sq | 0.13 | 0.18 | 0.15 | 0.09 | 0.16 | 0.04 | 0.12 |

**Note:** Q1, Q2 and Q4 are one-quarter-ahead through four-quarter-ahead forecasting horizons and Adj-R-Sq is adjusted R is squared. P-value is reported in parenthesis and *, **and *** denote significance at 1%, 5% and 10% levels.

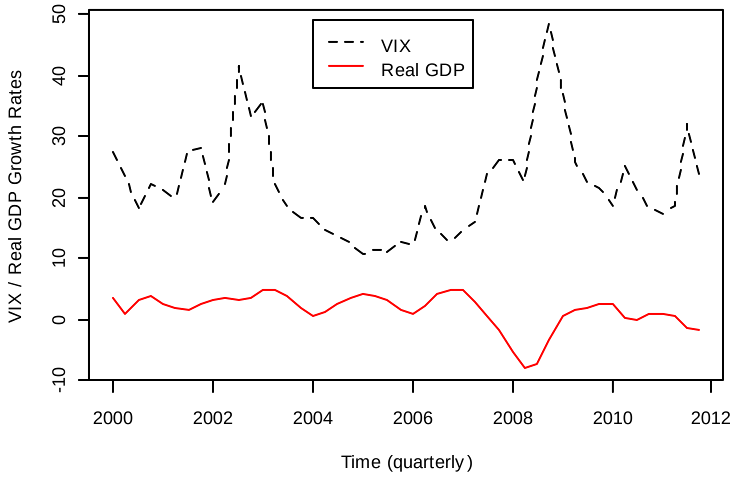
# Appendix 2

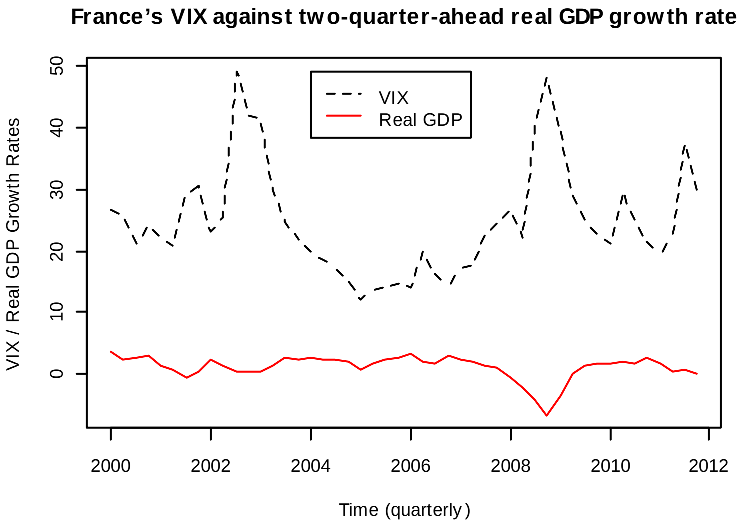
Gives a graphical presentation of the relationship between VIX and future output.

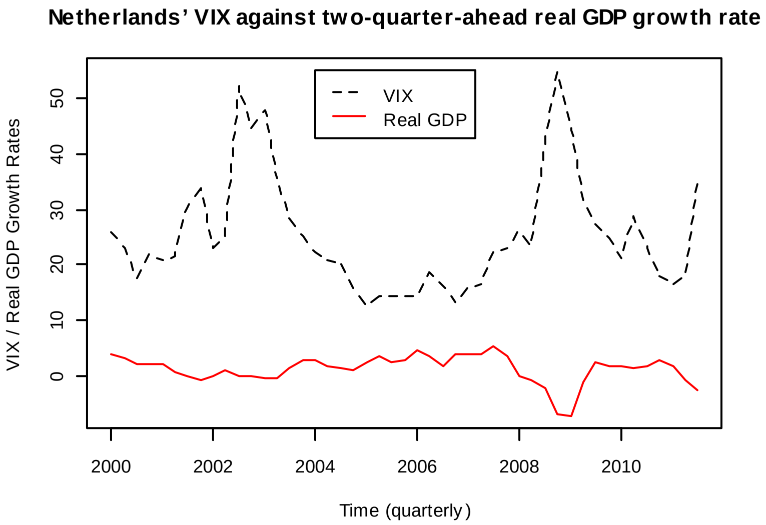
**Belgium's VIX against two-quarter-ahead real GDP growth rate**

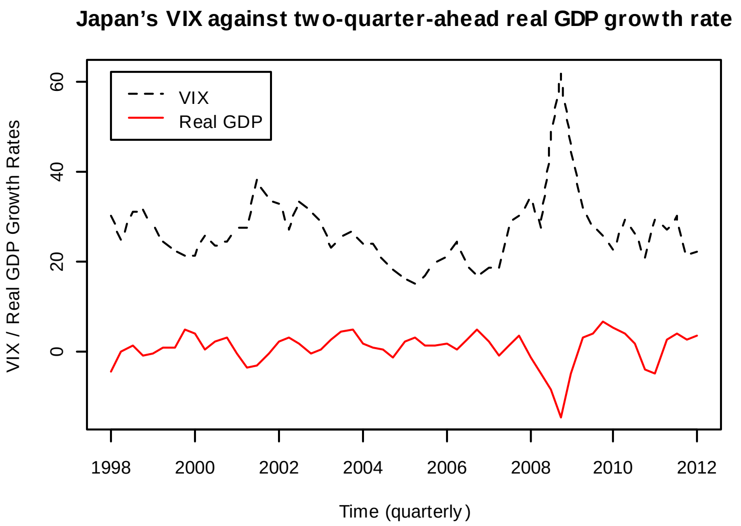



**UK's VIX against two-quarter-ahead real GDP growth rate**

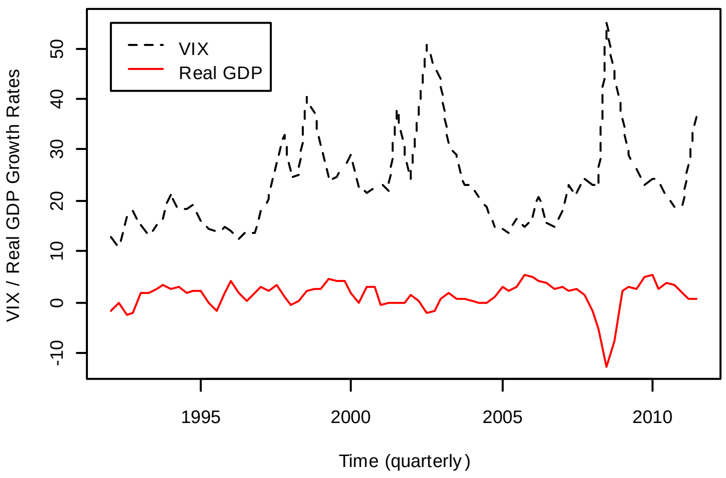



France’s VIX against two-quarter-ahead real GDP growth rate
VIX
Real GDP
VIX / Real GDP Growth Rates
0
10
20
30
40
50
2000
2002
2004
2006
2008
2010
2012
Time (quarterly)

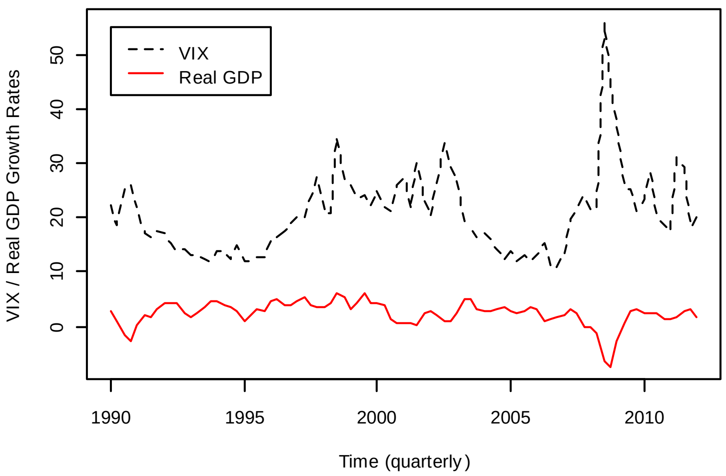

Netherlands’ VIX against two-quarter-ahead real GDP growth rate
VIX
Real GDP
VIX / Real GDP Growth Rates
0
10
20
30
40
50
2000
2002
2004
2006
2008
2010
Time (quarterly)


Japan’s VIX against two-quarter-ahead real GDP growth rate
VIX
Real GDP
VIX / Real GDP Growth Rates
0
20
40
60
1998
2000
2002
2004
2006
2008
2010
2012
Time (quarterly)

**Germany's VIX against two-quarter-ahead real GDP growth rate**




**US's VIX against two-quarter-ahead real GDP growth rate**



# Chapter 3: The Forecasting Properties of a Number of Output Leading Indicators: Evidence from South Africa


## Abstract

This chapter tests the in-sample and out-of-sample forecasting of output growth rates using the composite leading business cycle indicator (CLI) for South Africa, and then compares the results to the traditional term-structure of interest rate. The results show that CLI contains more in-sample forecasting information than the term structure of interest rate, and it is more consistent and stable on the out-of-sample forecasting.


## 1. Introduction

Market analysts, policymakers, and professional economists strive to know more about future developments of the macroeconomy. Economists have long thought that financial asset prices could be used to forecast future output. Nevertheless, it is only since the late 1980s that the relationship has been formally tested.[7] Stock returns and interest rate yields were found to have strong relationships with future economic growth, at least for developed countries. However, there are recent concerns about adopting financial assets prices as forecasting tools. The relationship might not be consistent over time, as shown later by Binswanger (2000), who ran the same regression used by Fama (1990) using a more later data set, and showed that stock returns have ceased to lead real economic activity.[8] In light of this, some countries are developing a composite business cycle leading indicator (CLI) index that synthesises all the signalling information, both from financial and non-financial variables, on the developments in the real sector (Gyomai & Wildi, 2012). There is a lack of evidence on the performance of this new variable against some traditional forecasting tools such as the yield curve. Thus, the major objective of this chapter is to explore the forecasting properties of South Africa's composite business cycle leading indicator vis-à-vis the yield curve.

By incorporating both financial and non-financial tools into one single hybrid variable, the CLI is expected to outperform any other single variable, both for short and long-run horizons. The CLI is constructed from financial assets (interest rate spread, stock market

7 See, e.g., Fischer and Merton (1984), Chen, Roll, and Ross (1986), Harvey (1989), Barro (1990), Fama (1990), Schwert (1990), among others.
8 Besides this finding, Carvalho and Gabaix (2010) attribute the macroeconomic fluctuations to microeconomic shocks. They posit that the recent fluctuations in output are a result of an increase in the size of the financial sector.

index, narrow money supply), non-financial assets (number of new passenger vehicles sold, number of building plans approved) and other macro variables such as the exports commodity price index, average hours worked, volume of manufacturing orders, job advertisements, and the CLI of other countries.  This is because these different forecasting tools carry different idiosyncratic forecasting information which when combined will, theoretically, increase forecasting accuracy. Even for documented financial instruments such as stock returns, interest rates, and interest rate spreads, their strength, extent, and consistency are still debatable.

Moreover, researchers have primarily focused on the in-sample prediction and failed to adequately explore the out-of-sample properties of this relationship (Fama, 1981; Khomo & Aziakpono, 2007; Moolman, 2002). This was as a result of limited data, or the methodology adopted that did not allow for out-of-sample analysis (for example, the Probit model of (Khomo & Aziakpono, 2007). The recent discovery by Binswanger (2000) that stock returns ceased to lead the real sector, at least in the case of the US, begs the question of whether an amalgamation of different economic variables improves effectiveness, consistency, and efficiency in forecasting output.

Even though there is profusion of evidence on the in-sample output predicting power of financial asset prices for developed countries, the same is not true for emerging economies. A few papers have attempted to explore this relationship for South Africa, but the results obtained are mixed and inconclusive. Moolman (2002) and Khomo and Aziakpono (2007) both employed the Probit model and modified Probit models to examine the yield curve's ability to forecast recession for South Africa. Although Khomo and Aziakpono (2007) incorporated the movements in the share index covering all listed shares, their analysis did not cater for out-of-sample analysis and the possibility of structural breaks. Since the most important property of forecasting tools is the ability to enable actual forecasting, out-of-sample analysis should be carried out to evaluate the forecasting power of any economic variables. Unfortunately, regardless of the importance of out-of-sample analysis, this area of forecasting has been given little attention.

The present study exploits the information content of the CLI to forecast output for South Africa. The CLI is an index constructed from 10 different economic indicators. The elements of the CLI are chosen based on their economic relevance and practical considerations. After identifying the leading indicator properties of these variables, principal component analysis is used to extract common information from these variables (see section 3 for details). The variables that are used to construct CLI include both financial and non-financial asset prices, among other variables. The variable obtained is termed the CLI, and we test its leading indicator information in this chapter. By examining the CLI and yield curve-real sector nexus, we extend prior literature in three important ways. Since some financial economists have shown that a naïve rule to stock returns forecasting outperforms most of the supposedly robust and optimal models such as sample-based mean-variance models (DeMiguel, Garlappi, & Uppal, 2009), we explore the prediction of output by the CLI vis-à-vis the yield curve. First, we use linear regressions to evaluate if South Africa's yield curve contains in-sample information to forecast future output. The results indicate that the yield curve contain information to forecast output. Second, we explore the forecasting information of the CLI and compare it to the performance of the yield curve. Empirical results show that even though both the CLI and the yield curve contain information that can be used to forecast output, CLI has a relatively higher adjusted R-squared. As pointed out by Estrella (2005), the recent inflation targeting by many developed countries has resulted in a reduction in the forecasting information contained in financial asset prices. By incorporating non-financial variables, the CLI performs better relative to any financial variable alone. Third, studies have shown that there exists an in-sample relationship between the yield curve and output growth. However, there is a lack of evidence on the out-of-sample performance (Harvey, 1997). So we explore the out-of-sample output forecasting properties for both the yield curve and the CLI. The econometric and diagnostic results show that CLI is more stable and consistent in forecasting output than the yield curve.

Following Stock and Watson (2003), we use nested models to examine the leading indicator properties of the candidate variables. This approach allows us to identify whether CLI or the yield curve contains forecasting information beyond that embodied in the lagged output. However, there is a noise factor that emanates from nested models that tends to misrepresent the forecasting accuracy. To address this, we use the methodology developed by Clark and West (2007) that addresses the noise factor and the upward bias emanating from the nested model. The model corrects for the likely upward bias in mean squared forecast error (MSFE) by adjusting the basic MSFE by a component of both the benchmark model and the unrestricted model. In addition, we investigate whether the identification of structural breaks improves forecasting accuracy using the Bai and Perron (1998) structural break test. This is superior to other tests as it allows testing for several structural breaks at unknown dates. It is worth noting that the behaviour of the out-of-sample MSFE is important in assessing the relationship's stability over time. To assess the stability of the mean squared forecast errors, we use Welch and Goyal (2008)'s diagnostic plots.

The rest of the chapter is organised as follows: Section 2 proceeds with review of related literature. Section 3 presents the data and outlines the econometric approach. Section 4 presents the results, and finally section 5 summarises and concludes the study.

## 2. Review of Related Literature

This section reviews related literature and it has three parts. First, we present the link between interest rates (both short and long-term) and future output, and second, we discuss the link between the stock market and the real sector. Finally we explore the literature on the nexus between uncertainty and the real sector.

### 2.1 Interest Rate, Term-Spread and the Real Sector

The term structure is, by definition, the difference between the long-term and short-term interest rate. Generally, the long-term interest rates are higher than short-term interest rates. The term structure then measures the slope of the yield curve. The steeper the yield curve is, the more the economy is expected to grow. A flattening yield curve indicates slower economic growth, with the inversion of the yield curve signalling a recession. The intuition is that when people anticipate a slowdown in economic activity, or a recession, they are incentivised to save more. In doing so, they save by demanding long-term bonds that pay off in bad times. The increased demand drives up the bond price and lowers the returns. Conversely, the short-term bond's demand goes down and the returns go up. If this happens, it is a sign that the economy is heading into a recession, and vice versa. From this intuition and analysis, there is a high possibility that interest rates contain valuable information about the future economic activity (see for example, Bordo and Haubrich 2008; Harvey, 1997).

Significant research in output focusing intensified during the late 1980s, and these include Harvey (1989), Estrella and Hardouvelis (1991), and Chen (1991). Most of these studies focused primarily on the in-sample predictive power of the slope of the yield curve. Harvey (1989) built his theoretical framework based on the consumption-based asset pricing model (CCAPM) and documented that expected real term structure contained useful forecasting information about future consumption growth. For the case of the US, he found evidence that term structure led the real sector, and the relationship is much stronger for the 1970s and 1980s. During this period the term structure contained more information than the lagged consumption and lagged stock returns. A more comprehensive analysis on the output forecasting ability of the yield curve was carried out by Estrella and Hardouvelis (1991), who went further to analyse its ability to predict recessions using the Probit model. They reached a conclusion that an upward sloping yield curve was associated with an increase in future real activity, particularly consumption (durables, non-durables, and services) and investment. Furthermore, they document that the slope of the yield curve contained more predictive information than the index of leading indicators: real short-term interest rates, lagged gross domestic product growth rates, and lagged inflation.

As evidence emerged from studies by different authors on the predicting ability of the yield curve in the case of the US, some economists also extended the analysis to different countries. By utilising the consumption-based asset pricing model, Harvey (1997), showed that the term structure contains useful information about future real activity for Canada. He found strong evidence of the Canadian term structure's forecasting ability compared to the US, and claimed that incorporating asset pricing theory improved upon the basic time series models. Smets and Tsatsaronis (1997) analysed the term structure-output relationship for the case of the US and Germany, and their results were similar to those of Harvey (1997). However, they found that even though the yield curve predicted the real activity for both countries, the term structure contained more useful information for Germany than for the US. They attributed the results to the different monetary policy stances of the two countries. Even though evidence suggests that the term-structure of interest rate contains output forecasting information for most developed countries,[9] the depth of the information content differs by country and little is known about South Africa (SA)[10].

The above analysis triggered further investigation into the stability of the term spread-output relationship which was raised by earlier authors.[11] One such study by Haubrich and Dombrosky (1996) assessed the stability of the yield curve's predicting ability for the US. Furthermore, they conducted pseudo out-of-sample analysis and rolling in-sample statistics, and concluded that the forecasting ability of the term spread weakened after 1985. This same outcome was confirmed in an independent research by Mody and Taylor (2003) who used

[9] Barro (1990), Harvey (1989)
[10] Khomo and Aziakpono (2007),Moolman (2002)
[11] For example, Bordo and Haubrich (2008) Haubrich and Dombrosky (1996)

monthly data for the US for the period 1964-2001 and concluded that the relationship broke down for the 1990s. They also proposed that the strong connection found by earlier research was due to high and volatile inflation. Nevertheless, the high-yield spread predicts the real activity during the 1990s.

Recent evidence for the case of the US still shows that interest rates in levels have a great role to play in forecasting. A paper by Ang, Piazzesi, and Wei (2006) showed that interest rate in levels (short-term interest rates) gave more forecasting power than interest rate spreads. Their analysis incorporated later data covering 1952-2001 in the context of a dynamic model for GDP growth and yields. They also suggested using the longest maturity yields and lagged GDP for empirical purposes, as this improved the results. Similarly, Bordo and Haubrich (2008) showed that using both the level and the slope of the yield curve improved prediction significantly more than either of the two employed alone. They extended their analysis starting as far back as 1875 through to 1997. For this period, the spread between commercial paper and corporate bonds predicted future growth. However, they were quick to point out that the relationship was not stable over time, and also depended on the methodology employed. Nevertheless, the predicting power was best during the post-World War II period. This is supported by evidence from Wright (2006) who employed a number of Probit models together with the level and the slope of the federal fund rates, and concluded that employing both the level of the federal fund rate and the term spread provided a superior fit, and a relatively better out-of- sample performance than the models with term spread alone.

Most of the studies conducted are for the US economy and some are for other developed economies. This chapter seeks to explore if the information content of the yield curve provides output forecasting information for an emerging economy such as South Africa. Furthermore, the construction of the CLI involves the use of both financial and non-financial assets, with interest rates spread being one of the vital variables. In addition, as suggested by Ang et al (2006) and Bordo and Haubrich (2008), the inclusion of the short-term interest rate in levels improves output forecasting, and the CLI does include both interest rate in levels and interest rate spreads. As suggested by the literature above, CLI could carry more forecasting information than the yield curve, which is what we seek to test against the traditional yield curve.

## 2.2 Stock Market and Future Real Activity

Theoretical models developed in this strand of literature predict that stock prices can be used to forecast future output. There is a profusion of empirical literature on this relationship, however, the results are of a mixed nature. Earlier literature established a strong relationship between the stock market and future economic growth (Barro, 1990; Fama, 1981; Harvey, 1989; Schwert, 1990). Recent literature documents that the relationship is weak and in some instances non-existent (Binswanger, 2000; Estrella, 2005). Hamori, Anderson, and Hamori (2002), using data for the US and Japan, found that the relationship breaks down and attributed this to speculative bubbles. In general, the weakening relationship is attributed to globalisation, inflation targeting, low variability of macro variables, and the possibility of break points in the data.

Even though the relationship is weakening for developed countries, the same is not true for emerging countries. Grabowski (2009) analysed the stock return-real sector relationship for the case of Poland, and found that stock returns led the real sector. Moreover, to show that the case of a weaker relationship is not universal, Siliverstovs and Duong (2006) analysed the relationship for the case of Germany, France, Italy, the Netherlands, and the UK, and reached the conclusion that the stock market had certain predictive information for the real economic activity. A similar result is reached by Chaudhuri and Smiles (2004) who documented that for Australia, there existed a stable long-run relationship between real stock returns and measures of aggregate real economic activity, including real GDP.

By concentrating on the most developed capital markets, Jay Choi, Hauser, and Kopecky (1999) used the co-integration approach to explore the predictive power of lagged stock returns for G-7 countries. They found that a long-run relationship existed between past values of stock returns and current industrial growth rates, except for Italy. However, they found that even though an out out-of-sample relationship existed between past values of stock returns and current industrial growth rate, the relationship was weak. Working with the G-7 countries, Hassapis and Kalyvitis (2002), also investigated the relationship between movements in current stock prices and future economic growth in the context of vector autoregression. They found that shocks on output and stock market prices had a stronger explanatory power for future economic growth and the valuation of capital. These results give the stock market a pivotal role to play in predicting output, and hence there is compelling evidence to include it in the CLI when using it in forecasting output.

Although the results on the effect of the stock market on real economic activity are mixed, the relationship seems to be strong in less-developed countries. This is primarily because of the high volatility in inflation and in economic fundamentals. As such, we expect a strong relationship between stock returns and economic growth for South Africa, even though the degree cannot be ascertained *a priori*. Since stock returns are used in the calculation of the CLI index, we explore the properties of this index in forecasting future economic activity for South Africa.

### 2.3 Uncertainty and Future Real Activity

High uncertainty increases the reward for waiting on the purchase of durable goods. The value of waiting increases as the future economic outlook becomes uncertain. Durable goods include irreversible investments such as acquisition of vehicles, construction, the purchase of new buildings and business investments in machinery and equipment. Compared to non-durable goods, the consumption of durable goods is cyclical, and tends to change in line with the real economic volatility. Even among durables goods, some have more explanatory powers than others. For the US, Davis and Heathcore (2005) show that residential investment is more than twice as volatile as the business investment, and that residential investment leads business cycles. Since residential investment is dominated by construction, they attribute the higher volatility to the labour-intensive nature of residential investment. This argument makes the inclusion of housing in South Africa's CLI an important ingredient, as there is evidence that it leads economic growth, at least in the case of the US (Davis & Heathcore, 2005).

On uncertainty and future economic activity, the arrival of new information (news) has been proven both theoretically and empirically to lead output growth. By constructing a model that factors in consumer expectations about the future productivity, Lorenzoni (2006) showed that a positive news shock results in short-run increases output, employment, and inflation but has no effect in the long-run. Likewise, Bloom, Bond, and Van Reenen (2007) argue that with partial irreversibility, an increase in uncertainty decreases the responsiveness of investment to demand shocks. An increase in uncertainty caused firms to be more careful on the choice of investment they undertake. The concept of irreversible investment helps in understanding why firms behave the way they do in light of a bleak economic future. For instance, a bleak economic future means that if a firm invests in capital, the capital itself will have a lower opportunity cost as a result of how narrowly defined it is. Bertola (1998) developed a theoretical model and showed that under the conditions of irreversible nature of real firm investment, uncertainty emanating from technology, demand, and the price of capital would lead a firm into reducing its commitment to undertaking more investment projects. Taking into account adjustment costs, time-varying uncertainty, and investment decisions, the theoretical model of Bloom et al. (2007) predicts a negative relationship between uncertainty and durable commitments. Furthermore, their study confirmed their theoretical assertions by using data from a panel of firms, since acquisition of new vehicles and building of houses are all forms of relatively irreversible investments, and there are theoretical implications on these variables leading output. The demand for durable goods and investments reflects the perceived uncertainty, and thus should be included in CLI. This extraction of output leading information from irreversible investment should increase the CLI's forecasting information for output.

For a firm to maintain its investment level, the increase in uncertainty should be met by a proportional increase in the marginal revenue product of capital. Justiniano, Primiceri, and Tambalotti (2010) reinforced the link between investment and business cycle by identifying shocks to the marginal efficiency of investment as being the major driver of fluctuations in output, labour hours at business cycle frequencies, and the actual investment over a cycle. In spite of this, the contribution of labour over the business cycle is negligible. On the other hand, Wang (2012) derives a labour-based model to generate a unified co-movement of the real sector elements as a result of a shock to the total factor productivity (TFP). The model shows that news shock on future TFP had an impact on current employment, and hence future output. In light of this, the inclusion of average hours worked in the CLI might enhance forecasting accuracy. In addition, if there is high uncertainty in an economy, firms are more likely to be sceptical of hiring new workers. This in turn hampers the growth rate of a nation's output.

On the empirical front, Görtz and Tsoukalas (2011), using a two-sector DSGE model for the US, investigated the role news shock plays as a driving force for business cycles. Particularly, they found the shocks with regards to the future quality of capital had a significant effect on output, consumption, aggregate investment, and aggregate hours at business cycle frequencies. Their data rejected the conventional avenue through which a shock on capital affects the real sector via the TFP approach. However, the shocks to capital quality explain the early 1990s recession, and the recent recession triggered by the financial crisis. Relying on the same model (DSGE) and using the US post-war data, Schmitt-Grohé and Uribe (2012) found that forward-looking agents reacted to expected exogenous changes to economic fundamentals before such changes happen. The effect of this forward-looking nature by economic agents leads to the anticipated shock, explaining about 50% of the fluctuations in output, investment, and employment. Given that economic agents are forward-looking, all commitments on irreversible investment are subjected to these shocks, and hence their relevance in business cycles.

Combining the stock market and news to explain future economic fluctuations, Beaudry and Portier (2004) showed that the joint effect of these two elements affected output with a lag. Since the stock market captures and disseminates information quickly, the shocks emanating from the news about the stock market and future technological opportunities are made available today, but affect output in the future. If the shock is favourable, this will lead to an increase in consumption, investment, and hours worked, which all precede productivity growth by a couple of quarters. An empirical investigation by Beaudry and Portier (2004) found that a joint shock from stock prices and news accounts for 50% of business cycles for the US. Lamla, Lein, and Sturm (2007) confirmed this result using the VAR methodology. They showed that news and its transmission mechanism had a significant effect on expectations about the future, which in turn affect the real sector. Since news is captured in the CLI along with other economic indicators, the CLI should contain more forecasting information than news and stock returns combined.

Unlike previous research that included, separately, interest rate spreads, stock returns, or interest rate in levels, and only limits the analysis to financial variables, the current research incorporates different measures of economic leading indicators into one index (the CLI) and tests the forecasting information of this index. Kneller and Young (2001) argue in favour of combining different sources of shocks that affect economic activity. They advocate harnessing the forecasting information content from different sectors, as these contain idiosyncratic information about the future. Particularly, their investigation suggested that uncertainty captured by inflation rate reflects the uncertainty caused by immediate small shocks, while oil price volatility indicates uncertainty generated by one-off world shocks to the economy. Their results lead to the conclusion that volatility emanating from different sources reduces long-run economic growth.

## 3. Data and Methodology

In this section, we present the data used, how it was constructed, and where it was collected from. Then, we outline the econometric procedure. However, it is useful to provide a brief review of the South African economy first, before discussing data and methodology.

### 3.1 A brief overview of the South African (SA) economy

The South African economy is the second largest on the continent of Africa, and SA is the only African member of the Group of 20. Its GDP per capita at a constant 2005 international dollar stood at $9,477 as of 2009. The country has well-developed legal, financial, and physical infrastructure. The commercial bank assets alone constitute about 120% of GDP, pension assets 112% of GDP, and long-term life insurance assets at 80 percentage points to GDP. By 2007, the market capitalisation ratio of South Africa's stock exchange surpassed that of most emerging economies such China and Russia, and even Australia, as it stood at 250% to GDP. The average inflation rate for the period 1982 through to 2010 stood at 9.7%,[12] which is relatively high compared with most developed nations. This implies that the forecasting ability of asset prices might be higher for South Africa relative to low inflation countries, as suggested by Baltzer and Kling (2007).

SA's population stands at just more than 50 million. Of this population, there are 165 motor vehicles per 1000 people. For the year 2012 alone, South Africa sold 623,914 new vehicles. Imports to GDP ratio and exports to GDP ratio stood at 31% and 28% respectively as of 2012. The service sector and manufacturing, as percentages of GDP, were 67% and 13.4% as of 2011, and the household final expenditure ratio to GDP stood at 59.4%.

### 3.2 Data and Definition of Variables

The data is comprised of three variables, real gross domestic product (RGDP), yield curve, and the composite leading business cycle indicator (CLI), which are collected from the Reserve Bank of South Africa.

The yield curve (term structure of interest rates) is the difference between the return on 10-year bonds and three-month Treasury bills. The CLI is an index constructed by the Reserve Bank of South Africa based on different economic variables that have been chosen for different, but complementing, idiosyncratic characteristics that help in predicting output.

[12] Data obtained from the World Bank and the Reserve Bank of South Africa.

The choice for economic variables used in the construction of the CLI for SA is also dictated by the characteristics of the SA economy. It is noted that SA is a small, open economy with Taiwan, the Republic of Korea, and G7 countries (except Canada) as major export destinations, and as such their CLI is important in predicting SA's future output. There were many possible candidate predictors available for the construction of the CLI index, but those chosen were based primarily on economic significance and frequency of publication of the time series. For the construction of the CLI, initially the variables are normalised and then dynamic factor analysis is applied to extract the common information embodied in these variables. The decomposition distinguishes the short-term irregularities (idiosyncratic noise) from the trend. All the economic variables considered are given an equal weight as they enter into the composite leading indicator, except two (details of which are given below).

The index consists of 10 leading indicators and is constructed by the Reserve Bank of South Africa (Venter and Pretorius, 2004; Venter, 2005). The description of variables follows.

#### 3.2.1 Interest rate spread: 10-year government bonds minus 91-day Treasury bills

The yield curve has been documented both theoretically and empirically to aid forecasting. The rationale behind this assertion is that a dollar that pays in bad times is worth more than a dollar that pays in good times. So if economic agents expect a slowdown or a recession, they will move away from short-term investments, for example, 90-day Treasury bills to long-term investments such as 10-year bonds. This has the effect of increasing the 10-year bond's price and a decline in its return; simultaneously the opposite happens for the 90-day Treasury bills. This will lead to the flattening of the yield curve, or even its inversion. The inversions of the yield curve precede major US recessions.

#### 3.2.2 Number of new passenger vehicles sold (percentage change over 12 months)

Just like the investment in long-term immovable properties, the cost of waiting goes down when there is high uncertainty. However, if uncertainty about the future goes down or is low, the acquisition of passenger automobiles goes up. The volume of new cars sold might contain information about economic agents' sentiments about the future.

#### 3.2.3 Composite leading business cycle indicator of South Africa's major trading-partner countries (percentage change over 12 months)

From 1970 to date, SA's exports to GDP ratio averaged 30%. The inclusion of this variable is important as the developments in the major trading partner countries have an impact on the future output of SA. The list includes the US, Japan, Germany, France, the UK, Italy, the Republic of Korea, and Taiwan.

### 3.2.4 Commodity price index for SA's main export commodities

The value of a country's export sector in forecasting cannot be undervalued. An increase in price of SA export commodities will make them less competitive on the international market, which will then feed back into the local economy as a signal to reduce future output.

### 3.2.5 Index of prices of all classes of shares traded on the Johannesburg Stock Exchange (JSE)

There is empirical evidence linking stock prices with future output for developed countries. This comes with the background that the financial sector is faster to adopt and process new information than the real sector variables. The real sector variables such as GDP and investment react to any new information with a lag. With an increase in efficiency, if economic agents expect more output in the future, they will buy more shares on the stock market as they come with increased dividends payment. The effect of this is to increase the index of all shares.

### 3.2.6 Job advertisements: The Sunday Times (percentage change over 12 months)

If firms anticipate an increase in demand of their output in the future they will start the hiring today to meet the future demand. Likewise, if the same firms expect a slowdown in the economy, they will begin reducing their labour hiring, and in worst case scenarios, shed workers. An increase in job advertisements can be safely interpreted as a firm's anticipation of an increase in future output.

### 3.2.7 Real M1 (six-month smoothed growth rate)

M1 money supply is defined as notes and coins in circulation, cheque and transmission deposits of the private sector with the monetary sector, *plus* demand deposits of the private sector with the monetary sector. As shown by Bordo and Haubrich (2008), for the case of the US, M1 money supply contains information about the future output. Anticipation by the monetary authorities of an increase in output in the economy will be met by an increase in money supply to lubricate transactions in the economy.

#### 3.2.8 Number of building plans approved: Flats, townhouses, and houses larger than 80 square metres

In uncertain times, the value of waiting goes up. In light of this, when firms and the general economic agencies are uncertain about the performance of the economy, they tend to turn away from long-term investments, for example construction of manufacturing buildings and houses. However, if they expect a boom in the economy, uncertainty goes down and there will be more investment in long-term properties.

#### 3.2.9 Volume of orders in Manufacturing sector (half-weight)

This is primarily for short-term forecasting. An increase in the volume of orders implies an increase in output in the near future, and vice versa.

#### 3.2.10 Average hours worked per factory worker in manufacturing (half-weight)

Respondents are asked to indicate whether they expect the average number of hours worked per factory worker to increase, stay the same, or decrease compared to the same quarter of the previous year. As in the case of volume of orders in manufacturing sector, this variable is likely to contain only short-horizon forecasting information. When firms expect the demand of their commodities to go up, they employ more labour hours to meet the expected demand, and hence an increase in output.[13]

The conversion of these forecasting variables into a single index brings in a single hybrid forecasting variable, which is intended to outperform any other variable in forecasting.

### 3.3 The construction of the CLI

Total industrial production and quarterly GDP data, at constant price, are used as reference series. The variables to be included in the CLI series are chosen on how well they lead the reference series, among other characteristics. The inclusion of each series is supported by economic theory and is representative of the larger economy rather than narrowly-defined area. Apart from the relevance of the series, some practical issues were taken into consideration. Since the CLI series are constructed at a monthly level, series with a monthly frequency were preferred. The ease of accessibility and timeliness of series was considered and also the availability of long-time series data. Each candidate indicator was tested for its performance with regard to the cyclical turning point of reference series. Then the cross-

[13] The collection of data and construction of the CLI is done by the Reserve Bank of South Africa

correlation was used to assess the average lead of the indicator, synthesise the information of the resemblance of the series in question and the cyclical profile of the reference series. To evaluate the strength of the wavelength relationship between the indicator and reference series, a cross-spectral analysis is used. In particular, the proportion of variance explained by the indicator at a point of the reference series (coherence), and the time difference between the indicator and the reference series (mean delay).

Finally, factor models that measure the co-movement of many time series are used to extract the common information from a set of indicators, which is then used in the construction of the CLI. Each indicator is estimated by eliminating the idiosyncratic noise or short-term irregularities affecting its indicator. In construction of the index, either a "growth cycle approach" or "deviation from trend" approach are adopted. This is done because the growth trend of a series might inhibit the co-movement of the series in question with other series, and to do this the phase-average trend method developed by NBER (US) is used (Venter, 2005).

### 3.4 Theoretical Framework

This sections deals with the theoretical connection between our proposed forecasting variables and future output. There are a number of theoretical links proposed in the literature that link the variables used in the construction of the CLI and future output. These variables can be broken down into financial and non-financial asset prices. Non-financial asset prices are used to capture the level of uncertainty in an economy as in Jaimovich and Rebelo (2009), and Bloom et al. (2012). On the other hand, the theoretical connection between financial asset prices and future output is modelled from the consumption-based capital asset pricing model (CCAPM). This approach supports the use of financial variables (interest rate in levels, interest rate spreads, and the stock returns) as predictors of output.

We present three models that analyse the theoretical connection between the elements of the CLI and future output. The first two models link the financial prices with future output, and the last one outlines how uncertainty affects future output. We will start by outlining the econometric approach suggested in Harvey (1997) that maximises a representative economic agent's utility subject to the stochastic endowment in an exchange economy. Second, we explore the properties of the CCAPM model developed by Epstein and Zin (1991), and finally we present how uncertainty as proposed by Jaimovich and Rebelo (2009) leads to economic fluctuations.

### 3.4.1 Constant Relative Risk Aversion model

Harvey (1997) begins by presenting an exchange economy in which the endowment can either be consumed or invested, $P_{i,j}$ , in *N* assets with different maturity periods, *J*.

The consumer maximises the following objective function:

$$\max_{\{c_t\{P_{i,j,t}\}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \delta^t \left[ U(C_t) \middle| Z_0 \right], \quad i=1,\dots,N : j=1,\dots,k, \tag{1}$$

where $\delta$ is the consumer's constant discounting factor. The consumer should maximise utility at time *t* subject to the endowment and proceeds from sale of assets already owned in order to finance current consumption and acquire new assets.

The first order condition that characterise the solution to this portfolio choice problem is given by:

$$E_t\left( \delta^j \frac{U^{'}(C_{t+j})}{U^{'}(C_t)}(1+R_{i,j,t}) - 1 \middle| Z_t \right) = 1 \quad \text{for} \quad i = 1,\dots,N;\ j=1,\dots..k, \tag{2}$$

where $R_t$ is the real *j*-period return on real asset *i* from period *t* to *t+j*, all the information available about the economy at time *t* are captured by $Z_t$, $\delta^j \frac{U^{'}(C_{t+j})}{U^{'}(C_t)}$ is the marginal rate of substitution between time *t* and *t+j*, and $\delta$ is a constant time discounting factor.

By assuming that the specific utility function takes the form:

$$U(C,\alpha) = \frac{C^{1-\alpha}-1}{1-\alpha}, \ \alpha > 1 \tag{3}$$

Substituting the first derivative of this utility function gives:

$$E_t\left( \delta^j \left[ \frac{C_t}{C_{t+j}} \right]^{\alpha} (1+R_{j,t}) \right) = 1 \tag{4}$$

If we assume a joint lognormal distribution of consumption and returns, then rearranging (4) yields:

$$E_t \Delta c_{t:t+k} = E_t \theta r_{jt} + j\theta\rho - \theta v_{jt} / 2 \quad (5)$$

where $\Delta c$ is log consumption growth rate, $r$ is the log of $1+R$, $\rho = -\ln(\delta)$ is the consumer's rate of time preference, $\theta = \alpha^{-1}$ is the risk tolerance, and $v_{ji}$ represents the conditional variance of the log interest rate plus the log consumption growth.

To assess the predictable information in the term structure of interest rates, equation (5) can be written for $j = 1$ and $j = k$ and, differencing it gives an equation to predict k-step-ahead consumption growth rate:

$$\Delta c_{t+1:t+k} = a + \theta r_t + u_{t+k} \quad (6)$$

where $r_t$ is term spread, $\Delta c$ is consumption growth rate, and $u_{t+k}$ is an error term.

This empirical equation shows that the term spread can be used as a predictor of consumption at *k* ahead forecasting period. Running a regression and using *t-test* to test for statistical significance of $\theta$, gives evidence on whether the information embodied in the term structure helps in predicting future consumption.

### 3.4.2 Epstein and Zin Model

The second theoretical link is derived from the Epstein and Zin (1991) consumption preferences model. The consumer is assumed to have Kreps-Porteus Generalised Isoelastic Preferences (GIP) with constant relative risk aversion (CRRA) parameter $\gamma$, and constant elasticity of substitution (CES) parameter $(1/\rho)$. The utility function is given by the relation below:

$$V(W_t) \equiv \max\{C, W\}\left((1-\beta)C_t^{1-\rho} + \beta[E_t V(W_{t+1}^{1-\gamma})]^{1/\theta}\right)^{1/1-\rho} \quad (7)$$

where $C_t$ is consumption in period *t*, $W_t$ is total wealth, $0 < \beta < 1$ is the subjective time discounting factor, $V_t$ is the agent's utility at time *t*, and $\theta = (1-\gamma)/(1-\rho)$ is a measure of the deviation of the agent's preferences from the time additive isoelastic expected utility function.

To solve the utility function, the following budget constraint should be satisfied:

$$W_{t+1} = R_{mt+1}(W_t - C_t) \qquad t \geq 1 \tag{8}$$

$$R_{m,t+1} = R^f + \sum_{i=1}^{N} w_{it}(R_{it+1} - R^f) \tag{9}$$

where $R_{m,t+1}$ is the return on aggregate wealth. Portfolio weights are given by, $w_{it}$, $R$ is an *n*x*1* vector of returns on risky stocks, and $R^f$ is the risk-free rate.

Solving (7) with respect to optimal C, gives the following Euler equation:

$$E_t\left[\beta^{\theta}\left(\frac{C_{t+1}}{C_t}\right)^{-\rho\theta} R^{\theta}_{t+1}\right] = 1 \tag{10}$$

The first order condition with respect to $w_{it}$ can be written as:

$$E_t\left[\left(\frac{C_{t+1}}{C_t}\right)^{-\rho\theta} R^{\theta-1}_{mt+1} R_{it+1}\right] = E_t\left[\left(\frac{C_{t+1}}{C_t}\right)^{-\rho\theta} R^{\theta-1}_{mt+1}\right] R^f \tag{11}$$

From the Euler equation in (10) and the definition of returns in (11), yields:

$$E_t\left[\left(\frac{C_{t+1}}{C_t}\right)^{-\rho\theta} R^{\theta-1}_{mt+1}\left(R^f + \sum_{i=1}^{N} w_{it}(R_{it+1} - R^f)\right)\right] \tag{12}$$

From (10), the equilibrium risk free rate is such that:

$$E_t\left[\left(\frac{C_{t+1}}{C_t}\right)^{-\rho\theta} R^{\theta-1}_{mt+1}\right] = \frac{1}{R^f} \tag{13}$$

Multiplying both sides of (11) by $\beta^{\theta}$ and using the result in (13), the Euler equation for any risk asset *i* becomes:

$$E_t\{\beta^{\theta}(C_{t+1}/C_t)^{-\rho\theta} R^{\theta-1}_{mt+1} R_{it+1}\} = 1 \qquad i = 1.......N\,, \quad \forall t, i \tag{14}$$

where $R_{it+1} = 1 + r_{it+1}$ and $r_{it+1}$ is the random return on asset $i$ between time $t$ and $t+1$, and $m$ is the claim on aggregate wealth. Solving this Euler equation recursively yields:

$$E_t\{\beta^{j\theta}(C_{t+j}/C_t)^{-\rho\theta}R_{mt+j}^{\theta-1}R_{it+j}\}=1 \quad i=1.......N \quad j=1.......k \tag{15}$$

The stochastic discounting factor for asset returns given in equation (15) depends on the changes in aggregate consumption and changes in aggregate wealth portfolio returns. It is a common practice to adopt $R_{mt+j}$ as a measure of aggregate stock market return from time *t* to time *t* + *j* (see Harvey, 1989 and 1997), and $R_{t+j} \equiv R_{it+j}$ is the yield on *j* period government bond.

By assuming that consumption and financial assets are realisations from homoskedastic and jointly lognormal process, we obtain a linear forecasting equation of the form:

$$E_t\Delta c_{t:t+j}=\Phi_j+[(\theta-1)/\theta\rho]E_t rm_{t+j}+(\theta\rho)^{-1}E_t r_{i+j} \tag{16}$$

where $\Phi_j$ depends on the conditional variance of the consumption-return process and the model's parameters and is assumed to be constant, $\Delta c_{t:t+j}$ is the log consumption growth rate from period *t* to *t* + *j*, and $rn$ is the logarithm of $Rm$ .

The equation (16) can be written for *j* = *1* (short-term) and *j* = *k* (long-term) as follows:

$$E_t\Delta c_{t:t+1}=\Phi_1+[(\theta-1)/\theta\rho]E_t rm_{t+1}+(\theta\rho)^{-1}E_t r_{i+1} \tag{17}$$

$$E_t\Delta c_{t:t+k}=\Phi_j+[(\theta-1)/\theta\rho]E_t rm_{t+k}+(\theta\rho)^{-1}E_t r_{i+k} \tag{18}$$

By differencing these two equations, we derive the following model to forecast consumption growth rate:

$$E_t\Delta c_{t+1:t+k}=\alpha+[(\theta-1)/\theta\rho]E_t MTS_t+(\theta\rho)^{-1}E_t NYR_t \tag{19}$$

Equation (19) shows real change in consumption growth rate and the asset prices, market term spread $(MTS_t=rm_{t+k}-rm_{t+1})$, and nominal yield spread $(NYR_t=r_{t+k}-r_{t+1})$. This equation can be transformed into an econometric model of the form:

$$\Delta c_{t+1:t+k}=\alpha+[(\theta-1)/\theta\rho]MTS_t+(\theta\rho)^{-1}NYR_t+\xi_{t+k} \tag{20}$$

Where $\xi_{t+k}$, is an error term.

In practice, economic growth can proxy consumption growth,[14] as we are concerned about the overall behaviour of the economy. If we assume $\gamma = \rho$ which implies $\theta = 1$, equation 20 decomposes to the (Harvey, 1997) model, where only the yield spread appears as a regressor. The results of these theoretical postulates recognise the potential of forecasting information embodied in the elements of the CLI, namely stock returns, short-term interest rates, and long-term interest rates. If the hypotheses advanced by these two CCAPM are true, then the inclusion of these stock prices in the construction of the CLI is likely to give a higher forecasting power.

Reinforcing this line of thought is Estrella et al. (2003), who argue that the countercyclical nature of monetary policy may have an effect on the yield curve. For example, a contractionary monetary policy conducted by increasing short-term interest rates leads to the flattening of the yield curve, which will in turn result in a reduction in future output. By combining the IS model, Taylor rule, and the Phillips curve, Estrella (2005) shows the linear connection between future output and the yield curve. The IS-LM models generally show the channel through which current interest rate dynamics aid in explaining the flow of output; this is similar to what is predicted by the real business cycle (RBC) models. The Euler equations from CCAPM are similar to those of the RBC models, as they show the nexus between the yield curve and expected productivity shocks.

Hence, the literature concurs on the impact of current interest rates on future output, but proposes a number of channels through which the current yield curve position is positively related to future output. Furthermore, the theoretical foundations suggest that both interest rates and stock returns have a major role to play in the economy. Furthermore, there is a co-movement of the stock prices and commodity price such as gold and hence, this justifies the inclusion of a commodity price index in the construction of CLI.

### 3.4.3 Uncertainty

The final approach deals with the propositions of Jaimovich and Rebelo (2009) who developed a model that takes into account the shocks to total factor productivity (TFP) – both contemporaneous shocks and those of news. Information received as news affects the flow of

[14] (Harvey, 1989:1997); Bordo and Haubrich, (2008); Stock and Watson (2003) among others)

economic fundamentals. Economic information received is this period is incorporated by economic agents in their decision-making and affects the real sector in the next period.

Jaimovich and Rebelo (2009) consider a two-sector model: investment and consumption. Agents in this model are assumed to maximise lifetime utility, $U$ , that takes the form:

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \frac{(C_t - \psi N_t^{\theta} X_t)^{1-\sigma} - 1}{1-\sigma}, \tag{21}$$

$$X_t = C_t^{\gamma} X_{t-1}^{1-\gamma}, \tag{22}$$

where $C_t$ and $N_t$ are consumption, and hours worked respectively. Agents internalise the dynamics of $X_t$ when choosing a preference that maximises their utility. The introduction of $X_t$ makes the preference non-time-separable in consumption and hours worked. Other variables are parameters that take values $0 < \beta < 1, \theta > 1, \psi > 0$ and $\sigma > 0$ .

Output ($Y_t$) is produced via a Cobb-Douglas production function using capital and labour:

$$Y_t = A_t (u_t K_t)^{1-\alpha} N_t^{\alpha} \tag{23}$$

where $A_t$ is total factor productivity (TFP), $K_t$ is capital, $N_t$ is hours worked, and $u_t$ is the rate of capital utilisation, and the output produced can either be used for investment $I_t$ or consumed, that is:

$$Y_t = {I_t}/{z_t} + C_t \tag{24}$$

where $z_t$ represents the current state of technology for the production of capital goods and is interpreted as investment-specific technological progress.

Combining equations (23) and (24) gives:

$$A_t (u_t K_t)^{1-\alpha} N_t^{\alpha} = {I_t}/{z_t} + C \tag{25}$$

Capital accumulation is given by:

$$K_{t+t} = I_t\left[1-\phi\left(\frac{I_t}{I_{t-1}}\right)\right] + \left[1-\delta(u_t)\right]K_t \tag{26}$$

where $\phi(.)$ represents investment adjustment costs, and $\delta(u_t)$ is the rate of capital depreciation.

Since $X$ is constant, after it is normalised to 1, the first order conditions of this economy are:

$$(C_t - \psi N_t^{\theta})^{-\sigma} = \lambda_t, \tag{27}$$

$$\theta\psi N_t^{\theta-1} = \alpha A_t (u_t K_t)^{1-\alpha} N_t^{\alpha-1}, \tag{28}$$

$$\lambda_t(1-\alpha)A_t u_t^{-\alpha} K_t^{1-\alpha} N_t^{\alpha} = \eta_t \delta'(u_t)K_t \tag{29}$$

$$\eta_t = \beta E_t\left\{\lambda_{t+1}(1-\alpha)A_{t+1}u_{t+1}^{1-\alpha}K_{t+1}^{-\alpha}N_{t+1}^{\alpha} + \eta_{t+1}\left[1-\delta(u_{t+1})\right]\right\}, \tag{30}$$

$$\lambda_t / z_t = \eta_t\left[1-\phi\left(\frac{I_t}{I_{t-1}}\right) - \phi'\left(\frac{I_t}{I_{t-1}}\right)\frac{I_t}{I_{t-1}}\right] + E_t\left[\beta\eta_{t+1}\phi'\left(\frac{I_{t+1}}{I_t}\right)\left(\frac{I_{t+1}}{I_t}\right)^2\right], \tag{31}$$

where $\lambda_t$ and $\eta_t$ are Lagrange multipliers for equations 3.5 and 3.6 respectively.

By setting the parameter values as dictated by the literature, they solve the model by linearising it around steady state. Calibration results show a co-movement response of variables to both the contemporaneous shocks to $A_t$ and $z_t$ and to current news about the future values of $A_t$ and $z_t$. This model suggests that the receipt of unanticipated positive news today about the future economic productivity leads to an increase in consumption, investment, hours worked, average labour productivity, capital utilisation, and hence output. When the shock in $A_t$ is realised, it immediately and directly impacts output. However, news about the future values of the $A_t$ only affect output through changes in labour supply and capital accumulated before the actual shock. On the other hand, the impact of $z_t$ on output occurs when the news is received, rather than when the shock is realised.

Filtering of information in an economy is processed by firms, and this information will affect $A_t$ via the change in employment (both the average hours worked and the number of new hires). The shock on $A_t$ can be interpreted as an increase in uncertainty and that will lead to a slowdown in future economic growth. This model provides support for the variables used in the construction of the CLI of South Africa, such as number of new passenger vehicles sold, the stock market index, job advertisements, number of building plans approved, and volume of manufacturing orders, as they all capture the uncertainty element in an economy. It is important to include these variables in forecasting as they directly have an effect on $A_t$ and $z_t$. Shocks to $A_t$ and $z_t$ affects the components of the CLI through a reduction in manufacturing orders, and any commitment on irreversible investment such as acquisition of new machinery and vehicles, and construction of factories and new residential houses.

### 3.4.4 Econometric Model

From the above theory it is clear that future output is affected by financial and non-financial factors. As presented by Stock and Watson (2003) and Bordo and Haubrich (2008), short-term interest, yield curve, stock returns, and exchange rate – which gives information about the external economy – all contain output forecasting information. In addition, Lorenzoni (2006) and Görtz and Tsoukalas (2011) show that new information (news) affects future output. This gives survey information on job advertisements, average hours worked, and the volume of orders in manufacturing sector relevance in predicting output. In addition, Bertola (1998) and Bloom et al. (2007) show that uncertainty in the economy leads to a reduction in irreversible and partially-irreversible investment. Based on this rationale, we include both financial and non-financial factors as elements of the CLI that might contain output forecasting information. To investigate whether the proposed elements of CLI lead output, we estimate with the following model:

$$y_{t+k} = f(y_t, ts_t, v_t, cli_t^o, cpi_t, si_t, ja_t, m1_t, bp_t, o_t, l_t)$$

where $y_{t+k}$ is the real growth rate of output from period *t* to *t+k*, $y_t$ is lagged output growth rate, $ts_t$ is interest rate spread, $v_t$ is the number of new passenger vehicles sold, $cli_t^o$ is the composite leading business cycle indicator of South Africa's major trading-partner countries, $cpi_t$ is the commodity price index for the country's main export commodities, $si_t$ is the index of prices of all classes of shares traded on the Johannesburg Stock Exchange, $ja_t$ is the percentage change over 12 months in job advertisements, $m1_t$ is six-month smoothed growth rate of real M1 money supply, $bp_t$ is the number of building plans approved $o_{t,}$ is the volume of orders in manufacturing sector, and $l_t$ is the average hours worked per factory worker in manufacturing.

All the variables on the right-hand side of the above equation (except lagged output growth rate) are normalised, and then dynamic factor analysis is applied to extract the common information embodied in these variables. The next task is to test if this hybrid index carries output forecasting information for both the in-sample and out-of-sample forecasting windows.

## 3.5 Econometric Issues

The methods to analyse the forecasting content of the variables is divided into two categories; the in-sample and out-of-sample methods. The out-of-sample analysis uses rolling regressions, and for robustness we conduct recursive estimates. This if followed by Clark and West (2007) analysis and diagnostic plots.

### 3.5.1 In-sample Analysis

The in-sample specification takes the form:

$$y_{t+k} = \beta_0 + \beta_1 CV + \sum_{i=1}^{4} \alpha_i y_{t-i} + \varepsilon_t \tag{32}$$

where $y_{t+k}$ is the annualised quarterly real gross domestic product (GDP) growth rate over the next k periods and, mathematically, represented as $y_{t+k} = \frac{400}{k}\ln(\frac{y_{t+k}}{y_t})$ and $y_{t-i} = 400\ln(\frac{y_{t-i+1}}{y_{t-i}})$. The parameters $\beta_0, \beta_1$ and $\alpha_i$ are unknown parameters, and $CV$ is candidate variable to be tested if it predicts output (CLI or yield curve).

To evaluate if today's candidate variable helps in predicting output, we run the above equation and test the null hypothesis that $\beta_1 = 0$, that is, it does not contain any forecasting information, against the alternative that it contains predictive information, $\beta_1 \neq 0$. Since the nature of the specification involves overlapping data, autocorrelation and heteroskedasticity are a possibility, and to address this we utilise Newey and West (1987) HAC standard errors.

### 3.5.2 Out-of-sample analysis

The fundamental objective is to be able to carry out actual forecasting. To test for forecasting ability, we use the above equation to conduct simulated out-of-sample analyses. Specifically, we use the rolling regression and recursive estimation to obtain the simulated forecasts.

Rolling regression starts by selecting a fixed window period, *m*, and based on this regression, forecasts the output in period *t+1,* and obtains the difference between the actual output in period *t+1* and the forecast (forecast error). The next step will be to drop the initial data point and add another new data point, in turn use this regression to make a forecast. As in our case the data is quarterly and ranges from 1970:1 through 2009:4 and $m$ = 60, the equation is regressed with only data from 1970:1 to 1984:4. After obtaining the parameter estimates, we then use this equation to forecast output for 1985:1 as if 1 is actually in 1984:4. The next step is to get the difference between the actual output and the simulated forecast output (forecast error). After that, we run the regression for the period 1970:2 through 1985:1 to determine the forecast error for 1985:2, and continue up to the end of the sample. The regressions are then allowed to roll over the entire sample.

The second approach utilises "recursive regression". This approach starts with a sample size *m* as in rolling regressions. However, the sample size is allowed to grow as each step forecast is made. For example, by assuming the same sample period as above, we run regression based on data from 1970:1 to 1984:4 and forecast 1985:1 as if 1 was actually in 1984:4. The next regression is regressed for the period 1970:1 through 1985:1 and obtains the forecast error. This is continued until the end of the sample.

After obtaining the forecast errors, we follow two main methods to assess the predictive ability: The ratio of the mean squared forecast error (MSFE), and regression analysis proposed by Clark and West (2007). Lastly, we conduct diagnostic plots as suggested by Welch and Goyal (2008).

**a) First approach**

The first approach utilises the ratio of MSFE as in Stock and Watson (2003). Let $\hat{y}_{t,t+k}$ and $\hat{y}_{CV,t+k}$ be the benchmark and unrestricted forecast of $y_{t+k}$. The benchmark model only contains lagged depended variables, while the unrestricted model contains both the lagged dependent variables and the candidate forecasting variables to be tested. The ratio of mean squared forecasting error is given by:

$$[n^{-1}\sum_{t=m+1}^{T-k}(y_{t+k}-\hat{y}_{cv,t+k})^{2}]/[n^{-1}\sum_{t=m+1}^{T-k}(y_{t+k}-\hat{y}_{t,t+k})^{2}] \tag{33}$$

where $n = T - m - k - 1$, $T$ is the overall sample size, and $m$ is the length of the initial window period.

If this ratio is less than 1, then the unrestricted model performs better than the benchmark model, and hence either CLI or the yield curve help in forecasting future output.

**b) Second Approach**

This approach adopts the more recently-developed mechanism of forecasting by Clark and West (2007). The approach tests significance of the difference between the MSFE of the benchmark model and the adjusted MSFE of the unrestricted model.

Let $y_{t+k}$ be the actual output in period $t + k$, with $\hat{y}_{t,t+k}$ and $\hat{y}_{cv,t+k}$ being the forecast of output using a benchmark model and unrestricted model respectively. The forecast errors for benchmark model and unrestricted model are given by $y_{t+k}-\hat{y}_{t,t+k}$ and $y_{t+k}-\hat{y}_{cv,t+k}$ respectively.

The MSFE for the benchmark model is given by;

$$\hat{\sigma}_{1}^{2} = n^{-1}\sum_{t=m+1}^{T-k}(y_{t+k}-\hat{y}_{t,t+k})^{2}, \tag{34}$$

And the adjusted MSFE for the unrestricted model is given by:

$$\hat{\sigma}_{s}^{2}-adj = n^{-1}\sum_{t=m+1}^{T-k}(y_{t+k}-\hat{y}_{cv,t+k})^{2} - n^{-1}\sum_{t=m+1}^{T-k}(\hat{y}_{t,t+k}-\hat{y}_{cv,t+k})^{2} \tag{35}$$

To test the significance of the difference between the two MSFE, we run the variable $\hat{f}_{t+k}$, defined below on a constant, and test the significance of the constant.

$$\hat{f}_{t+k} = (y_{t+k} - \hat{y}_{t,t+k})^2 - [(y_{t+k} - \hat{y}_{cv,t+k})^2 - (\hat{y}_{t,t+k} - \hat{y}_{cv,t+k})^2] \tag{36}$$

If the test rejects the zero coefficient of the constant, then the forecasting equation is superior to the benchmark model.

### 3.5.3 Structural Stability Tests

To test the stability of the predictive model, we analyse the out-of-sample behaviour of the cumulated squared forecast errors (SFEs). This is a graphical diagnostic approach of Welch and Goyal (2008) and the loci to be plotted are given by the equation:

$$Net - SSE(\tau_0, \tau_1) = \sum_{\tau_0}^{\tau_1}\left( (y_{t+k} - \hat{y}_{t,t+k})^2 - [(y_{t+k} - \hat{y}_{cv,t+k})^2 - (\hat{y}_{t,t+k} - \hat{y}_{cv,t+k})^2] \right) \tag{37}$$

where $\tau_0$ and $\tau_1$ are the beginning and end dates of the forecasting period respectively, and $Net-SSE(\tau_0, \tau_1)$ is the cumulative difference sum of squared forecast errors between the two models. An increase in line indicates an increase in performance of the prediction model, and a decrease indicates a better performance of the benchmark model. If the forecasting model is stable, then the plots should steadily increase over time.

Several approaches to testing structural breaks have been put forward, among them the Lagrange Multiplier (LM) tests (Andrews, 1993), and Predictive PR tests (Ghysels, Guay, & Hall, 1998). However, these popular break point tests do not consider multiple breaks in the forecasting relationship. Obviously, for larger sample periods, there is a high chance of finding more than one break point. South Africa has seen five different central bank chiefs since 1970 (1967-1980, 1981-1989, 1889-1999, 1999-2009 and 2009-present (Reserve (Bank of SA, 2013)). Central bank governors tend to have different monetary policy stances depending on their objectives. As noted by Estrella (2005), the central bank's preference towards low inflation or output stabilisation might be responsible for breaks, and generally there is a relatively high turnover of different monetary regimes over time with different reaction functions. Fortunately, recently developed tests by (Bai & Perron, 1998) capture multiple breaks at unknown dates. After running the above structural break test, the results shows that, contrary to the expectations, there were no structural breaks in our data.

# 4 Results

This section reports the empirical results on real gross domestic product prediction by CLI and the yield curve for South Africa. The in-sample results are presented first, followed by out-of-sample results and interpretation.

### 4.1 In-sample Results

Table 1 below reports the in-sample results on the CLI and yield curve ability to predict output at the one quarter through eight quarter forecasting horizons. After controlling for heteroskedasticity and autocorrelation by using Newey and West (1986) HAC standard errors, the results showed that both the CLI and yield curve were statistically significant at least at the 1% level of statistical significance, for all forecasting horizons. The CLI model was more statistically significant, as depicted by the p-values, and had a relatively high adjusted R-squared for all forecasting horizons.

**Table 10: CLI and yield curve in-sample forecasting results (equation 32)**

| Variable/ quarter | Quarter 1 | Quarter2 | Quarter4 | Quarter8 |
|---|---|---|---|---|
| CLI | 0.10*** | 0.12*** | 0.13*** | 0.11*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| $\bar{R}^2$ | 0.22 | 0.30 | 0.36 | 0.33 |
| TS | 0.33*** | 0.37*** | 0.36*** | 0.25*** |
| | (0.01) | (0.00) | (0.00) | (0.01) |
| $\bar{R}^2$ | 0.19 | 0.23 | 0.19 | 0.11 |

**Note:** CLI and TS represents the composite leading indicator and the term spread for South Africa for the period 1970Q1-2010Q4, and $\bar{R}^2$ is the adjusted R squared. P-value is reported in parenthesis, and *** denote significance at 1%, level.

The results above show that both the CLI and yield curve contained in-sample forecasting information. The results were in line with the findings of Khomo and Aziakpono (2007) and Moolman (2002), who showed that the yield curve contained information which helps in pinpointing business cycle turning points through the use of Probit models. However, the linear relationship presented here has the advantage of being able to show the in-sample and out-of-sample performance. What is more important in forecasting is to carry out the actual forecasting. To test the CLI and yield curve's ability to carry out the actual output prediction, we conducted simulated out-of-sample analyses, and the results are reported in the following section.

### 4.2 Out-of-Sample Results

This section reports the simulated out-of-sample results. We start by presenting results from the rolling regressions and we proceed to carry out robust analysis (recursive estimates) before presenting cumulative squared forecasting errors plots as proposed by Welch and Goyal (2008).

#### 4.2.1 Rolling method results

The out-of-sample results are divided into two: the first reports results of the ratio of the means squared forecasting error (MSFE), and the second reports the regression results from Clark and West (2007) econometric specifications.

**Table 11: Ratio of Mean Squared forecasting error (MSFE) (equation 33)**

| Horizon<br>Variable | Quarter 1 | Quarter 2 | Quarter 4 | Quarter 8 |
|---|---|---|---|---|
| CLI | 2.19* | 1.40* | 1.42* | 1.25* |
| TS | 1.72* | 0.99 | 1.07* | 1.09* |

(*) shows that the MSFE of the candidate model outperforms the benchmark model.

Table 11 shows the results of the ratio of the MSFE of each of the candidate models to the benchmark model. When the ratio is greater than 1, it implies that the candidate model, on average, generated a smaller error in forecasting than the benchmark model (lagged variables of the dependent variables). The ratios for the CLI and the yield curve were both at their highest at the one quarter forecasting horizon, implying the forecasting information was stronger at short forecasting horizons. For one quarter ahead forecast, on average, the CLI model was more precise than the benchmark model by a magnitude of more than double.

However, as the forecasting horizon is extended, the forecasting power of CLI to the benchmark model weakened, but the ratio was still higher than 1, implying that the model with CLI did better in actual forecasting that the benchmark model. On the other hand, the yield curve lost significance in forecasting output at a two-quarter forecasting horizon. However, it gained significance for four and eight quarter forecasting horizons, although it was marginally above 1.

Given that the MSFE ratios may be misleading, as pointed out by Clark and West (2007), it is important to take into account the noise factor generated when using nested models to forecast. To address this, we ran the econometric approach proposed by Clark and West (2007) and the results are reported in the table below.

Table 12 reports regression results of the squared forecasting errors of the two candidate models regressed on a constant, after accounting for the noise factor. The results for CLI were statistically significant for all forecasting horizons. After accounting for the noise factor for all forecasting horizons, the results rejected the null hypothesis that the difference in forecasting errors between the benchmark model and the CLI model were statistically not different from zero. This implies that the use of CLI in forecasting improved forecasting accuracy for up to two years ahead. On the other hand, for one quarter ahead, the yield curve was statistically insignificant in forecasting output. This implies that the test accepted the null hypothesis that the yield curve carried no further forecasting information beyond that embodied in the lagged variables of the dependent variable. However, from second quarter through eight quarter forecasting horizons, the yield curve did help in reducing forecasting errors, while the CLI carried more forecasting information than both the benchmark and the yield curve models.

**Table 12: Clark and West (2007) results on the CLI and TS (equation 36)**

| Horizon<br>Variable | Quarter 1 | Quarter 2 | Quarter 4 | Quarter 8 |
|---|---|---|---|---|
| CLI | 1.78*** | 2.19*** | 2.04*** | 1.45*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| TS | 0.60 | 0.87** | 1.24*** | 1.26*** |
| | (0.13) | (0.03) | (0.01) | (0.00) |

**Note:** CLI and TS represents the composite leading indicator and the term spread for South and P-value is reported in parenthesis, and **, and *** denote significance at 5% and 1% level respectively.

The results above were contrary to the findings of Estrella and Hardouvelis (1991) that the slope of the yield curve contains more forecasting information than the index of leading indicators: real short-term interest rates, lagged gross domestic product growth rates, and lagged inflation. However, they confirmed the assertion and findings by Stock and Watson (2003) that harnessing the predicting information from an array of predictors helps in improving forecasting accuracy.

### 4.2.2 Robustness Analysis – Recursive method results

To test for robustness, we obtain the MSFE from recursive regressions, beginning at the same date as the rolling regression. The ratio of the candidate model's MSFE to that of the benchmark model are given in the table below.

Similar to the results obtained using rolling regressions, the MSFE ratios of CLI model to that of the benchmark model ratios were all greater than 1, signalling a superior forecasting power of the CLI model to that of the benchmark model. However, the MSFE ratios of the yield curve to that of the benchmark model were only marginally greater than 1 for eight quarters forecasting horizon.

**Table 13: Ratio of Mean Squared forecasting error (MSFE) (equation 33)**

| Horizon<br>Variable | Quarter 1 | Quarter 2 | Quarter 4 | Quarter 8 |
|---|---|---|---|---|
| CLI | 1.28* | 1.44* | 1.48* | 1.19* |
| TS | 0.93 | 0.90 | 0.94 | 1.01* |

(*) shows that the MSFE of the candidate model outperforms the benchmark model.

However, as shown in table 14 below, a similar result to rolling estimates emerged after controlling for the noise factor. From two quarters forecasting horizons through to eighth quarters, the tests rejected that the yield curve does not contain more forecasting information beyond that embodied in the lagged variables of the dependent variables.[15]

**Table 14: Out-of-sample performance of the CLI and Yield Curve ((equation 36)**

| Horizon<br>Variable | Quarter 1 | Quarter 2 | Quarter 4 | Quarter 8 |
|---|---|---|---|---|
| CLI | 1.88*** | 2.44*** | 2.91*** | 1.87*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| TS | 0.72 | 0.92* | 1.16** | 1.28*** |
| | (0.14) | (0.06) | (0.02) | (0.01) |

**Note:** CLI and TS represents the composite leading indicator and the term spread for South and P-value is reported in parenthesis and *, **, and *** denote significance at 10%, 5%, and 1% level respectively.

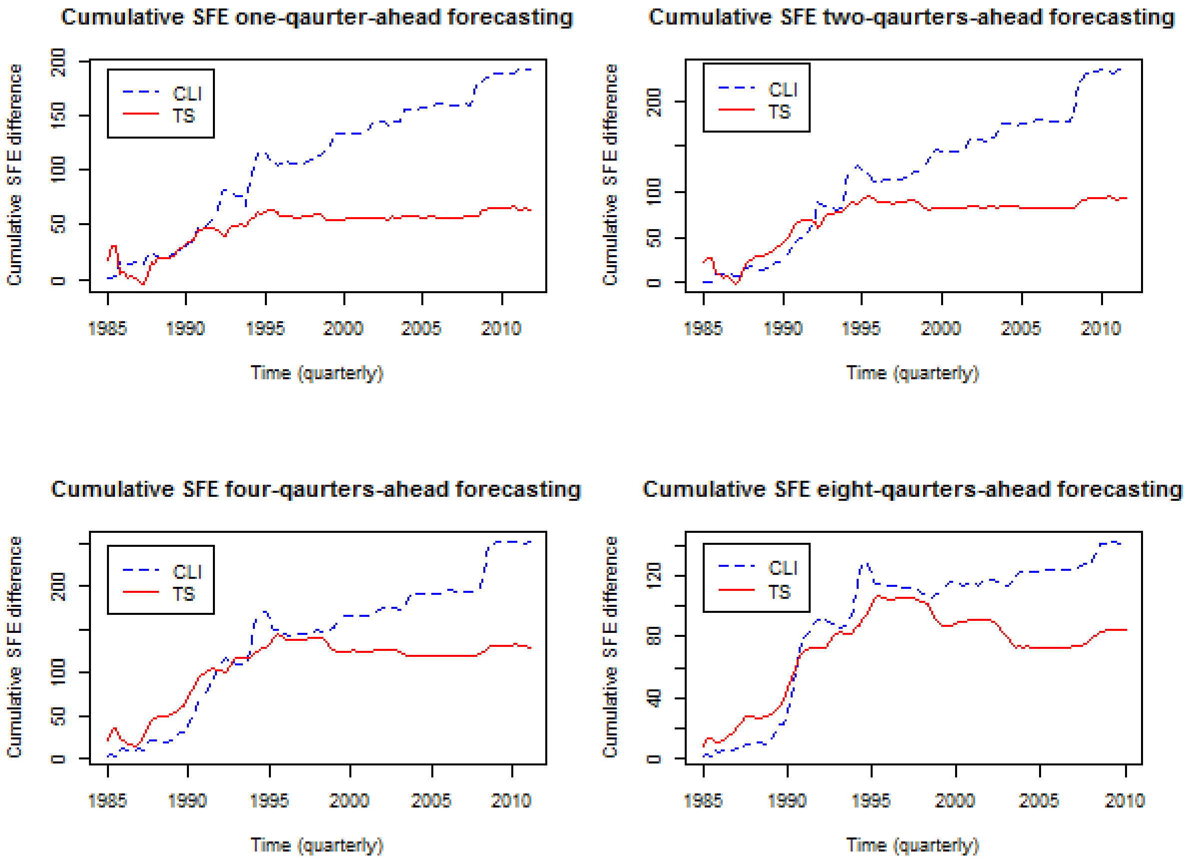
However, a near-identical result emerged regarding the CLI. The regression coefficients were statistically significant for the entire forecasting horizons considered, implying both rolling regressions and recursive regression confirmed that the CLI carries forecasting information beyond that embodied in the benchmark model.

### 4.2.3 Cumulative Squared Forecasting Errors Plots

Welch and Goyal (2008) propose the use of diagnostic plots to evaluate the forecasting information embodied in each candidate forecasting model by plotting the difference between its squared out-of-sample forecasting errors to that of the benchmark model. The following graphs present the dynamics of the cumulative squared forecasting errors difference

[15] Structural break tests suggest no structural breaks.

relationship between the benchmark model and the CLI and the yield curve (TS) models, over time.




Particularly, the graphs plot the cumulative SFEs of the benchmark model *minus* the cumulative SFEs of the candidate model (CLI or TS), adjusted for the noise factor associated with nested models (Clark and West, 2007). The relative performance of the CLI is represented by the dotted blue line, and that of the TS is represented by the solid red line. An increase in the line indicates that the respective candidate model outperformed the benchmark model, and a decrease in line indicates better performance of the benchmark model.

There are key conspicuous features to note: First, both candidate models (CLI and TS) performed well relative to the benchmark model prior to the year 1995. This might be explained by an increase in globalisation and lower volatility of macroeconomic variables. Second, both models performed relatively better at longer horizons than short horizons relative to the benchmark model for the period prior to 1995 (measured by the slope of the plots). Third, during the period 1995-2007, CLI performed better than the benchmark model while the TS model did as well as the benchmark model or worse. Lastly, at short forecasting horizon (one and two quarters) the CLI magnitude of forecasting accuracy was higher than that of the TS over longer forecasting periods (four and eight quarters) where its forecasting power was diluted (represented by the vertical distance between the two plots). However, when we conducted the tests proposed by Bai and Perron (1998), we failed to pinpoint any structural breaks in the data.

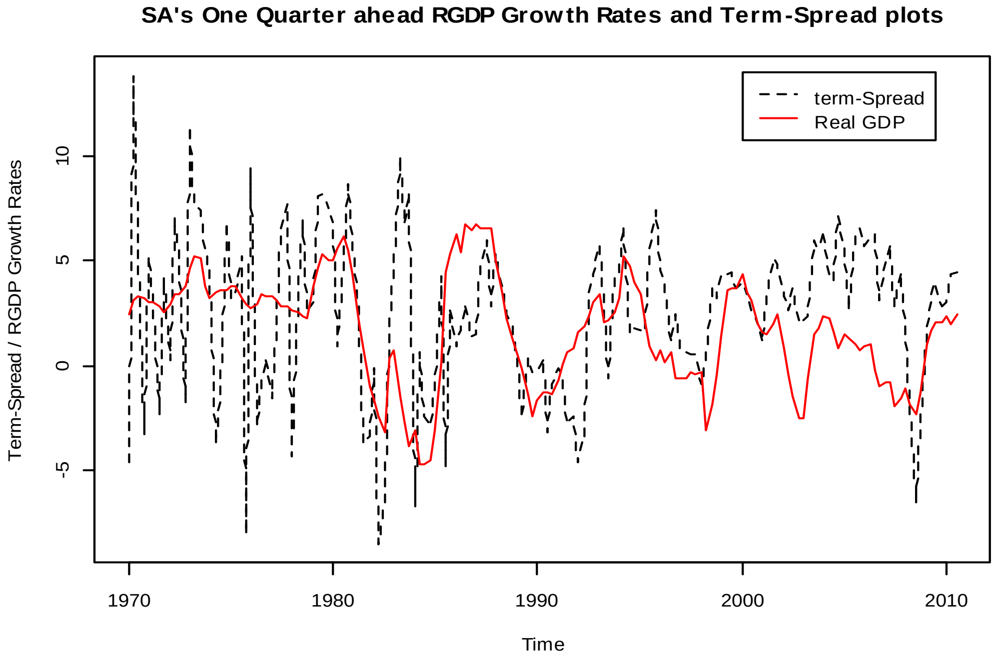
# 5 Conclusion

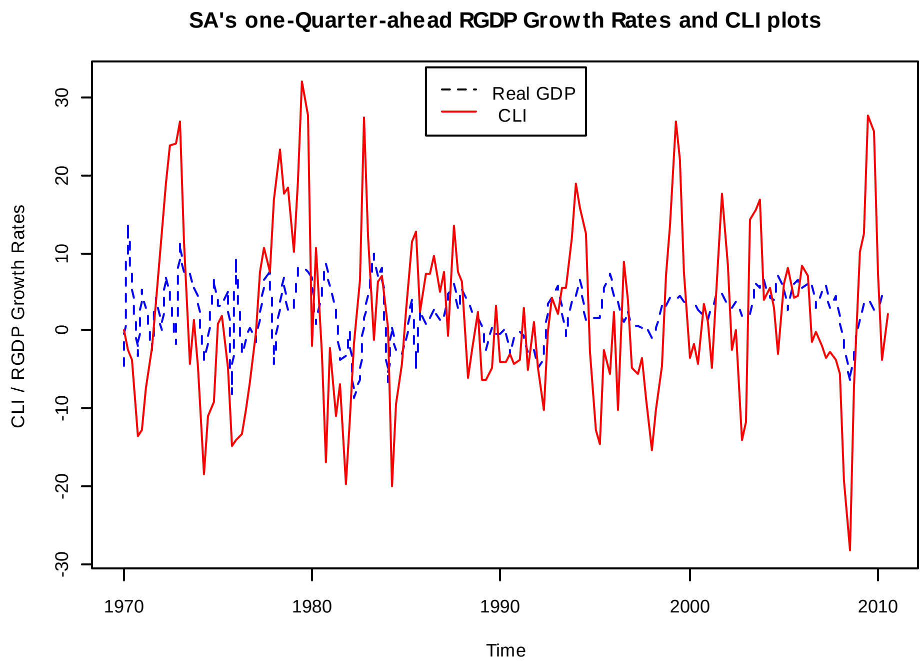
The main objective of this chapter is to empirically test whether CLI for South Africa has any forecasting information, and to compare the CLI to the predictive power of the yield curve. The simplicity and straightforward nature of the yield curve led to it being tested in many developed countries. There is overwhelming evidence that the yield curve contains output forecasting information, even though it has been weakening and this is in line with the findings of Estrella (2005), Estrella Rodrigues & Schich (2003) and Cieslak & Povala (2013). The empirical evidence we have documented for South Africa runs in line with the previous research. The term-structure of interest rates carries in-sample forecasting information. Although we find that the in-sample output forecasting power of the yield curve was significant, the statistical significance of the CLI was more significant and hence more reliable, compared to the yield curve.

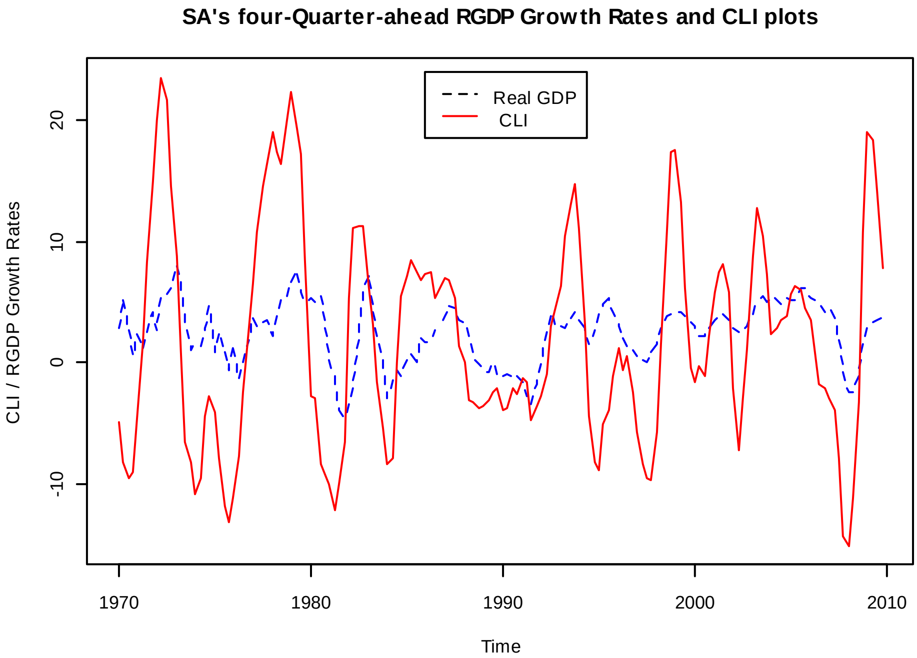
Extending the tests to out-of-sample, by utilising the mean squared forecasting error and addressing for the upward bias emanating from the nested model, we find empirical evidence that CLI contained statistically and economically significant output forecasting information for up to eight quarters ahead. This is superior compared to the term structure, which was either insignificant for the first quarter, or relatively weak for the rest of the forecasting period. On the other hand, cumulative squared forecasting errors plots showed that both models performed better than the benchmark model prior to 1995. However, the CLI performed better in recent years than the yield curve, and was more consistent in forecasting. Overall, the ability for CLI to forecast output outperformed both the benchmark model and the yield curve. It is worth noting that the yield curve did better in out-of-sample forecasting than the benchmark model.

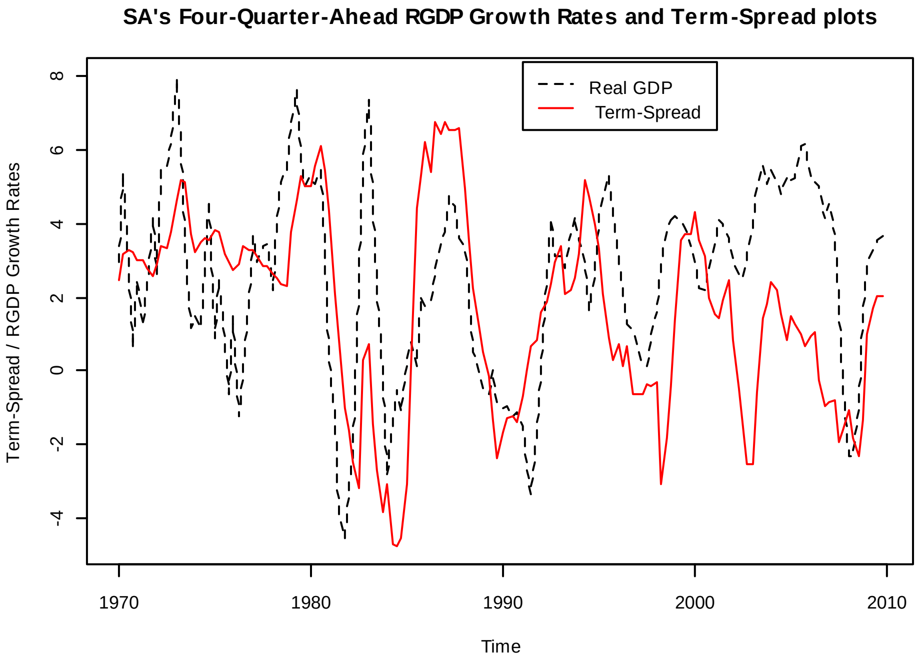
On the policy front, the results suggest that South African policymakers could adopt the composite leading indicator in forecasting output, as it increases forecasting accuracy compared with the traditional forecasting tools such as the yield curve. To further improve on the forecasting accuracy of the CLI, we recommend they factor in other forecasting tools that have been identified as carrying significant forecasting information, for example, implied stock market volatility, and some components of the futures market.

## Appendix 3


SA's One Quarter ahead RGDP Growth Rates and Term-Spread plots
term-Spread
Real GDP
Term-Spread / RGDP Growth Rates
-5
0
5
10
1970
1980
1990
2000
2010
Time


SA's one-Quarter-ahead RGDP Growth Rates and CLI plots
Real GDP
CLI
CLI / RGDP Growth Rates
-30
-20
-10
0
10
20
30
1970
1980
1990
2000
2010
Time


SA's four-Quarter-ahead RGDP Growth Rates and CLI plots
Real GDP
CLI
CLI / RGDP Growth Rates
-10
0
10
20
1970
1980
1990
2000
2010
Time


SA's Four-Quarter-Ahead RGDP Growth Rates and Term-Spread plots
Real GDP
Term-Spread
Term-Spread / RGDP Growth Rates
-4
-2
0
2
4
6
8
1970
1980
1990
2000
2010
Time

# Chapter 4: The Nexus between Financial Sector Volatility and Macroeconomic Volatility

## Abstract

The main objective of this chapter is to evaluate the intra-relationship between the volatility of financial variables, and to investigate their link with macroeconomic volatility for six industrialised countries. Results indicate that implied stock market volatility (VIX) led both the Treasury bill rate volatility (TB) and term structure volatility (TS). On the relationship between finance and the macroeconomy, the empirical results show that the relationship between VIX and inflation volatility was statistically significant in all countries except the UK and France. In addition, uncertainty in an economy measured by real output growth volatility and inflation rate volatility could be predicted by VIX. The results also suggest that there was a statistically significant relationship between TB and the volatilities of real GDP growth rate for all countries except Japan and the US. Conversely, the relationship between TB and inflation rate volatility was weak for all countries.

## 1 Introduction

Recent years have seen a renewed interest in understanding the dynamic underpinnings of the workings of the financial markets, and linking this understanding with macroeconomic activity. Research on ascertaining the determinants and forecasting of stock returns, bond markets, and output dominates the literature. The results of the research show that stock returns and interest rates could be used to forecast output, even though the volume of the information content differs across countries and time.[16] However, little has been done with regards to the determinants and the dynamics of volatility of these financial variables and their relationship with macroeconomic volatility (Diebold & Yilmaz, 2008). It is known that financial volatility measures the variation in financial variables, whereas macroeconomics volatility measures the degree of variation in aggregated economic elements such as unemployment, national income, rate of growth in real gross domestic product (GDP), inflation, and price levels, among others. The main objectives of this chapter are, first, to explore the intra-relationship between the volatility of financial variables and, second, to investigate their link with macroeconomic volatility.

[16]See Fama (1990); Guo (2002); Mao and Wu (2007)

Financial volatility measures the variation in financial variables. High financial sector volatility and macroeconomic volatility triggers uncertainty in the economy that leads to adverse effects on the economy. Higher macroeconomic volatility causes firms to temporarily halt hiring of labour and acquisition of new investment. Bloom (2009) shows that this type of volatility induces uncertainty in an economy. This uncertainty leads to a fall in productivity as firms freeze on reallocation of resources across units. Empirical evidence suggests that there is a negative relationship between macroeconomic volatility and economic growth rates (Ayhan Kose, Prasad, & Terrones, 2005; Imbs, 2007; Ramey & Ramey, 1994). A similar result is confirmed by Dabušinskas, Kulikov and Randveer (2013), who show that macroeconomic volatility is negatively related to economic growth. Since every economy strives to attain sustained economic growth, this begs the question of what variables are associated with macroeconomic volatility, and whether these variables be used in predicting the macroeconomic volatility.

In addition to negative growth impacts, high uncertainty as a result of high financial and macroeconomic volatility causes high inflation volatility, which could bring a large negative impact to the economy. There are a number of costs associated with both high inflation and high inflation volatility. First, relatively high inflation reduces the international competitiveness of local commodities, which leads to a decline in the net export position. Second, high inflation leads to uncertainty, and uncertainty reduces investments and consumer spending, which leads to lower economic growth. Other costs such as those of shoe leather and menu items, increase with the level of inflation and inflation rate volatility. Once the central bank loses its grip on controlling inflation, the cost of reducing it rise at an increasing rate with each increment in inflation. High inflation rates require higher interest rates and low government expenditure to alleviate price instability. This has higher spill-over effects, especially on economic growth, through reduced aggregate demand and an increase in unemployment.

With the number of countries that targets inflation rising to 26 (including emerging and low-income countries), price stability has been taken as a key to foster economic growth (Roger, 2010). Forecasting and controlling inflation rate and inflation expectation are essential to a successful monetary policy. Inflation innovations induce noise in the macroeconomic system that makes future choice of an optimum diversification on capital markets difficult. In addition, the induced noise makes the general financial planning cumbersome both for the households and government. Since the economy is primarily run by two instruments – fiscal policy and monetary policy – unanticipated high volatility of inflation will exert a negative impact on the budget. In turn, short-run macroeconomic stabilisation becomes challenging to attain, which causes large costs to society. In light of this, most developed countries have taken price stability as an essential focus, because a failure to do so likely brings large negative impacts.

In the extant literature, financial sector and macroeconomy volatility has been related with each other through the link between *second moment* and *first moment* of these variables. In particular, the connection between stock returns and macroeconomic volatility has been explored (Araújo, 2009; Binswanger, 2004; Rapach, 2001). Macroeconomic factors such as inflation rate, output growth, and exchange rates, among others, contribute towards the level of stock returns. While papers such as Guo (2002) link stock returns volatility with real sector growth rate, others such as Binswanger (2004) do the opposite, exploring the effect of macro shocks on stock prices and stock returns. However the link between financial sector volatility and macroeconomic volatility, that is, the link between the second moment of the financial sector and the second moment of macro economy, remains largely unexplored (Diebold & Yilmaz, 2008). This is important, especially for identifying forecasting instruments. In particular, to what extent does a shock to financial volatility impact macroeconomic volatility and how long does it take, and vice versa? Two influential papers have tried to analyse the second moment relationship. First, Schwert (1989), using time series data for the period 1857 to 1987, showed a weak relation between financial sector volatility and macroeconomic volatility. However, Diebold and Yilmaz (2008), using a more recent data set in a cross-sectional framework, showed that there is a strong connection between financial volatility and macroeconomic volatility.

As documented by Harvey (1989, 1997), and Stock and Watson (2003), both interest rate spreads and stock returns carry forecasting information for real output. While theory suggests stock prices are inversely related to bond yield, the issues of financial sector volatility are little known, especially with the newly-calculated implied stock market volatility index (VIX). The literature links *first moment* to *second moment* of financial variables and vice versa,[17] For example, Shiller and Beltratti (1992) showed that when long-term interest rate rises, real stock returns falls, and vice versa. Fama (1990) reaches a similar conclusion, noting that time-varying expected returns are one way to judge the rationality of

[17]See for example Guo (2002); Guo and Whitelaw (2000)

stock prices as implied by rational expectation present value models. However, there is lack of evidence in the literature on the dynamic relationship of the second moments of the financial variables.

Analysing the relationship between the second moments of the financial sector variables before linking them with the second moment of the macro economy is crucial in understanding the intra-connection for a number of reasons. Exploring the intra-connection of financial markets volatility will help in reducing risk and enabling optimum diversification on capital markets. Moreover, exploring financial sector volatility is essential for fixed income securities, derivatives pricing, and risk management. Portfolio managers regard the movement in interest rates as essential to their portfolios. Additionally, it has practical implications on assets allocation and other risk management strategies. Besides, a detailed understanding of the intra-financial markets volatility is imperative to the design of real sector forecasting tools. The knowledge of the degree to which a shock in these financial volatilities impacts the real sector helps in choosing forecasting candidates. Successfully disentangling this relationship will give government policymakers superior information on which policy measures to undertake in light of changing macroeconomic conditions.

By exploring and characterising the intra-financial volatility, and in turn linking it with macroeconomic volatility in the context of Vector Autoregressive (VAR) framework, we extend existing literature in three ways. First, since interest rate in levels, interest rate spreads, and stock returns have been used as predictors of real sector, an understanding of how a shock to these variables' volatilities affects other financial predictors' volatilities provides a basis for information extractions from these financial predictors to forecast macroeconomic factors. This is to say, the knowledge gained helps in extraction of information using such models as principal component analysis. In particular, the recently-developed implied stock volatility captured by the VIX index – which is deemed the "investors' fear gauge" (Whaley, 2000) – provides rich information on uncertainty as perceived by economic agents. Since the relationship between VIX and other financial volatilities is unknown, we analyse how the VIX index relates to the volatility of interest rate and interest rate spreads.

The second contribution is to trace how a shock in financial sector volatility affects output volatility, and vice versa. Since implied stock market volatility can be used to forecast output growth rate, the next question is by how much a shock in implied stock market volatility affects output volatility, and how long the shock takes to die out, and vice versa. We differ from Schwert (1989) by using implied volatility and a new data set for macroeconomic factors, and while Diebold and Yilmaz (2008) use cross-sectional data, we employ time series data and explore causality issues.

Third, we explore the shock dynamics between financial sector volatility and inflation rate volatility. Asset return volatility reflects uncertainty on prices;[18] this is to say higher inflation rate volatility is expected to result in higher implied stock market volatility. Inflation targeting has been a central goal of many developed countries recently, because when prices are not generally stable they tend to induce uncertainty and impedes economic growth. Likewise, if inflation increases, this induces more uncertainty and higher volatility in the financial sector. Shedding more light on the connection between inflation volatility with financial volatility and output volatility helps in policy formulation. Last, even though there is evidence of the shock relationship between output and inflation volatility, the relationship over the Great Moderation period (mid-1980s-2007) might have changed. During this period, the interest rate is associated with lower variability in output growth rates and low levels of inflation. We investigate if this relationship still holds with a recent data set, as this gives aid to policy formulation.

Results showed that there was a connection between the volatility of the Treasury bill rate (TB) and VIX. On the link between the financial sector and the macroeconomy, a strong relationship was found between VIX with inflation rate volatility and real gross domestic product's growth rate volatility (GDP). The impact ran from VIX to the macroeconomy, suggesting that VIX led the volatility of inflation and GDP. The TB and GDP relationship was strong, in which impulse response, variance decomposition, and Granger causality tests suggested a bi-directional causality.

The rest of the chapter is organised as follows: Section 2 proceeds with review of related literature. Section 3 presents the data and outlines the econometric approach. Section 4 presents results, and finally section 5 summarises and concludes

[18](Guo, 2002; Guo & Whitelaw, 2000); Schwert (1989), among others.

# 2 Review of related literature

This section provides the building block of our empirical model by evaluating related theoretical and empirical literature. First, the theoretical connection is presented, which is then followed by the review of empirical literature.

## 2.1 Theoretical literature review

There are a number of strands of literature that link finance to the macroeconomy, and vice versa. Guo and Whitelaw (2000) propose a theoretical framework in which stock market volatility contributes to stock returns. Guo (2002) extends this analysis to cover the effect of stock market volatility on output growth rate. Matching this approach are Bloom et al. (2007), who argue that an increase in uncertainty, for example high stock market volatility, will lead to a decrease in investment. Since financial markets receive and process information quality relatively faster than the real sector, any news shocks captured by the stock market volatility are disseminated quickly, and in turn drive business cycles (Görtz & Tsoukalas, 2011). This implies that an increase in stock market volatility might lead to an increase in output volatility. To further cement this argument, Beaudry and Portier (2004) assert that stock market and news shock have a significant effect on the real fundamentals, although it is affected with a lag.

Some theoretical proponents harness the information content of interest rates, uncertainty in prices, and expected profits to explain stock market volatility. For example, Binder and Merges (2001) propose a theoretical model where the volatility of stock prices is positively related to uncertainty in prices, interest rate in levels, and the risk premium term, but negatively related to the ratio of expected profits to expected revenues. An interesting point to note is the inclusion of riskless interest rate, as this may affect both the current and future stock market volatility. In addition, some theoretical proponents link stock market volatility to the variation in some elements of the real sector. For example, Duffee (2005) outlines a theoretical motivation that links conditional covariance and the conditional correlation between aggregate stock returns and aggregate consumption growth. In this theoretical proposition, stock returns and stock returns volatility are a function of covariance between stock returns and consumption growth. The derivation of this covariance leads to the formulation of a conditional second moment, which can then be subjected to empirical econometric analysis.

On the other hand, there are studies that propose that macroeconomic factors affect stock market volatility. Corradi, Distaso, and Mele (2013) developed a theoretical framework in which stock market volatility is explicitly related to industrial production, inflation, and unobservable factors. They used this model to investigate the effects of fluctuation in the macroeconomic variable on volatility and volatility-related risk-premia. Furthermore, Engle, Ghysels, and Sohn (2008) extended on the log linearisation of Campbell (1990) and Campbell and Shiller (1988), to show the effect of inflation and industrial production growth on stock market volatility. Veronesi (2000) proposed that an increase in macro uncertainty translated into an increase in volatility on the stock market. Furthermore, Bittlingmayer (1998) put forward the notion that economic and political uncertainty exerted a significant effect on stock market volatility. In addition, on the macroeconomic uncertainty and the interest rate market, Koeda and Kato (2010) developed a model inspired by the works of Clarida, Gali, and Gertler (1999) and Ang et al. (2006), that showed that macroeconomic uncertainty drives the movement in interest rate spreads.

The above-mentioned theoretical analysis has linked a first moment to a second moment. There are other studies that postulate the relationship between the second moments. In particular, Diebold and Yilmaz (2008) propose the theory behind their empirical investigation, where the connection between volatility of the real sector and that of the stock market is dictated by the financial economic theory. In particular, this type of relationship is implicitly reflected in the formulation of Hansen and Jagannathan (1990). They developed an inequality of "Sharpe ratios" representing stock market volatility and real fundamental volatility, and showed that an increase in financial sector volatility should be met by a corresponding increase in real sector volatility for the inequality to hold. This implies that the volatility of the equity market moves together with the volatility of the real sector.

Even though the volatility nexus between the stock market and the real sector is connected as highlighted above, others suggest that the magnitude of these volatilities are different at different times. The relationship between financial sector volatility and real sector volatility is strengthened during recession (Caporale & Spagnolo, 2003). This implies that although in general there is a bi-directional causality, these authors find that the spill-overs generally run from the financial market to macroeconomy.

One of the most influential contributions to the volatility nexus was made by Schwert (1989). He linked the financial sector and the macroeconomy volatilities by postulating that the volatility of real activities is reflected in the volatility of expected future cash flows and the discount rate. Since stock returns are measured in dollar values, an increase in inflation rate uncertainty should be reflected in an increase in stock returns volatility. This is in line with the dividend discount model of the likes of the “Gordon growth model”. The dividend discount model predicts that stock prices are a function of dividends. In turn, the level of dividends is influenced by the outcome from the real sector. In other words, the volatility of the affairs of the economy will be reflected in how dividends change, and these in turn affects the volatility of stock prices. “The theoretical basis for such a link can be found through a simple discounted present-value model for the stock price, from which it follows that the conditional variance of the stock price depends on the conditional variances of expected future cash flows and of future discount rates, and on the conditional covariance between them. Since the value of corporate equity on the aggregate level should in turn depend on the health of the economy, it is plausible that a change in the level of uncertainty about future macroeconomic conditions would produce – perhaps assuming constant discount rates – a proportional change in stock return volatility” (Liljeblom & Stenius, 1997).

On the other hand, the theoretical postulates of Creal and Wu (2014) posit that inflation rate, CBOE Volatility Index (VIX), and forecast dispersions from the Survey of Professional Forecasters (SPF) are all measures of uncertainty, but they tend to capture different aspects of the uncertainty in the economy. In light of this, they developed a model of the yield curve to capture both the dynamics of their conditional mean, and the term structure of interest rate volatilities. The implication of the model is that it can be used to reflect the uncertainty in the economy, for example inflation uncertainty, and GDP uncertainty. Cieslak and Povala (2013) proposed that high interest volatility might signal a high uncertainty in the macroeconomy. They pointed out that the short rate expectation reveals market expectations about the path of monetary policy, implying the short rate expectations’ volatility in the interest rate market reflects the uncertainty in the macroeconomy. Their model predicts that volatility rises in anticipation of recessions and during period of distress in asset markets.

Although the literature connecting the bond market with other volatilities is limited, the related literature posits that there is a link between macroeconomic uncertainties and bond market volatility. For example, Bollerslev and Wooldridge (1992) pointed out that the link between financial assets’ second moments is driven by speculative prices, while Jones, Lamont, and Lumsdaine (1998) attributed the link between macroeconomic news and bond market volatility to information flow that is characterised by clusters. They attributed the link in autocorrelation to the response of efficient markets, and they gave an example of how asset prices responded to uncertainty emanating from the Producer Price Indexes and labour market. On the same note, the mixture of distribution hypothesis (MDH) proposed by Clark (1973) and Harris (1987) suggests that if news arrives in clusters, the expectation would be that financial markets would exhibit positively auto-correlated volatility. With the background of this analysis, it is easier to see why implied stock market volatility's (deemed by Whaley (2000) "investor fear gauge") "second moment" may relate to bond market second moment.

The importance of macro news captured by VIX has an intuitive appeal for theoretical analysis. The uncertainty emanating from the macroeconomy can lead to high volatile interest rates and other asset prices. "Intuitively, aversion to state-uncertainty generates a high equity premium and a high return volatility because it increases the sensitivity of the marginal utility of consumption to news. In addition, it also lowers the interest rate because it increases the demand for bonds from investors who are concerned about the long-run mean of their consumption", (Veronesi, 2000). This shows the link between uncertainty from the macroeconomy and interest rate volatility.

The theory above suggests there is a connection between our variables of concern, the volatilities of short-term interest rate, yield curve, and implied stock market volatility captured by VIX. Consequently, these variables link with the macro economy, that is, the volatilities of real output growth and inflation. It is the aim of this chapter to explore how these variables are interrelated, and how each innovation to each variable in the system of these variables is passed on from one variable to the other. Before we do that, we present related empirical literature.

## 2.2 Empirical Literature review

Apart from the theoretical studies, the strand of empirical literature suggests a link between financial market volatility and the macroeconomic volatility. De Goeij and Marquering (2006) investigated the relationship between the bond market volatility at different maturities, concluding that the bond market incorporated information from the macroeconomy faster than any other sector. In addition, they showed that monetary policy announcements only have an effect on the volatility of short-term bonds. Since macro news has implications on the uncertainty, uncertainty in turn drove both the volatility of the macroeconomy and asset prices. This assertion makes the connection between these variables worth exploring. Arnold and Vrugt (2008), provided empirical evidence on the relationship between stock market volatility and the dispersion in economic forecasts.[19] They also showed that macroeconomic uncertainty explains and forecasts the realised volatilities of the Fama and French factors.

On the other hand, Cieslak and Povala (2013) split the interest rates into two categories – the short rate and the term structure – and investigated the relationship between their volatility and the state of the economy. They concluded that the volatility of the short rate rose just before and during financial stresses, while that of the yield curve rose after the financial stress. In addition, the short rate was highly correlated with measures of monetary policy uncertainty. Moreover, they showed that the term premium volatility co-moves with economic policy uncertainty. This was further solidified by the findings of Bekaert, Hoerova, and Duca (2013) who documented that a "lax" monetary policy was associated with a decrease in risk aversion, and monetary authorities responded to high uncertainty, captured by VIX, by easing the monetary policy.

On the financial asset volatility empirical nexus, there are mixed results empirically. Campbell and Taksler (2003) analysed the relationship between the volatilities of the bond market and the equity market. Even though they did not incorporate the stock market volatility directly, they showed that idiosyncratic firm-level volatility helped to explain the variations in yields, as much as captured by credit ratings. This is slightly different from the forward-looking implied volatility we use.

Fleming, Kirby, and Ostdiek (1998) explored the link between the stock, bond and money market and found volatility linkage. They found that the volatility is driven by a common underlying factor such as information about changes in inflation. In addition, when information changed the expectations in one market, it tended to have a ripple effect on other markets. Across stock, bond and money markets, any information that may emerge may lead to cross-market hedging. In light of this, the volatility of interest, interest rate spreads, and implied volatility should be highly connected. In turn, they should be connected to both inflation volatility and output volatility. However, we cannot say *a priori* to what extent and how they are connected unless we conduct the econometric estimates. In addition, Fleming et al. (1998) noted that the volatility linkage had become much stronger after the 1987 crash.

[19]Which is used to capture uncertainty

To establish the major drivers of stock market volatility, Kearney and Daly (1998) employed Australian data and showed that the major drivers of realised stock market volatility were inflation and interest rate volatility. However, this is contrary to the result of Shiller (1980), who documented, for the US, that changes in expected real interest rates should be much larger to justify the stock prices volatility, even larger than the changes in nominal interest rate. Kearney and Daly (1998) also noted that industrial production volatility was only indirectly associated with the stock market volatility. This implies that the relationship might not be constant over time, nor across countries.

The US data has in the past shown a weak relationship between realised stock market volatility and macroeconomic variables (Schwert, 1989) . Liljeblom and Stenius (1997) used volatilities of inflation rate, industrial production, money supply, and terms of trade, in the case of Finland, to explore the relationship between realised stock market volatility and macroeconomic volatility. They concluded that, unlike the US, the results were strong, and there existed a bi-directional causality between the stock market and the macroeconomic variables. Specifically focusing on realised volatility and output volatility, for the case of the US, Ahn and Lee (2006) showed that period of high volatility in stock market preceded high volatility in the real sector, and periods of high volatility in real sector was likely to be followed by increased volatility in output.

An extensive study by Brenner, Pasquariello, and Subrahmanyam (2006) analysed the effect of both expected and unexpected macroeconomic information on stock and bond markets, and showed that macroeconomic information has both statistical and economic significant impact on the bond and stock market. The bond returns volatility increased upon receiving the information and decreased afterwards, and is stronger for portfolios of short maturity bonds. While realised stock return volatility decreased just before announcement, it increased on announcement and subsequently decreased after announcement. Their result suggests heterogeneity of the impact of macroeconomic information on the bond and stock markets.

Even though the empirical evidence suggests a link between the financial variables and macroeconomic activity, there exists a gap in literature regarding the second moments, and in particular, the link between the second moment of the financial sector and that of the macroeconomy. For example, there is a literature gap on whether the shocks to the second moment of either a financial sector variable or macroeconomy variables affect each other both in magnitude and over time. More interesting is how the newly-developed implied stock market volatility index is both related to other second moments of the financial variables and macroeconomic variables. In addition, does exploring this link help in providing insights in forecasting any of the variables in the system? To explore these links, we present the following empirical formulation.

## 3 Data and Methodology

This section begins by providing the data sources and calculations. This is followed by the presentation and justification of the empirical model.

### 3.1 Data

The dataset was collected for six developed countries (Belgium, France, Germany, Japan, the UK, and the US) from two sources: The implied stock market volatility (VIX) index was collected from DataStream at a daily level, and for the case of the US, we used the S&P 500's VIX index. Implied volatility is a measure of the expectations of stock returns volatility over the next 30 calendar days. The VIX is constructed at intraday basis by taking the weighted average of the implied volatility of eight call and put options near-the-money, nearby, and second nearby option contracts. Since VIX is a newly-developed variable, the choice of countries selected is dictated by the availability of VIX data.

The arithmetic mean of a variable was taken to convert the data from daily frequencies to quarterly, and this is done to match the data with gross domestic product (GDP), which is measured at a quarterly level. The real GDP, short and long-term interest rates, and inflation were all collected from the International Financial Statistics (IMF). Following Diebold and Yilmaz (2008), the standard deviation of these variables was computed to construct the term structure (the difference between the 10-year bond rate and Treasury bill rate), volatility (TS), Treasury bill rate volatility (TB), inflation volatility (INF), and real GDP growth rate volatility (GDP)[20]. There were missing Treasury bill rate data for Germany, so we proxied the Treasury bill rate by money market rate. This means the standard deviation of money market rate (MR) and the standard deviation of the difference between the bond rate and money market rate (TS) were used to capture the respective volatilities. Quarterly data spanning for different periods depending on the length of each

[20] As suggested by Diebold and Yilmaz (2008), we measure volatility as the residuals from an AR (3) model fit to real GDP growth rate volatility and yields similar conclusions.

country's VIX index was used, namely, Belgium and the UK 2000Q1-2012Q1, France 2000Q1-2012Q1, German 1992Q1-2011Q4, Japan 1998Q1-2012Q2 and the US 1990Q1-2012Q1.

### 3.2 The econometric model

The empirical task at hand involved running a Vector Autoregressive Model (VAR) and traced the impact of all endogenous variables upon each other via impulse response functions and variance decomposition. In addition a Granger causality test was performed to test the causal relationship between our variables in the Granger sense.

#### 3.2.1 Vector Autoregressive Model

Inspired by the theory presented above in the literature review section that suggests a bi-directional connection between the financial sector and the macroeconomic sector, we suggest a VAR as the econometric model to test the hypotheses implied by this theory. The VAR model, developed by Sims (1980), represents dynamic models that are used to test theories that imply a particular link of the time series economic variables. The set-up of VAR is such that current values of a set of variables are explained by past values of the variables involved. In a VAR system with *k* lags, each variable being forecast is regressed against its own values in each of the *k* preceding periods, against the values in each of the *k* previous periods of all the other variables being forecast. This is to say, in a VAR model, all variables are treated as endogenous; hence it is an *n*-equation, *n*-variable linear model in which each variable is in turn explained by its own lagged values, plus past values of the remaining *n-1* variables. It provides a systematic way to capture rich dynamic interactions of multiple time series. VAR models are superior to other models in that they do not need the imposition of *a priori* restrictions, for example, exclusion restrictions on reduced form matrices, hence achieving more efficient estimation. Especially given the hypothesis we want to investigate, VAR gives the right analysis as it focuses on the effects of endogenous innovations, or shock, unlike other approaches that model shocks as exogenous changes in the level of the policy variable (Renato Jr, 2001).

In this case, the relationship between these different volatilities is best captured by the VAR framework, because a VAR model provides tools (implied response functions and variance decomposition) to capture how the shock to one variable is passed to the other, and in what manner. Secondly, this model can estimate the proportion of variation in one variable explained by other variables. One way is through impulse response functions (IRF) generated from Cholesky decomposition that shows the dynamic response of variables to shock disturbances within the system. However, these shock are correlated and cannot be identified. To rectify this problem we used Cholesky decomposition to orthogonalize the shocks. The IRF generated thus traces the responses of reduced form shock to detect the time path of the effect of shocks on the endogenous variables over time. This is imperative when trying to pinpoint the lag time and the full impact time taken by a shock. On the other hand, variance decomposition (VD) disaggregates the proportion of movement in one variable due to the shocks from other variables. Therefore, it measures the proportion over time of the variation in one variable due to each shock from another variable. This captures the relative importance of variables in the system. These tools are powerful in analysing the existence and degree of strength among variables of interest.

Following Canova, Gambetti, and Pappa (2007), we propose the following specification:

$$y_t = A_0 + \sum_{j=1}^{\rho} B_j y_{t-j} + \varepsilon_t$$

where $y_t$ is a vector of endogeneous variable. In the first section of the estimation, this vector contains implied stock market volatility, three months Treasury bill rate and the term spread. In the second part of analysis this vector will include one of the above financial variable with inflation and GDP. $A_0 = (a_1 a_2 .....a_n)$is an nx1 vector of constants , $B_j$ are an n x n matrices associated with each *j*, and $\varepsilon_t$ is an nx1 Gaussian white noise with mean zero and constant covariance, $\sum$ .

The ability of a VAR to assign each variable its own equation explaining the changes in the variable in question, in response to its own current and past values and the current and past values of all the variables in the model, helps in capturing the innovation and interdependency of multiple times series variables. This specification enables us to analyse how shocks to each financial variable are transmitted throughout the system of other financial variables, and in turn how the shocks to any of the financial volatilities affect inflation and real output volatilities, and vice versa. It is worth noting that impulse response shock conducted in this paper is based on a reduced-form VAR; hence, a different ordering of variables could potentially have an effect on the estimated IRFs. However, we order the variables starting with the least endogenous, as dictated by theory.

### 3.2.2 Granger Causality Test

The Granger causality test was proposed by Granger (1969) and refined by Sims (1972). This econometric technique tests whether a time series is useful in forecasting the other variables by evaluating the F-test statistic. Specifically, a time series X is said to Granger-cause another time series Y if it can be shown that the series X values provide statistically significant information about the future values of series Y. The null hypothesis is that X does not Granger-cause Y. A significant p-value leads to the rejection of the null hypothesis, and concludes that variable X Granger-causes variable Y. Causality can be uni-directional, that is, it can run only from one variable to the other. In our case, it can run from VIX to TB. If a bi-directional causality exists there will be a feedback effect, that is, causality runs from one variable to the other and, in turn, from that variable back to the former. However, if the p-value is not statistically significant, we fail to reject the null and conclude that the variables are independent. It is important to note that Granger causality can imply a correlation between variables rather than causality. However, for prediction purposes, the co-movement of variables is what matters for forecasting accuracy.

# 4 Empirical Results

This section reports the empirical results on the relationship between intra-financial volatility and, in turn, with the macroeconomic volatility. Results on the intra-financial volatility are reported first, and the link with the macroeconomic volatility is reported second. Failure to account for stationarity in time series data results in spurious regressions. We thus used the Augmented Dickey Fuller test to test for stationarity. The VIX data was stationary, at least at the 10% level, for all countries except France, however after taking first difference the data becomes stationary. For TB and TS the data were not stationary for Belgium, the UK and France. First differencing is conducted and subsequent tests review that the data were stationary.

Given the time span of the data, we used at most three variables in each VAR model so as to conserve the degrees of freedom. It is known that in VAR models, estimations with optimal lag increases efficiency (Lütkepohl, 2005). To compute optimal lag length, we use the final prediction error (FPE), Akaike information criterion (AIC), and Schwarz information criterion (SC). In cases of contradiction of the optimal lag length, the lag length selected by at least two of the information criteria is chosen. The optimal lag length is reported on top of each graph in the appendix. Appendix 1 reports the results on the intra-financial sector volatility, while Appendix 2 reports the results on the interconnection between financial volatility and the macroeconomic volatility, namely inflation and real GDP growth rate volatility. In reporting empirical results, TB is the volatility for Treasury bills, TS is the volatility of the term structure, VIX is implied stock market volatility, GDP is the volatility on growth rate in annualised real GDP, and INF is the volatility of inflation. As dictated by theory, the variables are ordered in decreasing exogeneity starting with VIX, TB and finally TS.

### 4.1 Intra-Financial Volatility Results

This section reports results from three statistical estimations, namely, accumulated impulse response functions (AIRF), variance decomposition (VD) and Granger causality tests, in that order for the six countries under investigation. We use AIRF to analyse the full effect of shock of one variable on another variable. In addition, cumulating the responses smooths the spikiness of the differenced variables, giving easier inference.

#### 4.1.1 Belgium

The (AIRF) for Belgium as shown on chart 1 depicts that VIX had an initially negative effect which quickly turned positive on both the TB and TS, however, it was insignificant. The results showed that a one standard deviation shock to TB rate had a positive and statistically significant effect on TS, and the accumulated shock reached its maximum after about three quarters. The rest of the results were statistically insignificant. A similar pattern emerged from the VD, TB explained slightly above 41% of the forecast variance in TS. On the other hand, VIX explained 21% and 15% of the forecast variance in TB and TS respectively.

#### 4.1.2 The UK

The impact of a shock from VIX on TB and TS started negative in the first three quarters and then turned positive, however, the impact was statistically insignificant. A one standard deviation shock to TB was statistically significant on TS, but a one standard deviation shock to TS had a statistically insignificant effect on TB. This shows that a shock on short-term interest rate volatility had an insignificant effect on the yield curve volatility. All other AIRF were statistically insignificant. The VD confirmed the AIRF results by showing that TB explained 30% of the forecast variance in TS. On the other hand, VIX explained 8% apiece of the forecast variance in both TB and TS, with not much significant effect of these two variables on VIX.

### 4.1.3 France

The AIRF demonstrated that a one standard deviation shock to TB led to an increase in volatility in TS, whereas the impact of a shock to VIX on TB was barely significant. The VD showed that VIX explained 21% and 26% of the variation was forecast variance of TB and TS. A shock to TB explained a large proportion of variation in TS of about 36%.

### 4.1.4 Germany

Germany's AIRF showed that a one standard deviation shock to VIX had a positive and significant impact on the volatility of the money rate (MR). The accumulated effect continued even after 2.5 years. Moreover, a one standard deviation shock to MR caused a positive and significant impact on TS, reaching its maximum after about nine quarters. All other shocks other than from the variable in question were insignificant. This pattern was confirmed by the VD, which showed that VIX explained only 14% of the TS forecasting variance while explaining about 47% of MR after 10 quarters. The VD of TS and MR on VIX was about 3% combined.

### 4.1.5 Japan

Japan was the only country with a positive and statistically significant accumulated response of VIX to a one standard deviation innovation to TB. The effect reached its maximum after about eight quarters. All other IRF were statistically insignificant, except a shock from the variable in question. The VD shows that TB explained about 30% of the forecast variance in VIX. Both the IRF and the VD showed that VIX was poor at explaining changes in TB and TS. However, unlike other countries, the relationship between TB and TS for Japan was weak, with TB explaining less than 1% of forecasting variance of TS.

### 4.1.6 The US

As in the case of Germany, accumulated innovations from the VIX affected the TB positively, becoming significant after fourth quarter and insignificant after about 10 quarters. Other than own shocks from the variable in question, all other shock were not significant. The VD showed that a significant 21% of forecast variance of TB was attributed to VIX, but a shock to VIX only explained about 2% of forecast error variance of TS. On the other hand, the relationship between TB and TS was weak.

### 4.1.7 Results of Pairwise Granger causality tests

Table 7 reports the results from pairwise Granger causality tests. Even though the IRF for Belgium failed to find a meaningful relationship between VIX with TB and TS, Granger causality tests suggested that the causality ran from VIX to TB and TS. All the causality tests for the UK failed to reject the null hypothesis, suggesting that the variables in question did not cause each other.

As suggested by IRFs for Germany, VIX was significant in causing MR, in the Granger causality sense. This implied that the information content in current VIX and its lagged values had some statistically significant forecasting power on MR, at all levels of significance. In addition, VIX Granger-caused TS and the short rate volatility measured by MR Granger-caused TS for Germany. For the case of Japan, there existed a bi-directional causality between VIX and TB, with the relationship much stronger running from TB to VIX. However, there was no statistically significant causality relationship between all other variables. The Granger causality tests for the case of the US were in line with Germany and Japan, which showed that implied volatility (VIX) statistically Granger-caused TB. This confirmed the results obtained from the VD and IRF.

Except for the case of Japan, it seems the two countries (Germany and the US) with the longest VIX data set had the impact running from VIX to TB. This suggests that since VIX is a relatively new variable, these two countries, by adopting it early, have built the capital base for enriching the information content of VIX which, in turn, is used as a barometer ahead of other variables. As a matter of speculative suggestion, the results point to the notion that over time the information content of VIX increases the longer the time the variable had been in existence. This is because, given its attractive properties in capturing uncertainty, the economic agents developed trust in the measure.

### 4.2 Financial and Macro-Economic Volatilities

This section reports the results on the link between the financial sector and the macroeconomy, specifically on how TB, TS, and VIX are linked with GDP and INF. As suggested by theory we order the variables with decreasing exogeneity, that is, the order of

VAR used is financial variable, INF and GDP. This is to say, GDP and INF are estimated with each of the financial sector variables to give three VAR models. Again, this was done so as to preserve the degrees of freedom. The figures and tables are reported in Appendix 2, with the lag length reported in parenthesis at the top of each figure.

### 4.2.1 Belgium

The IRF for Belgium suggested that a one standard deviation shock to INF increased VIX after about two quarters before VIX returned to its previous value after another two more quarters. The effect of a one standard deviation shock to INF resulted in a positive shock on VIX, which became barely statistically significant two quarters after the shock. The VD suggested that a one standard deviation shock to INF would explain about 20% of the variations on VIX after about six quarters, as opposed to about 12% explanation on INF to a shock on VIX. Even though a one standard deviation shock to VIX had a positive effect on GDP, the shock was not statistically significant; the same applied to the response of VIX to GDP, and INF to GDP. However, the response of GDP to a one standard deviation shock to INF was positive and statistically significant after about two quarters, and the shock died out after about two quarters. The shock was large and explained about 28% of the variation on the GDP’s volatility after about four quarters. The causality test ran from VIX to INF, GDP to VIX, and from INF to GDP. However, the rest were statistically insignificant.

A one standard deviation shock to TB had a positive effect on INF on and GDP, however, the shocks were statistically insignificant. The VD showed that a TB explained only about 6% and 4% of the variances in INF and GDP after about five quarters respectively. However, GDP explained about 17% of the variations in TB after the same number of quarters. Granger causality tests reviewed that there was a bi-directional causality between TB and GDP. Otherwise, pairwise Granger causality test were statistically insignificant.

The IRF showed that the relationship between TS and other two variables in the system were insignificant. The VD showed that TS failed to explain at least a 10% variation in either INF or GDP. This result was also confirmed by Granger causality test, which failed to find any causality between the variable TS and INF and GDP.

### 4.2.2 The UK

The IRF showed that a one standard deviation shock to INF had a positive effect on VIX, and the effect became statistically significant immediately but died after about four quarters. The response of GDP to a one standard deviation shock to VIX was positive but barely significant after two quarters, and died immediately after that. The VD showed that a one standard deviation shock to INF explained about 30% variation in VIX after about five quarters. The relationship between INF and GDP was insignificant. Granger causality test only reviewed that the causality ran from INF to VIX, with all other pairwise tests statistically insignificant.

Only the effect of a one standard deviation shock to GDP on TB was positive and statistically significant, with GDP explaining about 16% of the variations in TB after about five quarters. However, after those five quarters, TB explained only about its maximum of about 7% and 4% of the variations in GDP and INF respectively. A similar relationship was observed between TS and GDP. A one standard deviation shock to GDP was positive and died out after about two quarters. This led to GDP explaining about 10% of forecast error variance in TS after about four quarters, and did not go beyond 10.25% after 10 quarters. Granger causality tests failed to reject the null that the variables in the system did not cause each other, except for a bi-directional causality between TS and GDP.

### 4.2.3 France

According to the IRF for France, the only significant relationship in an equation containing VIX, INF, and GDP was the effect of VIX on GDP. A one standard deviation shock to VIX had a positive effect on GDP, but the effect died out after about two quarters. The response of INF to shocks on GDP and VIX were positive but insignificant. Likewise, the response of INF to VIX was insignificant but positive. The VD showed that, after about five quarters, VIX explained about 19% of the variations in GDP, while INF only explained about 8%. VIX and GDP explained about 9% and 4% of the variations in INF respectively. Granger causality confirmed that there was only one statistically significant pairwise test, that is, a unidirectional causality ran from VIX to GDP.

Even though the IRF of TB and INF to GDP, and of GDP to INF, were positive, they were statistically insignificant. According to the VD, TB explained only about 12 % and 13% of the variations in INF and GDP respectively, while GDP and INF explained about 11% and 13% of the variations in TB after about five quarters respectively. In the Granger sense, causality ran from INF to VIX and GDP, and there was a bi-directional causality between GDP and VIX.

The IRF and the VD failed to find a meaningful relationship between TS with the VD and GDP. It was only a shock to INF that explained about 24% of the variations in GDP, and in turn GDP explained about 16% of the variations in INF. However, Granger causality tests rejected any causal relationship.

### 4.2.4 Germany

The IRF for Germany showed that a one standard deviation shock to VIX had an initially positive and statistically significant effect on INF and GDP before turning negative and statistically insignificant. All other IRF were statistically insignificant. This result is confirmed by the VD that showed that a one standard deviation shock to VIX explained forecast error variance of INF and GDP of about 18% and 38% after eight quarters, respectively. Granger causality tests revealed that VIX Granger-caused INF and GDP. However, all other pairwise Granger causality tests were statistically insignificant.

There was a statistically significant relationship between the MR and GDP, as shown by the IRF, however, the impact was short-lived. This result was in line with the VD, which showed that a shock to GDP would explain about 15% of the variation in MR, and in turn MR explained about 25% of the variations in GDP after about eight quarters. INF did not have any meaningful relationship with GDP and VIX. There was bi-directional Granger causality relationship between GDP and MR; all other relationships were statistically insignificant.

The relationship between TS, INF, and GDP was mostly statistically insignificant. However, IRF of INF to a one standard deviation shock to TS was positive and statistically significant, and lasted for relatively long period, that is, about six quarters. Nevertheless, the VD showed that a mere 8% of the variations in INF were attributed to a shock to TS after about eight quarters. The impact of a shock to INF on GDP started positive and quickly turned negative. INF explained about 12% of the variation in GDP, and this was the maximum it reached for the entire period under investigation. On causality issue, TS Granger-caused INF.

### 4.2.5 Japan

As suggested by IRF, a one standard deviation shock to VIX had a positive and statistically positive effect on INF and GDP, but only lasted for about three quarters for INF, and relatively longer for GDP, standing at about five quarters. All other IRF were statistically insignificant. The same result was produced by the VD, which showed that a shock to VIX explained about 14% and 33% of the variations in INF and GDP, respectively, after about six quarters. Similar to the previous case of Germany, Granger causality tests yielded a unidirectional causality running from VIX to INF and GDP.

On the relationship between TB, INF, and GDP, IRF revealed that a one standard deviation shock to TB had an immediate negative impact on INF and GDP that turned positive after about two quarters, but was statistically insignificant. It was only the impact of a shock to GDP that became barely significant at quarter 3, but all other relationships were insignificant. Of all the relationships, the impact of GDP on TB was the highest. The VD showed that GDP explained about 12% of the variations in TB after five quarters. TB explained only about 7% and 8% of the variations in INF and GDP after the same number of quarters. However, Granger causality tests failed to find any statistically significant relationship between the three variables. The IRF, the VD, and Granger causality tests failed to find any meaningful relationship between TS, INF and GDP.

#### 4.2.6 The US

Similar to the case of Germany, IRF for the US showed that a one standard deviation shock to VIX caused a significant and positive impact on INF and GDP, but it lasted for about three quarters before the shock died out. A one standard deviation shock to INF caused the volatility of GDP to increase but it was barely significant after two quarters. Other than the above-mentioned significant relationships, all other IRF were statistically insignificant. The VD confirmed the above result by showing that the combined explanation of the volatility of INF and GDP on VIX was only about 6% after six quarters. However, VIX explained about 25% of the variation in INF after six quarters, compared to only 11% from GDP. As suggested by the VD, the variations in GDP attributed to a shock to VIX peaked after five quarters to stand at about 36%, while INF explained about 6% after the same period. In the Granger sense, the causality ran from VIX to INF and GDP, confirming the above analysis. Also, GDP Granger-caused INF.

The relationship between TB, INF, and GDP was relatively weak, as shown by the INF. The effect of one standard deviation shock on TB had a positive effect on INF and GDP, but it was only significant for about two quarters, and all other INF were statistically insignificant. The VD showed that both INF and GDP did not have a significant effect on the variations on TB, explaining a maximum of about 2% after 10 quarters. However, TB and

GDP explained about 15% each for the variations in INF. A causality test showed that GDP Granger-caused INF.

As with other countries, the relationship between TS and the other two macro variables was weak. The IRF showed no statistically significant relationship between TS, INF, and GDP, except the previously-documented INF–GDP relationship. The VD showed that a one standard deviation shock to INF and GDP would only explain a maximum value of about 6% combined, while a shock to TS explained a maximum of about 1.5% and 5% of the variations in INF and GDP respectively. A Granger causality test accepted the null hypothesis that there was no causality between TS and the two macro variable volatility (INF and GDP).

# 5 Conclusion

The statistical analysis for the financial sector volatility produced mixed results. All AIRF for Belgium, the UK, France, and Germany suggested that a one standard deviation innovation in TB imposed a statistically significant impact on TS, suggesting that TB could be used as a potential TS predictor. However, the shock to all other variables did not seem to carry enough information to affect other variables. All three statistical inferences (IRF, VD and Granger causality tests), in the case of Japan, indicated that there was reverse causality between TB and VIX. However, for Germany and the US there was a strong, unidirectional causality running from VIX to TB. This is to say a shock to VIX explained a statistically significant proportion of what would subsequently happen to TB. The overall results have policy implications for professionals in fixed income securities, derivatives pricing, and risk management. If portfolio managers in Japan, Germany and the US observe a positive shock to VIX, they should accordingly change their portfolio allocations as this will be followed by an increase in short-term interest volatility. This result is particularly important to estimate what professional forecasters would predict, as in Ghysels and Wright (2009).

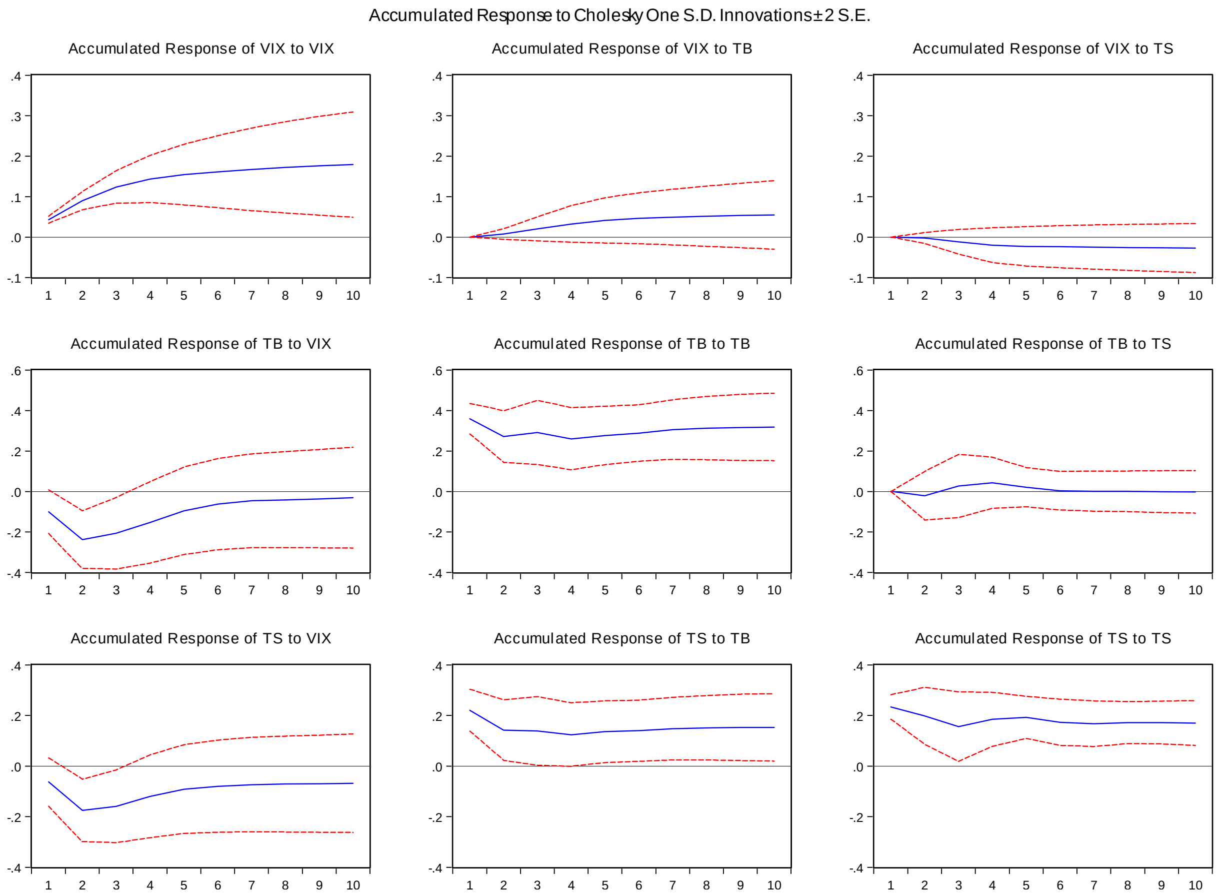
On the relationship between finance and the macroeconomy, empirical results sit in between Schwert (1989) and Diebold and Yilmaz (2008) findings. The latter find a strong relationship between the second moments of the financial sector and macroeconomic variables, while the former documents a weak relationship. The relationship between TS and our two macroeconomic variables was weak and largely statistically insignificant, confirming the result of Schwert (1989). However, there was a statistically significant relationship between the TB and GDP for all countries except Japan and the US. This result is in line with the findings of Bordo and Haubrich (2008), Harvey (1997), Haubrich and Dombrosky (1996) and Poke and Wells (2009) who show that the financial sector leads growth. Conversely, the relationship between TB and INF rate volatility was weak for all countries.

A notable significant relationship was recorded between VIX and macroeconomic volatility. The relationship between VIX and INF was statistically significant in all countries except for the UK and France. The effect ran from VIX to INF, suggesting that VIX could be used in forecasting inflation rate. In addition, the relationship between VIX and GDP was statistically significant except for Belgium and the UK. This implies that the uncertainty in an economy measured by real output growth volatility can be predicted by implied stock market volatility. This results tallies with the predictions of Guo (2002), Bloom (2009) and Bloom and Van Reenen (2007) that uncertainty negatively affects GDP. It is worth mentioning that if implied stock market volatility is to be used to forecast output growth rate volatility, its ability to forecast significantly weakens after a few quarters. As predicted by the Great Moderation period’s empirical results, the relationship between inflation rate volatility and output volatility is weak. The relationship was only statistically significant for Belgium and France, running from inflation to GDP. Only the US had real output growth rate volatility Granger-causing inflation.

On the policy front, overall results suggest that VIX could be used to forecast other financial variables’ volatility, and TB can be adopted as an indicator for TS. This can be adopted by fixed income managers when they seek to improve the health of their portfolios. For government policymakers, the results show that VIX can be adopted as a candidate in forecasting INF, and appropriate action taken to keep INF in check so as to reduce uncertainty in an economy. In addition, both TB and VIX carry GDP forecasting information. If the objective of a government is to foster economic growth through reducing output growth volatility, the TB and VIX are perfect candidates to forecast output growth volatility.

# Appendix 4

## Fig.1: Belgium, (lag length, 2)




## Table 1: Corresponding Variance Decomposition For Belgium

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| VIX | 100 | 98.58 | 94.18 | 91.32 | 90.25 | 89.94 | 89.85 | 89.81 | 89.79 | 89.76 |
| TB | 0 | 1.25 | 4 | 5.96 | 7 | 7.34 | 7.43 | 7.46 | 7.49 | 7.51 |
| TS | 0 | 0.17 | 1.81 | 2.72 | 2.75 | 2.72 | 2.73 | 2.73 | 2.73 | 2.73 |
| The variance decomposition of TB | | | | | | | | | | |
| VIX | 7.19 | 17.46 | 17.66 | 18.85 | 20.31 | 20.73 | 20.81 | 20.82 | 20.83 | 20.84 |
| TB | 92.81 | 82.26 | 80.71 | 79.41 | 77.72 | 77.14 | 77.06 | 77.06 | 77.05 | 77.04 |
| TS | 0 | 0.28 | 1.63 | 1.74 | 1.98 | 2.13 | 2.13 | 2.12 | 2.13 | 2.13 |
| The variance decomposition of TS | | | | | | | | | | |
| VIX | 3.71 | 13.09 | 13.09 | 13.99 | 14.52 | 14.55 | 14.57 | 14.57 | 14.57 | 14.57 |
| TB | 45.34 | 43.05 | 42.36 | 41.7 | 41.48 | 41.33 | 41.33 | 41.33 | 41.33 | 41.33 |
| TS | 50.96 | 43.86 | 44.55 | 44.31 | 44.01 | 44.12 | 44.1 | 44.1 | 44.1 | 44.1 |

**Fig.2: The UK, (lag length, 1)**

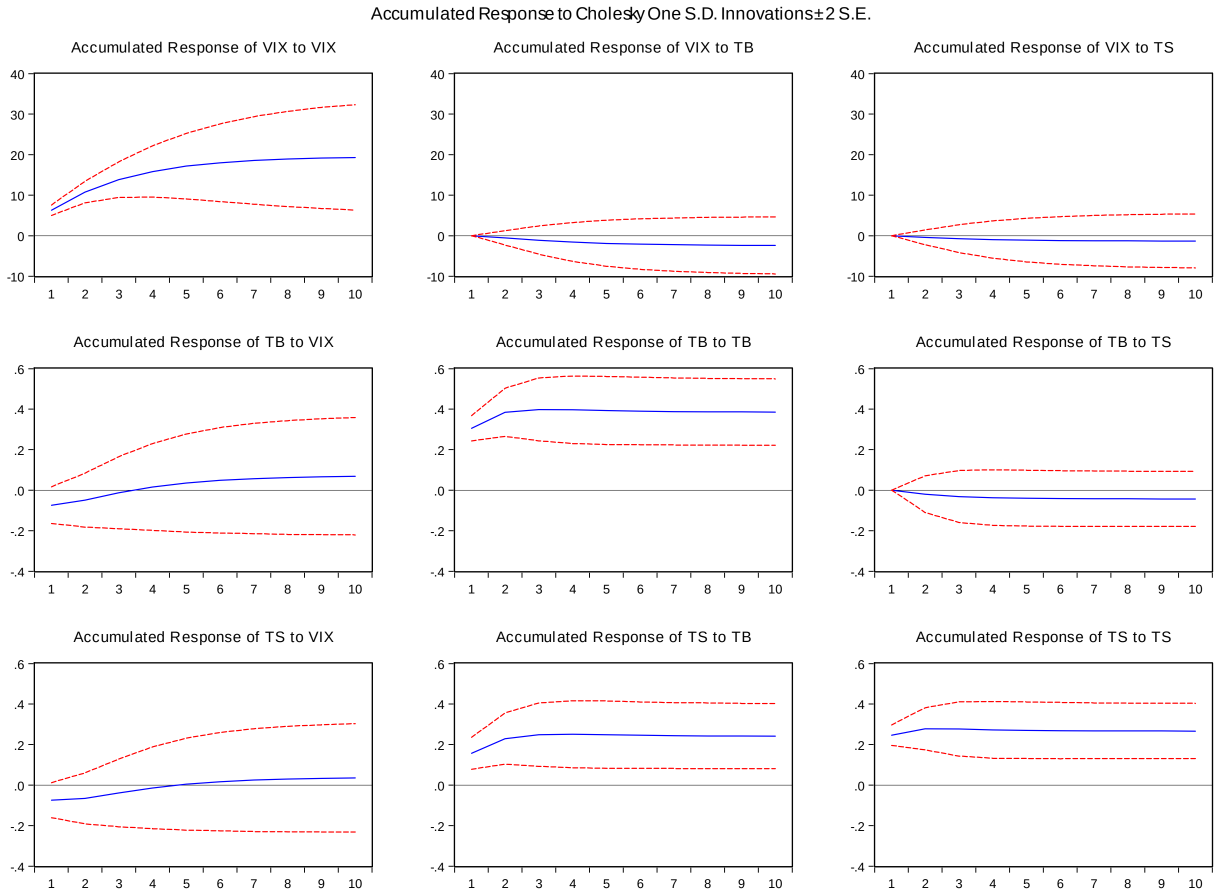



**Table 2: Corresponding Variance Decomposition for the UK**

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| VIX | 100 | 99.19 | 98.67 | 98.42 | 98.31 | 98.27 | 98.25 | 98.24 | 98.23 | 98.23 |
| TB | 0 | 0.51 | 0.92 | 1.13 | 1.23 | 1.27 | 1.28 | 1.29 | 1.3 | 1.3 |
| TS | 0 | 0.3 | 0.41 | 0.45 | 0.46 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 |
| The variance decomposition of TB | | | | | | | | | | |
| VIX | 5.61 | 5.81 | 6.94 | 7.64 | 7.97 | 8.11 | 8.17 | 8.2 | 8.21 | 8.21 |
| TB | 94.39 | 93.8 | 92.55 | 91.83 | 91.49 | 91.35 | 91.29 | 91.26 | 91.25 | 91.25 |
| TS | 0 | 0.39 | 0.51 | 0.53 | 0.54 | 0.54 | 0.54 | 0.54 | 0.54 | 0.54 |
| The variance decomposition of TS | | | | | | | | | | |
| VIX | 6.15 | 5.83 | 6.53 | 7.11 | 7.41 | 7.55 | 7.6 | 7.63 | 7.64 | 7.64 |
| TB | 27.1 | 30.68 | 30.73 | 30.54 | 30.44 | 30.4 | 30.38 | 30.37 | 30.37 | 30.37 |
| TS | 66.75 | 63.49 | 62.74 | 62.36 | 62.15 | 62.06 | 62.02 | 62 | 61.99 | 61.99 |

**Fig. 3: France, (lag length, 2)**

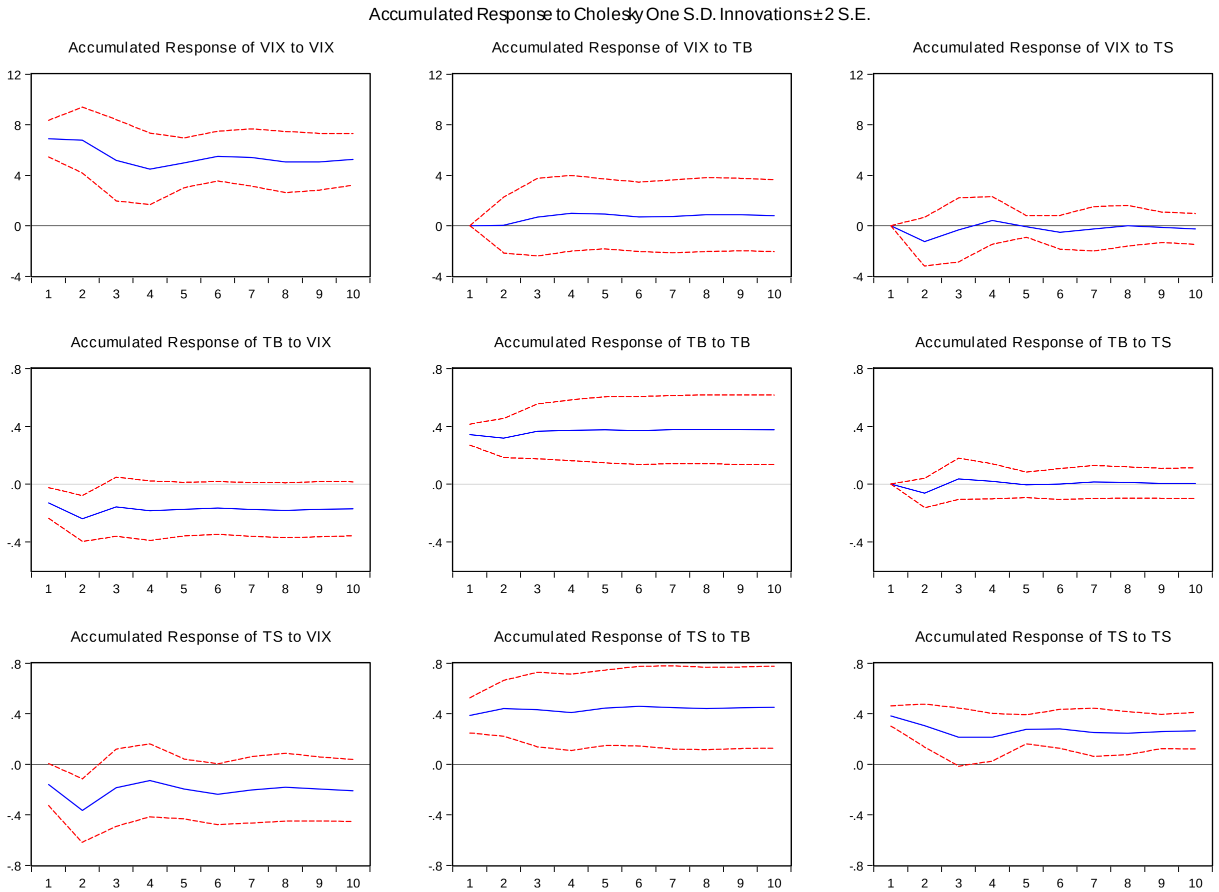
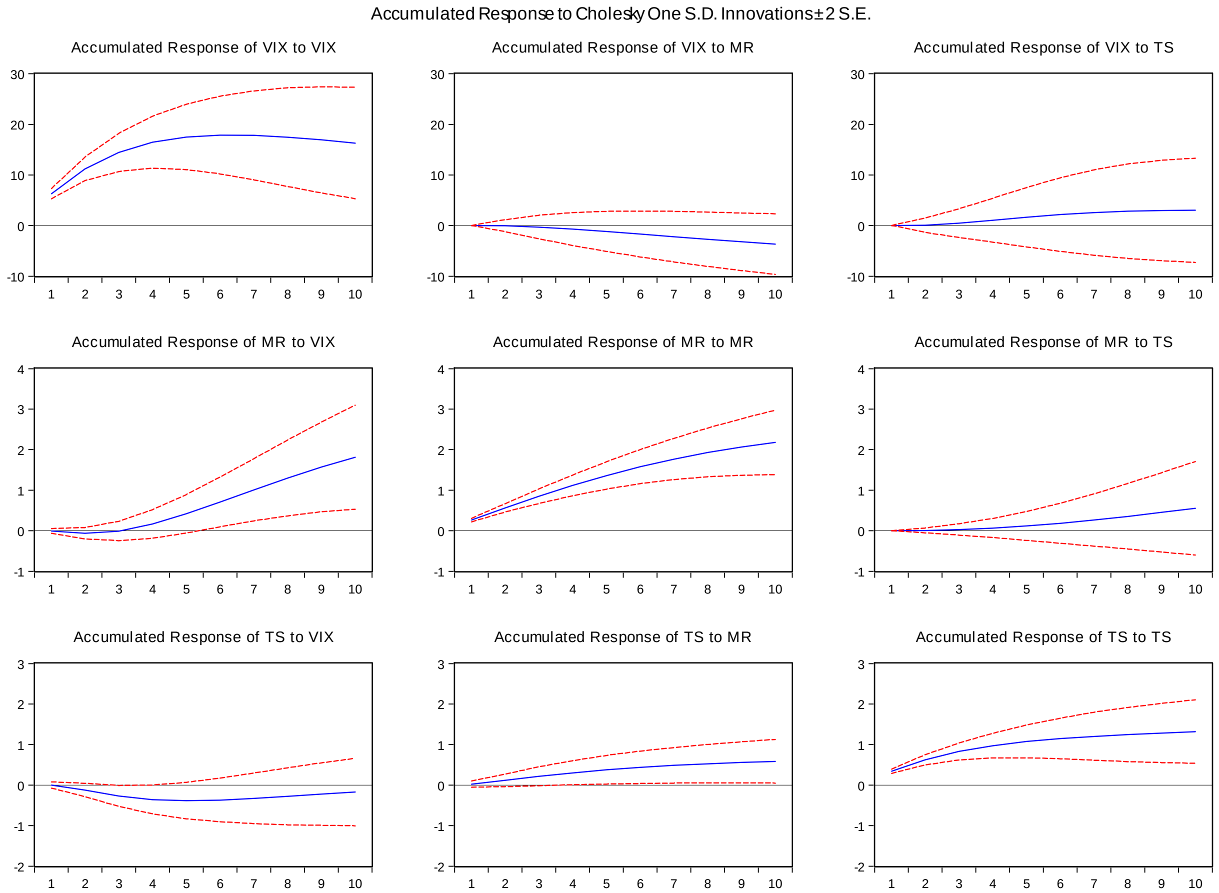



**Table 3: Corresponding Variance Decomposition for France**

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| VIX | 100 | 96.74 | 94.61 | 93.48 | 93.09 | 92.68 | 92.56 | 92.44 | 92.42 | 92.38 |
| TB | 0 | 0 | 0.74 | 0.91 | 0.91 | 0.99 | 0.99 | 1.02 | 1.02 | 1.03 |
| TS | 0 | 3.25 | 4.65 | 5.61 | 6.01 | 6.33 | 6.45 | 6.54 | 6.56 | 6.59 |
| The variance decomposition of TB | | | | | | | | | | |
| VIX | 12.62 | 19.19 | 21.1 | 21.41 | 21.38 | 21.4 | 21.4 | 21.42 | 21.44 | 21.44 |
| TB | 87.38 | 78.25 | 70.82 | 70.39 | 70.09 | 70.06 | 69.95 | 69.93 | 69.89 | 69.89 |
| TS | 0 | 2.56 | 8.08 | 8.21 | 8.53 | 8.54 | 8.65 | 8.65 | 8.67 | 8.67 |
| The variance decomposition of TS | | | | | | | | | | |
| VIX | 8.07 | 18.27 | 24.34 | 24.91 | 25.43 | 25.71 | 25.86 | 25.94 | 25.96 | 25.98 |
| TB | 46.5 | 40.94 | 36.9 | 36.68 | 36.13 | 36.01 | 35.86 | 35.83 | 35.8 | 35.79 |
| TS | 45.43 | 40.79 | 38.76 | 38.41 | 38.44 | 38.28 | 38.28 | 38.24 | 38.25 | 38.23 |

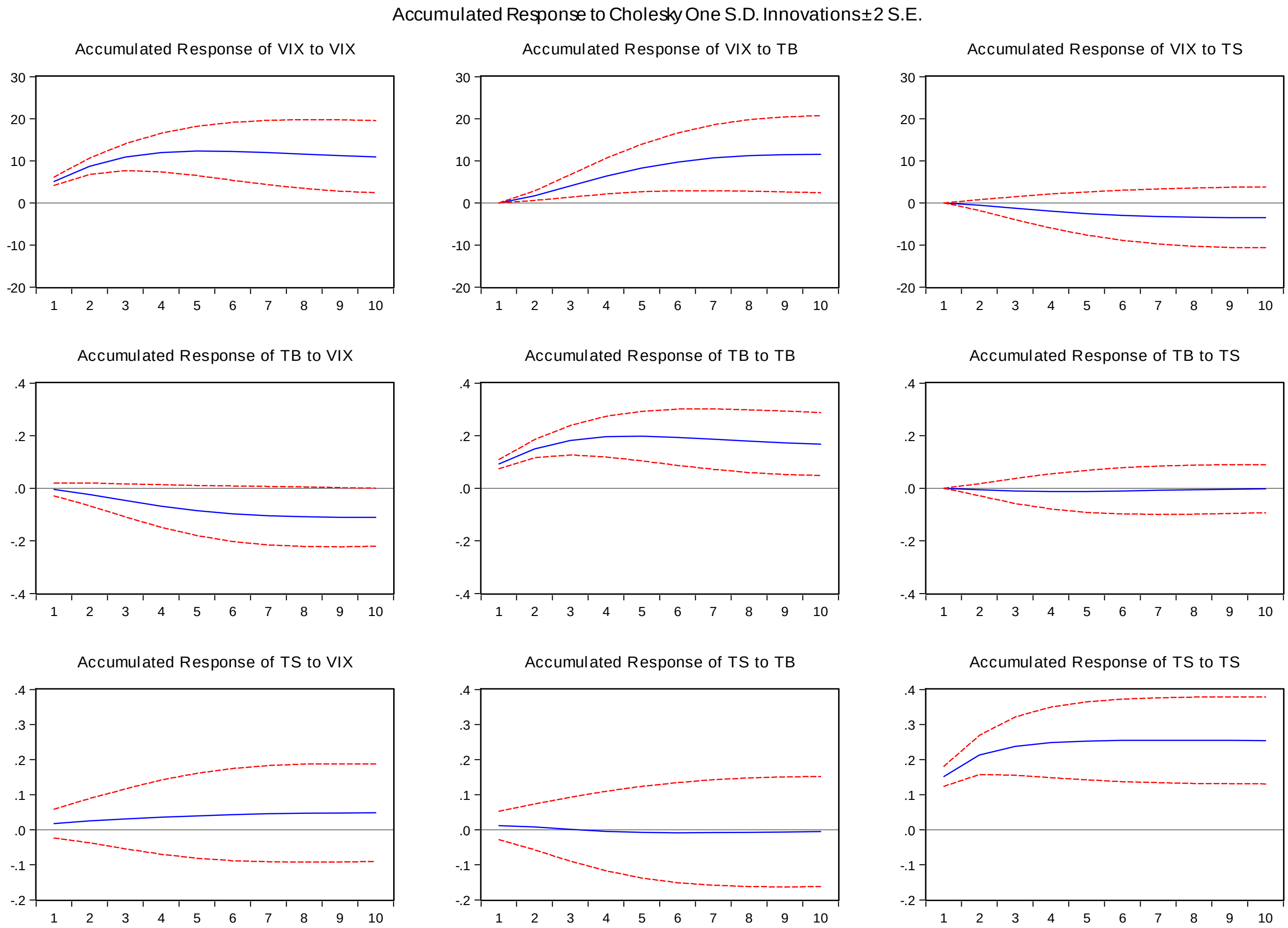
## Fig.1: Germany, (lag length, 2)




## Table 4: Corresponding Variance Decomposition for Germany

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| VIX | 100 | 99.99 | 99.68 | 99.08 | 98.38 | 97.74 | 97.23 | 96.83 | 96.54 | 96.31 |
| TB | 0 | 0 | 0.09 | 0.29 | 0.56 | 0.88 | 1.21 | 1.53 | 1.81 | 2.04 |
| TS | 0 | 0.01 | 0.22 | 0.63 | 1.06 | 1.38 | 1.56 | 1.64 | 1.66 | 1.65 |
| The variance decomposition of TB | | | | | | | | | | |
| VIX | 0.04 | 2.31 | 2.74 | 10.56 | 21.03 | 30.13 | 36.92 | 41.67 | 44.88 | 47.01 |
| TB | 99.96 | 97.67 | 97.05 | 88.93 | 78.07 | 68.44 | 61.03 | 55.59 | 51.67 | 48.86 |
| TS | 0 | 0.02 | 0.21 | 0.5 | 0.9 | 1.43 | 2.05 | 2.74 | 3.45 | 4.13 |
| The variance decomposition of TS | | | | | | | | | | |
| VIX | 0.01 | 6.88 | 12.37 | 13.35 | 12.92 | 12.66 | 12.86 | 13.36 | 13.94 | 14.46 |
| TB | 0.37 | 4.34 | 6.63 | 8.17 | 9.32 | 10.12 | 10.61 | 10.87 | 10.99 | 11.04 |
| TS | 99.62 | 88.77 | 81 | 78.49 | 77.75 | 77.22 | 76.54 | 75.78 | 75.07 | 74.5 |

## Fig.5 Japan, (lag length, 1)




## Table 5: Corresponding Variance Decomposition for Japan

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| VIX | 100 | 92.44 | 82.64 | 74.95 | 70.22 | 67.84 | 66.89 | 66.63 | 66.62 | 66.66 |
| TB | 0 | 6.86 | 15.81 | 22.86 | 27.22 | 29.42 | 30.31 | 30.55 | 30.57 | 30.53 |
| TS | 0 | 0.7 | 1.55 | 2.19 | 2.56 | 2.74 | 2.8 | 2.82 | 2.81 | 2.81 |
| The variance decomposition of TB | | | | | | | | | | |
| VIX | 0.23 | 3.09 | 6.57 | 9.42 | 11.21 | 12.07 | 12.36 | 12.41 | 12.39 | 12.36 |
| TB | 99.77 | 96.61 | 93.01 | 90.15 | 88.37 | 87.5 | 87.17 | 87.09 | 87.08 | 87.09 |
| TS | 0 | 0.3 | 0.42 | 0.43 | 0.42 | 0.44 | 0.47 | 0.51 | 0.53 | 0.54 |
| The variance decomposition of TS | | | | | | | | | | |
| VIX | 1.26 | 1.32 | 1.4 | 1.47 | 1.53 | 1.56 | 1.58 | 1.59 | 1.6 | 1.6 |
| TB | 0.59 | 0.56 | 0.71 | 0.81 | 0.84 | 0.84 | 0.84 | 0.85 | 0.85 | 0.85 |
| TS | 98.16 | 98.12 | 97.89 | 97.73 | 97.64 | 97.59 | 97.57 | 97.56 | 97.55 | 97.55 |

**Fig. 6: The US, (lag length, 2)**

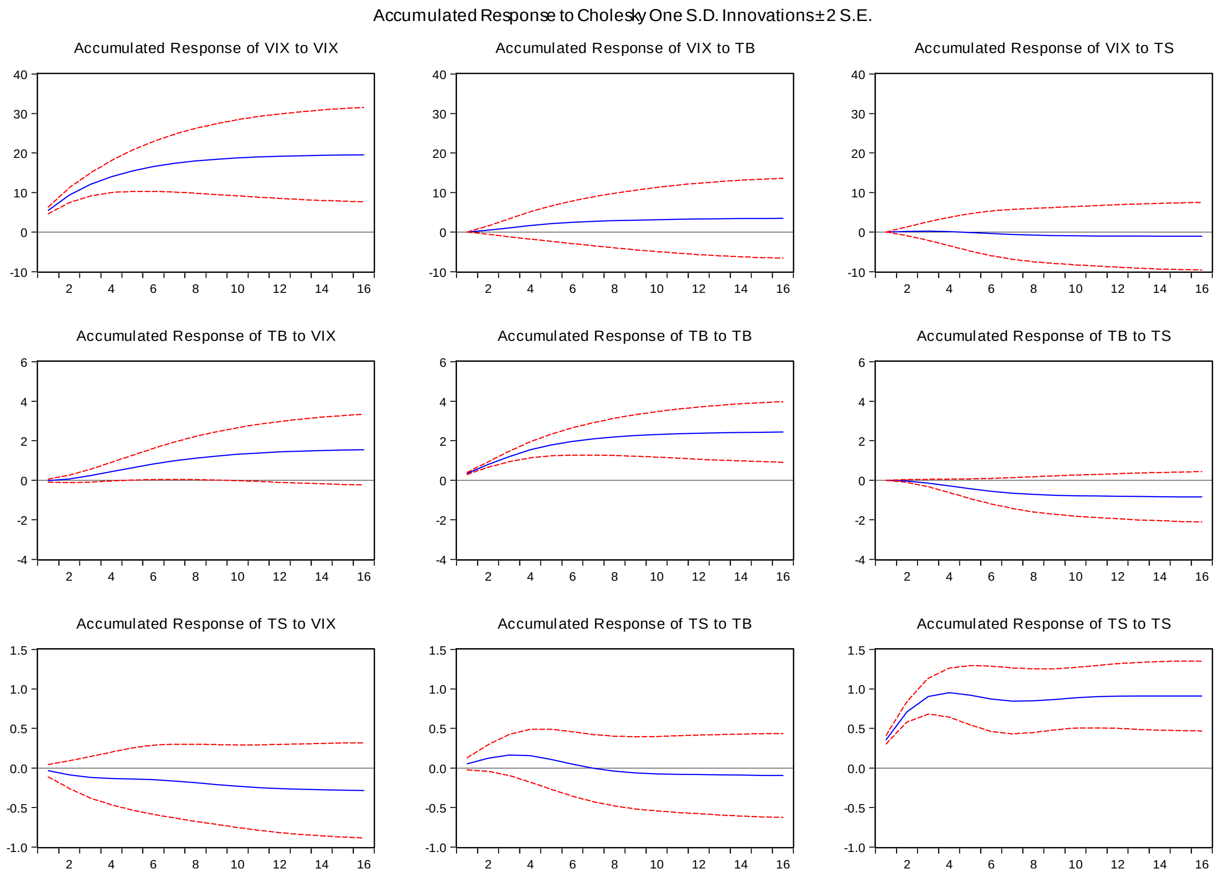



**Table 6: Corresponding Variance Decomposition for the US**

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| VIX | 100 | 99.45 | 98.8 | 98.29 | 97.91 | 97.65 | 97.49 | 97.41 | 97.36 | 97.34 |
| TB | 0 | 0.48 | 1.14 | 1.63 | 1.92 | 2.06 | 2.13 | 2.17 | 2.2 | 2.22 |
| TS | 0 | 0.07 | 0.07 | 0.08 | 0.17 | 0.29 | 0.38 | 0.42 | 0.43 | 0.44 |
| The variance decomposition of TB | | | | | | | | | | |
| VIX | 0.34 | 2.39 | 6.41 | 10.57 | 14.08 | 16.71 | 18.55 | 19.77 | 20.55 | 21.04 |
| TB | 99.66 | 97.04 | 91.31 | 84.87 | 79.42 | 75.62 | 73.28 | 71.93 | 71.15 | 70.69 |
| TS | 0 | 0.56 | 2.27 | 4.56 | 6.5 | 7.67 | 8.17 | 8.3 | 8.3 | 8.27 |
| The variance decomposition of TS | | | | | | | | | | |
| VIX | 0.9 | 1.44 | 1.62 | 1.68 | 1.67 | 1.67 | 1.74 | 1.88 | 2.03 | 2.16 |
| TB | 2.08 | 2.98 | 3.1 | 3.1 | 3.76 | 4.8 | 5.61 | 6 | 6.12 | 6.14 |
| TS | 97.02 | 95.58 | 95.28 | 95.22 | 94.57 | 93.53 | 92.66 | 92.13 | 91.85 | 91.71 |

**Table 7: Granger Causality Test results**

| *Country:* | Belgium | UK | France | Germany | Japan | US |
|---|---|---|---|---|---|---|
| *Null Hypothesis* | | | | | | |
| TB➔ VIX | 0.26 | 0.51 | 0.89 | 0.41 | 0.01*** | 0.58 |
| VIX ➔TB | 0.01*** | 0.22 | 0.06* | 0.01*** | 0.06* | 0.01*** |
| TS➔ VIX | 0.80 | 0.44 | 0.36 | 0.93 | 0.41 | 0.87 |
| VIX ➔TS | 0.03** | 0.35 | 0.07* | 0.02** | 0.96 | 0.83 |
| TS ➔TB | 0.85 | 0.57 | 0.15 | 0.53 | 0.56 | 0.12 |
| TB ➔TS | 0.69 | 0.32 | 0.47 | 0.05** | 0.58 | 0.41 |

***, **and * denote significance at 1%, 5% and 10% levels respectively.

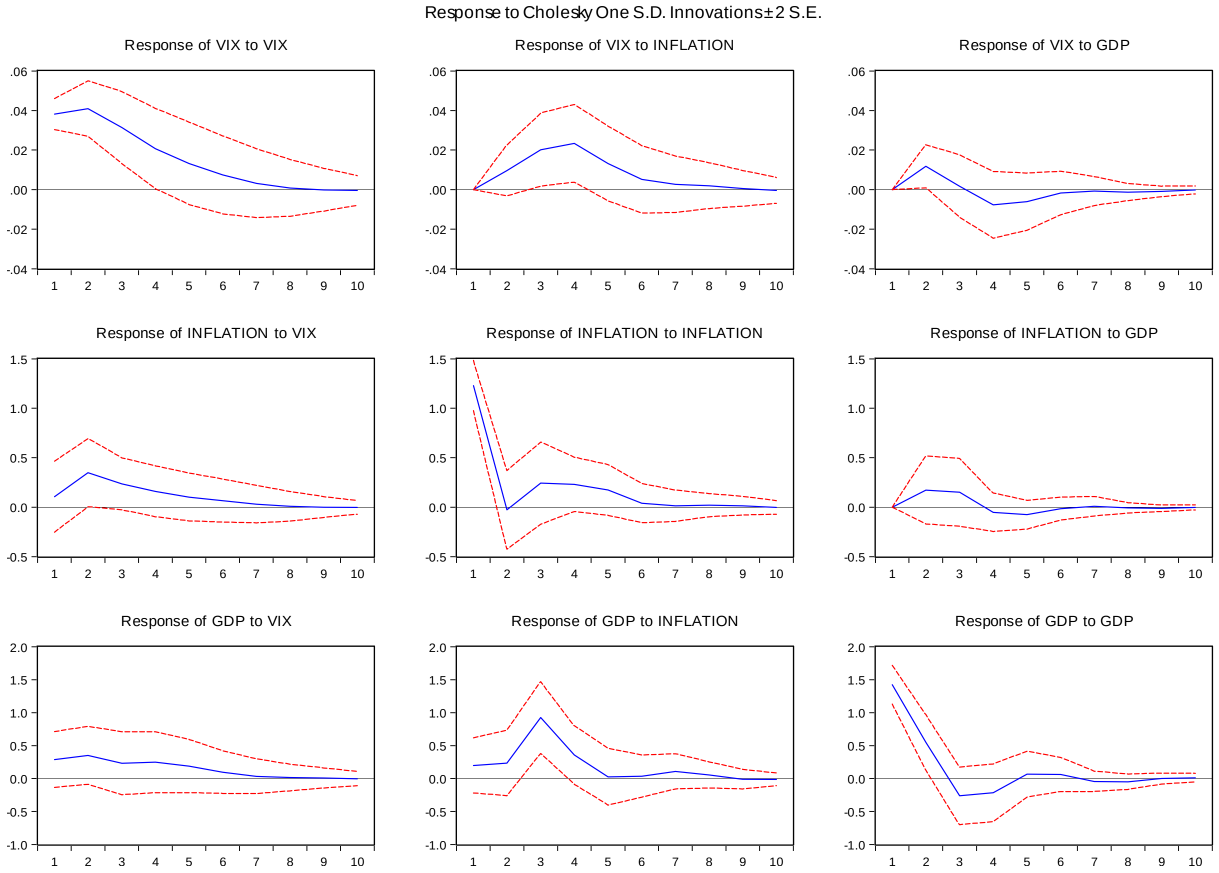
**Table 8: Summary of Impulse response**

| | Belgium | UK | France | Germany | Japan | US |
|---|---|---|---|---|---|---|
| TB➔ VIX | insignificant | insignificant | insignificant | significant | insignificant | insignificant |
| VIX ➔TB | insignificant | insignificant | insignificant | insignificant | insignificant | significant |
| TS➔ VIX | insignificant | insignificant | insignificant | insignificant | insignificant | insignificant |
| VIX ➔TS | insignificant | insignificant | insignificant | insignificant | insignificant | insignificant |
| TS ➔TB | insignificant | insignificant | insignificant | insignificant | insignificant | insignificant |
| TB ➔TS | significant | significant | significant | significant | insignificant | significant |

Key TB➔ VIX, this means the response of VIX to a shock on TB

# Appendix 5
# Belgium

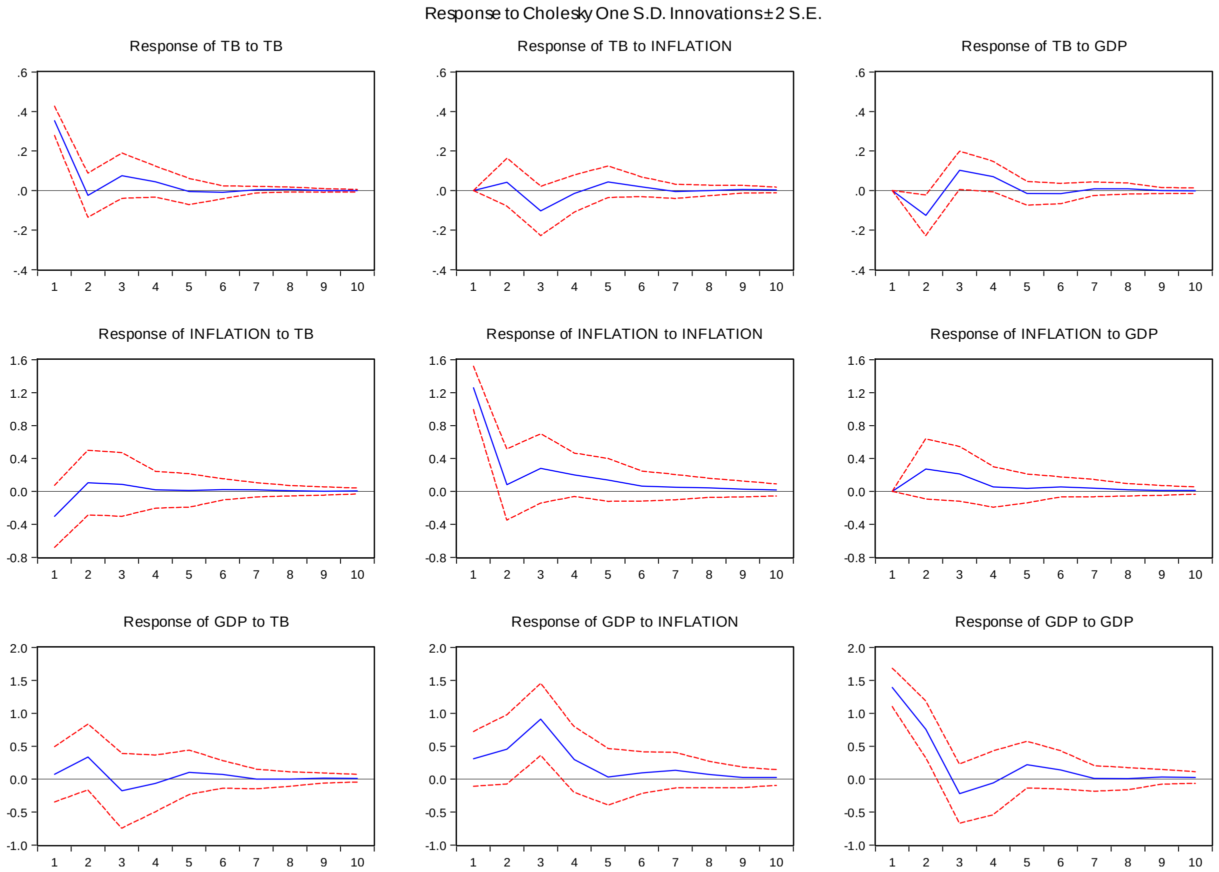
### Fig. 7: Impulse Response of VIX, Inflation and GDP (Lag length, 2)




### Table 9: Corresponding Variance Decomposition

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| VIX | 100 | 93.11 | 86.48 | 78.45 | 76.38 | 76.24 | 76.18 | 76.12 | 76.1 | 76.1 |
| Inflation | 0 | 2.76 | 10.54 | 18.08 | 19.76 | 19.91 | 19.97 | 20.01 | 20.02 | 20.02 |
| GDP | 0 | 4.13 | 2.99 | 3.47 | 3.86 | 3.85 | 3.85 | 3.87 | 3.88 | 3.88 |
| The variance decomposition of Inflation | | | | | | | | | | |
| VIX | 0.73 | 7.93 | 10.37 | 11.29 | 11.55 | 11.74 | 11.78 | 11.78 | 11.78 | 11.78 |
| Inflation | 99.27 | 90.29 | 86.74 | 85.81 | 85.31 | 85.12 | 85.07 | 85.07 | 85.07 | 85.07 |
| GDP | 0 | 1.78 | 2.88 | 2.9 | 3.14 | 3.14 | 3.14 | 3.15 | 3.15 | 3.15 |
| The variance decomposition of GDP | | | | | | | | | | |
| VIX | 3.86 | 7.83 | 7.2 | 8.34 | 9.16 | 9.36 | 9.36 | 9.35 | 9.35 | 9.35 |
| Inflation | 1.82 | 3.59 | 26.36 | 28.06 | 27.79 | 27.72 | 27.92 | 27.95 | 27.95 | 27.95 |
| GDP | 94.32 | 88.58 | 66.46 | 63.6 | 63.05 | 62.91 | 62.73 | 62.7 | 62.7 | 62.7 |

## Fig. 8: Impulse Response of TB, Inflation and GDP (Lag length, 2)




## Table 9:Corresponding Variance Decomposition

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| TB | 100 | 87.74 | 77.21 | 75.25 | 74.37 | 74.14 | 74.1 | 74.06 | 74.05 | 74.04 |
| Inflation | 0 | 1.24 | 7.36 | 7.19 | 8.16 | 8.32 | 8.33 | 8.32 | 8.34 | 8.35 |
| GDP | 0 | 11.01 | 15.43 | 17.57 | 17.47 | 17.54 | 17.57 | 17.61 | 17.61 | 17.61 |
| The variance decomposition of Inflation | | | | | | | | | | |
| TB | 5.47 | 5.82 | 5.79 | 5.68 | 5.63 | 5.63 | 5.64 | 5.64 | 5.63 | 5.63 |
| Inflation | 94.53 | 90 | 87.92 | 88.02 | 88.07 | 87.94 | 87.86 | 87.86 | 87.85 | 87.85 |
| GDP | 0 | 4.18 | 6.29 | 6.3 | 6.3 | 6.43 | 6.5 | 6.51 | 6.51 | 6.52 |
| The variance decomposition of GDP | | | | | | | | | | |
| TB | 0.27 | 4.07 | 3.93 | 3.93 | 4.14 | 4.23 | 4.21 | 4.21 | 4.21 | 4.21 |
| Inflation | 4.64 | 10.23 | 29.41 | 30.95 | 30.5 | 30.49 | 30.8 | 30.88 | 30.89 | 30.89 |
| GDP | 95.09 | 85.71 | 66.67 | 65.12 | 65.35 | 65.28 | 64.99 | 64.91 | 64.9 | 64.9 |

**Fig. 9: Impulse Response of TS, Inflation and GDP (Lag length, 2)**

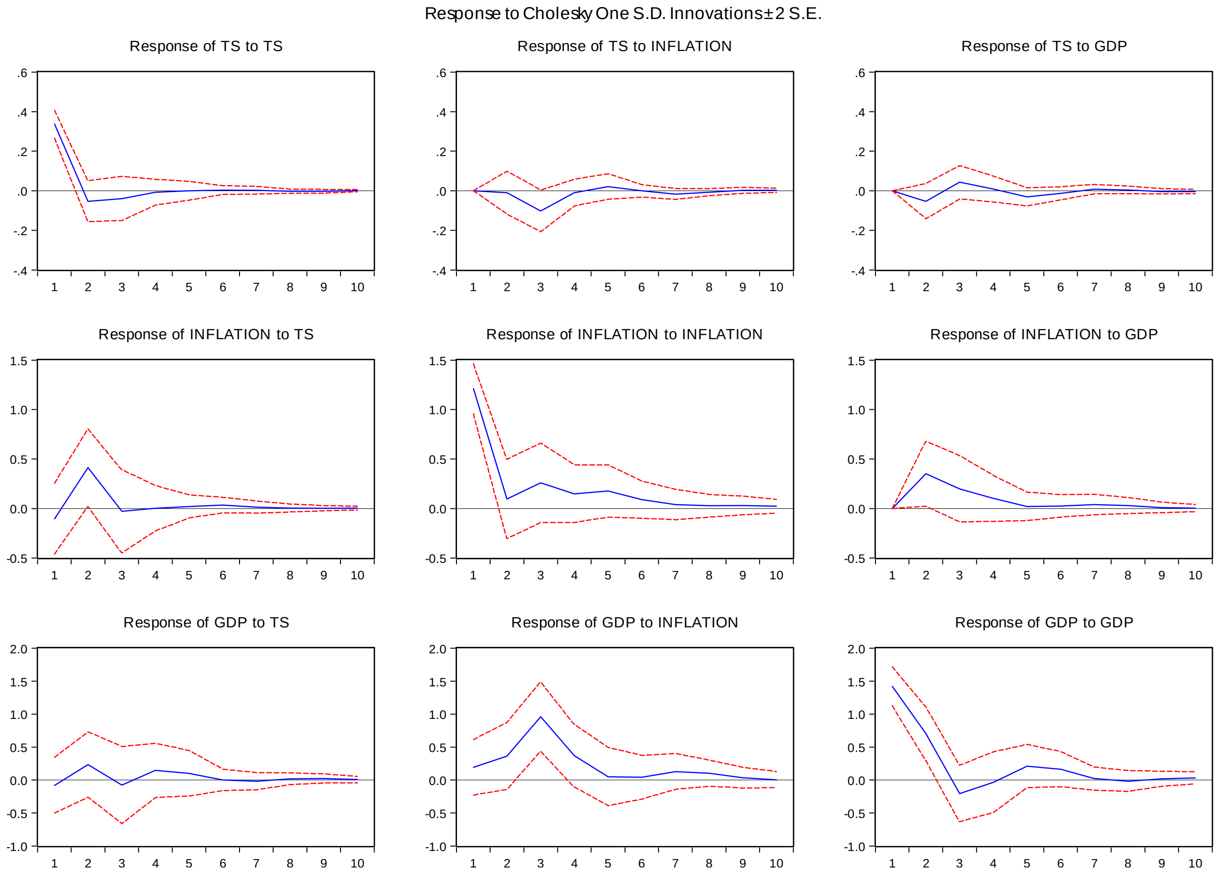
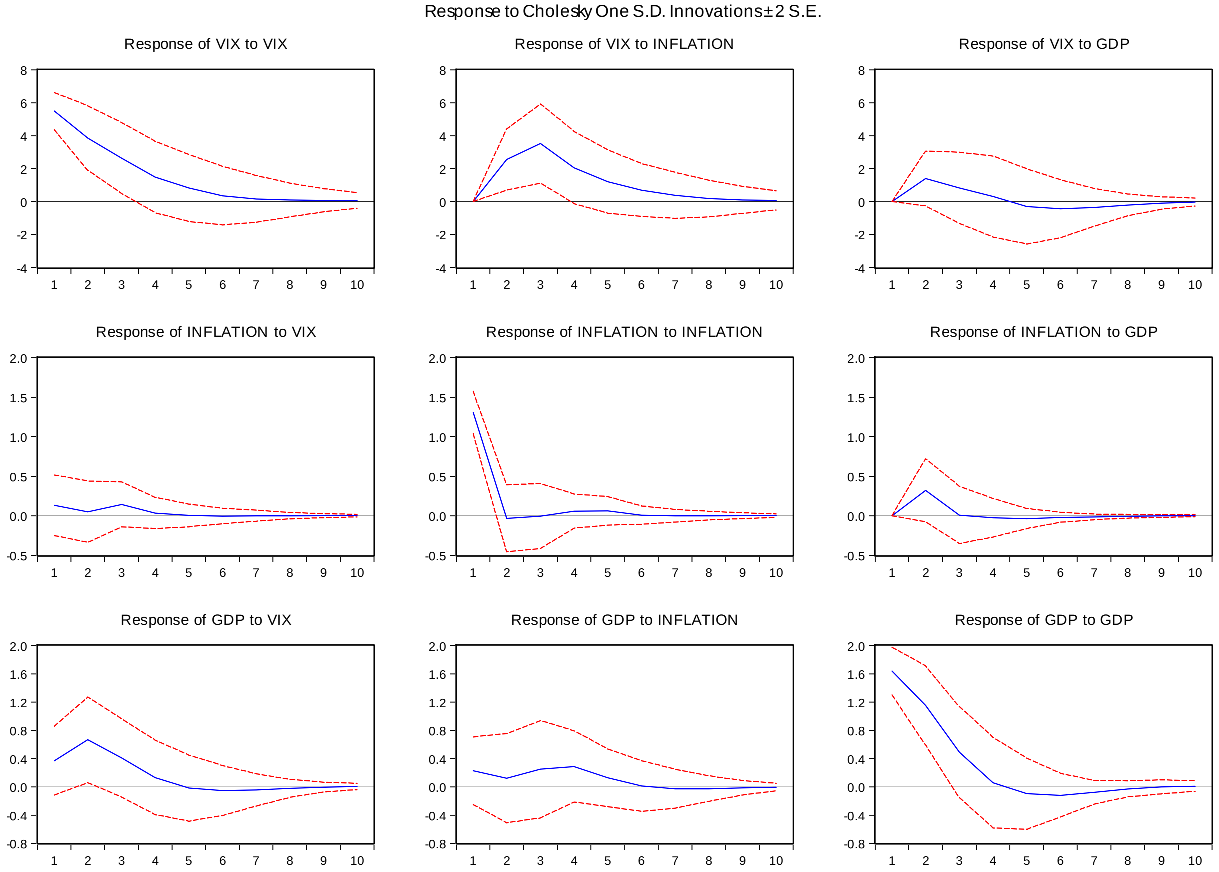



**Table 10: Corresponding Variance Decomposition**

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| TS | 100 | 97.57 | 88.6 | 88.49 | 87.57 | 87.45 | 87.24 | 87.19 | 87.18 | 87.17 |
| Inflation | 0 | 0.08 | 7.9 | 7.97 | 8.22 | 8.21 | 8.39 | 8.43 | 8.43 | 8.43 |
| GDP | 0 | 2.35 | 3.49 | 3.54 | 4.21 | 4.34 | 4.37 | 4.39 | 4.4 | 4.41 |
| The variance decomposition of Inflation | | | | | | | | | | |
| TS | 0.73 | 10.19 | 9.66 | 9.49 | 9.36 | 9.37 | 9.36 | 9.36 | 9.35 | 9.35 |
| Inflation | 99.27 | 82.88 | 81.73 | 81.5 | 81.76 | 81.75 | 81.7 | 81.67 | 81.67 | 81.67 |
| GDP | 0 | 6.93 | 8.61 | 9.01 | 8.89 | 8.88 | 8.94 | 8.98 | 8.98 | 8.97 |
| The variance decomposition of GDP | | | | | | | | | | |
| TS | 0.31 | 2.22 | 1.8 | 2.27 | 2.49 | 2.47 | 2.47 | 2.47 | 2.48 | 2.48 |
| Inflation | 1.76 | 6.11 | 29.36 | 31.66 | 31.26 | 31.08 | 31.37 | 31.55 | 31.56 | 31.55 |
| GDP | 97.93 | 91.67 | 68.84 | 66.08 | 66.24 | 66.44 | 66.16 | 65.98 | 65.95 | 65.96 |

## The UK

### Fig. 10: Impulse Response of VIX, Inflation and GDP (Lag length, 2)




### Table 11: Corresponding Variance Decomposition

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| VIX | 100 | 84.18 | 70.68 | 67.67 | 66.65 | 66.17 | 65.97 | 65.91 | 65.9 | 65.9 |
| Inflation | 0 | 12.15 | 25.71 | 28.9 | 29.9 | 30.19 | 30.26 | 30.27 | 30.27 | 30.27 |
| GDP | 0 | 3.67 | 3.61 | 3.43 | 3.44 | 3.64 | 3.77 | 3.82 | 3.83 | 3.83 |
| The variance decomposition of Inflation | | | | | | | | | | |
| VIX | 1.03 | 1.12 | 2.22 | 2.28 | 2.27 | 2.27 | 2.27 | 2.27 | 2.27 | 2.27 |
| Inflation | 98.97 | 93.23 | 92.18 | 92.11 | 92.06 | 92.04 | 92.03 | 92.03 | 92.03 | 92.03 |
| GDP | 0 | 5.66 | 5.6 | 5.62 | 5.67 | 5.69 | 5.7 | 5.7 | 5.7 | 5.7 |
| The variance decomposition of GDP | | | | | | | | | | |
| VIX | 4.76 | 12.43 | 14.52 | 14.57 | 14.5 | 14.51 | 14.52 | 14.53 | 14.53 | 14.53 |
| Inflation | 1.78 | 1.4 | 2.49 | 4.02 | 4.3 | 4.29 | 4.3 | 4.31 | 4.32 | 4.32 |
| GDP | 93.47 | 86.17 | 82.99 | 81.42 | 81.2 | 81.2 | 81.18 | 81.16 | 81.16 | 81.16 |

**Fig. 11: Impulse Response of TB, Inflation and GDP (Lag length, 1)**

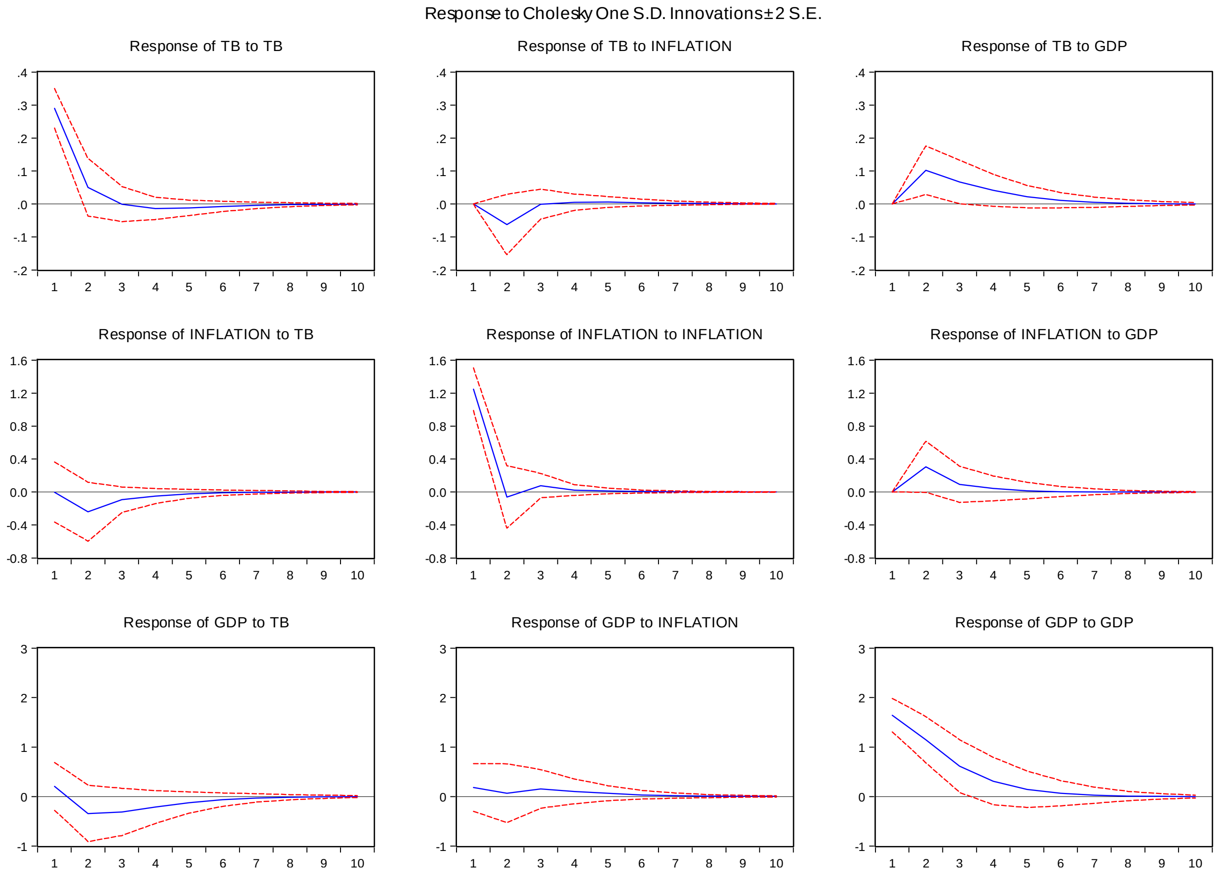



**Table 12: Corresponding Variance Decomposition**

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| TB | 100 | 85.88 | 82.28 | 80.99 | 80.62 | 80.53 | 80.51 | 80.51 | 80.51 | 80.51 |
| Inflation | 0 | 3.82 | 3.66 | 3.62 | 3.63 | 3.64 | 3.64 | 3.64 | 3.64 | 3.64 |
| GDP | 0 | 10.3 | 14.05 | 15.39 | 15.75 | 15.83 | 15.85 | 15.85 | 15.85 | 15.85 |
| The variance decomposition of Inflation | | | | | | | | | | |
| TB | 0 | 3.41 | 3.88 | 4.01 | 4.04 | 4.04 | 4.04 | 4.04 | 4.04 | 4.04 |
| Inflation | 100 | 91.14 | 90.26 | 90.04 | 90 | 90 | 90 | 90 | 90 | 90 |
| GDP | 0 | 5.45 | 5.86 | 5.95 | 5.96 | 5.96 | 5.96 | 5.96 | 5.96 | 5.96 |
| The variance decomposition of GDP | | | | | | | | | | |
| TB | 1.53 | 3.81 | 5.49 | 6.25 | 6.5 | 6.57 | 6.59 | 6.59 | 6.59 | 6.59 |
| Inflation | 1.22 | 0.9 | 1.31 | 1.49 | 1.56 | 1.58 | 1.58 | 1.58 | 1.58 | 1.58 |
| GDP | 97.25 | 95.28 | 93.2 | 92.27 | 91.95 | 91.85 | 91.83 | 91.83 | 91.83 | 91.83 |

**Fig. 12: Impulse Response of TS, Inflation and GDP (Lag length, 1)**

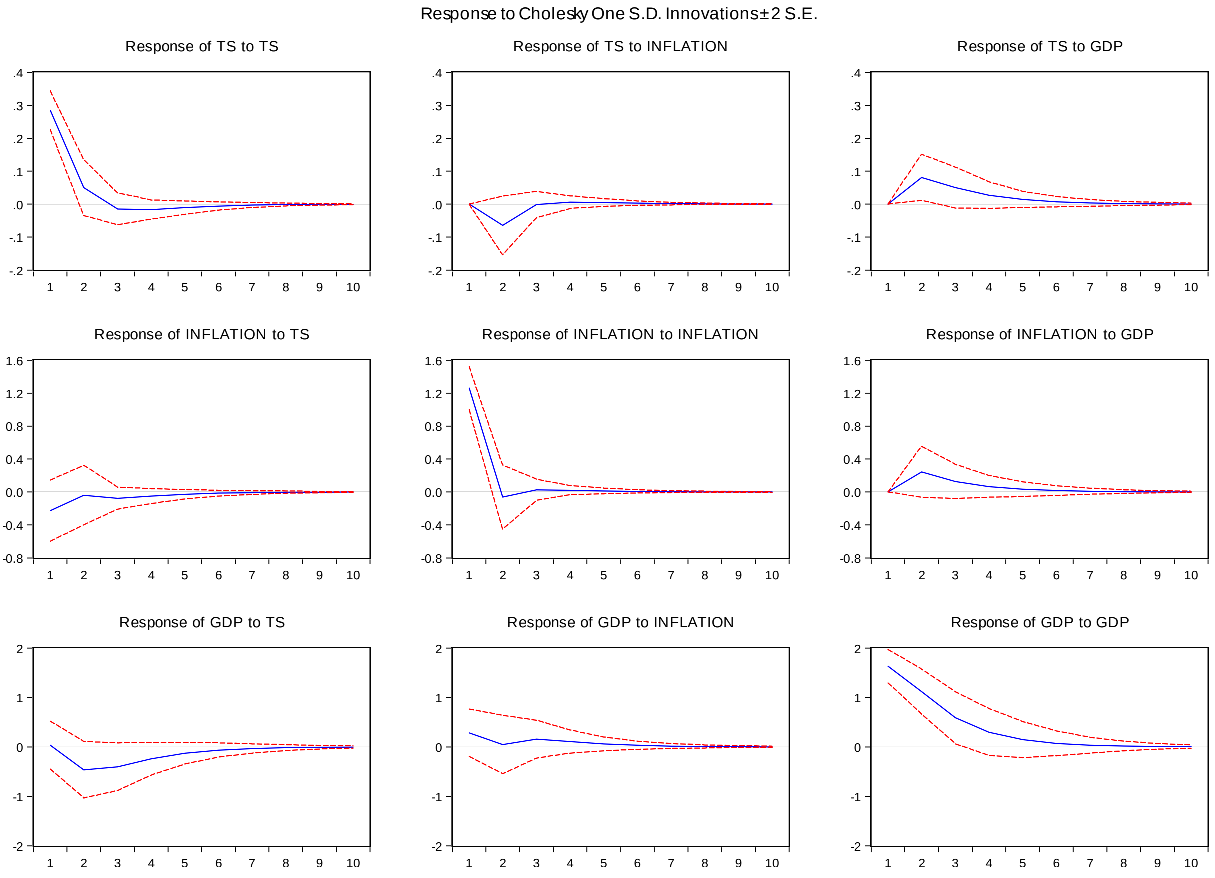
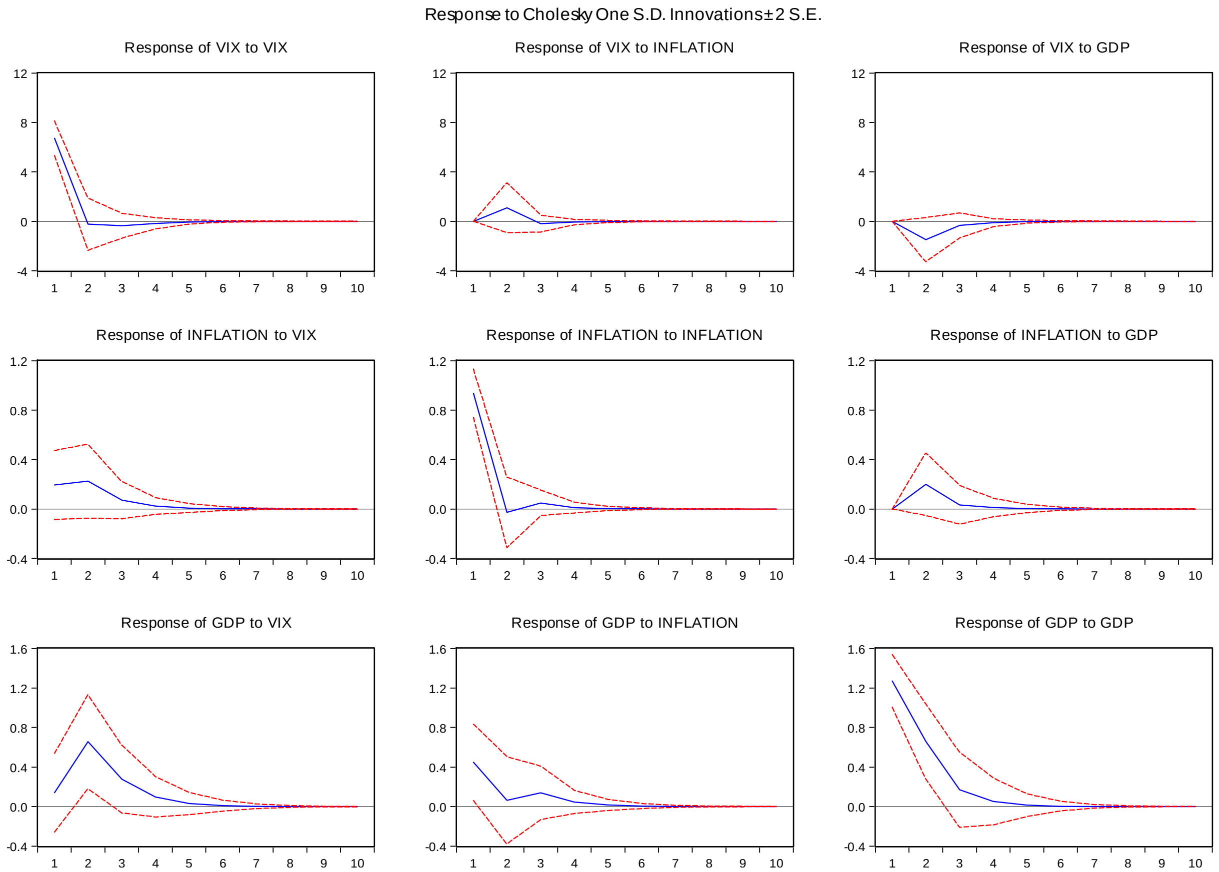



**Table 13: Corresponding Variance Decomposition**

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| TS | 100 | 88.59 | 86.32 | 85.67 | 85.5 | 85.46 | 85.45 | 85.45 | 85.45 | 85.45 |
| Inflation | 0 | 4.43 | 4.3 | 4.29 | 4.3 | 4.3 | 4.31 | 4.31 | 4.31 | 4.31 |
| GDP | 0 | 6.98 | 9.37 | 10.03 | 10.2 | 10.24 | 10.25 | 10.25 | 10.25 | 10.25 |
| The variance decomposition of Inflation | | | | | | | | | | |
| TS | 3.15 | 3.12 | 3.42 | 3.55 | 3.59 | 3.6 | 3.6 | 3.61 | 3.61 | 3.61 |
| Inflation | 96.85 | 93.4 | 92.18 | 91.81 | 91.71 | 91.69 | 91.68 | 91.68 | 91.68 | 91.68 |
| GDP | 0 | 3.49 | 4.4 | 4.64 | 4.7 | 4.71 | 4.71 | 4.71 | 4.71 | 4.71 |
| The variance decomposition of GDP | | | | | | | | | | |
| TS | 0.04 | 5.1 | 7.94 | 8.86 | 9.12 | 9.19 | 9.2 | 9.21 | 9.21 | 9.21 |
| Inflation | 2.95 | 1.98 | 2.27 | 2.43 | 2.48 | 2.5 | 2.5 | 2.5 | 2.5 | 2.5 |
| GDP | 97.01 | 92.92 | 89.79 | 88.7 | 88.39 | 88.31 | 88.29 | 88.29 | 88.29 | 88.29 |

## France

### Fig. 13: Impulse Response of VIX, Inflation and GDP (Lag length, 1)




### Table 14: Corresponding Variance Decomposition

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| VIX | 100 | 93.03 | 92.77 | 92.74 | 92.74 | 92.74 | 92.74 | 92.74 | 92.74 | 92.74 |
| Inflation | 0 | 2.46 | 2.52 | 2.53 | 2.53 | 2.53 | 2.53 | 2.53 | 2.53 | 2.53 |
| GDP | 0 | 4.51 | 4.71 | 4.73 | 4.73 | 4.73 | 4.73 | 4.73 | 4.73 | 4.73 |
| The variance decomposition of Inflation | | | | | | | | | | |
| VIX | 4.12 | 8.8 | 9.22 | 9.27 | 9.28 | 9.28 | 9.28 | 9.28 | 9.28 | 9.28 |
| Inflation | 95.88 | 87.25 | 86.74 | 86.68 | 86.68 | 86.68 | 86.67 | 86.67 | 86.67 | 86.67 |
| GDP | 0 | 3.96 | 4.03 | 4.05 | 4.05 | 4.05 | 4.05 | 4.05 | 4.05 | 4.05 |
| The variance decomposition of GDP | | | | | | | | | | |
| VIX | 1.08 | 16.63 | 18.61 | 18.85 | 18.88 | 18.88 | 18.88 | 18.88 | 18.88 | 18.88 |
| Inflation | 10.94 | 7.58 | 7.92 | 7.95 | 7.96 | 7.96 | 7.96 | 7.96 | 7.96 | 7.96 |
| GDP | 87.98 | 75.8 | 73.47 | 73.19 | 73.16 | 73.16 | 73.16 | 73.16 | 73.16 | 73.16 |

**Fig. 14: Impulse Response of TB, Inflation and GDP (Lag length, 1)**

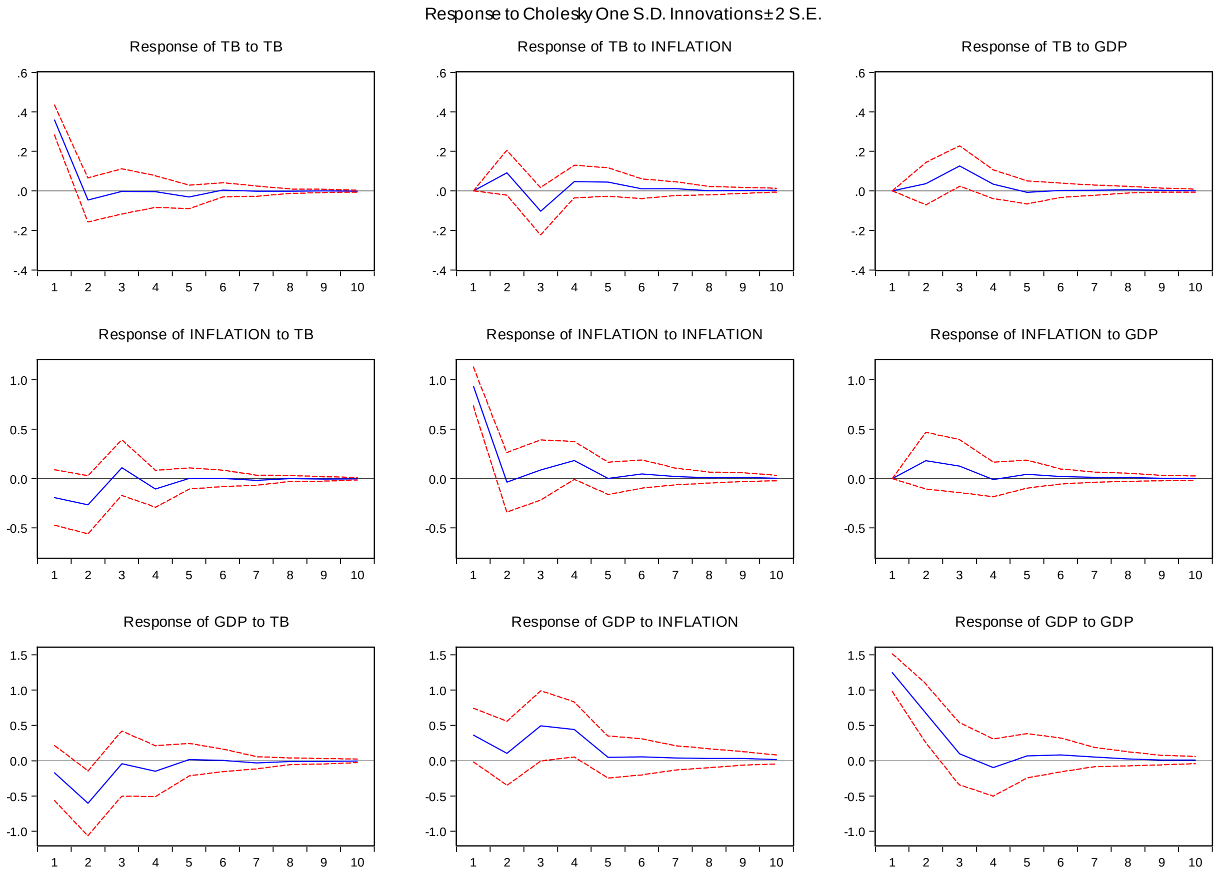



**Table 15: Corresponding Variance Decomposition**

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| TB | 100 | 93.04 | 78.36 | 76.82 | 76.06 | 76.01 | 75.95 | 75.94 | 75.93 | 75.93 |
| Inflation | 0 | 6.01 | 11.39 | 12.47 | 13.39 | 13.44 | 13.5 | 13.49 | 13.5 | 13.5 |
| GDP | 0 | 0.95 | 10.25 | 10.71 | 10.56 | 10.55 | 10.55 | 10.57 | 10.57 | 10.57 |
| The variance decomposition of Inflation | | | | | | | | | | |
| TB | 4.07 | 10.61 | 11.42 | 11.95 | 11.93 | 11.9 | 11.92 | 11.92 | 11.92 | 11.92 |
| Inflation | 95.93 | 86.16 | 83.96 | 83.6 | 83.46 | 83.46 | 83.43 | 83.42 | 83.42 | 83.41 |
| GDP | 0 | 3.23 | 4.63 | 4.45 | 4.62 | 4.64 | 4.66 | 4.67 | 4.67 | 4.67 |
| The variance decomposition of GDP | | | | | | | | | | |
| TB | 1.78 | 15.57 | 14.23 | 13.92 | 13.89 | 13.85 | 13.86 | 13.85 | 13.85 | 13.85 |
| Inflation | 7.61 | 5.55 | 13.73 | 19.15 | 19.18 | 19.22 | 19.24 | 19.26 | 19.29 | 19.29 |
| GDP | 90.61 | 78.87 | 72.05 | 66.93 | 66.93 | 66.93 | 66.9 | 66.89 | 66.86 | 66.86 |

**Fig. 15: Impulse Response of TS, Inflation and GDP (Lag length, 1)**

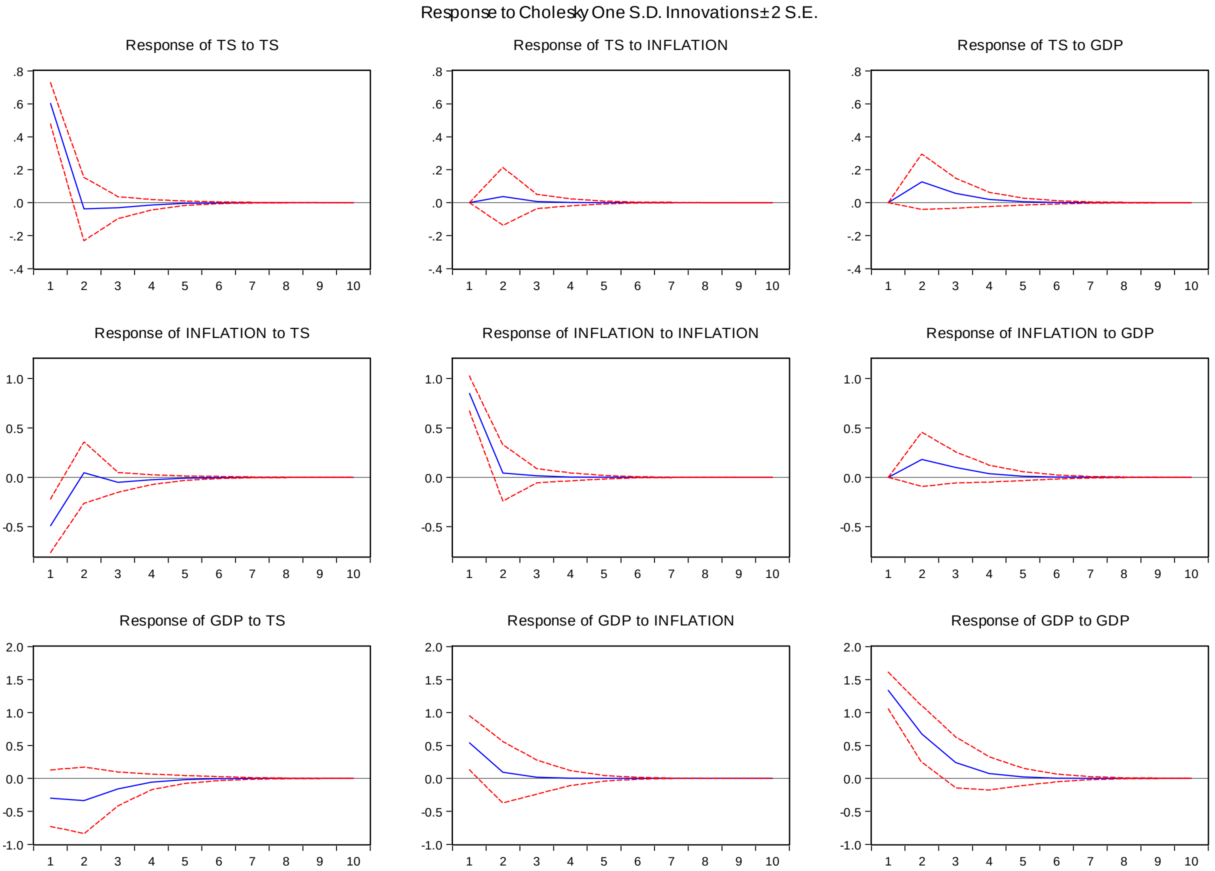



**Table 16: Corresponding Variance Decomposition for France**

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| TS | 100 | 95.48 | 94.67 | 94.58 | 94.57 | 94.57 | 94.57 | 94.57 | 94.57 | 94.57 |
| Inflation | 0 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 |
| GDP | 0 | 4.16 | 4.95 | 5.04 | 5.05 | 5.05 | 5.05 | 5.05 | 5.05 | 5.05 |
| The variance decomposition of Inflation | | | | | | | | | | |
| TS | 24.99 | 24.29 | 24.24 | 24.25 | 24.26 | 24.26 | 24.26 | 24.26 | 24.26 | 24.26 |
| Inflation | 75.01 | 72.44 | 71.54 | 71.41 | 71.4 | 71.4 | 71.4 | 71.4 | 71.4 | 71.4 |
| GDP | 0 | 3.27 | 4.21 | 4.34 | 4.35 | 4.35 | 4.35 | 4.35 | 4.35 | 4.35 |
| The variance decomposition of GDP | | | | | | | | | | |
| TS | 4.19 | 7.4 | 8.09 | 8.17 | 8.18 | 8.18 | 8.18 | 8.18 | 8.18 | 8.18 |
| Inflation | 13.46 | 10.95 | 10.64 | 10.61 | 10.61 | 10.61 | 10.61 | 10.61 | 10.61 | 10.61 |
| GDP | 82.36 | 81.65 | 81.27 | 81.22 | 81.22 | 81.22 | 81.22 | 81.22 | 81.22 | 81.22 |

## Germany

**Fig. 16: Impulse Response of VIX, Inflation and GDP (Lag length, 4)**

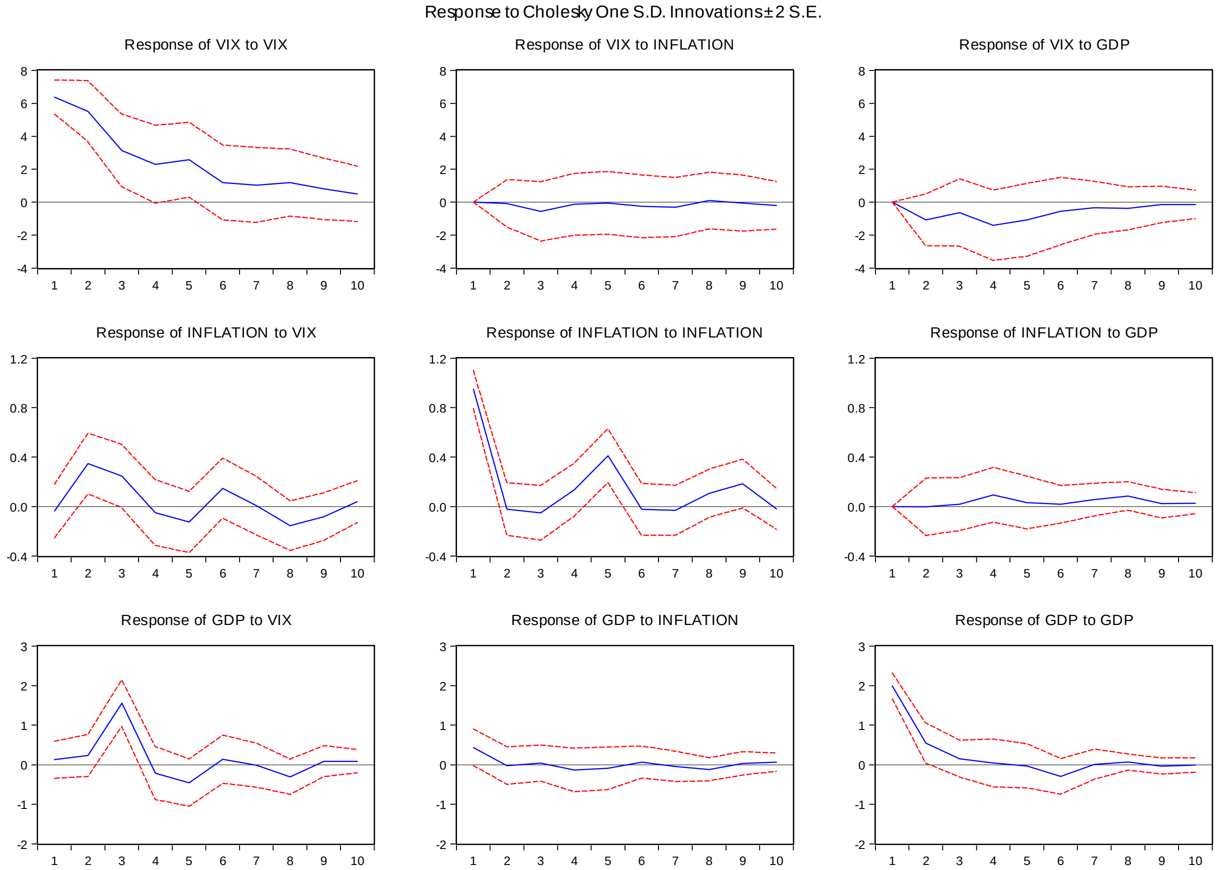



**Table 17: Corresponding Variance Decomposition**

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| VIX | 100 | 98.4 | 97.74 | 95.71 | 94.86 | 94.59 | 94.45 | 94.39 | 94.4 | 94.36 |
| Inflation | 0 | 0.01 | 0.39 | 0.38 | 0.35 | 0.41 | 0.5 | 0.5 | 0.5 | 0.53 |
| GDP | 0 | 1.6 | 1.87 | 3.91 | 4.79 | 5 | 5.05 | 5.11 | 5.1 | 5.1 |
| The variance decomposition of Inflation | | | | | | | | | | |
| VIX | 0.15 | 11.96 | 16.85 | 16.62 | 15.46 | 16.84 | 16.79 | 18.03 | 17.97 | 18.05 |
| Inflation | 99.85 | 88.04 | 83.12 | 82.55 | 83.74 | 82.35 | 82.17 | 80.44 | 80.51 | 80.39 |
| GDP | 0 | 0 | 0.03 | 0.83 | 0.8 | 0.81 | 1.04 | 1.53 | 1.52 | 1.57 |
| The variance decomposition of GDP | | | | | | | | | | |
| VIX | 0.38 | 1.54 | 35.68 | 35.99 | 37.76 | 37.46 | 37.45 | 38.14 | 38.19 | 38.24 |
| Inflation | 4.56 | 4.22 | 2.77 | 3 | 3.02 | 3.03 | 3.06 | 3.2 | 3.21 | 3.26 |
| GDP | 95.06 | 94.23 | 61.56 | 61.01 | 59.22 | 59.51 | 59.49 | 58.66 | 58.6 | 58.5 |

**Fig. 17: Impulse Response of MR, Inflation and GDP (Lag length, 4)**

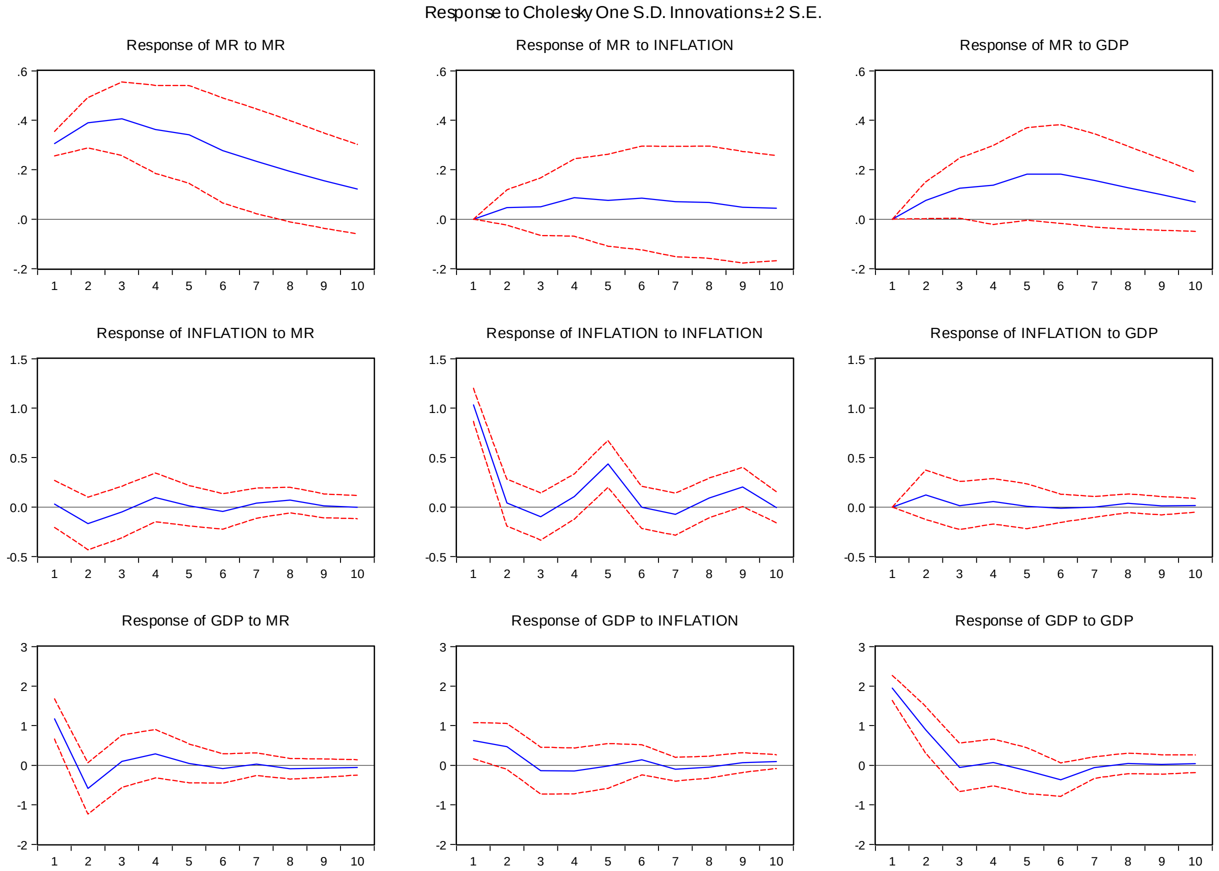



**Table 18: Corresponding Variance Decomposition**

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| MR | 100 | 96.82 | 93.96 | 91.09 | 87.73 | 84.72 | 82.98 | 81.91 | 81.38 | 81.12 |
| Inflation | 0 | 0.87 | 1.09 | 2.07 | 2.41 | 2.92 | 3.19 | 3.46 | 3.56 | 3.68 |
| GDP | 0 | 2.31 | 4.96 | 6.84 | 9.85 | 12.35 | 13.83 | 14.63 | 15.06 | 15.21 |
| The variance decomposition of Inflation | | | | | | | | | | |
| MR | 0.09 | 2.6 | 2.79 | 3.56 | 3.07 | 3.22 | 3.31 | 3.63 | 3.53 | 3.53 |
| Inflation | 99.91 | 96.08 | 95.87 | 94.86 | 95.57 | 95.41 | 95.33 | 94.92 | 95.05 | 95.03 |
| GDP | 0 | 1.33 | 1.33 | 1.58 | 1.36 | 1.37 | 1.36 | 1.45 | 1.41 | 1.43 |
| The variance decomposition of GDP | | | | | | | | | | |
| MR | 24.66 | 24.8 | 24.82 | 25.62 | 25.57 | 25.1 | 25.06 | 25.13 | 25.17 | 25.17 |
| Inflation | 6.91 | 8.78 | 9.02 | 9.16 | 9.14 | 9.2 | 9.33 | 9.34 | 9.39 | 9.49 |
| GDP | 68.43 | 66.42 | 66.16 | 65.22 | 65.29 | 65.69 | 65.61 | 65.53 | 65.44 | 65.34 |

**Fig. 18: Impulse Response of TS, Inflation and GDP (Lag length, 1)**

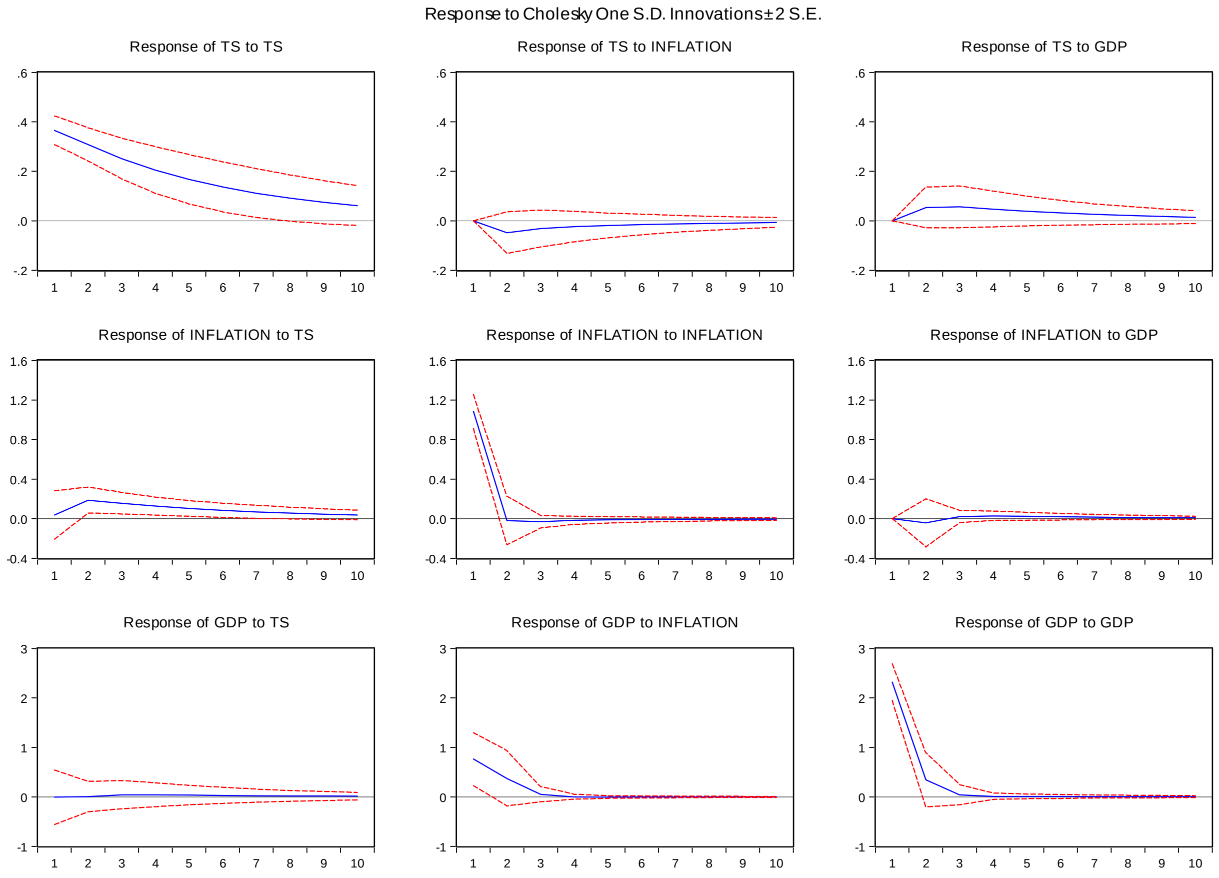
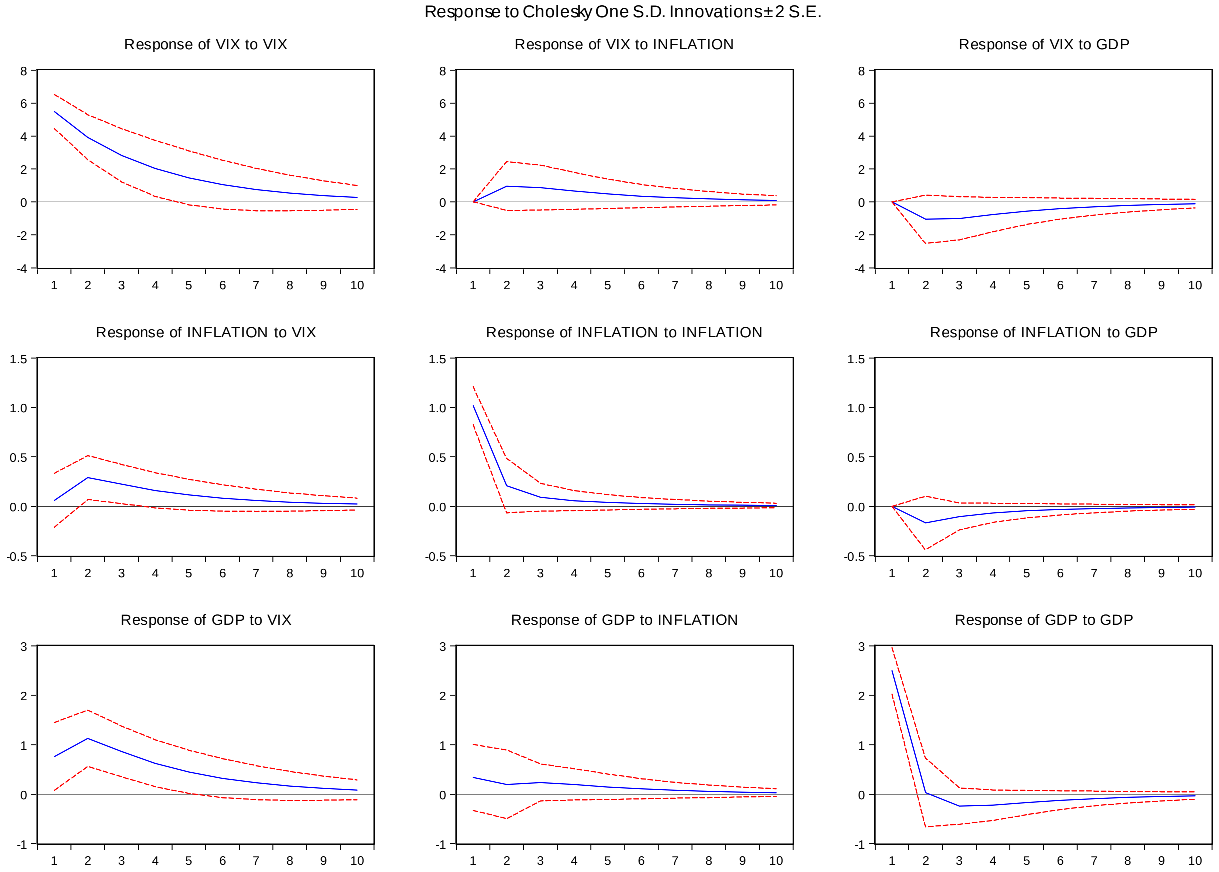



**Table 19: Corresponding Variance Decomposition**

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| TS | 100 | 97.76 | 96.88 | 96.47 | 96.25 | 96.13 | 96.05 | 96 | 95.97 | 95.95 |
| Inflation | 0 | 1.01 | 1.12 | 1.13 | 1.14 | 1.14 | 1.15 | 1.15 | 1.15 | 1.15 |
| GDP | 0 | 1.23 | 2 | 2.39 | 2.61 | 2.73 | 2.8 | 2.85 | 2.88 | 2.9 |
| The variance decomposition of Inflation | | | | | | | | | | |
| TS | 0.12 | 2.99 | 4.92 | 6.13 | 6.92 | 7.44 | 7.78 | 8.01 | 8.16 | 8.26 |
| Inflation | 99.88 | 96.86 | 94.9 | 93.63 | 92.79 | 92.25 | 91.89 | 91.65 | 91.49 | 91.38 |
| GDP | 0 | 0.15 | 0.18 | 0.24 | 0.28 | 0.31 | 0.33 | 0.34 | 0.35 | 0.36 |
| The variance decomposition of GDP | | | | | | | | | | |
| TS | 0 | 0 | 0.03 | 0.06 | 0.08 | 0.09 | 0.1 | 0.1 | 0.11 | 0.11 |
| Inflation | 9.75 | 11.59 | 11.62 | 11.62 | 11.61 | 11.61 | 11.61 | 11.61 | 11.61 | 11.61 |
| GDP | 90.25 | 88.41 | 88.35 | 88.33 | 88.31 | 88.3 | 88.29 | 88.28 | 88.28 | 88.28 |

## Japan

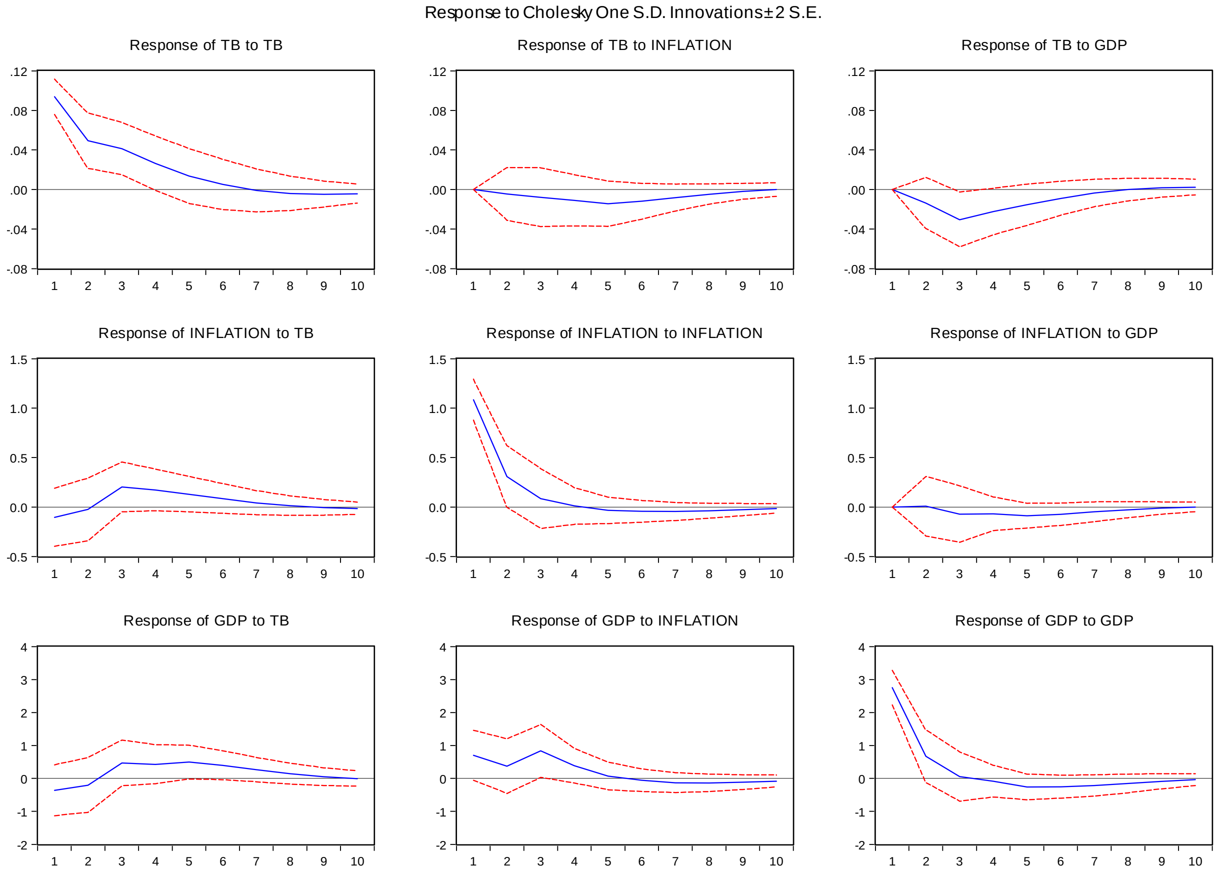
### Fig. 19: Impulse Response of VIX, Inflation and GDP (Lag length, 1)




### Table 20: Corresponding Variance Decomposition

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| VIX | 100 | 95.74 | 93.4 | 92.29 | 91.76 | 91.5 | 91.37 | 91.3 | 91.27 | 91.25 |
| Inflation | 0 | 1.93 | 2.93 | 3.4 | 3.62 | 3.72 | 3.78 | 3.8 | 3.82 | 3.83 |
| GDP | 0 | 2.33 | 3.67 | 4.31 | 4.62 | 4.78 | 4.85 | 4.89 | 4.91 | 4.92 |
| The variance decomposition of Inflation | | | | | | | | | | |
| VIX | 0.34 | 7.33 | 10.89 | 12.61 | 13.46 | 13.89 | 14.11 | 14.22 | 14.28 | 14.31 |
| Inflation | 99.66 | 90.28 | 86 | 84.02 | 83.05 | 82.57 | 82.32 | 82.19 | 82.13 | 82.09 |
| GDP | 0 | 2.39 | 3.11 | 3.37 | 3.49 | 3.54 | 3.57 | 3.59 | 3.59 | 3.6 |
| The variance decomposition of GDP | | | | | | | | | | |
| VIX | 8.38 | 22.52 | 28.55 | 31.19 | 32.44 | 33.05 | 33.36 | 33.52 | 33.6 | 33.64 |
| Inflation | 1.64 | 1.85 | 2.29 | 2.58 | 2.73 | 2.81 | 2.85 | 2.87 | 2.88 | 2.89 |
| GDP | 89.98 | 75.63 | 69.16 | 66.23 | 64.83 | 64.14 | 63.79 | 63.61 | 63.52 | 63.47 |

## Fig. 20: Impulse Response of TB, Inflation and GDP (Lag length, 1)




## Table 21: Corresponding Variance Decomposition

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| TB | 100 | 98.18 | 91.52 | 88.22 | 85.88 | 84.73 | 84.31 | 84.21 | 84.2 | 84.19 |
| Inflation | 0 | 0.19 | 0.59 | 1.32 | 2.58 | 3.41 | 3.81 | 3.94 | 3.96 | 3.95 |
| GDP | 0 | 1.63 | 7.89 | 10.46 | 11.54 | 11.86 | 11.88 | 11.85 | 11.85 | 11.86 |
| The variance decomposition of Inflation | | | | | | | | | | |
| TB | 0.91 | 0.89 | 3.92 | 5.94 | 7.01 | 7.46 | 7.55 | 7.55 | 7.55 | 7.56 |
| Inflation | 99.09 | 99.11 | 95.7 | 93.34 | 91.72 | 90.92 | 90.66 | 90.61 | 90.6 | 90.59 |
| GDP | 0 | 0 | 0.39 | 0.72 | 1.27 | 1.63 | 1.79 | 1.84 | 1.85 | 1.85 |
| The variance decomposition of GDP | | | | | | | | | | |
| TB | 1.58 | 1.93 | 3.98 | 5.67 | 7.84 | 9.17 | 9.69 | 9.82 | 9.82 | 9.82 |
| Inflation | 5.99 | 7.1 | 13.55 | 14.55 | 14.15 | 13.88 | 13.88 | 13.97 | 14.06 | 14.11 |
| GDP | 92.43 | 90.97 | 82.47 | 79.78 | 78 | 76.95 | 76.44 | 76.21 | 76.11 | 76.07 |

**Fig. 21: Impulse Response of TS, Inflation and GDP (Lag length, 1)**

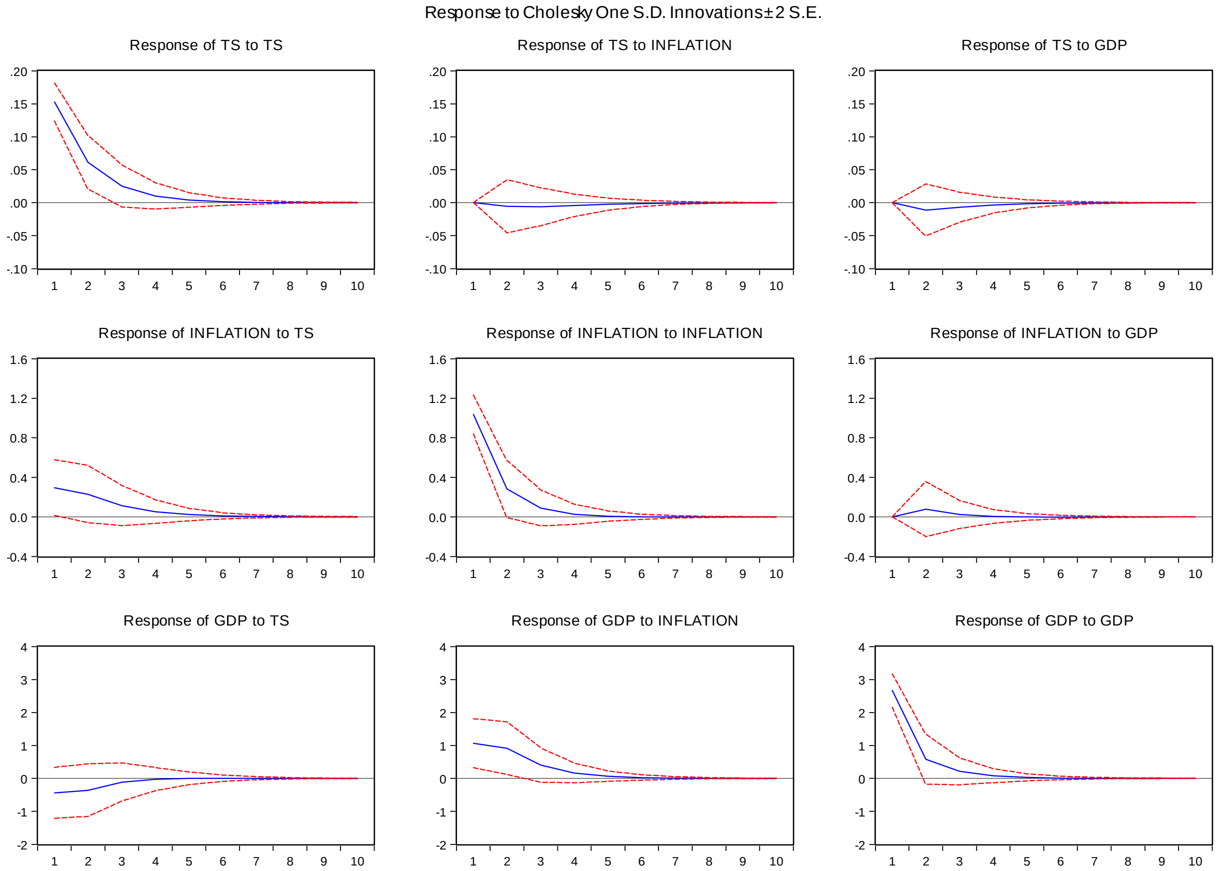
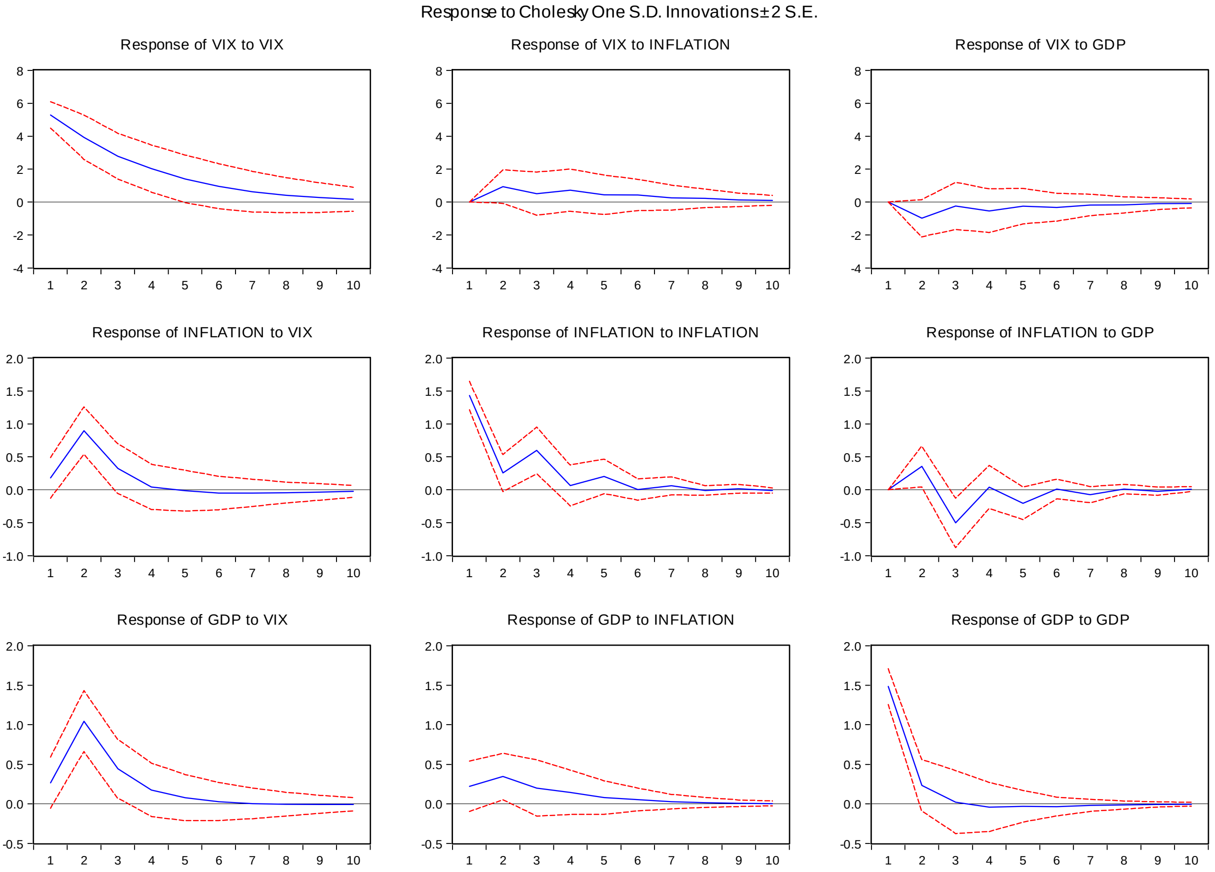



**Table 22: Corresponding Variance Decomposition**

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| TS | 100 | 99.42 | 99.12 | 99.01 | 98.98 | 98.98 | 98.98 | 98.97 | 98.97 | 98.97 |
| Inflation | 0 | 0.12 | 0.26 | 0.32 | 0.34 | 0.35 | 0.35 | 0.35 | 0.35 | 0.35 |
| GDP | 0 | 0.46 | 0.62 | 0.66 | 0.67 | 0.67 | 0.68 | 0.68 | 0.68 | 0.68 |
| The variance decomposition of Inflation | | | | | | | | | | |
| TS | 7.56 | 10.83 | 11.63 | 11.81 | 11.85 | 11.85 | 11.86 | 11.86 | 11.86 | 11.86 |
| Inflation | 92.44 | 88.7 | 87.86 | 87.69 | 87.65 | 87.64 | 87.64 | 87.64 | 87.64 | 87.64 |
| GDP | 0 | 0.47 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| The variance decomposition of GDP | | | | | | | | | | |
| TS | 2.26 | 3.27 | 3.31 | 3.31 | 3.31 | 3.31 | 3.31 | 3.31 | 3.31 | 3.31 |
| Inflation | 13.46 | 20.25 | 21.43 | 21.63 | 21.66 | 21.67 | 21.67 | 21.67 | 21.67 | 21.67 |
| GDP | 84.28 | 76.48 | 75.25 | 75.06 | 75.03 | 75.03 | 75.02 | 75.02 | 75.02 | 75.02 |

# US

## Fig. 22: Impulse Response of VIX, Inflation and GDP (Lag length, 2)




## Table 23: Corresponding Variance Decomposition

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| VIX | 100 | 95.94 | 95.96 | 94.93 | 94.7 | 94.34 | 94.22 | 94.12 | 94.08 | 94.06 |
| Inflation | 0 | 1.94 | 2.13 | 2.84 | 3.05 | 3.28 | 3.37 | 3.43 | 3.46 | 3.47 |
| GDP | 0 | 2.13 | 1.91 | 2.23 | 2.26 | 2.38 | 2.41 | 2.45 | 2.46 | 2.47 |
| The variance decomposition of Inflation | | | | | | | | | | |
| VIX | 1.59 | 27.29 | 24.89 | 24.89 | 24.36 | 24.41 | 24.39 | 24.43 | 24.45 | 24.46 |
| Inflation | 98.41 | 68.65 | 65.13 | 65.11 | 64.75 | 64.71 | 64.61 | 64.58 | 64.55 | 64.54 |
| GDP | 0 | 4.06 | 9.98 | 10 | 10.88 | 10.88 | 10.99 | 10.99 | 11 | 11 |
| The variance decomposition of GDP | | | | | | | | | | |
| VIX | 3.07 | 32.49 | 35.61 | 35.91 | 35.95 | 35.92 | 35.91 | 35.91 | 35.91 | 35.91 |
| Inflation | 2.12 | 4.69 | 5.44 | 5.9 | 6.04 | 6.11 | 6.12 | 6.13 | 6.13 | 6.13 |
| GDP | 94.81 | 62.82 | 58.95 | 58.18 | 58.01 | 57.97 | 57.97 | 57.97 | 57.97 | 57.96 |

**Fig. 23: Impulse Response of TB, Inflation and GDP (Lag length, 2)**

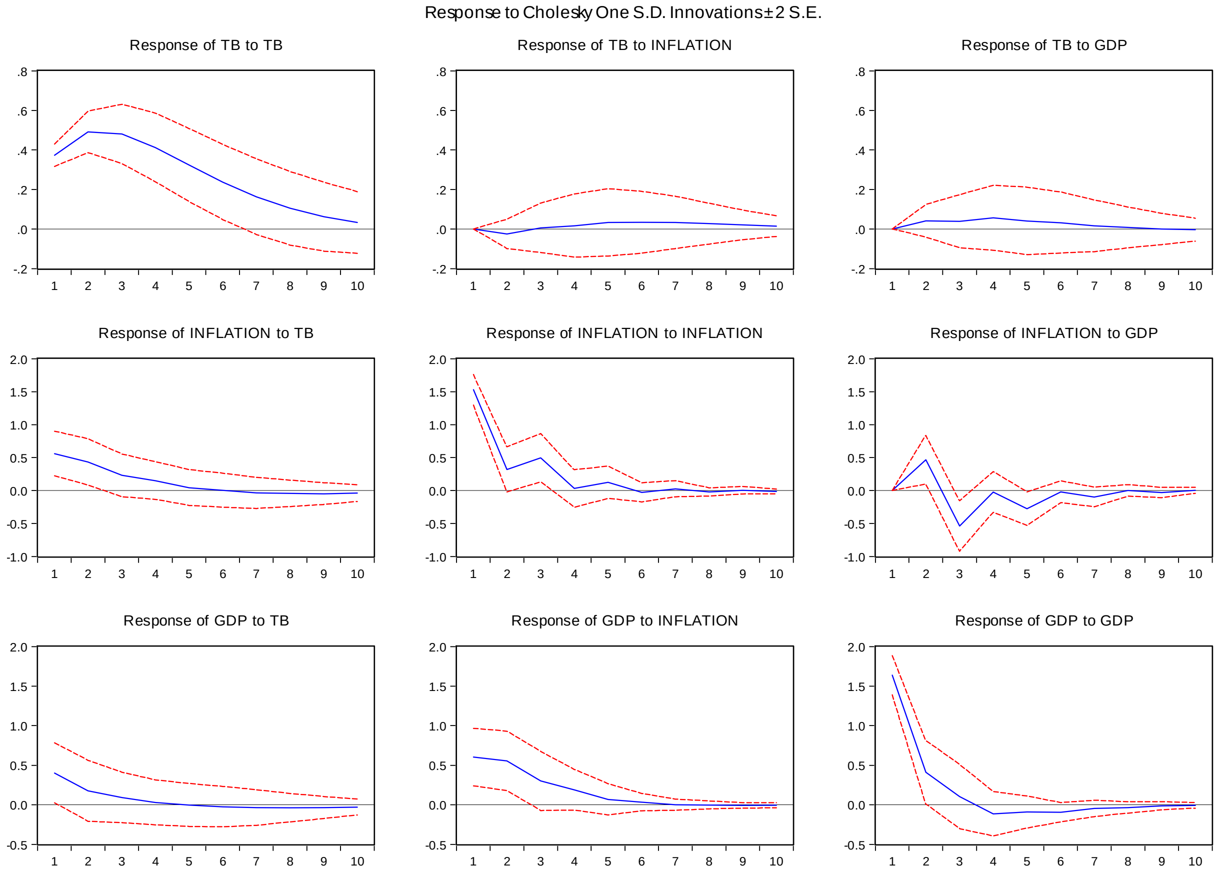



**Table 24: Corresponding Variance Decomposition**

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| TB | 100 | 99.41 | 99.38 | 99.07 | 98.88 | 98.71 | 98.61 | 98.55 | 98.51 | 98.49 |
| Inflation | 0 | 0.15 | 0.1 | 0.11 | 0.22 | 0.33 | 0.44 | 0.5 | 0.54 | 0.56 |
| GDP | 0 | 0.44 | 0.52 | 0.81 | 0.9 | 0.95 | 0.95 | 0.95 | 0.94 | 0.94 |
| The variance decomposition of Inflation | | | | | | | | | | |
| TB | 11.85 | 15.86 | 14.78 | 15.29 | 14.97 | 14.97 | 14.96 | 14.99 | 15.04 | 15.07 |
| Inflation | 88.15 | 77.22 | 71.67 | 71.23 | 69.92 | 69.92 | 69.72 | 69.69 | 69.63 | 69.61 |
| GDP | 0 | 6.93 | 13.55 | 13.48 | 15.11 | 15.12 | 15.32 | 15.31 | 15.33 | 15.32 |
| The variance decomposition of GDP | | | | | | | | | | |
| TB | 5.03 | 5.18 | 5.25 | 5.21 | 5.19 | 5.19 | 5.22 | 5.26 | 5.28 | 5.31 |
| Inflation | 11.34 | 18.06 | 19.91 | 20.57 | 20.63 | 20.6 | 20.58 | 20.56 | 20.56 | 20.55 |
| GDP | 83.63 | 76.76 | 74.84 | 74.22 | 74.18 | 74.21 | 74.2 | 74.18 | 74.16 | 74.14 |

**Fig. 24: Impulse Response of TS, Inflation and GDP (Lag length, 2)**

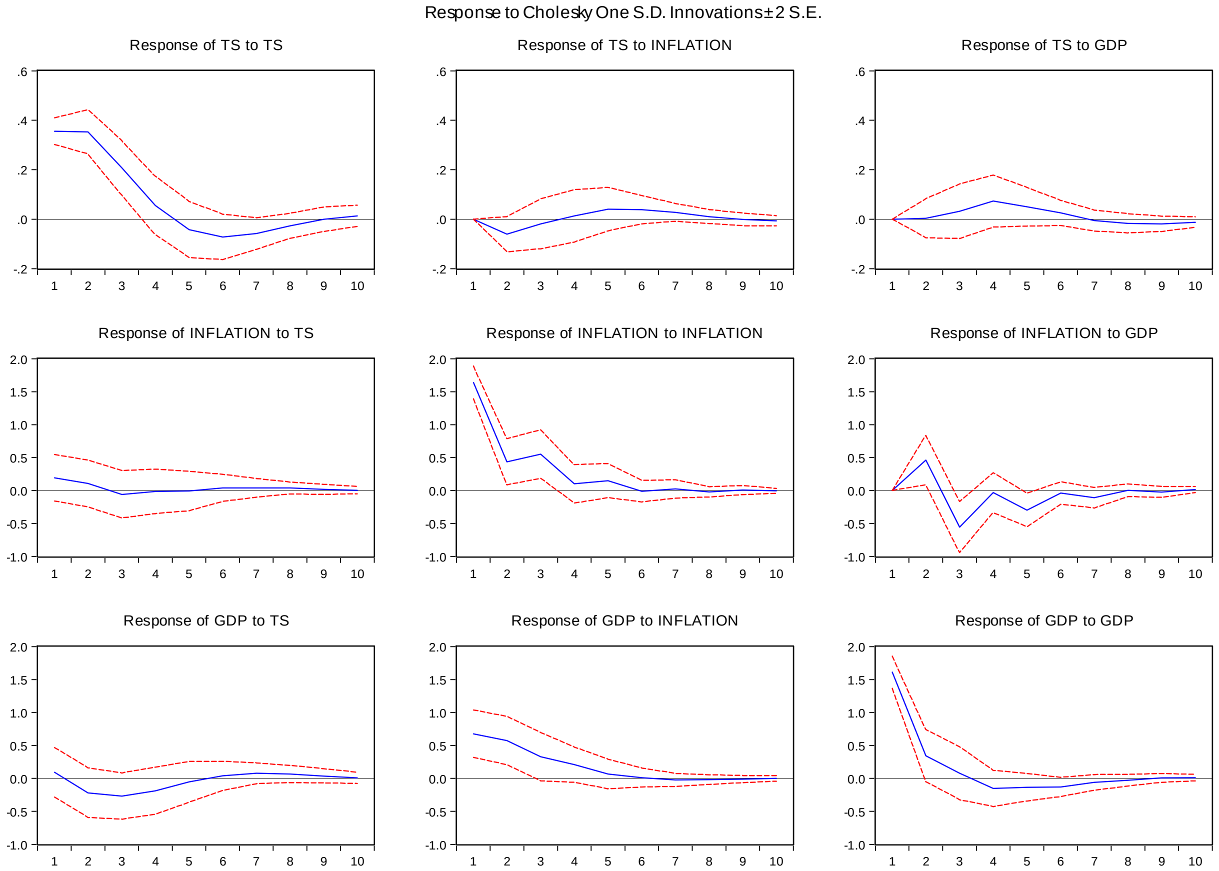



**Table 25: Corresponding Variance Decomposition**

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| The variance decomposition of VIX | | | | | | | | | | |
| TS | 100 | 98.53 | 98.28 | 96.55 | 95.3 | 94.75 | 94.59 | 94.48 | 94.37 | 94.32 |
| Inflation | 0 | 1.46 | 1.37 | 1.39 | 1.88 | 2.29 | 2.49 | 2.51 | 2.51 | 2.52 |
| GDP | 0 | 0 | 0.35 | 2.07 | 2.82 | 2.95 | 2.93 | 3.01 | 3.12 | 3.16 |
| The variance decomposition of Inflation | | | | | | | | | | |
| TS | 1.36 | 1.54 | 1.38 | 1.38 | 1.35 | 1.39 | 1.42 | 1.46 | 1.47 | 1.47 |
| Inflation | 98.64 | 91.67 | 84.76 | 84.78 | 82.94 | 82.87 | 82.59 | 82.56 | 82.54 | 82.54 |
| GDP | 0 | 6.78 | 13.86 | 13.84 | 15.72 | 15.74 | 15.99 | 15.98 | 15.99 | 15.99 |
| The variance decomposition of GDP | | | | | | | | | | |
| TS | 0.27 | 1.57 | 3.42 | 4.24 | 4.29 | 4.3 | 4.44 | 4.55 | 4.59 | 4.59 |
| Inflation | 15.02 | 22.18 | 23.96 | 24.45 | 24.41 | 24.29 | 24.25 | 24.22 | 24.21 | 24.21 |
| GDP | 84.71 | 76.26 | 72.62 | 71.31 | 71.31 | 71.4 | 71.31 | 71.23 | 71.2 | 71.2 |

**Table 26: Granger Causality Test results**

| *Country:* | Belgium | UK | France | Germany | Japan | US |
|---|---|---|---|---|---|---|
| *Null Hypothesis* | | | | | | |
| INFLATION ➔ VIX | 0.19 | 0.01*** | 0.42 | 0.96 | 0.21 | 0.18 |
| VIX ➔ INFLATION | 0.04** | 0.76 | 0.18 | 0.01*** | 0.02** | 0.01*** |
| GDP ➔ VIX | 0.02** | 0.22 | 0.26 | 0.30 | 0.23 | 0.36 |
| VIX ➔ GDP | 0.26 | 0.22 | 0.01*** | 0.01*** | 0.01*** | 0.01*** |
| GDP➔ INFLATION | 0.13 | 0.21 | 0.26 | 0.96 | 0.85 | 0.01*** |
| INFLATION ➔ GDP | 0.01*** | 0.82 | 0.84 | 0.73 | 0.21 | 0.11 |
| INFLATION ➔ TB | 0.13 | 0.37 | 0.05** | 0.53 | 0.60 | 0.39 |
| TB ➔ INFLATION | 0.82 | 0.33 | 0.13 | 0.64 | 0.22 | 0.39 |
| GDP ➔ TB | 0.01*** | 0.02** | 0.09* | 0.09* | 0.12 | 0.63 |
| TB ➔ GDP | 0.04** | 0.05** | 0.06* | 0.01*** | 0.32 | 0.95 |
| GDP➔ INFLATION | 0.13 | 0.11 | 0.44 | 0.96 | 0.85 | 0.01*** |
| INFLATION ➔ GDP | 0.01*** | 0.97 | 0.09* | 0.73 | 0.21 | 0.11 |
| INFLATION ➔ TS | 0.18 | 0.28 | 0.55 | 0.24 | 0.75 | 0.12 |
| TS ➔ INFLATION | 0.21 | 0.97 | 0.53 | 0.01*** | 0.33 | 0.90 |
| GDP ➔ TS | 0.37 | 0.07* | 0.11 | 0.38 | 0.51 | 0.39 |
| TS ➔ GDP | 0.41 | 0.04** | 0.38 | 0.78 | 0.63 | 0.18 |
| GDP➔ INFLATION | 0.13 | 0.11 | 0.26 | 0.68 | 0.85 | 0.01*** |
| INFLATION ➔ GDP | 0.01*** | 0.97 | 0.84 | 0.35 | 0.21 | 0.11 |

***, **and * denote significance at 1%, 5% and 10% levels respectively.

**Table 27: Summary of Impulse response**

| *Country:* *Null Hypothesis* | Belgium | UK | France | Germany | Japan | US |
|---|---|---|---|---|---|---|
| INF ➔ VIX | significant | insignificant | insignificant | insignificant | insignificant | insignificant |
| VIX ➔ INF | significant | significant | insignificant | significant | significant | significant |
| GDP ➔ VIX | insignificant | insignificant | insignificant | insignificant | insignificant | insignificant |
| VIX ➔ GDP | insignificant | significant | significant | significant | significant | significant |
| GDP➔ INF | insignificant | insignificant | insignificant | insignificant | insignificant | insignificant |
| INF ➔ GDP | significant | insignificant | significant | insignificant | insignificant | significant |
| INF ➔ TB | insignificant | insignificant | insignificant | insignificant | significant | significant |
| TB ➔ INF | insignificant | insignificant | insignificant | insignificant | insignificant | insignificant |
| GDP ➔ TB | insignificant | significant | insignificant | significant | significant | insignificant |
| TB ➔ GDP | insignificant | insignificant | insignificant | insignificant | significant | insignificant |
| GDP➔ INF | insignificant | insignificant | insignificant | insignificant | insignificant | insignificant |
| INF ➔ GDP | significant | insignificant | significant | insignificant | significant | significant |
| INF ➔ TS | insignificant | insignificant | insignificant | insignificant | insignificant | insignificant |
| TS ➔ INF | insignificant | insignificant | insignificant | significant | insignificant | insignificant |
| GDP ➔ TS | insignificant | insignificant | insignificant | insignificant | insignificant | insignificant |
| TS ➔ GDP | insignificant | significant | insignificant | insignificant | insignificant | insignificant |
| GDP➔ INF | significant | insignificant | insignificant | insignificant | insignificant | insignificant |
| INF ➔ GDP | significant | insignificant | insignificant | insignificant | significant | significant |

Key INF➔ VIX, this means the response of VIX to a shock on INF

# Chapter 5: Summary and conclusion

This chapter summarises the main findings and conclusions from the three papers in chapters two through four.

Paper 1

This paper tested the leading indicator information properties of the newly-developed implied stock market volatility captured by VIX. The VIX index is constructed on an intraday basis by taking the weighted average of the implied volatility of both calls and puts options. The VIX is weighted to reflect the implied volatility of 30 calendar day options. The approach to test this variable stems from the notion that financial variables tend to collect and process information at a faster rate than the real sector.

First, the results on the relationship between VIX and stock returns suggested that the VIX index carried information to forecast stock returns for Belgium, Germany, Japan, and the US. Second, the results on forecasting output suggested that VIX contained information to forecast output for Belgium, France, Germany, Japan, and the Netherlands. In addition, combining VIX with stock returns increased forecasting accuracy. Last, by exploiting the econometric approach of Clark and West (2007), we explored the simulated out-of-sample output forecasting properties of the VIX. The results indicated that VIX has real-time forecasting power of output growth for Germany, however the results were weak for the US. This could be attributed to weaker information content of the VIX index in earlier years. By splitting the sample into two, as suggested by Bai and Perron (1998) and Chow (1960) structural break tests, before and after 1997, the results showed that the VIX variable had gained more forecasting ability. One explanation to that finding is the risk hedging following the Asian financial crisis in 1997.

The above findings have important policy implications. First, funds managers could use VIX to forecast stock returns and allocate their portfolios accordingly. Second, policymakers could adopt VIX as a forecasting variable, and to increase forecasting accuracy, VIX should be used injunction with other forecasting variables. Our recommendation is based on a sample of a few countries, and we recommend that for future research, the VIX variable be constructed for more countries, especially the emerging economies, and evaluate the leading indicator properties of the VIX index. In addition, what is more important is to carry out actual forecasting; as more data points become available, this will give clearer results if simulated real-time forecasting is conducted.

Paper two

The second essay is driven by the findings of  and Eickmeier and Ziegler (2008), which show that including more forecasting variables and using dynamic factor models increases forecasting accuracy, respectively. In this paper we explored the output growth forecasting power of the composite leading business cycle indicator (CLI) for the case of South Africa and compared it with the traditional term-structure of interest rate (TS). The CLI is constructed from 10 different variables that include financial and non-financial asset prices.

In-sample forecasting results showed that both the CLI and yield curve carry some information to forecast output growth. Furthermore, CLI and TS contained statistically and economically significant out-of-sample output growth forecasting information for up to eight quarters ahead. Yet TS is insignificant at one-quarter-ahead out-of-sample output growth forecasting. The Clark and West (2007) test showed that, as indicated by the test coefficient, CLI was more powerful in forecasting output as it reduced the forecasting error significantly compared to the TS. To test for the stability of the out-of-sample forecasting power of these two variables we drew from Welch and Goyal (2008) cumulative squared forecasting errors diagnostic plots. The results showed that prior to about 1993, information content of TS was superior to CLI at relatively longer forecasting horizon. However, cumulative squared forecasting errors plots showed that CLI was a more stable model than TS, notwithstanding that both models were relatively more stable at shorter horizon forecasting as compared to longer horizons. Overall, CLI contained more output growth forecasting information and its information content was more stable than the CLI.

From these findings, it is clear that a combination of forecasting tools increases accuracy, and as such for practical output growth predictions the CLI should be preferred as a forecasting tool relative to TS. It is worth noting, however, that CLI forecasting accuracy decreased beyond 4-quarters. As a result, we suggest the addition of other forecasting tools to the construction of the CLI. These include a survey of professional forecasters, implied stock market volatility, and derivatives from futures markets, among others. Since South Africa is an emerging economy, derivatives from the futures markets of primary industry such as the mining and agricultural sector should enhance the forecasting information and stability of the forecasting ability of the CLI.

Third paper

In the third paper, we first analysed how the volatilities of financial sector were related in the context of a VAR framework and in particular, we looked at the Treasury bill rate, the term structure of interest rate, and the implied stock market volatilities. Second, we explored how these financial volatilities were related to macroeconomy volatility and, in particular, output growth and inflation volatility. We marked use of impulse response functions, variance decomposition, and the Granger causality tests in analysing the relationship between these variables.

Our inferences for Japan, from impulse response functions and variance decomposition, suggested that there is a bi-directional relationship between Treasury bill rate volatility (TB) and implied stock market volatility (VIX), and a reverse causality between these variables existed in the Granger sense. In addition, impulse response functions for Belgium, England, and France suggested that a one standard deviation innovation in TB imposed a statistically significant impact on term structure volatility (TS). Also, for Germany and the US, there was a strong unidirectional causality running from VIX to TB. Mixed results were documented for term structure volatility and the other variables. On the policy front, when professionals in fixed income securities, derivatives pricing, and risk management in Japan, Germany, and the US observe a positive shock to VIX, they should accordingly adjust their portfolio mix. This is to say, as they observe the implied stock market volatility shocks, they should re-allocate their portfolios depending on the direction of the shock, as VIX carries forecasting information on short-term interest rates.

Statistical results on the relationship between financial volatility and macroeconomic volatility suggested that most of the variability in macroeconomic volatility was explained by VIX. Specifically, for all countries except the UK, the effect ran from VIX to INF, suggesting that VIX could be used in forecasting INF rate volatility, and there exists a statistically significant relationship between VIX and real GDP growth rate volatility (GDP) for Belgium and the UK. This has policy implications in that that VIX carries prediction information on macroeconomic uncertainty measured by the volatility of real GDP and INF volatility (INF). However, VIX's ability to forecast real GDP volatility was only strong at short horizon forecasting. The relationship between INF and output volatility was weak, confirming most findings in the recent Great Moderation period. On the relationship between TS and our two macroeconomic variables, our results suggested a weak relationship, as they were largely statistically insignificant, which is similar to the findings of Schwert (1989).

## References

Ahn, E. S., & Lee, J. M. (2006). Volatility relationship between stock performance and real output. *Applied Financial Economics, 16*(11), 777-784.

Alexopoulos, M., & Cohen, J. (2009). Uncertain times, uncertain measures. *University of Toronto Department of Economics Working Paper, 352*.

Andrews, D. W. (1993). Tests for parameter instability and structural change with unknown change point. *Econometrica: Journal of the Econometric Society*, 821-856.

Ang, A., Piazzesi, M., & Wei, M. (2006). What does the yield curve tell us about GDP growth? *Journal of econometrics, 131*(1), 359-403.

Araújo, E. (2009). Macroeconomic shocks and the co-movement of stock returns in Latin America. *Emerging markets review, 10*(4), 331-344.

Arnold, I. J., & Vrugt, E. B. (2008). Fundamental uncertainty and stock market volatility. *Applied Financial Economics, 18*(17), 1425-1440.

Ayhan Kose, M., Prasad, E. S., & Terrones, M. E. (2005). Growth and Volatility in an Era of Globalization. *IMF Staff Papers*, 31-63.

Bai, J., & Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *econometrica*, 47-78.

Baillie, R. T., & DeGennaro, R. P. (1990). Stock returns and volatility. *Journal of financial and Quantitative Analysis, 25*(2), 203-214.

Baltzer, M., & Kling, G. (2007). Predictability of future economic growth and the credibility of monetary regimes in Germany, 1870–2003. *Applied Economics Letters, 14*(6), 401-404.

Banerjee, P. S., Doran, J. S., & Peterson, D. R. (2007). Implied volatility and future portfolio returns. *Journal of Banking & Finance, 31*(10), 3183-3199.

Barro, R. J. (1990). The stock market and investment. *Review of Financial Studies, 3*(1), 115-131.

Beaudry, P., & Portier, F. (2004). Stock prices, news and economic fluctuations: National Bureau of Economic Research.

Bekaert, G., Hoerova, M., & Duca, M. L. (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics, 60*(7), 771-788.

Bertola, G. (1998). Irreversible investment. *Research in Economics, 52*(1), 3-37.

Binder, J. J., & Merges, M. J. (2001). Stock market volatility and economic factors. *Review of Quantitative Finance and Accounting, 17*(1), 5-26.

Binswanger, M. (2000). Stock returns and real activity: is there still a connection? *Applied Financial Economics, 10*(4), 379-387.

Binswanger, M. (2004). How do stock prices respond to fundamental shocks? *Finance Research Letters, 1*(2), 90-99.

Bittlingmayer, G. (1998). Output, stock volatility, and political uncertainty in a natural experiment: Germany, 1880–1940. *The Journal of Finance, 53*(6), 2243-2257.

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *The journal of political economy*, 637-654.

Blair, B. J., Poon, S.-H., & Taylor, S. J. (2010). Forecasting S&P 100 volatility: the incremental information content of implied volatilities and high-frequency index returns *Handbook of Quantitative Finance and Risk Management* (pp. 1333-1344): Springer.

Blanchard, O., Dell'Ariccia, G., & Mauro, P. (2010). Rethinking macroeconomic policy. *Journal of Money, Credit and Banking, 42*(s1), 199-215.

Bloom. (2009). The impact of uncertainty shocks. *econometrica, 77*(3), 623-685.

Bloom, Bond, S., & Van Reenen, J. (2007). Uncertainty and investment dynamics. *The review of economic studies, 74*(2), 391-415.

Bloom, Floetotto, M., Jaimovich, N., Saporta-Eksten, I., & Terry, S. J. (2012). Really uncertain business cycles: National Bureau of Economic Research.

Bluhm, H., & Yu, J. (2001). Forecasting volatility: Evidence from the German stock market.

Bollerslev, T., & Wooldridge, J. M. (1992). Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. *Econometric reviews, 11*(2), 143-172.

Bordo, M. D., & Haubrich, J. G. (2008). The yield curve as a predictor of growth: Long-run evidence, 1875-1997. *The Review of Economics and Statistics, 90*(1), 182-185.

Borio, C., Furfine, C., & Lowe, P. (2001). Procyclicality of the financial system and financial stability: issues and policy options. *BIS papers, 1*, 1-57.

Brenner, M., Pasquariello, P., & Subrahmanyam, M. G. (2006). *Financial Markets and the Macro Economy*. Paper presented at the AFA 2007 Chicago Meetings Paper.

Campbell, J. Y. (1990). A variance decomposition for stock returns: National Bureau of Economic Research.

Campbell, J. Y. (1999). Asset prices, consumption, and the business cycle. *Handbook of macroeconomics, 1*, 1231-1303.

Campbell, J. Y., Lettau, M., Malkiel, B. G., & Xu, Y. (2001). Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *The Journal of Finance, 56*(1), 1-43.

Campbell, J. Y., & Shiller, R. J. (1988). Stock prices, earnings, and expected dividends. *The Journal of Finance, 43*(3), 661-676.

Campbell, J. Y., & Taksler, G. B. (2003). Equity volatility and corporate bond yields. *The Journal of Finance, 58*(6), 2321-2350.

Canova, F., Gambetti, L., & Pappa, E. (2007). The Structural Dynamics of Output Growth and Inflation: Some International Evidence*. *The Economic Journal, 117*(519), C167-C191.

Caporale, G. M., & Spagnolo, N. (2003). Asset prices and output growth volatility: the effects of financial crises. *Economics Letters, 79*(1), 69-74.

Carvalho, V. M., & Gabaix, X. (2010). The great diversification and its undoing: National Bureau of Economic Research.

Chaudhuri, K., & Smiles, S. (2004). Stock market and aggregate economic activity: evidence from Australia. *Applied Financial Economics, 14*(2), 121-129.

Chauvet, M., Senyuz, Z., & Yoldas, E. (2010). What does financial volatility tell us about macroeconomic fluctuations?

Chen. (1991). Financial investment opportunities and the macroeconomy. *The Journal of Finance, 46*(2), 529-554.

Chen, Roll, R., & Ross, S. A. (1986). Economic forces and the stock market. *Journal of business*, 383-403.

Choudhry, T. (2003). Stock market volatility and the US consumer expenditure. *Journal of Macroeconomics, 25*(3), 367-385.

Chow, G. C. (1960). Tests of equality between sets of coefficients in two linear regressions. *Econometrica: Journal of the Econometric Society*, 591-605.

Cieslak, A., & Povala, P. (2013). Information in the term structure of yield curve volatility. *Available at SSRN 1458006*.

Clarida, R., Gali, J., & Gertler, M. (1999). The science of monetary policy: A new Keynesian perspective. *Journal of Economic Literature, 37*, 1661-1707.

Clark, & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of econometrics, 138*(1), 291-311.

Clemente, J., Montañes, A., & Reyes, M. (1998). Testing for a unit root in variables with a double change in the mean. *Economics Letters, 59*(2), 175-182.

Cole, R. A., Moshirian, F., & Wu, Q. (2008). Bank stock returns and economic growth. *Journal of Banking & Finance, 32*(6), 995-1007.
Corradi, V., Distaso, W., & Mele, A. (2013). Macroeconomic determinants of stock volatility and volatility premiums. *Journal of Monetary Economics, 60*(2), 203-220.
Creal, D. D., & Wu, J. C. (2014). Interest Rate Uncertainty and Economic Fluctuations: National Bureau of Economic Research.
Cutler, D. M., Poterba, J. M., & Summers, L. H. (1989). What moves stock prices? *Journal of Portfolio Management, 15*, 4-12.
Dabušinskas, A., Kulikov, D., & Randveer, M. (2013). The impact of volatility on economic growth: Bank of Estonia.
Davis, M. A., & Heathcore, J. (2005). Housing and the Business Cycles. *International Economic Review, 46*(3).
De Goeij, P., & Marquering, W. (2006). Macroeconomic announcements and asymmetric volatility in bond returns. *Journal of Banking & Finance, 30*(10), 2659-2680.
DeMiguel, V., Garlappi, L., & Uppal, R. (2009). Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? *Review of Financial Studies*, *22*(5), 1915-1953.
Desai, P. (2000). Why did the Ruble collapse in August 1998? *American economic review*, 48-52.
Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics*, *13*(3), 253-263.
Diebold, F. X., & Yilmaz, K. (2008). Macroeconomic volatility and stock market volatility, worldwide: National Bureau of Economic Research.
Driessen, J., Lin, T.-C., & Lu, X. (2012). Why do option prices predict stock returns? *Available at SSRN 2023336*.
Duffee, G. R. (2005). Time variation in the covariance between stock returns and consumption growth. *The Journal of Finance, 60*(4), 1673-1712.
Eickmeier, S., & Ziegler, C. (2008). How successful are dynamic factor models at forecasting output and inflation? A meta‐analytic approach. *Journal of Forecasting, 27*(3), 237-265.
Engle, R. F., Ghysels, E., & Sohn, B. (2008). *On the economic sources of stock market volatility*. Paper presented at the AFA 2008 New Orleans Meetings Paper.
Epstein, L. G., & Zin, S. E. (1991). Substitution, risk aversion, and the temporal behavior of consumption and asset returns: An empirical analysis. *Journal of political Economy*, 263-286.
Estrella, A. (2005). Why Does the Yield Curve Predict Output and Inflation?*. *The Economic Journal, 115*(505), 722-744.
Estrella, A., & Hardouvelis, G. A. (1991). The term structure as a predictor of real economic activity. *The Journal of Finance, 46*(2), 555-576.
Estrella, A., Rodrigues, A. P., & Schich, S. (2003). How stable is the predictive power of the yield curve? Evidence from Germany and the United States. *Review of Economics and Statistics, 85*(3), 629-644.
Fama, E. F. (1981). Stock returns, real activity, inflation, and money. *The American economic review*, 545-565.
Fama, E. F. (1990). Term-structure forecasts of interest rates, inflation and real returns. *Journal of Monetary Economics, 25*(1), 59-76.
Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *The journal of political economy*, 607-636.

Fischer, S., & Merton, R. C. (1984). *Macroeconomics and finance: The role of the stock market.* Paper presented at the Carnegie-Rochester Conference Series on Public Policy.

Fleming, J., Kirby, C., & Ostdiek, B. (1998). Information and volatility linkages in the stock, bond, and money markets. *Journal of financial Economics, 49*(1), 111-137.

Fornari, F., & Mele, A. (2013). Financial volatility and economic activity. *J. Financ. Manag. Markets Inst., 1*, 155-198.

French, K. R., Schwert, G. W., & Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of financial Economics*, *19*(1), 3-29.

Galbraith, J. W., & Tkacz, G. (2000). Testing for asymmetry in the link between the yield spread and output in the G-7 countries. *Journal of International Money and Finance, 19*(5), 657-672.

Ghysels, E., Guay, A., & Hall, A. (1998). Predictive tests for structural change with unknown breakpoint. *Journal of econometrics, 82*(2), 209-233.

Ghysels, E., & Wright, J. H. (2009). Forecasting professional forecasters. *Journal of Business & Economic Statistics*, *27*(4), 504-516.

Gilchrist, S., Sim, J., & Zakrajsek, E. (2010). *Uncertainty, financial frictions, and investment dynamics.* Paper presented at the 2010 Meeting Papers.

Goldstein, M. (1998). *The Asian financial crisis*: IIE.

Görtz, C., & Tsoukalas, J. (2011). News and financial intermediation in aggregate fluctuations. *MPRA Paper 34113, University Library of Munich, Germany*.

Grabowski, S. (2009). The Financial Indicators Leading Real Economic Activity–the Case of Poland. *Central European Journal of Economic Modelling and Econometrics, 1*(4), 311-332.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, 424-438.

Guo, H. (2002). Stock market returns, volatility, and future output. *Federal Reserve Bank of St. Louis Review, 84*(September/October 2002).

Guo, H., & Savickas, R. (2006). Idiosyncratic volatility, stock market volatility, and expected stock returns. *Journal of Business & Economic Statistics, 24*(1), 43-56.

Guo, H., & Whitelaw, R. F. (2000). Risk and Return: Some New Evidence. *Working Paper No. 2001–001A, Federal Reserve Bank of St. Louis*.

Gyomai, G., & Wildi, M. (2012). OECD Composite Leading Indicators for G7 Countries: a Comparison of the Hodrick-Prescott Filter and the Multivariate Direct Filter Approach: OECD Publishing.

Hamori, S., Anderson, D. A., & Hamori, N. (2002). Stock returns and real activity: new evidence from the United States and Japan. *Quarterly Journal of Business and Economics*, 95-114.

Hansen, L. P., & Jagannathan, R. (1990). Implications of security market data for models of dynamic economies: National Bureau of Economic Research Cambridge, Mass., USA.

Harris, L. (1987). Transaction data tests of the mixture of distributions hypothesis. *Journal of financial and Quantitative Analysis, 22*(02), 127-141.

Harvey, C. R. (1989). Forecasts of economic growth from the bond and stock markets. *Financial Analysts Journal*, 38-45.

Harvey, C. R. (1997). The relation between the term structure of interest rates and Canadian economic growth. *Canadian Journal of Economics, 30*(1), 169-193.

Hassapis, C. (2003). Financial variables and real activity in Canada. *Canadian Journal of Economics/Revue canadienne d'économique, 36*(2), 421-442.

Hassapis, C., & Kalyvitis, S. (2002). Investigating the links between growth and real stock price changes with empirical evidence from the G-7 economies. *The Quarterly Review of Economics and Finance, 42*(3), 543-575.

Haubrich, J. G., & Dombrosky, A. M. (1996). Predicting real growth using the yield curve. *Economic Review, 32*, 26-35.

He, P., & Yau, S.-T. (2007). *Forecasting stock market volatility using implied volatility*. Paper presented at the American Control Conference, 2007. ACC'07.

Henry, O. T., Olekalns, N., & Thong, J. (2004). Do stock market returns predict changes to output? Evidence from a nonlinear panel data model. *Empirical Economics, 29*(3), 527-540.

Imbs, J. (2007). Growth and volatility. *Journal of Monetary Economics, 54*(7), 1848-1862.

Jaditz, T., Riddick, L. A., & Sayers, C. L. (1998). Multivariate nonlinear forecasting using financial information to forecast the real sector. *Macroeconomic Dynamics, 2*(03), 369-382.

Jaimovich, N., & Rebelo, S. (2009). Can news about the future drive the business cycle. *American economic review, 99*(4), 1097–1118.

Jansen, W. J., & Nahuis, N. J. (2003). The stock market and consumer confidence: European evidence. *Economics Letters, 79*(1), 89-98.

Jay Choi, J., Hauser, S., & Kopecky, K. J. (1999). Does the stock market predict real activity? Time series evidence from the G-7 countries. *Journal of Banking & Finance, 23*(12), 1771-1792.

Jones, C. M., Lamont, O., & Lumsdaine, R. L. (1998). Macroeconomic news and bond market volatility. *Journal of financial Economics, 47*(3), 315-337.

Justiniano, A., Primiceri, G. E., & Tambalotti, A. (2010). Investment shocks and business cycles. *Journal of Monetary Economics, 57*(2), 132-145.

Kearney, C., & Daly, K. (1998). The causes of stock market volatility in Australia. *Applied Financial Economics, 8*(6), 597-605.

Khomo, M. M., & Aziakpono, M. J. (2007). Forecasting recession in South Africa: a comparison of the yield curve and other economic indicators. *South African Journal of Economics, 75*(2), 194-212.

Kneller, R., & Young, G. (2001). Business Cycle Volatility, Uncertainty and Long‐run Growth. *The Manchester School, 69*(5), 534-552.

Koeda, J., & Kato, R. (2010). The Role of Uncertainty in the Term Structure of Interest Rates: A Macro-Finance Perspective. *CIRJE F-Series CIRJE-F-724, CIRJE, Faculty of Economics, University of Tokyo*.

Lamla, M. J., Lein, S., & Sturm, J.-E. (2007). News and business cycle comovement: Working paper.

Lee, B.-S. (1992). Causal relations among stock returns, interest rates, real activity, and inflation. *The Journal of Finance, 47*(4), 1591-1603.

Liljeblom, E., & Stenius, M. (1997). Macroeconomic volatility and stock market volatility: empirical evidence on Finnish data. *Applied Financial Economics, 7*(4), 419-426.

Lorenzoni, G. (2006). A theory of demand shocks: National Bureau of Economic Research.

Lütkepohl, H. (2005). *New introduction to multiple time series analysis*: Springer Science & Business Media.

Madsen, J. B., Dzhumashev, R., & Yao, H. (2013). Stock returns and economic growth. *Applied Economics, 45*(10), 1257-1271.

Mao, Y., & Wu, R. (2007). Does the stock market act as a signal for real activity? Evidence from Australia. *Economic Papers: A journal of applied economics and policy, 26*(2), 180-192.

Merton, R. C. (1980). On estimating the expected return on the market: An exploratory investigation. *Journal of financial Economics, 8*(4), 323-361.
Mody, A., & Taylor, M. P. (2003). The high-yield spread as a predictor of real economic activity: evidence of a financial accelerator for the United States. *IMF Staff papers*, 373-402.
Moolman, E. (2002). The term structure as a predictor of recessions. *JOURNAL FOR STUDIES IN ECONOMIC AND ECONOMETRICS, 26*(3), 43-52.
Newey, W. K., & West, K. D. (1986). A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix: National Bureau of Economic Research Cambridge, Mass., USA.
Nishina, K., Maghrebi, N., & Kim, M.-S. (2006). Stock market volatility and the forecasting accuracy of implied volatility indices. *Discussion papers in Economics and Business*(06-09).
Peña, J. I., & Rodríguez, R. (2007). On the economic link between asset prices and real activity. *Journal of Business Finance & Accounting, 34*(5‐6), 889-916.
Poke, J., & Wells, G. (2009). The Term Spread and GDP Growth in Australia*. *Economic Record, 85*(269), 121-131.
Poterba, J. M. (2000). Stock market wealth and consumption. *Journal of economic perspectives, 14*(2), 99-118.
Ramey, G., & Ramey, V. A. (1994). Cross-country evidence on the link between volatility and growth: National bureau of economic research.
Rapach, D. E. (2001). Macro shocks and real stock prices. *Journal of Economics and Business, 53*(1), 5-26.
Raunig, B., & Scharler, J. (2010). Stock Market Volatility and the Business Cycle. *Monetary Policy & The Economy Q, 2*, 54-63.
Raunig, B., & Scharler, J. (2011). Stock Market Volatility, Consumption and Investment; An Evaluation of the Uncertainty Hypothesis Using Post-War US Data (Vol. 168): Austrian Central Bank Working Papers.
Renato Jr, R. (2001). Two Decades of Vector Autoregression (VAR) Modeling: A Survey: University of the Philippines School of Economics.
Roger, S. (2010). Inflation targeting turns 20. *Finance & Development, 47*(1), 46-49.
Romer, C. D. (1990). The great crash and the onset of the great depression. *The Quarterly Journal of Economics, 105*(3), 597-624.
Schmitt‐Grohé, S., & Uribe, M. (2012). What's news in business cycles. *Econometrica, 80*(6), 2733-2764.
Schrimpf, A., & Wang, Q. (2010). A reappraisal of the leading indicator properties of the yield curve under structural instability. *International Journal of Forecasting, 26*(4), 836-857.
Schwert, G. W. (1989). Why does stock market volatility change over time? *The Journal of Finance, 44*(5), 1115-1153.
Schwert, G. W. (1990). Stock returns and real activity: A century of evidence. *The Journal of Finance, 45*(4), 1237-1257.
Shiller, R. J. (1980). Do stock prices move too much to be justified by subsequent changes in dividends? : National Bureau of Economic Research Cambridge, Mass., USA.
Shiller, R. J., & Beltratti, A. E. (1992). Stock prices and bond yields: Can their comovements be explained in terms of present value models? *Journal of Monetary Economics, 30*(1), 25-46.
Siliverstovs, B., & Duong, M. H. (2006). On the role of stock market for real economic activity: Evidence for Europe: DIW-Diskussionspapiere.
Sims, C. A. (1972). Money, income, and causality. *The American economic review*, 540-552.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: Journal of the Econometric Society*, 1-48.

Smets, F., & Tsatsaronis, K. (1997). *Why does the yield curve predict economic activity?: dissecting the evidence for Germany and the United States*: Centre for Economic Policy Research.

Song, B.-H. (2003). Uncertainty, volatility, and growth rate. *The university of Kansas working papers series in theoretical and applied economics*.

Stock, J. H., & Watson, M. W. (2003). Forecasting Output and Inflation: The Role of Asset Prices. *Journal of Economic Literature, 41*(3), 788-829.

Stoll, H. R. (2006). Electronic trading in stock markets. *The Journal of Economic Perspectives, 20*(1), 153-174.

Swanson, N. R., & White, H. (1997). A model selection approach to real-time macroeconomic forecasting using linear models and artificial neural networks. *Review of Economics and Statistics, 79*(4), 540-550.

Verhofer, M., Ammann, M., & Skovmand, D. (2009). Implied and Realized Volatility in the Cross-Section of Equity Options. *International Journal of Theoretical and Applied Finance, 12*(06), 745-765. doi: doi:10.1142/S0219024909005440

Veronesi, P. (2000). How does information quality affect stock returns? *The Journal of Finance, 55*(2), 807-837.

Wang, P. (2012). Understanding Expectation‐Driven Fluctuations: A Labor‐Market Approach. *Journal of Money, Credit and Banking, 44*(2‐3), 487-506.

Welch, I., & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies, 21*(4), 1455-1508.

Whaley, R. E. (2000). The investor fear gauge. *The Journal of Portfolio Management, 26*(3), 12-17.

Wright, J. H. (2006). The yield curve and predicting recessions. *Finance and Economics, Discussion Series 2006-07, Federal Reserve Board*.

Yan, S. (2011). Jump risk, stock returns, and slope of implied volatility smile. *Journal of financial Economics, 99*(1), 216-233.

Yang, M. J., & Liu, M.-Y. (2012). The forecasting power of the volatility index in emerging markets: Evidence from the Taiwan stock market. *International Journal of Economics and Finance, 4*(2), p217.