Testing the Asymmetric Effects of Financial Conditions in South Africa: A Nonlinear Vector Autoregression Approach[1]

Mehmet Balcilar[a], Kirsten Thompson[b,*], Rangan Gupta[b], Reneé van Eyden[b]

[a] *Department of Economics, Eastern Mediterranean University, Famagusta, North Cyprus, via Mersin 10, Turkey*
[b] *Department of Economics, University of Pretoria, Pretoria 0002, South Africa*
[*] *Corresponding author. Email address: kirsten.thompson@lantic.net*

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. We use a financial conditions index (FCI) for South Africa previously constructed from 16 financial variables to test whether the South African economy responds in a nonlinear and asymmetric way to unexpected changes in financial conditions. To this end, we make use of a nonlinear logistic smooth transition vector autoregressive model (LSTVAR), which allows for a smooth evolution of the economy, governed by a chosen switching variable between periods of high and low financial volatility. We find that the South African economy responds nonlinearly to financial shocks, and that manufacturing output growth and Treasury Bill rates are more affected by financial shocks during upswings. Inflation responds significantly more to financial changes during recessions.

Keywords: financial conditions index; nonlinear vector autoregression; LSTVAR; asymmetry

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1. Introduction

The global financial crisis of 2007-08, and its severe impact on many of the world's economies, has demonstrated the necessity for a better understanding of financial conditions and their impact on the macroeconomy. Thompson, Van Eyden and Gupta (2013a) construct 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[2]; and they find using a forecast encompassing approach (2013b) that this FCI has good out-of-sample forecasting ability for the key macroeconomic variable of growth in manufacturing production. The aim of this paper is to investigate whether Thompson, *et al.*'s (2013a) FCI has an asymmetric effect on output, interest rates and inflation, in other words to test whether there exists nonlinearity between South Africa's financial market conditions and its macroeconomy.

Hubrich, D'Agostino, Červená, Ciccarelli, Guarda, Haavio, Jeanfils, Mendicino, Ortega, Valderrama and Valentinyiné Endrész (2013:47) 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) 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, we use the impulse response functions (IRFs) generated from a nonlinear VAR to investigate the two types of asymmetries mentioned above. Specifically, we analyse: (1) if the effects of a shock 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

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[2] See Thompson, *et al.* (2013a) for a full discussion of FCI's in practice, literature pertaining thereto, as well as the econometric methodology used in estimating this FCI.

switching variable. In choosing a threshold, we 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), our model allows for smooth regime transitions (as opposed to discrete shifts), which is a more realistic representation of the macroeconomic variables over business cycle switches. This general way of modelling is a logistic smooth transition vector autoregression (LSTVAR) which is a multivariare extension of the logistic transition autoregression proposed byTeräsvirta and Anderson (1992)[3].

We assess the results of two LSTVAR models – one has inflation as a switching variable, and one has a different switching variable for each equation within the VAR. We find, using both models, that the South African economy is indeed asymmetric in its responses to financial shocks – manufacturing output growth is more affected by financial shocks during recessions, while inflation and interest rates respond more during upswings. The size of the financial shock, however, matters little for the response of the economy.

The remainder of this paper is organised as follows: Section 2 discusses the data used in the compilation of the FCI and in the nonlinear VARs; while Section 3 provides details on the econometric methodology used. Section 4 presents the empirical results, namely the linearity test results, the LSTVAR estimation results and the impulse response functions. Section 5 concludes the paper.

2. Data

The FCI estimated in Thompson, *et al.* (2013a) is compiled using principal components analysis (PCA) applied to a set of sixteen monthly financial variables (see Table 5 in the Appendix) over the period 1966M02–2012M01. Thompson, *et al.* (2013a) 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, inflation or interest rate effects. They also address the issue of parameter non-constancy and structural breaks through the implementation of rolling-window estimation techniques, using windows of 120 months in length. The estimated rolling-window FCI can be viewed in Figure 3 in the Appendix, and shows graphically how well the index picks up recessions in the South African economy. Positive values of the FCI indicate "positive" financial conditions, and *vice versa* for "negative" financial conditions[4].

A nonlinear VAR is estimated using this FCI 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

[3] For a discussion on the use of nonlinear forecasting models versus linear models, as well as of regime-switching models, see Camacho (2004).
[4] For a discussion and mapping of South African business cycle trends and the FCI, refer to Thompson *et al.* (2013a).

inflation (*INF*) – the month-on-month rate of change in the consumer price index (CPI); and the 3-month Treasury Bill yield (*TB*).

3. Econometric Methodology

We follow the process of Tsay (1989), also used in Weise (1999) and Camacho (2004): first, we specify a linear VAR and use lag length criteria tests to obtain the VAR's specification; second, we 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; and third, we test the various models in terms of their response characteristics.

We 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. A simplified version applicable to the present context follows.

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

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

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:

$$X_t = C + G(L)X_{t-1} + (\theta_0 + \theta(L)X_{t-1})F(z_t) + u_t \tag{2}$$

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:

$$F(z_t) = \frac{1}{1+e^{-\gamma(z_t-c)}} - \frac{1}{2}, \gamma > 0 \tag{3}$$

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 our model, we first need to conduct linearity tests to determine whether asymmetry is in fact relevant in our case. Following Weise (1999), we 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)). We then follow Weise's (1999) three-step procedure described in Granger and Teräsvirta (1993) and

Teräsvirta and Anderson (1992) to test the null hypothesis, $H_0: \gamma = 0$, against the alternative of $H_1: \gamma > 0$ for each equation in the system. We 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:

$$X_{it} = \beta_{i0} + \sum_{j=1}^{pk} \beta_{ij} W_{jt} + u_{it} \tag{4}$$

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:

$$u_{it} = \alpha_{i0} + \sum_{j=1}^{pk} \alpha_{ij} W_{jt} + \sum_{j=1}^{pk} \delta_i z_t W_{jt} + v_{it} \tag{5}$$

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[5].

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, $H_0: \gamma = 0$ in all equations, is performed. The estimated variance-covariance matrices of the residuals from equations (4) and (5) 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 we perform linearity tests to ascertain whether a nonlinear VAR is indeed preferable over a standard linear VAR in this context. We go on to estimate a selection of LSTVAR models and assess their response characteristics.

4. Empirical Results

a. 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 comparison, with the ordering presented as *FCI*, *MPG*, *INF*, and *TB*. The Schwarz information criterion suggests a two-lag model[6].

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

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[5] Inference is made using bootstrapped *p*-values.

[6] 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.

Table 1 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 1 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, we test the following possibilities as switching variables: FCI_{t-2}, MPG_{t-2}, INF_{t-2} and TB_{t-2}. Furthermore, we 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[7]: 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.

Table 1. 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.

b. 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[8]. This is in contrast to Weise

[7] The choices of switching variables are based on the outcomes of the LM linearity tests.
[8] CUSUM tests (see results in the appendices) on the individual equations within the VAR indicate an absence of structural breaks.

(1999) who fixes the threshold, c, and slope, γ, parameters at certain values and estimates the STVAR model equation by equation using OLS. We use nonlinear least squares so that we do not have to impose any subjective restrictions.

In terms of the speed of adjustment parameter, γ, the results in Table 2 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[9]. 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.

Table 2. Selected estimation output

Switching Variable	*MSE*	*Threshold, c*	*Speed of adjustment, γ*	*Percentage of observations in upper regime*	*Percentage 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 (3), 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

[9] Graphs of the transition functions of the two chosen models are found in the Appendix. Graphs of the transition functions of all of the tested switching variables are available upon request.

incorporating GDP growth and growth in the Conference Board Composite Index of Leading Indicators.

The MSE statistics[10] in Table 2, along with the values of c and γ, assist us in making a decision as to the "best" model that we will use as the benchmark model. Of the single-switch models, we choose the model which has INF_{t-2} as a switching variable, and we compare this against the 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[11]. The 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[12].

Table 3. 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: $linearity$, 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.

We 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: $linearity$) 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 3 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.

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

[10] 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.
[11] 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.
[12] We 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.

dynamic response characteristics inherent in generalised impulse response functions (GIRFs). We perform this analysis in the following section.

c. Impulse Responses

We now use GIRFs from the two chosen estimated LSTVAR models to test the asymmetry of shocks to financial conditions in these systems. We 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 asymmetric effects; and (3) whether this asymmetry in (1) and (2) is affected by the size of the shock[13].

Weise (1999) has 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 incorporate "random history" (i.e. it must treat ω_{t-1} in equation 6 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:

$$GI_X(n, v_t, \omega_{t-1}) = E[X_{t+n} | v_t, \omega_{t-1}] - E[X_{t+n} | \omega_{t-1}], n = 0, 1, \ldots \tag{6}$$

where GI_X is the GIRF of X, n is the forecast horizon, v_t is the shock[14] 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. We run our 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, we take each time point in the sample as an initial period and generate 1 000 bootstrap GIRFs from each initial period, taking

[13] Note that all GIRFs shown in this paper 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.
[14] 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.

the mean response as the response at this point. There are 547 initial periods in our sample, leading to 547 000 bootstrapped impulse responses for each step.

Table 4. 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 VAR
		Lower regime	Upper regime	Lower regime	Upper regime	
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 in the GIRF graphs in Figure 1 and Figure 2). 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.

The GIRFs in response to positive and negative *FCI* shocks of varying sizes with their bootstrapped 68% (1 SE) confidence intervals are shown in the appendices. We 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 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.

In quantifying how much asymmetry matters in the response of the economy to unexpected changes in financial conditions, we begin by ascertaining whether positive and negative financial conditions have asymmetric effects. When we consider the results in Table 4, 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, we 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, we again refer to the results in Table 4. 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, we 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 1 and Figure 2 show that upper and lower regimes in both of our chosen models exhibit different magnitudes of responses[15]. Table 4's results confirm Figure 1 and Figure 2, 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, where we recall that upper regime periods correspond to periods of financial loosening and financial stability, while lower regimes are related to periods of volatile and tight financial conditions. In the model with four switching variables, we see that *INF* and *TB* respond more during periods of lower regimes, *INF* significantly so.

Figures 1 and 2 also show that there is differing behaviour in the responses of the key macroeconomic variables to financial changes. We see that 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)).

[15] All GIRFs for all variables and all shocks are available upon request.

Figure 1. Asymmetry in upturns and downturns: Model with INF_{t-2} as switching variable

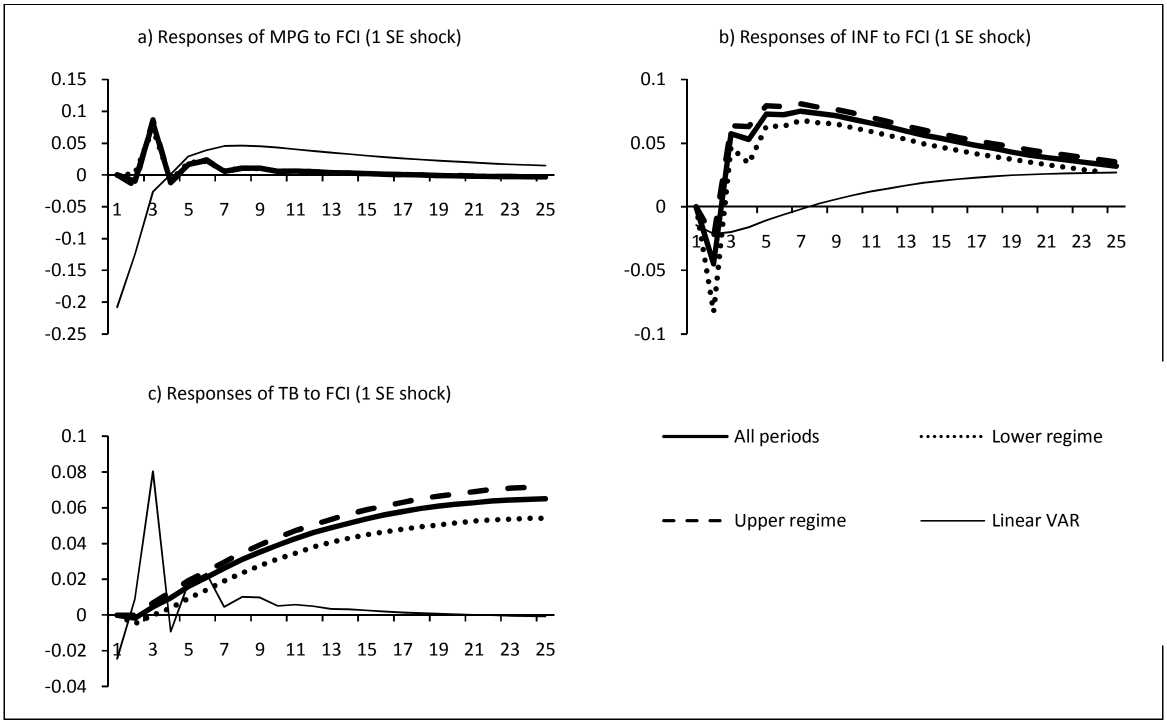
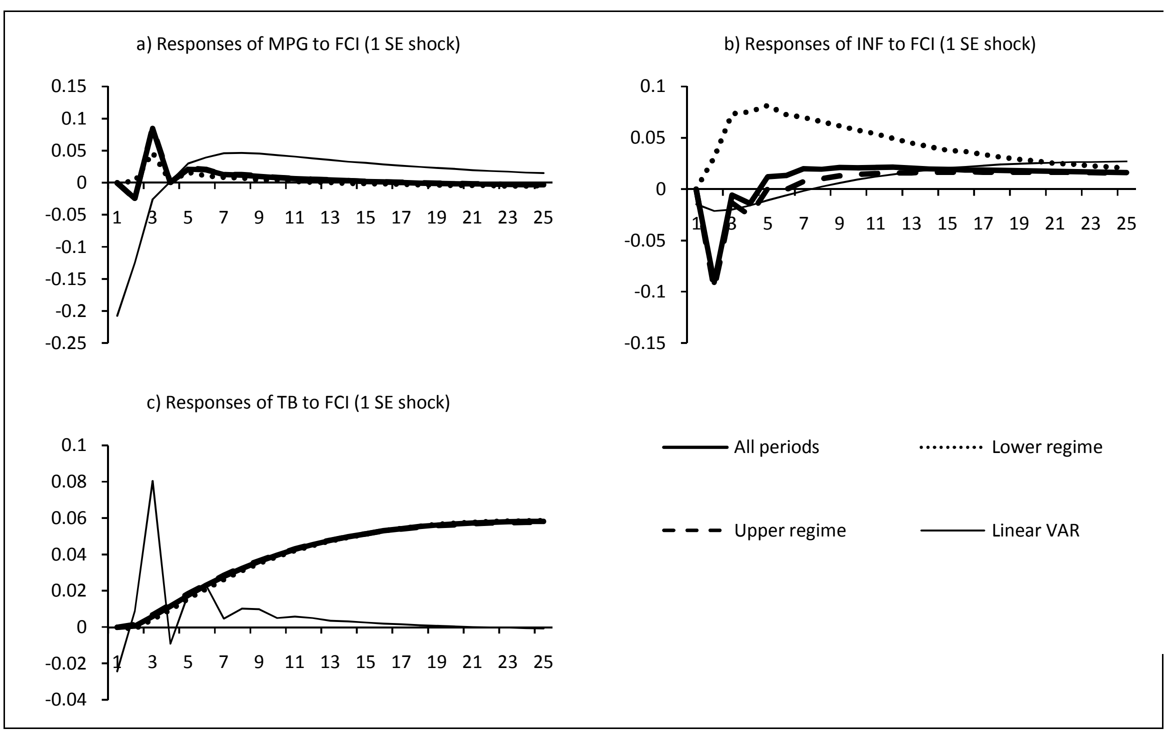


Figure 2. Asymmetry in upturns and downturns: 4-switch model



We 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 rates 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.

5. Conclusions

The aim of this paper was to investigate whether shocks to an FCI for South Africa estimated by Thompson, *et al.* (2013a) has an asymmetric effect on output, interest rates and inflation. To this end, we made use of a nonlinear LSTVAR, which allows for the transition of a chosen switching variable between two regimes. We 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.

We 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 and interest rates respond 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 we look at the reactions of *TB* and *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.

Future research into this topic will take the form of smoothly-evolving time-varying parameter (TVP) VARs along the lines of Baumeister, Durinck and Peersman (2008) and Koop and Korobolis (2013), in order to ascertain whether financial shocks at different times in South Africa's economic history have differing macroeconomic impacts. This will be of further interest considering that even though CUSUM tests indicate an absence of structural breaks, Bai and Perron's (2003*a,* 2003*b*) breakpoint tests do provide evidence of structural breaks. Hence, a TVP-VAR which treats each point in time as a regime would allow for possible breaks.

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7. Appendix

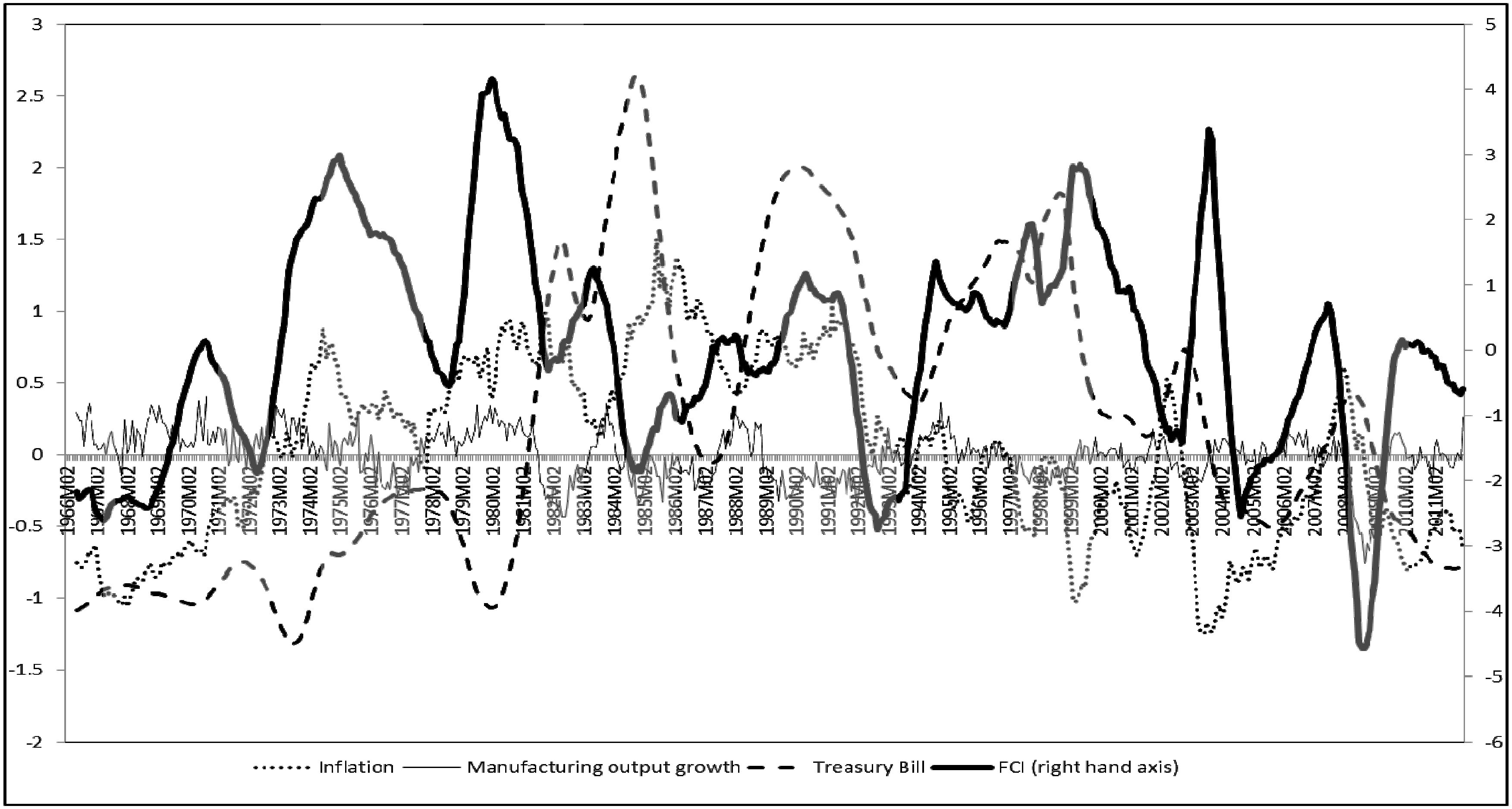
Table 5. Variables used to construct and test the FCI

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 by South African CPI, 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 by relative US-SA CPI, first log difference
D_LSP500	S&P500 Composite Price Index	Seasonally adjusted, deflated by US CPI, 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[16] (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). 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, and non-stationary series are differenced to be made stationary. All data is standardised.

[16] Thompson, *et al.* (2013a) 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 they chose the FCI including M3 since it is theoretically a more inclusive measure.

Figure 3. **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.

Figure 4. CUSUM test results for structural breaks

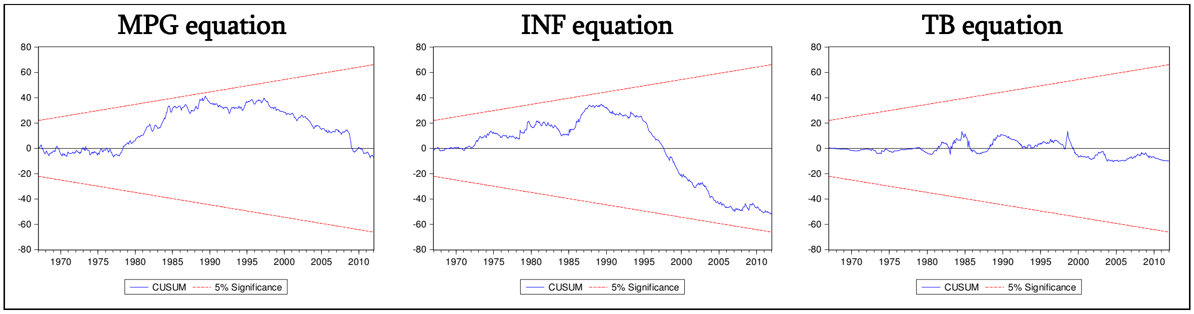


Figure 5. Transition function: 4-Switch model version 1

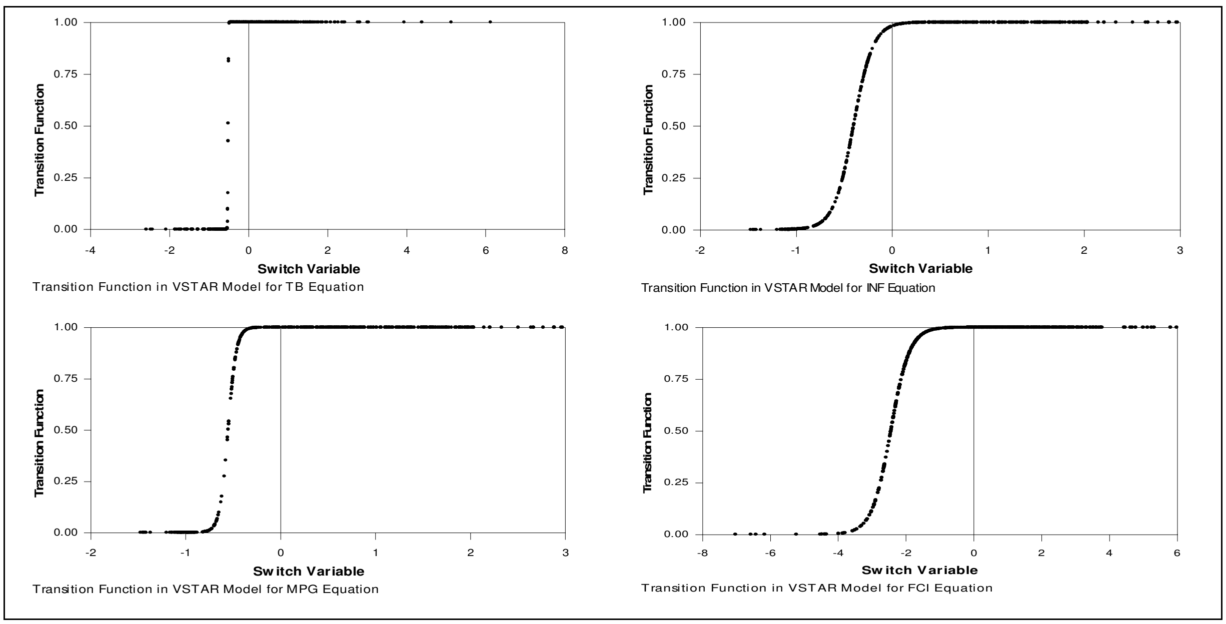


Figure 6. Transition function: model with INF_{t-2} as switching variable

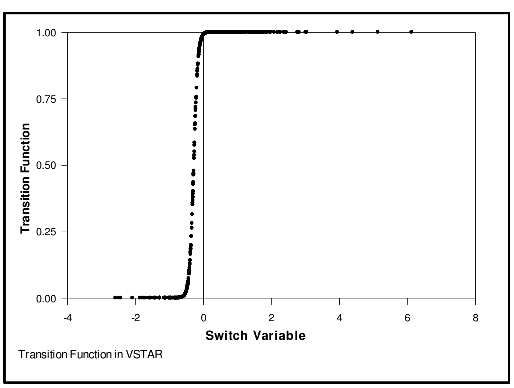
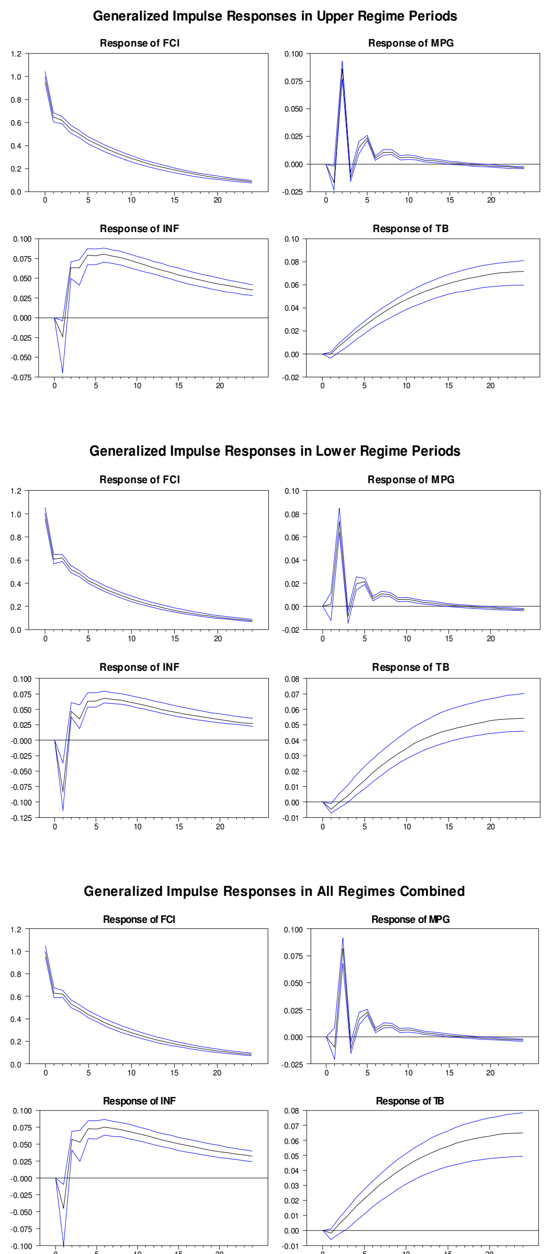
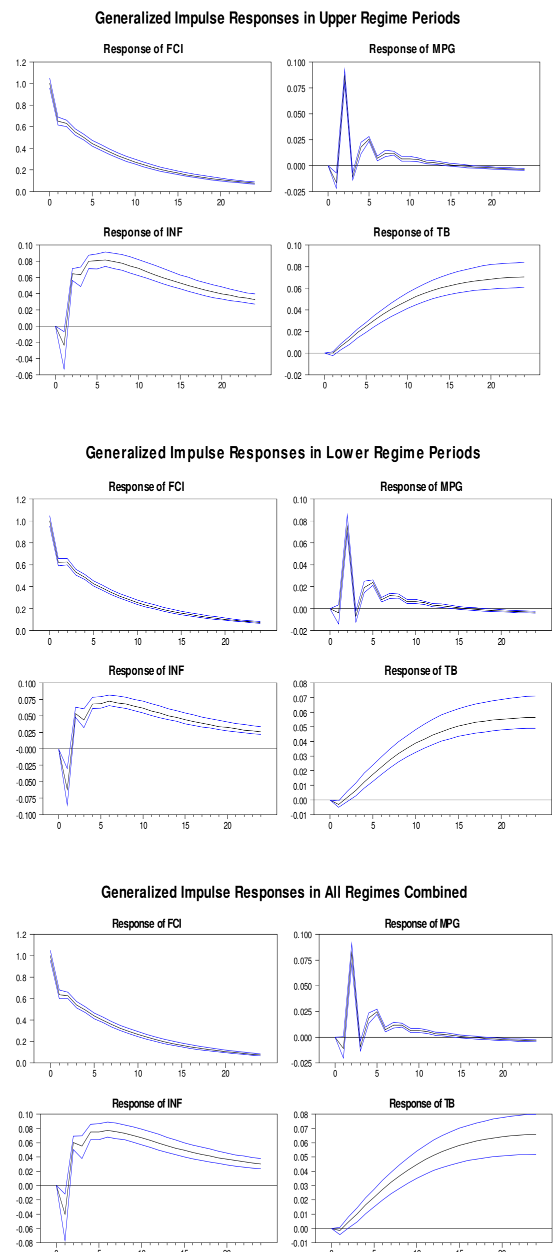
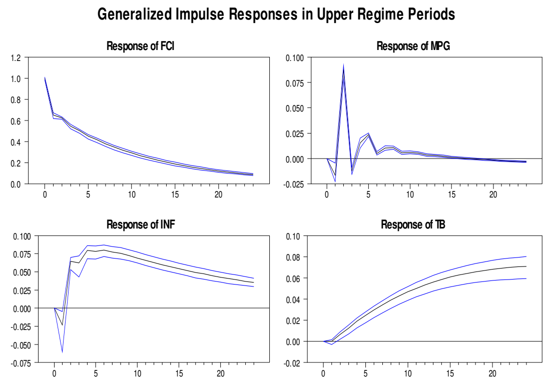
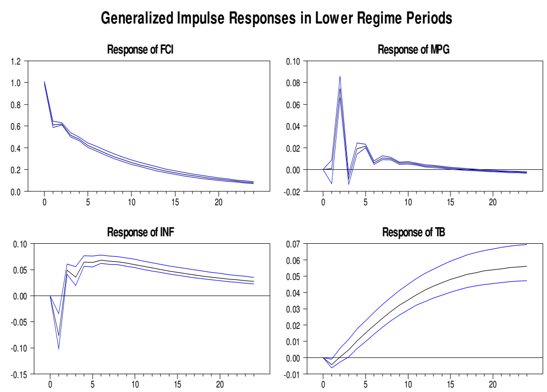


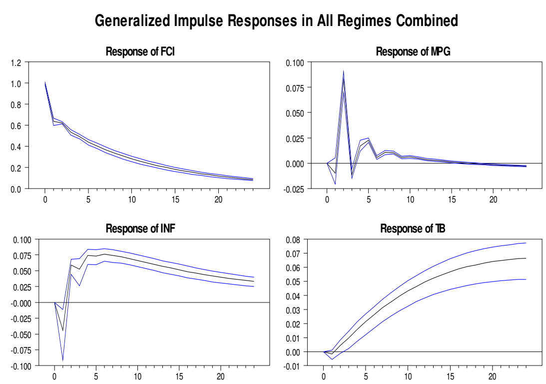
Figure 7. Impulse response functions and 68% confidence bands: Model with INFt-2 as switching variable

Responses to 1SE FCI shock	Responses to -1SE FCI shock
	

Responses to 3SE FCI shock







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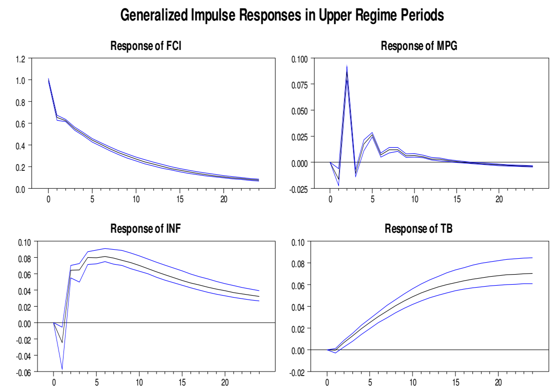
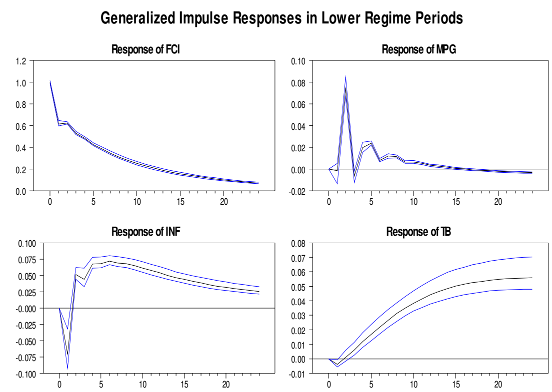




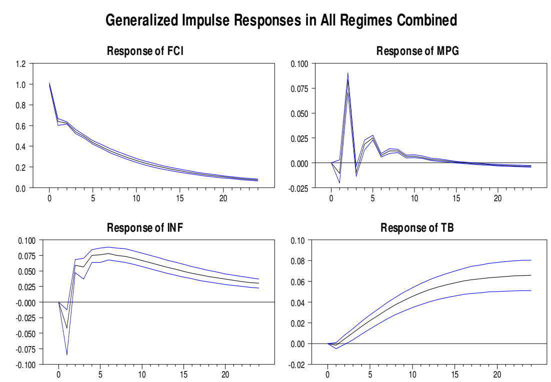
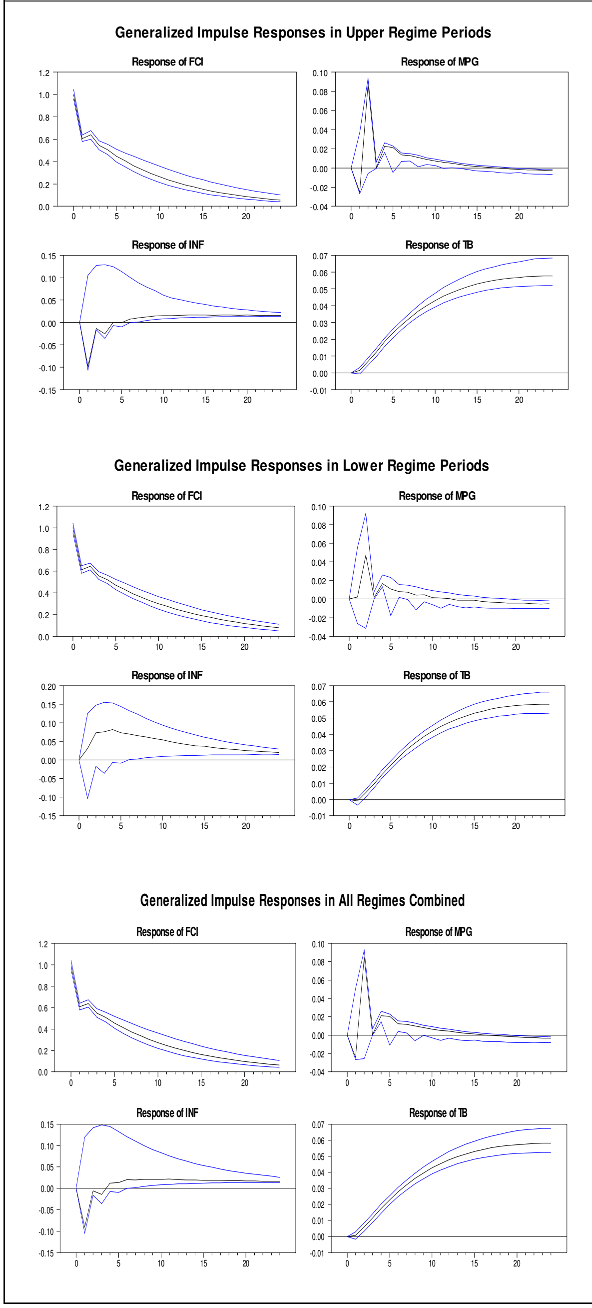
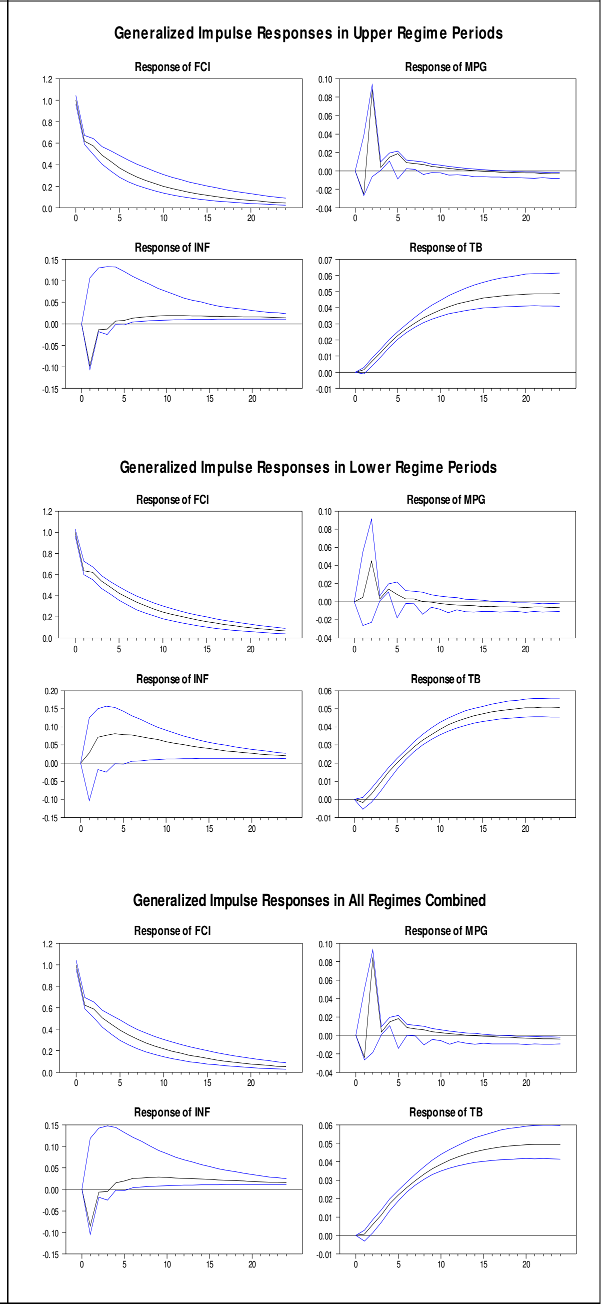


Figure 8. Impulse response functions and 68% confidence bands: 4-Switch model version 1

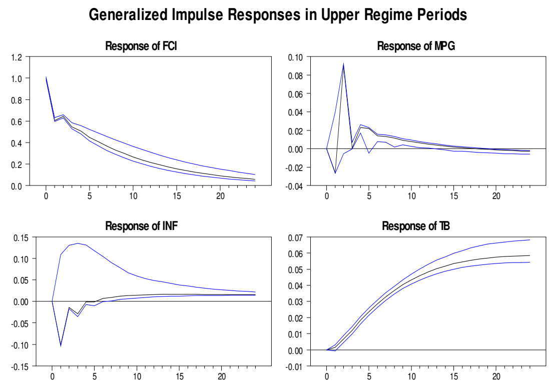
Responses to 1SE FCI shock

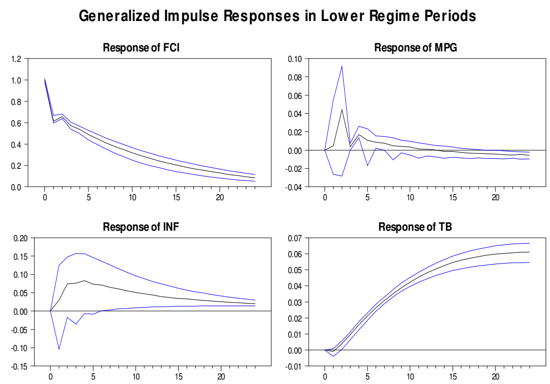


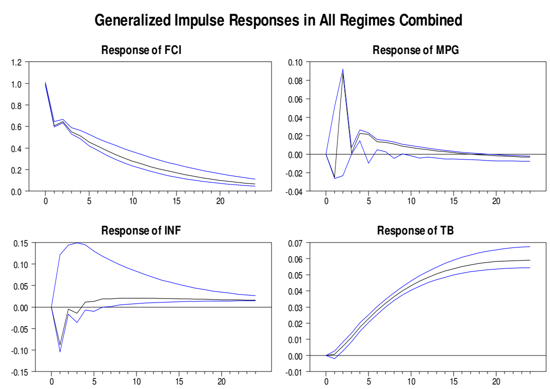
Responses to -1SE FCI shock



Responses to 3SE FCI shock







Responses to -3SE FCI shock