UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

ESSAYS ON THE FINANCIAL CONDITIONS INDEX FOR SOUTH AFRICA

by

KIRSTEN THOMPSON

Submitted in fulfilment of the requirements for the degree

PhD (Economics)

in the

FACULTY OF ECONOMIC AND MANAGEMENT SCIENCES

at the

UNIVERSITY OF PRETORIA

JULY 2014

ACKNOWLEDGEMENTS

I wish to express my sincere gratitude to a number of people, without whom I would never have been able to complete my studies.

Firstly, to my supervisors Prof Reneé van Eyden, Prof Rangan Gupta and Dr Christiane Baumeister, I am most grateful for your support and unrelenting patience. This research would not be complete without your advice. I also thank Prof Mehmet Balcilar for his inputs and advice for Chapter 4 of this thesis.

To my colleagues (and friends) Charlotte and Corneli, thank you for all of the emotional and spiritual support given to me over the years with respect to my research, and thank you for allowing me to fit my studies into my work life. I am eternally thankful to Christa for all of the practical assistance with my children during "crunch-times". I also wish to thank Hettie and Emmerine for their continuous support, and for always ensuring that my family and I remained fed! Mostly, however, it is the love and fellowship from these adopted sisters and mother of mine that I cherished the most during this journey.

To my parents, Gerard and Sally, I am thankful for your continuous encouragement, support and love, from childhood right through until adulthood. Your constant belief in me is my source of inspiration and courage for ALL things in my life.

I am the most indebted to my husband, Craig, who was a rock of support throughout my degree, and who had to put up with an absent wife through many a weekend and holiday. I am forever grateful to him for his love and strength through some hard times. To my daughters, Emma and Rachel, I am sorry for being such an absent mother, and I hope that computers do not remain your mortal enemy forever!

Finally, I am thankful to my Great Redeemer, for "I can do all things through Him who strengthens me" (Philippians 4:13). Without the blessings and grace of the Lord, none of this research would exist.

Kirsten Thompson

July 2014

ESSAYS ON THE FINANCIAL CONDITIONS INDEX FOR SOUTH AFRICA

by

KIRSTEN THOMPSON

Supervisor:	Prof Reneé van Eyden
Co-supervisor:	Prof Rangan Gupta
Co-supervisor:	Dr Christiane Baumeister
Department:	Economics
Degree for which the thesis is submitted:	PhD (Economics)

Abstract

The negative consequences of financial instability for the world economy during the recent financial crisis have highlighted the need for a better understanding of financial conditions by policy-makers and decision-makers all over the world, and more importantly, their impact on the real economy. It is for this reason that I conduct a study of South Africa's financial conditions and their impact on and implications for the real macroeconomy.

In order to meet this objective, I construct a financial conditions index (FCI) for the South African economy so as to ascertain whether: (1) financial conditions in South Africa have long-term effects on the macroeconomy; (2) South Africa's FCI can be regarded as an early warning system, and; (3) the nature of the impact of the FCI on the macroeconomy is linear or nonlinear.

This thesis begins with the compilation of an FCI for South Africa using a number of different approaches. The best FCI is chosen from these alternatives, namely a rolling-window principal components analysis (PCA) approach. The FCI is then purged of endogenous macroeconomic feedback effects emanating from output, interest rates and inflation. The performance of this FCI is evaluated by assessing its ability to pick up

turning points in the South African business cycle, and by running in-sample causality (forecast) tests against the major macroeconomic variables of output, inflation and an interest rate. It is found that the FCI does a good job of reflecting recessionary periods in South Africa, and causality tests indicate that this FCI is a good in-sample predictor of industrial production growth and the Treasury Bill yield, but a weak predictor of inflation.

I then go on to ascertain whether this FCI has good out-of-sample forecasting ability with respect to the major macroeconomic variables, as compared to the 16 individual financial time series which make up the FCI. A host of forecast encompassing tests are conducted, and their results are adjusted for data-mining. It is found that the estimated FCI has good out-of-sample forecasting ability with respect to manufacturing output growth at the one, three and six month horizons, while it has no predictive power for inflation and the Treasury bill yield. Therefore, the FCI can be regarded as a leading indicator of manufacturing output growth.

Finally, the FCI is inserted into a nonlinear vector autoregressive (VAR) framework, so as to test for asymmetry in the effects that financial conditions may have on the macroeconomic variables of output, interest rates and inflation in South Africa. I make use of a nonlinear logistic smooth transition vector autoregression (LSTVAR), which allows for the transition of a chosen switching variable between upper and lower regimes. I estimate two such models: one with inflation as a switching variable; and one which allocates a different switching variable to each equation within the LSTVAR. I find that the South African economy is strongly nonlinear in its responses to financial shocks, and that manufacturing output growth and interest rates are more affected by financial shocks during upswings, while inflation responds more during downswings.

TABLE OF CONTENTS

CHAPTER 1: Introduction 10
1.1 Background 10
1.1.1 Identify an appropriate FCI for South Africa 10
1.1.2 Use the identified FCI in forecasting exercises of major macroeconomic variables 11
1.1.3 Use the identified FCI in structural analysis exercises in a vector autoregression (VAR) framework 11
1.2 Importance and Benefits of the Study 11
1.3 Outline of the study 12
CHAPTER 2: Identifying a financial conditions index for South Africa 14
2.1 Introduction 14
2.2 Literature review 17
2.3 Econometric methodology 20
2.4 Data 21
2.5 Empirical Results 23
2.5.1 FCI Indices 23
2.5.2 Evaluating the performance of FCI indices 28
2.6 In-sample causality testing 30
2.7 Conclusions 33
CHAPTER 3: Testing the Out-of-Sample Forecasting Ability of a Financial Conditions Index for South Africa 34
3.1 Introduction 34
3.2 Data 35
3.3 Econometric Methodology 36
3.3.1 Theil's U Test 38
3.3.2 MSE-T and MSE-F Tests 39
3.3.3 ENC-T and ENC-NEW Tests 40
3.3.4 Bootstrapping Procedure 41
3.4 Empirical Results 42
3.4.1 Out-of-Sample Forecasting Performance 42
3.4.2 Data-Mining 44
3.4.3 Predictor Significance 45
3.5 An Illustration as of 2012M02 47
3.6 Conclusions 48
CHAPTER 4: Testing the Asymmetric Effects of Financial Conditions in South Africa: A Nonlinear Vector Autoregression Approach 49
4.1 Introduction 49
4.2 Data 50
4.3 Econometric Methodology 51
4.4 Empirical Results 52
4.4.1 Linearity Tests 52
4.4.2 LSTVAR estimation results 54
4.4.3 Impulse Responses 57
4.5 Conclusions 62

CHAPTER 5: General conclusions and areas of future research 63
5.1 Introduction 63
5.2 Summary of key findings 63
5.3 Contributions of this study 64
5.4 Areas of future research 65
REFERENCES 66
APPENDICES 71
A.1 Data appendix 71
A.2 Unit root test results 75
A.3 Principal Components Methodology 81
A.4 Alternative FCIs 82
A.5 Forecasting results 83
A.6 Weise's (1999) LSTVAR Methodology 101
A.7 Structural break test results in LSTVAR Model 103
A.8 LSTVAR Transition functions 105
A.9 Generalised Impulse Response Functions 107

LIST OF TABLES

Table 1. Variables used to construct and purge the FCI 22
Table 2. Marginal R^2 from sub-sample regressions 25
Table 3. Correlation coefficients between estimated FCIs 28
Table 4. Wald causality test results 32
Table 5. Out-of-sample forecasting performance, dependent variable: Manufacturing production growth 42
Table 6. Out-of-sample forecasting performance, dependent variable: Inflation 43
Table 7. Out-of-sample forecasting performance, dependent variable: Treasury Bill 43
Table 8. Out-of-sample forecasting performance after data-mining adjustments 45
Table 9. Least Squares Estimates of λ 46
Table 10. First round LM tests for linearity 54
Table 11. Selected estimation output 55
Table 12. Second round linearity tests 57
Table 13. Responses of *MPG*, *INF* and *TB* to various shocks of *FCI* after 25 months 59
Table A1. Variables used to construct FCI and in forecasting and VAR models 71
Table A2. Descriptive statistics of data series used in models 74
Table A3. In- and out-of-sample forecasting for xt: FCI (Sample: 1986:01 – 2012:01) 83
Table A4. In- and out-of-sample forecasting: Manufacturing production growth as dependent variable (Sample: 1986:01 – 2012:01) 84
Table A5. In- and out-of-sample forecasting: Inflation as dependent variable (Sample: 1986:01 – 2012:01) 89
Table A6. In- and out-of-sample forecasting: Treasury Bill as dependent variable (Sample: 1986:01 – 2012:01) 94
Table A7. Data-mining critical values: Manufacturing output growth (Sample: 1986:01 – 2012:01) 99
Table A8. Data-mining critical values: Inflation (Sample: 1986:01 – 2012:01) 99
Table A9. Data-mining critical values: Treasury Bill (Sample: 1986:01 – 2012:01) 100
Table A10. Bai and Perron (2003*a, b*) test: *MPG* equation 103
Table A11. Bai and Perron (2003*a, b*) test: *INF* equation 104
Table A12. Bai and Perron (2003*a, b*) test: *TB* equation 104

LIST OF FIGURES

Figure 1. Performance of various FCIs 27
Figure 2. Estimated rolling-window purged FCI compared with key macroeconomic variables (12-month moving averages) 37
Figure 3. Forecasts of manufacturing output growth 47
Figure 4. Transition function: INF_{t-2} as switching variable 56
Figure 5. Transition function: 4-switch model version 1 56
Figure 6. Asymmetry in upturns and downturns: Model with $\boldsymbol{INFt-2}$ as switching variable 61
Figure 7. Asymmetry in upturns and downturns: 4-switch model 61
Figure A1. Graphs of data series used in models 72
Figure A2. Alternative rolling-window and recursive FCIs 82
Figure A3. CUSUM test results for structural breaks in LSTVAR models 103
Figure A4. LSTVAR(2) with FCI_{t-2} as switcher 105
Figure A5. LSTVAR(2) with MPG_{t-2} as switcher 105
Figure A6. LSTVAR(2) with INF_{t-2} as switcher 105
Figure A7. LSTVAR(2) with TB_{t-2} as switcher 105
Figure A8. LSTVAR(2) 4 switch version 1 105
Figure A9. LSTVAR(2) 4 switch version 2 106
Figure A10. Linear VAR: Cumulative GIRFs with 68% bootstrapped confidence intervals (CIs) 107
Figure A11. LSTVAR with INF_{t-2} as switcher: Responses of shock to *FCI* of 1SE with 68% bootstrapped CIs 108
Figure A12. LSTVAR with INF_{t-2} as switcher: Responses of shock to *FCI* of -1SE with 68% bootstrapped CIs 109
Figure A13. LSTVAR with INF_{t-2} as switcher: Responses of shock to *FCI* of 3SE with 68% bootstrapped CIs 110
Figure A14. LSTVAR with INF_{t-2} as switcher: Responses of shock to *FCI* of -3SE with 68% bootstrapped CIs 111
Figure A15. LSTVAR with INF_{t-2} as switcher: Responses of shock to *MPG* of 1SE with 68% bootstrapped CIs 112
Figure A16. LSTVAR with INF_{t-2} as switcher: Responses of shock to *MPG* of -1SE with 68% bootstrapped CIs 113
Figure A17. LSTVAR with INF_{t-2} as switcher: Responses of shock to *MPG* of 3SE with 68% bootstrapped CIs 114
Figure A18. LSTVAR with INF_{t-2} as switcher: Responses of shock to *MPG* of -3SE with 68% bootstrapped CIs 115
Figure A19. LSTVAR with INF_{t-2} as switcher: Responses of shock to *INF* of 1SE with 68% bootstrapped CIs 116
Figure A20. LSTVAR with INF_{t-2} as switcher: Responses of shock to *INF* of -1SE with 68% bootstrapped CIs 117
Figure A21. LSTVAR with INF_{t-2} as switcher: Responses of shock to *INF* of 3SE with 68% bootstrapped CIs 118
Figure A22. LSTVAR with INF_{t-2} as switcher: Responses of shock to *INF* of -3SE with 68% bootstrapped CIs 119
Figure A23. LSTVAR with INF_{t-2} as switcher: Responses of shock to *TB* of 1SE with 68% bootstrapped CIs 120

Figure A24. LSTVAR with INF_{t-2} as switcher: Responses of shock to *TB* of -1SE with 68% bootstrapped CIs 121
Figure A25. LSTVAR with INF_{t-2} as switcher: Responses of shock to *TB* of 3SE with 68% bootstrapped CIs 122
Figure A26. LSTVAR with INF_{t-2} as switcher: Responses of shock to *TB* of -3SE with 68% bootstrapped CIs 123
Figure A27. LSTVAR with 4 switching variables version 1: Responses of shock to *FCI* of 1SE with 68% bootstrapped CIs 124
Figure A28. LSTVAR with 4 switching variables version 1: Responses of shock to *FCI* of -1SE with 68% bootstrapped CIs 125
Figure A29. LSTVAR with 4 switching variables version 1: Responses of shock to *FCI* of 3SE with 68% bootstrapped CIs 126
Figure A30. LSTVAR with 4 switching variables version 1: Responses of shock to *FCI* of -3SE with 68% bootstrapped CIs 127
Figure A31. LSTVAR with 4 switching variables version 1: Responses of shock to *MPG* of 1SE with 68% bootstrapped CIs 128
Figure A32. LSTVAR with 4 switching variables version 1: Responses of shock to *MPG* of -1SE with 68% bootstrapped CIs 129
Figure A33. LSTVAR with 4 switching variables version 1: Responses of shock to *MPG* of 3SE with 68% bootstrapped CIs 130
Figure A34. LSTVAR with 4 switching variables version 1: Responses of shock to *MPG* of -3SE with 68% bootstrapped CIs 131
Figure A35. LSTVAR with 4 switching variables version 1: Responses of shock to *INF* of 1SE with 68% bootstrapped CIs 132
Figure A36. LSTVAR with 4 switching variables version 1: Responses of shock to *INF* of -1SE with 68% bootstrapped CIs 133
Figure A37. LSTVAR with 4 switching variables version 1: Responses of shock to *INF* of 3SE with 68% bootstrapped CIs 134
Figure A38. LSTVAR with 4 switching variables version 1: Responses of shock to *INF* of -3SE with 68% bootstrapped CIs 135
Figure A39. LSTVAR with 4 switching variables version 1: Responses of shock to *TB* of 1SE with 68% bootstrapped CIs 136
Figure A40. LSTVAR with 4 switching variables version 1: Responses of shock to *TB* of -1SE with 68% bootstrapped CIs 137
Figure A41. LSTVAR with 4 switching variables version 1: Responses of shock to *TB* of 3SE with 68% bootstrapped CIs 138
Figure A42. LSTVAR with 4 switching variables version 1: Responses of shock to *TB* of -3SE with 68% bootstrapped CIs 139

LIST OF ABBREVIATIONS

AD-AS	Aggregate demand-aggregate supply
AIC	Akaike information criterion
AR	Autoregressive
ARDL	Autoregressive distributed lag model
BIC	Bayesian information criterion
CI	Confidence interval
CPI	Consumer price index
CUSUM	Cumulative sum
DMA	Dynamic model averaging
DMS	Dynamic model selection
FAVAR	Factor-augmented vector autoregression
FCI	Financial conditions index
FIFA	Fédération Internationale de Football Association
FSI	Financial stress index
G-7	Group of seven developed nations (US, Japan, France, Germany, Italy, UK and Canada)
GDP	Gross domestic product
GIRF	Generalised impulse response function
IT	Information technology
IRF	Impulse response function
JSE	Johannesburg Stock Exchange
LM	Lagrange Multiplier
LSTVAR	Logistic smooth transition vector autoregression
MCI	Monetary conditions index
MSE	Mean squared error
MSFE	Mean squared forecast error
OLS	Ordinary least squares
PC	Principal component
PCA	Principal components analysis
RMSFE	Root mean squared forecast error
SARB	South African Reserve Bank
SE	Standard error
SIC	Schwarz Information Criterion
SSR	Sum of squared residuals
STVAR	Smooth transition vector autoregression
TAR	Threshold autoregression
TVP-FAVAR	Time-varying parameter factor-augmented vector autoregression
TVP-VAR	Time-varying parameter vector autoregression
UK	United Kingdom
US(A)	United States (of America)
VAR	Vector autoregression

CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

The global financial crisis that began in 2007-08 demonstrated how severe the impact of financial markets' stress on real economic activity can be. In the wake of the financial crisis policy-makers and decision-makers all over the world identified the critical need for a better understanding of financial conditions, and more importantly, their impact on the real economy. It is for this reason that I propose a study of South Africa's financial conditions and their impact on and implications for the real macroeconomy.

In order to meet this objective, I construct a financial conditions index (FCI) for the South African economy. I will use this FCI to test three broad hypotheses:

- Do financial conditions in South Africa have long-term effects on the macroeconomy?
- Can South Africa's FCI be regarded as an early warning system? (Is the FCI an appropriate and valid forecasting tool?)
- What is the nature of the impact of the FCI on the macroeconomy – is it linear or nonlinear?

The ultimate purpose of this study can be split into three objectives.

1.1.1 Identify an appropriate FCI for South Africa

In this study I will compile an FCI for South Africa using a number of different approaches, namely: a simple weighted average; principal components analysis (PCA); recursive PCA; and rolling-window PCA. Furthermore, I will test whether to purge the FCI of endogenous macroeconomic feedback effects emanating from output, interest rates and inflation.

The "best" FCI for South Africa will be chosen from these alternatives by evaluating their various performances by comparing their ability to pick up turning points in the South African business cycle, and by running in-sample causality (forecast) tests against the major macroeconomic variables of output, inflation and an interest rate.

1.1.2 Use the identified FCI in forecasting exercises of major macroeconomic variables

This part of the study will ascertain whether the "best" chosen FCI has good out-of-sample forecasting ability with respect to the major macroeconomic variables of output, inflation and interest rates as compared to individual financial time series. A host of forecast encompassing tests will be conducted, and these will be validated using data-mining tests. This will enable me to determine whether the FCI can be regarded as a leading indicator of any of these three macroeconomic variables.

1.1.3 Use the identified FCI in structural analysis exercises in a vector autoregression (VAR) framework

The "best" chosen FCI will be inserted into a nonlinear VAR framework, so as to test for asymmetry in the effects that financial conditions may have on the macroeconomic variables of output, interest rates and inflation in South Africa. This will be conducted by using the nonlinear VAR to run impulse response analyses, to assess whether there are different effects during periods of positive vs. negative financial conditions.

1.2 IMPORTANCE AND BENEFITS OF THE STUDY

This study offers a number of contributions to the existing literature on financial conditions in South Africa:

- I will construct an FCI over a sample period that is three decades longer than existing indices.
- This FCI will comprise a wider coverage of applicable and relevant financial variables than others, with the added benefit of being more "all-encompassing".
- I will make use of rolling-window estimation techniques that allow me to account for parameter instability and to capture the real-time constraints faced by a policymaker.
- The FCI will be structurally analysed within the context of a nonlinear VAR, as opposed to the convention in the literature of utilising a structural VAR, factor-augmented VAR (FAVAR) or time-varying parameter VAR (TVP-VAR). This nonlinear technique is tested due to the possibility of financial conditions (and hence economic activity) exhibiting nonlinear reactions in response to monetary

policy – i.e. differing responses during upswings than during downswings; and differing responses to positive versus negative shocks.

- I will test the use of a single switching variable versus multiple switching variables between regimes in the nonlinear VAR applications. The motivation for testing a multiple switch model lies in the rationale that this approach does not restrict the nonlinear dynamics of the each equation to be governed by the same switching variable, and hence is more flexible.

1.3 OUTLINE OF THE STUDY

The main part of this thesis is split into three chapters, each chapter dedicated to addressing the three broad objectives and hypotheses mentioned above. Each chapter comprises an introductory literature review, a data discussion, an econometric methodology overview, and an empirical results section.

Chapter 2 identifies the FCI to be used for assessing South African financial conditions – one which adequately captures trends in economic activity, and one which can be used as an early-warning system for predicting downswings in the economy. A variety of modelling approaches are tested in devising the index, and causality tests are run to assess whether the estimated FCI is a good in-sample predictor of the macroeconomic variables of industrial production growth, the Treasury Bill yield, and inflation.

In chapter 3, I use the chosen FCI in a series of forecast encompassing tests to investigate whether it can act as an 'early warning indicator' for impending macroeconomic instability caused by deteriorating financial conditions, by means of out-of-sample forecasting tests. To this end I test whether the estimated FCI does better than its individual financial components in forecasting key macroeconomic variables, namely output growth, inflation and the Treasury Bill yield. I also compare the forecasting ability of the FCI against that of the 16 financial variables which comprise the index.

The aim of chapter 4 is to investigate whether the FCI has an asymmetric effect on output, interest rates and inflation; in other words to test whether there is potential nonlinearity between South Africa's financial market conditions and its macroeconomy. In so doing, I apply linearity tests and model selection criteria to all equations in a linear VAR to determine if nonlinearity is present, and to obtain candidates for the switching variable between regimes of a nonlinear VAR. I test the usefulness of a nonlinear VAR with a single switching variable versus one with multiple switching variables by comparing their response characteristics.

Chapter 5 presents a conclusion to the thesis, focusing on its key contributions to the literature, as well as areas of future research.

CHAPTER 2: IDENTIFYING A FINANCIAL CONDITIONS INDEX FOR SOUTH AFRICA[1]

2.1 INTRODUCTION

The global financial crisis that began in 2007-08 demonstrated how severe the impact of financial markets' stress on real economic activity can be. In the wake of the financial crisis policy-makers and decision-makers all over the world identified the critical need for a better understanding of financial conditions, and more importantly, their impact on the real economy. Indeed, Borio and Lowe (2002) strongly make the point that even during times of sound and credible economic policy, financial instability remains a threat. In order to allow for a timely assessment of economy-wide financial conditions and their impact on the macro economy, I construct an FCI for the South African economy. I also evaluate whether the resulting FCI can act as an 'early warning system'. This in turn may indicate whether monetary policy should take broader financial conditions into account. This chapter offers three main contributions to the existing literature on financial conditions in South Africa: (i) I construct an FCI over a sample period that is three decades longer than existing indices; (ii) my FCI comprises a wider coverage of financial variables than others; and (iii) I make use of rolling-window estimation techniques, that allows me to account for parameter instability and to capture the real-time constraints faced by a policymaker[2]. I evaluate the performance of my constructed FCIs by comparing their ability to pick up turning points in the South African business cycle, and by running in-sample causality (forecast) tests.

2.2 THE USEFULNESS OF AN FCI

One of the primary aims of FCIs is to capture a single quantitative measure of financial stress. Hakkio and Keeton (2009) list several key features of financial stress (and therefore key reasons for the need to monitor this stress), namely:

- Increased uncertainty about financial assets' fundamental values, which will generally lead to volatility in the assets' market values, and which sometimes even reflects uncertainty about the macroeconomy and its sectors.

---

[1] This chapter is a modified version of University of Pretoria Department of Economics Working Paper Series, 2013(33), and is also forthcoming in *Studies in Economics and Finance*.

[2] As discussed later in this chapter, the rolling-window nature of the FCI is representative of economic agents having only the information available for a specific window of the sample between say period (t-m) and t when making a decision in time t, as opposed to a "static" FCI which has the full set of information at all points in the sample.

- Increased uncertainty about the behaviour of other investors, which impacts the expected returns of assets, and hence can lead to volatility in prices.
- Increased asymmetry of information between lenders and borrowers or buyers and sellers of financial assets, which can lead to the problems of moral hazard and adverse selection.
- Decreased demand for risky assets (or a flight to quality) will lead to a widening spread between the rates of return on "safe" and "risky" assets, which in turn will increase borrowing costs for risky borrowers.
- Decreased demand for illiquid assets (or a flight to liquidity) will lead to a widening spread between the rates of return on liquid and illiquid assets, which in turn will increase borrowing costs for the firms that issue illiquid securities.

As mentioned in the introductory paragraph above, the impact of financial stress on the real macroeconomy has been demonstrated as severe in recent years. Specifically, Hakkio and Keeton (2009) identify three potential channels through which financial stress can translate into reduced economic activity. The first channel is associated with the uncertainty that financial stress brings (see the first two bullet points in the list directly above). Uncertainty leads to volatility of asset prices, which in turn can lead to firms' reluctance to make important decisions regarding labour and capital investments. Households will also be circumspect in their spending and investment decisions due to uncertainty regarding future wealth. Ultimately, real economic activity will contract.

The second channel is driven by higher costs of borrowing. The flights to liquidity and quality described above, along with asymmetric information, will result in higher interest rates on business and consumer debt, with the typical result of depressed spending and investment, leading to a shrinking economy.

The third channel is related to the tightening of credit standards and associated diminished willingness of banks to lend, with similar associated effects as the second channel described above.

In addition to these linkages between financial and real economic conditions, Dudley (2010:1) identifies the importance of monetary policy in the financial system and claims that "monetary policy works its magic through its effect on financial conditions… because the level of the federal funds rate influences other financial market variables… and it is these variables that influence real economic activity". Hatzius, Hooper, Mishkin, Schoenholtz, and Watson (2010) highlight the case of the US economy in the wake of the global financial crisis, and particularly the ensuing "unconventional" monetary policy approaches (namely low policy rates, quantitative easing and credit easing) – "naturally, policymakers would like to know how less conventional policy tools affect financial conditions and the economy" (Hatzius, *et al.*, 2010:1). However, the authors go on to caution that this link is not straightforward, due to the following reasons:

- The transmission channel between financial conditions and economic activity changes over time.
- Factors other than monetary policy play a role in affecting financial conditions, and these factors also vary over time.
- The responses of financial conditions themselves to policy decisions will also evolve over time.
- The performance of the real economy is affected by factors other than financial conditions.

Nevertheless, an FCI can be an effective tool for policymakers, "especially in periods when the link between policy setting and financial conditions seems weak, or when the policy tools in use are stretched beyond their normal range. Just as a Taylor-type rule can inform (and helpfully constrain) the use of policy discretion, an FCI can serve as one guide to the effective stance of policy, after taking into account all (of) the other factors that affect financial variables" (Hatzius, *et al.*, 2010:5).

An FCI will measure financial **conditions** (encompassing financial **stress**), namely the "current state of financial variables that influence economic behaviour and (thereby) the future state of the economy" (Hatzius, *et al.*, 2010:1). An FCI should specifically measure financial **shocks** – exogenous shocks to financial conditions that influence future economic activity, and which are "purged" of "endogenous reflection or embodiment in financial variables of past economic activity" (Hatzius, *et al.*, 2010:1).

Mayes and Viren (2001) also highlight the usefulness of an FCI, which stems from its ability to summarise the impact of a central bank's policy decision "on financial prices, which can be related to future output and inflation". An FCI is more comprehensive than a monetary conditions index (MCI) which typically only includes interest rates and real exchange rates, while an FCI additionally incorporates data on asset prices and/or financial activity measures. The early literature on FCIs (see for example Goodhart and Hofmann (2001), Mayes and Viren (2001), Goodhart and Hofmann (2002), Lack(2003), Montaglioni and Napolitano (2004), and Castro (2008)) suggested the use of a narrow data set incorporating an interest rate, an exchange rate and one or two asset prices – usually house prices and/or share prices. These ideas have recently been broadened to include a multitude of financial indicators.

One of the desired characteristics of an FCI is that it comprises high-frequency data which can easily be updated, thereby providing timely estimates (and forecasts) at much shorter intervals than typical economic forecasts based on macroeconomic variables. In South Africa especially, a monthly FCI would be most valuable in an environment where macroeconomic forecasts are generally restricted to a quarterly basis, at best.

There are of course also limitations to the usefulness and applicability of FCIs. Many existing FCIs can be regarded as "rudimentary, … *ad hoc* and incomplete" (Dudley, 2010:3). A more serious issue is that of the changing dynamics of financial systems, and therefore the changing importance of selected financial variables over time – hence the reason I estimate a rolling-window FCI. Another criticism of FCIs pertains to the choice of variables – it is becoming more acceptable to include large numbers of variables as components of the indices, however the choices are largely subject to some form of selection bias (and despite this, important variables may still be overlooked). Furthermore, including more variables rather than less may improve results, not necessarily due to solid theoretical fundamentals, but rather because they "soak up variability in real GDP" (Dudley, 2010: 4). Also related to variable choice is the instability that asset prices present, particularly when forecasting (Stock and Watson, 2003). Another criticism of FCIs, particularly large, complex ones, is that they may be difficult and cumbersome to estimate and update.

2.3 LITERATURE REVIEW

Hatzius, *et al.* (2010) have compiled an FCI for the USA from a sizeable set of 45 quarterly financial variables, which are split into five categories of data encompassing prices, quantities, surveys, liquidity and credit measures. The factors of the FCI are estimated through iterative least squares regressions of the unbalanced panel on level and lagged values of real GDP and GDP inflation. They find that their FCI has relatively unstable predictive performance, which is however improved when macroeconomic influences are purged.

Due to the need for estimating and monitoring FCIs, a number of different methods for constructing these indices have been developed in the recent literature. Hatzius, *et al.* (2010) split these into two broad methodological categories: a weighted-sum approach and a principal components approach. The Kalman filter approach can be added to this list (Gumata, Klein and Ndou (2012), and Koop and Korobilis (2013)).

Weighted sum approach:

Indices estimated according to this approach include the Bloomberg FCI (Rosenberg, 2009), which is a daily FCI estimated as an equal weighted average of three sub-indices, themselves equal-weighted averages of 10 variables in total. Goodhart and Hofmann (2001) estimate FCIs for the G-7 countries comprising short-rates, exchange rates, house prices and share prices (i.e. an extension of an MCI). The weights of these variables are determined by reduced-form coefficients in an aggregate demand equation as well as impulse responses from a vector autoregresion (VAR). They find, however, that these FCIs have poor out-of-sample forecasting performance when compared to random-walk forecasts. Gauthier, Graham and Liu (2004) construct FCIs for Canada using three approaches: weights derived from an IS-Phillips curve; weights from a VAR's impulse-response functions; and by taking the first principal component from a principal components analysis (PCA) approach. They find that the two weighted-sum approaches present better FCIs than the PCA approach, particularly with respect to out-of-sample forecasting ability. Swiston (2008) estimates an FCI for the US by obtaining weights from the impulse responses from a VAR, and finds encouraging evidence of forecasting ability with respect to GDP. Citi's FCI is a weighted average of six monthly financial variables, where the weights are determined by the reduced-form parameters of the chosen variables regressed on the Conference Board's coincident index (Diclemente, Schoenholtz and D'Antonio, 2008). Oet, Bianco, Gramlich and Ong (2012) construct a financial stress index (FSI) for the USA using a weighted average approach applied to 16 spread measures, as opposed to using volatility measures, so as to create an index capturing stress in six financial markets.

Principal components approach:

The principal components approach to estimating an FCI has been pursued by English, Tsatsaronis and Zoli (2005), who estimate FCIs for Germany, the UK and the USA, using PCA, with 35 financial variables making up the FCI in the case of Germany, 37 for the UK and 47 for the USA. They find that the FCIs show promise as forecasters of output and investment, particularly at longer lags. Hakkio and Keeton (2009) compile the Federal Reserve Bank of Kansas City's FCI by taking the first principal component of 11 monthly financial indicators. Brave and Butters (2011) estimate an FCI for the USA based on an unbalanced panel of 100 financial variables of differing frequencies, using a combination of PCA and the Kalman filter. They find that a forecast based on the portion of the FCI that is not explained by its historical dynamics exhibits good promise. Rapach and Strauss (2011) create FCIs for the G-7 nations to assess the empirical relevance of financial sector shocks on business-cycle fluctuations. They do so by taking the first principal component of a set of 10 quarterly financial variables, and perform tests using structural VARs and a factor-augmented VAR (FAVAR). They find significant evidence of in- and out-of-sample Granger causality between financial conditions and industrial production growth, and also that forecasting gains are concentrated in the period of the global financial crisis of 2007-08.

Kalman filter approach:

Koop and Korobilis (2013) estimate a number of alternative FCIs for the USA using both PCA and the Kalman filter approach, and apply dynamic model averaging (DMA) and dynamic model selection (DMS) on time-varying parameter FAVARs (TVP-FAVARs) and on constant parameter FAVARs which incorporate these FCIs. The FCIs are estimated from 20 quarterly financial variables. They find that DMS and DMA lead to improved forecasts of macroeconomic variables, and that a simple benchmark VAR provides better predictive performance than a FAVAR or TVP-FAVAR. Montaglioni and Napolitano (2004) estimate FCIs for the USA, Canada and the Euro area applying a Kalman filter; and use these estimated FCIs to test the interactions between financial conditions and monetary policy through the augmentation of forward-looking Taylor rules. Castro (2008) does the same for the UK, the USA and the Euro area.

South African FCIs:

The literature on FCIs for South Africa is rather limited. Gumata, *et al.* (2012) estimate an FCI for South Africa using the alternative approaches of PCA and a Kalman filter; applied to quarterly data over the period 1999Q1 to 2011Q4. My research represents an improvement on the data frequency and length of this sample. The authors find that their PCA-based FCI has good out-of-sample forecasting characteristics for GDP growth when compared to a simple AR model. Kasai and Naraidoo (2011) estimate an FCI for the purposes of including it in a monetary policy reaction function for the South African Reserve Bank (SARB). Their index is constructed as the average of monthly data spanning five variables, over the period January 2000 to December 2008. Quantec (2007) estimates an FCI for South Africa over the period 1997 to 2007 as the weighted average of a short rate, a yield spread, excess money supply growth, company earnings yield and an exchange rate.

Koop and Korobilis (2013) indicate that there are three issues involved in the construction of an FCI: (i) the selection of financial variables; (ii) identifying/calculating the weights for combining these variables into an index; and (iii) assessing the relationship between the FCI and the real economy. Following these processes, in (i) I identify a set of 16 monthly financial variables, significantly expanding the coverage of my FCI over others. In answering (ii) I utilise PCA methodology, but I enhance this by testing a rolling-window approach, and by purging the FCI of endogenous macroeconomic feedback. For step (iii), I assess the suitability of the estimated FCIs qualitatively (graphically), and by conducting in-sample causality tests, out-of-sample forecasting tests (in Chapter 3), and impulse response analysis in a nonlinear VAR framework (in Chapter 4).

The layout of the remainder of this chapter is as follows: Section 2.4 provides a brief overview of the econometric methodology used in estimating the indices, followed by a discussion of the data used in Section 2.5. Section 2.6 presents the results of the estimated FCIs, and causality testing is conducted in Section 2.6. Section 2.7 concludes the chapter.

2.4 ECONOMETRIC METHODOLOGY

The indices estimated in this study are compiled using PCA[3]. PCA has the useful objective of combining many variables into a few linear combinations or principal components (factors), and is thus widely used in index number generation. PCA extracts a common factor, in this case FCI_t, from a group of p variables, X_t:

$$\boldsymbol{X_t} = \boldsymbol{\beta FCI_t} + \boldsymbol{U_t} \tag{1}$$

where $\boldsymbol{X_t}$ is a vector of p standardised financial variables, $\boldsymbol{\beta}$ is a $p \times m$ coefficient matrix, $\boldsymbol{FCI_t}$ is a vector of $m \times 1$ unobserved variables, and $\boldsymbol{U_t}$ is a $p \times 1$ error vector.

Suggested by Dudley (2010) and similarly to Koop and Korobilis (2013), Gumata *et al.* (2012), Brave and Butters (2011) and Hatzius *et al.* (2010) I purge the FCI of any potential endogenous feedback effects, so as to ensure that it captures only information about pure financial shocks and not past economic activity. However, where Gumata *et al.* (2012) purge only economic activity, I, similar to Hatzius *et al.* (2010), also purge inflation; and, like Koop and Korobilis (2013), also purge interest rates from the FCI; so as to fully

[3] PCA methodology is discussed in further detail in Appendix A.3.

remove monetary policy influences. This is achieved by regressing the FCI on the growth in the index of manufacturing production (MPG_t), CPI inflation (INF_t)[4] and the nominal 3-month Treasury Bill yield (TB_t) as follows:

$$\widehat{FCI}_t = \alpha + \beta MANUFN\_GR_t + \delta INFL_t + \theta TBILLN_t + \epsilon_t \qquad (2)$$

In Equation (2), $\hat{\epsilon}_t$ is regarded as the estimated purged FCI, and is uncorrelated with *MPG*, *INF* and *TB*. The next section provides an overview of the data used in the models.

2.5 DATA

Variables used in FCIs are typically confined to "include anything that characterises the supply or demand of financial instruments relevant for economic activity. This list might comprise a wide array of asset prices and quantities (both stocks and flows), as well as indicators of potential asset supply and demand. The latter may range from surveys of credit availability to the capital adequacy of financial intermediaries" (Hatzius, et al., 2010:1). Dudley (2010) splits the key variables that ought to be included in an FCI into two categories: neoclassical variables (yield curve and stock prices); and non-neoclassical (credit availability).

There is a trade-off between the breadth of coverage for an extended time period and the frequency of the data. Financial variables are available at a higher frequency but often over shorter time periods than macroeconomic variables. Another distinguishing feature of financial variables is that they tend to exhibit greater volatility. However, an FCI that incorporates a large variety of financial data series may not necessarily suffer from increased volatility, since the inclusion of each additional series will decrease the weights of all of the variables included, some of which may be volatile.

My dataset contains 16 monthly financial variables which encompass domestic and global financial measures, shown in Table 1. The aim is to have a dataset sizeable enough to cover the spectrum of financial indicators (including asset prices, liquidity, credit, financial activity and volatility measures), and which is parsimonious enough so as to restrict the FCI to one principal component, as well as being of a significant sample length. However, as noted by Hatzius, *et al.* (2010), there is significant tension between wide variable coverage and long history when it comes to financial data. The chosen series encompass measures in levels, as well as volatility measures, and, as with English *et al.* (2005), are intended to represent, *inter alia*, the "financial determinants of spending by

[4] Manufacturing growth and CPI inflation are calculated as the rate of change between successive months.

households and businesses", as well as fit the requirements of Dudley's (2010) neoclassical and non-neoclassical variables.

I include data on asset prices, namely share and house prices as well as dividend yields, to represent the value of households' and firms' wealth, and therefore also representing their capacity to borrow and cost of borrowing. I also incorporate the volatility of these asset prices to capture the possible effects of market imbalances. I include four interest rate spreads (two long spreads, a short spread and a term spread) to represent the costs of various forms of capital, as well as the risks associated, and the profitability of banks. Credit and money aggregates are included to capture both the demand for and supply of credit and money. Finally, I incorporate global financial pressures through the US Federal Funds Rate and the S&P500 index, and international economic conditions are captured by a US confidence measure, while global effects on the South African economy are integrated via the real rand-US dollar exchange rate.

The data series specifically include: South African financial asset prices; South African property prices; global asset prices; the real rand-US dollar exchange rate; the yield on the Johannesburg Stock Exchange (JSE); a global indicator of confidence; four South African interest rate spread measures, namely the bond spread, mortgage spread, Treasury bill spread and term spread; US monetary policy measured by the Federal Funds Rate; South African M3 money supply growth; credit extended to the South African private sector; South African government bond volatility, South African house price volatility, and South African asset price volatility. The data set covers the significant sample of 1966M02 – 2012M01. The US Census X-12 procedure is used to seasonally adjust the data for series not already seasonally adjusted. Unit roots are tested for using the Ng-Perron (2001) procedure[5], and non-stationary series are differenced to be made stationary. Finally, all data is standardised[6] before compiling the alternative FCIs.

Table 1. Variables used to construct and purge the FCI

Name	*Description*	*Transformation(s)*
ALSI_VOL	Stock exchange volatility (South Africa)	Square of the first log difference of the All-Share Index
CONFUSN	University of Michigan US Consumer Sentiment Index	N/A
D_LALSI	FTSE/JSE All-Share Index (South Africa)	Seasonally adjusted, deflated, first log difference
D_LHOUSEP	Absa House Price Index (medium house size $141m^2$–$220m^2$) (South Africa)	Deflated by South African CPI, first log difference
D_LPSCE	Credit extended to domestic private sector (South Africa)	Deflated by South African CPI, first log difference

[5] Unit root test results are available in Appendix A.2.
[6] Standardising the data enables analysis and comparison of the sizes of the impacts of the FCIs.

Name	*Description*	*Transformation(s)*
D_LRD	Rand-US dollar exchange rate	Seasonally adjusted, deflated, first log difference
D_LSP500	S&P500 Composite Price Index	Seasonally adjusted, deflated, first log difference
DIVN	Johannesburg Stock Exchange dividend yield (South Africa)	Seasonally adjusted
FED	US Federal Funds market rate	Deflated by US CPI
GBINDEX_VOL	Government bond volatility (South Africa)	Square of the first log difference of Government Bond Return Index
HOUSEP_VOL	House price volatility (South Africa)	Square of the first log difference of House Price Index
INF	Month-on-month growth in CPI (South Africa)	Seasonally adjusted, month-on-month rate of change
M3_GR	Month-on-month growth in M3 money supply[7] (South Africa)	Seasonally adjusted, deflated, month-on-month rate of change
MPG	Month-on-month growth in Manufacturing Production Index (South Africa)	Month-on-month rate of change
SPREADN_BOND	Long-term bond spread between Eskom Corporate Bond yield and 10-year Government Bond yield (South Africa)	N/A
SPREADN_MORT	Mortgage spread between mortgage loan borrowing rate and 3-month Treasury Bill yield (South Africa)	N/A
SPREADN_TBILL	Short-term spread between prime overdraft rate and 3-month Treasury Bill yield (South Africa)	N/A
SPREADN_TERM	Term spread between 10-year Government Bond yield and 3-month Treasury Bill yield (South Africa)	N/A
TB	3-month Treasury Bill yield (South Africa)	N/A

Notes: All data is extracted from the Global Financial Database (https://www.globalfinancialdata.com). *INF*, *MPG* and *TB* are used to purge the *FCI*, and are not used in its initial PCA construction.

2.6 EMPIRICAL RESULTS

2.5.1 FCI Indices

In choosing the best available FCI for South Africa, a number of different methods are used to compile indices, and these are compared graphically to isolate a subset of indices, which are then compared with each other using causality tests. The original set of indices is compiled using two techniques: a simple averaging procedure, and various permutations of PCA. A comparison of these indices indicates that the simple average did not perform as well as the PCA-FCI, especially with regard to tracking recessions in the economy. I tested different PCA approaches resulting in four different FCIs from which to choose. Firstly, I tested the use of rolling-window PCA vs. static (i.e. non-rolling-window) PCA. Then, for each of these, I tested whether it is preferable to purge the index

[7] I tested the inclusion of M1 growth vs. M3 growth through graphical comparison and correlation coefficients between the two FCIs and found that they were very similar, nearly identical in fact, so I chose the FCI including M3 since it is theoretically a more inclusive measure.

of the endogenous feedback effects of output, inflation and interest rates (i.e. purged vs. un-purged)[8].

The idea of estimating a rolling-window FCI arises from comparing the PCA-estimated FCI over shorter time periods with one estimated for the full sample. This comparison highlights that their performance varies significantly over time. This evidence calls for an assessment of the relevance of the individual components of the FCI over shorter ten-year (120-month) sub-samples. This is done using a procedure similar to Ludvigson and Ng (2009 and 2010), namely regressing the individual financial variables (X_t) on the FCI, one at a time, over sub-samples, and using the resultant R^2 statistics to determine the importance of each variable. These results are shown in Table 2, and indicate that not only are the chosen variables relevant within the FCI[9], but also that these variables' importance varies over time. This is evident from the fact that the R^2 statistics vary dramatically between sub-samples and over the full sample. This is possibly due to the substantial size of the sample and provides further case for estimating a rolling-window FCI to capture time variation of the weights assigned to the financial variables within the index. A rolling-window FCI is also relevant when considering that not only the relative importance of the individual data series within the index is time-variant, but also the impact of the FCI on the real economy changes over time.

Goodhart and Hofmann (2001) noted the potential problem of not accounting for time-varying parameters or weights, especially over a sample as long as mine, due to, for example, changing exchange rate regimes, changing monetary policy stances, oil shocks, labour disputes, changing macroeconomic policy paradigms, political shifts, and asset price bubbles – i.e. due to structural breaks. Koop and Potter (2007) and Bauwens, Koop, Korobilis and Rombouts (2011) higlight the negative consequences for inference and forecasting of ignoring instability in macroeconomic and financial time series[10], which leads to the advocation of the use of change-point models.

---

[8] I also tested the efficacy and applicability of a recursive-PCA FCI, but it did not perform as well as the rolling-window approach.

[9] An R^2 value of 0.05 or above is regarded as acceptable.

[10] Pesaran, Pettenuzzo and Timmermann (2006) list output growth, inflation, exchange rates, interest rates and stock returns as typical series suffering from structural breaks – all of which I use in this research.

Table 2. Marginal R^2 from sub-sample regressions

X_t	*Full-sample*	*1966m02 – 1969m12*	*1970m01 – 1979m12*	*1980m01 – 1989m12*	*1990m01 – 1999m12*	*2000m01 – 2012m01*
CONFUSN	0.22	0.03	0.02	0.10	0.06	0.47
D_ALSI	0.10	0.004	0.11	0.08	0.19	0.16
D_LHOUSEP	0.18	0.31	0.15	0.07	0.11	0.40
D_LRD	0.003	0.02	0.01	0.00	0.06	0.004
D_LSP500	0.11	0.44	0.05	0.07	0.11	0.16
DIVN	0.27	0.01	0.58	0.06	0.21	0.22
FED	0.02	0.002	0.003	0.02	0.04	0.16
M3_GR	0.16	0.21	0.07	0.24	0.25	0.20
SPREADN_BOND	0.27	0.003	0.52	0.04	0.002	0.56
SPREADN_MORT	0.01	0.04	0.00	0.003	0.00	0.06
SPREADN_TBILL	0.15	0.03	0.25	0.14	0.06	0.06
SPREADN_TERM	0.004	0.04	0.007	0.03	0.01	0.17
ALSI_VOL	0.08	0.08	0.05	0.09	0.20	0.11
GBINDEX_VOL	0.007	0.02	0.001	0.02	0.05	0.04
HOUSEP_VOL	0.02	0.15	0.01	0.02	0.01	0.04
D_LPSCE	0.12	0.26	0.06	0.19	0.15	0.13

Gauthier, *et al.* (2004) criticise FCIs for ignoring dynamics and for parameter instability. Gumata, *et al.* (2012) also note that a PCA-constructed FCI will lack a dynamic pattern due to the assumption of the factor being stationary with zero mean – hence they constructed an alternative FCI using a dynamic Kalman filter approach. Koop and Korobilis (2013) estimate TVP-FAVARs to incorporate time-variation. I choose to address the issue of parameter non-constancy through the implementation of rolling-window PCA.

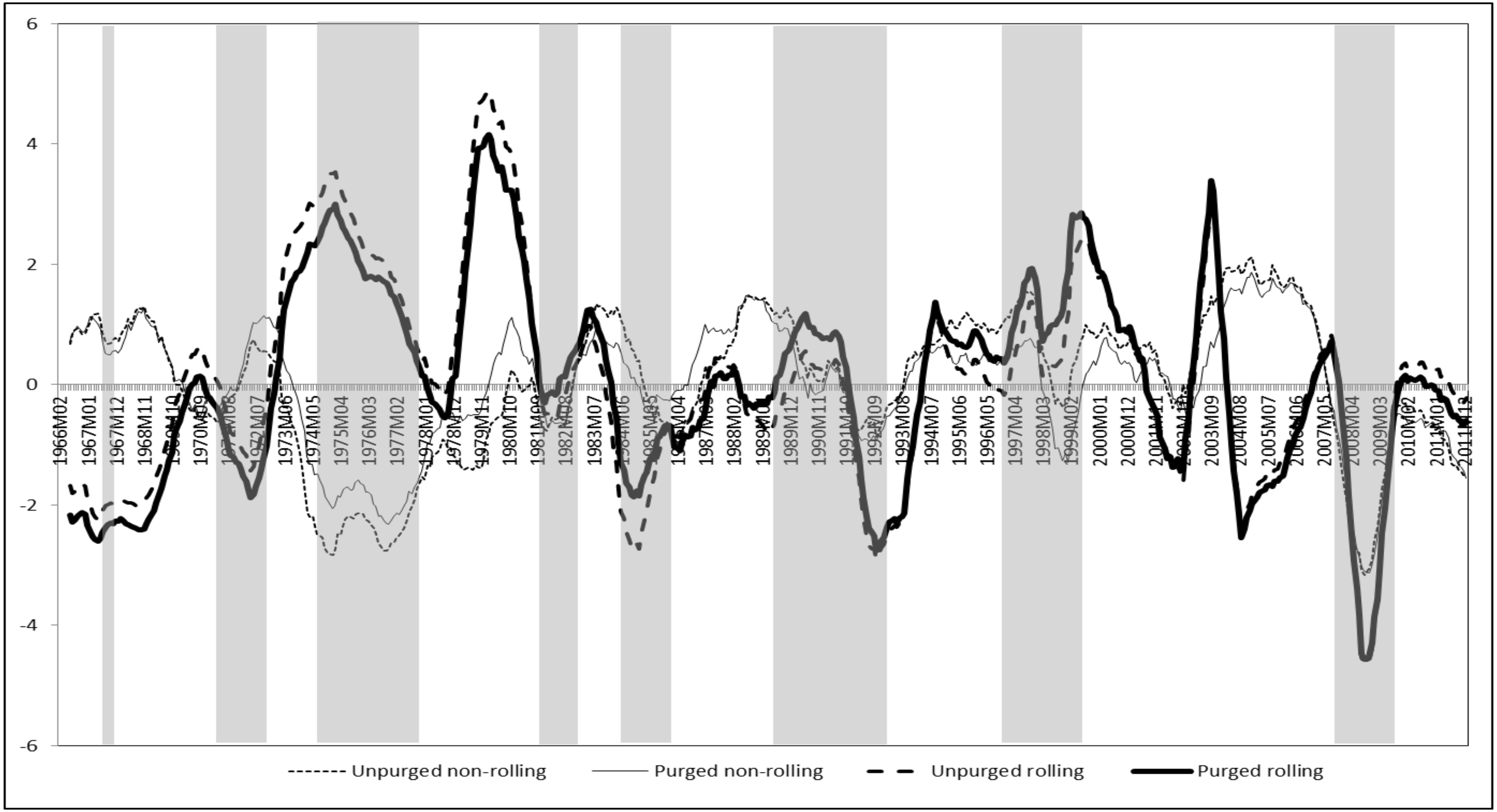
In deriving a rolling-window FCI, the first principal component is once again selected. This time, however, PCA is run on my set of 16 variables in fixed-length moving windows "sequentially from the beginning to the end of the sample by adding one observation from ahead and dropping one from behind" (Nyakabawo, Miller, Balcilar, Das and Gupta (2013)). Each rolling window is 120 months in length. As identified by Nyakabawo *et al.* (2013), the rolling-window approach trades off the conflicting objectives of parameter accuracy and model representativeness: the former is achieved with higher degrees of freedom (i.e. longer samples) and the latter is improved by smaller windows. I test window sizes of 12, 24, 36, 48, 60, 72, 84, 96 and 120 months and find that although the results are largely similar for many of the windows, qualitatively and quantitatively the 120 month window size performs best (see Appendix A.4 for a graph of FCIs estimated using all window sizes).

This rolling-window estimation of the FCI allows us to account for time-varying conditions, which is important given that the sample spans 552 observations. The usefulness of this rolling estimation becomes more apparent when one considers that economic agents make decisions based only on the information they have available at a particular point in time. The non-rolling FCI is estimated using full information at all times throughout the sample, whereas the rolling FCI is estimated at each point in time, *t*, using only the information available within the chosen window of the sample that ends in time *t*. This rolling FCI is also purged of the effects of economic activity, interest rates and inflation.

Figure 1 shows trends in the 12-month moving averages of the various estimated FCIs. I compare moving averages graphically since the volatility of the high-frequency monthly data makes graphical interpretation difficult. The grey vertical bars represent periods of recession in the South African economy. An upward movement in the estimated FCI represents an improvement (loosening) in financial conditions, and a downward trend indicates a worsening (tightening) of financial conditions. The estimated FCIs are discussed later in this chapter in a decade-by-decade comparison.

Table 3 provides the correlation coefficients between the four estimated FCIs over the full sample and decade-long sub-samples. It is evident that over the full sample as well as the shorter sub-samples, the most similar FCIs are the non-rolling-purged and non-rolling-un-purged; as well as the rolling-purged and rolling-un-purged. Therefore, I will treat two FCIs as representative of all four for which I conduct further testing in section 2.6: the non-rolling-purged (or "static" PCA-estimated) and rolling-purged indices.

Figure 1. Performance of various FCIs



Notes: The grey vertical bars represent periods of recession in the South African economy. An upward movement in the FCI represents an improvement (loosening) in financial conditions, and a downward movement in the FCI represents a worsening (tightening) of financial conditions.

Table 3. Correlation coefficients between estimated FCIs

Correlation coefficients	Non-rolling -un-purged	Rolling-un-purged	Rolling-purged	Non-rolling -purged
Full sample				
Non-rolling-un-purged	1	0.10	0.11	0.88
Rolling-un-purged		1	0.99	0.12
Rolling-purged			1	0.12
Non-rolling-purged				1
1966M02 – 1969M12				
Non-rolling-un-purged	1	-0.48	-0.43	0.91
Rolling-un-purged		1	0.99	-0.35
Rolling-purged			1	-0.28
Non-rolling-purged				1
1970M01 – 1979M12				
Non-rolling-un-purged	1	0.23	0.19	0.85
Rolling-un-purged		1	0.995	0.17
Rolling-purged			1	0.15
Non-rolling-purged				1
1980M01 – 1989M12				
Non-rolling-un-purged	1	-0.20	-0.20	0.77
Rolling-un-purged		1	0.99	0.01
Rolling-purged			1	-0.003
Non-rolling-purged				1
1990M01 – 1999M12				
Non-rolling-un-purged	1	0.23	0.20	0.85
Rolling-un-purged		1	0.99	0.07
Rolling-purged			1	0.05
Non-rolling-purged				1
2000M01 – 2012M01				
Non-rolling-un-purged	1	0.49	0.47	0.94
Rolling-un-purged		1	0.99	0.50
Rolling-purged			1	0.49
Non-rolling-purged				1

2.5.2 Evaluating the performance of FCI indices

In this section I conduct a period-by-period analysis to assess whether the proposed FCIs are in line with important events in South Africa, in particular whether they can pick up recessionary episodes in a satisfactory way. This evaluation helps to identify the FCI that performs best and to gauge whether FCIs are a good early warning indicator for financial turmoil.

The 1960s and 1970s

A brief recession in 1967 (bottoming at -7.1 per cent GDP growth in the fourth quarter of 1967) is picked up by both the rolling-purged and rolling-un-purged indices, but not by the non-rolling FCIs. This recession precedes a period of growth in South Africa, driven by stability and gold exports. A recession from January 1971 to August 1972 (quarterly GDP growth was lowest at -3.2 per cent in the second quarter of 1971) is captured by both rolling FCIs. Following on from this period, the rolling FCIs rise after an increase in the gold price.

All of the FCIs exhibit the recession of 1974 to 1977 (when GDP growth hit a low of -7.7 per cent in the second quarter of 1976), which was characterised by the after-effects of the first oil price shock, double-digit inflation, the collapse of the Angolan and Mozambican colonies in 1975 and the Soweto uprising in 1976. The rolling-purged and rolling-un-purged indices lagged the recession slightly.

The 1980s

Driven by record gold prices and exchange rate and current account improvements, the economy boomed in the late 1970s and early 1980s, reflected in all of the FCIs reaching a peak during that period. This boom was however immediately followed by a recessionary period between September 1981 and March 1983 (average quarterly GDP growth over the period was -3.1 per cent and a trough of -8.2 per cent was reached in the fourth quarter of 1982), caused in part by excessive inflation, large current account deficits and rapid exchange rate depreciation. All of the FCIs dip during this period, and then rise in the brief recovery that followed.

The recession of 1984 to 1986 (average quarterly GDP growth over the period was -1.8 per cent), a result largely of international sanctions and a debt-standstill agreement to limit burgeoning current account deficits, is captured by all of the FCIs. The rolling-un-purged index exhibits the deepest trough while the two non-rolling indices are the mildest during this period, and lag the recession slightly. This is followed by an upswing, which all of the indices reflect.

The 1990s

All of the FCIs go on to enter a recessionary period, led by political uncertainty, between March 1989 and May 1993 (average quarterly GDP growth amounted to -0.6 per cent over the period), preceding an upswing in the three years that follow. The non-rolling FCIs lag the mild recession of 1996 to 1999 (GDP growth was -0.9 per cent in the third quarter of 1998), which was driven by high crime levels, uncertainty, net capital outflows, weakened domestic demand, the Asian crisis and high debt levels. The rolling indices do not capture this recessionary period.

The 2000s[11]

Following a recovery in commodity prices and improving Asian and European outlooks in 1999, along with capital inflows and increased confidence, the non-rolling FCIs recovered and increased at similar levels in 2000. The FCIs for South Africa estimated by Gumata, *et al.* (2012) are rather flat during this period; whilst Kasai and Naraidoo's (2011) index shows an upswing. This is followed by a dip in the rolling FCIs, albeit not during a recession, due to the IT boom-bust of the early 2000s (and its associated stock market volatility) and the Rand crisis of late 2001 – a dip which is also captured by Kasai and Naraidoo (2011) and by Gumata, *et al.*'s (2012) FCIs. My non-rolling indices (as well as Gumata, *et al.*'s (2012) and Kasai and Naraidoo's (2011)) pick up again in the mid-2000s on the back of higher commodity prices, emerging market growth and increased expenditure growth. The rolling indices indicate volatility thereafter, driven in part by interest rate movements which influence the various spread measures used in the construction of the FCIs.

All of the FCIs capture the trough in 2007 to 2009, with the rolling indices reaching their lowest levels of the entire FCI sample (quarterly GDP growth bottomed at -6.3 per cent in the first quarter of 2009). Gumata, *et al.*'s (2012) and Kasai and Naraidoo's (2011) FCIs also pick up this crisis period in South Africa. This is in line with the timing of the global financial crisis as well as a domestic electricity supply crisis. The indices recover again in early 2010 due to the increased confidence and construction associated with the FIFA World Cup™ hosted in South Africa in that year. However, this is followed by a drop again in late 2010 and 2011, the result of the Euro crisis and continuing domestic uncertainty and credit down-grades.

In section 2.6 causality testing is used to determine which of the non-rolling or the rolling FCI (both purged) is the best predictor of economic activity.

2.6 IN-SAMPLE CAUSALITY TESTING

I conduct a series of in-sample causality tests to assess whether the estimated FCIs are indeed adequate indicators of economic activity, and whether they can in fact be regarded as an 'early warning system'.

[11] Gumata, *et al.*'s (2012) and Kasai and Naraidoo's (2011) samples begin at this time, so comparison between my FCIs with theirs can only take place from this part of the sample.

Similar to Rapach and Weber (2004), I set up an autoregressive distributed lag (ARDL) model:

$$\sum_{i=1}^{h} \Delta y_{t+i} = \alpha + \sum_{i=0}^{q_1-1} \beta_i \Delta y_{t-i} + \sum_{i=0}^{q_2-1} \gamma_i FCI_{t-i} + \varepsilon_{t+h} \qquad (3)$$

where y_t is the variable of choice (manufacturing growth, Treasury Bill yield and inflation), q_1 and q_2 are the ARDL lags, and h is the in-sample forecast horizon (set to 24 months in this instance). This model is used to conduct a Wald test[12] by using the full sample of observations to test the null hypothesis of $\gamma_0 = \cdots = \gamma_{q_2-1} = 0$. Rejection of the null hypothesis leads to the conclusion that the FCI has forecasting ability (therefore, has causality) with respect to y_t.

The results of these tests are found in Table 4, and indicate that there is stronger in-sample predictability (or causality) between the rolling FCI and industrial production growth than for the non-rolling FCI[13]. With respect to the Treasury Bill yield, both the non-rolling and the rolling FCIs exhibit strong causality. There is no evidence of causality between the non-rolling FCI and the inflation rate, whilst the rolling FCI presents causality at the one-month horizon only[14]. These causality results lead to three broad conclusions: 1) the estimated FCIs are good predictors of economic activity and the Treasury Bill yield; 2) the rolling FCI appears to be the 'best' performing index with respect to output growth, over and above the non-rolling FCI; and 3) both FCI measures exhibit weak predictability (causality) in terms of inflation, given that inflation is known to be highly autoregressive (persistent) in nature. Specific conclusions related to the chosen rolling FCI's results are: it best exhibits causality with respect to industrial production growth at the more desirable longer horizons between 12 and 24 months; and it Granger-causes the Treasury Bill yield at all horizons bar the first month.

The previous two sections have therefore indicated that the FCI estimated using rolling-window PCAis superior to the FCI which is estimated using non-rolling (static) PCA. Furthermore, I find that the FCI has good causality with respect to economic activity in South Africa, and has good in-sample predictive ability.

[12] Inference of this Wald statistic is based on a bootstrapping procedure described in Rapach and Weber (2004), originally found in Kilian (1999).

[13]These results are similar in a sense to Gumata, *et al.* (2012), who found that their two FCIs for South Africa do Granger Cause GDP growth.

[14] English, *et al.* (2005) also found through forecasting exercises that financial factors are less effective in predicting inflation than is the case with output.

Table 4. Wald causality test results

Horizon (h) months ahead:	1m	3m	6m	9m	12m	15m	18m	21m	24m
Rolling-window (purged) FCI as independent variable									
y_t: Industrial production growth									
q_1	2	12	12	5	12	12	11	8	11
q_2	2	1	5	2	12	6	8	8	5
Wald (*p*-value)	5.76 (0.19)	2.51 (0.41)	9.13 (0.16)	4.37 (0.40)	25.54 (0.03)**	22.27 (0.03)**	28.66 (0.02)**	39.95 (0.002)***	22.95 (0.04)**
y_t: Treasury bill									
q_1	12	12	12	12	12	12	12	12	12
q_2	2	2	7	6	3	3	3	3	3
Wald (*p*-value)	8.10 (0.17)	17.29 (0.03)**	21.10 (0.008)***	21.85 (0.02)**	22.13 (0.02)**	22.67 (0.01)**	23.18 (0.02)**	23.30 (0.02)**	22.86 (0.02)**
y_t: Inflation									
q_1	1	6	6	12	12	12	12	12	12
q_2	12	2	1	1	1	1	1	1	2
Wald (*p*-value)	27.86 (0.04)**	10.31 (0.20)	6.80 (0.34)	4.65 (0.53)	5.40 (0.43)	4.68 (0.45)	4.96 (0.44)	4.55 (0.48)	7.17 (0.33)
"Static" (purged) FCI as independent variable									
y_t: Industrial production growth									
q_1	2	12	12	8	12	11	11	11	11
q_2	2	1	4	2	2	1	3	3	6
Wald (*p*-value)	21.98 (0.02)**	7.78 (0.16)	8.55 (0.19)	4.66 (0.43)	4.05 (0.49)	1.98 (0.59)	5.02 (0.47)	8.90 (0.33)	10.44 (0.25)
y_t: Treasury bill									
q_1	12	12	12	12	12	12	12	12	12
q_2	2	2	10	8	7	6	10	10	7
Wald (*p*-value)	8.39 (0.13)	15.97 (0.03)**	19.64 (0.02)**	15.95 (0.05)*	14.48 (0.07)*	12.84 (0.12)	15.14 (0.08)*	15.46 (0.06)*	13.47 (0.16)
y_t: Inflation									
q_1	6	6	12	12	12	12	12	12	12
q_2	4	3	8	8	8	3	8	8	8
Wald (*p*-value)	2.24 (0.69)	0.42 (0.90)	7.08 (0.47)	11.07 (0.33)	10.55 (0.34)	8.77 (0.42)	12.39 (0.25)	13.03 (0.22)	12.69 (0.25)

Notes: Wald is the in-sample F-statistic used to test the null hypothesis of no Granger-causality (bootstrapped *p*-values in parenthesis). ***/**/* indicates rejection of the null hypothesis (i.e. there is evidence of Granger causality) at the 1/5/10% level of significance.

2.7 CONCLUSIONS

The aim of this chapter was to identify an appropriate FCI for South Africa – one which adequately captures trends in economic activity, and one which can be used as an early-warning system for predicting downswings in the economy. I tested a variety of approaches, but settled on applying rolling-window PCA to a set of sixteen monthly financial variables, and then purging this index of endogeneity from output, inflation and interest rates. Causality tests indicated that this FCI is a good in-sample predictor of industrial production growth and the Treasury Bill yield, but a weak predictor of inflation.

CHAPTER 3: TESTING THE OUT-OF-SAMPLE FORECASTING ABILITY OF A FINANCIAL CONDITIONS INDEX FOR SOUTH AFRICA[15]

3.1 INTRODUCTION

The previous chapter constructed a financial conditions index (FCI) for South Africa to capture in a single indicator the full spectrum of financial variables that affect the South African economy. The aim of this chapter is to investigate whether that FCI can act as an 'early warning indicator' for impending macroeconomic instability caused by deteriorating financial conditions by means of out-of-sample forecasting tests. The premise here is based on the fact that asset prices (a major component of the FCI) are regarded as useful predictors of inflation and output growth (Stock and Watson, 2003)[16]. However, forecasts based on individual asset prices tend to be unstable, and combination approaches are preferable (Stock and Watson, 2003). To this end I test whether the estimated FCI does better than its individual financial components in forecasting key macroeconomic variables, namely output growth, inflation and an interest rate.

This forecasting exercise is conducted with caution, and the techniques are chosen specifically to hopefully address issues associated with the use of asset prices in forecasting real economic activity noted by Stock and Watson (2003:801) (remembering that the FCI largely comprises asset prices): namely, the "underlying relations themselves depend on economic policies, macroeconomic shocks, and specific institutions and thus evolve in ways that are sufficiently complex that real-time forecasting confronts considerable model uncertainty".

The concept 'forecast encompassing' is used to examine the forecasting ability of these variables following Rapach and Weber (2004). They consider the forecasting power of ten financial variables with respect to real GDP growth and industrial production growth in the US over the period 1985M01 to 1999M04, to test and complement a similar study by Stock and Watson (2003)[17]. The forecast encompassing approach used in this chapter is based on two sets of out-of-sample forecasts for output growth, inflation, and the Treasury Bill yield. The two forecasts are obtained from an autoregressive distributed lag (ARDL) model including one financial variable at a time, and a benchmark autoregressive (AR) model. An optimal composite forecast is formed as the convex combination of these

[15] This chapter is a modified version of University of Pretoria Department of Economics Working Paper Series, 2013(83), and is also forthcoming in *Emerging Markets, Finance and Trade*.
[16] See Stock and Watson's (2003) paper for an overview of the use of asset prices in forecasting output and inflation.
[17] See Rapach and Weber (2004) for a comprehensive review of the original, and more recent, literature pertaining to out-of-sample forecasting ability.

two forecasts and is interpreted as follows: if the optimal weight attached to the ARDL model's forecast is zero, then the ARDL model does not contain information that is useful for forecasting the chosen macroeconomic variable *apart from the information already contained* in the AR benchmark model. In other words, the AR model's forecasts encompass those of the ARDL model. Instead, if the optimal weight attached to the ARDL model's forecast is larger than zero, then the ARDL model *does* contain information that is useful for forecasting the chosen macroeconomic variables in addition to the information already contained in the AR benchmark model. The generic null hypothesis for these tests can then be stated as: the AR benchmark out-of-sample forecast encompasses the ARDL out-of-sample forecast (where the ARDL model includes the selected financial variable or the FCI); i.e. that the AR model is the "better" forecasting model, which implies that the selected financial variable or FCI is not relevant in forecasting the chosen macroeconomic variable.

So for each financial variable and the FCI, recursive out-of-sample forecasts of manufacturing output growth, inflation and the Treasury Bill yield are constructed over the out-of-sample period of 1986M01–2012M01, using an ARDL model that includes the chosen financial variable or FCI as an explanatory variable. As suggested by Rapach and Weber (2004), I test the above null hypothesis of an encompassing AR model forecast using various statistics proposed by Harvey, Leybourne and Newbold (1998) and Clark and McCracken (2001).

The remainder of the chapter is organised as follows: Section 3.2 presents a brief discussion of the data used in the forecast encompassing exercises; while Section 3.3 presents Rapach and Weber's (2004) econometric methodology used in the forecast encompassing tests, including derivations of the five test statistics used for inference. The empirical out-of-sample forecast results are presented in Section 3.4, along with adjustments made to the test statistics so as to account for data-mining, as well as discussions of the individual predictors' economic significance (for those predictors surviving data-mining), and Section 3.5 provides the forecasting performance of the estimated FCI. Section 3.6 concludes the chapter.

3.2 DATA

In compiling the FCI in the previous chapter, I choose series that encompass measures in levels, as well as volatility measures. The data series included in the compilation of the FCI are found in Table 1 in Chapter 2, and are discussed in Section 2.5. The data set covers the sample of 1966M02 – 2012M01. The data series used in the forecasting exercises in this chapter include: the estimated FCI; each of its sixteen individual component series; a measure of output growth – the month-on-month rate of change in South Africa's Manufacturing Production Index; a measure of inflation – the month-on-month rate of change in the CPI; and the 3-month Treasury Bill yield. The latter three series are the macroeconomic variables with respect to which I test the FCI's forecasting ability. Figure 2 shows the three macroeconomic series compared graphically to the estimated FCI.

3.3 ECONOMETRIC METHODOLOGY

The forecast encompassing test used in this research follows Rapach and Weber (2004), and more details on the econometric methodology can be found in that paper. I consider the unrestricted ARDL model:

$$\sum_{i=1}^{h} \Delta y_{t+i} = \alpha + \sum_{i=0}^{q_1-1} \beta_i \Delta y_{t-i} + \sum_{i=0}^{q_2-1} \gamma_i x_{t-i} + \varepsilon_{t+h} \tag{4}$$

where y_t is the variable of interest to be forecasted (manufacturing growth, Treasury Bill yield and inflation), q_1 and q_2 are the ARDL lags, x_t is the FCI or one of the sixteen financial variables used in the construction of the FCI, and h is the forecast horizon (set to a maximum of 24 months in this instance)[18]. The following recursive procedure is used to simulate the out-of-sample forecasting ability of the individual financial data series and the FCI: First, divide the total sample of T observations into the in-sample period, spanning R observations, and the out-of-sample period, spanning P observations (in this instance, the out-of-sample period is 1986M01–2012M01).

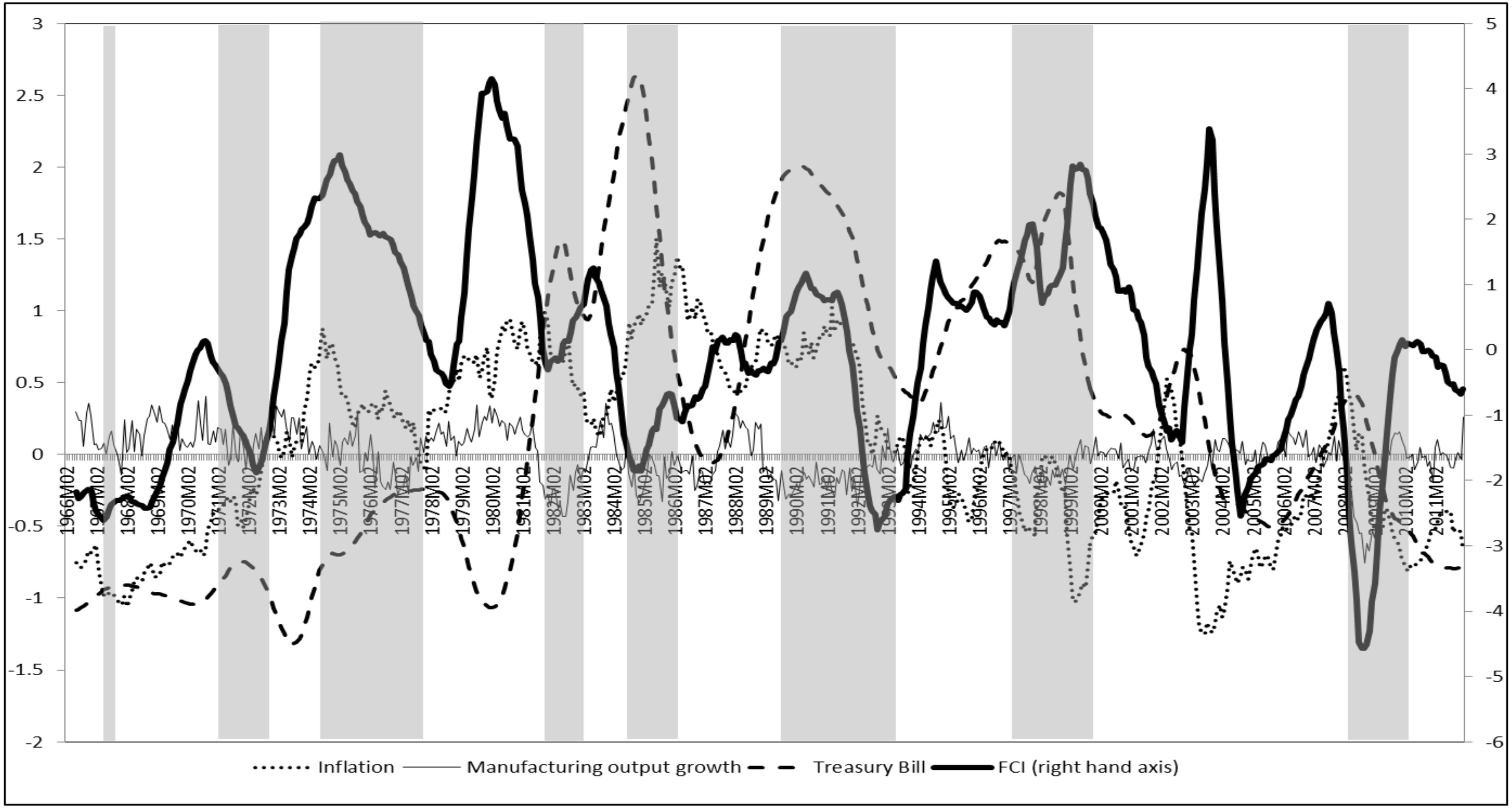
Next, compute an out-of-sample forecast from the *unrestricted* model, Equation (4), by estimating (4) using ordinary least squares (OLS) over the period R. Use the OLS parameter estimates and observations for x_{R-i} $(i = 0, \dots q_1 - 1)$ and Δy_{R-i} $(i = 0, \dots q_2 - 1)$ to construct a forecast for z_{R+h} based on:

$$\hat{z}_{1,R+h} = \hat{\alpha}_{1,R} + \sum_{i=0}^{q_1-1} \hat{\beta}_{1,R,i} \Delta y_{R-i} + \sum_{i=0}^{q_2-1} \hat{\gamma}_{1,R,i} x_{R-i} \tag{5}$$

where $\hat{\alpha}_{1,R}$, $\hat{\beta}_{1,R,i}$ $(i = 0, \dots q_1 - 1)$ and $\hat{\gamma}_{1,R,i}$ $(i = 0, \dots q_2 - 1)$ are the OLS estimates of Equation (4)'s α, β_i $(i = 0, \dots q_1 - 1)$ and γ_i $(i = 0, \dots q_2 - 1)$ respectively, using data from period R.

[18] This model can be used to conduct a test of the in-sample forecasting ability of x_t by running a Wald test with H_0: $\gamma_0 = \cdots = \gamma_{q2-1} = 0$. Rejection of the null hypothesis indicates that there is evidence of in-sample forecasting ability/Granger causality. See Chapter 2, Table 4, for these in-sample results with respect to the FCI. Results pertaining to the individual financial series are available in Appendix A.5.

Figure 2. Estimated rolling-window purged FCI compared with key macroeconomic variables (12-month moving averages)



Notes: The grey vertical bars represent periods of recession in the South African economy. The series are represented as 12-month moving averages since the volatility of the high-frequency monthly data makes graphical interpretation difficult. Positive values of the FCI indicate "positive" financial conditions, and vice versa for "negative" financial conditions.

The unrestricted forecast error is:

$$\hat{u}_{1,R+h} = z_{R+h} - \hat{z}_{1,R+h} \tag{6}$$

An out-of-sample forecast from a *restricted* model is then computed, which is equivalent to estimating Equation (4) by OLS with $\gamma_0 = \cdots = \gamma_{q_2-1} = 0$ over the period *R*. From this, formulate a forecast:

$$\hat{z}_{0,R+h} = \hat{\alpha}_{0,R} + \sum_{i=0}^{q_1-1} \hat{\beta}_{0,R,i} \Delta y_{R-i} \tag{7}$$

where $\hat{\alpha}_{0,R}$ and $\hat{\beta}_{0,R,i}$ $(i = 0, \dots q_1 - 1)$ are the OLS estimates of Equation (4)'s α and β_i $(i = 0, \dots q_1 - 1)$ respectively. The restricted forecast error is:

$$\hat{u}_{0,R+h} = z_{R+h} - \hat{z}_{0,R+h} \tag{8}$$

A second set of forecasts are generated by updating the procedure with one period, i.e. use data from period *R*+1. In other words, form restricted and unrestricted forecasts for $z_{(R+1)+h}$, along with the restricted and unrestricted forecast errors, $\hat{u}_{1,(R+1)+h}$ and $\hat{u}_{0,(R+1)+h}$.

The process is repeated until the end of the sample, arising at two sets of *T–R–h+1* recursive out-of-sample forecast errors for the unrestricted and restricted models, namely $\{\hat{u}_{1,t+h}\}_{t=R}^{T-h}$ and $\{\hat{u}_{0,t+h}\}_{t=R}^{T-h}$. These forecast errors form the basis of the test statistics used in determining the most appropriate forecasting model (unrestricted vs. restricted; i.e. including financial variables or FCI vs. excluding these variables), which follow below.

I use five tests to compare the forecasts from the restricted and unrestricted models to determine whether the FCI and/or individual financial variables are relevant in forecasting the three macroeconomic variables. These tests (also see Rapach and Weber (2004)) are discussed below.

3.3.1 Theil's U Test

If the root mean squared forecast error (RMSFE) of the unrestricted ARDL model ($RMSFE_{UR}$) is less than the RMSFE of the restricted model ($RMSFE_R$), then this model is the "better" forecasting model with lower forecasting error. Therefore, if $U = \frac{RMSFE_{UR}}{RMSFE_R}$, a result of $U < 1$ will indicate that the unrestricted ARDL model (i.e. the model including the financial variable or FCI as a predictor) forecasts are superior to those of the simple AR model[19].

3.3.2 MSE-T and MSE-F Tests

In a more "formal" statistical manner, the MSFE of the two models is compared using the Diebold and Mariano (1995) and West (1996) statistic. The loss differential between the two models is calculated as:

$$\hat{d}_{t+h} = \hat{u}^2_{0,t+h} - \hat{u}^2_{1,t+h} \tag{9}$$

while:

$$\bar{d} = (T - R - h + 1)^{-1} \sum_{t=R}^{T-h} \hat{d}_{t+h} = \widehat{MSFE}_0 - \widehat{MSFE}_1 \tag{10}$$

and:

$$\hat{S}_{dd} = \sum_{j=-J}^{J} K(\tfrac{j}{J}) \hat{\Gamma}_{dd}(j) \tag{11}$$

where:

$$\hat{\Gamma}_{dd}(j) = (T - R - h + 1)^{-1} \sum_{t=R+j}^{T-h} (\hat{d}_{t+h} - \bar{d})(\hat{d}_{t+h-j} - \bar{d}) \tag{12}$$

and, in line with Clark and McCracken (2004), the Bartlett kernel is used, $K\left(\frac{j}{J}\right) = 1 - \left[\frac{j}{J+1}\right]$, with $J = [1.5h]$ for $h > 1$ and $\hat{S}_{dd} = \hat{\Gamma}_{dd}(0)$ for $h = 1$. The test statistic is represented as:

$$\text{MSE-T} = \boldsymbol{(T - R - h + 1)^{-0.5} \cdot \bar{d} \cdot \hat{S}_{dd}^{-0.5}} \tag{13}$$

McCracken's (2007) variation of this statistic is:

$$\text{MSE-F} = \boldsymbol{(T - R - h + 1) \cdot \bar{d} / \widehat{MSFE}_1} \tag{14}$$

where:

$$\widehat{MSFE}_1 = (T - R - h + 1)^{-1} \sum_{t=R}^{T-h} \hat{u}^2_{1,t+h} \tag{15}$$

Inference of *MSE-T* and *MSE-F* is, as recommended by Clark and McCracken (2004), based on a bootstrapping procedure[20] along the lines of Kilian (1999); and tests the null hypothesis of equal forecasting ability between the restricted and unrestricted models.

---

[19] Strictly speaking, Theil's *U* uses a random walk model as a benchmark. In my applications, I follow Rapach and Weber (2004) in using the AR model as benchmark, but still refer to the ratio of the RMSFEs from the restricted and unrestricted models as Theil's U.

3.3.3 ENC-T and ENC-NEW Tests

Another way to compare forecasts between alternative models is based on the concept of forecast encompassing. Using the out-of-sample forecasts for the unrestricted (Equation (5)) and restricted (Equation (7)) models, a convex combination of the two, z_{t+h}, can be treated as an optimal composite out-of-sample forecast:

$$\hat{z}_{c,t+h} = \lambda \hat{z}_{1,t+h} + (1-\lambda)\hat{z}_{0,t+h} \tag{16}$$

where $0 \leq \lambda \leq 1$. If $\lambda = 0$, then the restricted model's forecast encompasses the unrestricted model's forecast; i.e. the FCI or financial variables are not relevant in forecasting y_t. The null hypothesis of H_0 : $\lambda = 0$ (the restricted AR out-of-sample forecast encompasses the unrestricted ARDL out-of-sample forecast) is tested using the following statistic (Harvey, *et al.* (1998)):

$$\text{ENC-T} = \boldsymbol{(T - R - h + 1)^{0.5} \cdot \bar{c} \cdot \hat{S}_{cc}^{-0.5}} \tag{17}$$

where:

$$\hat{c}_{t+h} = \hat{u}_{0,t+h}(\hat{u}_{0,t+h} - \hat{u}_{1,t+h}) \tag{18}$$

while:

$$\bar{c} = (T - R - h + 1)^{-1} \sum_{t=R}^{T-h} \hat{c}_{t+h} = \widehat{MSFE}_0 - \widehat{MSFE}_1 \tag{19}$$

and:

$$\hat{S}_{cc} = \sum_{j=-J}^{J} K(\tfrac{j}{J})\hat{\Gamma}_{cc}(j) \tag{20}$$

where:

$$\hat{\Gamma}_{cc}(j) = (T - R - h + 1)^{-1} \sum_{t=R+j}^{T-h} (\hat{c}_{t+h} - \bar{c})(\hat{c}_{t+h-j} - \bar{c}) \tag{21}$$

and, once again, the Bartlett kernel is used: $K\left(\frac{j}{J}\right) = 1 - \left[\frac{j}{J+1}\right]$, with $J = [1.5h]$ for $h > 1$ and $\hat{S}_{cc} = \hat{\Gamma}_{cc}(0)$ for $h = 1$. Clark and McCracken's (2001) variation of this statistic is:

$$\text{ENC-NEW} = \boldsymbol{(T - R - h + 1) \cdot \bar{c}/\widehat{MSFE}_1} \tag{22}$$

These *ENC* test statistics are essentially based on the difference between the variance of the restricted model's forecast errors, and the covariance of the restricted and

[20] The *MSE-T* and *MSE-F* statistics are assumed to be asymptotically normally distributed (West, 1996). However McCracken (2007) shows that they have a non-standard asymptotic distribution at $h = 1$ when comparing nested models' forecasts – as is the case in this application – and that the distribution is in fact a function of stochastic integrals of quadratics of Brownian motion for *MSE-T*, and a function of stochastic integrals of Brownian motion for *MSE-F*. Clark and McCracken (2004) similarly show that the limiting distribution is also non-standard for $h > 1$ when comparing nested models' forecasts. Therefore bootstrapped inference as proposed in Kilian (1999) is recommended.

unrestricted models' forecast errors. As with the *MSE* statistics, inference here is also based on bootstrapped parameters[21].

Clark and McCracken (2001, 2004) in Rapach and Weber (2004) show that these four test statistics above have good size properties (when based on bootstrapped inference); and that the power of the tests can be ranked as follows (most to least powerful)[22]: *ENC-NEW*, *ENC-T*, *MSE-F* and *MSE-T*.

3.3.4 Bootstrapping Procedure

The bootstrapping procedure used to enable inference of these test statistics (from Rapach and Weber, 2004) is Clark and McCracken's (2007) version of Kilian (1999). Suppose, under H_0: the financial variable x_t has no forecasting power with respect to y_t, that:

$$\Delta y_t = a_0 + \sum_{i=1}^{p_1} a_i \Delta y_{t-i} + e_{1,t} \tag{23}$$

and:

$$x_t = b_0 + \sum_{i=1}^{p_2} b_i \Delta y_{t-i} + \sum_{i=1}^{p_3} c_i x_{t-i} + e_{2,t} \tag{24}$$

where the disturbance vector, $e_t = (e_{1,t}, e_{2,t})'$, is independently and identically distributed with covariance matrix Σ.

For a detailed exposition of the recursive procedure used in conducting the bootstrapping used in this chapter, refer to Rapach and Weber (2004:721-722). Each of the four test statistics described in Equations (13), (14), (17) and (22) are calculated 500 times, resulting in empirical distributions for these statistics. The *p*-value for each is the proportion of the bootstrapped statistic greater than the original statistic.

The estimated out-of-sample test statistics for the FCI are reported in Table A3 in Appendix A.5, and are summarised along with the results for all sixteen financial variables in Table 5, Table 6 and Table 7 below. The results are based on the Akaike Information Criterion (AIC) and are for forecast horizons of 1, 3, 6, 9, 12, 15, 18, 21 and 24 months. Values for q_1 and q_2 are considered from 0 up to 24. The results are representative of the out-of-sample period of 1986M01–2012M01. Similar results for the out-of-sample periods 1973M01–2012M01 and 2000M01–2012M01 are available upon request.

[21] Clark and McCracken (2001) show that for nested models and for $h = 1$, *ENC-T* has a non-standard limiting distribution; while *ENC-NEW* has a non-standard asymptotic distribution. For $h > 1$ in nested models, Clark and McCracken (2004) show that *ENC-T* and *ENC-NEW* have non-standard asymptotic distributions. Thus, bootstrapped inference is once again recommended.

[22] The authors use extensive Monte Carlo simulations with nested models to ascertain these properties.

3.4 EMPIRICAL RESULTS[23]

3.4.1 Out-of-Sample Forecasting Performance

Table 5 reports, for each variable, the horizon at which that variable has significant forecasting ability for output growth according to the tests outlined above. Table 6 and Table 7 show the same for the forecasting ability of inflation and the Treasury Bill yield respectively. Table 5 shows that the estimated FCI is a significant out-of-sample predictor of manufacturing output growth at all horizons (when considering the *ENC-NEW* and *ENC-T* statistics, the two most powerful statistics). Share prices, house prices, M3 growth, the term spread, government bond volatility and private sector credit extension also have good out-of-sample forecasting ability at multiple horizons; while dividend yields appear to have weaker ability (i.e. at only the one month horizon).

Table 5. Out-of-sample forecasting performance, dependent variable: Manufacturing production growth

Independent variable x_t is…	*…significant according to:* MSE-T for h horizons*	*MSE-F for h horizons*	*ENC-T for h horizons*	*ENC-NEW for h horizons*
FCI	h=6	h=6, 9	h=1, 3, 6, 9, 12, 15, 18, 21	h=1, 3, 6, 9, 12, 15, 18, 21, 24
D_LALSI	h=1	h=1, 3	h=1	h=1, 3, 6, 9, 15, 18, 21, 24
D_LHOUSEP	h=3	h=1, 3	h=1, 3, 6	h=1, 3, 6, 9
DIVN	-	-	-	h=1
M3_GR	-	-	h=9	h=1, 3, 6, 9, 15
SPREADN_TERM	h=1, 24	h=1, 24	h=1, 3, 6, 21, 24	h=1, 3, 6, 9, 18, 21, 24
GBINDEX_VOL	h=1, 3, 6, 9, 12	h=1, 3, 6, 9, 12	h=1, 3, 6, 9, 12	h=3
D_LPSCE	-	-	-	h=6, 9, 12, 15, 18, 21

In the case of inflation (Table 6), the FCI exhibits forecasting ability at multiple horizons, but this time according to the less powerful *MSE-F* and *MSE-T* tests. Strong out-of-sample forecasting ability is attributed to share prices, the Rand-Dollar exchange rate, the Federal Funds rate, M3 growth, mortgage and bill spreads and private sector credit extension. House prices have weaker forecasting ability.

The FCI is again a strong out-of-sample predictor at multiple horizons in Table 7, this time of the Treasury Bill yield. House prices, the Rand-Dollar exchange rate, M3 growth,

[23] My results are obtained using Gauss code written by David E. Rapach, which are available for download from http://sites.slu.edu/rapachde/home/research.

bond and term spreads, house price volatility and private sector credit extension are also strong predictors of the Treasury Bill at multiple horizons; while dividend yields and government bond volatility exhibit predictability at either shorter horizons or according to the *MSE-F* and *MSE-T* tests only.

Table 6. Out-of-sample forecasting performance, dependent variable: Inflation

Independent variable x_t is…	*…significant according to:*			
	MSE-T for h horizons	*MSE-F for h horizons*	*ENC-T for h horizons*	*ENC-NEW for h horizons*
FCI	h=9, 12, 15, 18	h=12, 15, 18	-	-
D_LALSI	h=6, 9, 12, 15, 18, 21, 24	h=6, 9, 12, 15, 18, 21, 24	h=9, 12, 15, 18	h=12, 15, 18, 21, 24
D_LHOUSEP	-	h=1	h=1	h=1
D_LRD	h=3, 6, 9, 12, 15	h=3, 6, 9, 12, 15, 18, 21	h=1, 3, 6, 9, 12, 15	h=1, 3, 6, 9, 12, 15, 18, 21, 24
FED	h=3, 6, 9, 12, 15, 18, 21, 24	h=3, 6, 9, 12, 15, 18, 21, 24	h=3, 6, 9, 12, 15, 18, 21, 24	h=1, 3, 6, 9, 12, 15, 18, 21, 24
M3_GR	h=6, 9, 12, 15, 18, 21	h=6, 9, 12, 15, 18, 21, 24	h=6, 9, 12, 15, 18, 21, 24	h=6, 9, 12, 15, 18, 21, 24
SPREADN_MORT	h=1, 3, 6, 9, 12, 15, 18, 21, 24	h=1, 3, 6, 9, 12, 15, 18, 21	h=1, 3, 6, 9, 12, 15, 18, 21, 24	h=1, 3
SPREADN_TBILL	h=1, 3, 6, 9, 12, 15, 18, 21, 24	h=1, 3, 6, 9, 12, 15, 18, 21, 24	h=1, 3, 9, 12, 15, 18, 21, 24	h=1, 3
D_LPSCE	h=12, 15, 18, 21, 24	h=9, 12, 15, 18, 21, 24	h=12, 15, 18, 21, 24	h=1, 3, 6, 12, 15, 18

Table 7. Out-of-sample forecasting performance, dependent variable: Treasury Bill

Independent variable x_t is…	*…significant according to:*			
	MSE-T for h horizons	*MSE-F for h horizons*	*ENC-T for h horizons*	*ENC-NEW for h horizons*
FCI	-	-	h=18, 21	h=9, 15, 18, 21, 24
D_LHOUSEP	-	-	-	h=1, 3, 6, 9, 12, 15, 18, 21, 24
D_LRD	-	-	h=1	h=1, 3, 6, 9, 12, 15, 18, 21, 24
D_LSP500	h=18	-	-	-
DIVN	h=3, 6, 9, 12, 18	h=3, 6, 18	h=3, 6	-
M3_GR	h=6, 9, 12, 15, 18, 21, 24	h=6, 9, 12, 15, 18, 21, 24	h=6, 9, 12, 15, 18, 21, 24	h=9, 12, 15, 18, 21, 24
SPREADN_BOND	h=3, 6	h=3, 6	h=3, 6, 21, 24	h=3, 6, 9, 12, 15, 18, 21, 24
SPREADN_TERM	-	-	h=24	h=15, 18, 21, 24
GBINDEX_VOL	-	-	-	h=1
HOUSEP_VOL	h=6, 9, 12	h=1, 9, 12	h=1, 6, 9, 12	h=1
D_LPSCE	-	-	h=3, 6, 9, 12, 15, 18, 21, 24	h=3, 6, 9, 12, 15, 18, 21, 24

Notes for Table 5, Table 6 and Table 7: *MSE-T* and *MSE-F* test the null hypothesis of equal forecasting ability between the restricted and unrestricted models. *ENC-T* and *ENC-NEW* test the null hypothesis that the restricted model forecast encompasses the unrestricted model forecast.

3.4.2 Data-Mining

The results in Table 5, Table 6 and Table 7 above indicate that there is significant evidence of out-of-sample forecasting ability for the FCI and for many financial variables with respect to output growth, inflation and the Treasury Bill yield. However, where much of the research on out-of-sample forecast encompassing ends at this point, I follow Rapach and Weber (2004) and decide to consider the possibility that, due to the large number of variables considered (17 including the FCI), I may have engaged in data-mining. Therefore, in line with Rapach and Weber (2004), I test the robustness of my results by controlling for data mining using the Inoue and Kilian (2004) bootstrapping procedure[24].

Until this point, the null hypothesis has been that none of the 16 financial variables has out-of-sample forecasting ability, against an alternative of at least one variable having forecasting power. Suppose now that the null hypothesis is *H0*: the largest *ENC-NEW* statistic across the 16 financial variables equals zero, against an alternative hypothesis that it is larger than zero.

$$\Delta y_t = a_0 + \sum_{i=1}^{p_1} a_i \Delta y_{t-i} + e_{1,t} \qquad (25)$$

and:

$$x_{t,j} = b_{0,j} + \sum_{i=1}^{p_{2,j}} b_{i,j} \Delta y_{t-i} + \sum_{i=1}^{p_{3,j}} c_{i,j} x_{t-i,j} + e_{2,t,j}, j = 1, \dots 16^{25} \qquad (26)$$

where the disturbance vector, $e_t = (e_{1,t}, e_{2,t,1}, \dots, e_{2,t,16})'$, is independently and identically distributed with covariance matrix Σ.

For a discussion on the recursive procedure used to conduct the bootstrapping exercise, see Rapach and Weber (2004:733-734). Each of the four out-of-sample test statistics previously described in Equations (13), (14), (17) and (22) are then calculated for each of the $x_{t,j}$ variables ($j = 1, \dots 16$), and the maximum of each of the out-of-sample statistics across the 16 predictors is stored. This process is repeated 500 times, resulting in empirical distributions for these statistics, which are used to compute 10%, 5% and 1% critical values for each of the maximal statistics.

The data-mining-robust critical values are reported in Table A7, Table A8 and Table A9 in Appendix A.5, and Table 8 below shows which variables are now significant out-of-sample forecasters of manufacturing production growth, inflation and the Treasury Bill

[24] Hoover and Perez (2000) present the case that if data-mining 'must' be engaged in, then statistical inference should be adjusted so that critical values are made to be stricter.

[25] Note that in running the data-mining programs, I exclude the FCI as an explanatory variable, since it contains the information of the 16 financial variables.

yield, after data-mining is accounted for. As can be seen from the table, the number of predictors for each macroeconomic variable has decreased significantly due to the data-mining adjustments. Furthermore, the FCI is now regarded as an out-of-sample predictor for manufacturing output growth only.

Table 8. Out-of-sample forecasting performance after data-mining adjustments

Independent variable x_t is…	*…significant according to:*				*…in forecasting macroeconomic variable, y_t*
	MSE-T for h horizons…	*MSE-F for h horizons…*	*ENC-T for h horizons…*	*ENC-NEW for h horizons…*	
FCI				**h=1, 3, 6**	Manufacturing production growth
SPREADN_TERM		h=1	h=1		
GBINDEX_VOL	h=3				
D_LHOUSEP				h=1	Inflation
D_LRD				h=3, 6	
FED		h=6, 9, 12, 15, 18, 21, 24			
M3_GR	h=12, 15		h=9, 12, 15		
SPREADN_MORT	h=1, 3, 6, 9, 12, 18, 21	h=1	h=1, 15, 18, 21		
M3_GR		h=9	h=9, 12, 15, 18, 21	h=9, 12, 15, 18	Treasury Bill
D_LPSCE				h=6, 9, 15	

Notes: *MSE-T* and *MSE-F* test the null hypothesis of equal forecasting ability between the restricted and unrestricted models. *ENC-T* and *ENC-NEW* test the null hypothesis that the restricted model forecast encompasses the unrestricted model forecast.

3.4.3 Predictor Significance

The results above indicate that for the FCI and a number of the financial variables, a forecast of manufacturing production growth, inflation and the Treasury Bill yield generated by an ARDL model incorporating said financial variables, is superior to a simple AR forecasting model. However, these results do not provide insight as to *how much* the financial variables actually improve the forecasts – highlighting the need to ascertain the "forecasting significance" of the financial variables[26]. Therefore, Table 9 below provides the values of λ, the estimated weight of the unrestricted model in Equation (16)'s optimal composite out-of-sample forecast, for those variables in Table 8 above that "survived" the data-mining adjustments according to the *ENC-T* and *ENC-NEW* statistics[27]. Recall that $0 \leq \lambda \leq 1$, and if $\lambda = 0$, then the restricted model's forecast encompasses the unrestricted model's forecast; i.e. the financial variables are not relevant

[26] Rapach and Weber (2004) claim that this is essentially similar to establishing the economic significance of a parameter estimate (vs. the statistical significance).
[27] Note that results are presented only for the forecast horizons deemed significant in Table 8.

in forecasting y_t. Therefore, as $\lambda \rightarrow 1$, the unrestricted model's forecast is more important in generating the optimal composite forecast[28].

The results shown in Table 9 indicate that the term spread is significantly quantitatively important in generating an optimal composite forecast of manufacturing production growth ($\lambda > 0.9$); whilst the FCI is less so (however the importance of the FCI increases as the horizon length increases, reaching $\lambda = 0.6$ as h = 6). M3 growth is also significantly quantitatively important in generating an inflation forecast ($\lambda > 0.9$); whilst house prices and the Rand-Dollar exchange rate are slightly less so ($\lambda \approx 0.6$ and $\lambda \approx 0.7$ respectively). M3 growth is again regarded as a relatively important predictor, this time for the Treasury Bill, with $\lambda \approx 0.7$ at various horizons. The smallest estimates of λ are observed in the equation of private sector credit extension as a predictor of the Treasury Bill yield ($\lambda \approx 0.4$).

Table 9. Least Squares Estimates of λ

y_t: Manufacturing production growth					
x_t: FCI	*$h = 1$*	*$h = 3$*	*$h = 6$*		
Theil's *U*	0.996	0.974	0.943		
λ	0.266	0.472	0.629		
x_t: SPREADN_TERM	*$h = 1$*				
Theil's *U*	0.985				
λ	0.977				
y_t: Inflation					
x_t: D_LHOUSEP	*$h = 1$*				
Theil's *U*	0.978				
λ	0.561				
x_t: D_LRD	*$h = 3$*	*$h = 6$*			
Theil's *U*	0.964	0.932			
λ	0.547	0.746			
x_t: M3_GR	*$h = 9$*	*$h = 12$*			
Theil's *U*	0.908	0.939			
λ	0.939	0.985			
y_t: Treasury Bill yield					
x_t: M3_GR	*$h = 9$*	*$h = 12$*	*$h = 15$*	*$h = 18$*	*$h = 21$*
Theil's *U*	0.917	0.914	0.917	0.924	0.930
λ	0.705	0.691	0.694	0.702	0.752
x_t: D_LPSCE	*$h = 6$*	*$h = 9$*	*$h = 15$*		
Theil's *U*	0.973	0.967	0.958		
λ	0.430	0.432	0.433		

Notes: If Theil's U < 1 then RMSFE of the unrestricted model is < RMSFE of the restricted model, indicating the relevance of the individual financial variables as "forecasters" (i.e. lower Theil's *U* values are preferable). λ is the estimated weight of the unrestricted model's out-of-sample forecast in Equation (16), and is estimated with an intercept in Equation (16).

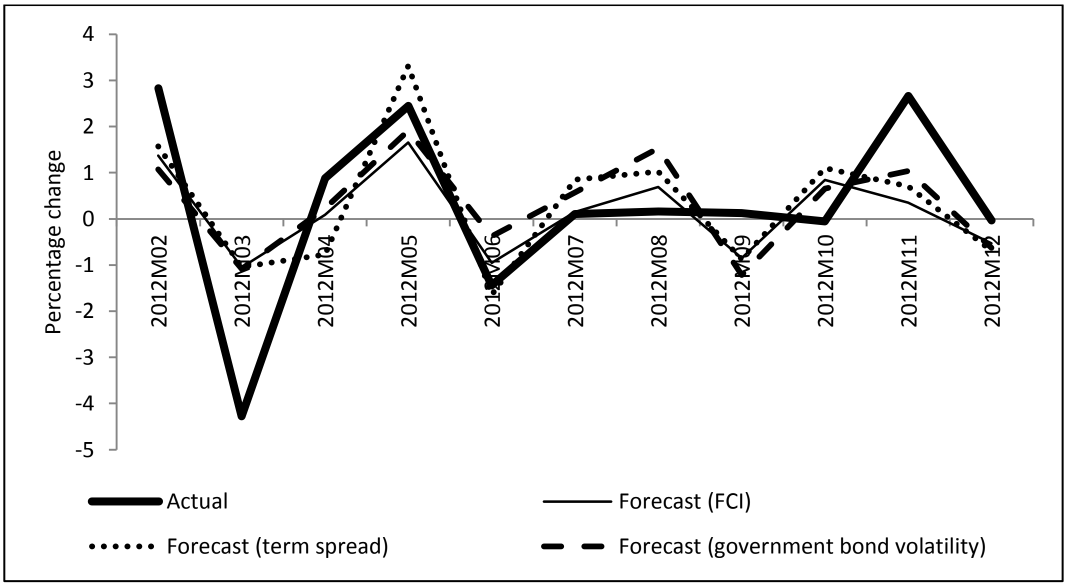
[28] Note that in certain instances for x_t = M3 and x_t = SPR_MORT, λ was found to have inconsistent values (i.e. >1). I take the approach of Rapach and Weber (2004) who experienced similar issues in their research, and disregard these results.

The U statistics in all instances in Table 9 also show that the RMSFEs of the unrestricted optimal composite forecast models' forecasts are superior to (smaller than) the RMSFEs of the restricted benchmark AR models' forecasts.

3.5 AN ILLUSTRATION AS OF 2012M02

Figure 3 provides an illustration of the usefulness of the variables surviving the data-mining adjustment for forecasting manufacturing output growth, y_t, generated using the unrestricted ARDL model in Equation 4 as of 2012M02. x_t represents the variables "surviving" the data-mining adjustments in Table 8, namely the FCI, the term spread, and government bond volatility. The forecasts are generated 11 months ahead for the period from 2012M02 to 2012M12[29]. The figure shows that all three predictors present good forecasts of y_t, and the RMSE statistics[30] for the FCI (1.403), term spread (1.461) and government bond volatility (1.432) indicate that the FCI is the best predictor out of the three[31].

Figure 3. Forecasts of manufacturing output growth



[29] *Ex ante* forecasting over this period is done by using the estimate of the model until 2012M01, and forecasting without updating the estimates.
[30] The RMSE statistic is calculated as the square root of the average of the squares of the errors.
[31] Note that an absence of available time series of alternative FCIs for South Africa makes it impossible for me to compare my FCI against the performance of others for the country.

3.6 CONCLUSIONS

The objective of this chapter was to test the out-of-sample forecasting ability of a 16-variable FCI constructed in Chapter 2 using rolling-window PCA, which was furthermore purged of the endogenous feedback effects of the macroeconomic variables of output growth, inflation and interest rates. The aim was to test whether the estimated FCI does better than its individual financial components in forecasting key macroeconomic variables, namely output growth, inflation and an interest rate. The forecast encompassing approach of Rapach and Weber (2004) was used, and four test statistics in particular were assessed. Inference based on these statistics was adjusted for the potential problem of data-mining using bootstrapping procedures, and it was found that the estimated FCI has out-of-sample forecasting ability with respect to manufacturing output growth at the one, three and six month horizons, while it has no predictive power for inflation (this is similar to Stock and Watson's (2003) conclusions) and the Treasury bill yield. Furthermore, the λ parameter on this FCI indicates relative 'strength' as an economic predictor, with a value of 0.6 at the 6 month horizon. An illustration of generating forecasts of manufacturing output growth using the FCI as of 2012M02 demonstrates the promise of this approach, with smaller RMSE statistics than alternative predictors of output. This finding concurs with Stock and Watson (2003:825) who found that "combination forecasts reliably improve upon the AR benchmark and forecasts based on individual predictors[32]". This therefore highlights the possibility of using the rolling-window estimated FCI as an early warning indicator for impending macroeconomic instability caused by deteriorating financial conditions. This is of particular use for those with the tasks of producing high-frequency economic forecasts, such as financial analysts.

[32] Although the authors found that simple averaging of unreliable forecasts was sufficient to "average out" instability and improve forecasting performance, the authors did state the need for "fully articulated statistical or economic models" as part of future research to produce more sophisticated combination forecasts (Stock and Watson (2003:825)).

CHAPTER 4: TESTING THE ASYMMETRIC EFFECTS OF FINANCIAL CONDITIONS IN SOUTH AFRICA: A NONLINEAR VECTOR AUTOREGRESSION APPROACH[33]

4.1 INTRODUCTION

The aim of this chapter is to investigate whether the previously estimated FCI has an asymmetric effect on output, interest rates and inflation, in other words to test whether there is potential nonlinearity between South Africa's financial market conditions and its macroeconomy. This is especially pertinent for monetary policy, due to the linkage of monetary policy to the real economy via financial conditions; and due to the fact that, ironically, increased economic stability during upswings appears to increase financial volatility (and hence the importance of financial conditions) during recessions (Dudley, 2010).

Hubrich, D'Agostino, Červená, Ciccarelli, Guarda, Haavio, Jeanfils, Mendicino, Ortega, Valderrama and Valentinyiné Endrész (2013) suggest that more pronounced impacts of financial sector shocks on the real macroeconomy should be expected during financial crises or periods of high financial stress. The rationale is that effects of the credit channel will come into force, and the resultant deterioration in consumer demand will lead to macroeconomic contraction. Hubrich, *et al.* (2013:47) point out that financial stress "affects real-financial linkages because asymmetric information and uncertainty impede borrower-lender relationships and can induce credit rationing. This might imply asymmetric effects and transmission of financial shocks across regimes". They test this hypothesis for the euro area by incorporating a financial stress index into a Markov-switching Bayesian VAR, so as to investigate potential nonlinearities in the interaction between financial conditions and the macroeconomy. Two broad types of asymmetries are considered: (1) asymmetry between regimes (i.e. between different parts of the business cycle, generally between upswings and downswings); and (2) asymmetric responses to positive versus negative shocks.

Weise (1999) uses a nonlinear vector autoregression (VAR) approach to investigate whether monetary policy has asymmetric effects on output and prices. Similarly, I use the impulse response functions (IRFs) generated from a nonlinear VAR to investigate the two types of asymmetries mentioned above. Specifically, I analyse: (1) if the effects of a shock

[33] This chapter is a modified version of University of Pretoria Department of Economics Working Paper Series, 2014(14), and is currently under review at *Studies in Nonlinear Dynamics & Econometrics*.

to financial conditions in South Africa are larger in downturns than in upturns (i.e. if the effects vary over the business cycle); (2) whether positive and negative financial conditions shocks have asymmetric effects; and, (3) whether this asymmetry in (1) and (2) is affected by the size of the shock.

Weise's (1999) model uses real output growth as a switching variable. Instead of fixing the coefficients on all variables within the VAR (except for the monetary variable) in response to the switching variable, Weise (1999) sets up an aggregate demand-aggregate supply (AD-AS) model in structural form. All of the coefficients of the reduced form model vary in response to the switching variable. In choosing a threshold, I test the use of the FCI versus inflation, output growth or interest rates as individual switching variables, as well as allowing for each equation within the VAR to have an individual switching variable (i.e. four switches in total). As in Weise (1999), my model allows for smooth regime transitions (as opposed to discrete shifts), which is a more realistic description of the macroeconomic variables over business cycle switches. This general way of modelling is a logistic smooth transition vector autoregression (LSTVAR) which is a multivariate extension of the logistic transition autoregression proposed by Teräsvirta and Anderson (1992)[34].

The remainder of this chapter is organised as follows: Section 4.2 discusses the data used in the compilation of the FCI and in the nonlinear VARs; while Section 4.3 provides details on the econometric methodology used. Section 4.4 presents the empirical results, namely the linearity test results, the LSTVAR estimation results and the impulse response functions. Section 4.5 concludes the chapter.

4.2 DATA

A nonlinear VAR is estimated using the FCI constructed in chapter 2 (see the appendices for further information) along with a measure of output growth (*MPG*) – the month-on-month rate of change in South Africa's Manufacturing Production Index; a measure of inflation (*INF*) – the month-on-month rate of change in the consumer price index (CPI); and the 3-month Treasury Bill yield (*TB*).

[34] For a discussion on the use of nonlinear forecasting models versus linear models, as well as of regime-switching models, see Camacho (2004).

4.3 ECONOMETRIC METHODOLOGY

I follow the process of Tsay (1989), also used in Weise (1999) and Camacho (2004). First, I specify a linear VAR and use lag length criteria tests to obtain the VAR's specification. Second, I apply linearity tests and model selection criteria to all equations in the VAR to determine if nonlinearity is present and to obtain candidates for the switching variable. Third, I test the various models in terms of their response characteristics.

I use a structural STVAR model developed by Weise (1999), where asymmetry is incorporated into a simple AD-AS framework. The methodology that is taken from Weise (1999) is for the case of a model incorporating money, prices and output (see the Appendices for their full model). A simplified version applicable to the present context follows.

For the purposes of comparison, consider a linear VAR model:

$$X_t = C + G(L)X_{t-1} + u_t \tag{27}$$

where $X_t = (FCI_t, MPG_t, INF_t, TB_t)'$ and $G(L)$ is a polynomial in the lag operator. In the nonlinear equivalent, all of the parameters in X and $G(L)$ are functions of a switching variable, z_t. Thus, the smooth transition vector autoregression (STVAR) is given by:

$$X_t = C + G(L)X_{t-1} + (\theta_0 + \theta(L)X_{t-1})F(z_t) + u_t \tag{28}$$

where $G(L)$ and $\theta(L)$ are p^{th}-order polynomials in the lag operator, and $F(z_t)$ is a transition function bounded between 0 and 1. In this case of the LSTVAR, $F(z_t)$ is a logistic function:

$$F(z_t) = \frac{1}{1+e^{-\gamma(z_t-c)}} - \frac{1}{2}, \gamma > 0 \tag{29}$$

where c is the threshold parameter around which the dynamics of the model change, with $\lim_{(z_t-c)\to-\infty} F(z_t) \to 0$ and $\lim_{(z_t-c)\to\infty} F(z_t) \to 1$. γ is the speed of adjustment parameter, and as γ approaches zero, $F(z_t)$ converges to a constant and the model becomes a linear VAR. As γ approaches infinity, the model becomes a threshold autoregression where the model's dynamics change sharply at c, such as the threshold autoregression (TAR) models discussed by Tsay (1989) and others (see Tsay (1989) for a summary of other research on TARs).

Before estimating the model, linearity tests first need to be conducted to determine whether asymmetry is in fact relevant in this case. Following Weise (1999), I base the linearity tests on Taylor series expansions of $F(z_t)$ around $\gamma = 0$. In the case of the switching variable, z_t, being one of the explanatory variables, X_t, Camacho (2004) avoids an identification problem by using a third-order Taylor expansion (as opposed to a first-order expansion, as used by Weise (1999)). I then follow Weise's (1999) three-step procedure described in Granger and Teräsvirta (1993) and Teräsvirta and Anderson (1992) to test the null hypothesis, $H_0\colon \gamma = 0$, against the alternative of $H_1\colon \gamma > 0$ for each equation in the system. I consider a k-variable VAR with p lags, where $W_t = (X_{1t-1}, X_{1t-2}, \dots, X_{1t-p}, X_{2t-1}, \dots, X_{kt-p})$, and where z_t is known. The first step is to collect the residuals, $\hat{u}_{it}$, from the following restricted regression:

$$X_{it} = \beta_{i0} + \sum_{j=1}^{pk} \beta_{ij} W_{jt} + u_{it} \tag{30}$$

and use these to determine $SSR_0 = \sum \hat{u}_{it}^2$.

The second step is to collect the residuals, $\hat{v}_{it}$, from the following unrestricted regression:

$$u_{it} = \alpha_{i0} + \sum_{j=1}^{pk} \alpha_{ij} W_{jt} + \sum_{j=1}^{pk} \delta_i z_t W_{jt} + v_{it} \tag{31}$$

and use these to determine $SSR_1 = \sum \hat{v}_{it}^2$. The third and final step is to calculate the LM-statistic, namely, $LM = \frac{T(SSR_0 SSR_1)}{SSR_0} \sim \chi^2(pk)$, where T is the sample size[35].

The above procedure tests for linearity equation by equation. To test for linearity in the system as a whole, a likelihood ratio test of the null hypothesis, $H_0\colon \gamma = 0$ in all equations, is performed. The estimated variance-covariance matrices of the residuals from equations (30) and (31) are $\Omega_0 = \frac{\sum \hat{u}_t \hat{u}_t'}{T}$ and $\Omega_1 = \frac{\sum \hat{v}_{it} \hat{v}_{it}'}{T}$ respectively, and these are used to derive the test statistic, $LR = T\{\log|\Omega_0| - \log|\Omega_1|\} \sim \chi^2(pk^2)$. Instead of relying on the asymptotic distributions, the p-values of the tests are obtained using 1 000 parametric model-based bootstrap iterations, so as to guard against distributional assumptions and finite sample problems.

In the following section I perform linearity tests to ascertain whether a nonlinear VAR is indeed preferable over a standard linear VAR in this context. I go on to estimate a selection of LSTVAR models and assess their response characteristics.

4.4 EMPIRICAL RESULTS

4.4.1 Linearity Tests

The null hypothesis of a linear standard four-variable VAR is tested against the alternative of a LSTVAR. The four variables are *FCI*, *MPG*, *INF* and *TB*. Both the linear and nonlinear VARs have the same ordering and specification, for the purposes of

[35] Inference is made using bootstrapped p-values.

comparison, with the ordering presented as *FCI*, *MPG*, *INF*, and *TB*. The Schwarz information criterion suggests a two-lag model[36].

I include an *a priori* selection of switching variables, namely the first and second lags of *FCI*, *MPG*, *INF* and *TB*.

Table 10 presents the results of the linearity tests. It is evident that there is nonlinearity in each of the equations, and in the VAR system as a whole. Furthermore, each of the variables – *FCI*, *MPG*, *INF* and *TB* – exhibit potential as switching variables. Weise (1999) theoretically proposes inflation as a switching variable, as do Ball, Mankiw and Romer (1988), Ball and Mankiw (1994), and Tsiddon (1993). Weise's (1999) empirical results point towards inflation and output growth as potential switching variables. In a single-equation case, Teräsvirta and Anderson (1992) suggest choosing the switching variable based on the LM statistic in Table 10 with the smallest bootstrapped *p*-value. Given that all of the significant *p*-values within each equation are nearly identical at ≈0, and their associated *LM* statistics are very close to each other in value, I test the following possibilities as switching variables: FCI_{t-2}, MPG_{t-2}, INF_{t-2} and TB_{t-2}. Furthermore, I extend the case to include a separate switching variable for each equation, and test two such models. This approach does not restrict the nonlinear dynamics of the each equation to be governed by the same switching variable, and hence is more flexible. Version 1 has the following switching variables[37]: FCI_{t-2} in the *FCI* equation; TB_{t-1} in the *MPG* equation; TB_{t-2} in the *INF* equation; and INF_{t-1} in the *TB* equation. Version 2 of the 4-switch model has the following switching variables: FCI_{t-2} in the *FCI* equation; MPG_{t-2} in the *MPG* equation; INF_{t-2} in the *INF* equation; and TB_{t-2} in the *TB* equation. Indeed, the *p*-values of these tests are smaller than the *p*-values of the single switch variable cases, implying that the extended models better capture the nonlinear dynamics.

[36] The Akaike Information Criterion suggests 6 lags. This model was tested, however was found not to perform as well as the 2-lag models, likely due to over-parameterisation.
[37] The choices of switching variables are based on the outcomes of the LM linearity tests.

Table 10. First round LM tests for linearity

Switching Variable	*FCI Equation LM*	*MPG Equation LM*	*INF Equation LM*	*TB Equation LM*	*VAR System LM*
FCI_{t-1}	171.7965***	298.3281***	32.7984	137.5205***	770.6697***
FCI_{t-2}	168.4439***	16.4148	132.4527***	31.3825	375.3350***
MPG_{t-1}	163.9970***	18.4456	177.0351***	34.3354	429.5872***
MPG_{t-2}	160.0466***	66.7112***	20.5804	151.4532***	440.0684***
INF_{t-1}	167.9873***	68.6489***	12.8395	229.9851***	557.2017***
INF_{t-2}	166.2219***	262.5497***	83.9057***	19.8860	627.2075***
TB_{t-1}	165.6655***	267.5810***	79.4406***	18.0611	628.0866***
TB_{t-2}	155.3648***	47.2514***	204.8648***	75.6107***	531.5056***

Notes: *** implies rejection of the null hypothesis, $H_0: \gamma = 0$, at the 1% level of significance, i.e. it implies nonlinearity (and specifically, a LSTVAR specification) in the selected equation(s). *p*-values are obtained from bootstrapping using 1 000 iterations.

4.4.2 LSTVAR estimation results

Following Rahman and Serletis (2010), the unrestricted LSTVAR models with the switching variables identified above are estimated using nonlinear least squares, extending the univariate approach in Teräsvirta and Anderson (1992) to the multivariate case[38]. This is in contrast to Weise (1999) who fixes the threshold, *c*, and slope, γ, parameters at certain values and estimates the STVAR model equation by equation using OLS. I use nonlinear least squares so that I do not have to impose any subjective restrictions.

In terms of the speed of adjustment parameter, γ, the results in Table 11 show that there is a sharp transition between states when FCI_{t-2} and MPG_{t-2} are the switching variables, however there is a smoother, slower transition between states when INF_{t-2} and TB_{t-2} are the switching variables. Version 1 of the 4-switch model has smooth transition in the *FCI*, *MPG* and *INF* equations, and sudden transition in the *TB* equation. Version 2 of the 4-switch model has smooth transition in the *FCI* and *TB* equations, and sudden transition in the *MPG* and *INF* equations[39]. In all instances, except perhaps the *TB* equation of the 4-switch model version 2, γ appears to be significantly more than 0, thereby indicating nonlinear models in each case.

[38] CUSUM tests (see results in Appendix A.7) on the individual equations within the VAR indicate an absence of structural breaks.
[39] Graphs of the transition functions for all tested models are found in Appendix A.8.

Table 11. Selected estimation output

Switching Variable	*MSE*	*Threshold, c*	*Speed of adjustment, γ*	*% of observations in upper regime*	*% of observations in lower regime*
FCI_{t-2}	2.360	1.797***	227.192	18	82
MPG_{t-2}	2.360	-0.769***	411.434	80	20
INF_{t-2}	2.349	-0.270***	16.464	56	44
TB_{t-2}	2.359	-0.449***	6.262**	67	33
4-switch version 1:	2.345				
FCI equation *(switch: FCI_{t-2})*		-2.432***	3.612	90	10
MPG equation *(switch: TB_{t-1})*		-0.548***	22.910	71	29
INF equation *(switch: TB_{t-2})*		-0.400***	9.823	64	36
TB equation *(switch: INF_{t-1})*		-0.506***	199.000***	68	32
4-switch version 2:	2.350				
FCI equation *(switch: FCI_{t-2})*		-2.432***	3.418	90	10
MPG equation *(switch: MPG_{t-2})*		0.035	199.000***	49	51
INF equation *(switch: INF_{t-2})*		-0.114***	199.000***	50	50
TB equation *(switch: TB_{t-2})*		-0.985***	0.715	90	10

Notes: ***/**/* indicates parameter significance at the 1/5/10% level. The γ parameter in the model which has INF_{t-2} as the switching variable is significant at the 12.5% level.

The threshold parameter, *c*, provides insight into the different "regimes" which the LSTVAR distinguishes between. Camacho (2004) found that, when applied to models including GDP growth rates, a logistic transition function, as in equation (29), has the useful property of locating "the model either near to, or far from, recessions, depending on the switching expression's values". Specifically, if $F(z_t) \to 0$, this represents recessionary periods, while $F(z_t) \to 1$ is representative of expansionary periods. Camacho (2004) reached this conclusion using a model incorporating GDP growth and growth in the Conference Board Composite Index of Leading Indicators.

The MSE statistics[40] in Table 11, along with the values of c and γ, assist in making a decision as to the "best" model that I will use as the benchmark model. Of the single-switch models, I choose the model which has INF_{t-2} as a switching variable, and compare this to the 4-switch model, version 1. The transition functions of these two chosen models are shown in Figure 4 and Figure 5 below.

[40] Other model selection criteria, such as AIC and BIC, were assessed, however, due to the fact that the function values for all models were identical, so were the AIC and BIC statistics.

Figure 4. Transition function: *INF_{t-2}* as switching variable

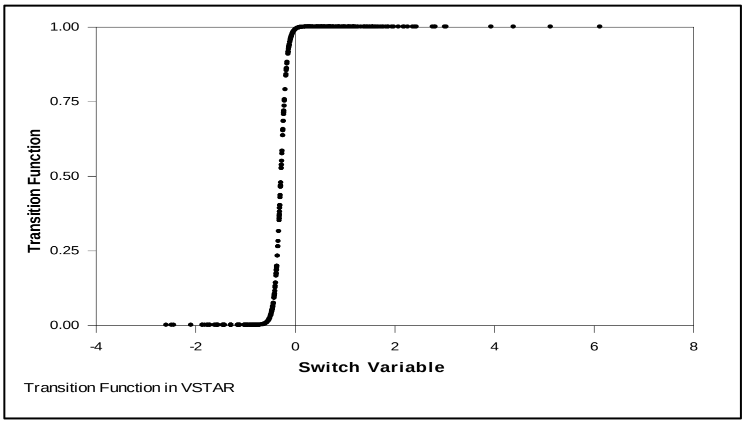
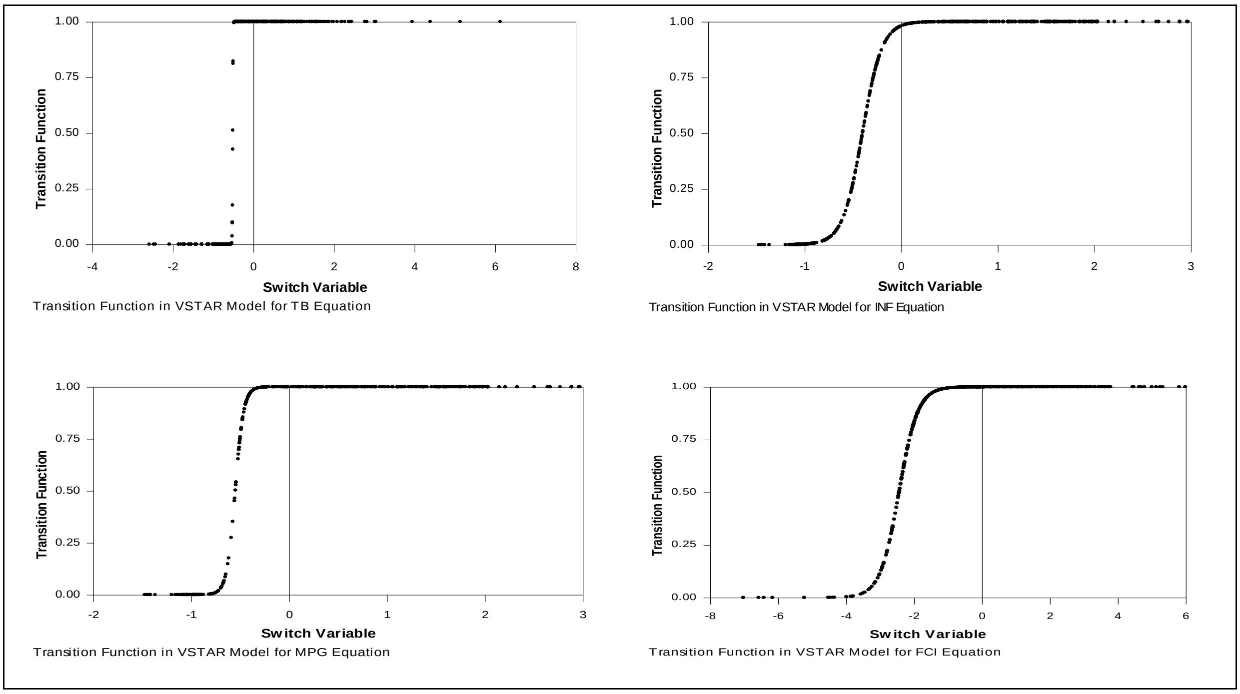


Figure 5. Transition function: 4-switch model version 1



An important characteristic of the LSTVAR models estimated here is that all of the variables interact dynamically and co-move in response to shocks in any of the equations of the LSTVARs. The choice of switching variable in each model is dependent upon statistical goodness-of-fit, which implies that the upper and lower regimes of the models are *not* necessarily determined by the nature of the switching variable itself, but rather by the asymmetric and dynamic interactions of the variables within the LSTVAR[41]. The

[41] Therefore, for example, even though the single-switch model has inflation as the switching variable, it appears that a large *financial* shock moves the system into a crisis regime, because the other variables, *MPG* and *TB*, along with *INF*, dynamically respond to this shock.

lower regime periods of these two chosen models tend to correspond to periods of financial tightening and financial volatility. The upper regimes, conversely, are related to periods of stable and loose financial conditions[42].

I test these two models again for linearity, by testing the null hypothesis that the coefficients on $F(z_t)$ are equal to zero (i.e. $H_0\colon linearity$) in each equation individually and in the joint LSTVAR system. As in Weise (1999), the F-tests are constructed from Wald statistics with White's (1980) heteroskedasticity-consistent coefficient matrix, with bootstrapped inference. Table 12 shows that linearity is again rejected in favour of the full LSTVAR model with INF_{t-2} as a switching variable, and in the *FCI* and *MPG* equations of that model. In the model with four switching variables, linearity is again rejected in the *INF* equation and in the full LSTVAR.

Table 12. Second round linearity tests

Model	*F-statistic*				
	FCI equation	*MPG equation*	*INF equation*	*TB equation*	*LSTVAR*
INF_{t-2} as switching variable	186.4407***	2.8711***	0.6845	1.012	87.2739***
4-switch model (version 1)	1.3942	1.5319	1.6744**	1.6195	1.6785*

Notes: ***/**/* implies rejection of the null hypothesis, $H_0\colon linearity$, at the 1/5/10% level of significance, i.e. it implies nonlinearity within that equation of the LSTVAR specification. p-values are obtained from bootstrapping using 1 000 iterations.

Rahman and Serletis (2010) point out that it is difficult to fully understand and interpret nonlinear models based on parameter estimates only, and that it is important to also consider the dynamic response characteristics inherent in generalised impulse response functions (GIRFs). This analysis is performed in the following section.

4.4.3 Impulse Responses

GIRFs from the two chosen estimated LSTVAR models are now used to test the asymmetry of shocks to financial conditions in these systems. I test three hypotheses: (1) whether the effects of a shock to financial conditions in South Africa are larger in upturns or in downturns; (2) whether positive and negative financial conditions shocks have

[42] I also note that in the individual equations of the 4-switch model, the upper (lower) regimes correspond to economic booms (recessions), periods of high (low) inflation, and periods of above- (below-) average interest rates.

asymmetric effects; and (3) whether this asymmetry in (1) and (2) is affected by the size of the shock[43].

Weise (1999) and Van Dijk, Teräsvirta and Franses (2002) have identified certain key differences between the impulse response functions (IRFs) from nonlinear and linear models. Unlike in a linear model, where the IRF is invariant to history, the nonlinear GIRF incorporates "random history" (i.e. it must treat ω_{t-1} in equation (32) as a random variable). Furthermore, future shocks in a nonlinear model are to be drawn from a distribution and their effects averaged out over a large number of draws; whereas future shocks can be set equal to zero in a linear model. Lastly, shocks of different sizes have the potential to generate different responses in a nonlinear model, unlike a linear model's IRF, which is invariant to the size of the shock. These characteristics pertaining to a linear model mean that an IRF can be generated from the estimated coefficients of the VAR; however nonlinear GIRFs must be computed by simulating the model.

The impulse responses are calculated using a methodology described by Rahman and Serletis (2010), which in turn is derived from Koop, Pesaran and Potter (1996). A GIRF is computed as the difference between the responses of the forecast of selected variables to a one-time shock, compared to a baseline (no shock) scenario:

$$GI_X(n, v_t, \omega_{t-1}) = E[X_{t+n}|v_t, \omega_{t-1}] - E[X_{t+n}|\omega_{t-1}], n = 0, 1, \ldots \qquad (32)$$

where GI_X is the GIRF of X, n is the forecast horizon, v_t is the shock[44] used to generate the GIRF, ω_{t-1} represents the initial values of the model's variables (their "history"), and $E[\cdot]$ is the expectations operator. I run my GIRFs over 25 months, and use 1 000 bootstrapped iterations to combine all possible responses and take all possible VAR orderings into account. Typically, the GIRF of the STVAR is history-dependent and the initial period at which the GIRFs are calculated will have an impact. In order to control for initial period dependence, I take each time point in the sample as an initial period and generate 1 000 bootstrap GIRFs from each initial period, taking the mean response as the response at this point. There are 547 initial periods in the sample, leading to 547 000 bootstrapped impulse responses for each step.

The GIRFs in response to positive and negative *FCI* shocks of varying sizes with their bootstrapped 68% (1 SE) confidence intervals are shown in Appendix A.9. I find that the directions of the GIRFs make economic sense: *MPG* responds to a shock in *FCI* with initial volatility, finally reaching a moderately negative position; *INF* increases in

[43] Note that all GIRFs shown in this chapter are standardised by dividing the impulses by the size and direction (sign) of the shock, so as to ensure comparability. Therefore, negative shock results are normalised to be positive, so any differences in the IRFs of positive versus negative shocks will purely be due to asymmetry.

[44] The shock in this case is either a positive or a negative shock to FCI, and is either one or three standard deviations from the linear model in size.

response to financial tightening; and *TB* also increases, probably in response to monetary tightening due to the aforementioned inflationary effects. In the model with INF_{t-2} as a switching variable all of the GIRFs are significant; however *MPG* and *TB* responses take one month to become significant in all regimes. In the model with 4 switching variables, *MPG* responses are significant between months 3 and 4, and again from month 16 onwards, in all regimes. *INF* responses are significant from month 6 onwards in all regimes. All other responses are wholly significant.

Table 13. Responses of *MPG*, *INF* and *TB* to various shocks of *FCI* after 25 months

		INF_{t-2} as switch		4-switch model (version 1)		Linear
		Lower regime	Upper regime	Lower regime	Upper regime	VAR
1 SE shock to *FCI*						
MPG	Negative shock	0.075	0.086	0.045	0.087	0.046
	Positive shock	0.073	0.087	0.047	0.088	
INF	Negative shock	0.072	0.082	0.082	0.019	0.027
	Positive shock	0.068	0.081	0.082	0.017	
TB	Negative shock	0.056	0.071	0.051	0.049	0.081
	Positive shock	0.054	0.072	0.059	0.058	
3 SE shock to *FCI*						
MPG	Negative shock	0.074	0.087	0.043	0.089	0.046
	Positive shock	0.074	0.087	0.044	0.090	
INF	Negative shock	0.072	0.081	0.080	0.019	0.027
	Positive shock	0.068	0.080	0.084	0.017	
TB	Negative shock	0.056	0.070	0.050	0.045	0.081
	Positive shock	0.056	0.071	0.061	0.058	

Notes: These figures are derived from the maximum value of the responses, over 25 months, of the variables in the left-hand column to a shock in *FCI* (i.e. from the maximum point of the GIRF graphs in Figure 6 and Figure 7). The impulses and their responses are standardised. The size of the negative (positive) shocks to *FCI* are -1.988 (1.988) for a 1 SE shock, and -5.964 (5.964) for a 3 SE shock.

In quantifying how much asymmetry matters in the response of the economy to unexpected changes in financial conditions, I begin by ascertaining whether positive and negative financial conditions have asymmetric effects. When I consider the results in Table 13, this appears to be the case. In the model with INF_{t-2} as a switching variable, *MPG*, *INF* and *TB* respond more to a negative shock of *FCI* during a downswing than to a positive shock. There is less differentiation between responses to negative and positive shocks during upswings. Conversely, in the model with four switching variables, I find that *MPG* and *TB* respond more to a positive shock of *FCI* during both upswings and downswings than to a negative shock. There is little differentiation between the responses of *INF* to positive and negative financial shocks in both upper and lower regimes.

To determine whether the asymmetry between positive and negative shocks is affected by the size of the shock, I again refer to the results in Table 13. The evidence here shows very little difference between the responses to a small and a large shock (moving from 1 standard error (SE) to 3 SE shocks).

In testing whether financial shocks are more severe in economic upturns or downturns, I assess the impact of a shock in the system to *FCI* and compare the responses of key variables in the upper (lower) regimes – which is where the switching variable takes on values higher (lower) than the threshold, *c*. The GIRFs in Figure 6 and Figure 7 show that upper and lower regimes in both of the chosen models exhibit different magnitudes of responses. Table 13's results confirm Figure 6 and Figure 7, indicating asymmetry in the responses of the South African macroeconomy to financial shocks. It is clear that in both the model with INF_{t-2} as the switching variable and in the 4-switch model, *MPG* responds to an *FCI* shock with a significantly larger magnitude in an upper regime than in a lower regime. *INF* and *TB* also have larger responses in upper regimes in the single-switch model (recall that lower regime periods correspond to periods of financial tightening and financial volatility, while upper regimes are related to periods of stable and loose financial conditions). In the model with four switching variables, it is evident that *INF* responds significantly more during periods of lower regimes, while *TB* shows no differentiation between regimes.

Figure 6 and Figure 7 also show that there is differing behaviour in the responses of the key macroeconomic variables to financial changes. The response of *TB* in both models is significantly more stable and persistent than the *INF* and *MPG* responses, which are more volatile. This makes sense due to the delayed nature of adjustments to interest rates, especially in an official inflation-targeting monetary policy regime, such as in South Africa. The slight persistence of inflationary responses may in turn be due to the fact that inflation can be regarded as a global phenomenon (Neely and Rapach (2011), Ciccarelli and Mojon (2008)).

Figure 6. Asymmetry in upturns and downturns: Model with INF_{t-2} as switching variable

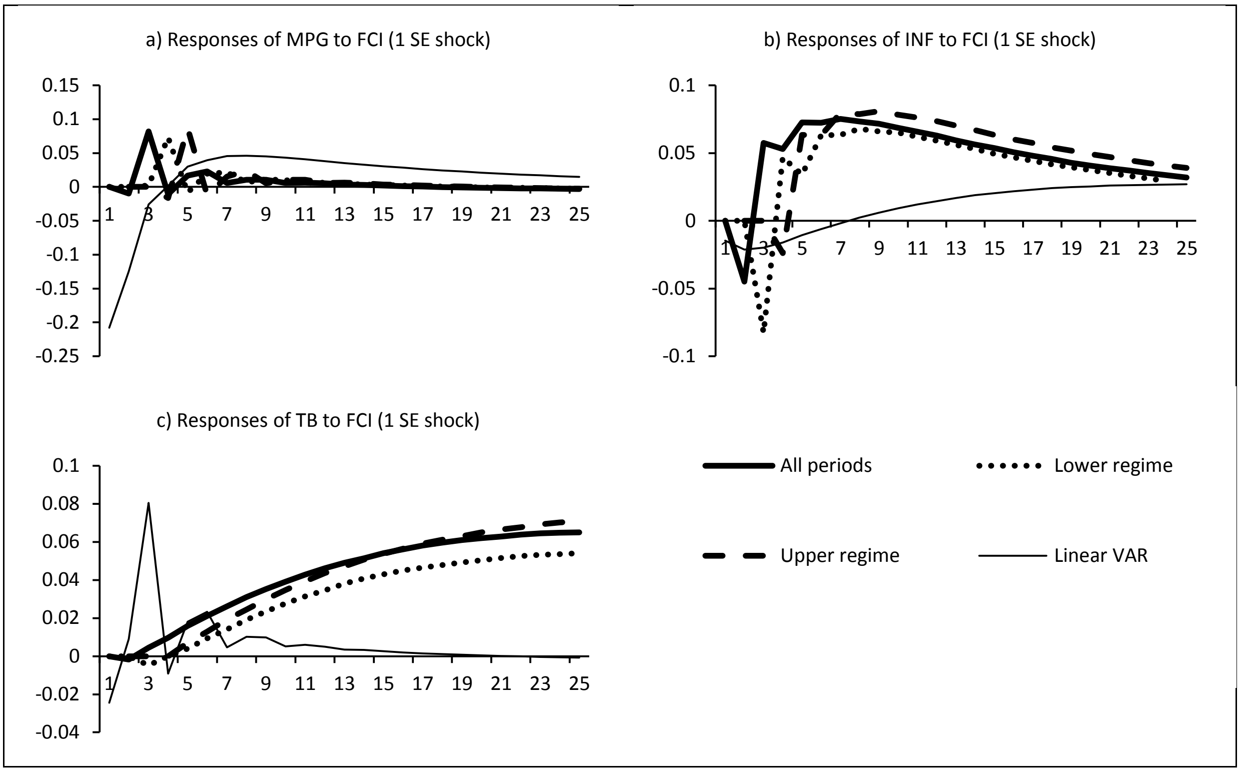
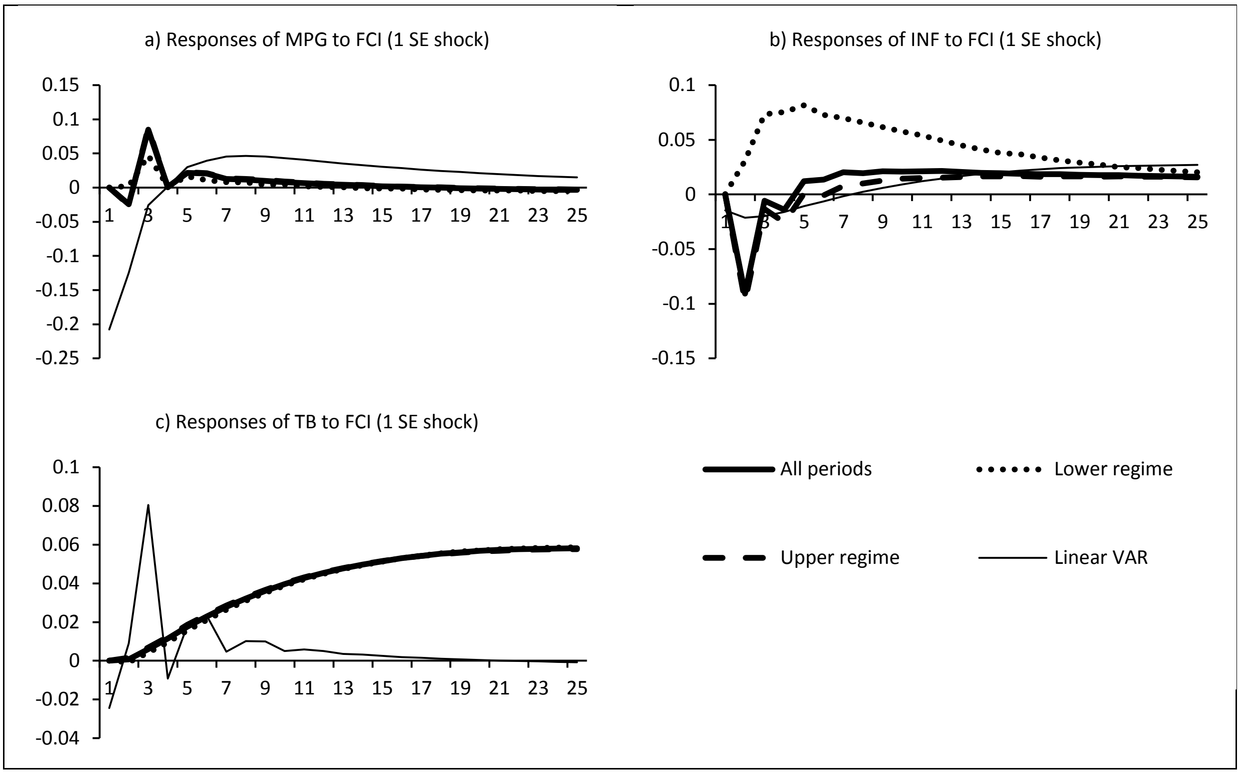


Figure 7. Asymmetry in upturns and downturns: 4-switch model



I have thus proven in this section that the South African economy is nonlinear in its responses to financial shocks. Specifically, manufacturing output growth, inflation and Treasury Bill yields are more affected by financial shocks during upswings in the single-switch model. In the model with four switching variables, inflation responds significantly more to financial changes during recessions. The size of the financial shock, however, only has a moderate impact on the response of the economy.

4.5 CONCLUSIONS

The aim of this chapter was to investigate whether shocks to an FCI for South Africa in chapter 2 has an asymmetric effect on output, interest rates and inflation. To this end, I made use of a nonlinear LSTVAR, which allows for the transition of a chosen switching variable between two regimes. I estimated two such models: one with inflation as a switching variable; and one which allocated a different switching variable to each equation within the LSTVAR – this latter model resulted in two different regimes for each of the four equations.

I have found that the South African economy is strongly nonlinear in its responses to financial shocks, and that manufacturing output growth is more affected by financial shocks during upswings, while inflation responds more during downswings in the four-switch model. The size of the financial shock, however, matters little for the response of the economy. A key implication for monetary policy in South Africa is that policy responses themselves should be nonlinear in response to financial crises (as evidenced by the differing GIRFs for a linear VAR compared to the various nonlinear models). Specifically, if I look at the reactions of *INF* in the four-switch model, monetary policy should be significantly more reactive to a financial crisis when the economy is already in a recession, compared to when the economy is in an upswing. This knowledge of nonlinearity in response to shocks is imperative for consideration by policy-makers and regulators.

CHAPTER 5: GENERAL CONCLUSIONS AND AREAS OF FUTURE RESEARCH

5.1 INTRODUCTION

The global financial crisis that began in 2007-08 demonstrated how severe the impact of financial markets' stress on real economic activity can be. In the wake of the financial crisis policy-makers and decision-makers all over the world identified the critical need for a better understanding of financial conditions, and more importantly, their impact on the real economy. It is for this reason that I conducted this study of South Africa's financial conditions and their impact on and implications for the real macroeconomy.

In order to meet this objective, I constructed an FCI for the South African economy. I used this FCI to investigate three broad hypotheses:

- Do financial conditions in South Africa have long-term effects on the macroeconomy?
- Can South Africa's FCI be regarded as an early warning system? (Is the FCI an appropriate and valid forecasting tool?)
- What is the nature of the impact of the FCI on the macroeconomy – is it nonlinear or linear?

5.2 SUMMARY OF KEY FINDINGS

In answering these three questions above, I began by compiling an FCI for South Africa using a number of different approaches, namely: a simple weighted average; principal components analysis (PCA); recursive PCA; and rolling-window PCA. The "best" FCI was chosen from these alternatives, namely the rolling-window approach. I then purged this FCI of endogenous macroeconomic feedback effects emanating from output, interest rates and inflation. I evaluated the performance of this FCI by assessing its ability to pick up turning points in the South African business cycle, and by running in-sample causality (forecast) tests against the major macroeconomic variables of output, inflation and an interest rate. I found that the FCI does a good job of reflecting recessionary eras in South Africa, and causality tests indicated that this FCI is a good in-sample predictor of industrial production growth and the Treasury Bill yield, but a weak predictor of inflation. This finding is valuable for researchers into South African financial conditions.

I then went on to ascertain whether this "best" chosen FCI has good out-of-sample forecasting ability with respect to the major macroeconomic variables, as compared to the 16 individual financial time series which make up the FCI. A host of forecast encompassing tests were conducted, and their results were adjusted for data-mining. It was found that the estimated FCI has good out-of-sample forecasting ability with respect to manufacturing output growth at the one, three and six month horizons, while it has no predictive power for inflation and the Treasury Bill yield. Therefore, the FCI can be regarded as a leading indicator of manufacturing output growth. This is of particular use for those whose job it is to conduct high-frequency forecasts of economic activity – namely market participants and portfolio managers.

Finally, the FCI was inserted into a nonlinear VAR framework, so as to test for asymmetry in the effects that financial conditions may have on the macroeconomic variables of output, interest rates and inflation in South Africa. To this end, I made use of a nonlinear LSTVAR, which allows for the transition of a chosen switching variable between upper and lower regimes. I estimated two such models: one with inflation as a switching variable; and one which allocated a different switching variable to each equation within the LSTVAR. I found that the South African economy is strongly non-linear in its responses to financial shocks, and that manufacturing output growth and interest rates are more affected by financial shocks during upswings, while inflation responds more during downswings. The size of the financial shock, however, matters little for the response of the economy. This knowledge of nonlinearity is imperative for consideration by policy-makers and regulators.

5.3 CONTRIBUTIONS OF THIS STUDY

This study offers a number of contributions to the general literature on financial conditions in South Africa.

Firstly, with respect to the construction of the FCI (chapter 2), I construct an FCI over a sample period that is three decades longer than existing indices; and my FCI comprises a wider coverage of financial variables than others. Furthermore, I make use of rolling-window estimation techniques which allow me to account for parameter instability and to capture the real-time constraints faced by a policymaker.

Secondly, with respect to the forecasting ability of the FCI (chapter 3), I take into account the potential problem of data-mining and adjust the out-of-sample forecasting procedure for this.

Finally, with respect to a structural analysis of the dynamic response characteristics of key macroeconomic variables to a shock to the FCI (chapter 4), I incorporate the estimated FCI into a nonlinear LSTVAR, which has not been done before. Furthermore, I extend the concept of nonlinearity to a multiple, rather than a univariate case; and I allow for a smooth transition between regimes, as opposed to discrete shifts. In terms of choosing a threshold, I test the option of allowing for each equation within the VAR to have an individual switching variable (i.e. four switches in total), a technique which is not present in the literature.

5.4 AREAS OF FUTURE RESEARCH

The conclusion of this thesis does not represent a conclusion of the investigation into South Africa's FCI. Future areas of research include the following:

- In line with Koop and Korobilis (2013), I plan to construct an FCI using DMA, and compare it to the FCI estimated here.
- Also in line with Koop and Korobilis (2013), Baumeister, Durinck and Peersman (2008) and others, I will incorporate the estimated FCI(s) into a smoothly-evolving TVP-VAR or TVP-FAVAR so as to treat each point in time as a regime. This will control for structural breaks in the data – which will be of interest considering that even though CUSUM tests indicate an absence of structural breaks, Bai and Perron (2003a, 2003b) breakpoint tests do provide evidence of structural breaks.

REFERENCES

Bai, J. & Perron, P., 2003a. Computation and Analysis of Multiple Structural Change Models. *Journal of Applied Econometrics,* 18(1), pp. 1-22.

Bai, J. & Perron, P., 2003b. Critical values for multiple structural change tests. *The Econometrics Journal,* 6(1), pp. 72-78.

Ball, L. & Mankiw, N., 1994. Asymmetric Price Adjustment and Economic Fluctuations. *The Economic Journal,* 104(423), pp. 247-61.

Ball, L., Mankiw, N. & Romer, D., 1988. The New Keynesian Economics and the Output-Inflation Tradeoff. *Brookings Papers on Economic Activity,* Volume 1, pp. 1-65.

Baumeister, C., Durinck, E. & Peersman, G., 2008. Liquidity, inflation and asset prices in a time-varying framework for the euro area. *National Bank of Belgium Working Paper Series,* Volume 142.

Bauwens, L., Koop, G., Korobilis, D. & Rombouts, J., 2011. A Comparison of Forecasting Procedures for Macroeconomic Series: The Contribution of Structural Break Models. *CIRANO Scientific Series,* Issue 2011s-13.

Borio, C. & Lowe, P., 2002. Asset Prices, Financial and Monetary Stability: Exploring the Nexus. *Bank for International Settlements Papers,* Volume 114.

Brave, S. & Butters, R., 2011. Monitoring Financial Stability: A Financial Conditions Index Approach. *Federal Reserve Bank of Chicago Economic Perspectives,* Volume 1Q/2011, pp. 22-43.

Camacho, M., 2004. Vector Smooth Transition Regression Models for US GDP and the Composite Index of Leading Indicators. *Journal of Forecasting,* 23(3), p. 173–196.

Castro, V., 2008. Are Central Banks Following a Linear or Nonlinear (Augmented) Taylor Rule?. *Warwick Economic Research Papers,* Volume 872.

Ciccarelli, M. & Mojon, B., 2008. Global Inflation. *Federal Reserve Bank of Chicago Working Paper Series,* Volume WP 2008-05.

Clark, T. & McCracken, M., 2001. Tests of Equal Forecast Accuracy and Forecast Encompassing for Nested Models. *Journal of Econometrics,* 105(1), pp. 85-110.

Clark, T. & McCracken, M., 2004. Evaluating Long-Horizon Forecasts. *University of Missouri-Columbia Manuscript.*

Clements, M.P. & Harvey, D.I., 2007. Forecast combination and encompassing. In: Mills, T.C. & Patterson, K. (eds) *Palgrave Handbook of Econometrics: Vol 2 Applied Econometrics*. Houndmills, Hampshire: Palgrave Macmillan Ltd.

Diclemente, R., Schoenholtz, K. & D'Antonio, P., 2008. A View of the U.S. Subprime Crisis. *Citi Global Economic and Market Analysis - Special Report*, 26 September.

Diebold, F. & R.Mariano, 1995. Comparing Predictive Accuracy. *Journal of Business and Economic Statistics,* 13(2), pp. 253-263.

Dudley, W., 2010. *Comments on 'Financial Conditions Indexes: A New Look after the Financial Crisis'.* New York City, Remarks at the University of Chicago Booth School of Business Annual U.S. Monetary Policy Forum.

English, W., Tsatsaronis, K. & Zoli, E., 2005. Assessing the Predictive Power of Measures of Financial Conditions for Macroeconomic Variables. *Bank for International Settlements Papers,* Volume 22, pp. 228-252.

Gauthier, C., Graham, C. & Liu, Y., 2004. Financial Conditions Indexes for Canada. *Bank of Canada Working Paper Series,* Volume 2004-22.

Goodhart, C. & Hofmann, B., 2001. *Asset Prices, Financial Conditions, and the Transmission of Monetary Policy.* Stanford University, Conference on Asset Prices, Exchange Rates and Monetary Policy.

Goodhart, C. & Hofmann, B., 2002. Asset Prices and the Conduct of Monetary Policy. *Mimeo, London School of Economics.*

Granger, C. & Teräsvirta, T., 1993. *Modeling Nonlinear Economic Relationships.* New York: Oxford University Press.

Gumata, N., Klein, N. & Ndou, E., 2012. A Financial Conditions Index for South Africa. *IMF Working Paper,* Volume WP/12/196.

Hakkio, C. & Keeton, W., 2009. Financial Stress: What is it, How Can it be Measured, and Why Does it Matter?. *Federal Reserve Bank of Kansas City Economic Review.*

Harvey, D., Leybourne, S. & Newbold, P., 1998. Tests for Forecast Encompassing. *Journal of Business and Economic Statistics,* 16(2), pp. 254-259.

Hatzius, J. et al., 2010. Financial Conditions Indexes: A Fresh Look After the Financial Crisis. *National Bureau of Economic Research Working Paper,* Volume 16150.

Hoover, K. D. & Perez, S. J., 2000. Three Attitudes Towards Data Mining. *Journal of Economic Methodology,* 7(2), pp. 195-210.

Hubrich, K. D'Agostino, A., Červená M., Ciccarelli, M., Guarda, P., Haavio, M., Jeanfils, P.; Mendicino, C., Ortega, E., Valderrama, M.T., Valentinyiné Endrész, M., 2013. Financial Shocks and the Macroeconomy Heterogeneity and Non-Linearities. *European Central Bank Occasional Paper,* Issue 143.

Inoue, A. & Kilian, L., 2004. In-Sample or Out-of-Sample Tests of Predictability: Which One Should We Use?. *Econometric Reviews,* 23(4), pp. 371-402.

Kasai, N. & Naraidoo, R., 2011. The Opportunistic Approach to Monetary Policy and Financial Markets. *University of Pretoria Department of Economics Working Paper Series,* Volume 2011-03.

Kilian, L., 1999. Exchange Rates and Monetary Fundamentals: What Do We Learn from Long-Horizon Regressions?. *Journal of Applied Econometrics,* 14(5), pp. 491-510.

Kışınbay, T., 2007. The Use of Encompassing Tests for Forecast Combinations. *IMF Working Paper*, WP/07/264.

Koop, G. & Korobilis, D., 2013. A new Index of Financial Conditions. *MPRA Papers,* Volume 45463.

Koop, G., Pesaran, H. & Potter, S., 1996. Impulse Response Analysis in Non-linear Multivariate Models. *Journal of Econometrics,* 74(1), pp. 119-147.

Koop, G. & Potter, S., 2007. Estimation and Forecasting in Models with Multiple Breaks. *Review of Economic Studies,* Volume 74, pp. 763-789.

Lack, C., 2003. A Financial Conditions Index for Switzerland. *Bank for International Settlements Papers,* Volume 19, pp. 398-413.

Ludvigson, S. & Ng, S., 2009. Macro Factors in Bond Risk Premia. *The Review of Financial Studies,* Volume 22(12), pp. 5027-5067.

Ludvigson, S. & Ng, S., 2010. A Factor Analysis of Bond Risk Premia. In: A. Uhla & D. Giles, eds. *Handbook of Empirical Economics and Finance.* Boca Raton: Chapman and Hall, pp. 313-372.

Mayes, D. & Viren, M., 2001. Financial Conditions Indexes. *Bank of Finland Discussion Papers,* Volume 17/2001.

McCracken, M., 2007. Asymptotics for Out-of-Sample Tests of Granger Causality. *Journal of Econometrics,* 140(2), pp. 719-752.

Montaglioni, A. & Napolitano, O., 2004. Financial Conditions Index and Interest Rate Settings: A Comparative Analysis. *Istituto di Studi Economici Working Paper Series,* Volume 8.2005.

Neely, C. & Rapach, D., 2011. International Comovements in Inflation Rates and Country Characteristics. *Federal Reserve Bank of St. Louis Working Paper Series,* Volume WP 2008-025F.

Ng, S. & Perron, P., 2001. Lag length selection and the construction of unit root tests with good size and power. *Econometrica,* 69(6), pp. 1519-54.

Nyakabawo, W.; Miller, S.M.; Balcilar, M.; Das, S. & Gupta, R., 2013. Temporal Causality Between House Prices and Output in the U.S.: A Bootstrap Rolling-Window Approach. *University of Pretoria Department of Economics Working Paper Series,* Volume 2013-29.

Pesaran, M., Pettenuzzo, D. & Timmermann, A., 2006. Forecasting Time Series Subject to Multiple Structural Breaks. *Review of Economic Studies,* Volume 73, pp. 1057-1084.

Oet, M., Bianco, T., Gramlich, D. & Ong, S., 2012. Financial Stress Index: A Lens for Supervising the Financial System. *Federal Reserve Bank of Cleveland Working Paper Series,* Volume 12-37.Pesaran, M., Pettenuzzo, D. & Timmermann, A., 2006. Forecasting Time Series Subject to Multiple Structural Breaks. *Review of Economic Studies*, Volume 73, pp. 1057-1084.

Quantec, 2007. A financial conditions index for South Africa. *Economic Research Note*, 25 October 2007.

Rahman, S. & Serletis, A., 2010. The asymmetric effects of oil price and monetary policy shocks: A nonlinear VAR approach. *Energy Economics,* Volume 32, pp. 1460-1466.

Rapach, D. & Strauss, J., 2011. *Financial Sector Shocks and G-7 Business-Cycle Fluctuations.* St. Louis, Midwest Economics Association Meetings.

Rapach, D. & Weber, C., 2004. Financial Variables and the Simulated Out-of-Sample Forecastability of U.S. Output Growth Since 1985: An Encompassing Approach. *Economic Enquiry,* 42(4), pp. 717-738.

Rosenberg, M., 2009. Global Financial Market Trends & Policy. *Bloomberg Financial Conditions Watch*, 3 December.

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

Swiston, A., 2008. A U.S. Financial Conditions Index: Putting Credit Where Credit is Due. *IMF Working Paper Series,* Volume WP/08/161.

Teräsvirta, T. & Anderson, H., 1992. Characterizing Nonlinearities in Business Cycles Using Smooth Transition Autoregressive Models. *Journal of Applied Econometrics,* Volume 7, pp. 119-136.

Thoma, M.A. & Gray, J.A., 1998. Financial Market Variables Do Not Predict Real Activity. *Economic Inquiry*, 36(4), pp. 522-539.

Tsay, R., 1989. Testing and Modelling Threshold Autoregressive Processes. *Journal of the American Statistical Association,* 84(405), pp. 231-240.

Tsiddon, D., 1993. The (Mis)Behavior of the Aggregate Price Level. *Review of Economic Studies,* 60(4), pp. 889-902.

Van Dijk, D., Teräsvirta, T. & Franses, P. H., 2002. Smooth Transition Autoregressive Models – A Survey of Recent Developments. *Econometric Reviews*, 21(1), pp. 1-47.

Weise, C., 1999. The Asymmetric Effects of Monetary Policy: A Nonlinear Vector Autoregression Approach. *Journal of Money, Credit and Banking,* 31(1), pp. 85-108.

West, K., 1996. Asymptotic Inference about Predictive Ability. *Econometrica,* 64(5), pp. 1067-1084.

White, H., 1980. A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica,* 48(4), pp. 817-838.

APPENDICES

A.1 DATA APPENDIX

This appendix provides descriptive, graphical and statistical details on all of the variables used throughout this thesis.

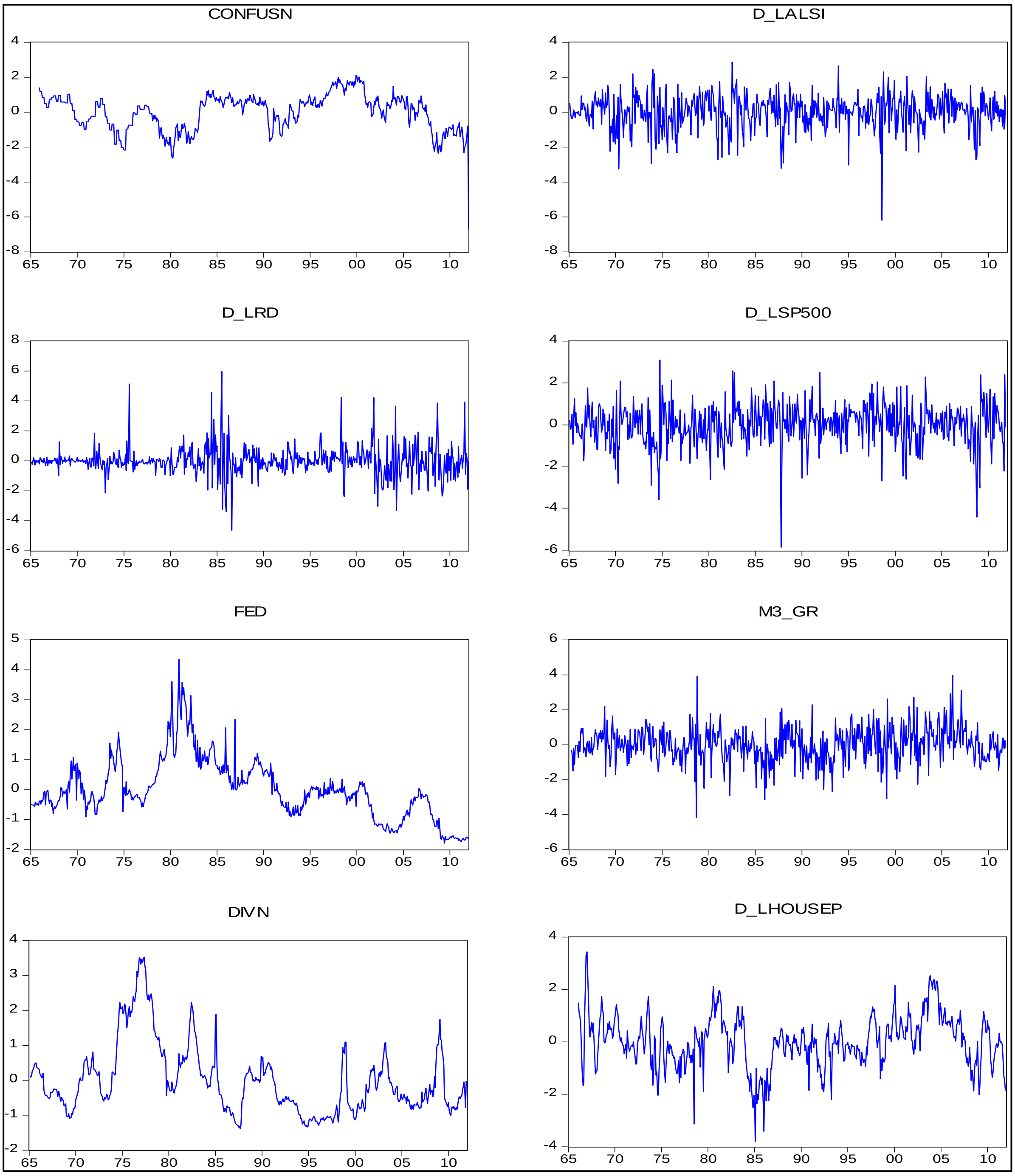
Table A1. Variables used to construct FCI and in forecasting and VAR models

Name	*Description*	*Transformation(s)*
ALSI_VOL	Stock exchange volatility (South Africa)	Square of the first log difference of the All-Share Index
CONFUSN	University of Michigan US Consumer Sentiment Index	N/A
D_LALSI	FTSE/JSE All-Share Index (South Africa)	Seasonally adjusted, deflated, first log difference
D_LHOUSEP	Absa House Price Index (medium house size $141m^2$–$220m^2$) (South Africa)	Deflated by South African CPI, first log difference
D_LPSCE	Credit extended to domestic private sector (South Africa)	Deflated by South African CPI, first log difference
D_LRD	Rand-US dollar exchange rate	Seasonally adjusted, deflated, first log difference
D_LSP500	S&P500 Composite Price Index	Seasonally adjusted, deflated, first log difference
DIVN	Johannesburg Stock Exchange dividend yield (South Africa)	Seasonally adjusted
FED	US Federal Funds market rate	Deflated by US CPI
GBINDEX_VOL	Government bond volatility (South Africa)	Square of the first log difference of Government Bond Return Index
HOUSEP_VOL	House price volatility (South Africa)	Square of the first log difference of House Price Index
INF	Month-on-month growth in CPI (South Africa)	Seasonally adjusted, month-on-month rate of change
M3_GR	Month-on-month growth in M3 money supply[45] (South Africa)	Seasonally adjusted, deflated, month-on-month rate of change
MPG	Month-on-month growth in Manufacturing Production Index (South Africa)	Month-on-month rate of change
SPREADN_BOND	Long-term bond spread between Eskom Corporate Bond yield and 10-year Government Bond yield (South Africa)	N/A
SPREADN_MORT	Mortgage spread between mortgage loan borrowing rate and 3-month Treasury Bill yield (South Africa)	N/A
SPREADN_TBILL	Short-term spread between prime overdraft rate and 3-month Treasury Bill yield (South Africa)	N/A
SPREADN_TERM	Term spread between 10-year Government Bond yield and 3-month Treasury Bill yield (South Africa)	N/A
TB	3-month Treasury Bill Yield (South Africa)	N/A

Notes: All data is extracted from the Global Financial Database (https://www.globalfinancialdata.com).

[45] I tested the inclusion of M1 growth vs. M3 growth through graphical comparison and correlation coefficients between the two FCIs and found that they were very similar, nearly identical in fact, so I chose the FCI including M3 since it is theoretically a more inclusive measure.

Figure A1. Graphs of data series used in models



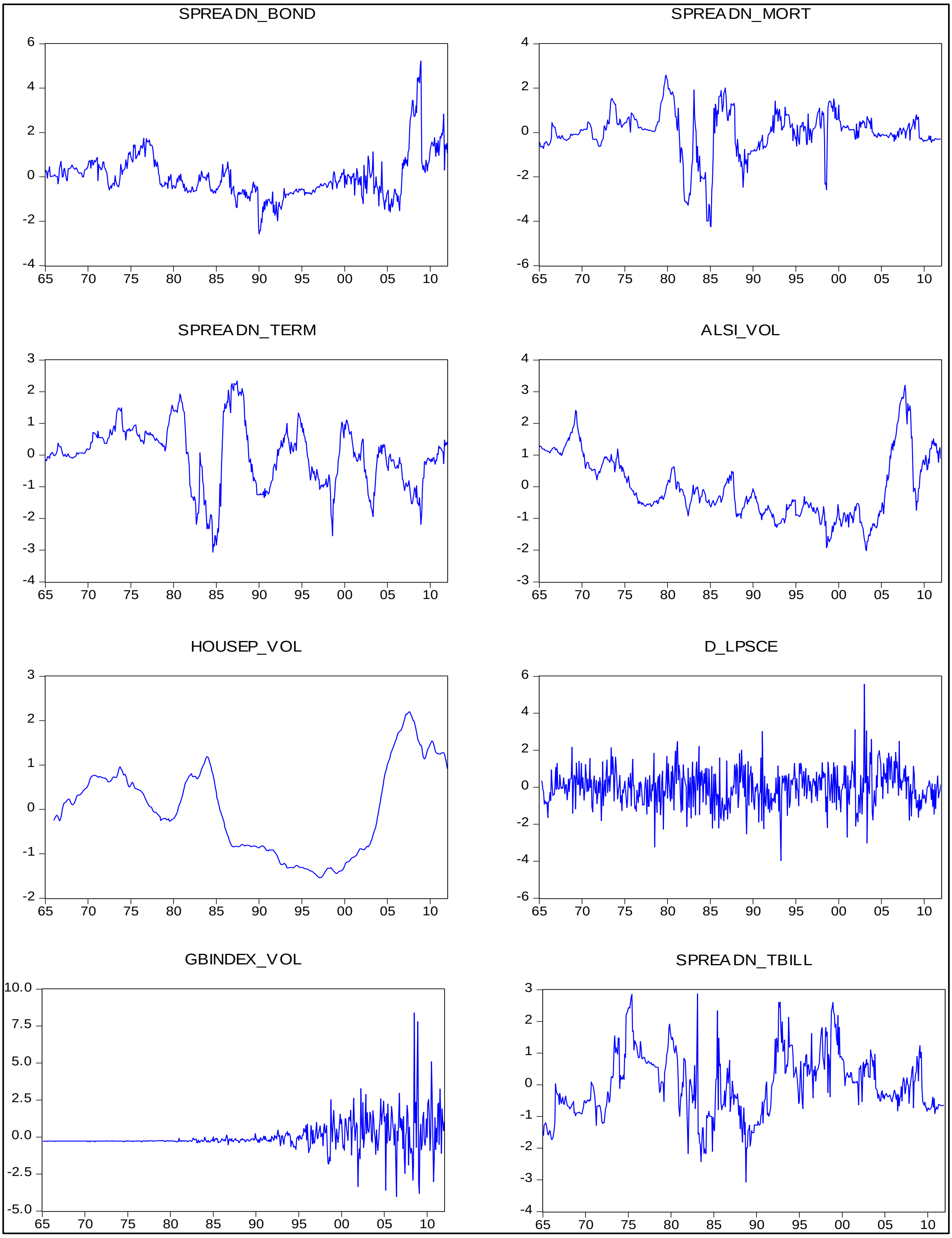

SPREADN_BOND
SPREADN_MORT
SPREADN_TERM
ALSI_VOL
HOUSEP_VOL
D_LPSCE
GBINDEX_VOL
SPREADN_TBILL

Table A2. Descriptive statistics of data series used in models

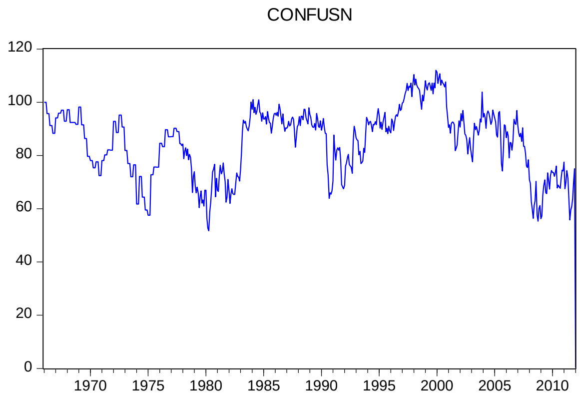
	CONFUSN	*D_LALSI*	*D_LHOUSEP*	*D_LRD*	*D_LSP500*	*DIVN*	*FED*	*M3_GR*
Mean	-0.016842	0.001230	1.09E-11	0.001404	-0.002098	-0.006941	0.011424	0.008466
Median	0.259765	0.099853	0.026503	-0.029036	0.078633	-0.286970	-0.101050	0.000206
Maximum	2.122374	2.864537	3.433848	5.968802	3.100168	3.521246	4.346589	3.978472
Minimum	-6.717129	-6.196047	-3.803468	-4.639893	-5.839150	-1.389342	-1.791335	-4.169193
Std. Dev.	1.037946	1.010185	1.000000	1.010497	1.007795	1.010468	1.008879	1.004965
Skewness	-0.793484	-0.853413	-0.102049	0.857814	-0.660932	1.338104	0.826477	-0.039452
Kurtosis	5.242381	5.753129	3.753092	9.719126	5.720158	4.618374	4.388242	4.368556
Jarque-Bera	173.5751	241.3384	14.00246	1106.071	210.3714	224.9682	107.1679	43.22096
Probability	0.000000	0.000000	0.000911	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	-9.296578	0.678739	6.00E-09	0.774826	-1.158016	-3.831670	6.306083	4.673443
Sum Sq. Dev.	593.6103	562.2807	551.0000	562.6283	559.6237	562.5963	560.8280	556.4852
	SPREADN_BOND	*SPREADN_MORT*	*SPREADN_TBILL*	*SPREADN_TERM*	*ALSI_VOL*	*GBINDEX_VOL*	*HOUSEP_VOL*	*D_LPSCE*
Mean	-0.003205	0.012848	0.034033	0.000954	-0.028140	0.006078	0.000448	0.010049
Median	-0.186873	0.109558	-0.037132	0.070632	-0.313645	-0.257044	0.060513	0.022964
Maximum	5.219083	2.587684	2.866142	2.340311	3.203468	8.394461	2.201444	5.571353
Minimum	-2.573919	-4.253341	-3.072645	-3.064864	-2.013580	-4.030822	-1.540386	-3.975221
Std. Dev.	1.011256	1.008050	0.986207	1.011623	0.994508	1.009969	1.000851	1.003113
Skewness	1.501805	-1.167794	0.334432	-0.297314	0.764907	2.423595	0.169610	0.189723
Kurtosis	7.600947	6.275064	3.114902	3.046849	3.155523	21.13622	1.949586	5.015838
Jarque-Bera	694.3788	372.1633	10.59337	8.182874	54.38390	8105.608	28.02410	96.77436
Probability	0.000000	0.000000	0.005008	0.016715	0.000000	0.000000	0.000001	0.000000
Sum	-1.769040	7.092127	18.78596	0.526872	-15.53345	3.355188	0.247410	5.546895
Sum Sq. Dev.	563.4744	559.9072	535.9047	563.8832	544.9643	562.0404	551.9387	554.4355

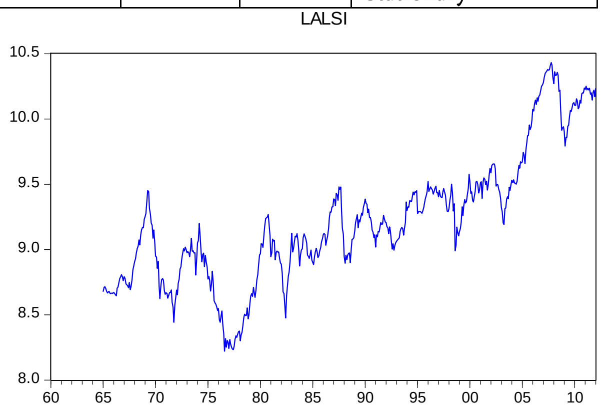
A.2 UNIT ROOT TEST RESULTS

This appendix presents the results of Ng-Perron (2001) unit root tests conducted on each data series, over the sample 1966M1 – 2012M1.

H_0: series has a unit root

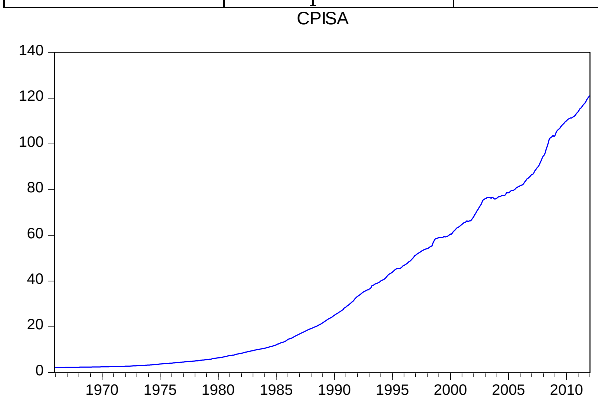
Series	*Structure of regression*	*Ng-Perron test stat*				*Conclusion*
		MZa	*MZt*	*MSB*	*MPT*	
LALSI	Trend, intercept	-11.17	-2.30	0.21	8.47	Non-stationary
	Intercept	0.32	0.16	0.49	19.96	Non-stationary
CONFUSN	Trend, intercept	-16.91*	-2.91*	0.17*	5.39**	Stationary
	Intercept	-8.82**	-2.01**	0.23**	3.13**	Stationary

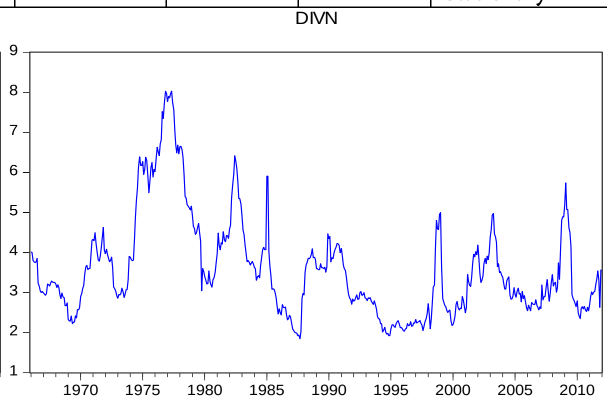




H0: series has a unit root

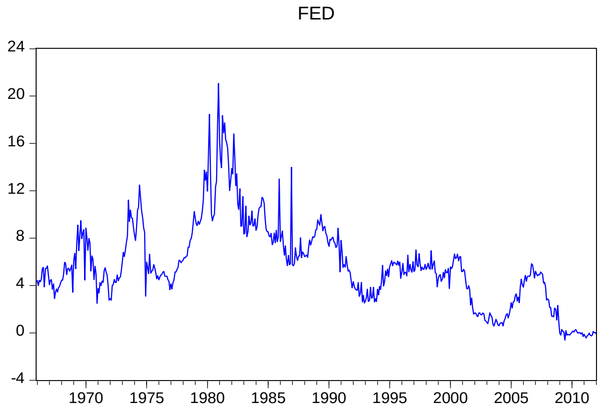
Series	*Structure of regression*	*Ng-Perron test stat*				*Conclusion*
		MZa	*MZt*	*MSB*	*MPT*	
CPISA	Trend, intercept	0.95	0.68	0.72	122.45	Non-stationary
	Intercept	3.42	11.22	3.28	1047.4	Non-stationary
DIVN	Trend, intercept	-18.62**	-3.05**	0.16**	4.91**	Stationary
	Intercept	-17.20***	-2.93***	0.17***	1.43***	Stationary

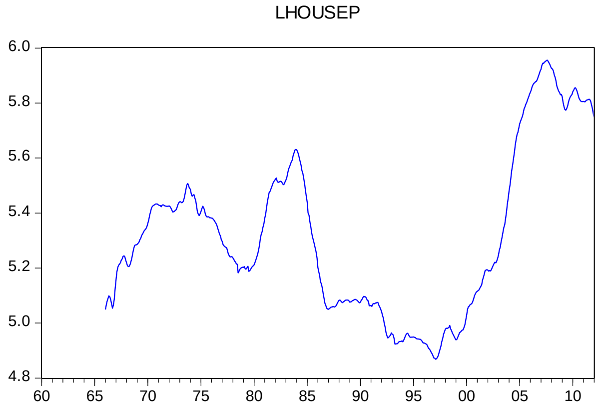




H_0: series has a unit root

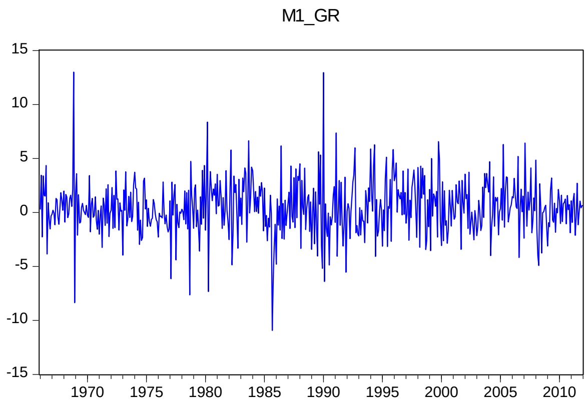
Series	*Structure of regression*	*Ng-Perron test stat*				*Conclusion*
		MZa	*MZt*	*MSB*	*MPT*	
FED	Trend, intercept	-7.93	-1.91	0.24	11.74	**Non-stationary**
	Intercept	-7.60*	-1.88*	0.25*	3.48*	**Stationary**
LHOUSEP	Trend, intercept	-4.49	-1.47	0.33	20.02	**Non-stationary**
	Intercept	-1.40	-0.58	0.41	11.97	**Non-stationary**

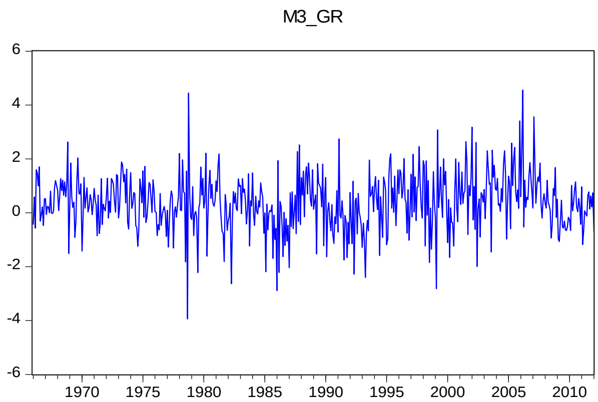




H_0: series has a unit root

Series	*Structure of regression*	*Ng-Perron test stat*				*Conclusion*
		MZa	*MZt*	*MSB*	*MPT*	
M1_GR	Trend, intercept	-141.87***	-8.42***	0.059***	0.64***	**Stationary**
	Intercept	-129.67***	-8.05***	0.06***	0.19***	**Stationary**
M3_GR	Trend, intercept	-117.02***	-7.63***	0.07***	0.84***	**Stationary**
	Intercept	-102.89***	-7.16***	0.07***	0.26***	**Stationary**



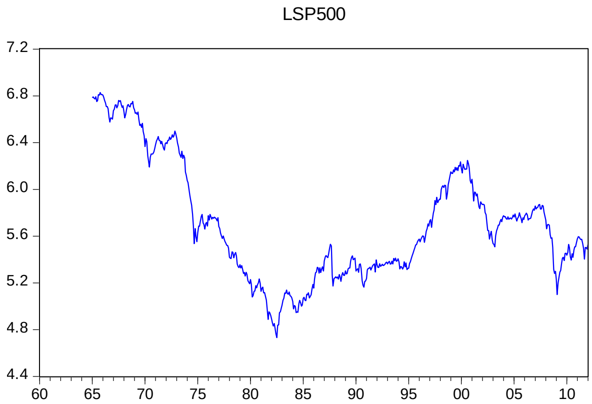


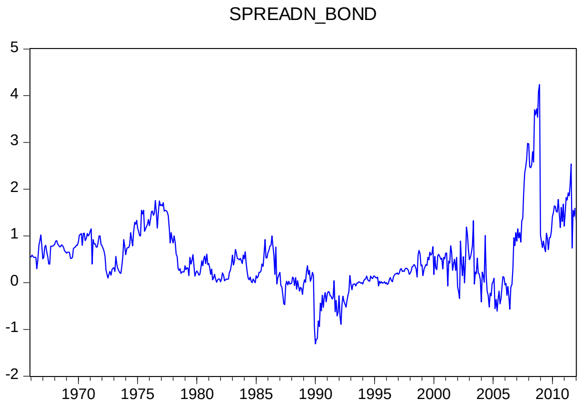
H0: series has a unit root

Series	*Structure of regression*	*Ng-Perron test stat*				*Conclusion*
		MZa	*MZt*	*MSB*	*MPT*	
LRD	Trend, intercept	-12.72	-2.49	0.20	7.34	**Non-stationary**
	Intercept	-4.16	-1.39	0.33	5.97	**Non-stationary**

H0: series has a unit root

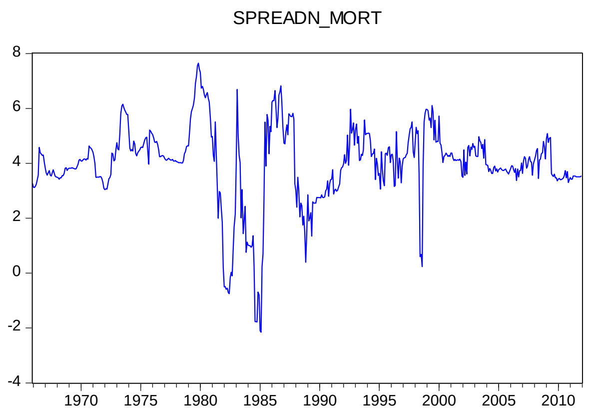
Series	*Structure of regression*	*Ng-Perron test stat*				*Conclusion*
		MZa	*MZt*	*MSB*	*MPT*	
SP500	Trend, intercept	-0.74	-0.50	0.68	87.74	**Non-stationary**
	Intercept	0.38	0.56	1.48	125.52	**Non-stationary**
SPREADN_BOND	Trend, intercept	-30.72***	-3.90***	0.13***	3.05***	**Stationary**
	Intercept	-26.29***	-3.56***	0.14***	1.16***	**Stationary**

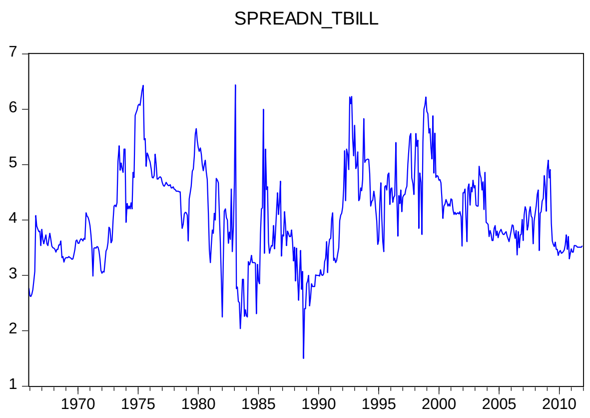




H0: series has a unit root

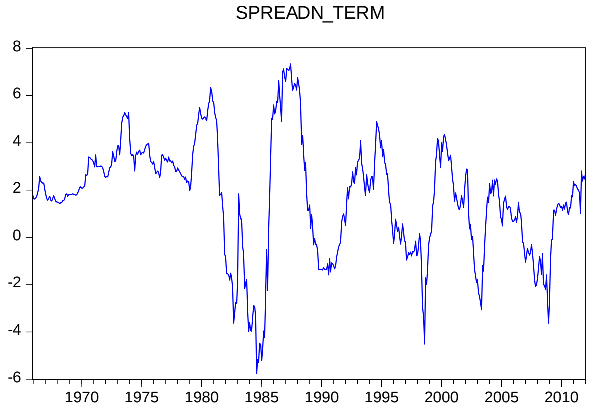
Series	*Structure of regression*	*Ng-Perron test stat*				*Conclusion*
		MZa	*MZt*	*MSB*	*MPT*	
SPREADN_MORT	Trend, intercept	-40.99***	-4.52***	0.11***	2.25***	**Stationary**
	Intercept	-36.96***	-4.30***	0.12***	0.66***	**Stationary**
SPREADN_TBILL	Trend, intercept	-33.29***	-4.04***	0.12***	2.94***	**Stationary**
	Intercept	-12.93**	-2.53**	0.20**	1.95**	**Stationary**

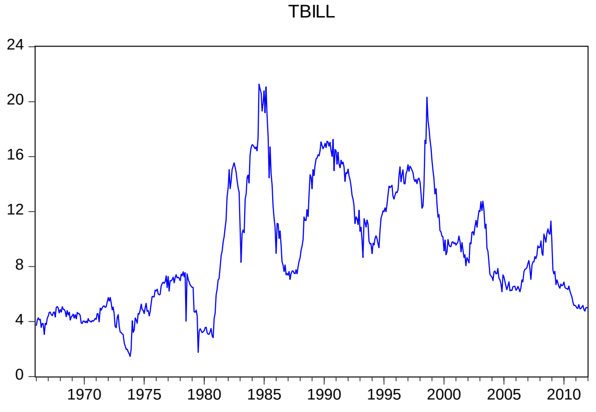




H0: series has a unit root

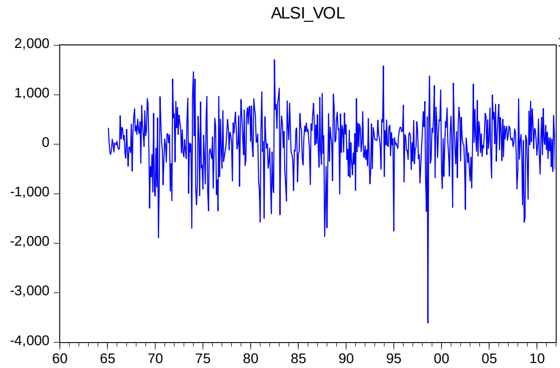
Series	*Structure of regression*	*Ng-Perron test stat*				*Conclusion*
		MZa	*MZt*	*MSB*	*MPT*	
SPREADN_TERM	Trend, intercept	-33.95***	-4.11***	0.12***	2.75***	**Stationary**
	Intercept	-32.48***	-4.03***	0.12***	0.77***	**Stationary**
TBILL	Trend, intercept	-11.55	-2.29	0.20	8.50	**Non-stationary**
	Intercept	-4.93	-1.57	0.32	4.98	**Non-stationary**

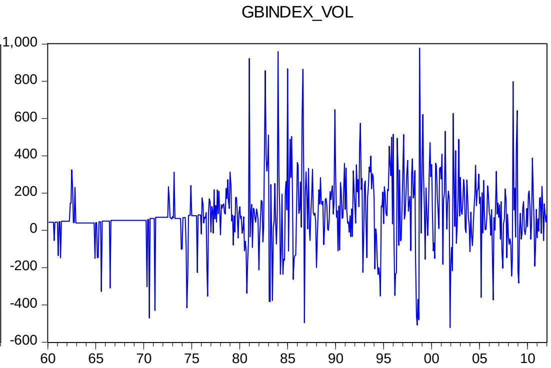




H0: series has a unit root

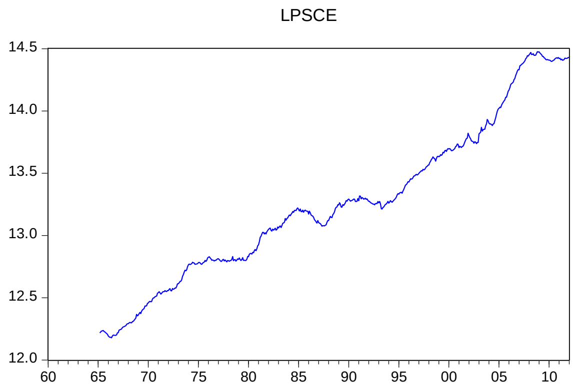
Series	*Structure of regression*	*Ng-Perron test stat*				*Conclusion*
		MZa	*MZt*	*MSB*	*MPT*	
ALSI_VOL	Trend, intercept	-276.77***	-11.75***	0.04***	0.35***	Stationary
	Intercept	-114.38***	-7.56***	0.07***	0.22***	Stationary
GBINDEX_ VOL	Trend, intercept	-288.37***	-12.01***	0.04***	0.32***	Stationary
	Intercept	-280.46***	-11.84***	0.04***	0.09***	Stationary

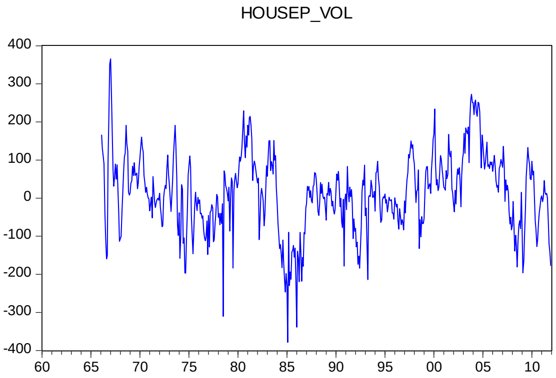




H0: series has a unit root

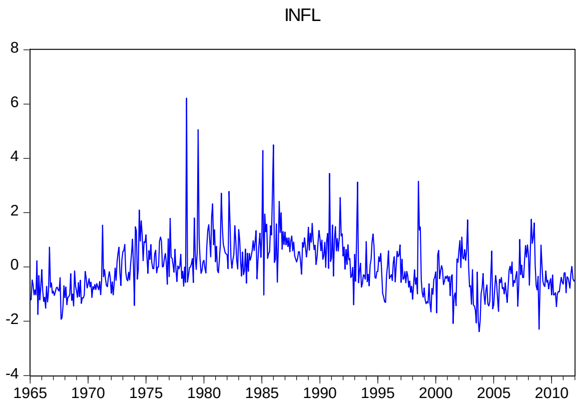
Series	*Structure of regression*	*Ng-Perron test stat*				*Conclusion*
		MZa	*MZt*	*MSB*	*MPT*	
HOUSEP_ VOL	Trend, intercept	-42.85***	-4.61***	0.11***	2.22***	Stationary
	Intercept	-22.05***	-3.19***	0.14***	1.56***	Stationary
LPSCE	Trend, intercept	-5.76	-1.66	0.29	15.76	Non-stationary
	Intercept	1.66	4.02	2.42	429.48	Non-stationary

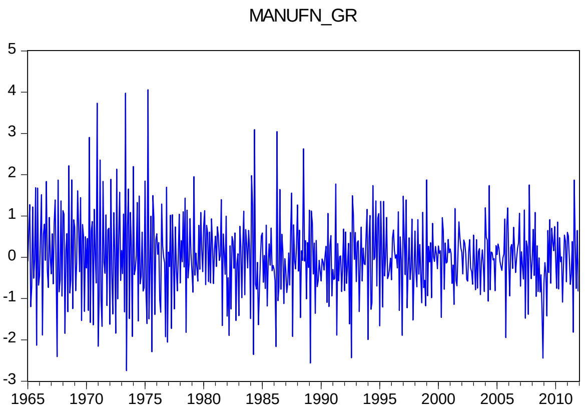




H0: series has a unit root

Series	*Structure of regression*	*Ng-Perron test stat*				*Conclusion*
		MZa	*MZt*	*MSB*	*MPT*	
INF	Trend, intercept	-12.26	-2.45	0.20	7.59	Non-stationary
	Intercept	-5.89*	-1.70*	0.29	4.22	Stationary/Non-stationary
D_INF	Trend, intercept	-37299.4***	-136.56***	0.00***	0.00***	Stationary
	Intercept	-1.27	-0.79	0.63	19.23	Non-Stationary
MANUFN_GR	Trend, intercept	-114.96***	-7.58***	0.07***	0.79***	Stationary
	Intercept	-112.24***	-7.49***	0.07***	0.22***	Stationary





A.3 PRINCIPAL COMPONENTS METHODOLOGY

The indices estimated in this study are compiled using PCA. PCA has the useful objective of combining many variables into a few linear combinations or principal components (factors), and is thus widely used in index number generation. The principal components are obtained by computing the eigenvalue decomposition of the observed variance matrix, and the first principal component accounts for the maximum variance. p Principal components can be created for p variables, however it is hoped that a minimum number of components can be used to account for maximum variance. The system of linear combinations generating the principal components (PC_i) from the original variables (X_i) with weights a_{pp} is as follows:

$$\begin{aligned} PC_1 &= \boldsymbol{a}_1'\boldsymbol{X} = a_{11}X_1 + a_{12}X_2 + \cdots + a_{1p}X_p \\ PC_2 &= \boldsymbol{a}_2'\boldsymbol{X} = a_{21}X_1 + a_{22}X_2 + \cdots + a_{2p}X_p \\ &\vdots \\ PC_p &= \boldsymbol{a}_p'\boldsymbol{X} = a_{p1}X_1 + a_{p2}X_2 + \cdots + a_{pp}X_p \end{aligned} \tag{33}$$

For the p variables in this system, the covariance matrix, $\sum$, and correlation matrix, ρ, have a set of p eigenvalues $\{\lambda_1, \lambda_2, \ldots, \lambda_p\}$ and p eigenvectors $\{e_1, e_2, \ldots, e_p\}$. The eigenvectors determine the weights in the linear combinations of the principal components, and if each eigenvector has elements e_{ik}:

$$\mathrm{e}_1 = \begin{bmatrix} e_{11} \\ e_{21} \\ \vdots \\ e_{p1} \end{bmatrix}, \mathrm{e}_2 = \begin{bmatrix} e_{12} \\ e_{22} \\ \vdots \\ e_{p2} \end{bmatrix}, \ldots, \mathrm{e}_p = \begin{bmatrix} e_{1p} \\ e_{2p} \\ \vdots \\ e_{pp} \end{bmatrix} \tag{34}$$

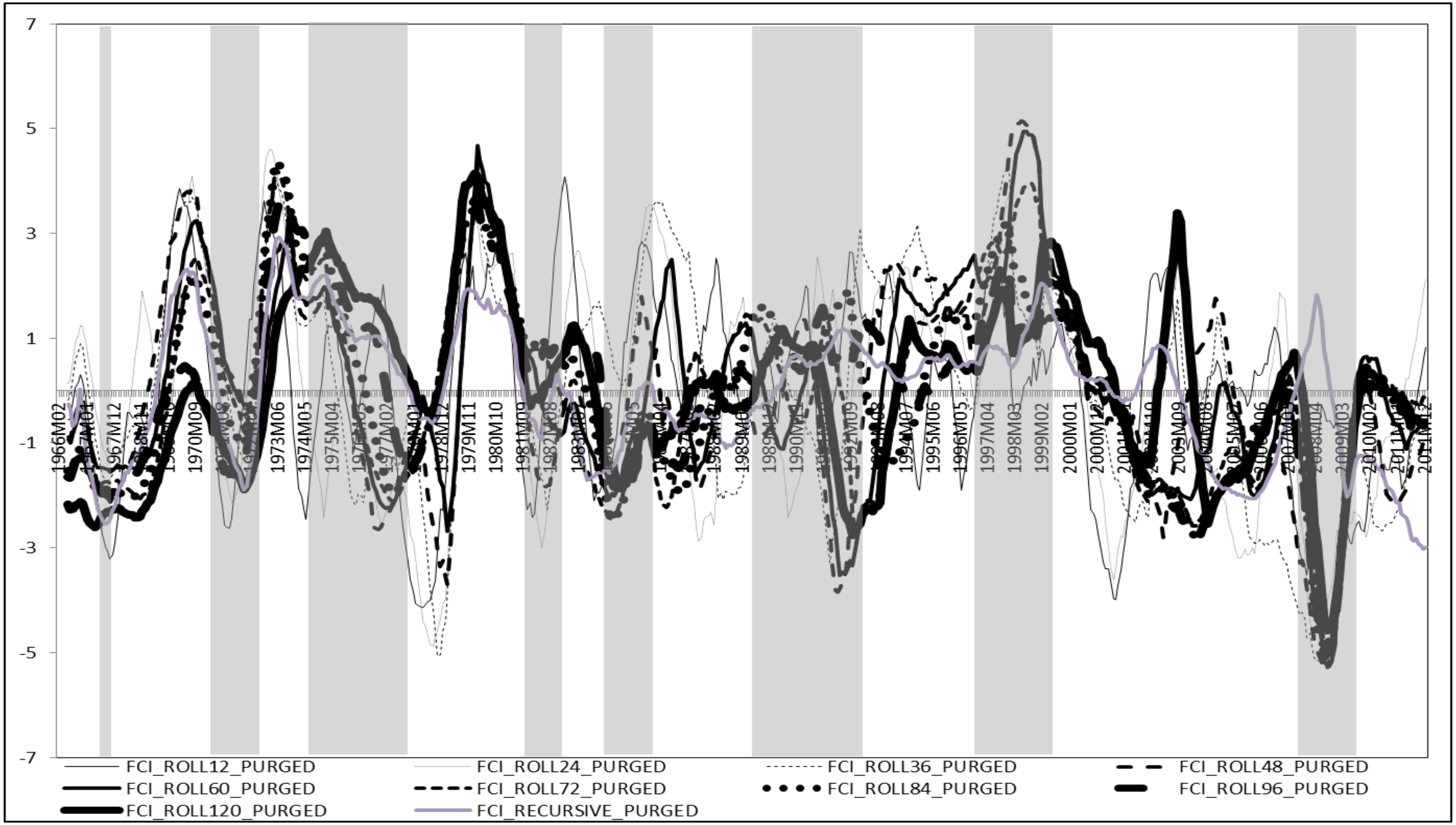
Then the principal components are represented as:

$$\begin{aligned} PC_1 &= e_{11}X_1 + e_{21}X_2 + \cdots + e_{p1}X_p \\ PC_2 &= e_{12}X_1 + e_{22}X_2 + \cdots + e_{p2}X_p \\ &\vdots \\ PC_p &= e_{1p}X_1 + e_{2p}X_2 + \cdots + e_{pp}X_p \end{aligned} \tag{35}$$

Each principal component's variance is equal to the corresponding eigenvalue, $\mathbf{Var}(\mathbf{PC_p}) = \boldsymbol{\lambda}_\mathbf{p}$. For the purposes of this study, I choose the first PC_1 as my factor or FCI, which accounts for 13 per cent of the total variance.

A.4 ALTERNATIVE FCIs

Figure A2. Alternative rolling-window and recursive FCIs



Notes: The grey vertical bars represent periods of recession in the South African economy. An upward movement in the *FCI* represents an improvement (loosening) in financial conditions, and a downward movement in the *FCI* represents a worsening (tightening) of financial conditions.

A.5 FORECASTING RESULTS

Table A3. In- and out-of-sample forecasting for x_t: FCI (Sample: 1986:01 – 2012:01)

Horizon (h) months ahead:	*1m*	*3m*	*6m*	*9m*	*12m*	*15m*	*18m*	*21m*	*24m*
Manufacturing production growth as dependent variable									
q_1	9	10	7	4	2	2	2	2	2
q_2	12	10	9	12	12	12	12	12	12
Wald	34.808 (0.000)***	23.057 (0.008)***	14.834 (0.064)*	22.267 (0.038)**	20.599 (0.058)*	25.111 (0.018)**	20.510 (0.046)**	27.421 (0.014)**	22.786 (0.026)**
Theil's U	1.032	1.005	**0.976**	**0.985**	1.029	1.049	1.060	1.058	1.066
MSE-T	-1.383 (0.678)	-0.105 (0.218)	0.392 (0.092)*	0.246 (0.140)	-0.586 (0.366)	-1.066 (0.574)	-1.450 (0.734)	-1.452 (0.754)	-1.477 (0.746)
MSE-F	-19.169 (0.984)	-2.973 (0.508)	15.121 (0.020)**	9.176 (0.060)*	-16.859 (0.726)	-27.096 (0.832)	-32.363 (0.858)	-31.488 (0.804)	-34.591 (0.872)
ENC-T	1.351 (0.058)*	1.585 (0.064)*	1.752 (0.048)**	2.068 (0.032)**	1.974 (0.048)**	2.155 (0.028)**	2.198 (0.042)**	2.109 (0.034)**	1.332 (0.114)
ENC-NEW	9.376 (0.002)***	23.158 (0.002)***	36.250 (0.004)***	40.079 (0.006)***	28.372 (0.030)**	26.080 (0.036)**	24.168 (0.056)*	23.177 (0.048)**	15.279 (0.082)*
Inflation as dependent variable									
q_1	12	12	12	12	12	12	12	12	12
q_2	1	1	1	1	1	2	2	1	1
Wald	0.008 (0.972)	0.598 (0.630)	2.046 (0.470)	3.502 (0.364)	4.084 (0.334)	7.583 (0.254)	6.655 (0.244)	3.189 (0.388)	2.740 (0.398)
Theil's U	1.004	1.008	1.003	**0.994**	**0.986**	**0.982**	**0.980**	**0.990**	**0.992**
MSE-T	-1.312 (0.668)	-1.907 (0.866)	-0.319 (0.280)	0.538 (0.084)*	0.967 (0.040)**	1.043 (0.062)*	0.928 (0.054)*	0.499 (0.134)	0.389 (0.184)
MSE-F	-2.612 (0.688)	-5.042 (0.684)	-1.739 (0.270)	3.955 (0.116)	8.446 (0.074)*	11.338 (0.078)*	12.086 (0.070)*	6.018 (0.140)	4.415 (0.174)
ENC-T	-1.089 (0.786)	-1.672 (0.914)	-0.051 (0.420)	0.842 (0.190)	1.300 (0.120)	1.378 (0.102)	1.258 (0.112)	0.817 (0.222)	0.701 (0.256)
ENC-NEW	-1.063 (0.850)	-2.187 (0.852)	-0.140 (0.416)	3.239 (0.236)	5.959 (0.186)	7.952 (0.156)	8.553 (0.154)	4.949 (0.252)	3.980 (0.266)
Treasury Bill as dependent variable									
q_1	12	12	12	2	2	11	11	11	10
q_2	6	9	9	8	12	6	6	6	6
Wald	13.285 (0.046)**	20.753 (0.012)**	19.123 (0.026)**	17.077 (0.062)*	27.514 (0.004)***	21.190 (0.020)**	22.263 (0.018)**	22.466 (0.024)**	20.861 (0.032)**
Theil's U	1.032	1.044	1.044	1.046	1.075	1.030	1.019	1.016	1.030
MSE-T	-1.969 (0.836)	-1.758 (0.812)	-1.254 (0.588)	-1.031 (0.520)	-1.440 (0.738)	-0.600 (0.338)	-0.404 (0.274)	-0.317 (0.262)	-0.577 (0.346)
MSE-F	-18.951 (0.972)	-25.903 (0.978)	-25.312 (0.916)	-26.117 (0.854)	-40.755 (0.906)	-17.113 (0.678)	-11.162 (0.526)	-8.946 (0.448)	-16.657 (0.650)
ENC-T	-0.410 (0.542)	-0.373 (0.528)	0.240 (0.298)	0.759 (0.174)	0.719 (0.210)	1.158 (0.116)	1.460 (0.098)*	1.613 (0.074)*	1.397 (0.100)
ENC-NEW	-1.859 (0.910)	-2.599 (0.892)	2.348 (0.214)	9.480 (0.086)*	9.796 (0.106)	18.307 (0.054)*	22.475 (0.046)**	24.622 (0.050)*	21.425 (0.058)*

Notes: *Wald* is the in-sample *F*-statistic used to test the null hypothesis of no Granger-causality (bootstrapped *p*-values in parenthesis). ***/**/* indicates rejection of the null hypothesis (i.e. there is evidence of in-sample Granger causality) at the 1/5/10% level of significance. If Theil's $U < 1$ then *RMSFE* of the unrestricted model is < *RMSFE* of the restricted model, indicating the relevance of the individual financial variables as "forecasters" (i.e. lower Theil's *U* values are preferable). *MSE-T* and *MSE-F* test the null hypothesis of equal forecasting ability between the restricted and unrestricted models (bootstrapped *p*-values in parenthesis). ***/**/* indicates rejection of the null hypothesis (i.e. the financial variables of the unrestricted model have out-of-sample forecasting ability) at the 1/5/10% level of significance. *ENC-T* and *ENC-NEW* test the null hypothesis that the restricted model forecast encompasses the unrestricted model forecast (bootstrapped *p*-values in parenthesis). ***/**/* indicates rejection of the null hypothesis (i.e. the financial variables of the unrestricted model are relevant in out-of-sample forecasting) at the 1/5/10% level of significance.

Table A4. In- and out-of-sample forecasting: Manufacturing production growth as dependent variable (Sample: 1986:01 – 2012:01)

Horizon (h) months ahead:	*1m*	*3m*	*6m*	*9m*	*12m*	*15m*	*18m*	*21m*	*24m*
x_t*: FCI*									
q_1	9	10	7	4	2	2	2	2	2
q_2	12	10	9	12	12	12	12	12	12
Wald	34.808 (0.000)***	23.057 (0.008)***	14.834 (0.064)*	22.267 (0.038)**	20.599 (0.058)*	25.111 (0.018)**	20.510 (0.046)**	27.421 (0.014)**	22.786 (0.026)**
Theil's U	1.032	1.005	**0.976**	**0.985**	1.029	1.049	1.060	1.058	1.066
MSE-T	-1.383 (0.678)	-0.105 (0.218)	0.392 (0.092)*	0.246 (0.140)	-0.586 (0.366)	-1.066 (0.574)	-1.450 (0.734)	-1.452 (0.754)	-1.477 (0.746)
MSE-F	-19.169 (0.984)	-2.973 (0.508)	15.121 (0.020)**	9.176 (0.060)*	-16.859 (0.726)	-27.096 (0.832)	-32.363 (0.858)	-31.488 (0.804)	-34.591 (0.872)
ENC-T	1.351 (0.058)*	1.585 (0.064)*	1.752 (0.048)**	2.068 (0.032)**	1.974 (0.048)**	2.155 (0.028)**	2.198 (0.042)**	2.109 (0.034)**	1.332 (0.114)
ENC-NEW	9.376 (0.002)***	23.158 (0.002)***	36.250 (0.004)***	40.079 (0.006)***	28.372 (0.030)**	26.080 (0.036)**	24.168 (0.056)*	23.177 (0.048)**	15.279 (0.082)*
x_t*: US Consumer Sentiment Index*									
q_1	9	12	7	4	2	2	2	2	5
q_2	3	1	1	1	12	12	12	12	12
Wald	0.528 (0.648)	0.209 (0.802)	0.137 (0.866)	0.112 (0.824)	22.803 (0.020)**	13.919 (0.126)	11.082 (0.178)	12.248 (0.162)	7.425 (0.246)
Theil's U	1.015	1.007	1.015	1.021	1.069	1.101	1.119	1.137	1.156
MSE-T	-1.718 (0.800)	-1.685 (0.810)	-1.508 (0.728)	-1.150 (0.544)	-1.671 (0.806)	-1.925 (0.854)	-2.055 (0.892)	-2.320 (0.964)	-2.566 (0.988)
MSE-F	-9.086 (0.888)	-4.123 (0.524)	-9.320 (0.536)	-12.280 (0.572)	-37.687 (0.846)	-52.453 (0.868)	-59.673 (0.824)	-66.305 (0.900)	-73.120 (0.868)
ENC-T	-1.044 (0.792)	-1.530 (0.920)	-1.375 (0.852)	-1.012 (0.738)	-1.166 (0.778)	-1.578 (0.864)	-1.792 (0.904)	-2.077 (0.968)	-2.329 (0.980)
ENC- NEW	-2.528 (0.942)	-1.814 (0.806)	-4.184 (0.796)	-5.301 (0.802)	-12.209 (0.902)	-19.335 (0.942)	-22.739 (0.936)	-25.307 (0.978)	-26.874 (0.962)
x_t*: All-Share Index*									
q_1	9	11	2	2	2	2	2	2	2
q_2	3	3	12	12	11	11	9	8	5
Wald	14.766 (0.046)**	7.001 (0.122)	18.910 (0.018)**	27.316 (0.002)***	24.449 (0.006)***	29.836 (0.000)***	14.013 (0.050)*	10.938 (0.098)*	11.230 (0.084)*
Theil's U	**0.993**	**0.996**	1.031	1.046	1.049	1.048	1.034	1.017	1.007
MSE-T	0.624 (0.042)**	0.257 (0.116)	-1.071 (0.610)	-1.296 (0.712)	-1.118 (0.628)	-1.085 (0.626)	-0.852 (0.568)	-0.639 (0.464)	-0.376 (0.828)
MSE-F	4.116 (0.004)***	2.189 (0.046)**	-18.360 (0.914)	-25.989 (0.932)	-27.695 (0.944)	-26.625 (0.938)	-18.882 (0.894)	-9.706 (0.854)	-3.750 (0.828)
ENC-T	1.727 (0.040)**	0.790 (0.162)	0.304 (0.264)	0.224 (0.308)	0.211 (0.332)	0.275 (0.284)	0.507 (0.258)	0.920 (0.192)	1.140 (0.120)
ENC- NEW	5.841 (0.016)**	3.274 (0.068)*	2.418 (0.074)*	1.890 (0.098)*	2.153 (0.102)	2.733 (0.078)*	4.359 (0.074)*	5.702 (0.068)*	4.809 (0.048)**
x_t*: House price index*									
q_1	9	12	7	4	2	3	3	3	2
q_2	2	2	12	12	12	12	10	7	1
Wald	14.924 (0.026)**	16.783 (0.034)**	30.692 (0.000)***	21.318 (0.028)*	31.234 (0.010)**	24.164 (0.028)**	29.349 (0.006)***	16.708 (0.078)*	2.756 (0.432)
Theil's U	**0.998**	**0.988**	1.008	1.005	1.017	1.030	1.019	1.014	1.001
MSE-T	0.216 (0.106)	0.647 (0.064)*	-0.257 (0.204)	-0.126 (0.190)	-0.379 (0.288)	-0.649 (0.412)	-0.542 (0.338)	-0.592 (0.342)	-0.082 (0.240)
MSE-F	1.566 (0.048)**	7.478 (0.028)**	-4.669 (0.456)	-2.934 (0.280)	-10.095 (0.636)	-17.135 (0.716)	-11.133 (0.572)	-8.091 (0.406)	-0.566 (0.232)
ENC-T	1.672 (0.036)**	2.002 (0.040)**	1.242 (0.098)*	1.247 (0.110)	0.857 (0.202)	0.328 (0.334)	0.294 (0.312)	0.045 (0.354)	0.560 (0.242)
ENC- NEW	6.323 (0.008)***	11.635 (0.010)**	10.762 (0.048)**	13.798 (0.060)*	10.650 (0.120)	3.759 (0.284)	2.568 (0.290)	0.262 (0.350)	1.904 (0.308)

Horizon (h) months ahead:	*1m*	*3m*	*6m*	*9m*	*12m*	*15m*	*18m*	*21m*	*24m*
x_t*: Rand-Dollar exchange rate*									
q_1	9	12	7	2	2	2	2	2	2
q_2	10	10	12	12	12	11	12	10	9
Wald	13.028 (0.054)*	14.175 (0.046)**	17.987 (0.024)**	18.560 (0.040)**	19.622 (0.032)**	20.306 (0.030)**	23.355 (0.022)**	27.686 (0.008)***	12.330 (0.086)*
Theil's U	1.048	1.059	1.075	1.112	1.132	1.127	1.133	1.121	1.085
MSE-T	-2.116 (0.876)	-2.531 (0.980)	-1.753 (0.844)	-1.850 (0.882)	-1.916 (0.888)	-1.911 (0.916)	-2.000 (0.942)	-1.962 (0.936)	-2.071 (0.932)
MSE-F	-27.999 (1.000)	-33.911 (0.998)	-41.586 (0.996)	-58.150 (1.000)	-66.185 (0.998)	-63.418 (0.994)	-65.426 (0.992)	-59.742 (0.992)	-43.493 (0.968)
ENC-T	0.117 (0.346)	-0.101 (0.442)	-0.237 (0.472)	-0.502 (0.594)	-0.349 (0.480)	-0.264 (0.498)	-0.065 (0.394)	-0.133 (0.434)	0.136 (0.346)
ENC- NEW	0.684 (0.214)	-0.554 (0.722)	-2.223 (0.890)	-5.431 (0.938)	-3.861 (0.902)	-3.090 (0.882)	-0.775 (0.748)	-1.434 (0.844)	1.190 (0.176)
x_t*: S&P500 index*									
q_1	9	12	7	4	2	2	2	3	2
q_2	1	1	1	1	1	1	1	1	1
Wald	1.684 (0.386)	0.009 (0.946)	0.794 (0.568)	0.016 (0.952)	0.138 (0.818)	0.018 (0.928)	0.136 (0.826)	0.000 (0.992)	0.067 (0.876)
Theil's U	1.000	1.005	1.003	1.005	1.006	1.006	1.006	1.004	1.005
MSE-T	-0.032 (0.152)	-0.597 (0.348)	-0.928 (0.542)	-0.727 (0.400)	-0.992 (0.538)	-0.699 (0.442)	-0.588 (0.398)	-0.790 (0.464)	-0.704 (0.454)
MSE-F	-0.103 (0.166)	-3.333 (0.718)	-1.931 (0.624)	-3.128 (0.642)	-3.635 (0.654)	-3.675 (0.726)	-3.618 (0.684)	-2.328 (0.606)	-2.671 (0.668)
ENC-T	0.749 (0.158)	-0.134 (0.448)	-0.711 (0.642)	-0.407 (0.498)	-0.733 (0.620)	-0.305 (0.468)	-0.124 (0.410)	-0.482 (0.514)	-0.227 (0.460)
ENC- NEW	1.209 (0.150)	-0.374 (0.604)	-0.734 (0.754)	-0.886 (0.702)	-1.329 (0.782)	-0.789 (0.704)	-0.373 (0.518)	-0.689 (0.664)	-0.426 (0.564)
x_t*: Dividend yield*									
q_1	10	12	2	5	2	2	5	2	5
q_2	3	1	9	8	5	5	5	4	5
Wald	16.070 (0.042)**	2.951 (0.374)	10.718 (0.104)	8.720 (0.148)	11.915 (0.114)	11.709 (0.100)	10.329 (0.184)	6.304 (0.286)	9.550 (0.240)
Theil's U	1.002	1.013	1.022	1.040	1.046	1.044	1.044	1.024	1.034
MSE-T	-0.206 (0.178)	-1.251 (0.582)	-0.848 (0.376)	-1.795 (0.800)	-1.582 (0.728)	-1.545 (0.710)	-1.450 (0.702)	-1.139 (0.552)	-1.374 (0.668)
MSE-F	-1.252 (0.390)	-8.129 (0.704)	-13.113 (0.642)	-22.745 (0.760)	-25.790 (0.702)	-24.836 (0.670)	-24.196 (0.570)	-13.587 (0.364)	-18.915 (0.444)
ENC-T	1.171 (0.108)	-0.677 (0.634)	0.044 (0.348)	-0.803 (0.654)	-0.816 (0.616)	-0.776 (0.606)	-0.668 (0.594)	-0.307 (0.484)	-0.537 (0.558)
ENC- NEW	3.614 (0.072)*	-2.040 (0.776)	0.338 (0.338)	-4.040 (0.694)	-5.882 (0.676)	-5.480 (0.636)	-4.486 (0.586)	-1.602 (0.436)	-2.726 (0.498)
x_t*: Federal Funds rate*									
q_1	9	12	7	4	2	2	2	2	5
q_2	4	7	4	8	7	11	12	12	12
Wald	4.897 (0.240)	9.940 (0.096)*	5.254 (0.286)	11.368 (0.098)*	8.674 (0.204)	31.242 (0.016)**	14.859 (0.096)*	19.368 (0.080)*	25.614 (0.028)**
Theil's U	1.020	1.015	1.019	1.014	1.027	1.036	1.055	1.068	1.102
MSE-T	-1.391 (0.694)	-1.265 (0.614)	-1.505 (0.720)	-0.766 (0.368)	-1.121 (0.530)	-1.242 (0.580)	-1.740 (0.808)	-2.007 (0.898)	-3.044 (0.986)
MSE-F	-12.059 (0.920)	-9.122 (0.812)	-11.380 (0.670)	-8.366 (0.414)	-15.754 (0.562)	-20.153 (0.558)	-30.110 (0.648)	-36.279 (0.692)	-51.244 (0.740)
ENC-T	-1.113 (0.830)	-0.549 (0.570)	-0.913 (0.726)	0.348 (0.282)	0.032 (0.382)	0.441 (0.290)	0.308 (0.262)	0.317 (0.316)	0.030 (0.374)
ENC- NEW	-4.118 (0.994)	-1.836 (0.772)	-3.286 (0.768)	1.958 (0.288)	0.233 (0.384)	4.104 (0.294)	3.325 (0.264)	3.812 (0.316)	0.367 (0.378)
x_t*: M3 money supply growth*									
q_1	9	12	4	2	2	2	2	2	2

Horizon (h) months ahead:	*1m*	*3m*	*6m*	*9m*	*12m*	*15m*	*18m*	*21m*	*24m*
q_2	6	7	7	6	5	3	2	1	1
Wald	7.853 (0.096)*	10.677 (0.082)*	16.003 (0.036)**	17.815 (0.022)**	19.729 (0.022)**	17.196 (0.040)**	6.641 (0.246)	1.238 (0.566)	0.070 (0.920)
Theil's U	1.038	1.036	1.058	1.031	1.030	1.025	1.026	1.017	1.014
MSE-T	-1.957 (0.850)	-1.176 (0.630)	-1.532 (0.762)	-0.806 (0.458)	-0.704 (0.416)	-0.691 (0.462)	-1.141 (0.602)	-1.374 (0.716)	-1.634 (0.828)
MSE-F	-22.427 (0.996)	-21.093 (0.982)	-32.760 (0.978)	-18.268 (0.866)	-17.584 (0.844)	-14.648 (0.776)	-14.828 (0.774)	-9.755 (0.714)	-8.044 (0.670)
ENC-T	0.537 (0.242)	0.873 (0.140)	1.080 (0.116)	1.513 (0.062)*	1.277 (0.112)	0.900 (0.192)	-0.008 (0.398)	-0.355 (0.470)	-1.074 (0.742)
ENC- NEW	3.123 (0.054)*	8.217 (0.014)**	13.619 (0.024)**	21.348 (0.024)**	19.330 (0.022)**	10.423 (0.074)*	-0.053 (0.398)	-1.262 (0.650)	-2.478 (0.748)
x_t*: Bond spread*									
q_1	9	12	7	4	2	2	2	3	2
q_2	2	1	1	1	1	1	1	1	1
Wald	3.501 (0.228)	1.218 (0.576)	1.256 (0.510)	1.342 (0.570)	0.966 (0.614)	0.831 (0.634)	0.676 (0.646)	0.539 (0.736)	0.342 (0.768)
Theil's U	1.006	1.013	1.042	1.062	1.103	1.125	1.142	1.149	1.166
MSE-T	-0.807 (0.432)	-1.352 (0.682)	-1.243 (0.582)	-1.164 (0.582)	-1.164 (0.590)	-1.197 (0.572)	-1.240 (0.610)	-1.225 (0.602)	-1.165 (0.586)
MSE-F	-3.763 (0.754)	-7.996 (0.776)	-24.238 (0.894)	-34.737 (0.914)	-53.685 (0.950)	-62.622 (0.960)	-69.205 (0.968)	-70.898 (0.934)	-76.624 (0.940)
ENC-T	0.171 (0.344)	-0.862 (0.740)	-0.981 (0.692)	-0.967 (0.708)	-0.987 (0.722)	-1.032 (0.686)	-1.082 (0.712)	-1.056 (0.730)	-0.965 (0.686)
ENC- NEW	0.382 (0.300)	-2.466 (0.862)	-9.105 (0.964)	-13.438 (0.976)	-20.287 (0.992)	-23.411 (0.992)	-25.471 (0.994)	-25.263 (0.976)	-25.507 (0.980)
x_t*: Mortgage spread*									
q_1	9	11	4	2	2	2	2	3	2
q_2	1	1	12	12	10	12	12	9	6
Wald	4.795 (0.188)	4.816 (0.246)	28.204 (0.008)***	28.933 (0.004)***	40.497 (0.000)***	25.920 (0.022)**	39.210 (0.004)***	25.007 (0.024)**	22.017 (0.040)**
Theil's U	1.017	1.019	1.060	1.085	1.057	1.077	1.067	1.007	**0.989**
MSE-T	-1.873 (0.836)	-1.254 (0.606)	-1.449 (0.708)	-1.136 (0.588)	-0.894 (0.442)	-0.937 (0.490)	-0.871 (0.450)	-0.185 (0.230)	0.291 (0.140)
MSE-F	-10.240 (0.916)	-11.277 (0.856)	-33.779 (0.970)	-45.733 (0.974)	-31.730 (0.886)	-41.384 (0.932)	-35.962 (0.876)	-4.285 (0.314)	6.434 (0.122)
ENC-T	-0.944 (0.734)	-0.151 (0.436)	-0.096 (0.454)	-0.217 (0.442)	-0.149 (0.402)	-0.170 (0.430)	-0.105 (0.414)	0.558 (0.216)	0.896 (0.190)
ENC- NEW	-2.559 (0.954)	-0.673 (0.564)	-0.658 (0.486)	-2.101 (0.586)	-1.977 (0.502)	-2.605 (0.558)	-1.468 (0.488)	5.906 (0.200)	9.998 (0.168)
x_t*: Bill spread*									
q_1	9	12	7	4	2	2	2	2	2
q_2	1	1	1	1	1	12	12	12	11
Wald	0.022 (0.906)	0.001 (0.990)	0.038 (0.936)	0.309 (0.752)	0.377 (0.736)	7.775 (0.196)	13.665 (0.082)*	10.539 (0.166)	10.931 (0.156)
Theil's U	1.001	1.003	1.003	1.004	1.008	1.037	1.051	1.060	1.057
MSE-T	-0.704 (0.364)	-1.057 (0.546)	-0.927 (0.504)	-0.725 (0.384)	-0.831 (0.440)	-2.023 (0.934)	-1.954 (0.872)	-1.704 (0.834)	-1.502 (0.756)
MSE-F	-0.806 (0.332)	-1.997 (0.386)	-2.063 (0.324)	-2.577 (0.246)	-4.796 (0.356)	-20.712 (0.756)	-27.918 (0.778)	-32.155 (0.828)	-30.492 (0.826)
ENC-T	-0.416 (0.546)	-0.781 (0.684)	-0.565 (0.592)	-0.272 (0.454)	-0.371 (0.492)	-1.160 (0.760)	-1.364 (0.816)	-1.335 (0.824)	-1.138 (0.748)
ENC- NEW	-0.240 (0.476)	-0.737 (0.580)	-0.636 (0.486)	-0.473 (0.394)	-1.013 (0.434)	-5.695 (0.774)	-9.360 (0.846)	-12.174 (0.894)	-11.203 (0.880)
x_t*: Term spread*									
q_1	9	11	7	2	2	2	2	3	2
q_2	1	12	12	12	12	12	12	9	8
Wald	16.780 (0.010)**	35.190 (0.000)***	55.440 (0.000)***	41.035 (0.000)***	41.415 (0.000)***	27.120 (0.014)**	39.553 (0.004)***	26.284 (0.024)**	22.274 (0.036)**

Horizon (h) months ahead:	1m	3m	6m	9m	12m	15m	18m	21m	24m
Theil's U	**0.988**	1.020	1.056	1.115	1.121	1.112	1.070	**0.994**	**0.936**
MSE-T	1.389 (0.012)**	-0.570 (0.270)	-0.549 (0.324)	-0.587 (0.374)	-0.548 (0.332)	-0.509 (0.340)	-0.370 (0.280)	0.050 (0.176)	0.689 (0.056)*
MSE-F	7.625 (0.002)***	-12.110 (0.838)	-31.996 (0.946)	-59.571 (0.980)	-61.822 (0.976)	-57.255 (0.922)	-37.347 (0.758)	3.813 (0.138)	40.940 (0.024)**
ENC-T	2.640 (0.004)***	2.022 (0.032)**	2.531 (0.016)**	1.020 (0.162)	0.620 (0.266)	0.568 (0.288)	0.811 (0.204)	1.498 (0.094)*	1.911 (0.044)**
ENC- NEW	7.167 (0.004)***	12.690 (0.016)**	24.377 (0.024)**	21.564 (0.054)*	17.258 (0.100)	17.086 (0.150)	22.095 (0.092)*	34.849 (0.056)*	46.186 (0.042)**
x_t: Stock exchange volatility									
q_1	9	12	7	4	2	2	2	2	2
q_2	1	1	1	1	1	1	12	11	12
Wald	0.002 (0.970)	1.175 (0.516)	0.498 (0.634)	0.112 (0.832)	0.036 (0.906)	0.395 (0.700)	12.534 (0.104)	3.897 (0.304)	18.892 (0.072)*
Theil's U	1.001	1.003	1.007	1.005	1.007	1.006	1.057	1.073	1.085
MSE-T	-2.091 (0.900)	-1.305 (0.660)	-0.817 (0.434)	-1.661 (0.828)	-1.968 (0.946)	-1.013 (0.616)	-2.038 (0.934)	-2.302 (0.964)	-2.504 (0.992)
MSE-F	-0.764 (0.358)	-1.700 (0.526)	-4.325 (0.692)	-2.738 (0.564)	-4.056 (0.716)	-3.614 (0.690)	-30.977 (0.932)	-38.550 (0.936)	-43.822 (0.936)
ENC-T	-1.992 (0.960)	-1.218 (0.816)	-0.351 (0.480)	-1.403 (0.850)	-1.906 (0.968)	-0.304 (0.502)	-1.307 (0.808)	-1.523 (0.896)	-1.451 (0.868)
ENC- NEW	-0.362 (0.632)	-0.750 (0.736)	-0.503 (0.622)	-0.897 (0.708)	-1.439 (0.820)	-0.234 (0.522)	-7.494 (0.936)	-9.947 (0.956)	-11.165 (0.976)
x_t: Government bond volatility									
q_1	9	12	7	4	2	2	12	3	2
q_2	1	1	1	1	1	12	12	12	12
Wald	2.679 (0.308)	4.978 (0.182)	2.486 (0.386)	5.875 (0.216)	4.670 (0.248)	18.055 (0.048)**	12.686 (0.122)	11.210 (0.140)	14.689 (0.082)
Theil's U	**0.998**	**0.993**	**0.994**	**0.989**	**0.994**	1.065	1.109	1.101	1.097
MSE-T	0.725 (0.040)**	1.919 (0.000)***	1.326 (0.020)**	1.467 (0.014)**	1.107 (0.032)**	-1.648 (0.830)	-2.214 (0.940)	-2.011 (0.928)	-1.980 (0.916)
MSE-F	1.302 (0.044)**	4.183 (0.014)**	3.692 (0.026)**	7.095 (0.026)**	3.792 (0.044)**	-35.216 (0.944)	-55.520 (0.946)	-51.170 (0.958)	-48.898 (0.978)
ENC-T	1.228 (0.068)*	2.167 (0.010)**	1.419 (0.076)*	1.890 (0.026)**	1.610 (0.056)*	-0.041 (0.408)	-0.944 (0.702)	-0.586 (0.582)	-0.126 (0.442)
ENC- NEW	1.090 (0.144)	2.492 (0.080)*	2.040 (0.148)	4.878 (0.102)	3.113 (0.128)	-0.382 (0.494)	-9.978 (0.944)	-5.589 (0.894)	-1.232 (0.760)
x_t: House price volatility									
q_1	9	12	7	4	2	2	2	3	2
q_2	1	1	1	1	1	1	1	1	1
Wald	0.107 (0.850)	0.000 (0.994)	0.037 (0.918)	0.001 (0.996)	0.185 (0.834)	0.426 (0.714)	0.266 (0.792)	0.357 (0.738)	0.095 (0.860)
Theil's U	1.001	1.002	1.002	1.003	1.007	1.013	1.018	1.026	1.030
MSE-T	-0.828 (0.446)	-1.624 (0.784)	-1.051 (0.536)	-0.847 (0.468)	-0.944 (0.550)	-1.032 (0.572)	-1.230 (0.678)	-1.314 (0.692)	-1.526 (0.754)
MSE-F	-0.456 (0.242)	-1.328 (0.350)	-1.524 (0.286)	-1.529 (0.300)	-4.213 (0.518)	-7.837 (0.642)	-10.636 (0.700)	-14.426 (0.720)	-16.840 (0.730)
ENC-T	-0.688 (0.654)	-1.584 (0.910)	-0.913 (0.708)	-0.783 (0.628)	-0.787 (0.690)	-0.798 (0.664)	-1.007 (0.752)	-1.042 (0.738)	-1.342 (0.802)
ENC- NEW	-0.188 (0.486)	-0.624 (0.604)	-0.652 (0.490)	-0.702 (0.508)	-1.745 (0.674)	-3.003 (0.756)	-4.329 (0.814)	-5.691 (0.810)	-7.255 (0.850)
x_t: Private sector credit extension									
q_1	9	10	7	7	4	3	6	3	3
q_2	2	12	12	12	12	12	10	8	5
Wald	1.279 (0.484)	13.836 (0.038)**	14.888 (0.034)**	14.083 (0.044)**	13.450 (0.068)*	15.294 (0.066)*	13.547 (0.084)*	10.352 (0.138)	6.311 (0.292)
Theil's U	1.008	1.058	1.051	1.044	1.042	1.045	1.041	1.028	1.016
MSE-T	-1.002 (0.506)	-2.347 (0.944)	-1.456 (0.756)	-1.141 (0.602)	-0.979 (0.490)	-0.892 (0.456)	-0.792 (0.418)	-0.770 (0.456)	-0.752 (0.422)

Horizon (h) months ahead:	*1m*	*3m*	*6m*	*9m*	*12m*	*15m*	*18m*	*21m*	*24m*
MSE-F	-4.848 (0.770)	-33.221 (0.992)	-29.333 (0.970)	-25.116 (0.910)	-23.864 (0.868)	-25.413 (0.864)	-23.072 (0.846)	-15.856 (0.826)	-9.130 (0.672)
ENC-T	0.282 (0.270)	-0.011 (0.400)	0.892 (0.136)	0.978 (0.166)	0.828 (0.184)	0.926 (0.168)	0.913 (0.172)	0.855 (0.190)	0.594 (0.228)
ENC- NEW	0.676 (0.186)	-0.076 (0.424)	8.986 (0.028)**	10.696 (0.036)**	9.099 (0.050)*	11.342 (0.066)*	10.718 (0.056)*	6.875 (0.098)*	2.784 (0.158)

Notes: *Wald* is the in-sample *F*-statistic used to test the null hypothesis of no Granger-causality (bootstrapped *p*-values in parenthesis). ***/**/* indicates rejection of the null hypothesis (i.e. there is evidence of in-sample Granger causality) at the 1/5/10% level of significance. If Theil's $U < 1$ then *RMSFE* of the unrestricted model is < *RMSFE* of the restricted model, indicating the relevance of the individual financial variables as "forecasters" (i.e. lower Theil's *U* values are preferable). *MSE-T* and *MSE-F* test the null hypothesis of equal forecasting ability between the restricted and unrestricted models (bootstrapped *p*-values in parenthesis). ***/**/* indicates rejection of the null hypothesis (i.e. the financial variables of the unrestricted model have out-of-sample forecasting ability) at the 1/5/10% level of significance. *ENC-T* and *ENC-NEW* test the null hypothesis that the restricted model forecast encompasses the unrestricted model forecast (bootstrapped *p*-values in parenthesis). ***/**/* indicates rejection of the null hypothesis (i.e. the financial variables of the unrestricted model are relevant in out-of-sample forecasting) at the 1/5/10% level of significance.

Table A5. In- and out-of-sample forecasting: Inflation as dependent variable (Sample: 1986:01 – 2012:01)

Horizon (h) months ahead:	*1m*	*3m*	*6m*	*9m*	*12m*	*15m*	*18m*	*21m*	*24m*
x_t: *FCI*									
q_1	12	12	12	12	12	12	12	12	12
q_2	1	1	1	1	1	2	2	1	1
Wald	0.008 (0.972)	0.598 (0.630)	2.046 (0.470)	3.502 (0.364)	4.084 (0.334)	7.583 (0.254)	6.655 (0.244)	3.189 (0.388)	2.740 (0.398)
Theil's U	1.004	1.008	1.003	**0.994**	**0.986**	**0.982**	**0.980**	**0.990**	**0.992**
MSE-T	-1.312 (0.668)	-1.907 (0.866)	-0.319 (0.280)	0.538 (0.084)*	0.967 (0.040)**	1.043 (0.062)*	0.928 (0.054)*	0.499 (0.134)	0.389 (0.184)
MSE-F	-2.612 (0.688)	-5.042 (0.684)	-1.739 (0.270)	3.955 (0.116)	8.446 (0.074)*	11.338 (0.078)*	12.086 (0.070)*	6.018 (0.140)	4.415 (0.174)
ENC-T	-1.089 (0.786)	-1.672 (0.914)	-0.051 (0.420)	0.842 (0.190)	1.300 (0.120)	1.378 (0.102)	1.258 (0.112)	0.817 (0.222)	0.701 (0.256)
ENC-NEW	-1.063 (0.850)	-2.187 (0.852)	-0.140 (0.416)	3.239 (0.236)	5.959 (0.186)	7.952 (0.156)	8.553 (0.154)	4.949 (0.252)	3.980 (0.266)
x_t: *US Consumer Sentiment Index*									
q_1	12	12	12	12	12	12	12	12	12
q_2	9	9	12	6	2	8	7	2	1
Wald	8.908 (0.150)	5.553 (0.308)	7.454 (0.232)	2.968 (0.466)	2.168 (0.548)	2.863 (0.560)	4.772 (0.462)	3.911 (0.494)	0.154 (0.890)
Theil's U	1.032	1.035	1.046	1.035	1.021	1.059	1.069	1.045	1.045
MSE-T	-3.078 (0.986)	-3.484 (1.000)	-3.508 (1.000)	-3.004 (0.996)	-1.746 (0.874)	-1.919 (0.866)	-1.832 (0.874)	-2.017 (0.896)	-2.196 (0.940)
MSE-F	-19.001 (0.952)	-20.437 (0.902)	-26.693 (0.828)	-20.189 (0.644)	-12.366 (0.444)	-32.330 (0.692)	-36.892 (0.704)	-24.838 (0.464)	-24.295 (0.546)
ENC-T	-1.762 (0.962)	-2.600 (0.994)	-2.738 (1.000)	-2.459 (0.994)	-1.538 (0.924)	-1.756 (0.922)	-1.631 (0.922)	-1.885 (0.936)	-2.140 (0.976)
ENC- NEW	-5.216 (0.992)	-7.089 (0.976)	-8.538 (0.916)	-7.404 (0.854)	-5.043 (0.714)	-11.919 (0.864)	-13.309 (0.870)	-10.422 (0.716)	-10.657 (0.742)
x_t: *All-Share Index*									
q_1	12	12	12	12	12	12	12	12	12
q_2	1	1	1	1	4	1	5	12	9
Wald	0.038 (0.902)	1.010 (0.508)	4.101 (0.226)	5.696 (0.186)	8.087 (0.100)	6.466 (0.146)	6.588 (0.158)	10.641 (0.100)	8.148 (0.140)
Theil's U	1.002	1.000	**0.997**	**0.994**	**0.977**	**0.993**	**0.977**	**0.974**	**0.968**
MSE-T	-1.254 (0.618)	-0.040 (0.178)	0.569 (0.078)*	1.561 (0.006)***	1.706 (0.006)***	1.688 (0.006)***	1.321 (0.028)**	0.774 (0.078)*	1.044 (0.080)*
MSE-F	-1.206 (0.468)	-0.085 (0.180)	1.602 (0.062)*	3.558 (0.042)**	14.548 (0.014)**	4.469 (0.026)**	14.098 (0.014)**	16.072 (0.014)**	19.572 (0.024)**
ENC-T	-1.138 (0.830)	0.263 (0.306)	1.137 (0.108)	2.003 (0.032)**	2.049 (0.028)**	2.110 (0.014)**	1.586 (0.058)*	1.113 (0.130)	1.408 (0.122)
ENC- NEW	-0.543 (0.700)	0.262 (0.302)	1.524 (0.152)	2.299 (0.136)	9.316 (0.042)**	2.883 (0.080)*	8.885 (0.042)**	11.639 (0.036)**	13.429 (0.052)*
x_t: *House price index*									
q_1	12	12	12	12	12	12	12	12	12
q_2	12	10	11	2	1	1	1	2	2
Wald	45.133 (0.026)**	36.167 (0.040)**	6.915 (0.248)	0.997 (0.656)	0.137 (0.862)	0.024 (0.944)	0.002 (0.980)	0.065 (0.888)	0.007 (0.982)
Theil's U	**0.994**	1.008	1.026	1.020	1.019	1.019	1.018	1.023	1.022
MSE-T	0.305 (0.134)	-0.678 (0.418)	-1.571 (0.796)	-1.868 (0.868)	-2.081 (0.940)	-2.371 (0.970)	-2.344 (0.952)	-2.215 (0.958)	-2.356 (0.970)
MSE-F	3.729 (0.072)*	-5.077 (0.598)	-15.313 (0.816)	-11.969 (0.650)	-11.346 (0.604)	-11.159 (0.554)	-10.568 (0.594)	-12.926 (0.592)	-12.201 (0.578)
ENC-T	2.697 (0.052)*	0.929 (0.256)	-1.088 (0.788)	-1.514 (0.890)	-1.842 (0.958)	-2.206 (0.986)	-2.243 (0.978)	-2.095 (0.966)	-2.259 (0.982)
ENC- NEW	17.229 (0.036)**	3.378 (0.232)	-5.025 (0.900)	-4.610 (0.804)	-4.698 (0.798)	-4.919 (0.750)	-4.852 (0.766)	-5.863 (0.762)	-5.636 (0.756)

Horizon (h) months ahead:	1m	3m	6m	9m	12m	15m	18m	21m	24m
x_t: Rand-Dollar exchange rate									
q_1	12	12	12	12	12	12	12	12	12
q_2	8	8	7	5	3	1	12	12	12
Wald	31.748 (0.002)***	19.172 (0.012)**	20.229 (0.008)***	14.892 (0.026)**	10.700 (0.108)	4.320 (0.246)	12.853 (0.068)*	12.518 (0.064)*	15.368 (0.054)*
Theil's U	1.019	**0.986**	**0.952**	**0.937**	**0.947**	**0.990**	**0.969**	**0.987**	**0.997**
MSE-T	-0.664 (0.360)	0.371 (0.074)*	0.890 (0.038)**	1.017 (0.036)**	0.932 (0.054)*	0.750 (0.096)*	0.453 (0.126)	0.213 (0.182)	0.054 (0.232)
MSE-F	-11.628 (0.926)	9.050 (0.004)***	31.795 (0.000)***	42.585 (0.000)***	34.440 (0.004)***	6.256 (0.026)**	19.047 (0.006)***	7.905 (0.028)**	1.882 (0.102)
ENC-T	1.122 (0.088)*	1.759 (0.030)**	1.873 (0.026)**	1.842 (0.022)**	1.759 (0.044)**	1.400 (0.90)*	1.244 (0.112)	1.105 (0.148)	0.994 (0.190)
ENC- NEW	8.811 (0.002)***	23.322 (0.000)***	38.811 (0.000)***	43.652 (0.000)***	34.534 (0.004)**	5.863 (0.056)*	27.341 (0.006)***	20.650 (0.022)**	16.861 (0.042)**
x_t: S&P500 index									
q_1	12	12	12	12	12	12	12	12	12
q_2	1	8	7	4	1	12	12	2	1
Wald	1.011 (0.526)	0.959 (0.496)	1.141 (0.518)	0.927 (0.582)	0.561 (0.620)	2.940 (0.360)	3.556 (0.292)	0.891 (0.560)	0.134 (0.818)
Theil's U	1.001	1.026	1.018	1.010	1.001	1.032	1.035	1.004	1.003
MSE-T	-0.467 (0.242)	-1.966 (0.878)	-1.189 (0.644)	-0.831 (0.474)	-0.287 (0.262)	-1.125 (0.636)	-1.184 (0.640)	-0.338 (0.310)	-0.380 (0.342)
MSE-F	-0.456 (0.194)	-15.389 (0.912)	-11.024 (0.826)	-6.029 (0.752)	-0.730 (0.314)	-18.348 (0.870)	-19.505 (0.868)	-2.488 (0.658)	-1.516 (0.536)
ENC-T	-0.268 (0.476)	-1.282 (0.842)	-0.587 (0.620)	-0.279 (0.474)	0.250 (0.294)	-0.708 (0.646)	-0.751 (0.642)	0.075 (0.346)	-0.052 (0.384)
ENC- NEW	-0.130 (0.432)	-4.420 (0.962)	-2.586 (0.874)	-0.959 (0.756)	0.304 (0.314)	-5.512 (0.896)	-5.815 (0.904)	0.265 (0.300)	-0.099 (0.398)
x_t: Dividend yield									
q_1	12	12	12	12	12	12	12	12	12
q_2	1	1	12	12	12	12	12	12	12
Wald	0.032 (0.920)	0.009 (0.972)	4.630 (0.338)	4.601 (0.382)	6.468 (0.298)	6.183 (0.314)	9.085 (0.208)	12.067 (0.162)	13.535 (0.124)
Theil's U	1.002	1.007	1.043	1.042	1.048	1.051	1.048	1.041	1.022
MSE-T	-0.943 (0.512)	-2.070 (0.892)	-2.235 (0.906)	-1.859 (0.846)	-1.603 (0.768)	-1.349 (0.652)	-1.093 (0.550)	-0.864 (0.454)	-0.504 (0.334)
MSE-F	-1.466 (0.470)	-4.450 (0.492)	-24.868 (0.866)	-24.050 (0.778)	-26.954 (0.708)	-28.325 (0.702)	-26.593 (0.702)	-22.639 (0.552)	-12.260 (0.416)
ENC-T	-0.811 (0.712)	-1.939 (0.980)	-1.782 (0.914)	-1.322 (0.828)	-1.217 (0.814)	-0.932 (0.676)	-0.598 (0.596)	-0.273 (0.490)	0.135 (0.384)
ENC- NEW	-0.620 (0.708)	-1.917 (0.740)	-7.824 (0.934)	-7.214 (0.868)	-7.676 (0.792)	-7.446 (0.734)	-5.722 (0.674)	-2.846 (0.520)	1.426 (0.382)
x_t: Federal Funds rate									
q_1	12	12	12	12	12	12	12	12	12
q_2	7	12	12	12	12	12	12	12	11
Wald	27.840 (0.010)**	41.266 (0.008)***	46.013 (0.004)***	23.092 (0.042)**	36.023 (0.012)**	32.096 (0.016)**	30.493 (0.026)**	32.104 (0.042)**	34.028 (0.012)**
Theil's U	1.005	**0.978**	**0.947**	**0.931**	**0.907**	**0.882**	**0.862**	**0.848**	**0.842**
MSE-T	-0.379 (0.322)	0.953 (0.070)*	1.522 (0.034)**	1.526 (0.052)*	1.779 (0.028)**	1.974 (0.022)**	2.065 (0.022)**	2.124 (0.022)**	2.135 (0.020)**
MSE-F	-3.047 (0.636)	13.944 (0.040)**	35.683 (0.020)**	46.819 (0.032)**	65.368 (0.014)**	85.261 (0.012)**	102.148 (0.014)**	114.853 (0.022)**	119.529 (0.014)**
ENC-T	1.572 (0.108)	2.205 (0.066)*	2.248 (0.058)*	2.128 (0.088)*	2.230 (0.052)*	2.237 (0.066)*	2.239 (0.076)*	2.225 (0.064)*	2.214 (0.068)*
ENC- NEW	5.369 (0.060)*	16.494 (0.046)**	29.049 (0.030)**	37.731 (0.072)*	49.654 (0.040)**	61.212 (0.028)**	71.113 (0.036)**	77.536 (0.044)**	78.942 (0.044)**
x_t: M3 money supply growth									
q_1	12	12	12	12	12	12	12	12	12

Horizon (h) months ahead:	*1m*	*3m*	*6m*	*9m*	*12m*	*15m*	*18m*	*21m*	*24m*
q_2	1	1	3	12	11	6	11	7	6
Wald	0.022 (0.932)	0.426 (0.662)	10.796 (0.110)	38.280 (0.008)***	41.985 (0.008)***	41.265 (0.018)**	38.897 (0.010)**	36.124 (0.026)**	31.844 (0.030)**
Theil's U	1.002	1.002	**0.986**	**0.956**	**0.939**	**0.926**	**0.941**	**0.945**	**0.952**
MSE-T	-1.727 (0.764)	-1.267 (0.628)	1.176 (0.044)**	1.586 (0.024)**	2.163 (0.014)**	2.644 (0.000)***	1.553 (0.030)**	1.453 (0.054)*	1.248 (0.126)
MSE-F	-1.096 (0.414)	-1.227 (0.498)	8.984 (0.028)**	28.379 (0.018)**	40.689 (0.020)**	49.375 (0.010)**	38.042 (0.018)**	35.032 (0.044)**	29.950 (0.066)*
ENC-T	-1.551 (0.900)	-1.027 (0.766)	2.028 (0.040)**	3.128 (0.008)**	3.560 (0.008)***	3.901 (0.000)***	2.754 (0.028)**	2.553 (0.040)**	2.358 (0.076)*
ENC- NEW	-0.486 (0.644)	-0.491 (0.642)	8.003 (0.076)*	32.157 (0.020)**	41.302 (0.020)**	43.893 (0.020)**	41.260 (0.022)**	35.818 (0.054)*	31.615 (0.066)*
x_t: Bond spread									
q_1	12	12	12	12	12	12	12	12	12
q_2	1	1	1	1	1	1	1	1	1
Wald	2.581 (0.374)	0.793 (0.652)	1.010 (0.654)	1.609 (0.600)	2.571 (0.478)	3.060 (0.456)	3.259 (0.472)	3.527 (0.452)	3.693 (0.488)
Theil's U	1.003	1.018	1.030	1.033	1.030	1.031	1.036	1.042	1.048
MSE-T	-0.742 (0.404)	-2.266 (0.928)	-2.207 (0.936)	-1.797 (0.860)	-1.455 (0.682)	-1.315 (0.652)	-1.294 (0.644)	-1.226 (0.624)	-1.239 (0.620)
MSE-F	-1.696 (0.508)	-11.141 (0.804)	-17.596 (0.782)	-19.265 (0.732)	-17.296 (0.620)	-17.787 (0.578)	-19.968 (0.642)	-23.004 (0.616)	-26.052 (0.634)
ENC-T	0.068 (0.412)	-1.806 (0.944)	-1.711 (0.942)	-1.208 (0.818)	-0.835 (0.674)	-0.739 (0.640)	-0.767 (0.632)	-0.762 (0.644)	-0.836 (0.670)
ENC- NEW	0.077 (0.412)	-4.157 (0.924)	-6.324 (0.900)	-5.915 (0.832)	-4.606 (0.692)	-4.611 (0.646)	-5.366 (0.696)	-6.352 (0.702)	-7.634 (0.714)
x_t: Mortgage spread									
q_1	12	12	12	12	12	12	12	12	12
q_2	1	1	1	5	6	3	2	3	12
Wald	9.706 (0.070)*	7.482 (0.128)	4.457 (0.296)	10.458 (0.130)	12.884 (0.072)*	7.691 (0.206)	6.076 (0.234)	6.347 (0.260)	23.945 (0.018)**
Theil's U	**0.986**	**0.982**	**0.986**	**0.979**	**0.984**	**0.983**	**0.981**	**0.980**	**0.984**
MSE-T	3.102 (0.002)***	2.351 (0.002)***	2.136 (0.002)***	2.136 (0.002)***	2.265 (0.004)***	2.856 (0.000)***	3.616 (0.000)***	3.638 (0.000)***	1.501 (0.032)**
MSE-F	8.800 (0.004)***	11.613 (0.002)***	9.049 (0.040)**	13.376 (0.044)*	10.154 (0.070)*	10.656 (0.086)*	11.539 (0.094)*	12.100 (0.082)*	9.751 (0.100)
ENC-T	3.393 (0.002)***	2.577 (0.008)***	2.372 (0.012)**	2.302 (0.008)***	2.529 (0.016)**	3.159 (0.004)***	3.972 (0.000)***	4.028 (0.000)***	2.924 (0.010)**
ENC- NEW	4.932 (0.020)**	6.583 (0.064)*	5.152 (0.140)	8.145 (0.156)	6.393 (0.182)	6.373 (0.210)	6.686 (0.186)	6.983 (0.210)	7.756 (0.196)
x_t: Bill spread									
q_1	12	12	12	12	12	12	12	12	12
q_2	1	1	1	1	1	1	1	1	1
Wald	5.505 (0.192)	7.904 (0.154)	6.275 (0.236)	6.936 (0.236)	7.236 (0.180)	8.413 (0.200)	9.439 (0.180)	10.543 (0.164)	10.308 (0.172)
Theil's U	**0.993**	**0.987**	**0.988**	**0.985**	**0.981**	**0.975**	**0.968**	**0.958**	**0.953**
MSE-T	1.507 (0.008)***	1.082 (0.036)**	0.860 (0.056)*	1.053 (0.034)**	1.176 (0.038)**	1.389 (0.034)**	1.596 (0.026)**	1.776 (0.022)**	1.864 (0.030)**
MSE-F	4.306 (0.010)**	8.282 (0.030)**	7.570 (0.060)*	9.538 (0.050)*	11.634 (0.062)*	15.765 (0.070)*	19.990 (0.060)*	26.015 (0.040)**	29.180 (0.054)*
ENC-T	2.033 (0.016)**	1.542 (0.086)*	1.298 (0.108)	1.498 (0.066)*	1.639 (0.066)*	1.884 (0.062)*	2.112 (0.048)**	2.358 (0.040)**	2.513 (0.040)**
ENC- NEW	2.958 (0.062)*	6.165 (0.086)*	5.889 (0.144)	7.055 (0.144)	8.441 (0.150)	11.142 (0.146)	13.747 (0.120)	17.873 (0.104)	20.184 (0.106)
x_t: Term spread									
q_1	12	12	12	12	12	12	12	12	12
q_2	1	1	1	2	2	3	1	12	12
Wald	0.000 (1.000)	0.066 (0.912)	0.147 (0.884)	1.071 (0.680)	0.763 (0.698)	1.183 (0.638)	0.228 (0.850)	10.352 (0.190)	11.408 (0.168)

Horizon (h) months ahead:	*1m*	*3m*	*6m*	*9m*	*12m*	*15m*	*18m*	*21m*	*24m*
Theil's U	1.003	1.005	1.011	1.013	1.015	1.019	1.021	1.063	1.084
MSE-T	-0.872 (0.426)	-0.969 (0.456)	-1.068 (0.490)	-1.061 (0.528)	-0.998 (0.516)	-1.014 (0.466)	-1.036 (0.534)	-2.465 (0.970)	-2.082 (0.922)
MSE-F	-1.561 (0.446)	-3.362 (0.398)	-6.405 (0.448)	-7.765 (0.406)	-8.609 (0.386)	-10.869 (0.410)	-11.825 (0.428)	-33.571 (0.712)	-43.336 (0.784)
ENC-T	-0.471 (0.584)	-0.555 (0.580)	-0.640 (0.640)	-0.576 (0.608)	-0.590 (0.598)	-0.603 (0.574)	-0.656 (0.644)	-1.946 (0.960)	-2.009 (0.952)
ENC- NEW	-0.423 (0.600)	-0.964 (0.558)	-1.932 (0.612)	-2.129 (0.568)	-2.563 (0.566)	-3.279 (0.538)	-3.771 (0.568)	-10.819 (0.792)	-12.856 (0.828)
x_t*: Stock exchange volatility*									
q_1	12	12	12	12	12	12	12	12	12
q_2	1	1	1	1	1	1	1	1	1
Wald	1.487 (0.430)	0.375 (0.724)	3.489 (0.328)	2.517 (0.372)	3.357 (0.316)	3.155 (0.342)	3.456 (0.294)	3.734 (0.290)	2.949 (0.344)
Theil's U	1.001	1.003	**0.999**	1.000	1.001	1.001	1.002	1.001	1.002
MSE-T	-0.208 (0.180)	-1.398 (0.714)	0.569 (0.102)	-0.137 (0.284)	-0.258 (0.282)	-0.321 (0.282)	-0.491 (0.378)	-0.333 (0.360)	-0.642 (0.456)
MSE-F	-0.536 (0.274)	-1.975 (0.568)	0.873 (0.138)	-0.178 (0.280)	-0.489 (0.310)	-0.617 (0.322)	-0.887 (0.466)	-0.690 (0.422)	-1.108 (0.500)
ENC-T	0.082 (0.376)	-1.069 (0.776)	1.174 (0.134)	0.052 (0.400)	-0.080 (0.454)	-0.151 (0.408)	-0.273 (0.490)	-0.050 (0.442)	-0.389 (0.522)
ENC- NEW	0.117 (0.346)	-0.706 (0.772)	0.988 (0.258)	0.033 (0.398)	-0.075 (0.458)	-0.144 (0.426)	-0.250 (0.552)	-0.051 (0.462)	-0.334 (0.560)
x_t*: Government bond volatility*									
q_1	12	12	12	12	12	12	12	12	12
q_2	2	1	1	1	1	1	1	1	1
Wald	6.451 (0.168)	0.163 (0.816)	1.294 (0.498)	0.936 (0.602)	1.482 (0.510)	1.104 (0.556)	1.842 (0.496)	1.803 (0.488)	1.496 (0.522)
Theil's U	1.014	1.003	1.001	1.002	**0.9995**	1.001	**0.998**	**0.997**	**0.999**
MSE-T	-1.370 (0.670)	-1.698 (0.816)	-0.301 (0.246)	-0.775 (0.442)	0.178 (0.166)	-0.404 (0.328)	0.751 (0.102)	1.021 (0.070)*	0.250 (0.162)
MSE-F	-8.780 (0.858)	-1.578 (0.512)	-0.549 (0.244)	-1.100 (0.368)	0.291 (0.184)	-0.659 (0.300)	1.384 (0.146)	1.725 (0.158)	0.510 (0.170)
ENC-T	0.065 (0.362)	-1.504 (0.880)	-0.123 (0.406)	-0.583 (0.598)	0.425 (0.294)	-0.133 (0.406)	0.935 (0.180)	1.143 (0.166)	0.465 (0.280)
ENC- NEW	0.208 (0.316)	-0.660 (0.702)	-0.113 (0.402)	-0.419 (0.550)	0.369 (0.338)	-0.111 (0.404)	0.917 (0.294)	1.056 (0.292)	0.501 (0.306)
x_t*: House price volatility*									
q_1	12	12	12	12	12	12	12	12	12
q_2	2	2	1	1	7	8	12	12	12
Wald	8.095 (0.122)	2.444 (0.412)	0.572 (0.680)	0.355 (0.720)	6.579 (0.232)	5.727 (0.246)	24.107 (0.032)**	21.341 (0.026)**	23.972 (0.044)**
Theil's U	1.001	1.007	1.005	1.003	1.012	1.010	1.010	1.014	1.022
MSE-T	-0.138 (0.162)	1.910 (0.858)	-1.687 (0.844)	-1.228 (0.624)	-1.307 (0.704)	-0.868 (0.474)	-0.491 (0.354)	-0.605 (0.410)	-0.884 (0.524)
MSE-F	-0.732 (0.296)	-4.384 (0.658)	-2.921 (0.464)	-1.554 (0.264)	-7.236 (0.628)	-6.128 (0.590)	-5.591 (0.588)	-7.948 (0.676)	-12.156 (0.746)
ENC-T	0.732 (0.168)	-1.468 (0.904)	-1.502 (0.876)	-1.119 (0.750)	-0.946 (0.704)	-0.403 (0.524)	0.301 (0.306)	0.280 (0.320)	0.211 (0.334)
ENC- NEW	1.966 (0.102)	-1.550 (0.810)	-1.231 (0.674)	-0.691 (0.462)	-2.132 (0.690)	-1.337 (0.576)	2.263 (0.258)	2.743 (0.218)	2.318 (0.250)
x_t*: Private sector credit extension*									
q_1	12	12	12	12	12	12	12	12	12
q_2	12	12	12	2	3	3	3	2	2
Wald	20.632 (0.052)*	23.869 (0.054)*	28.072 (0.052)*	6.662 (0.272)	9.786 (0.192)	11.373 (0.216)	12.374 (0.260)	11.091 (0.232)	10.339 (0.256)
Theil's U	1.037	1.022	**0.9996**	**0.983**	**0.972**	**0.965**	**0.952**	**0.961**	**0.966**
MSE-T	-1.863 (0.848)	-0.967 (0.568)	0.014 (0.236)	0.833 (0.112)	0.945 (0.092)*	1.117 (0.072)*	1.409 (0.072)*	1.470 (0.070)*	1.484 (0.060)*

Horizon (h) months ahead:	*1m*	*3m*	*6m*	*9m*	*12m*	*15m*	*18m*	*21m*	*24m*
MSE-F	-22.184 (0.994)	-13.097 (0.910)	0.239 (0.224)	10.830 (0.088)*	17.574 (0.060)*	22.268 (0.052)*	30.629 (0.066)*	24.088 (0.060)*	20.871 (0.066)*
ENC-T	0.845 (0.188)	1.144 (0.184)	1.633 (0.136)	1.822 (0.112)	2.220 (0.064)*	2.506 (0.048)**	2.755 (0.036)**	2.747 (0.040)**	2.756 (0.040)**
ENC- NEW	4.821 (0.060)*	7.202 (0.096)*	13.833 (0.080)*	10.788 (0.154)	19.498 (0.090)*	24.102 (0.086)*	29.347 (0.090)*	21.921 (0.114)	18.518 (0.124)

Notes: *Wald* is the in-sample *F*-statistic used to test the null hypothesis of no Granger-causality (bootstrapped *p*-values in parenthesis). ***/**/* indicates rejection of the null hypothesis (i.e. there is evidence of in-sample Granger causality) at the 1/5/10% level of significance. If Theil's $U < 1$ then *RMSFE* of the unrestricted model is < *RMSFE* of the restricted model, indicating the relevance of the individual financial variables as "forecasters" (i.e. lower Theil's *U* values are preferable). *MSE-T* and *MSE-F* test the null hypothesis of equal forecasting ability between the restricted and unrestricted models (bootstrapped *p*-values in parenthesis). ***/**/* indicates rejection of the null hypothesis (i.e. the financial variables of the unrestricted model have out-of-sample forecasting ability) at the 1/5/10% level of significance. *ENC-T* and *ENC-NEW* test the null hypothesis that the restricted model forecast encompasses the unrestricted model forecast (bootstrapped *p*-values in parenthesis). ***/**/* indicates rejection of the null hypothesis (i.e. the financial variables of the unrestricted model are relevant in out-of-sample forecasting) at the 1/5/10% level of significance.

Table A6. In- and out-of-sample forecasting: Treasury Bill as dependent variable (Sample: 1986:01 – 2012:01)

Horizon (h) months ahead:	*1m*	*3m*	*6m*	*9m*	*12m*	*15m*	*18m*	*21m*	*24m*
x_t: FCI									
q_1	12	12	12	2	2	11	11	11	10
q_2	6	9	9	8	12	6	6	6	6
Wald	13.285 (0.046)**	20.753 (0.012)**	19.123 (0.026)**	17.077 (0.062)*	27.514 (0.004)***	21.190 (0.020)**	22.263 (0.018)**	22.466 (0.024)**	20.861 (0.032)**
Theil's U	1.032	1.044	1.044	1.046	1.075	1.030	1.019	1.016	1.030
MSE-T	-1.969 (0.836)	-1.758 (0.812)	-1.254 (0.588)	-1.031 (0.520)	-1.440 (0.738)	-0.600 (0.338)	-0.404 (0.274)	-0.317 (0.262)	-0.577 (0.346)
MSE-F	-18.951 (0.972)	-25.903 (0.978)	-25.312 (0.916)	-26.117 (0.854)	-40.755 (0.906)	-17.113 (0.678)	-11.162 (0.526)	-8.946 (0.448)	-16.657 (0.650)
ENC-T	-0.410 (0.542)	-0.373 (0.528)	0.240 (0.298)	0.759 (0.174)	0.719 (0.210)	1.158 (0.116)	1.460 (0.098)*	1.613 (0.074)*	1.397 (0.100)
ENC-NEW	-1.859 (0.910)	-2.599 (0.892)	2.348 (0.214)	9.480 (0.086)*	9.796 (0.106)	18.307 (0.054)*	22.475 (0.046)**	24.622 (0.050)*	21.425 (0.058)*
x_t: US Consumer Sentiment Index									
q_1	12	12	12	2	2	2	11	12	12
q_2	3	10	10	10	10	10	10	10	10
Wald	3.529 (0.282)	15.903 (0.048)**	14.148 (0.082)*	13.138 (0.108)	12.945 (0.120)	13.117 (0.118)	12.924 (0.124)	12.043 (0.166)	11.819 (0.144)
Theil's U	1.007	1.019	1.016	1.064	1.089	1.117	1.096	1.112	1.142
MSE-T	-1.291 (0.598)	-1.664 (0.764)	-0.716 (0.382)	-2.308 (0.958)	-2.091 (0.926)	-1.936 (0.892)	-1.300 (0.616)	-1.301 (0.584)	-1.461 (0.688)
MSE-F	-4.508 (0.686)	-11.232 (0.772)	-9.425 (0.590)	-35.600 (0.848)	-47.208 (0.840)	-59.162 (0.872)	-49.412 (0.798)	-56.029 (0.752)	-67.616 (0.798)
ENC-T	0.117 (0.344)	0.733 (0.208)	1.107 (0.132)	-0.081 (0.436)	-0.386 (0.510)	-0.619 (0.558)	-0.189 (0.420)	-0.272 (0.466)	-0.503 (0.526)
ENC- NEW	0.206 (0.334)	2.376 (0.202)	7.101 (0.122)	-0.574 (0.444)	-3.823 (0.624)	-8.128 (0.742)	-3.203 (0.506)	-5.247 (0.568)	-10.121 (0.678)
x_t: All-Share Index									
q_1	12	12	12	2	2	2	11	11	11
q_2	1	1	1	1	1	1	1	1	1
Wald	2.235 (0.372)	0.488 (0.616)	0.013 (0.922)	0.006 (0.962)	0.018 (0.932)	0.099 (0.838)	0.561 (0.620)	0.737 (0.584)	1.049 (0.526)
Theil's U	1.022	1.015	1.016	1.019	1.013	1.009	1.005	1.004	1.003
MSE-T	-1.267 (0.662)	-1.330 (0.700)	-1.389 (0.694)	-1.266 (0.692)	-1.141 (0.678)	-1.055 (0.610)	-1.162 (0.706)	-1.169 (0.676)	-0.959 (0.606)
MSE-F	-13.339 (0.966)	-8.948 (0.888)	-9.675 (0.870)	-11.234 (0.834)	-7.549 (0.848)	-5.506 (0.814)	-2.852 (0.766)	-2.316 (0.714)	-1.551 (0.676)
ENC-T	-0.795 (0.750)	-0.720 (0.648)	-1.006 (0.722)	-0.949 (0.728)	-0.870 (0.714)	-0.819 (0.674)	-0.949 (0.742)	-0.967 (0.724)	-0.761 (0.692)
ENC- NEW	-3.992 (0.998)	-2.349 (0.942)	-3.450 (0.938)	-4.094 (0.926)	-2.815 (0.912)	-2.090 (0.886)	-1.143 (0.848)	-0.944 (0.806)	-0.610 (0.750)
x_t: House price index									
q_1	12	12	12	2	2	1	11	10	10
q_2	12	9	9	8	7	7	7	7	7
Wald	27.080 (0.004)***	12.606 (0.074)*	13.204 (0.062)*	15.917 (0.032)**	12.094 (0.096)*	9.399 (0.158)	9.423 (0.192)	9.299 (0.174)	8.732 (0.194)
Theil's U	1.030	1.027	1.036	1.076	1.101	1.117	1.080	1.089	1.101
MSE-T	-1.708 (0.812)	-0.757 (0.394)	-0.521 (0.348)	-0.769 (0.426)	-0.812 (0.444)	-0.788 (0.426)	-0.579 (0.332)	-0.654 (0.390)	-0.782 (0.432)
MSE-F	-18.017 (0.980)	-16.261 (0.918)	-21.106 (0.878)	-41.466 (0.954)	-53.055 (0.972)	-59.260 (0.962)	-42.437 (0.888)	-46.105 (0.896)	-50.894 (0.914)
ENC-T	0.869 (0.164)	0.909 (0.172)	1.138 (0.136)	1.238 (0.100)	1.153 (0.152)	1.049 (0.150)	1.195 (0.118)	1.099 (0.144)	0.946 (0.192)
ENC- NEW	4.513 (0.016)**	9.302 (0.030)**	21.480 (0.010)**	27.716 (0.008)***	28.498 (0.030)**	29.932 (0.020)**	37.338 (0.018)**	33.822 (0.020)**	27.072 (0.046)**

Horizon (h) months ahead:	*1m*	*3m*	*6m*	*9m*	*12m*	*15m*	*18m*	*21m*	*24m*
x_t: Rand-Dollar exchange rate									
q_1	12	6	6	2	2	2	2	2	2
q_2	12	12	12	12	12	12	12	12	9
Wald	34.652 (0.000)***	14.049 (0.046)**	13.110 (0.060)*	11.900 (0.064)*	11.775 (0.092)*	12.105 (0.090)*	10.507 (0.102)	9.769 (0.094)*	7.080 (0.166)
Theil's U	1.089	1.076	1.082	1.128	1.161	1.179	1.204	1.203	1.136
MSE-T	-2.121 (0.892)	-1.619 (0.790)	-1.614 (0.824)	-1.961 (0.932)	-1.861 (0.920)	-1.727 (0.860)	-1.667 (0.820)	-1.436 (0.806)	-1.186 (0.692)
MSE-F	-48.944 (1.000)	-42.598(1.000)	-45.073 (0.996)	-65.417 (1.000)	-77.804 (0.998)	-83.769 (0.998)	-91.734 (0.996)	-90.398 (1.000)	-65.434 (0.990)
ENC-T	1.336 (0.058)*	1.102 (0.118)	0.997 (0.126)	0.682 (0.200)	0.507 (0.246)	0.422 (0.282)	0.412 (0.252)	0.433 (0.274)	0.192 (0.362)
ENC- NEW	10.923 (0.000)***	10.957 (0.012)**	10.075 (0.024)**	8.409 (0.042)**	8.890 (0.056)*	10.227 (0.048)**	12.138 (0.018)**	15.305 (0.032)**	5.565 (0.082)*
x_t: S&P500 index									
q_1	12	12	12	2	2	2	11	11	11
q_2	1	1	1	1	1	1	1	1	1
Wald	0.425 (0.682)	1.196 (0.496)	0.092 (0.854)	0.159 (0.782)	0.019 (0.918)	0.018 (0.934)	0.650 (0.596)	0.851 (0.558)	1.228 (0.436)
Theil's U	1.002	1.001	1.002	1.005	1.003	1.003	**0.9995**	1.000	**0.999**
MSE-T	-0.795 (0.424)	-0.221 (0.202)	-0.847 (0.522)	-0.970 (0.528)	-1.035 (0.590)	-1.109 (0.638)	0.730 (0.086)*	-0.304 (0.320)	0.411 (0.132)
MSE-F	-1.068 (0.454)	-0.339 (0.216)	-1.404 (0.576)	-2.900 (0.688)	-2.021 (0.688)	-1.563 (0.602)	0.268 (0.160)	-0.225 (0.304)	0.331 (0.170)
ENC-T	-0.404 (0.552)	0.313 (0.304)	-0.443 (0.584)	-0.512 (0.556)	-0.643 (0.622)	-0.787 (0.666)	0.887 (0.160)	-0.158 (0.454)	0.629 (0.222)
ENC- NEW	-0.281 (0.524)	0.248 (0.306)	-0.383 (0.660)	-0.794 (0.774)	-0.651 (0.768)	-0.577 (0.704)	0.163 (0.326)	-0.057 (0.440)	0.249 (0.274)
x_t: Dividend yield									
q_1	12	12	12	4	2	2	11	11	10
q_2	9	1	1	4	1	1	1	2	5
Wald	15.678 (0.038)**	6.007 (0.256)	5.219 (0.306)	6.802 (0.274)	3.831 (0.416)	4.087 (0.400)	3.947 (0.436)	5.838 (0.364)	6.349 (0.342)
Theil's U	1.021	**0.988**	**0.982**	**0.993**	**0.993**	**0.992**	**0.981**	**0.997**	1.034
MSE-T	-1.560 (0.744)	1.698 (0.010)**	1.578 (0.014)**	0.568 (0.056)*	0.470 (0.084)*	0.477 (0.106)	0.992 (0.048)**	0.101 (0.170)	-0.536 (0.338)
MSE-F	-12.954 (0.948)	7.456 (0.036)**	11.609 (0.040)**	4.005 (0.102)	4.119 (0.100)	4.624 (0.122)	11.404 (0.090)*	1.749 (0.170)	-18.854 (0.466)
ENC-T	-0.021 (0.438)	2.071 (0.048)**	2.017 (0.044)**	1.288 (0.126)	0.890 (0.196)	0.927 (0.176)	1.405 (0.136)	0.466 (0.294)	-0.228 (0.494)
ENC- NEW	-0.085 (0.456)	4.587 (0.148)	7.489 (0.140)	4.659 (0.246)	3.826 (0.296)	4.426 (0.276)	8.337 (0.236)	3.987 (0.312)	-3.520 (0.550)
x_t: Federal Funds rate									
q_1	12	12	12	2	2	12	12	12	12
q_2	1	1	12	1	1	11	12	12	12
Wald	6.278 (0.192)	7.101 (0.198)	18.418 (0.044)**	7.544 (0.248)	7.848 (0.222)	14.067 (0.090)*	16.585 (0.072)*	19.227 (0.056)*	21.710 (0.058)*
Theil's U	1.001	**0.997**	1.019	**0.998**	1.002	1.076	1.107	1.133	1.172
MSE-T	-0.234 (0.180)	0.226 (0.130)	-0.916 (0.430)	0.062 (0.152)	-0.034 (0.160)	-1.111 (0.480)	-1.253 (0.596)	-1.287 (0.580)	-1.389 (0.658)
MSE-F	-0.913 (0.250)	1.689 (0.118)	-11.527 (0.576)	1.354 (0.146)	-0.909 (0.168)	-40.942 (0.714)	-54.574 (0.806)	-64.816 (0.780)	-78.888 (0.828)
ENC-T	0.908 (0.154)	1.407 (0.120)	0.711 (0.240)	1.370 (0.126)	1.179 (0.156)	-0.031 (0.416)	-0.192 (0.496)	-0.245 (0.468)	-0.355 (0.526)
ENC- NEW	1.774 (0.150)	5.302 (0.140)	4.413 (0.228)	16.101 (0.098)*	17.454 (0.112)	-0.546 (0.426)	-3.881 (0.562)	-5.548 (0.556)	-8.918 (0.656)
x_t: M3 money supply growth									
q_1	12	12	12	2	2	2	2	2	2

Horizon (h) months ahead:	*1m*	*3m*	*6m*	*9m*	*12m*	*15m*	*18m*	*21m*	*24m*
q_2	1	1	1	9	9	9	9	8	7
Wald	0.183 (0.736)	1.902 (0.402)	4.348 (0.256)	27.218 (0.000)***	25.622 (0.004)***	25.376 (0.006)***	23.931 (0.010)**	20.068 (0.016)**	15.770 (0.050)*
Theil's U	1.001	**0.999**	**0.995**	**0.948**	**0.949**	**0.946**	**0.948**	**0.944**	**0.950**
MSE-T	-0.974 (0.514)	0.229 (0.142)	0.699 (0.058)*	0.837 (0.054)*	0.738 (0.032)**	0.790 (0.072)*	0.822 (0.064)*	0.949 (0.054)*	0.923 (0.072)*
MSE-F	-0.800 (0.354)	0.384 (0.154)	2.809 (0.048)**	34.416 (0.000)***	33.650 (0.000)***	35.213 (0.004)***	33.702 (0.008)***	35.489 (0.008)***	31.345 (0.016)**
ENC-T	-0.690 (0.640)	0.802 (0.196)	1.466 (0.080)*	3.454 (0.004)***	3.421 (0.000)***	3.417 (0.000)***	3.290 (0.004)***	3.030 (0.006)***	2.666 (0.010)**
ENC- NEW	-0.283 (0.550)	0.668 (0.264)	2.917 (0.124)	74.039 (0.000)***	77.570 (0.000)***	76.076 (0.000)***	68.198 (0.004)***	59.406 (0.004)***	47.365 (0.008)***
x_t*: Bond spread*									
q_1	12	12	12	2	2	2	2	12	11
q_2	2	1	1	12	12	12	12	12	12
Wald	3.894 (0.258)	7.522 (0.180)	6.720 (0.216)	21.563 (0.018)**	24.691 (0.008)***	27.325 (0.018)**	29.189 (0.014)**	27.694 (0.014)**	30.361 (0.004)***
Theil's U	1.007	**0.991**	**0.987**	1.037	1.046	1.064	1.073	1.063	1.062
MSE-T	-0.737 (0.430)	1.076 (0.032)**	0.961 (0.060)*	-1.178 (0.602)	-0.915 (0.452)	-0.896 (0.434)	-0.824 (0.452)	-0.824 (0.440)	-0.675 (0.398)
MSE-F	-4.524 (0.770)	5.643 (0.032)**	8.305 (0.068)*	-21.179 (0.836)	-25.741 (0.806)	-34.646 (0.824)	-38.761 (0.840)	-33.895 (0.778)	-32.892 (0.736)
ENC-T	0.638 (0.246)	2.172 (0.022)**	2.018 (0.052)*	1.092 (0.146)	1.070 (0.150)	1.039 (0.150)	1.177 (0.150)	1.471 (0.088)*	1.655 (0.076)*
ENC- NEW	1.752 (0.132)	5.739 (0.062)*	8.826 (0.092)*	11.403 (0.080)*	18.026 (0.082)*	23.857 (0.046)**	32.906 (0.044)**	40.823 (0.036)**	53.946 (0.008)***
x_t*: Mortgage spread*									
q_1	12	12	9	6	4	5	4	3	3
q_2	9	9	11	2	1	1	1	1	1
Wald	16.136 (0.100)	8.563 (0.290)	7.047 (0.412)	3.852 (0.466)	3.028 (0.568)	3.727 (0.500)	4.214 (0.464)	4.070 (0.528)	3.695 (0.542)
Theil's U	1.075	1.071	1.090	1.099	1.110	1.139	1.139	1.138	1.138
MSE-T	-2.923 (0.988)	-2.147 (0.938)	-1.894 (0.876)	-1.423 (0.768)	-1.352 (0.758)	-1.363 (0.730)	-1.336 (0.736)	-1.331 (0.760)	-1.340 (0.710)
MSE-F	-41.905 (1.000)	-39.723 (0.998)	-48.588 (0.994)	-52.525 (0.990)	-57.074 (0.970)	-68.435 (0.966)	-67.743 (0.958)	-66.942 (0.968)	-66.012 (0.936)
ENC-T	-0.043 (0.504)	-0.020 (0.556)	0.080 (0.532)	-0.320 (0.588)	-0.519 (0.692)	-0.279 (0.548)	-0.182 (0.550)	-0.154 (0.546)	0.040 (0.488)
ENC- NEW	-0.316 (0.608)	-0.108 (0.558)	0.761 (0.500)	-4.520 (0.872)	-7.345 (0.916)	-5.117 (0.774)	-3.210 (0.674)	-2.585 (0.628)	0.733 (0.476)
x_t*: Bill spread*									
q_1	12	12	12	2	2	11	11	11	11
q_2	9	9	1	1	1	1	1	1	1
Wald	13.001 (0.068)*	6.510 (0.222)	0.141 (0.852)	0.452 (0.702)	0.289 (0.824)	0.050 (0.940)	0.041 (0.928)	0.032 (0.946)	0.020 (0.952)
Theil's U	1.033	1.035	1.011	1.006	1.010	1.024	1.029	1.034	1.042
MSE-T	-2.817 (0.966)	-4.250 (1.000)	-1.476 (0.740)	-1.237 (0.602)	-1.594 (0.794)	-1.715 (0.852)	-1.722 (0.830)	-1.713 (0.824)	-1.670 (0.844)
MSE-F	-19.659 (0.984)	-20.502 (0.936)	-6.411 (0.558)	-3.553 (0.276)	-6.014 (0.346)	13.843 (0.566)	-16.264 (0.542)	-19.137 (0.540)	-22.654 (0.616)
ENC-T	-0.909 (0.752)	-2.311 (0.992)	-1.429 (0.876)	-0.976 (0.732)	-1.461 (0.880)	-1.650 (0.932)	-1.653 (0.900)	-1.633 (0.910)	-1.595 (0.914)
ENC- NEW	-3.225 (0.970)	-5.118 (0.966)	-3.028 (0.812)	-1.391 (0.514)	-2.716 (0.602)	-6.362 (0.798)	-7.404 (0.788)	-8.590 (0.740)	-9.974 (0.798)
x_t*: Term spread*									
q_1	12	12	12	9	2	4	4	4	2
q_2	8	9	7	7	2	12	12	12	11
Wald	28.225 (0.060)*	21.895 (0.118)	17.627 (0.126)	18.577 (0.134)	5.892 (0.324)	42.579 (0.012)**	48.734 (0.012)**	51.090 (0.002)***	43.911 (0.014)**

Horizon (h) months ahead:	*1m*	*3m*	*6m*	*9m*	*12m*	*15m*	*18m*	*21m*	*24m*
Theil's U	1.088	1.098	1.078	1.067	1.058	1.134	1.203	1.233	1.144
MSE-T	-2.473 (0.960)	-2.009 (0.866)	-1.462 (0.740)	-1.021 (0.524)	-0.712 (0.438)	-0.644 (0.408)	-0.681 (0.438)	-0.669 (0.370)	-0.481 (0.312)
MSE-F	-48.532 (1.000)	-53.271 (1.000)	-43.011 (0.980)	-37.188 (0.916)	-32.386 (0.820)	-66.662 (0.958)	-91.402 (0.986)	-100.140 (0.988)	-68.388 (0.910)
ENC-T	0.430 (0.324)	0.180 (0.456)	0.434 (0.340)	0.885 (0.232)	0.393 (0.390)	1.201 (0.162)	1.163 (0.208)	-1.373 (0.122)	1.822 (0.094)*
ENC- NEW	3.352 (0.144)	2.147 (0.300)	5.470 (0.214)	13.043 (0.138)	6.255 (0.286)	32.415 (0.050)*	34.370 (0.064)*	43.340 (0.038)**	72.744 (0.026)**
x_t*: Stock exchange volatility*									
q_1	12	12	12	2	2	11	11	11	11
q_2	1	12	11	11	11	11	11	11	11
Wald	4.731 (0.222)	24.437 (0.018)**	16.714 (0.060)*	11.454 (0.126)	10.229 (0.126)	14.152 (0.094)*	14.485 (0.080)*	13.237 (0.106)	13.055 (0.114)
Theil's U	1.068	1.150	1.150	1.204	1.223	1.203	1.213	1.209	1.222
MSE-T	-0.864 (0.424)	-1.485 (0.742)	-1.283 (0.656)	-1.081 (0.646)	-1.048 (0.612)	-1.029 (0.568)	-1.013 (0.558)	-0.984 (0.568)	-0.986 (0.608)
MSE-F	-38.439 (0.992)	-75.877 (0.998)	-75.084 (0.994)	-94.543 (0.996)	-100.193 (0.998)	-92.266 (0.994)	-94.945 (0.994)	-92.527 (0.996)	-95.845 (0.996)
ENC-T	-0.748 (0.654)	-1.059 (0.786)	-0.900 (0.716)	-0.688 (0.700)	-0.646 (0.650)	-0.645 (0.586)	-0.608 (0.592)	-0.518 (0.564)	-0.509 (0.574)
ENC- NEW	-12.727 (1.000)	-20.304 (0.998)	-19.389 (1.000)	-19.689 (1.000)	-19.934 (0.998)	-18.993 (0.992)	-18.301 (0.992)	-15.479 (0.982)	-15.402 (0.972)
x_t*: Government bond volatility*									
q_1	12	8	8	8	9	12	12	12	3
q_2	11	11	11	12	12	12	11	11	11
Wald	38.406 (0.000)***	16.567 (0.034)**	12.616 (0.084)*	11.834 (0.096)*	12.914 (0.074)*	13.066 (0.072)*	14.986 (0.046)**	14.428 (0.046)**	9.784 (0.138)
Theil's U	1.071	1.120	1.178	1.256	1.290	1.265	1.221	1.219	1.245
MSE-T	-2.781 (0.966)	-2.718 (0.988)	-2.437 (0.984)	-2.366 (0.964)	-2.288 (0.954)	-2.069 (0.960)	-1.855 (0.908)	-1.818 (0.908)	-2.069 (0.954)
MSE-F	-39.877 (0.998)	-63.129 (1.000)	-86.073 (1.000)	-111.664 (0.628)	-120.380 (1.000)	-112.030 (1.000)	-97.471 (1.000)	-95.862 (1.000)	-102.766 (0.998)
ENC-T	0.647 (0.180)	-0.273 (0.496)	-0.667 (0.636)	-0.713 (0.628)	-0.418 (0.524)	-0.223 (0.462)	-0.153 (0.452)	-0.103 (0.418)	-0.662 (0.636)
ENC- NEW	3.607 (0.048)**	-1.406 (0.846)	-5.764 (0.960)	-9.279 (0.972)	-7.604 (0.942)	-4.890 (0.926)	-3.535 (0.898)	-2.303 (0.846)	-12.059 (0.962)
x_t*: House price volatility*									
q_1	12	12	12	2	2	2	11	11	10
q_2	6	1	1	1	1	1	4	1	1
Wald	24.083 (0.006)***	0.617 (0.638)	1.230 (0.538)	2.319 (0.400)	2.153 (0.448)	2.058 (0.444)	2.476 (0.416)	2.063 (0.504)	2.449 (0.424)
Theil's U	**0.998**	1.001	**0.995**	**0.987**	**0.990**	**0.996**	1.023	1.021	1.019
MSE-T	0.142 (0.108)	-0.168 (0.202)	0.843 (0.056)*	1.731 (0.008)***	1.019 (0.054)*	0.280 (0.138)	-0.528 (0.346)	-0.611 (0.366)	-0.546 (0.388)
MSE-F	1.047 (0.056)*	-0.414 (0.212)	2.914 (0.102)	7.889 (0.036)**	6.188 (0.068)*	2.600 (0.114)	-13.295 (0.744)	-11.986 (0.668)	-10.815 (0.688)
ENC-T	1.793 (0.026)**	0.118 (0.370)	1.523 (0.082)*	2.158 (0.020)**	1.563 (0.078)*	0.900 (0.166)	-0.063 (0.392)	-0.282 (0.468)	-0.169 (0.448)
ENC- NEW	6.180 (0.014)**	0.140 (0.388)	2.531 (0.190)	5.603 (0.124)	5.160 (0.134)	3.982 (0.176)	-0.729 (0.464)	-2.518 (0.674)	-1.537 (0.598)
x_t*: Private sector credit extension*									
q_1	12	12	2	2	2	1	10	10	10
q_2	1	7	6	6	6	7	9	9	9
Wald	2.733 (0.322)	13.037 (0.048)**	17.623 (0.018)**	16.790 (0.030)**	15.469 (0.050)*	13.908 (0.074)*	13.223 (0.072)*	13.045 (0.070)*	12.598 (0.076)*
Theil's U	1.012	1.005	1.020	1.024	1.034	1.030	1.007	1.004	1.012
MSE-T	-1.338 (0.652)	-0.123 (0.176)	-0.292 (0.242)	-0.292 (0.270)	-0.385 (0.288)	-0.330 (0.302)	-0.103 (0.218)	-0.077 (0.222)	-0.237 (0.272)

Horizon (h) months ahead:	*1m*	*3m*	*6m*	*9m*	*12m*	*15m*	*18m*	*21m*	*24m*
MSE-F	-7.435 (0.858)	-3.089 (0.692)	-11.811 (0.820)	-14.263 (0.852)	-19.489 (0.856)	-17.057 (0.814)	-4.050 (0.604)	-2.588 (0.522)	-7.068 (0.678)
ENC-T	-0.302 (0.466)	1.571 (0.032)**	2.008 (0.032)**	2.018 (0.024)**	2.057 (0.030)**	2.399 (0.026)**	2.596 (0.012)**	2.666 (0.004)***	2.451 (0.016)**
ENC- NEW	-0.819 (0.784)	18.252 (0.000)***	36.096 (0.000)***	41.523 (0.000)***	40.932 (0.002)***	51.990 (0.008)***	37.398 (0.014)**	31.660 (0.012)**	24.711 (0.032)**

Notes: *Wald* is the in-sample *F*-statistic used to test the null hypothesis of no Granger-causality (bootstrapped *p*-values in parenthesis). ***/**/* indicates rejection of the null hypothesis (i.e. there is evidence of in-sample Granger causality) at the 1/5/10% level of significance. If Theil's $U < 1$ then *RMSFE* of the unrestricted model is < *RMSFE* of the restricted model, indicating the relevance of the individual financial variables as "forecasters" (i.e. lower Theil's *U* values are preferable). *MSE-T* and *MSE-F* test the null hypothesis of equal forecasting ability between the restricted and unrestricted models (bootstrapped *p*-values in parenthesis). ***/**/* indicates rejection of the null hypothesis (i.e. the financial variables of the unrestricted model have out-of-sample forecasting ability) at the 1/5/10% level of significance. *ENC-T* and *ENC-NEW* test the null hypothesis that the restricted model forecast encompasses the unrestricted model forecast (bootstrapped *p*-values in parenthesis). ***/**/* indicates rejection of the null hypothesis (i.e. the financial variables of the unrestricted model are relevant in out-of-sample forecasting) at the 1/5/10% level of significance.

Table A7. Data-mining critical values: Manufacturing output growth (Sample: 1986:01 – 2012:01)

Horizon (h) months ahead:	*1m*			*3m*			*6m*			*9m*			*12m*		
Signif. level	10%	5%	1%	10%	5%	1%	10%	5%	1%	10%	5%	1%	10%	5%	1%
MSE-T	1.462	1.721	2.216	1.706	2.002	2.426	1.810	2.146	2.593	1.862	2.172	2.566	2.003	2.308	2.633
MSE-F	5.017	6.316	9.507	11.688	16.220	26.142	21.576	31.392	62.040	30.894	44.151	91.718	38.962	59.100	116.629
ENC-T	2.424	2.749	3.257	2.631	2.947	3.692	2.733	3.082	3.701	2.802	3.047	3.701	2.830	3.110	3.679
ENC- NEW	7.560	9.438	12.798	15.237	19.660	31.998	28.654	34.113	67.469	40.171	53.984	91.397	50.672	64.294	106.003
Horizon (h) months ahead:	*15m*			*18m*			*21m*			*24m*					
Signif. Level	10%	5%	1%	10%	5%	1%	10%	5%	1%	10%	5%	1%			
MSE-T	1.985	2.291	2.860	2.113	2.380	2.882	2.223	2.557	3.167	2.285	2.629	3.457			
MSE-F	50.496	69.384	136.545	62.009	81.822	169.537	69.937	97.042	197.734	73.639	107.495	186.938			
ENC-T	2.958	3.274	3.787	2.958	3.354	3.975	3.133	3.590	3.979	3.145	3.553	4.436			
ENC- NEW	58.429	77.733	123.427	69.120	91.071	161.215	77.761	102.705	193.248	85.866	114.643	204.596			

Table A8. Data-mining critical values: Inflation (Sample: 1986:01 – 2012:01)

Horizon (h) months ahead:	*1m*			*3m*			*6m*			*9m*			*12m*		
Signif. level	10%	5%	1%	10%	5%	1%	10%	5%	1%	10%	5%	1%	10%	5%	1%
MSE-T	1.869	2.481	4.375	2.015	2.581	3.526	1.997	2.312	3.456	2.110	2.451	3.232	2.126	2.414	3.212
MSE-F	7.988	13.168	32.691	19.116	32.928	62.406	32.219	48.348	91.542	45.311	69.742	112.691	54.117	73.578	120.357
ENC-T	3.171	3.811	5.910	3.163	3.928	4.860	3.019	3.486	4.723	3.037	3.373	4.039	3.037	3.381	4.005
ENC- NEW	12.225	15.967	28.720	22.811	34.051	58.586	37.278	52.352	92.852	57.352	72.151	114.307	65.315	82.882	133.810
Horizon (h) months ahead:	*15m*			*18m*			*21m*			*24m*					
Signif. Level	10%	5%	1%	10%	5%	1%	10%	5%	1%	10%	5%	1%			
MSE-T	2.171	2.510	3.260	2.355	2.648	3.128	2.311	2.669	3.388	2.347	2.651	3.500			
MSE-F	58.049	80.568	148.550	64.207	93.424	172.767	74.641	107.274	187.621	78.612	115.642	217.775			
ENC-T	3.093	3.315	3.990	3.150	3.374	4.159	3.229	3.597	4.303	3.323	3.737	4.339			
ENC- NEW	73.786	89.356	154.512	80.017	101.484	179.619	88.857	123.484	193.259	95.280	128.037	226.038			

Table A9. Data-mining critical values: Treasury Bill (Sample: 1986:01 – 2012:01)

Horizon (h) months ahead:	*1m*			*3m*			*6m*			*9m*			*12m*		
Signif. level	10%	5%	1%	10%	5%	1%	10%	5%	1%	10%	5%	1%	10%	5%	1%
MSE-T	1.520	1.724	2.163	1.742	1.981	2.406	1.738	2.020	2.845	1.854	2.130	2.836	1.899	2.184	2.801
MSE-F	6.167	7.620	15.479	12.538	15.198	29.998	22.007	26.825	70.474	28.711	39.478	62.352	37.511	50.186	65.141
ENC-T	2.765	3.161	3.977	2.919	3.238	3.852	2.796	3.165	3.746	2.845	3.209	3.727	2.887	3.209	3.804
ENC- NEW	11.510	15.781	24.419	18.317	22.676	33.983	27.737	34.239	61.712	38.389	45.381	68.956	47.020	54.181	86.643
Horizon (h) months ahead:	*15m*			*18m*			*21m*			*24m*					
Signif. level	10%	5%	1%	10%	5%	1%	10%	5%	1%	10%	5%	1%			
MSE-T	1.914	2.171	2.758	1.934	2.239	2.704	2.037	2.392	2.905	2.165	2.474	2.991			
MSE-F	44.064	55.651	80.062	50.677	65.494	88.620	55.828	73.260	111.002	63.960	90.264	154.627			
ENC-T	2.893	3.274	3.978	2.910	3.274	4.013	2.977	3.292	4.222	3.056	3.426	4.417			
ENC- NEW	51.913	64.678	109.027	60.272	78.075	112.763	68.498	88.789	137.973	78.218	102.649	170.944			

Notes for Table A7, Table A8 and Table A9: *MSE-T* and *MSE-F* test the null hypothesis of equal forecasting ability between the restricted and unrestricted models (bootstrapped *p*-values in parenthesis). ***/**/* indicates rejection of the null hypothesis (i.e. the financial variables of the unrestricted model have out-of-sample forecasting ability) at the 1/5/10% level of significance. *ENC-T* and *ENC-NEW* test the null hypothesis that the restricted model forecast encompasses the unrestricted model forecast (bootstrapped *p*-values in parenthesis). ***/**/* indicates rejection of the null hypothesis (i.e. the financial variables of the unrestricted model are relevant in out-of-sample forecasting) at the 1/5/10% level of significance.

A.6 WEISE'S (1999) LSTVAR METHODOLOGY

I use a structural model incorporating asymmetry developed by Weise (1999), where asymmetry is incorporated into a simple aggregate demand-aggregate supply (AD-AS) framework. The methodology that follows is taken from Weise (1999), for the case of a model incorporating money, prices and output.

Assume a neoclassical model with flexible prices, where potential output growth, y_t^p, is determined by a constant, y_0, and a technology shock, θ_t, with $E(\theta_t) = 0$:

$$y_t^p = y_0 + \theta_t \tag{36}$$

The AD equation is a quantity theory equation augmented with a general lag structure:

$$y_t^d = y_0 + \delta(m_t - p_t) + A(L)X_{t-1} + \eta_t \tag{37}$$

where p_t is price inflation, y_t is equilibrium output growth, $X_t = (y_t, p_t, m_t)'$ is a vector of endogenous variables, η_t is an AD or price shock, and m_t is the growth in money supply and is determined by a money supply rule:

$$m_t = m_0 - \phi y_t - \pi p_t + B(L)X_{t-1} + \mu_t \tag{38}$$

where μ_t is a monetary shock with $E(\mu_t) = 0$.

Due to price flexibility, p_t will adjust so that output demanded (equation (37)) will be equal to potential output (equation (36)), so that in full employment equilibrium:

$$p_t^* = m_t + \frac{1}{\delta}A(L)X_{t-1} + \frac{1}{\delta}(\eta_t - \theta_t) \tag{39}$$

When nominal rigidities exist, prices may temporarily deviate from equilibrium:

$$p_t = \alpha(z_t)p_{t-1} + \big(1 - \alpha(z_t)\big)p_t^*$$

$$= \big(1 - \alpha(z_t)\big)\left[m_t + \frac{1}{\delta}A(L)X_{t-1} + \frac{1}{\delta}(\eta_t - \theta_t)\right]/(1 - \alpha(z_t)L) \tag{40}$$

where z_t is a switching variable that represents the state of the economy, and $\alpha(z_t)$ is a price-stickiness parameter which varies according to z_t, and which does not take the form of an indicator variable, but rather takes on a functional form that allows for a smooth transition between states.

The structural model of the above equations may be represented in matrix form:

$$X_t = X_0 + C_0X_1 + C(L)X_{t-1} + D(L)\varepsilon_t \tag{41}$$

where $X_0 = (y_0, 0, m_0)'$, $\varepsilon_t = (\theta_t, \eta_t, \mu_t)'$, $C_0 = \begin{bmatrix} 0 & -\delta & \delta \\ 0 & 0 & 1-\alpha(z_t) \\ -\phi & -\pi & 0 \end{bmatrix}$, and *C(L)* and *D(L)* are polynomials in the lag operator. The reduced form is then given by a standard VAR, except that each of the estimated reduced-form coefficients is affected by the state of the economy, denoted by the switching variable, z_t:

$$X_t = (I - C_0)^{-1} X_0 + (I - C_0)^{-1} C(L) X_{t-1} + (I - C_0)^{-1} D(L) \varepsilon_t \qquad (42)$$

with

$$(I - C_0)^{-1} = \frac{1}{1+(1-\alpha(z_t))\pi + \alpha(z_t)\phi\delta} \cdot \begin{bmatrix} 1+(1-\alpha(z_t))\pi & -\delta(1+\pi) & \alpha(z_t)\delta \\ (\alpha(z_t)-1)\phi & 1+\phi\delta & 1-\alpha(z_t) \\ -\phi & \phi\delta - \pi & 1 \end{bmatrix} \qquad (43)$$

A functional form is specified for each of the reduced-form coefficients, and an unrestricted nonlinear VAR is estimated. Weise (1999) extends Teräsvirta and Anderson's (1992) single-equation smooth transition autoregression model to a multiple equation logistic smooth transition vector autoregression (LSTVAR). Weise (1999) also ignores the moving-average terms in equation (42) and sets $D(L) = D$. The reduced-form of the structural equation in (42) is given by the linear VAR:

$$X_t = X + G(L) X_{t-1} + u_t \qquad (44)$$

with $X = (I - C_0)^{-1} X_0$, $G(L) = (I - C_0)^{-1} C(L)$ and $u_t = (I - C_0)^{-1} D(L) \varepsilon_t = (I - C_0)^{-1} D \varepsilon_t$. All of the parameters in X and $G(L)$ are functions of the switching variable, z_t. The smooth transition vector autoregression (STVAR) is given by:

$$X_t = X + G(L) X_{t-1} + (\theta_0 + \theta(L) X_{t-1}) F(z_t) + u_t \qquad (45)$$

where $F(z_t)$ is a transition function bounded between 0 and 1. In this case of the LSTVAR, $F(z_t)$ is a logistic function:

$$F(z_t) = \frac{1}{1+e^{-\gamma(z_t - c)}} - \frac{1}{2}, \gamma > 0 \qquad (46)$$

where c is the threshold parameter around which the dynamics of the model change, with $\lim_{(z_t - c)\to -\infty} F(z_t) \to 0$ and $\lim_{(z_t - c)\to \infty} F(z_t) \to 1$. γ is the speed of adjustment parameter, and as γ approaches zero, $F(z_t)$ converges to a constant and the model becomes a linear VAR. As γ approaches infinity, the model becomes a threshold autoregression where the model's dynamics change sharply at c, such as the threshold autoregression (TAR) model discussed by Tsay (1989) and others (see Tsay (1989) for a summary of other authors' research on TARs).

A.7 STRUCTURAL BREAK TEST RESULTS IN LSTVAR MODEL

Figure A3. CUSUM test results for structural breaks

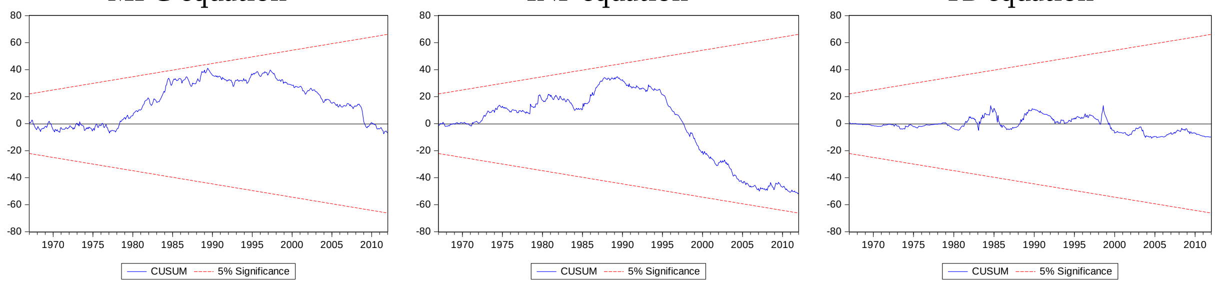


Table A10. Bai and Perron (2003*a, b*) test: *MPG* equation

Multiple breakpoint tests
Bai-Perron tests of L+1 vs. L sequentially determined breaks
Sample: 1966M02 2012M01
Included observations: 550
Breakpoint variables: C MPG(-1) MPG(-2) INF(-1) INF(-2) TB(-1) TB(-2) FCI(-1) FCI(-2)
Break test options: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Sequential F-statistic determined breaks: 1

Break Test	F-statistic	Scaled F-statistic	Critical Value**
0 vs. 1 *	5.969880	53.72892	25.65
1 vs. 2	2.443138	21.98824	27.66

* Significant at the 0.05 level.
** Bai-Perron (Econometric Journal, 2003) critical values.

Break dates:

	Sequential	Repartition
1	1977M11	1977M11

Table A11. Bai and Perron (2003*a, b*) test: *INF* equation

Multiple breakpoint tests
Bai-Perron tests of L+1 vs. L sequentially determined breaks
Sample: 1966M02 2012M01
Included observations: 550
Breakpoint variables: C MPG(-1) MPG(-2) INF(-1) INF(-2) TB(-1) TB(-2) FCI(-1) FCI(-2)
Break test options: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Sequential F-statistic determined breaks: 1

Break Test	F-statistic	Scaled F-statistic	Critical Value**
0 vs. 1 *	7.331743	65.98569	25.65
1 vs. 2	2.316475	20.84827	27.66

* Significant at the 0.05 level.
** Bai-Perron (Econometric Journal, 2003) critical values.

Break dates:

	Sequential	Repartition
1	1994M10	1994M10

Table A12. Bai and Perron (2003*a, b*) test: *TB* equation

Multiple breakpoint tests
Bai-Perron tests of L+1 vs. L sequentially determined breaks
Sample: 1966M02 2012M01
Included observations: 550
Breakpoint variables: C MPG(-1) MPG(-2) INF(-1) INF(-2) TB(-1) TB(-2) FCI(-1) FCI(-2)
Break test options: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Sequential F-statistic determined breaks: 2

Break Test	F-statistic	Scaled F-statistic	Critical Value**
0 vs. 1 *	4.326687	38.94018	25.65
1 vs. 2 *	4.578797	41.20918	27.66
2 vs. 3	2.205789	19.85210	28.91

* Significant at the 0.05 level.
** Bai-Perron (Econometric Journal, 2003) critical values.

Break dates:

	Sequential	Repartition
1	1983M03	1983M03
2	1996M12	1996M12

A.8 LSTVAR TRANSITION FUNCTIONS

Figure A4. LSTVAR(2) with FCI_{t-2} as switcher

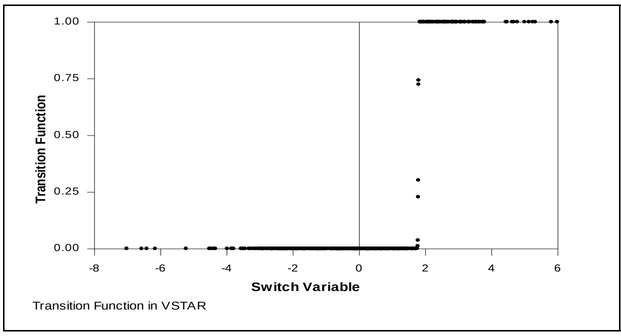


Figure A5. LSTVAR(2) with MPG_{t-2} as switcher

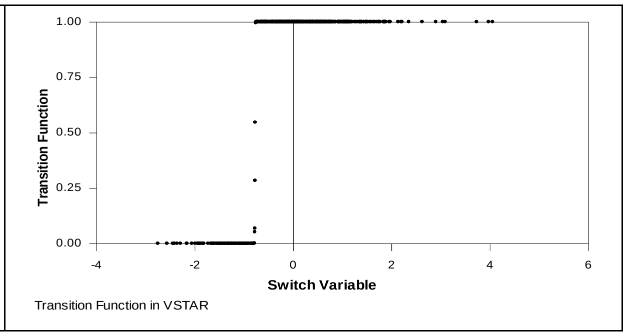


Figure A6. LSTVAR(2) with INF_{t-2} as switcher

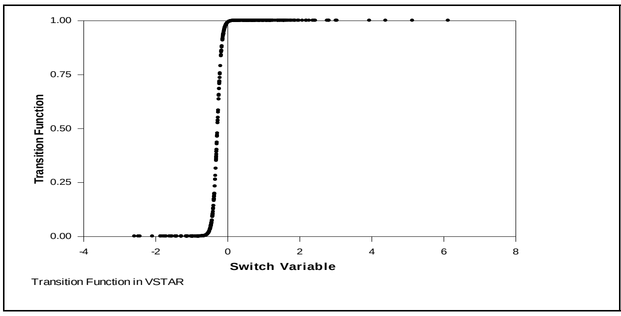


Figure A7. LSTVAR(2) with TB_{t-2} as switcher

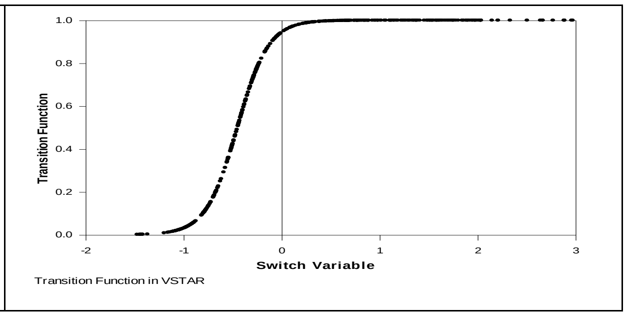


Figure A8. LSTVAR(2) 4 switch version 1

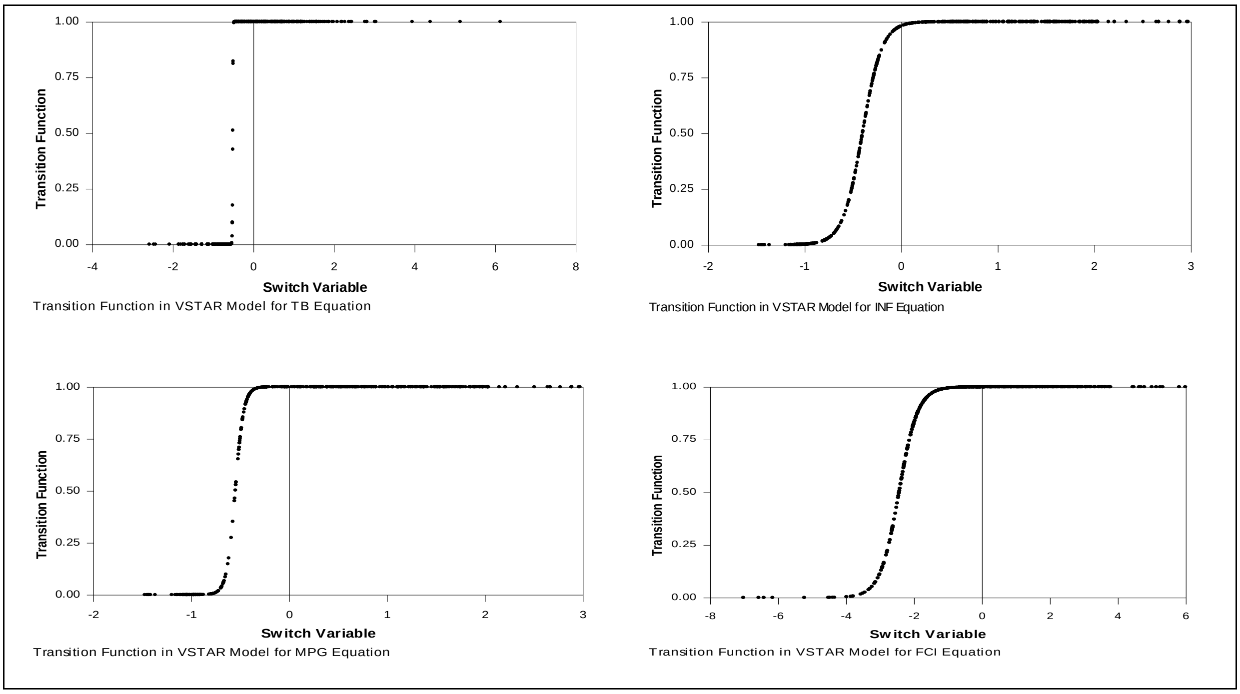
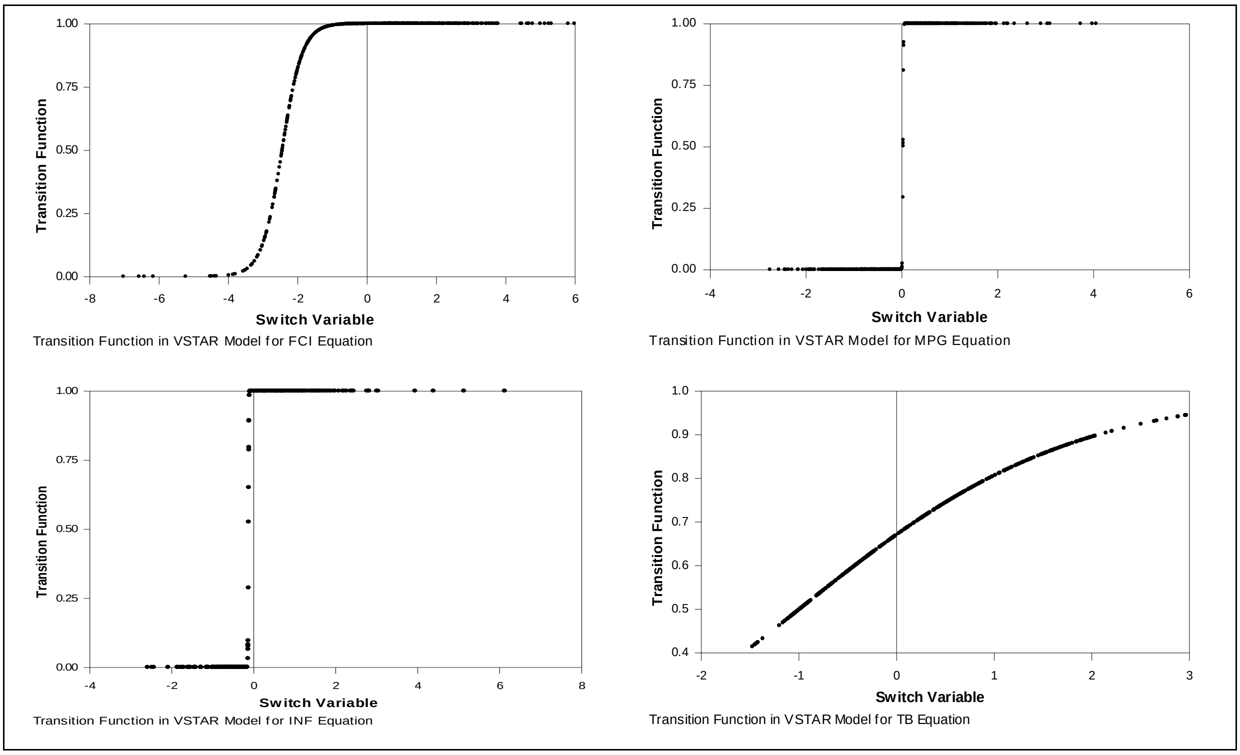


Figure A9. LSTVAR(2) 4 switch version 2



A.9 GENERALISED IMPULSE RESPONSE FUNCTIONS

Figure A10. Linear VAR: Cumulative GIRFs with 68% bootstrapped confidence intervals (CIs)

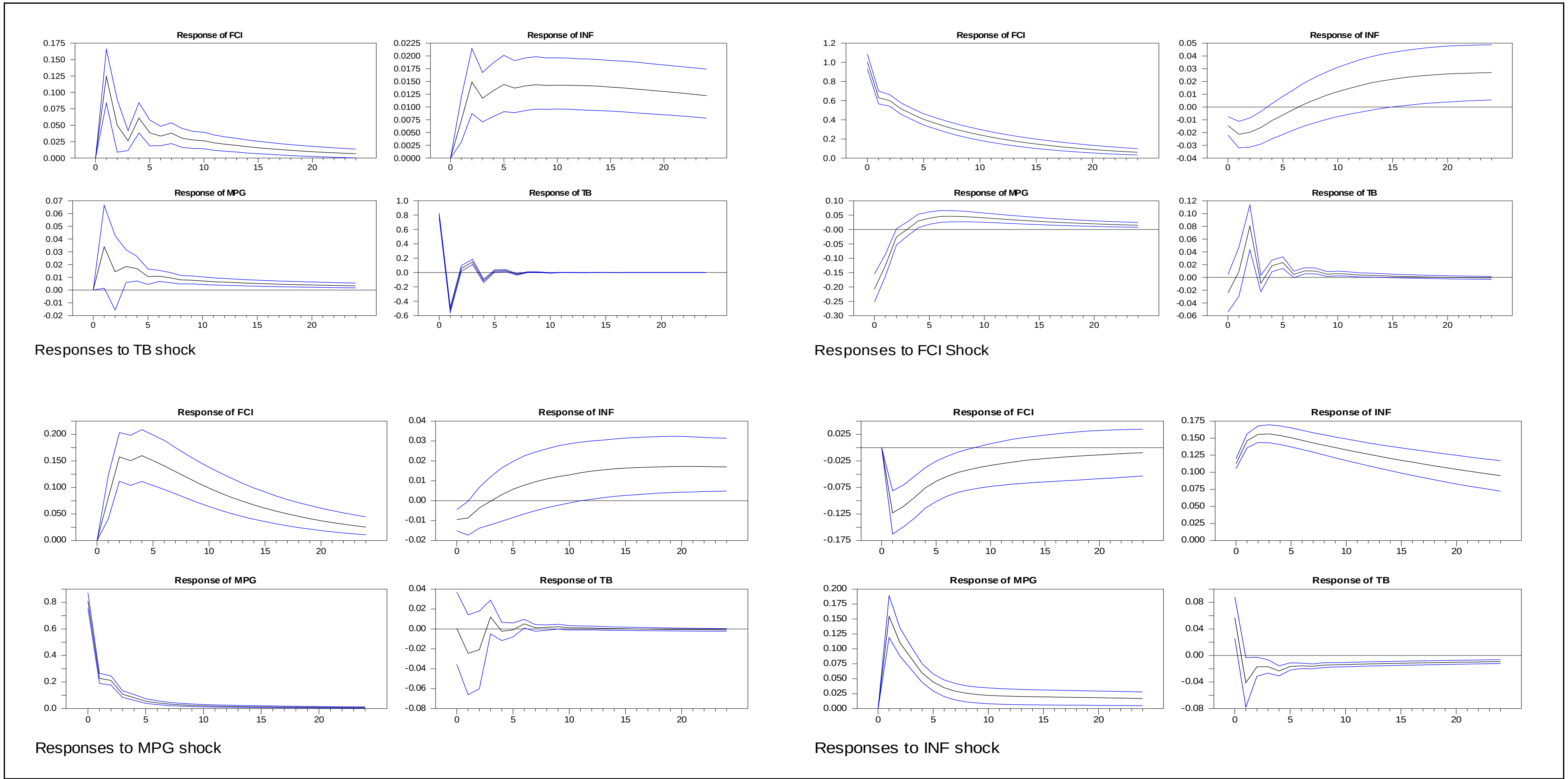


Figure A11. LSTVAR with INF_{t-2} as switcher: Responses of shock to *FCI* of 1SE with 68% bootstrapped CIs

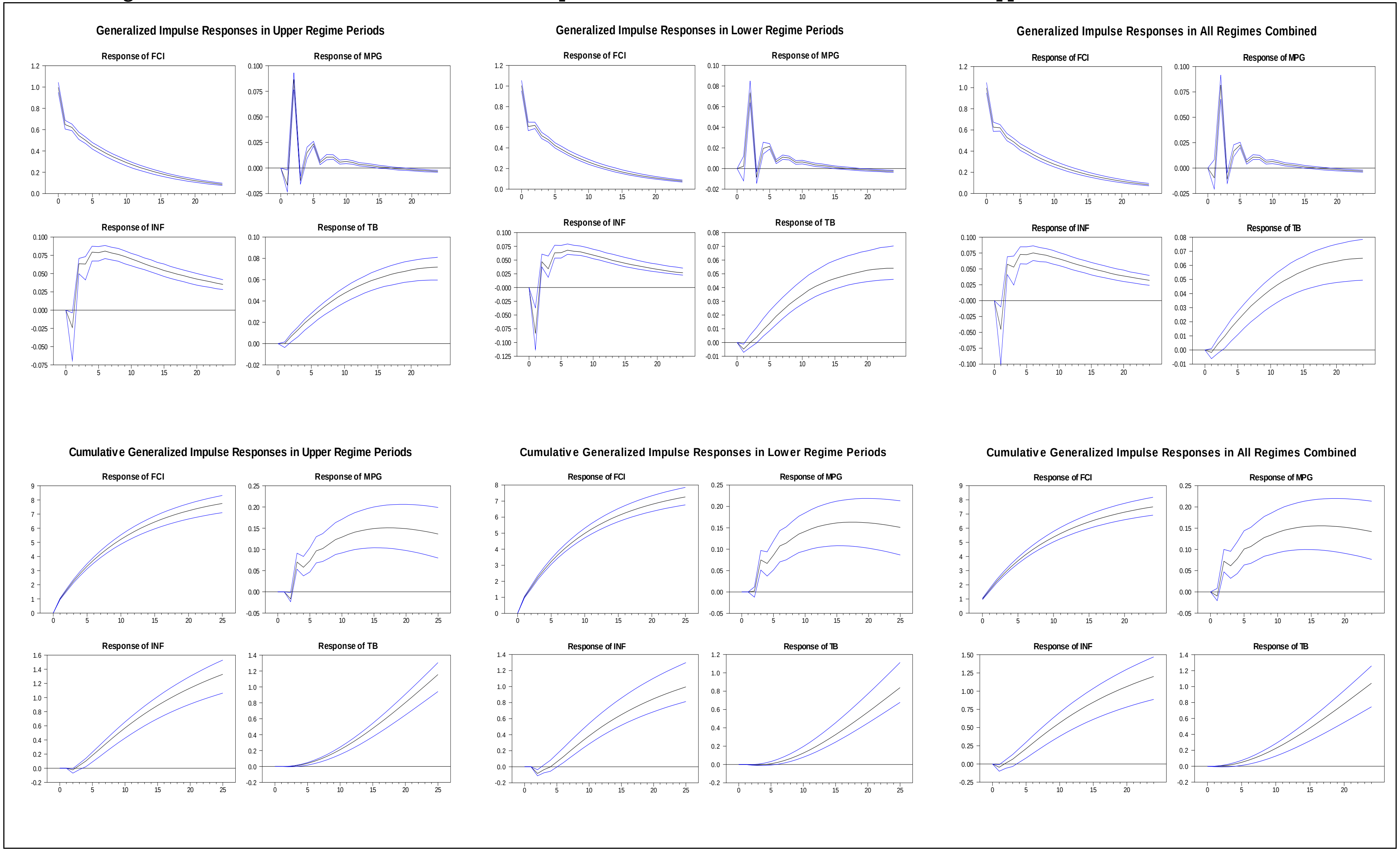


Figure A12. LSTVAR with INF_{t-2} as switcher: Responses of shock to *FCI* of -1SE with 68% bootstrapped CIs

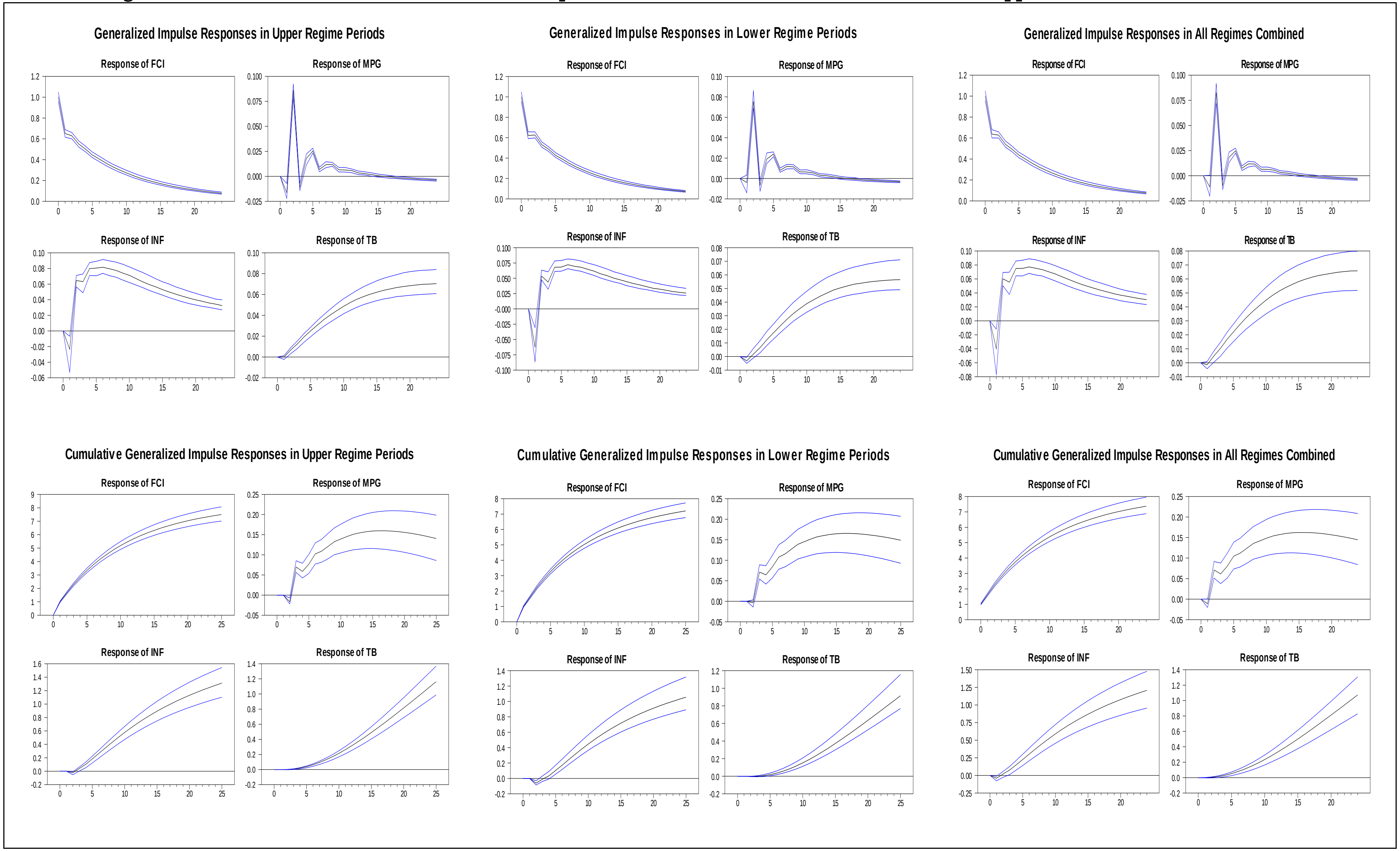


Figure A13. LSTVAR with INF_{t-2} as switcher: Responses of shock to *FCI* of 3SE with 68% bootstrapped CIs

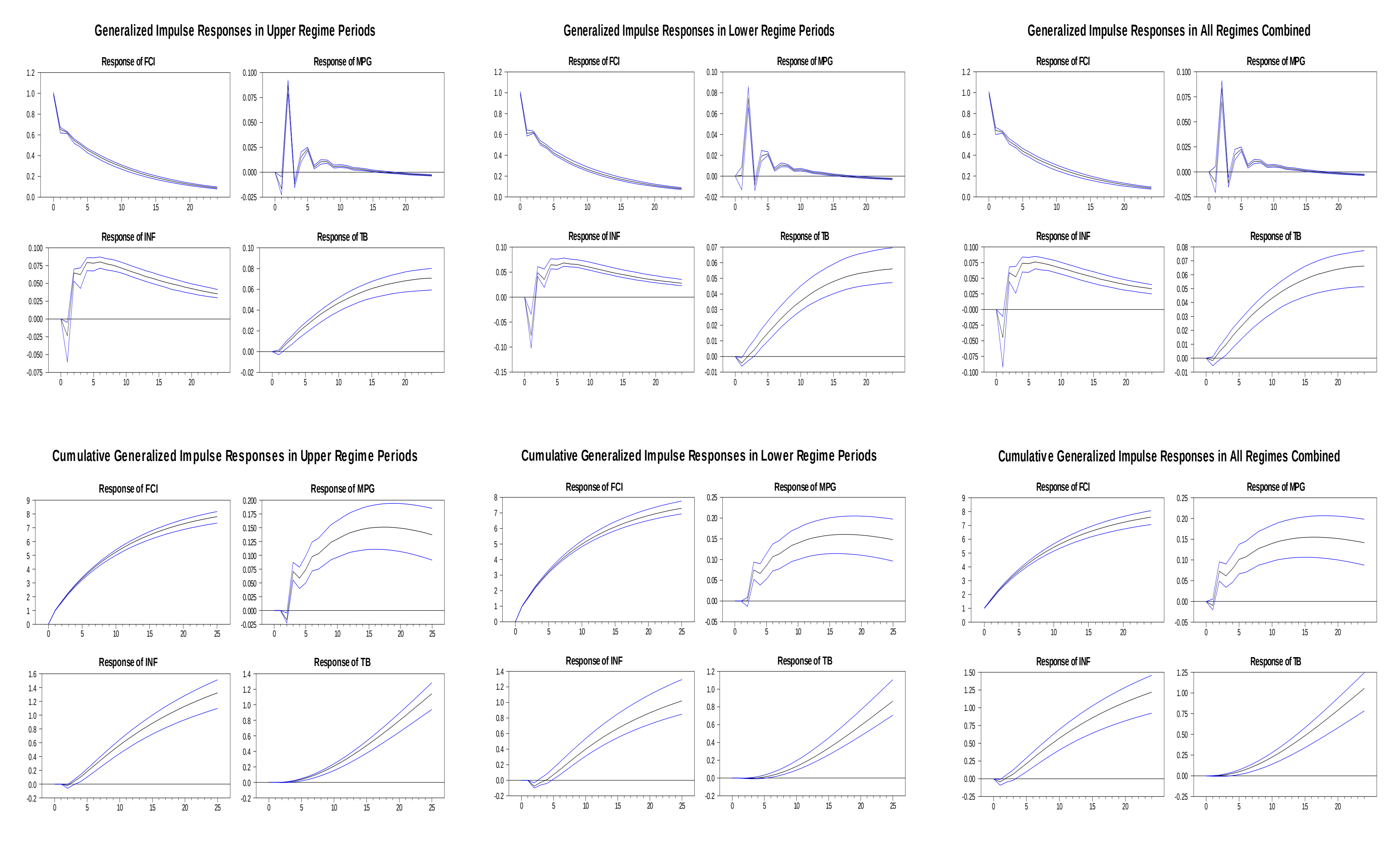


Figure A14. LSTVAR with INF_{t-2} as switcher: Responses of shock to *FCI* of -3SE with 68% bootstrapped CIs

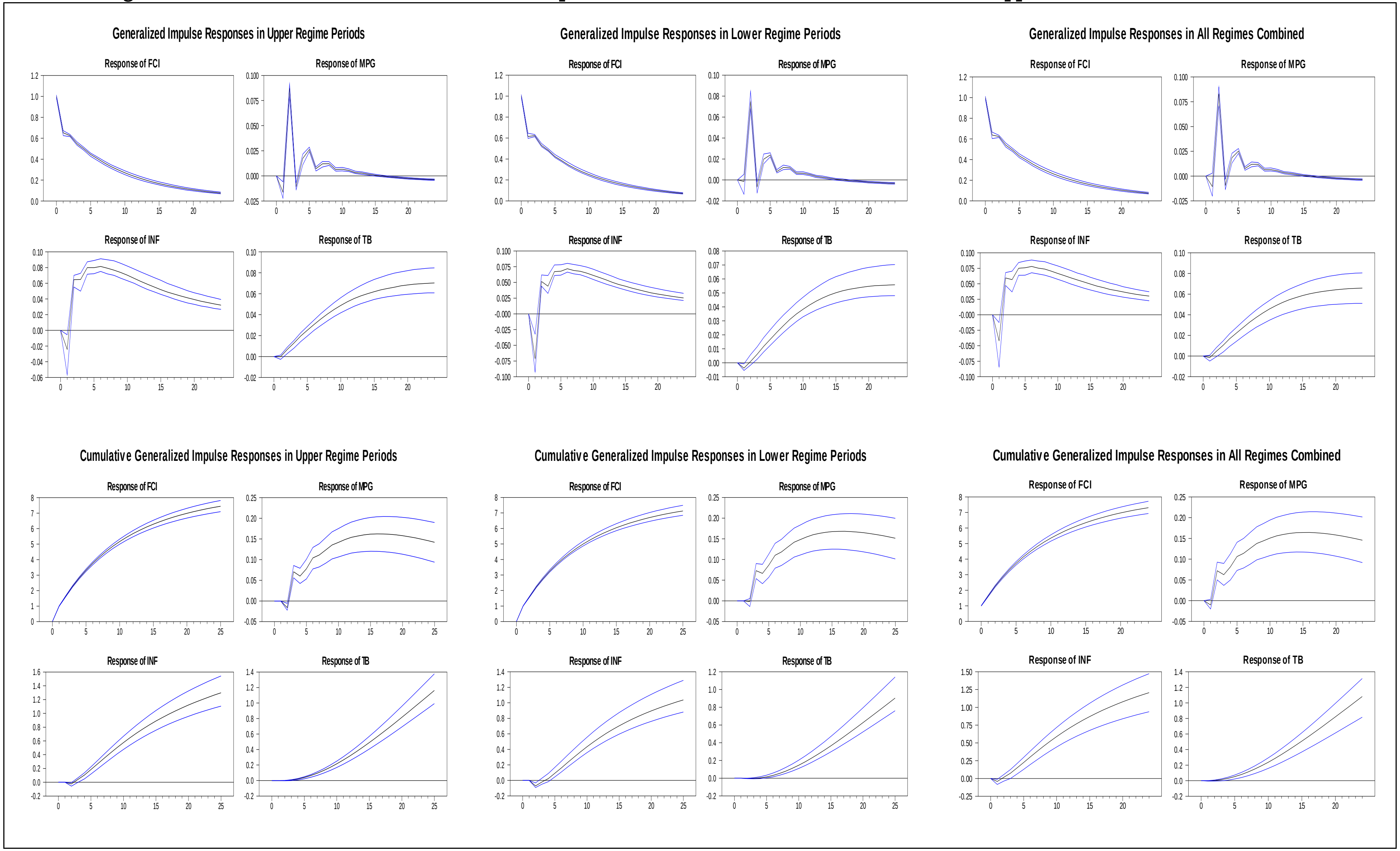


Figure A15. LSTVAR with INF_{t-2} as switcher: Responses of shock to MPG of 1SE with 68% bootstrapped CIs

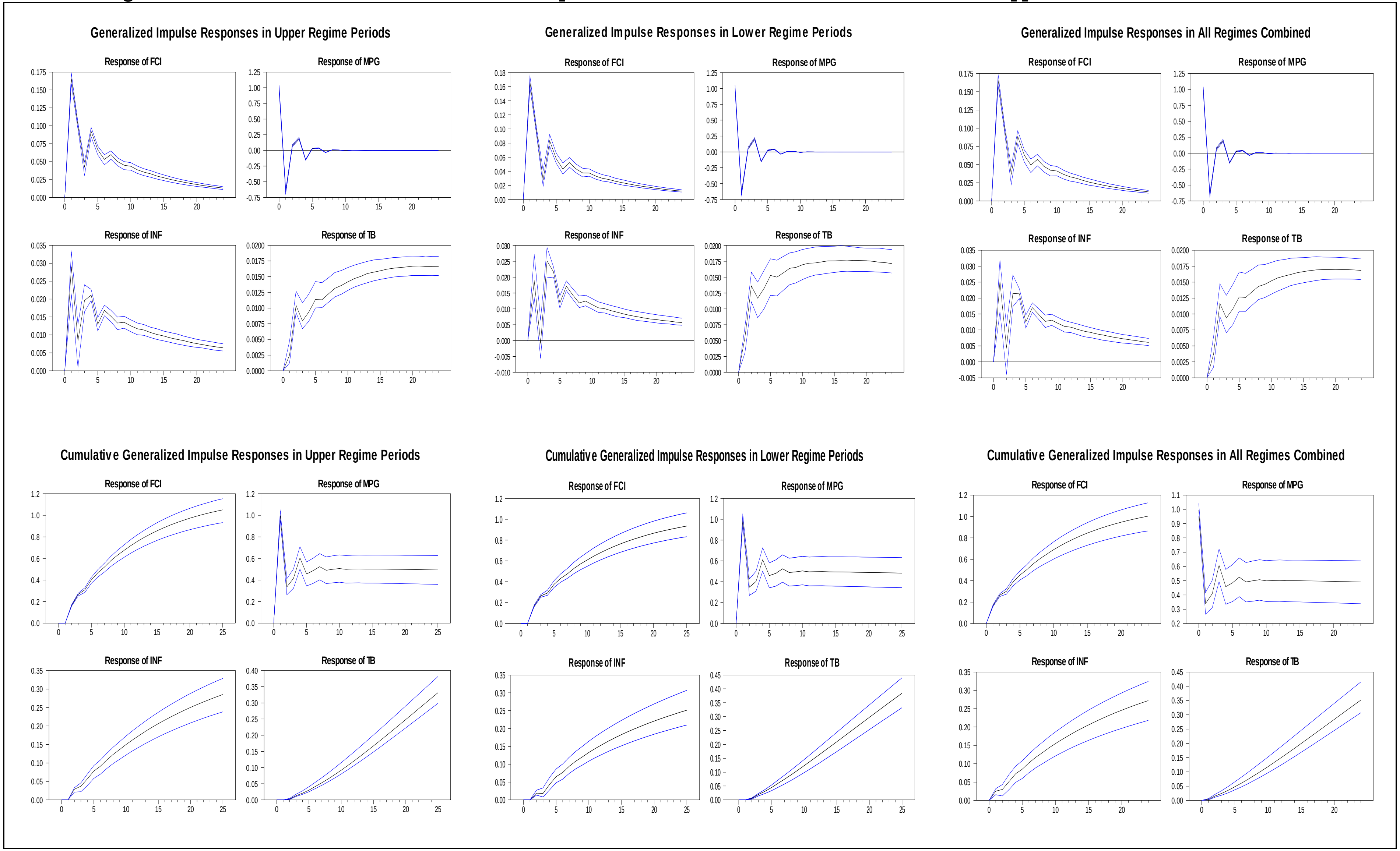


Figure A16. LSTVAR with INF_{t-2} as switcher: Responses of shock to MPG of -1SE with 68% bootstrapped CIs

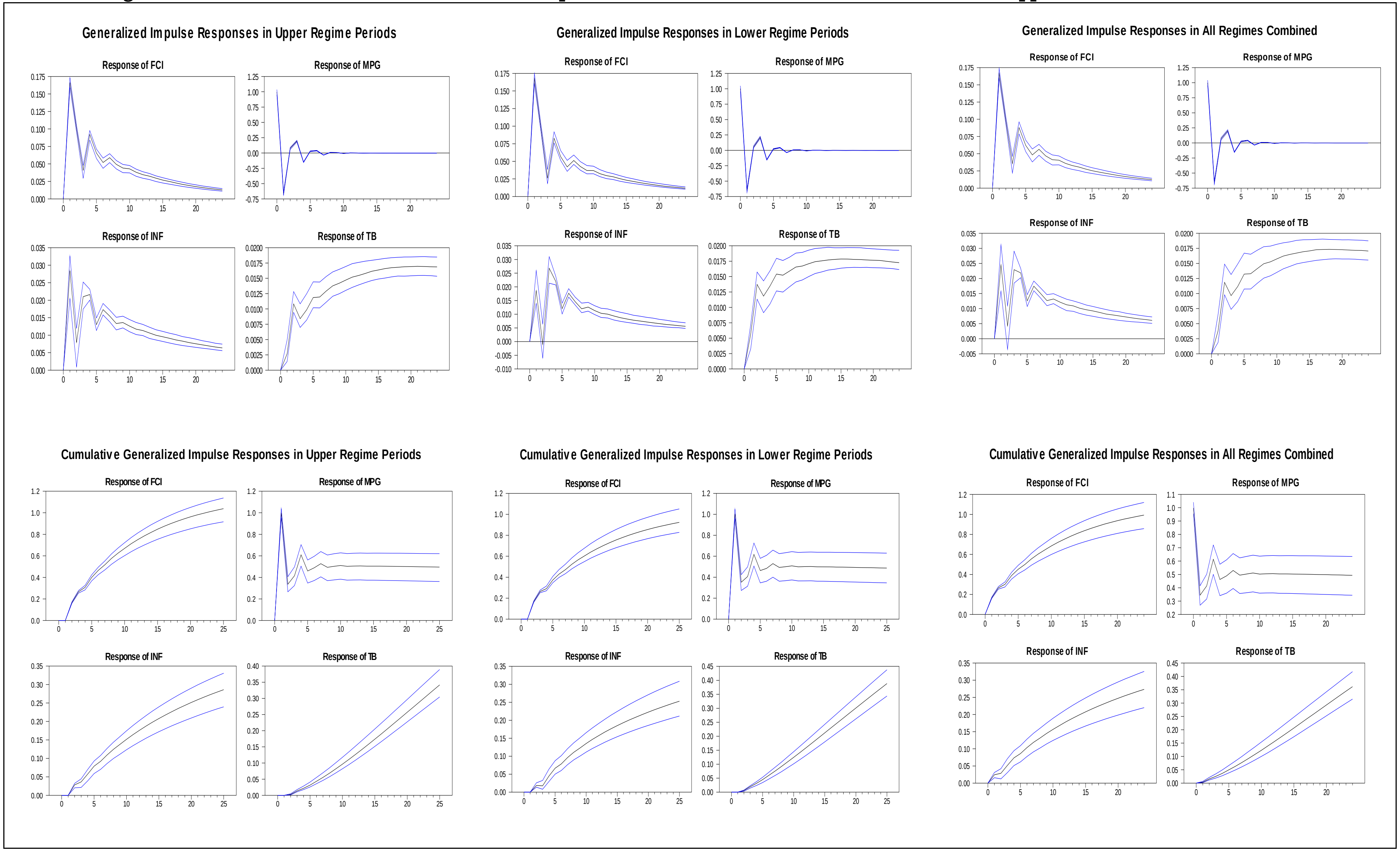


Figure A17. LSTVAR with INF_{t-2} as switcher: Responses of shock to *MPG* of 3SE with 68% bootstrapped CIs

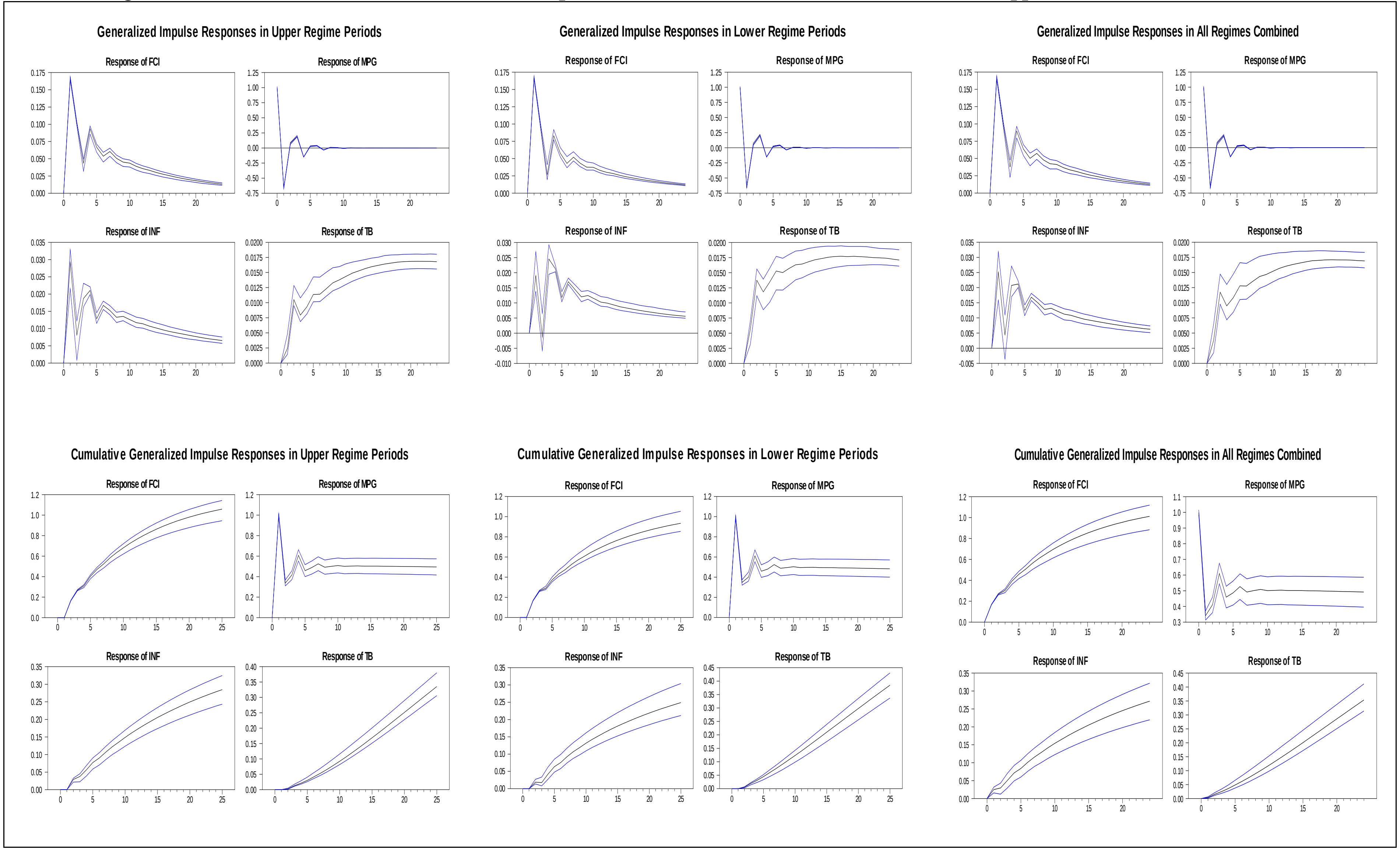


Figure A18. LSTVAR with INF_{t-2} as switcher: Responses of shock to MPG of -3SE with 68% bootstrapped CIs

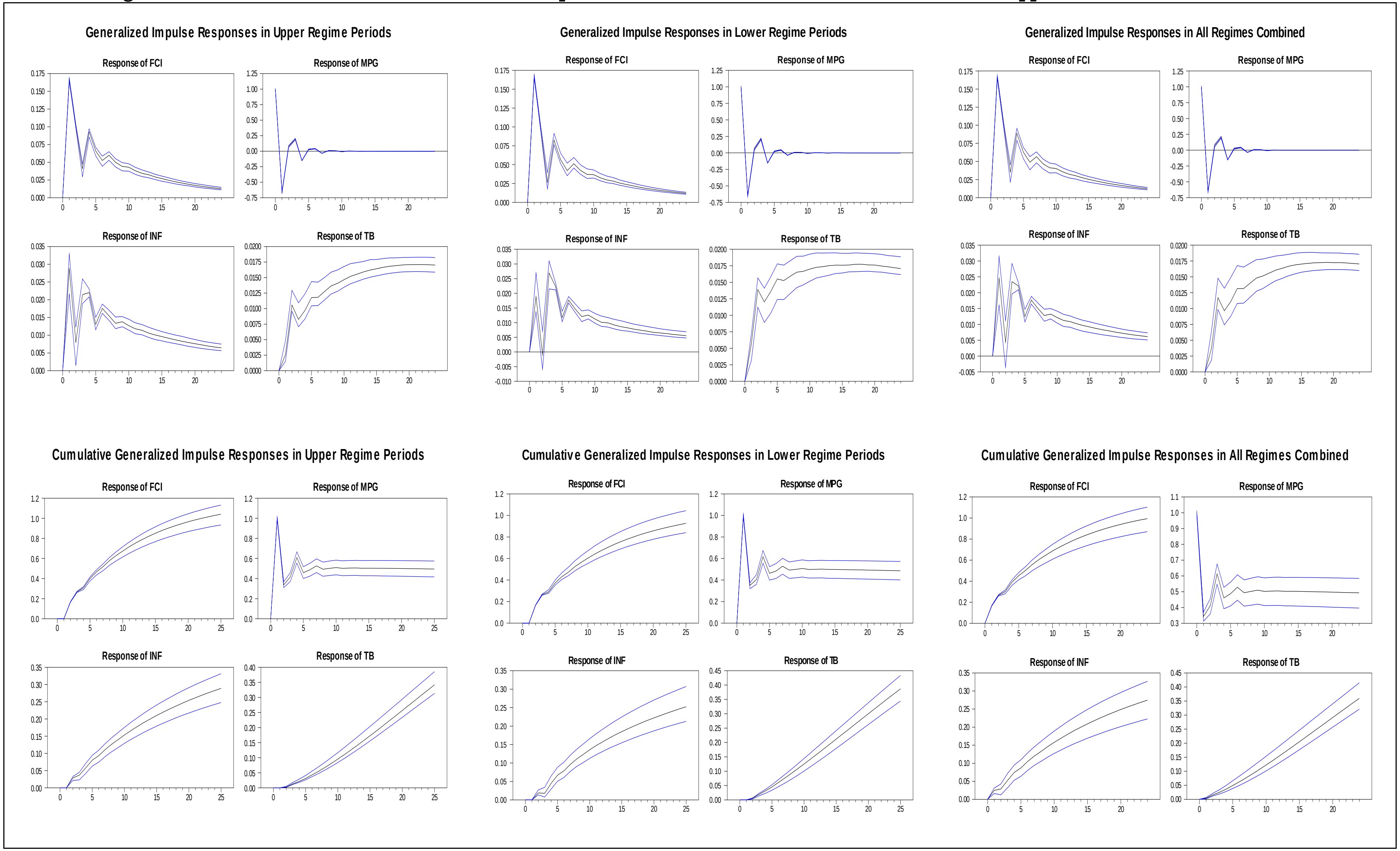


Figure A19. LSTVAR with INF_{t-2} as switcher: Responses of shock to INF of 1SE with 68% bootstrapped CIs

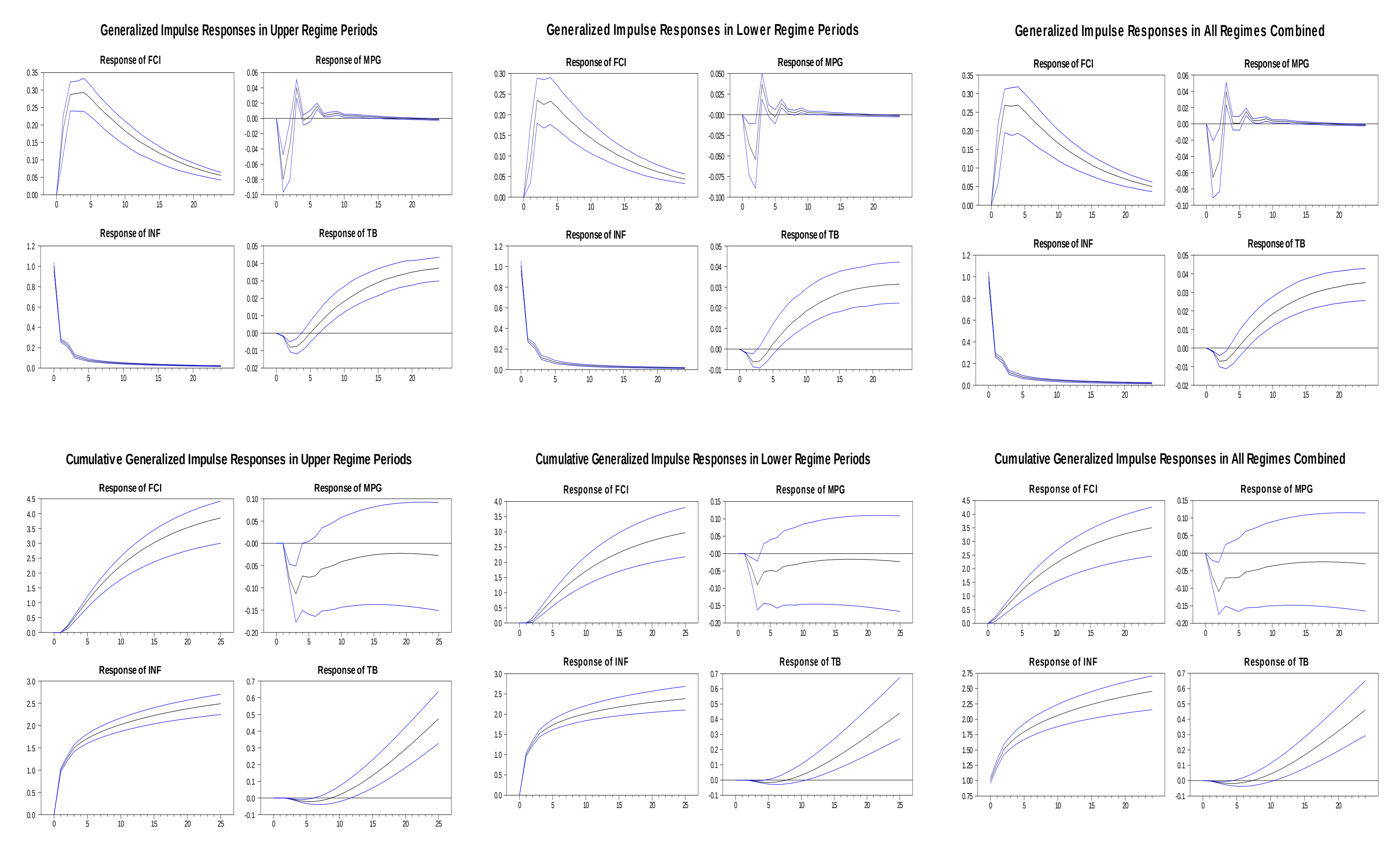


Figure A20. LSTVAR with INF_{t-2} as switcher: Responses of shock to INF of -1SE with 68% bootstrapped CIs

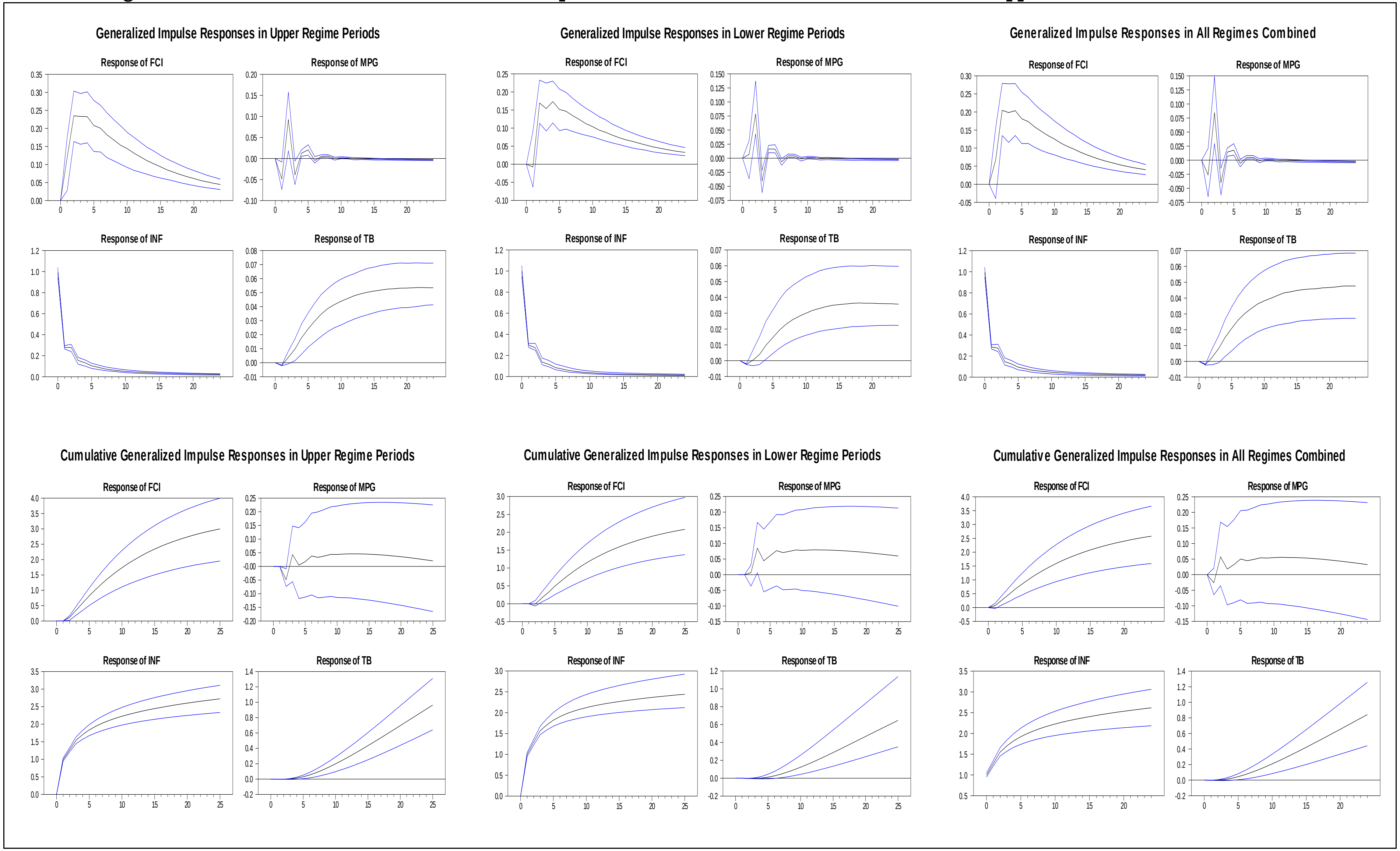


Figure A21. LSTVAR with INF_{t-2} as switcher: Responses of shock to *INF* of 3SE with 68% bootstrapped CIs

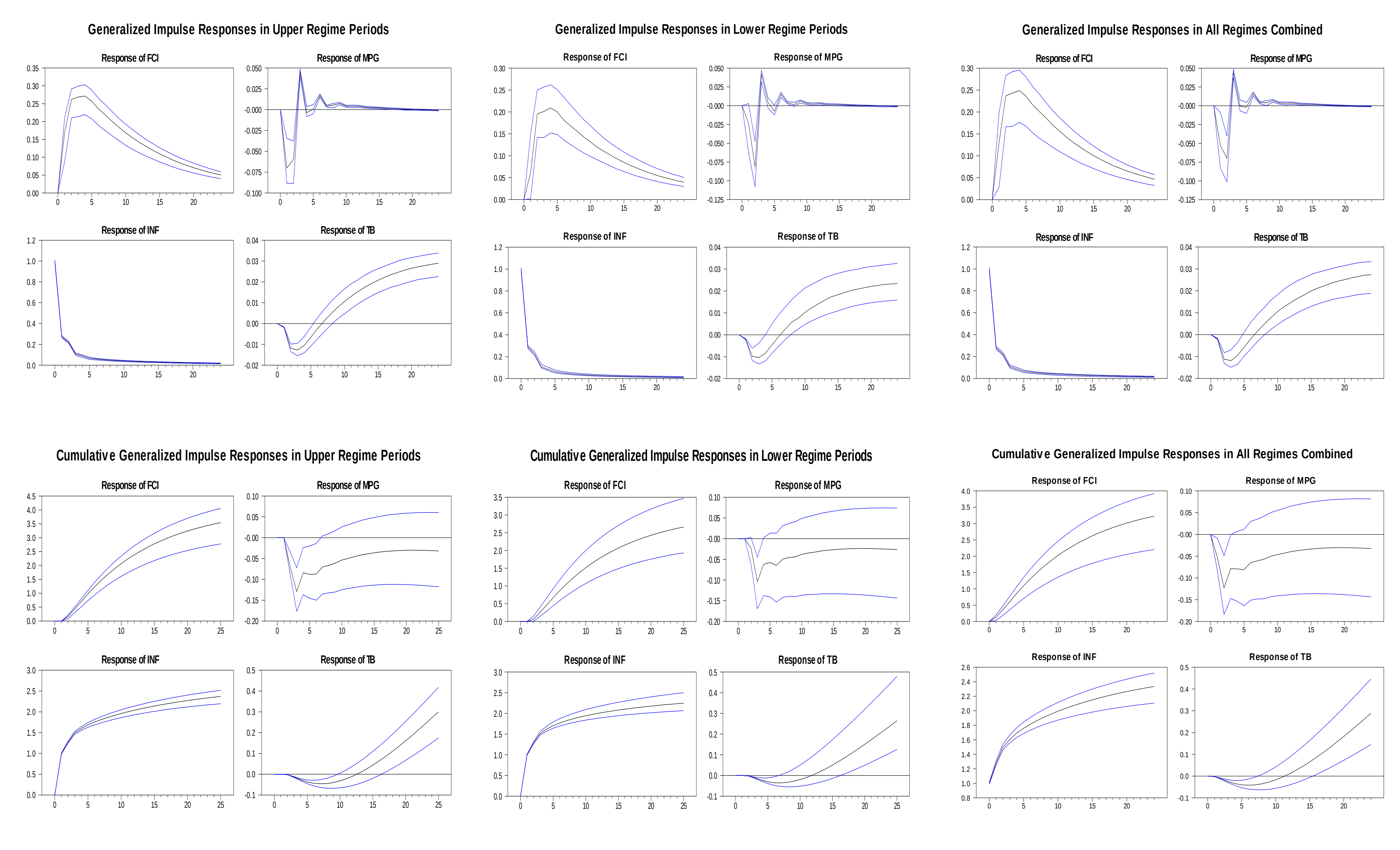


Figure A22. LSTVAR with INF_{t-2} as switcher: Responses of shock to INF of -3SE with 68% bootstrapped CIs

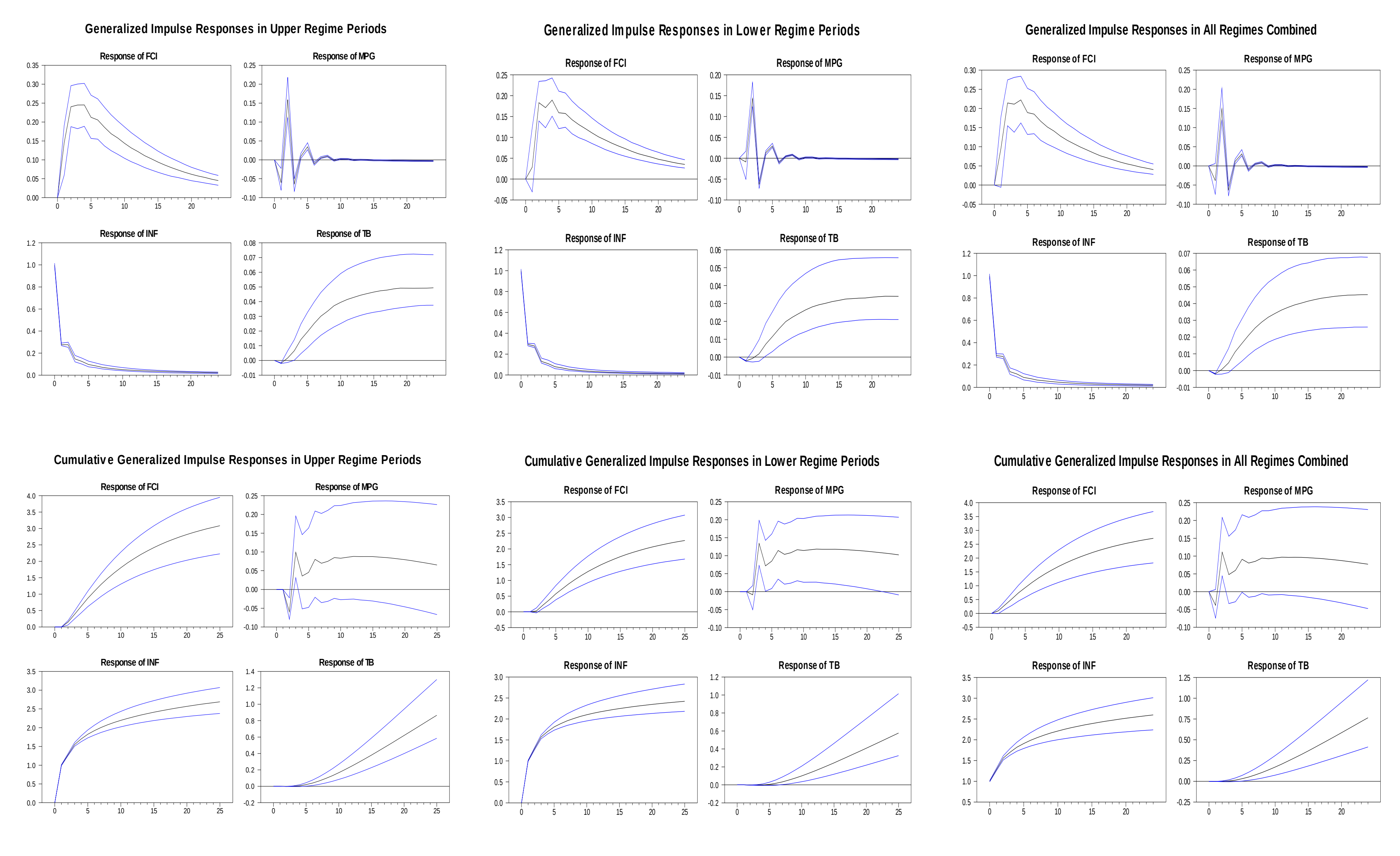


Figure A23. LSTVAR with INF_{t-2} as switcher: Responses of shock to TB of 1SE with 68% bootstrapped CIs

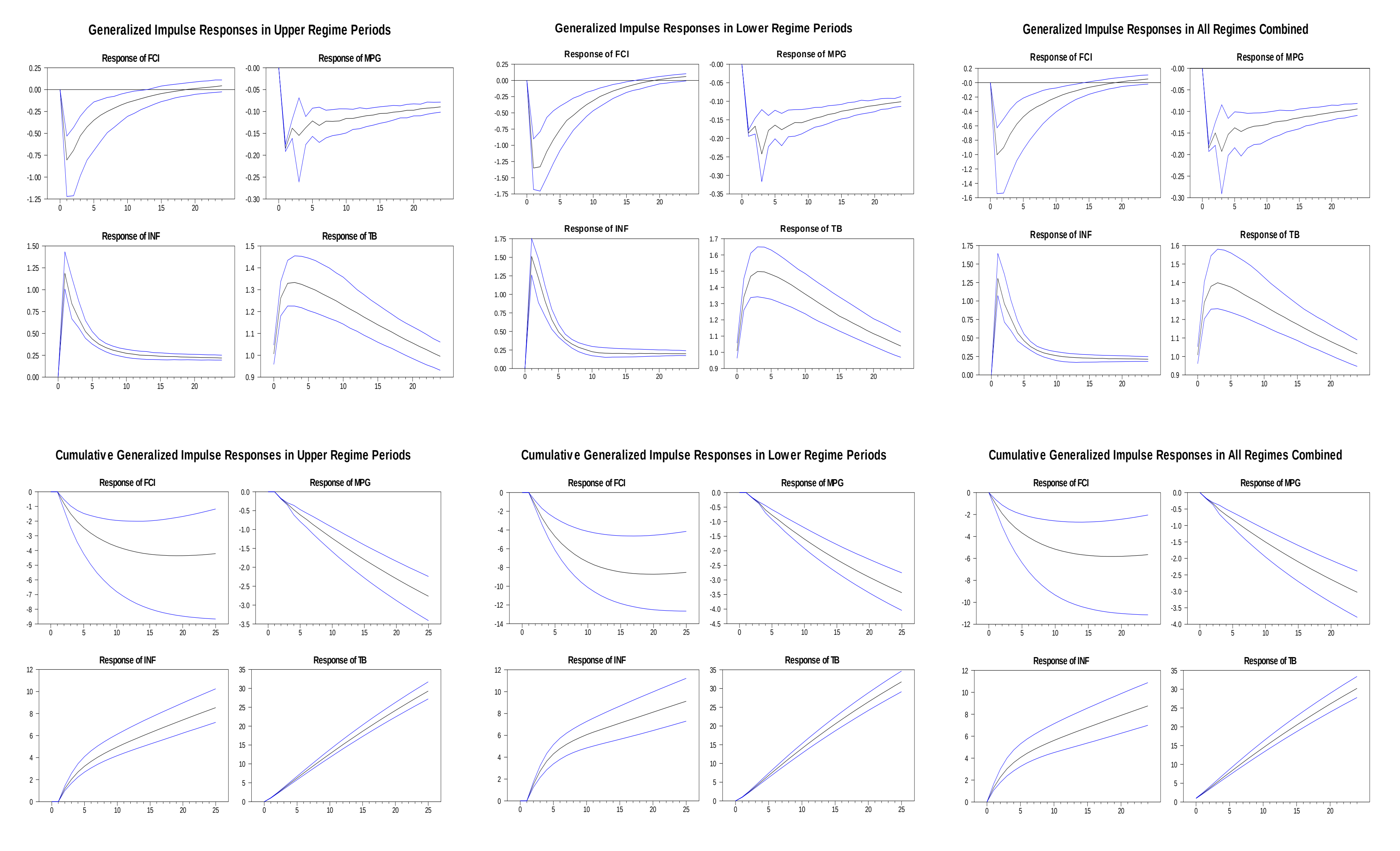


Figure A24. LSTVAR with INF_{t-2} as switcher: Responses of shock to TB of -1SE with 68% bootstrapped CIs

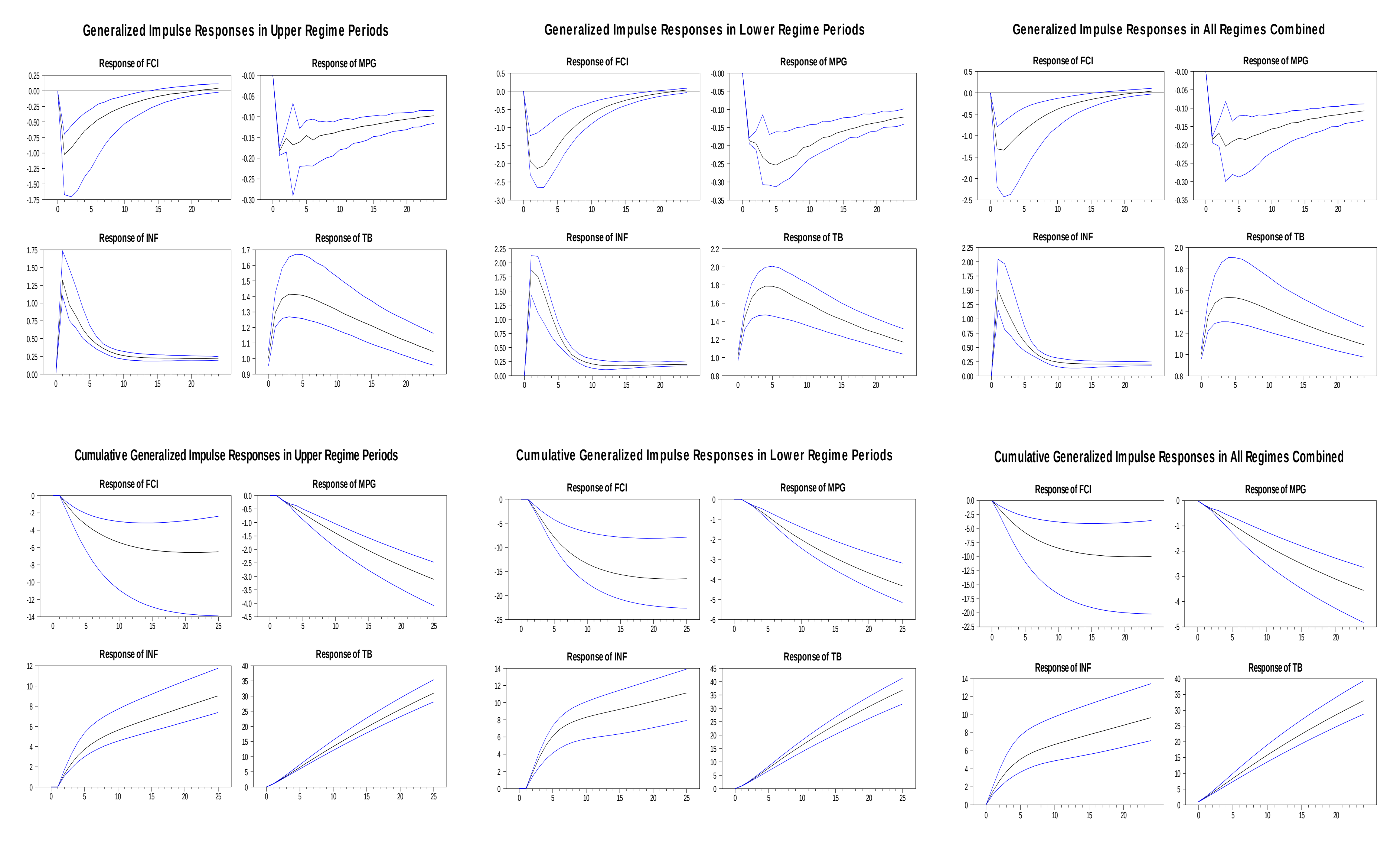


Figure A25. LSTVAR with INF_{t-2} as switcher: Responses of shock to TB of 3SE with 68% bootstrapped CIs

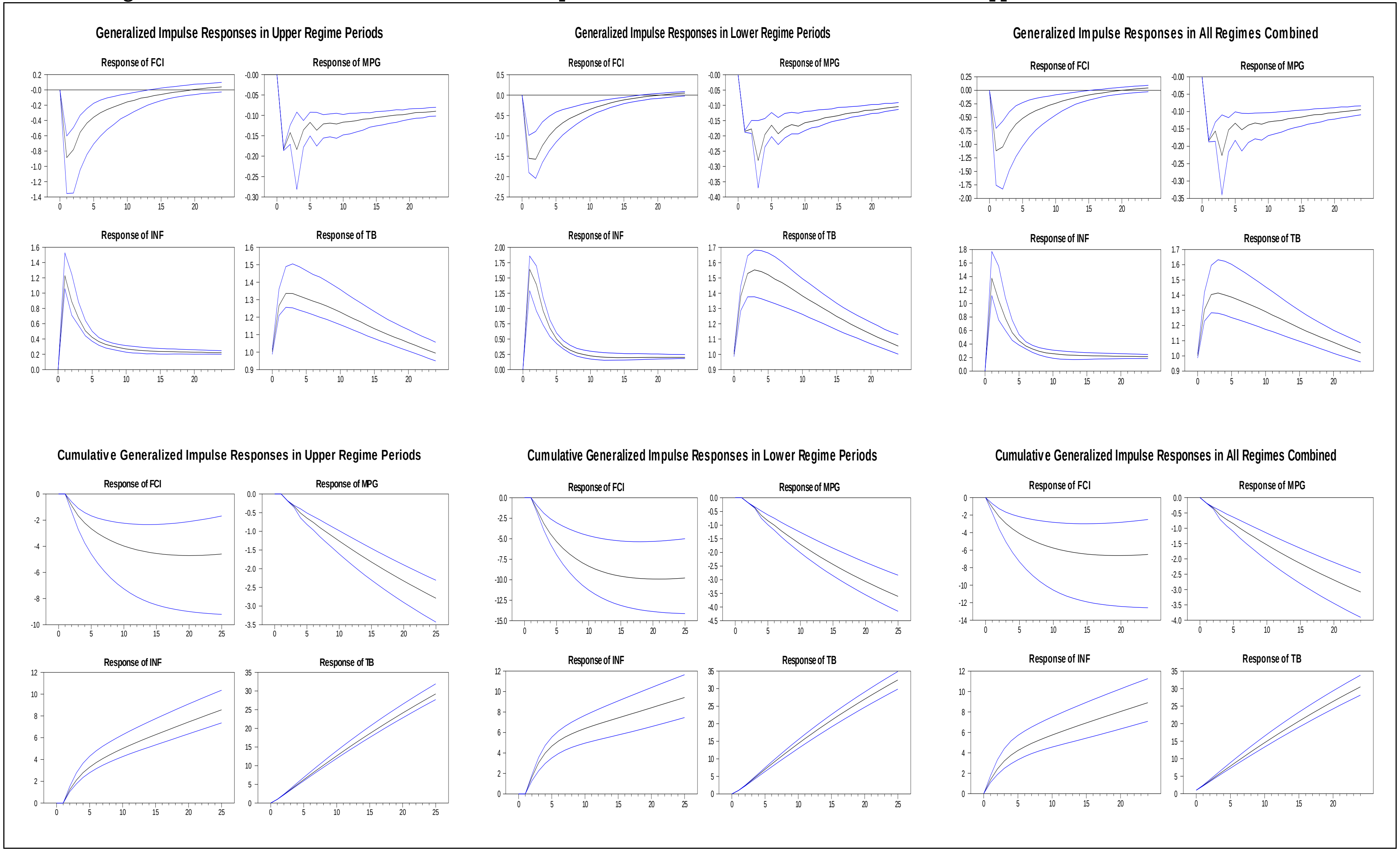


Figure A26. LSTVAR with INF_{t-2} as switcher: Responses of shock to *TB* of -3SE with 68% bootstrapped CIs

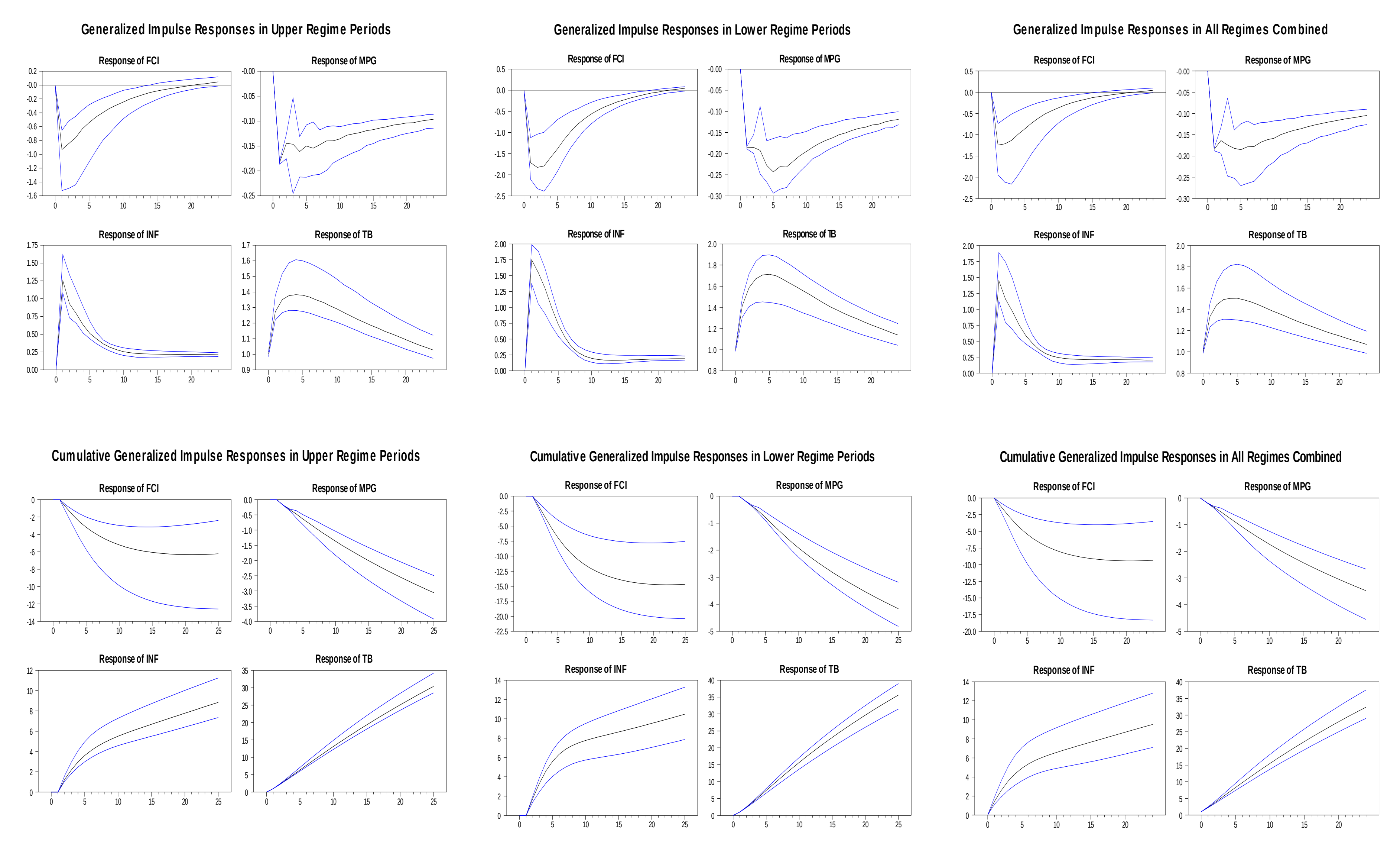


Figure A27. LSTVAR with 4 switching variables version 1: Responses of shock to *FCI* of 1SE with 68% bootstrapped CIs

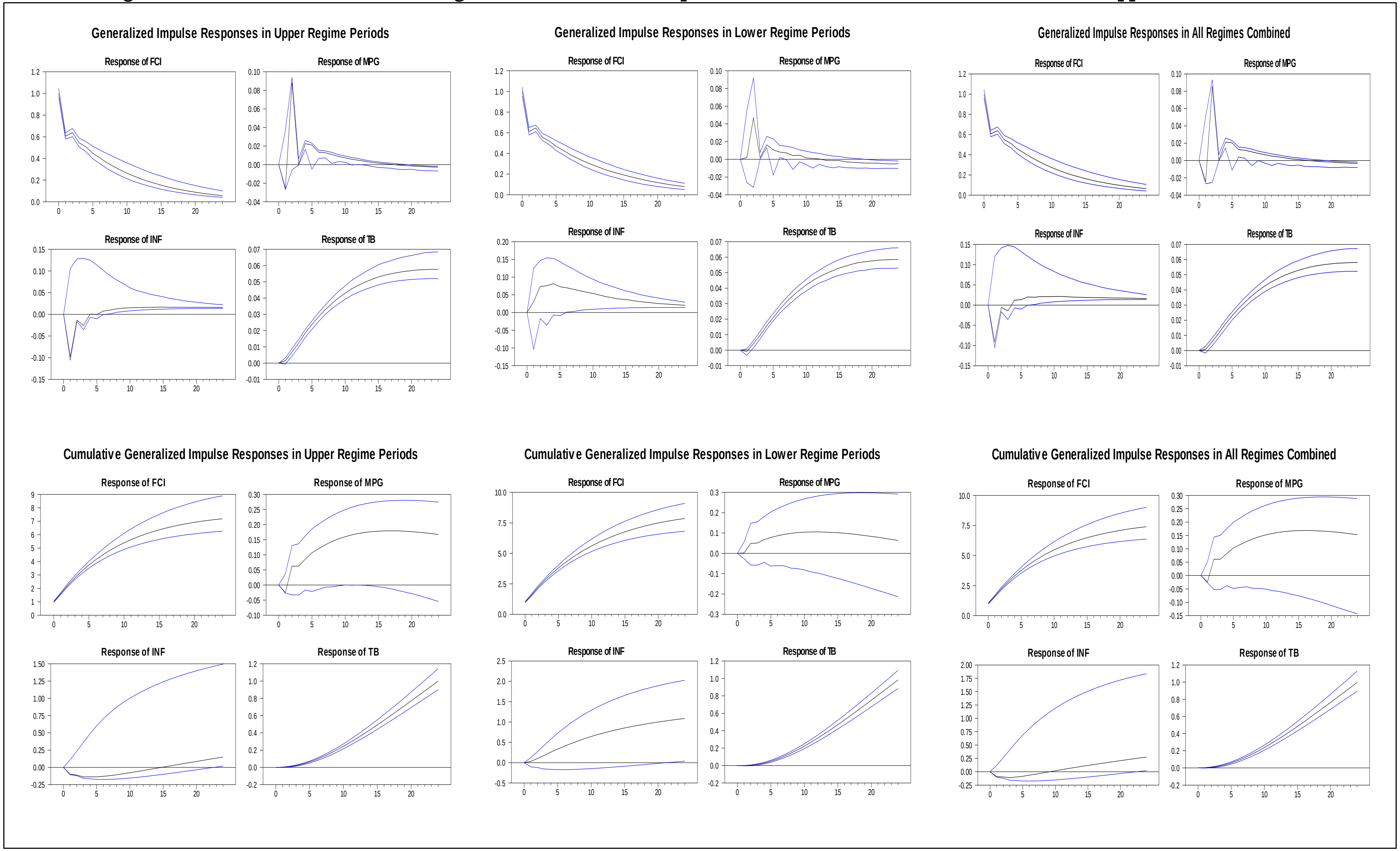


Figure A28. LSTVAR with 4 switching variables version 1: Responses of shock to *FCI* of -1SE with 68% bootstrapped CIs

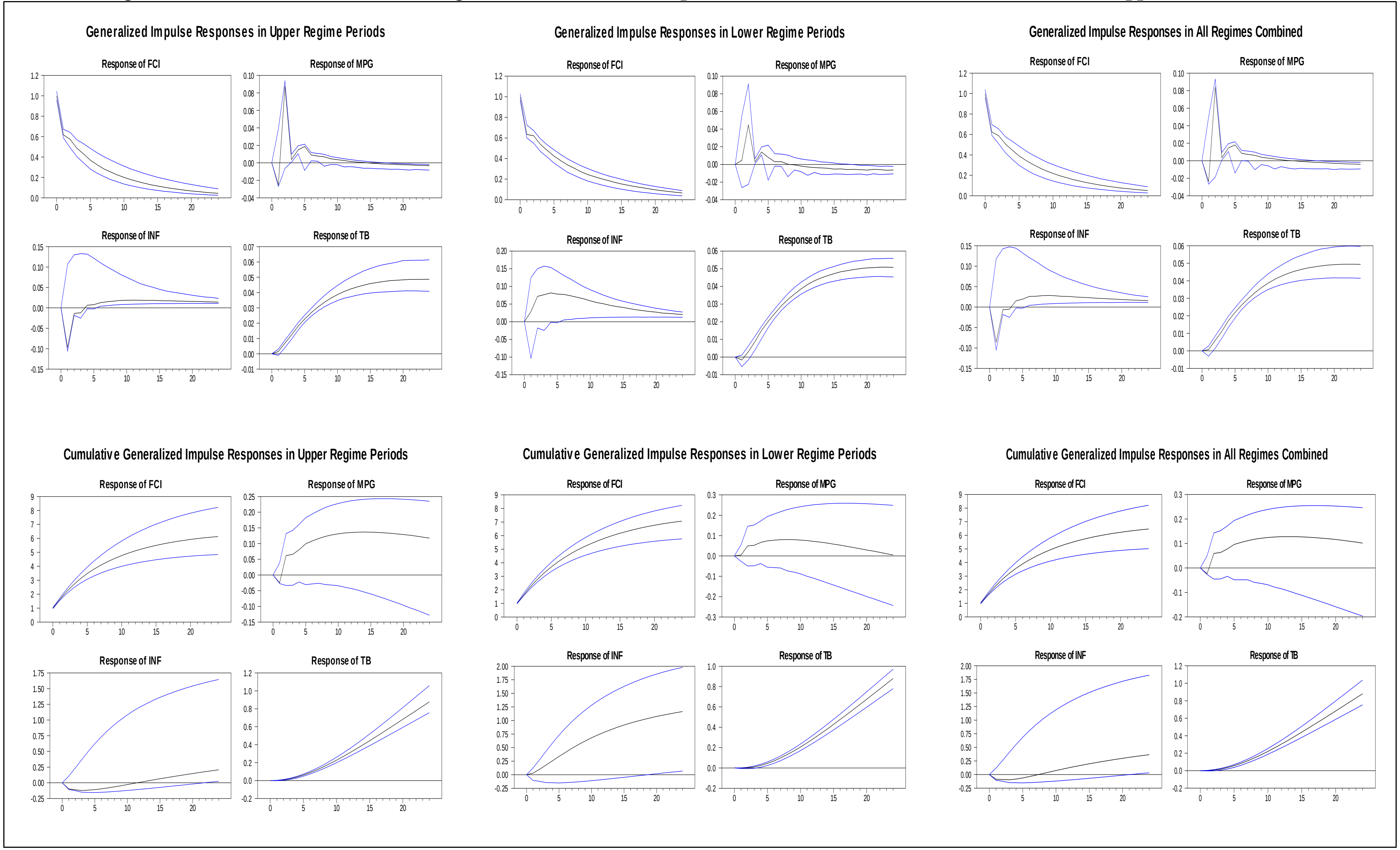


Figure A29. LSTVAR with 4 switching variables version 1: Responses of shock to *FCI* of 3SE with 68% bootstrapped CIs

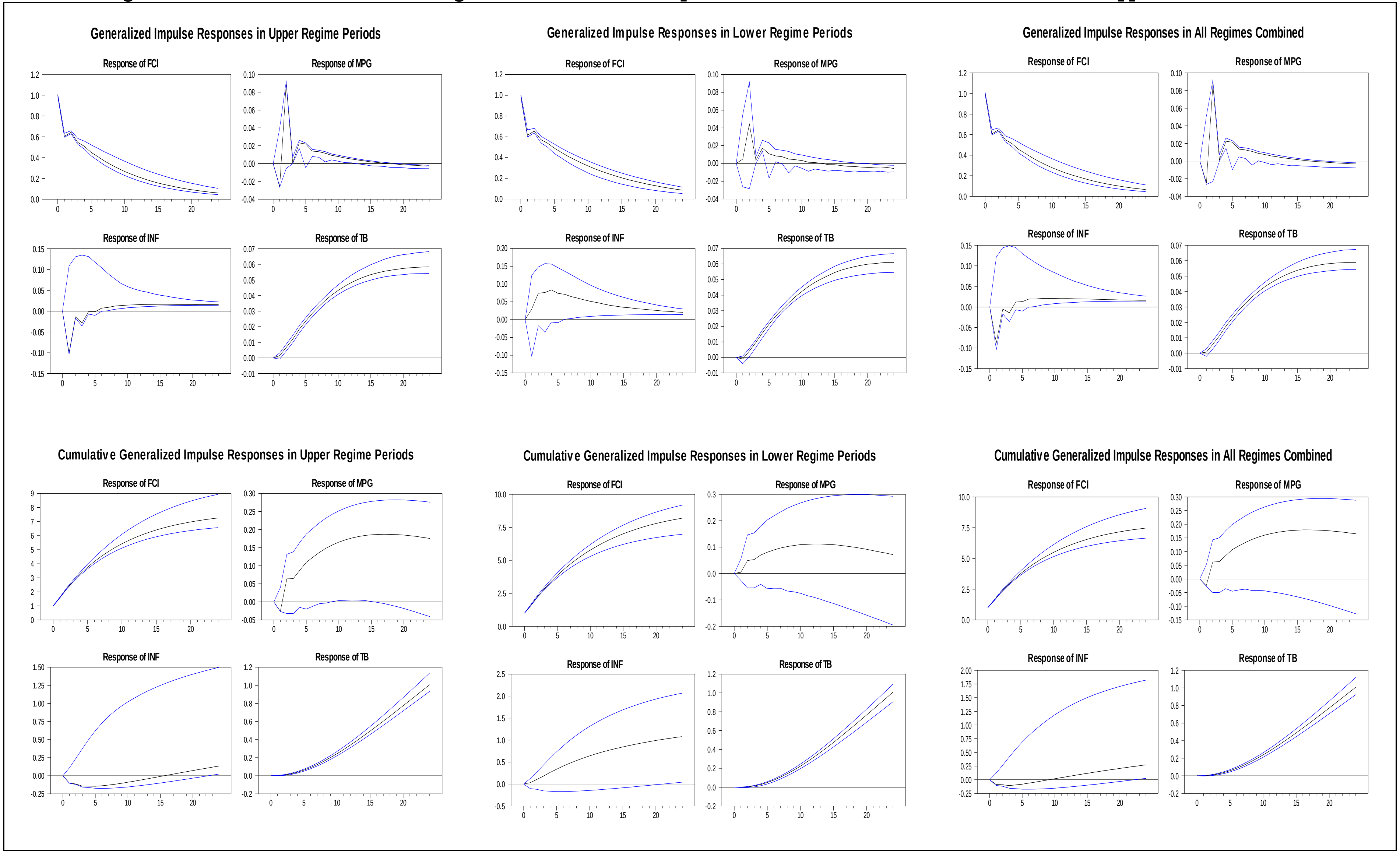


Figure A30. LSTVAR with 4 switching variables version 1: Responses of shock to *FCI* of -3SE with 68% bootstrapped CIs

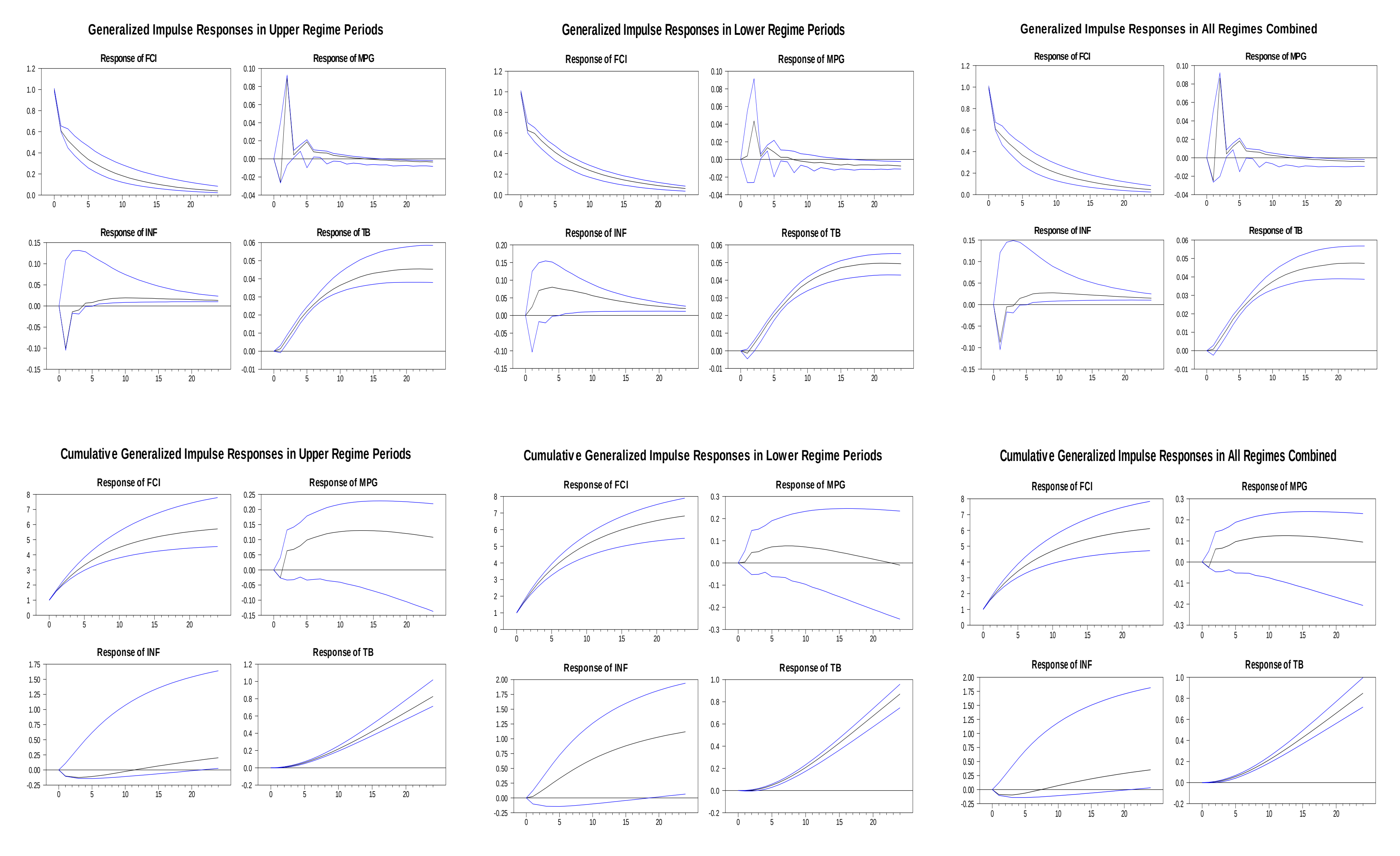


Figure A31. LSTVAR with 4 switching variables version 1: Responses of shock to *MPG* of 1SE with 68% bootstrapped CIs

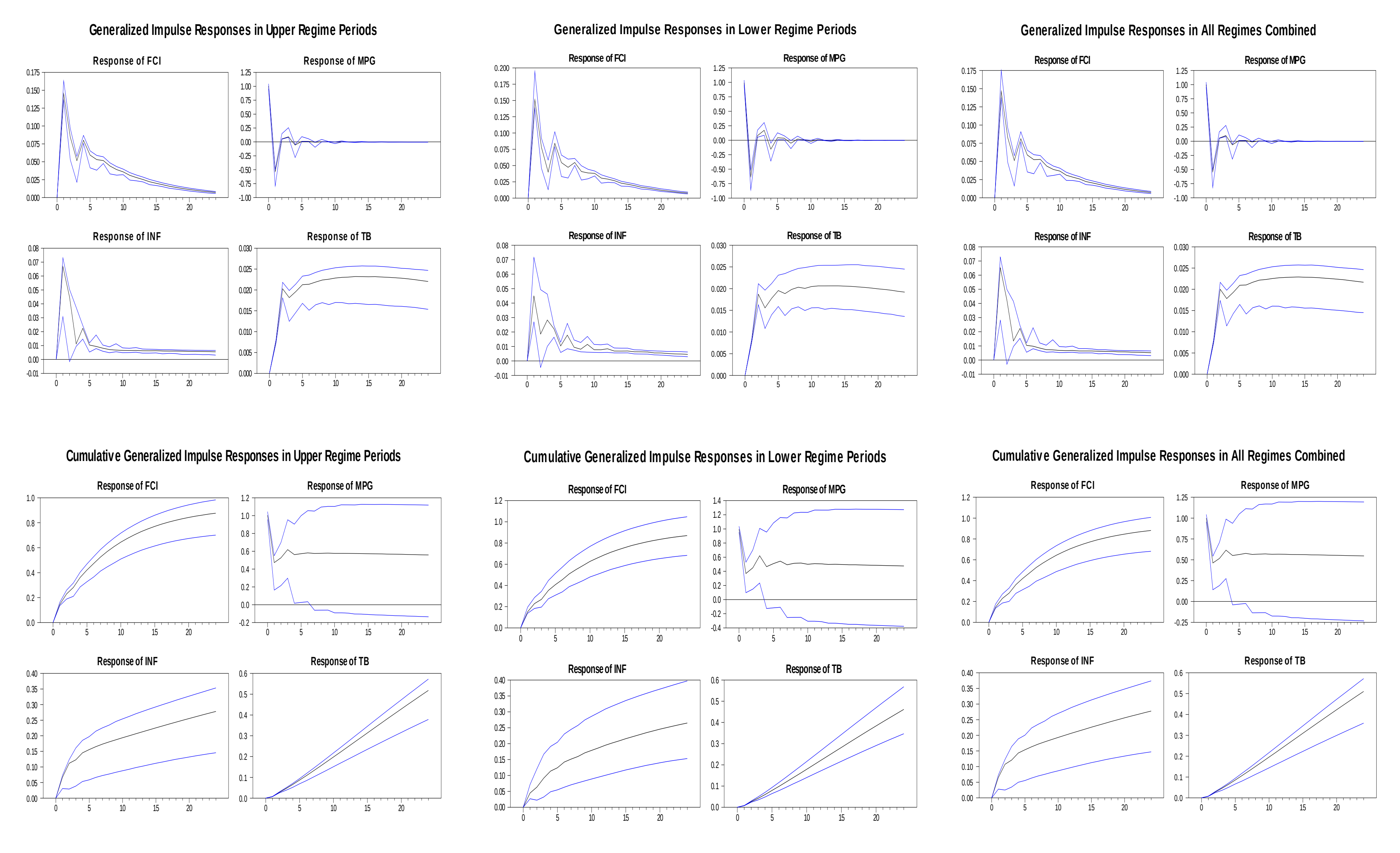


Figure A32. LSTVAR with 4 switching variables version 1: Responses of shock to *MPG* of -1SE with 68% bootstrapped CIs

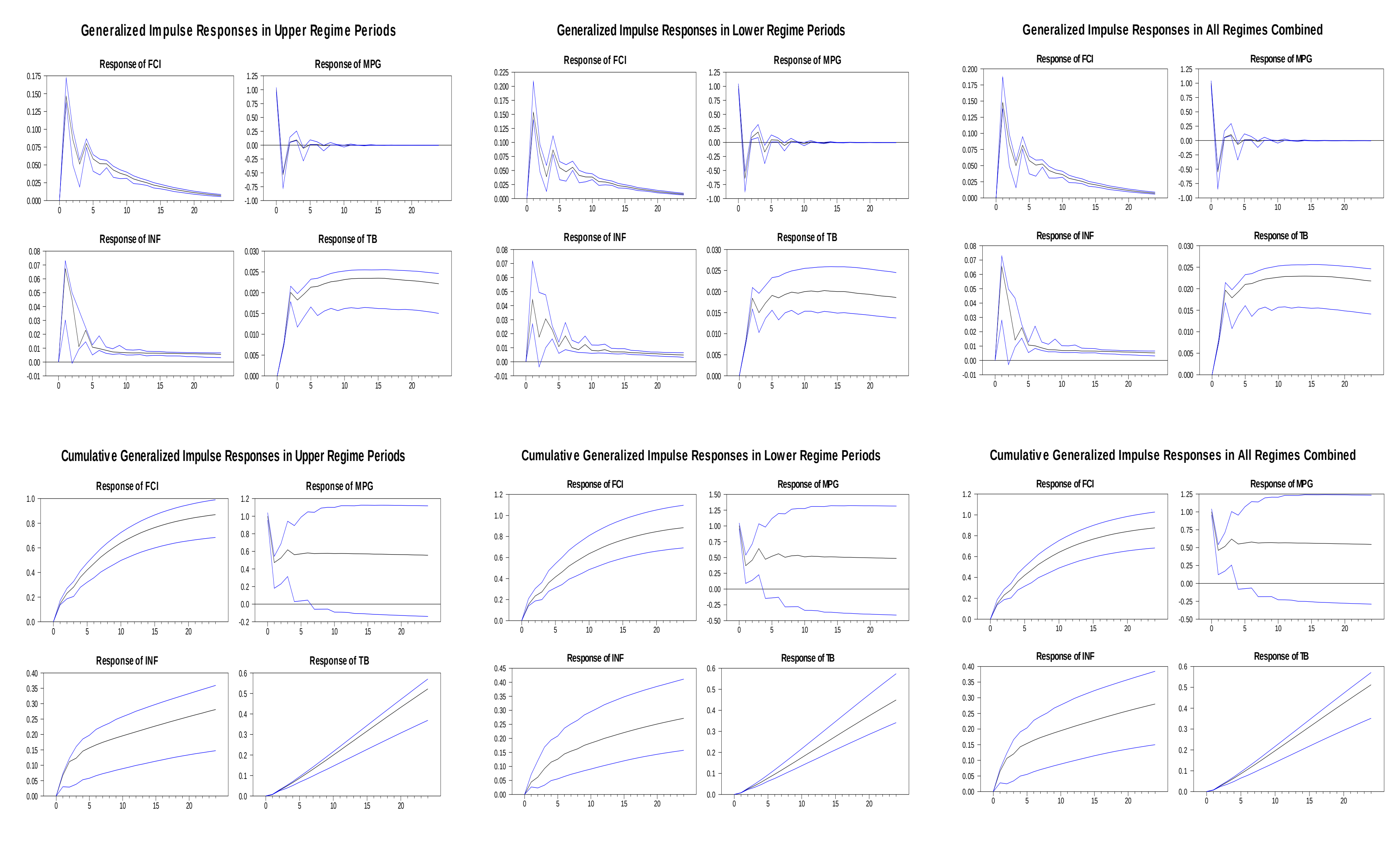


Figure A33. LSTVAR with 4 switching variables version 1: Responses of shock to *MPG* of 3SE with 68% bootstrapped CIs

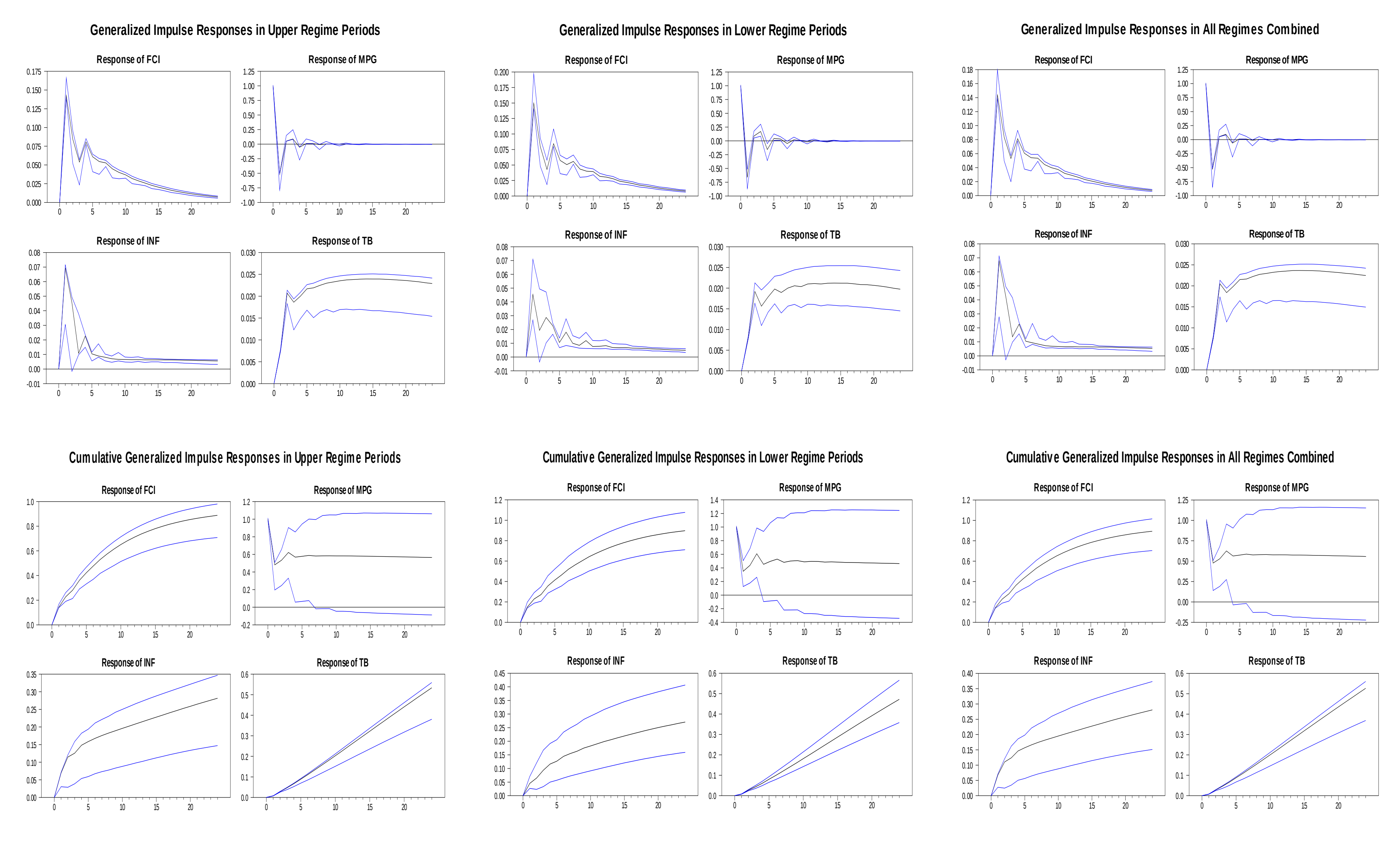


Figure A34. LSTVAR with 4 switching variables version 1: Responses of shock to *MPG* of -3SE with 68% bootstrapped CIs

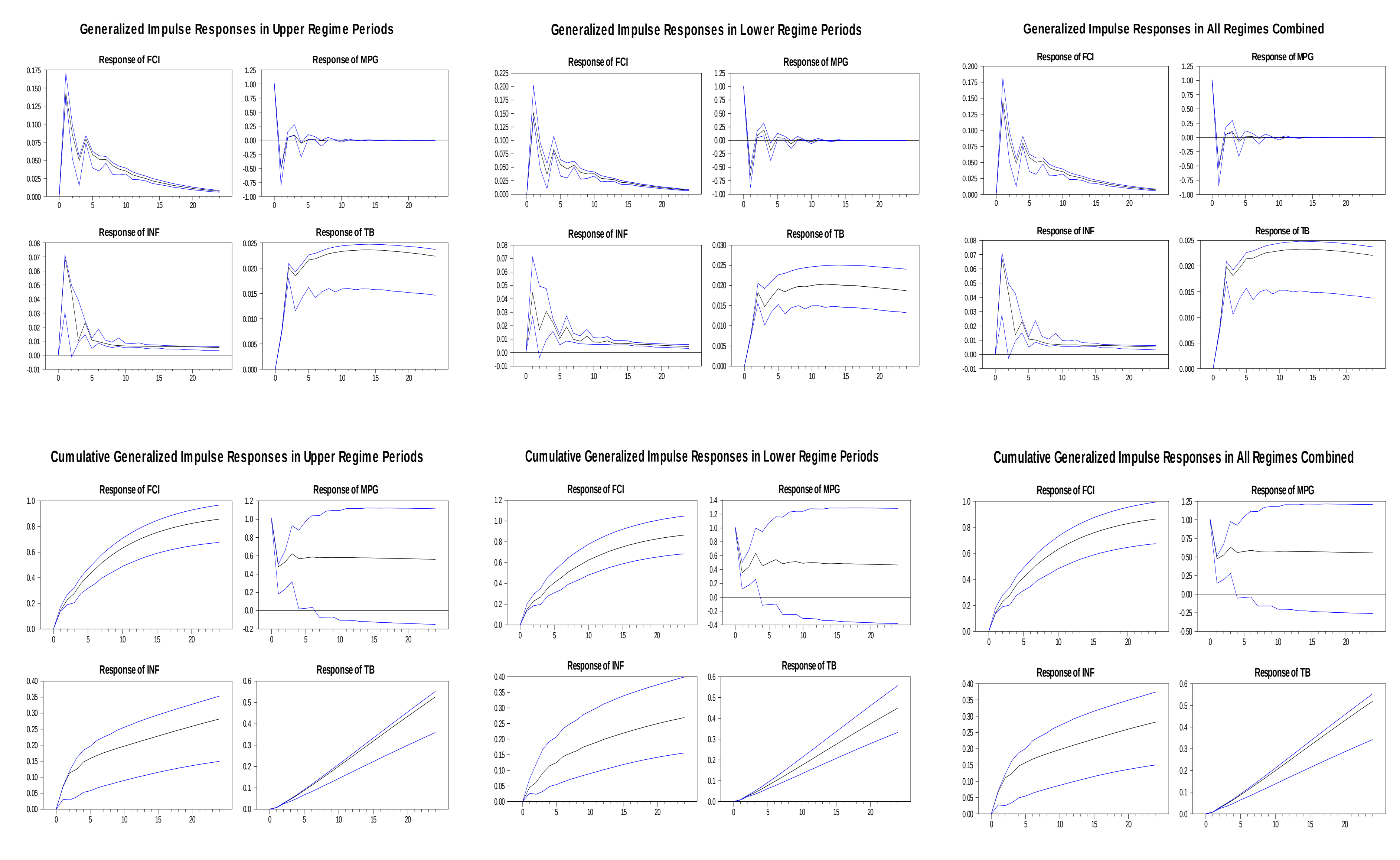


Figure A35. LSTVAR with 4 switching variables version 1: Responses of shock to *INF* of 1SE with 68% bootstrapped CIs

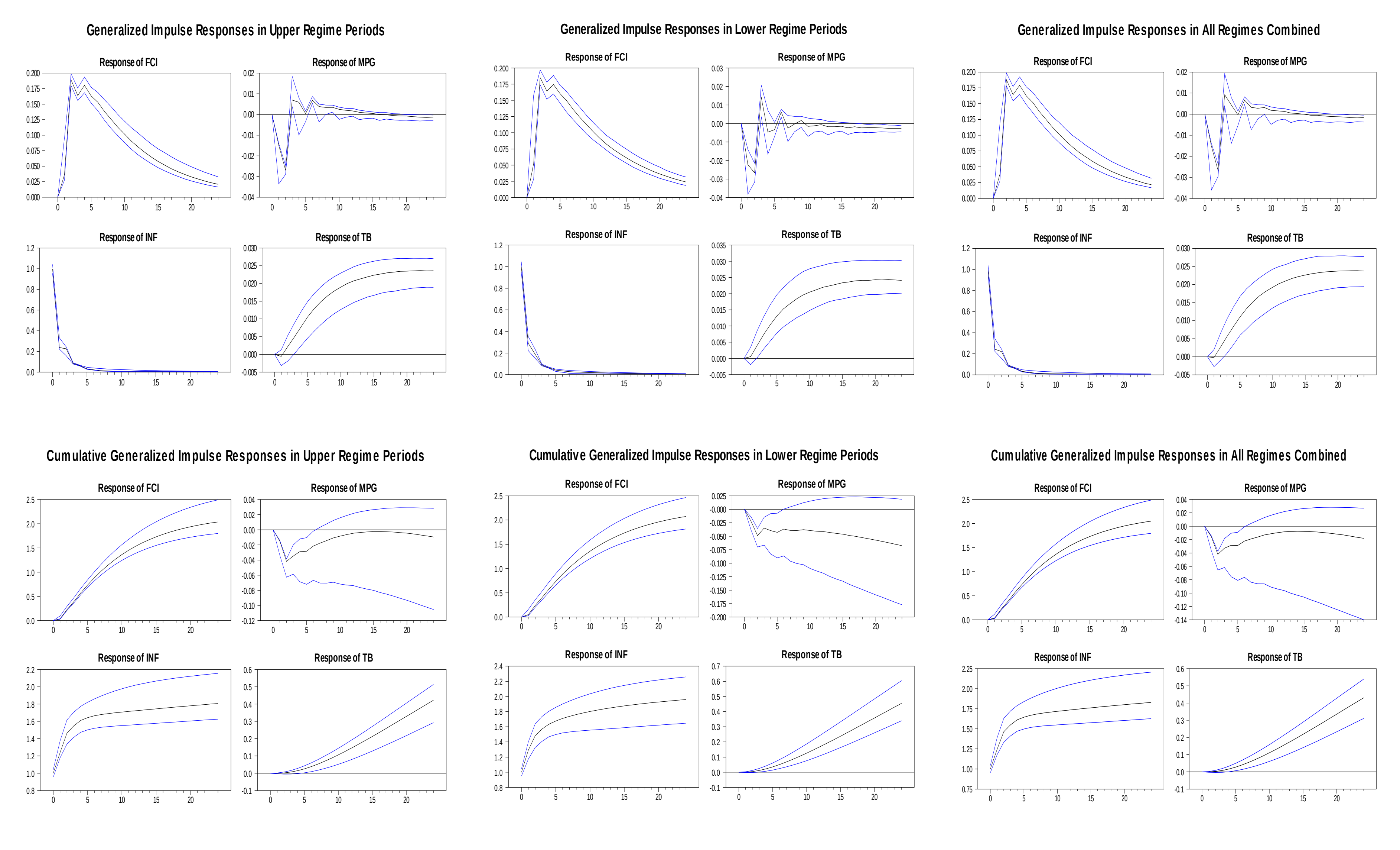


Figure A36. LSTVAR with 4 switching variables version 1: Responses of shock to *INF* of -1SE with 68% bootstrapped CIs

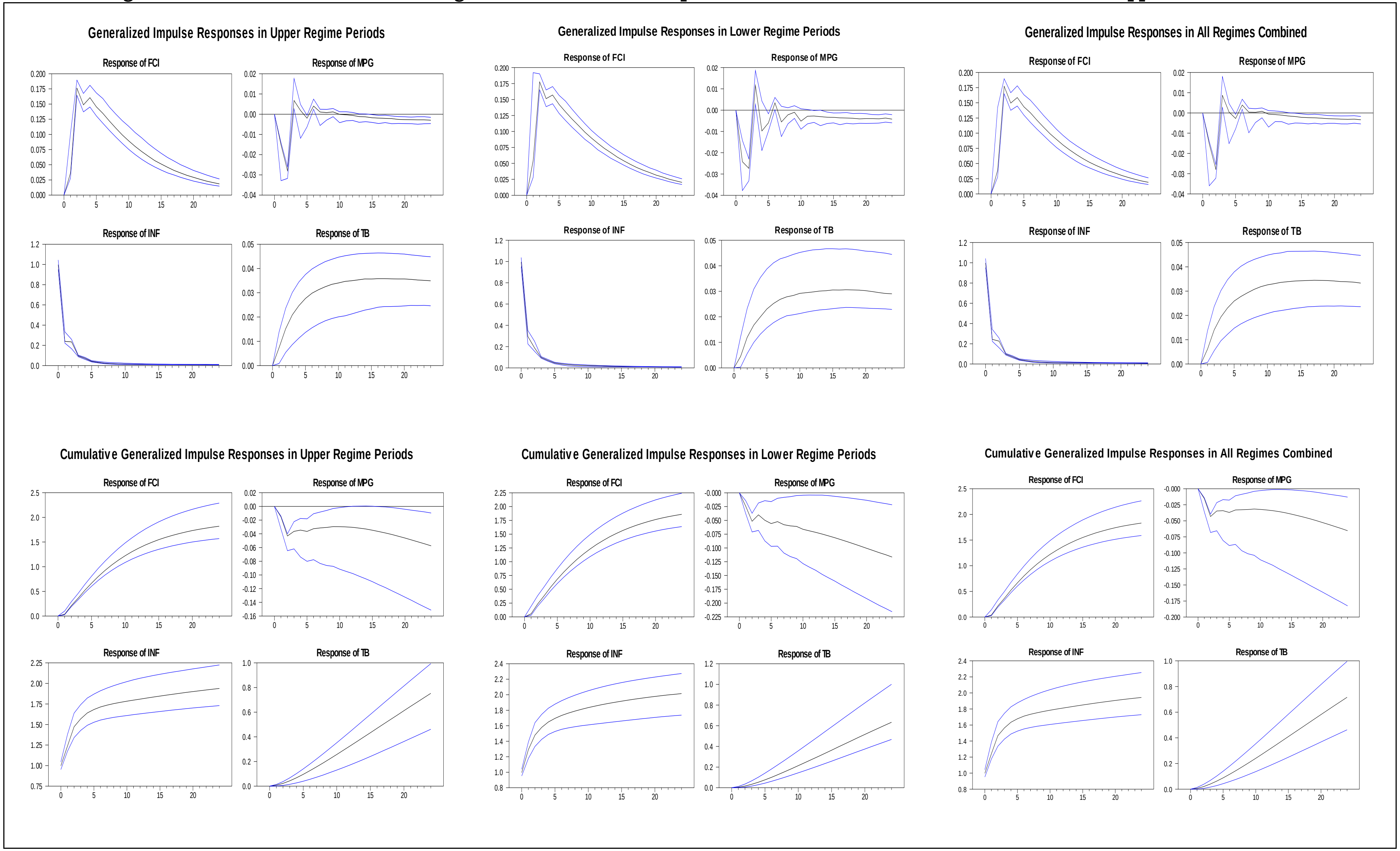


Figure A37. LSTVAR with 4 switching variables version 1: Responses of shock to *INF* of 3SE with 68% bootstrapped CIs

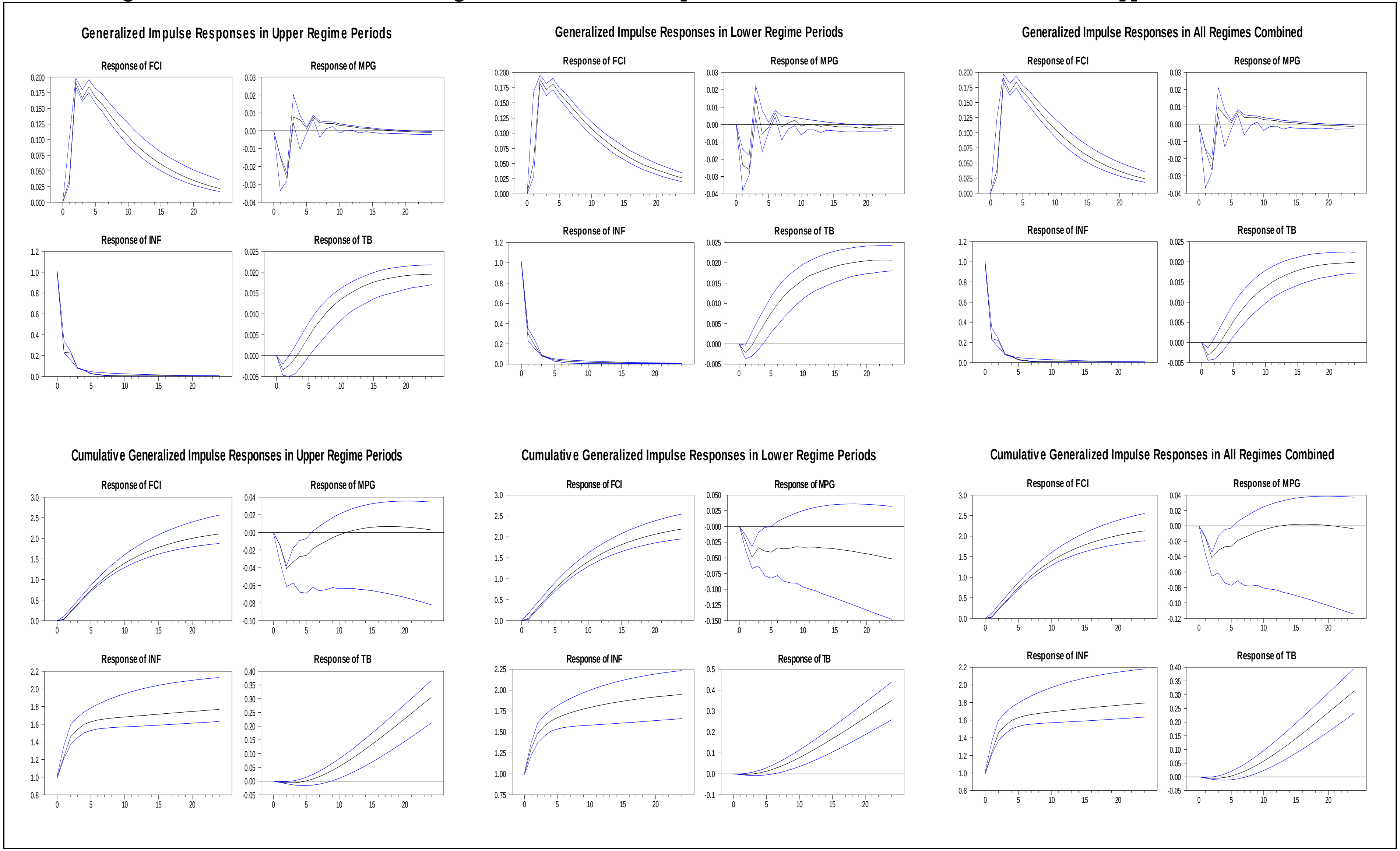


Figure A38. LSTVAR with 4 switching variables version 1: Responses of shock to *INF* of -3SE with 68% bootstrapped CIs

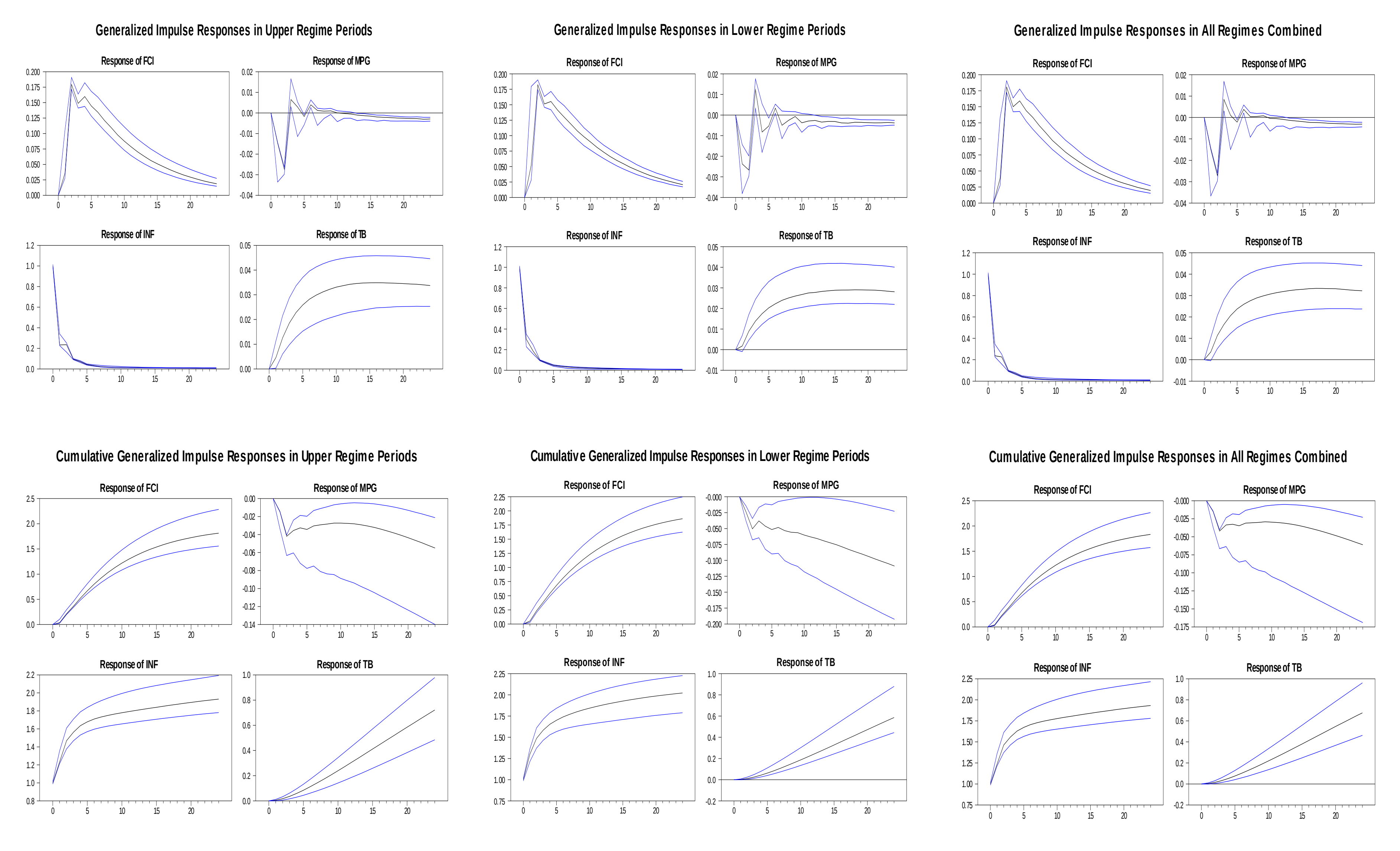


Figure A39. LSTVAR with 4 switching variables version 1: Responses of shock to *TB* of 1SE with 68% bootstrapped CIs

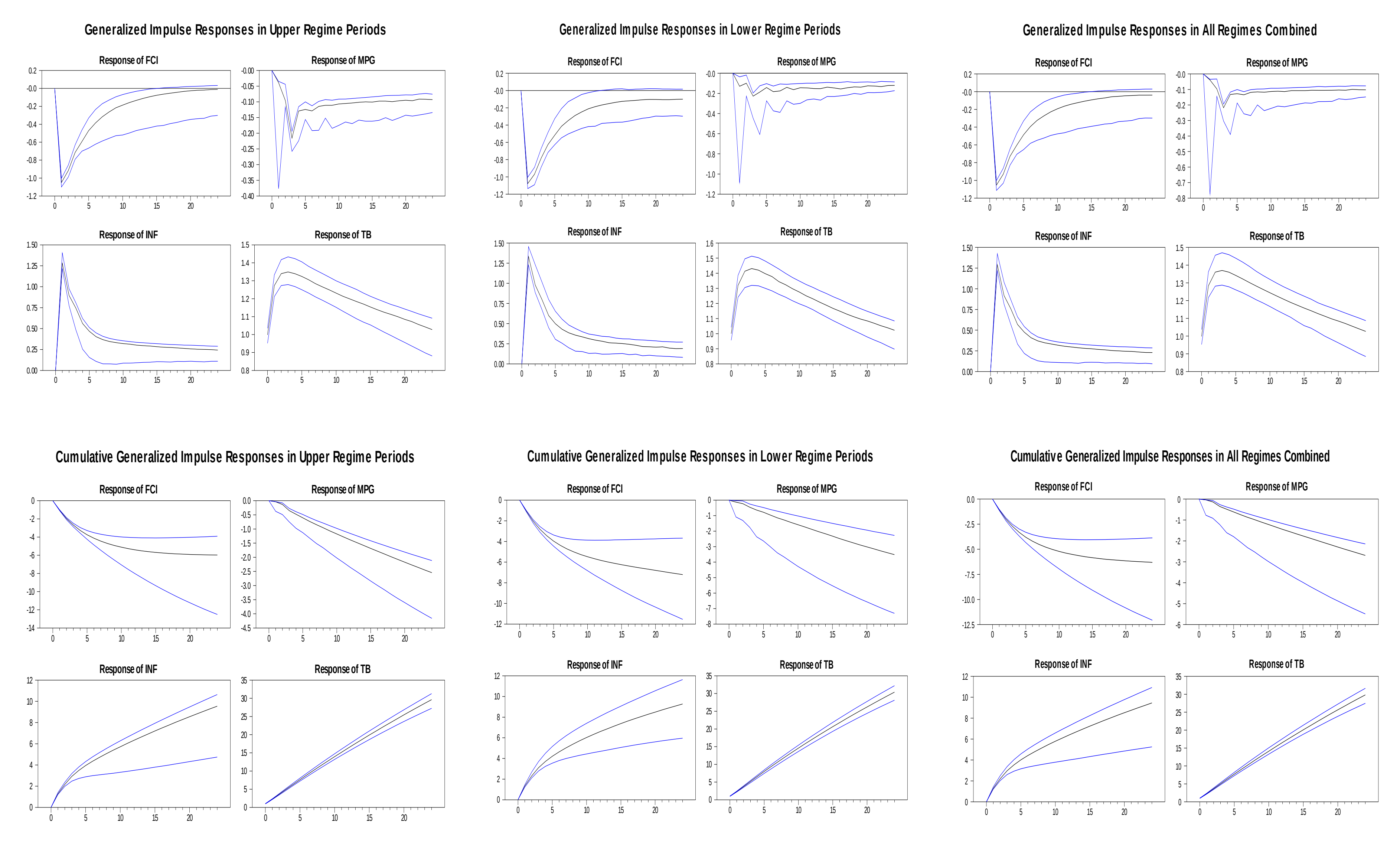


Figure A40. LSTVAR with 4 switching variables version 1: Responses of shock to *TB* of -1SE with 68% bootstrapped CIs

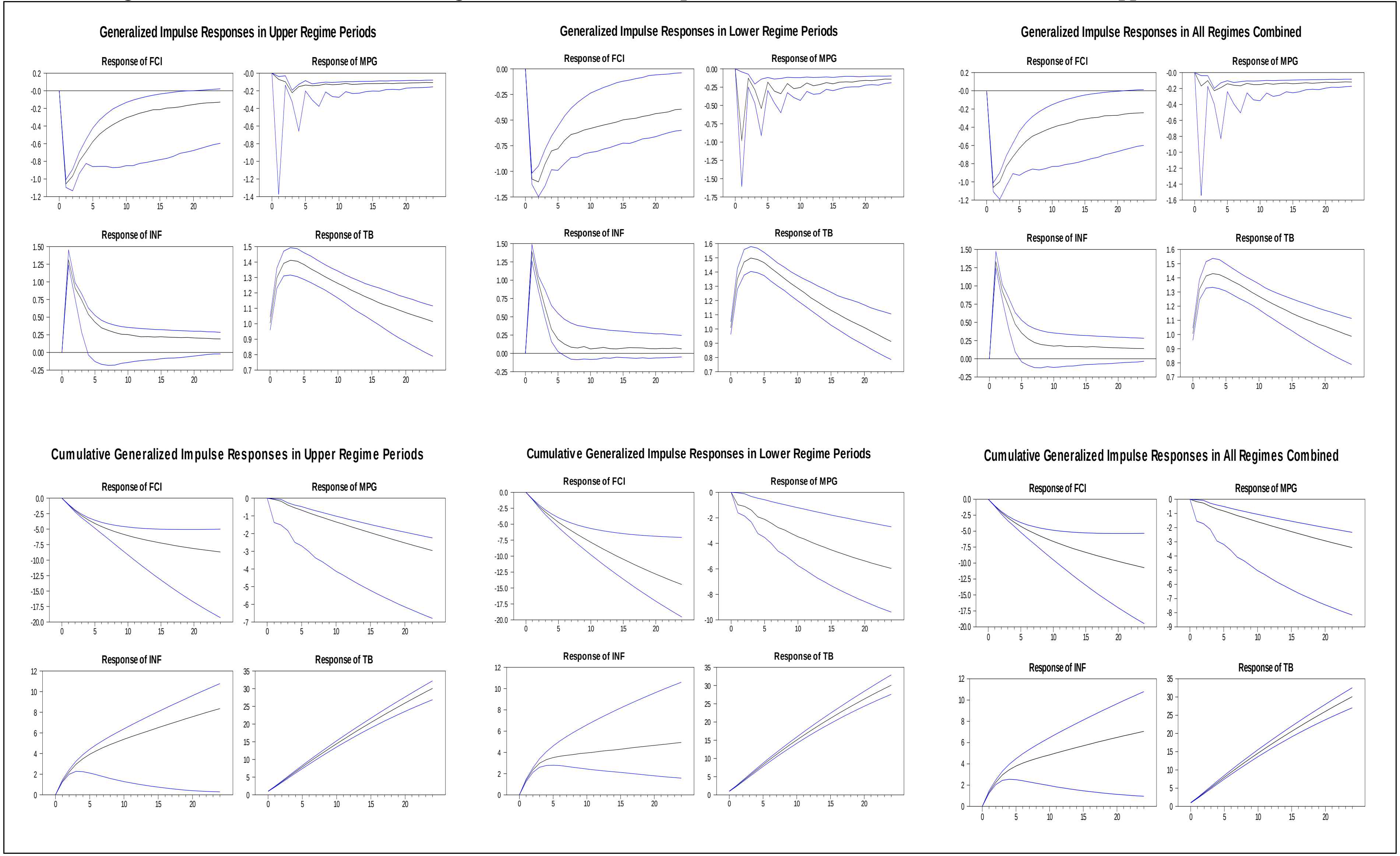


Figure A41. LSTVAR with 4 switching variables version 1: Responses of shock to *TB* of 3SE with 68% bootstrapped CIs

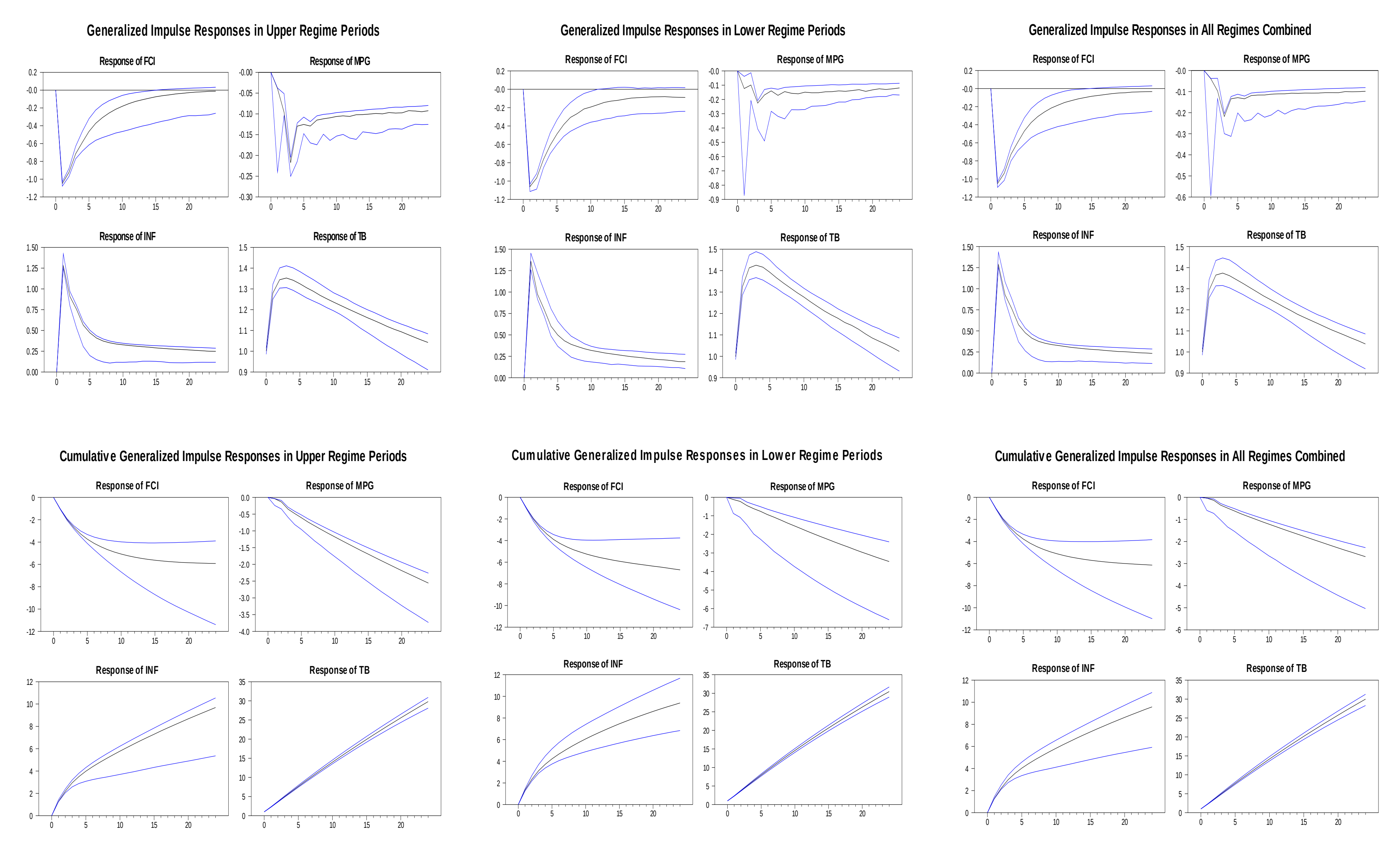


Figure A42. LSTVAR with 4 switching variables version 1: Responses of shock to *TB* of -3SE with 68% bootstrapped CIs