The Index of the Financial Safety (IFS) of South Africa and Bayesian Estimates for IFS Vector-Autoregressive Model

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April 2012

THE INDEX OF THE FINANCIAL SAFETY (IFS) OF SOUTH AFRICA AND BAYESIAN ESTIMATES FOR IFS VECTOR-AUTOREGRESSIVE MODEL

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Abstract

This paper proposes an approach to explore the strength of the financial system of a country against the possibility of financial perturbations appearing based on the construction of the Index of Financial Safety (IFS) of a country. The Markov Chain Monte Carlo (MCMC) and Gibbs sampler technique is used to estimate a Bayesian Vector Autoregressive Model of the IFS of South Africa for the period 1990Q1-2011Q1 and to forecast its value over the period 2011Q2-2017Q1. It is shown that the IFS could capture the disturbances in the financial system and the BVAR models with the non-informative and Minnesota priors could predict the future dynamics of IFS with sufficient accuracy.

JEL Classifications: G17, C11, C32, C53, E50

Keywords: Financial safety, index of financial safety (IFS), Bayesian Vector Autoregressive (BVAR) model, MCMC, Gibbs sampler, South Africa

1. INTRODUCTION

The recent global financial crisis has again emphasised the role of the financial system in maintaining global stability. Additionally, it has become evident that finance is the channel through which a state (or country) can possibly be controlled from outside its borders, and violations in the safety of the financial system within the country may lead to the strengthening of such control. It is therefore not surprising that the macro-prudential approach that focuses on safety and safeguarding the financial system attracts increasing attention. Research in this area is also on the increase.

Księżopolski (2004), Frejtag-Miki (1996), Kłosiński (2006), and Suchorukow (1996) have analysed certain aspects of the problems associated with economic and financial safety. On the other hand, Kaminsky, Lizondo and Reinhart (1998), Edison (2003), Frankel and Rose (1996), and Jakobs, Lestan and Kuper (2003), among others, have investigated the symptoms of threats to the economy caused by the financial system and indicators of financial crises. Among other indicators found one may distinguish the following: Financial Soundness Indicators (FSI) (see IMF, 2004); Monetary Condition Index (MCI) and Financial Conditions Index (FCI) (see van den End, 2006); Early Warning Indicators (see Edison, 2003; Frankel & Rose, 1996; Jakobs, Lestano & Kuper, 2003), and finally indicators of financial crises (see Burkart, Oliver & Coudert, 2002; Kaminsky, Lizondo & Reinhart, 1998).

Other authors focus on the construction of systemic risk measures (see, among others, Segoviano & Goodhart, 2009; Acharya, Pedersen, Philippon & Richardson, 2010; Huang, Zhou & Zhu, 2009, 2010), while there is a stratum of literature in which financial imbalances, such as credit and asset market bubbles, are analysed (see, among others, Misina & Tkacz, 2008; Barrell, Davis, Karim & Liadze, 2010).

Some of the recent approaches employed to forecast crises include Markov switching models (e.g. Abiad, 2003; Chen, 2005) or financial market tools (e.g. Malz, 2000; Crespo, Cuaresma & Slacik, 2007). Schwaab, Koopman and Lucas (2011) propose a unified econometric framework for the measurement of global macro-financial and credit risk conditions based on state space methods and the mixed-measurement dynamic factor model (MM-DFM), introduced by Koopman, Lucas and Schwaab (2010). This paper, related to Schwaab, Koopman and Lucas (2011), is based on the one by Giesecke and Kim (2010), and pays attention to the hazard rate approach towards contagion and observed macro-financial factors (no frailty).

The aim of this research is to analyse the financial safety of a country (South Africa) focussing specifically at the realisation of the possibility to forecast the various states of a financial

system through the construction of the Index of Financial Safety (IFS) as well as forecasting changes to the state of safety using Bayesian Vector Autoregressive (BVAR) modelling.

The methodological base of the research is formed by means of the macro-prudential approach, system analyses, the basic principles of the theory of logical inference, principal of parsimony, principal component analysis, Bayesian Vector Autoregressive (BVAR) modelling, Gibbs sampler and MCMC. The remainder of this paper is structured as follows. Section 2 focuses on the theory and method underlying the construct the Index of Financial Safety of a country. In Section 3 the methods of modelling and forecasting of the IFS based on Bayesian Vector Autoregressive model with the Markov Chain Monte Carlo (MCMC) and Gibbs sampler estimation techniques are presented. In Section 4 the empirical results for the constructed IFS of South Africa is presented, the Bayesian estimates of the IFS VAR is compared with different priors using quarterly data from South Africa and finally the forecast and impulse responses results of the IFS is presented. This paper concludes in Section 5.

2 CONSTRUCTION OF THE INDEX OF FINANCIAL SAFETY OF A COUNTRY

2.1 Financial safety of a country and its main indicators

The category "financial safety" is very broad. It consists of two main counterparts: "safety" and "financial". In general "safety" means the condition of being protected from or unlikely to cause danger, risk (Oxford Dictionary, 2011). Similar definitions may be found in other publications (see, among others, Berkowitz & Bock, 1965; Księżopolski, 2004).

The term "financial" indicates that the safety relates to financial system. The essence and the structure of the financial system are defined by the nature of financial relations among agents that may take on different forms. In the literature the financial system is often analysed from the point of view of financial market functioning (see, among others, Rouz & Fraiser, 1988; Bodie & Merton, 2003). The financial system may be defined as a system, which consists of institutional units and markets that interact, typically in a complex manner, for the purpose of mobilizing funds for investment, and providing facilities, including payment systems, for the financing of commercial activity (IMF, 2004).

It is hard to find a monolithic and commonly-accepted definition of financial safety or its structure. Suhorukov (2003, 2004) refers to financial safety as the protection of state finance or such a condition of the budget, tax, and currency systems, which guarantee the possibility to effectively

target state finance towards financial debt service and socio-economic development of the country. Kłosiński (2004) describes financial safety in terms of both an external dimension and an internal dimension. The external dimension of financial safety of a country is defined through possibilities of debt service and crisis resistance, while the internal dimension of the financial safety is described by the possibilities of financial institutions to implement interest rate policy changes.

For the purpose of this paper, we define the financial safety of a country as a state in which the financial system, and all elements of this system, is shielded against real and potential internal and external threats. In other words, financial safety indicates a very small probability of the appearance of a crisis in a financial system.

When the financial system is in a state of safety it should be able to provide for the implementation of all the functions of financial system. Based on the analysis of the literature, the main functions include the following (Melicher & Norton, 2011; Neave, 2009; Bodie & Merton, 2003; Crane *et al,* 1995):

- fiscal function, i.e. the supply of money resources to government through the optimum allocation of financial resources, methods of their allocation in space and time, liabilities, risk management, and the formation of a system of information;
- re-distributional function, i.e. at first, the allocation of resources between public and private sector, the realisation of the just distribution of profits in society and finally, the re-distribution in order to remove imbalances, caused by the market;
- promotional function, i.e. the integration of the financial system in the activities of separate subjects; and
- controlling function, which is related to the formation of an information base and the creation of mechanisms of financial control.

The evaluation of financial safety of a country should be based on the key indicators that (i) ensure the proper functioning of the financial system, and (ii) provide leading information on future performance. For international comparison as well as wide application it is also important that these indicators should be able to capture the financial system's functions on macro-level mentioned above, be suitable for most countries, both developing and developed (based on publicly available statistics), and be relatively easy to estimate and use.

Different theories provide proofs of different key indicators of how the financial system's functions should be implemented in order to ensure financial safety, through the identification of various sources of systemic crisis. For example, the theory of debt and financial fragility (commonly associated with Fisher, 1933; Minsky, 1977; Kindleberger, 1978 etc.) emphasises, among others, the

importance of rising corporate or household debt accumulation relative to assets as the indicators of financial system vulnerability. The monetarist approach (commonly referred to by Friedman and Schwarz, 1963) emphasises the growth of monetary aggregates as a factor which may precede instability in financial system. Therefore it focuses on monetary data and inflation. If one looks at the analysed problem from the point of view of asymmetric information and agency cost theory (see Mishkin, 1990, 1991 and others) the focus falls on the importance of net worth of borrowers as an indicator of potential moral hazard, which may be proxied by equity and property prices, or debt/equity ratios.

Thus, a central issue is to choose the correct combinations of variables which can offer consistent signals of changing conditions in financial safety for a country. This paper follows a Monetarist approach and the focus is therefore on monetary data. Together with GDP projections, the monetary data is used in order to assess the dynamics of monetary aggregate (such as *M1*, *M2* or *M3*) as the key monetary indicators as well as the velocity of money circulation. The interest rate may also assist in monetary conditions estimation, while the credit counterpart of financial safety may give an indication of incipient debt problems – following the theory of debt and financial fragility.

According to the main sub-systems of the financial system it is possible to distinguish the following main sub-types of financial safety: monetary safety, currency safety, stock market safety.

2.1.1 Monetary safety and its indicators

Monetary safety may be defined as a state of guarding a country's monetary system to ensure money performs its functions, i.e. that it serves as a medium of exchange, as a store of value, as a unit of accounting and as a standard of deferred payment. The aim of many monetary safety indicators is to identify the shares of the money aggregates and their dynamics, since the growth of "money in circulation" may complicate the control of the monetary system and money turnover.

Pertaining to monetary safety, some problems lie in the area of e-money, which can have influences on the exchange rate. These include, for example, that it may cause an increase in money supply and may have an influence within the context of money laundering. However, the identification of e-money in the macro-economic framework is difficult, because e-money is not included in money aggregates (for example to *M1*).

Therefore, the following core indicators will be used to identify the states of the condition of monetary safety:

- *the share of money in circulation relatively to M2 and GDP*, defined as follows:

$money\ in\ circulation/_{M2} \times 100\%$; and

$money\ in\ circulation/_{GDP} \times 100\%$;

- *the relation M2 to money in circulation,* defined as follows:

$M2/_{money\ in\ circulation}$;

- *the share of more liquid M1 in M2,* defined as*:*

$M1/_{M2} \times 100\%$;

- *measures of financial depth* as measured by one of the most popular measures of financial depth:

$M2/_{GDP} \times 100\%$;

- *money multiplier (ratio),* which is calculated as follows (monetary base is the sum of currency in circulation, reserve requirement and excess reserves (with the central bank)):

$M2/_{monetary\ base} \times 100\%$;

- *velocity of money circulation* (the speed at which money is exchanged, which is a kind of measure of liquidity and is unlikely to rise sufficiently to enable the monetary stimulus)

$GDP/_{M2}$;

- *interest rate (money market);* increase in this rate may signal tight liquidity in the banking system that may lead to worsen the incidence of Non Performing Loans (NPLs);

- *ratio of domestic credit (DC) to nominal GDP;* that gives an indication of the relative scale of the increase in domestic credit in relation to the size of the economy (it is observed that crises are often preceded by high domestic credit growth):

$total\ DC/_{GDP}$;

- *inflation as* measured by the wholesale or production price index *(PPI or WPI).*

2.1.2 Currency safety and its indicators

Currency safety refers to the ability of a financial system to provide an economic system with foreign currency in order to abide to the active balance of payments and the honouring of international

obligations, and to keep macro-economic indicators in the specified ranges to increase export and investments.

International reserves serves as defence of the exchange rates by authorities. Three indicators may therefore be useful in the currency safety analysis:

- *M*onetary rate, defined as follows*:*

$$monetary\ base\big/international\ reserves;$$

- *Coverage of import by international reserves,* calculated using the following ratio*:*

$$\textbf{international reserves}\big/\textbf{import} \times \textbf{100}\%.$$

- *Real effective exchange rate (REER),* as defined by the IMF (IFS database). For interpretation, take note that a very high level of REER indicates that a country may not be as competitive relative to other countries.

2.1.3 Stock market safety and its indicators

Stock market safety refers to stock market institutions that ensure the further development of the financial system and an adequate inter-sector, inter-industrial and inter-regional capital transfer.

Declines in the stock exchange index and in market capitalisation value may be signals of weakness of capital market which will spread to the real sector of the economy. Indicators such as the composite stock price index and the market capitalisation as a percentage of GDP are generally accepted leading indicators for financial markets (Bhattacharyay, 2003):

- *M2/market capitalisation* (the growth of market capitalisation not accompanied by growth in M2 may show the vulnerability of the stock market);
- *changes in the stock exchange index in % related to the previous quarter.*

Table 1 summarises the collection of financial safety indicators which will be used for the model of financial safety (stimulants and non-stimulants are explained below).

2.2 Constructing the Index of financial safety

To build the integrated index of the level of financial safety of a country based on the above-mentioned indicators, the following steps were undertaken:

- Data normalisation I, which include forming the collection of indicators, determining their optimum, cordon, extreme values and applying data normalisation;

- Data normalisation II: principle components, which implies estimating the weighted coefficients; and

- The calculation of the financial safety index of the country.

2.2.1. Data normalisation I: Optimum, cordon and extreme values

The values of the selected indicators may be in the form of the indicator's stimulants (the greater the value, the better), or non-stimulants (the lesser the value, the better). The difference between stimulants and non-stimulants lies in the nature of the influence i.e. direct or indirect. The relationship between the integral estimation *I* and indicator's stimulants is direct, and the relationship between *I* and the indicator's non-stimulants is indirect. The following values can be distinguished:

- optimum values of the selected indicators of financial safety (these values tend not to put the functioning of the financial system at risk);

- cordon values of the selected indicators of financial safety (these values may tend to put the functioning of the financial system at a slight risk); and

- extreme values of the selected indicators (these are values that put the functioning of the financial system at risk).

These values can either be determined by an expert or it may be specified using percentage borders (in the case of percentage borders usage, the indices of different countries may be compared):

- the optimum values: ± 5%;

- the cordon values: ± 15%;

- the extreme values: ± 25%.

Since financial safety is estimated through the collection of an element's indicators (*m*), and for the purpose of receiving the integral estimation, it is necessary to aggregate all the various indicators or signals into one complete set.

The aggregation of signals is based on the theory of the "value of superposition method" (the value of the whole equals the sum of the values of its constituents). Because the selected indicators have different information "directions", it is necessary to normalise information in order to perform

the additive aggregation. There are different methods of normalisation, but all of them in this situation will have an equalisation of empiric (x_i) values with the optimum (x_{optim}) values, cordon (x_{cordon}) values, and extreme ($x_{extreme}$) values.

x_{ij} ($i=1,...,n$; $j=1,..,m$) are indicators that characterise the financial safety of a country, and therefore the integral index will be calculated in the following way:

$$I_i = \sum_{j=1}^{m} a_{ij} z_{ij} , \tag{1}$$

where a_{ij} is a weighted coefficient that defines the degree of the deposit of the j - indicator into the integral index of the i- element of the financial safety system; z_{ij} - is the value of the normalised x_{ij} indicator.

The values of the *I* index have to lie on a scale from '0' (when all x_{ij} have the 'worst' values) to '1' (when all x_{ij} have the 'best' values).

The "normalisation I" of the variables is realised by means of the following method:

$$z_{ij} = \begin{cases} 1, x_{optym}^{min} \le x_{ij} \le x_{optym}^{max}, x - stimulant/no\ stimulant; \\ \frac{x_{ij}-x_{cordon}^{min}}{x_{cordon}^{max}-x_{cordon}^{min}}, x_{cordon}^{min} \le x_{ij} \le x_{cordon}^{max}, x - stimulant; \\ \frac{x_{cordon}^{max}-x_{ij}}{x_{cordon}^{max}-x_{cordon}^{min}}, x_{cordon}^{min} \le x_{ij} \le x_{cordon}^{max}, x - no\ stimulant; \\ \frac{x_{ij}-x_{extreme}^{min}}{x_{extreme}^{max}-x_{extreme}^{min}}, x_{extreme}^{min} \le x_{ij} \le x_{extreme}^{max}, x - stimulant; \\ \frac{x_{extreme}^{max}-x_{ij}}{x_{extreme}^{max}-x_{extreme}^{min}}, x_{extreme}^{min} \le x_{ij} \le x_{extreme}^{max}, x - no\ stimulant. \end{cases} \tag{2}$$

where, z_{ij} is the normalised value of indicator x_{ij}, x_{ij} is the raw data for the index of the financial safety calculation; x_{optym}^{min} and x_{optym}^{max} are the minimum and maximum optimum values; x_{cordon}^{min} and x_{cordon}^{max} are the minimum and maximum of the cordon values; and $x_{extreme}^{min}$ and $x_{extreme}^{max}$ are the minimum and maximum of the extreme values, respectively.

2.2.2 Data normalisation II: Calculation of the weighted coefficients (w_{ij})

The purpose of data normalisation II is to transform the raw data, possibly strongly correlated between themselves, in new, uncorrelated components' factors. For this purpose, the method of factor analysis is suitable, especially principal component methodology.

Technically, a principal component (Kaiser, 1958) can be defined as a linear combination of optimally weighted observed variables. It is possible to calculate a score for each subject on a given principal component. The general manner in which to compute scores on the first component created in a principal component analysis is the following:

$$C_1 = b_{11}(X_1) + b_{12}(X_2) + \dots b_{1p}(X_p), \tag{3}$$

where C_1 is the first component extracted; b_{1p} is the regression coefficient or weight for observed variable p; and X_p is the subject's score on observed variable p.

To make the transformation into the set with the values from '0' to '1', a varimax rotation will be applied. A varimax rotation is the process during which coordinates used in principal component analysis are changed, in order to maximise the sum of the variances of the squared loadings. It therefore seeks a basis that represents each individual in the most economic way. Therefore, each individual can be well described by a linear combination of only a few base functions (Kaiser, 1958):

$$R_{VARIMAX} = \arg\max_R \left(\sum_{j=1}^{k} \sum_{i=1}^{p} (\Lambda R)_{ij}^4 - \frac{\gamma}{p} \sum_{j=1}^{k} \left(\sum_{i=1}^{p} (\Lambda R)_{ij}^2 \right)^2 \right), \tag{4}$$

where $\gamma = 1$ for *VARIMAX*.

There are three stages in building the main component parts of models:

- the calculation of the correlation matrix, R, or the calculation based on the raw data;
- the calculation of d_{ij} – the weights of the factors;
- the identification of main component parts.

Relations between primary signals and component parts are described by the linear combination:

$$y_i = \sum_{j}^{m} c_{ij} G_j , \tag{5}$$

where y_i is a standardised value of the signal i; and c_{ij} is a loading of component j in the summarised dispersion of the collection of indicators of the element I of the financial safety (% total of variance). G_j can further be depicted as the following linear combinations:

$$G_j = \sum_{j}^{m} d_{ij} x_{ij} , \tag{6}$$

where d_{ij} is the weight of the factor and x_{ij} is the indicator of the factor. The weight coefficients a_{ij} are calculated as follows:

$$a_{ij} = \frac{c_{ij} \cdot |d_{ij}|}{\sum c_{ij} |d_{ij}|}. \qquad (7)$$

The calculation of the integral index of financial safety (*IFS*) of a country is then as follows:

$$IFS_j = \sum_i a_{ij} \cdot z_{ij}, \qquad (8)$$

where a_{ij} - are the weight coefficients, obtained from the equation (7), z_{ij} - are the normalised values of indicators x_{ij}, obtained from the equation (2).

3. MODELING AND FORECASTING OF THE IFS OF SOUTH AFRICA

To forecast *IFS of a country,* different techniques may be used, for example:

- logit/probit models (see Berg & Pattillo, 1999b; Eichengreen, Barry, Rose & Wyplosz, 1995; Frankel & Rose, 1996; Jakobs, Lestano, Gehard & Kuper, 2003; among others);
- Markov-switching models (see Alvarez-Plata & Schrooten, 2003; Fratzscher, 1999; Jeanne & Masson, 2000; Schweickert, Rainer, Lucio Vnhas de Souza, Alvarez-Plata & Schrooten, 2003; among others);
- Krigin's method (see Ripley, 1987; Ripley, 1987; Kozintseva, 1999; among others); and
- State-space models and the Kalman filter (see Uhlmann, 2004; among others).

In this paper, the BVAR approach with the MCMC and Gibbs sampler will be used, because it may provide better out-of-sample forecasts Moreover, the Bayesian hypothesis is particularly natural for prediction, because it takes model uncertainty into account. Bayesian inference delivers an integrated approach to:

- inference (including 'estimation' and 'testing');
- prediction (with a full accounting for uncertainty); and
- decision (with likelihood and loss).

The Gibbs sampler is a technique which is used to generate random variables from a distribution indirectly, without having to calculate the density. The Gibbs sampler generates a Markov chain of random variables, which converge to the distribution of interest *f(x)*. Empirical Bayes estimators help provide shrinkage over unrestricted least square estimates (Banbura, Giannone

& Reichlin, 2010; Doan, Litterman & Sims, 1984; Koop, Korobilis & Litterman, 1984; 1990). This method was described by Metropolis, Rosenbluth, Rosenbluth, Teller and Teller (1953), and further developed by Hastings (1970). More recently, Gelfand and Smith (1990) re-opened the Gibbs sampler by testing its potential in a wide variety of conventional statistical problems. The detailed historical aspects of the process of development of MCMC and Gibbs sampling are analysed in Robert and Casella (2011).

Consider the VAR(p) model:

$$y_t = \delta + \Phi_1 y_{t-1} + ... + \Phi_p y_{t-p} + \varepsilon_t \ . \tag{11}$$

In its simple, reduced form, the VAR model appears as follows:

$$Y_t = X_t B + \varepsilon_t, \varepsilon_t \sim N(0, \Sigma) \tag{9}$$

or

$$y_t = Z_t \beta + \varepsilon_t, \tag{10}$$

where

$$Z_t = I_M \otimes X_t \ . \tag{11}$$

In (9), Y is a T x n matrix with t^{th} row given by y_t' where y_t is a vector of n dependent variables; X is a T x K matrix; $K=(1+pn)$ because each row contains p lags of each dependent variable and an intercept: (1, y`t-1,…,y`t-p); B is a matrix of coefficients; ε_t is a T x n matrix of independent errors with t^{th} row given by ε_t'; $\beta = vec(B)$ is a vector of I elements. Therefore, the number of the coefficients will exceed the numbers of the observation.

The lag length may be searched by using information criteria: Akaike information criteria (*AIC*), Schwarz criteria (*SC*) and Hannan and Quinn criteria (*HQ*), which are defined as follows (for more details see Lutkepohl, 1991; Koreisha & Pukkila, 1993) and the lag length of the VAT in levels that minimise the information criteria were chosen:

$$AIC(p) = \ln|\hat{\Sigma}_u(p) + \frac{2}{T} kn^2; \tag{12}$$

$$SC(p) = \ln|\hat{\Sigma}_u(p) + \frac{\ln(T)}{T} kn^2; \tag{13}$$

$$HQ(p) = \ln|\hat{\Sigma}_u(p) + 2\frac{\ln(\ln(T))}{T}kn^2, \tag{14}$$

where $\hat{\Sigma}_u(p)$ is MLE of Σ_u.

The OLS estimates of:

$$\hat{B} = (X'X)^{-1}(X'Y), \tag{15}$$

$$\hat{S} = (Y - X\hat{B})'(YY - X\hat{B}), \tag{16}$$

and

$$\hat{\Sigma} = \hat{S}/(T-K) \tag{17}$$

are needed during the estimation of the BVAR model.

The Bayesian approach combines the likelihood function with the prior, which becomes very important as the number of parameters increases relative to the sample size. In this article, the BVAR model estimations will be used in combination with the following priors (Korabilis, 2009; Koop & Korabilis, 2010):

- M-C Integration (non-informative prior, natural conjugate prior, Minnesota prior);
- Gibbs sampler (Independent Normal-Wishart and SSVS in mean-Wishart).

3.1. Non-informative priors

Non-informative priors, introduced by Laplace in 1812, are a uniform, possibly improper distribution over the parameter space. The non-informative prior presents the posterior distributions for all possible priors and its attractiveness lies in the fact that even if it may be improper, it still leads to a proper posterior. This kind of prior is a function that is used in place of a subjective prior distribution, when little or no prior information is available. For the details, see Kass and Wasserman (1996), who give a review of many methods of generating non-informative priors.

Jeffreys (1946) proposed a method of generating non-informative priors, which is invariant to transformations of the parameter vector. In our case, Jeffreys' prior on α is the following:

$$p(\alpha, \Sigma) \propto |\Sigma|^{-(M+1)/2}. \tag{18}$$

and the conditional posteriors are of the following form:

$$\alpha \mid \Sigma, y \sim N(\hat{\alpha}, \Sigma), \tag{19}$$

$$\alpha \mid \Sigma \sim IW(\hat{S}, T - K). \tag{20}$$

3.2. The natural conjugate prior

Natural conjugate priors are those where the prior, likelihood and posterior come from the same family of distributions. The natural conjugate prior is of the following form:

$$\alpha \mid \Sigma \sim N(\underline{\alpha}, \Sigma \otimes \underline{V}), \tag{21}$$

and $\Sigma^{-1} \sim W(\underline{v}, S^{-1})$. $\tag{22}$

The posterior belongs to the same distribution family as the prior. The posterior on α is the following:

$$\alpha \mid \Sigma, y \sim N(\overline{\alpha}, \Sigma \otimes \overline{V}), \tag{23}$$

where

$$\overline{V} = (\underline{V}^{-1} + X'X)^{-1}, \tag{24}$$

$$\overline{\alpha} = vec(\overline{A}), \tag{25}$$

$$\overline{A} = \overline{V}(\underline{V}^{-1}\underline{A} + X'X\hat{A}). \tag{26}$$

The posterior on Σ is the following:

$$\Sigma^{-1} \mid y \sim W(\overline{v}, \overline{S}^{-1}), \tag{27}$$

where

$$\overline{v} = T + \underline{v}, \tag{28}$$

$$\overline{S} = S + \underline{S} + \hat{A}'X'X\hat{A} + \underline{A}'\underline{V}^{-1}\underline{A} - \overline{A}'(\underline{V}^{-1} + X'X)\overline{A}. \tag{29}$$

$\underline{V}$, $\underline{v}$, $\underline{S}$, $\underline{A}$, and $\underline{\alpha}$ are chosen prior hyper-parameters.

3.3. The Minnesota prior

The Minnesota prior (see Litterman, 1985; Kadiyala & Karlsson, 1997; Kenny, Meyler & Quinn, 19984; Korobilis, 2009; and others) mainly denotes the restriction of the hyper- parameters of β (the prior for β is normal, the posteriors are similar to the Natural conjugate prior case and Σ is assumed to be known). The Minnesota prior has one great advantage: it leads to simple posterior inference involving only the Normal distribution. One disadvantage of the Minnesota prior is that it does not provide a full Bayesian treatment of Σ as an unknown parameter and ignores any uncertainty in this parameter.

3.4. The Gibbs sampler

In its very simple form, the Gibbs sampler for *P(Y)* is:

$$P = \prod_{j=1}^{m} P(j), \tag{30}$$

where

$$P_{y',y}^{(j)} = \begin{cases} 0 & \text{if } y'_{-j} \neq y_{-j} \\ P(Y_j = y'_j \,|\, Y_{-j} = y_{-j} & \text{if } y'_{-j} = y_{-j} \end{cases}. \tag{31}$$

Either the independent Normal-Wishart Prior-Posterior algorithm or the Minnesota Prior may be applied for this model. The first one is a very general prior:

$$p(\beta, \Sigma^{-1}) = p(\beta)p(Z^{-1}), \tag{32}$$

where

$$\beta \sim N(\underline{\beta}, \underline{V}_{\beta}), \tag{33}$$

$$\Sigma^{-1} \sim W(\underline{v}, \underline{S}^{-1}), \tag{34}$$

In this case, the prior covariance matrix $\underline{V}_{\beta}$ may be not only in the restrictive $\Sigma \otimes \underline{V}$ form of the natural conjugate prior, but also in other forms. The conditional posteriors are as follows:

- posterior on $\beta = vec(B)$:

$$\beta \mid y, \Sigma^{-1} \sim N(\overline{\beta}, \overline{V}_\beta), \tag{35}$$

where

$$\overline{\beta} = \overline{V}_\beta (\underline{V}_\beta^{-1} \underline{\beta} + \sum_{i=1}^{T} Z_t' \Sigma^{-1} y_t), \tag{36}$$

$$\underline{V}_\beta = (\underline{V}_\beta^{-1} \underline{\beta} + \sum_{i=1}^{T} Z_t' \Sigma^{-1} Z_t)^{-1}; \tag{37}$$

- posterior on Σ:

$$\Sigma^{-1} \mid y, \beta \sim W(\overline{v}, \overline{S}^{-1}), \tag{38}$$

where

$$\overline{v} = T + \underline{v}, \tag{39}$$

$$\overline{S} = \underline{S} + \sum_{t=1}^{T} (y_t - Z_t \beta)(y_t - Z_t \beta)'. \tag{40}$$

In this paper, the Gibbs sampler will be used in the Independent Normal-Wishart prior with a subjectively chosen prior of hyper-parameters, and SSVS in mean-Wishart. SSVS uses the Gibbs sampler to simulate a sample from the posterior distribution (See George, Sun & Ni, 2008 and Korobilis, 2009 for the details). The main advantage of SSVS is its fast and efficient simulation of the Gibbs sampler.

3.5. Forecast

Two types of the forecasts may be applied, namely iterative and *h*-step ahead. The iterative forecasts can be defined as follows:

$$Y_{(t)} = A_0 + Y_{(t-1)} A_1 + \dots + Y_{(t-p)} A_p + e_{(t)}, \tag{41}$$

and direct *h*-step ahead forecasts are given by:

$$Y_{(t+h)} = A_0 + Y_{(t)} A_1 + \dots + Y_{(t-p+1)} A_p + e_{(t+h)}. \tag{42}$$

All models are evaluated using the following criteria. Firstly, the Mean Square Forecast Error, *MSFE* (Korobilis, 2009; Koop & Korobilis, 2010):

$$MSFE_{i,t}^{h} = \sqrt{(\hat{y}_{i,t+h|t} - y_{i,t+h}^{0})^2}, \tag{43}$$

where $\hat{y}_{i,t+h|t}$ is the time $t+h$ prediction of variable IFS by using data available up to time t, $y^0_{i,t+h}$ is the observed value of variable IFS at the time $t+h$. This approach only uses the point forecasts and ignores the rest of the predictive distribution. Therefore, it is motivated to also use the predictive likelihood to evaluate the received forecast of the entire predictive density (Geweke & Amisano, 2011):

$$\sum_{\tau=\tau_0}^{T-h} \log[\, p(y_{\tau+h} = y^0_{\tau+h} \mid Data_\tau)]\,, \tag{44}$$

The predictive likelihood is the predictive density for $y_{\tau+h}$ that is estimated at the actual outcome $y^0_{\tau+h}$; $p(y^0_{\tau+h} \mid Data_\tau)$ based on information available at time τ.

3.6 Impulse responses

Impulse response functions show the dynamic effects of innovations in chosen time series on the IFS of a country. In general, the impulse responses are nonlinear functions of the VAR coefficients and Σ. Therefore, posterior simulation methods are required for all priors. The most common usages of VAR impulse responses to orthogonal shocks are based upon Cholesky's decomposition of Σ, which depends on the ordering of variables. Koop *et al.* (1996) and Pesaran and Shin (1998) proposed generalised impulse responses, which are also nonlinear functions of Σ and B, but independent of variable ordering.

The impulse responses of y_t to a shock that occurred j periods earlier, is

$$H_j = \sum_{i=1}^{j} B_i H_{j-i}\,, \tag{45}$$

where B is a coefficient matrix; $B_i = 0$ for i larger than lag L and $B_0 = I$ (I is the p by p identity matrix). Orthogonalisation of the errors is performed through the Cholesky decomposition of the covariance matrix Σ and is defined as:

$$\Sigma = \Psi'\Psi\,, \tag{46}$$

where Ψ is an upper triangular positive definite matrix. The VAR error vector is included in a structural shock vector u_t, which is estimated as follows:

$$u'_t = \varepsilon_t \Psi^{-1}. \tag{47}$$

The response of y'_t to a unit shock of the ith element of u'_{t-j} is the ith row of:

$$Z_j = \Psi H_j \tag{48}$$

The impulse responses are nonlinear functions of (B; Ψ), which makes frequentist inference deriving difficult, but does not pose difficulties for Bayesian computations as long as posteriors of (B; Ψ) are available.

4. EMPIRICAL RESULTS

4.1. Data

Based on the variables to be used, as described in Table 1, the following time-series are used for the construction of a Index of Financial Safety for South Africa (source: International Financial Statistics database; 1992Q1-2011Q1): M0, M1, M2, M3, money in circulation, GDP, total reserves (minus gold), exchange rate (ZARs per USD), real effective exchange rate, import, money market interest rate, share prices: industrial commercial, and market capitalisation. Data of total domestic credits was obtained from the Reserve Bank of South Africa. All other indicators needed for the Index of Financial Safety construction have been calculated based on the above-mentioned data.

4.2 Index of Financial Safety of South Africa

The optimum (±5%), cordon (±15%), and extreme (±25%) values of the chosen variables for South Africa are as follows (Table 2).

Based on the table of correlation (see Table 3 below), the variables that have the most material influence on the IFS, are as follows: exchange rate (ZAR per USD and real effective); money aggregates (M0; M1, M2 and M3); GDP and domestic credits; total reserves; and money in circulation. In the last place are share prices and market capitalisation (Table 3).

After applying normalisation I and normalisation II (principle component analysis), the following results are eminent (the weights) (Table 4). The largest weights are observed for the

following variables: *Money in circulation/M2*100, PPI/WPI, GDP/M2, M1/M2*100%, M2/GDP*100.*

By using (8), the index of financial safety (*IFS*) is calculated. The dynamics of this index are shown in Figure 1 below.

In general, the Index of Financial Safety of South Africa caught the main perturbations in the financial system of South Africa.

When analysing the period from 2005Q1 to 2007Q4, the most tangible downside dynamics of the IFS counterparts of South Africa were in the following variables: *Total domestic credit/GDP*; *PPI/WPI*; *M2/market capitalisation*. Moreover, the following counterparts make the smallest contribution to the integrated IFS: *M2/M0, M2/Money in circulation, changes of share price index, coverage import by reserves* (Figure 2).

4.3 Bayesian Vector Autoregressive Model of the IFS of South Africa: forecast and impulse responses

The estimation and forecasting of the IFS were completed with the MatLab programme. Bayesian estimation, prediction and impulse response analysis in VAR models were performed using the MCMC technique and the Gibbs sampler, as well as the use of posterior simulation. There were initially 16 dependent variables with different priors (five types of priors have been applied) and lag orders. For each sample draw the posterior from 10 000 MCMC cycles after 1 000 burn-in runs was applied. For modelling and forecasting, we applied *ln* transformation to the raw data that had initially been used for the construction of the Index of Financial Safety of South Africa (*M0, M1, M2, M3, money in circulation, GDP, money market interest rates, total reserves (minus gold), exchange rate (Rands per US Dollar), coverage of import by reserve, total domestic credits, PPI/WPI, market capitalisation, share prices: indust & comm, reer*). Therefore, for *n*= 85 and *p*= 3, $K=(1+pn) = 256$, α contains $nK = 21\ 760$ elements, Σ is parameter rich and contains $n(n+1)/2=3655$ elements. Consequently, the number of coefficients far exceeds the number of observations.

Based on the information criteria (see equations (12)-(14)), the lag length has been chosen to be 1 and 2 (dependent on the number of variables). The number of times to obtain a draw from the predictive density for each generated draw of the parameters equals to 24 quarters. The number of forecast periods is $h = 1$. For such short-term forecasts ($h = 1$), the multivariate VAR models offer accurate forecasts. Furthermore, when $h = 1$, direct and iterated forecasts are very similar, since it is possible to estimate and forecast with exactly the same specifications. During forecasting, the parameters of the VAR model remain constant in the out-of-sample period.

Dependent on the model specification and the choice of prior hyper-parameters, there are 10 competing forecasting models (for 16 variables) and 10 BVAR models with the three variables, which have the most tangible influence on the ISF. The results of the forecast accuracy comparisons of *IFS* for South Africa are indicated in Table 5 and Table 6. The estimation shows that the higher lag order causes aggravation of *MSFE* and predictive likelihood. Moreover, better results were obtained with the Minnesota and non-informative priors.

The prediction of the IFS of South Africa, based on a BVAR model with the different list of variables, was also undertaken. The best results were received with the list with the 3 and 4 variables, which have the most tangible influences on the IFS dynamics. Therefore, the iterated forecasts based on the BVAR(2) with the Minnesota priors model showed the best results (Table 6) among the other models.

The resultant impulse response functions, generated by the BVAR model, are meaningful in the case when innovations are serially and mutually uncorrelated. Consequently, the orthogonalisation of the innovations through a Choleski decomposition of the estimated variance was applied. Therefore, having done this, the innovations can be interpreted as the unanticipated shocks to the chosen variables. The results of impulse response simulation are presented in Figure 4. The forecast of the South Africa *IFS* until 2017Q1 is presented in Figure 5.

Impulse response functions associated with the negative shocks to the IFS and analysed factors of South African Index of Financial Safety are plotted in Figure 4. All the indicators which were used in the modelling were simultaneously subjected to a negative shock in the BVAR model. . The response for the IFS shows that, the peak effects on financial safety for South Africa and the chosen financial indicators occur, approximately, at 2 to 3 quarters. The exceptions are the following*: total domestic credits* (the peak lasts from 12 to 14 quarter), total reserves (the peak lasts from 10 to 14 quarter), *PPI/WPI*. The following variables in general show synchronised dynamics with the IFS: M2, coverage of import by reserves, and M1. In the first year after a shock the following indicators also show synchronised dynamics with the IFS: the money market interest rate and the share price index. This implies that the monitoring of the M2, level of reserves relative to imports and the M1 are critical in forecasting future financial safety of the South African financial system. Since interest rates and the share price affect the financial sector with a lag, it might be worthwhile to monitor these indicators as well in order to avoid crises over the longer term.

The impulse responses in Figure 4 imply a lack of synchronization between the following variables: M0 and M2, M2 and M3, market capitalisation and share price index (in the first two quarters), M0 and money in circulation (in the first two quarters). This confirms that the M2 rather than the M3 is a better indicator of financial safety in South Africa. In addition, less emphasis should be placed on the share market capitalisation in favour of price movements.

5 CONCLUDING REMARKS

In this study, the Index of Financial Safety (*IFS*) has been built and used to explore the strength of the South African financial system and to forecast the possibility of financial perturbations appearing. For this purpose of the IFS, the financial safety of a country is defined as a state in which the financial system, and all elements of this system, is shielded against real and potential internal and external threats.

The results showed that the *IFS* applied to South Africa is able to catch the main perturbations in the SA financial system. Additionally, an analysis of the SA *IFS* counterparts indicate that the indicators with the most negative dynamics during the perturbations are: *Total domestic credit/GDP*; *PPI/WPI*; *M2/market capitalisation.* Moreover, the following counterparts make the smallest contribution to the integrated *IFS* of South Africa: *M2/M0*, *M2/Money in circulation*, *changes of share price index*, *coverage import by reserves.* This provides the base for identification of the weakest sides of the financial system during the perturbations.

To forecast the future states of the *IFS*, the BVAR models with the MCMC and Gibbs sampler and also with different priors and number of variables were used. These types of the models provided better out-of-sample forecasts. In the case of South African *IFS* the iterated forecasts based on the BVAR(2) with the Minnesota priors model showed the best results among the other models.

The forecast showed that financial stability of South Africa had peaked at the end of 2011-beginning of 2012 and will have a downside trend until 2013, which will be associated with high volatility. This research shows that the monetary magnitude M2, the level of reserves relative to imports and the M1 are critical in forecasting future financial safety of the South African financial system, and confirms the importance of the M2 for the financial system.

Future research may focus on testing a similar *IFS* using different countries. Furthermore, research could be expanded to determine whether the *IFS* can be used as a common integrated indicator to determine violations in financial systems or as a way to estimate the investment risk level of different countries.

APPENDIX

Table 1: The collection of financial safety indicators for the model of financial safety of a country

Financial safety indicators	Character of financial safety indicators
Money in circulation/M2*100	non-stimulant
Money in circulation/GDP*100	non-stimulant
M1/M2*100%	stimulant
M2/GDP*100	stimulant
M2/M0	stimulant
PPI / WPI	non-stimulant
Money market interest rates %	non-stimulant
GDP/M2	stimulant
M2/Money in circulation	non-stimulant
Monetary base/reserves	Stimulant
Coverage of import by reserves	Stimulant
Total domestic credit/GDP	non-stimulant
M2/ market capitalisation	non-stimulant
Changes of share price index % to a previous quarter	Stimulant
Real effective exchange rate	non-stimulant

Table 2: The optimum, cordon and extreme values of the chosen variables for the IFS of South Africa

Variable	Extreme value, min	Cordon value, min	Optimum value, min	Optimum value, max	Cordon value, max	Extreme value, max	Stimulant (1)/ noStimulant(0)
Money in circulation/M2*100	5,00	5,67	6,34	7,01	7,67	8,34	0
Money in circulation/GDP*100	25,05	28,39	31,73	35,07	38,40	41,74	0
M1/M2*100%	37,61	42,62	47,64	52,65	57,67	62,68	1
M2/GDP*100%	386,39	437,91	489,43	540,95	592,47	643,99	1
M2/M0	11,23	12,73	14,23	15,72	17,22	18,72	1
Money market interest rates %	8,60	9,75	10,90	12,04	13,19	14,34	0
GDP/M2	0,15	0,17	0,19	0,21	0,23	0,25	0
M2/Money in circulation	11,86	13,44	15,02	16,60	18,18	19,77	0
Monetary base / international reserves	1,63	1,85	2,06	2,28	2,50	2,72	0
Exchange rate changes, in % to previous quarter	1,65	1,87	2,09	2,32	2,54	2,76	0
Coverage of import by international reserves	55,37	62,75	70,13	77,51	84,90	92,28	1
Total domestic credits/GDP	4,97	5,63	6,29	6,96	7,62	8,28	0
PPI / WPI	62,16	70,45	78,73	87,02	95,31	103,60	1
M2/ market capitalization	0,34	0,38	0,43	0,47	0,51	0,56	0
Changes of stock exchange index, in % to a previous quarter	1,65	1,87	2,09	2,32	2,54	2,76	1
real effective exchange rate	82,43	93,42	104,41	115,41	126,40	137,39	0

Table 3: The correlation among raw data and the IFS of South Africa

	M0	M1	M2	M3	money in circulation	GDP	money market interest rates	total reserves (minus gold)	exchange rate	coverage of import by reserve	total domestic credits	PPI/WPI	market capitalization	share prices: indust & comm	reer	IFS
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	1,0	0,3027	0,3017	0,3021	0,2689	0,3018	-0,383	0,2717	0,3356	0,2201	0,3016	0,3001	0,1840	0,3157	-0,418	**0,6603**
2		1,0	0,9982	0,9987	0,9944	0,9986	-0,751	0,9780	0,8359	0,9151	0,9979	0,9979	0,8769	0,8743	-0,649	**0,5963**
3			1,0	0,9993	0,9957	0,9992	-0,747	0,9786	0,8367	0,9151	0,9994	0,9979	0,8734	0,8724	-0,652	**0,5952**
4				1,0	0,9957	0,9999	-0,752	0,9774	0,8362	0,9141	0,9996	0,9988	0,8743	0,8717	-0,648	**0,5950**
5					1,0	0,9955	-0,726	0,9720	0,8095	0,9078	0,9960	0,9941	0,9033	0,8555	-0,616	**0,5399**
6						1,0	-0,752	0,9773	0,8365	0,9140	0,9996	0,9989	0,8745	0,8723	-0,649	**0,5954**
7							1,0	-0,704	-0,561	-0,690	-0,751	-0,7455	-0,644	-0,629	0,3311	**-0,5390**
8								1,0	0,8397	0,9579	0,9774	0,9766	0,8922	0,8532	-0,659	**0,5854**
9									1,0	0,7697	0,8369	0,8379	0,7107	0,6256	-0,899	**0,7189**
10										1,0	0,9142	0,9099	0,8780	0,8097	-0,604	**0,5531**
11											1,0	0,9982	0,8738	0,8718	-0,651	**0,5937**
12												1,0	0,8738	0,8743	-0,651	**0,5953**
13													1,0	0,7449	-0,565	**0,4613**
14														1,0	-0,467	**0,4209**
15															1,0	**-0,7492**
16																1,0

Table 4: The results of the principle component analysis and weights calculation

	Factor 1 loadings (varimax normalise)	*Factor 2 loadings (varimax normalise)*	d_{ij}	c_{ij}	$c_{ij}|d_{ij}|$	*a*
Money in circulation/M2*100	0,781206	0,243858	**0,781206**	30,46212	23,7972	**0,103938**
Money in circulation/GDP*100	0,532307	-0,090542	**0,532307**	30,46212	16,21521	**0,070822**
M1/M2*100%	0,702824	-0,424879	**0,702824**	30,46212	21,40951	**0,093509**
M2/GDP*100	0,699833	-0,272181	**0,699833**	30,46212	21,3184	**0,093111**
M2/M0	0,430397	0,033543	**0,430397**	30,46212	13,1108	**0,057263**
PPI / WPI	0,792598	0,290244	**0,792598**	30,46212	24,14422	**0,105454**
Money market interest rates %	0,024118	0,198719	**0,198719**	16,26934	3,233034	**0,014121**
GDP/M2	0,770550	-0,482037	**0,770550**	30,46212	23,47259	**0,10252**
M2/Money in circulation	0,092798	0,638760	**0,638760**	16,26934	10,3922	**0,04539**
Monetary base / reserves (Monetary rate)	-0,187895	0,051803	**0,051803**	16,26934	0,842804	**0,003681**
Coverage of import by reserves	0,640050	0,440528	**0,640050**	30,46212	19,49729	**0,085157**
Total Domestic Credit/GDP	-0,020375	0,879227	**0,879227**	16,26934	14,30444	**0,062477**
M2/ market capitalization	0,685355	0,268613	**0,685355**	30,46212	20,87737	**0,091185**
Changes of share price index % to a previous quarter	-0,237694	-0,032194	**-0,032194**	16,26934	0,523776	**0,002288**
Rreal effective exchange rate	0,519236	-0,586758	**0,519236**	30,46212	15,81702	**0,069083**
Expl. Var	4,534956	2,474763		**Sum**	228,9559	1
Prp. Total	0,302330	0,164984				

Table 5: Comparison of the BVAR model estimation results of IFS of South Africa

Priors[1]		NJ	M	NonI	INW	SSVSiW	NJ	M	NonI	INW	SSVSiW
lags		1	1	1	1	1	2	2	2	2	2
MSFE	M0	2,3292577e-05	0,00268223	3,535040e-05	0,00040734156	0,10287748533	4,1545403e-05	0,0246732293	0,00251229777	0,00984856798	0,008308742
	M1	0,00014347	0,00010923	0,00014867	0,00012561	4,1386e-06	0,00074716	0,00050384	0,00077226	0,00056936	0,00025364
	M2	0,0008429	0,0013437	0,0008290	0,0011421	0,0031844	0,0016007	0,0011756	0,0012817	0,0012574	0,0021938
	M3	0,00052799415	0,00064872237	0,000516649150	0,000614400836	0,001406873055	0,000868468507	0,000213504937	0,000123795667	0,00015443292	0,0009242778
	money in circulation	0,00260412047	0,00447501630	0,0025560149	0,00293957041	0,0026066547	0,00112915541	0,00128843076	0,00191756737	0,00179447061	0,002797356
	GDP	0,000141931	1,21793177e-05	0,000144464198	7,15550422e-05	0,001132591191	0,000919106207	3,31498070e-05	1,69274413e-07	0,0001111920	0,000471517
	money market interest rates	4,5093446e-05	0,0027600602	4,9415493e-05	0,0012806063	0,0009459642	0,0008051437	0,0004558299	0,0001376121	0,0005978822	0,002858819
	total reserves (minus gold)	0,0207282541	0,0124535886	0,0205447930	0,0079372295	0,0032208824	0,0120122521	0,0146495586	0,0026462366	0,0302528200	0,010985223
	exchange rate	0,00196444073	8,98904247e-05	0,00199000477	0,00038245995	0,00015942504	0,000879922	0,00036939555	0,00314696206	2,0724445e-06	0,000334405
	coverage of import by reserve	0,0102452664	0,0028365291	0,0100987933	0,0020485903	0,000823893	1,3376016e-05	0,0026264398	0,0571025563	2,3160094e-05	0,002732572
	total domestic credits	0,00235076674	0,00204798523	0,00230780372	0,00212203930	0,00275555545	0,00188946743	0,00228493991	0,00271920777	0,00280658704	0,002823953
	PPI/WPI	3,9935250e-05	6,1784332e-05	3,7706296e-05	5,2597776e-05	0,0006673664	0,0004308627	0,0008806631	0,0017275082	0,0006883207	0,000450232
	market capitalization	0,00037913316	7,31210551e-05	0,000355310937	0,000172418693	0,002808720530	3,78576551e-05	6,28234402e-05	0,002660289046	0,00015546487	0,000477278
	share prices: indust & comm	0,00335582229	0,00358422243	0,0033553500	0,0029769625	0,00413298352	0,00124107791	0,00054782134	0,00156586145	0,00143478265	0,001905269
	reer	0,0069453	0,0041266	0,00697055	0,00493594	0,00201517	0,00085058	0,0035341	0,01025317	0,00238106	0,00217569
	IFS	0,0079023	0,00083498	0,00821320	0,00166085	0,00564401	0,00386820	0,00997271	0,02076783	0,01721235	0,00611762
Log PL[2]		10,966756	13,45963	10,8576	4,8487156	3,6022941	5,6386814	**8,9797424**	-32,59397	-1,472273	2,366055

[1] – NJ - Natural conjugate, M – Minnesota, NonI – Non-informative, INW - Independent Normal-Wishart (Gibbs sampler), SSVSiW - SSVS in mean-Wishart SSVS in mean-SSVS in covariance; [2] - predictive likelihood

Figure 1: Dynamics of the estimated Index of Financial Safety (IFS) of South Africa (1990Q1-2011Q1)
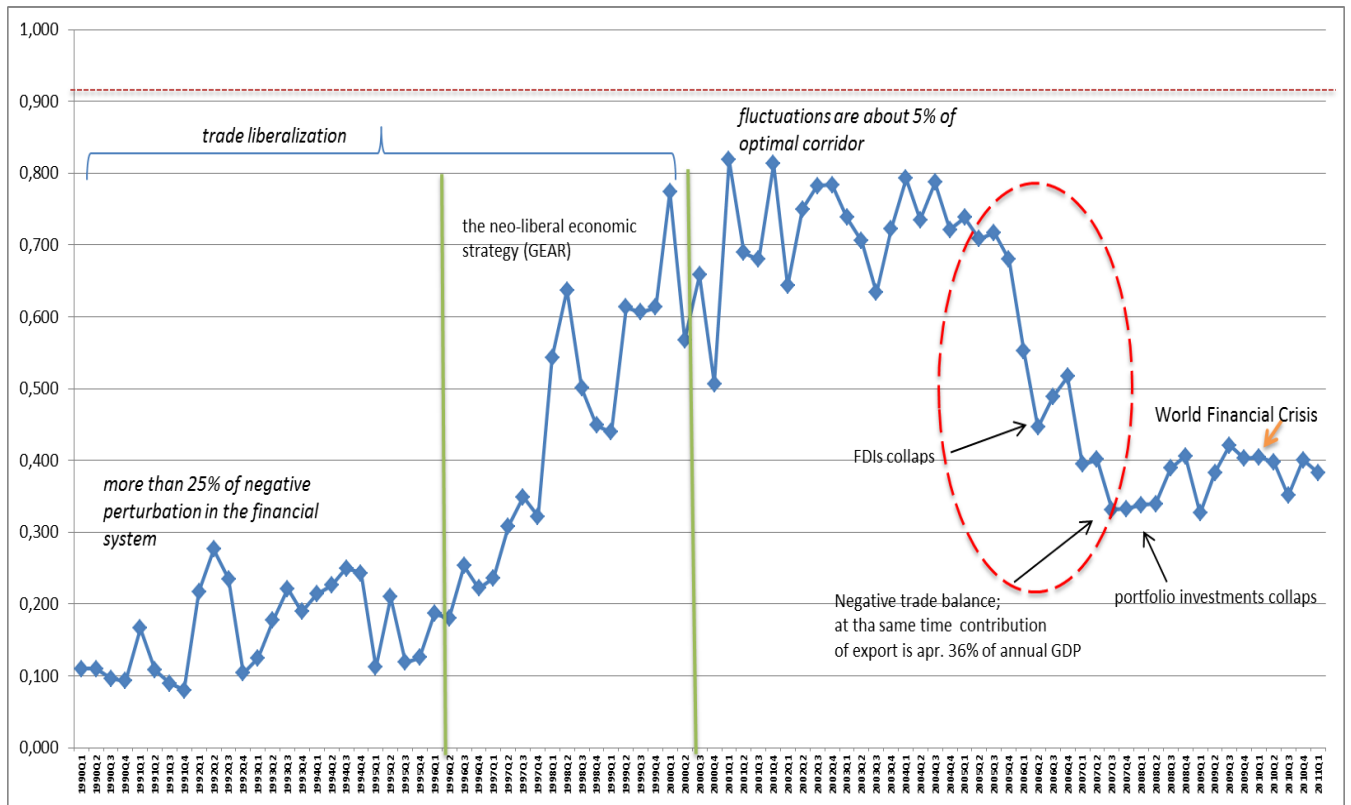
Figure 2: Downside dynamics of the IFS counterparts of South Africa in the period from 2005Q1 to 2007Q4
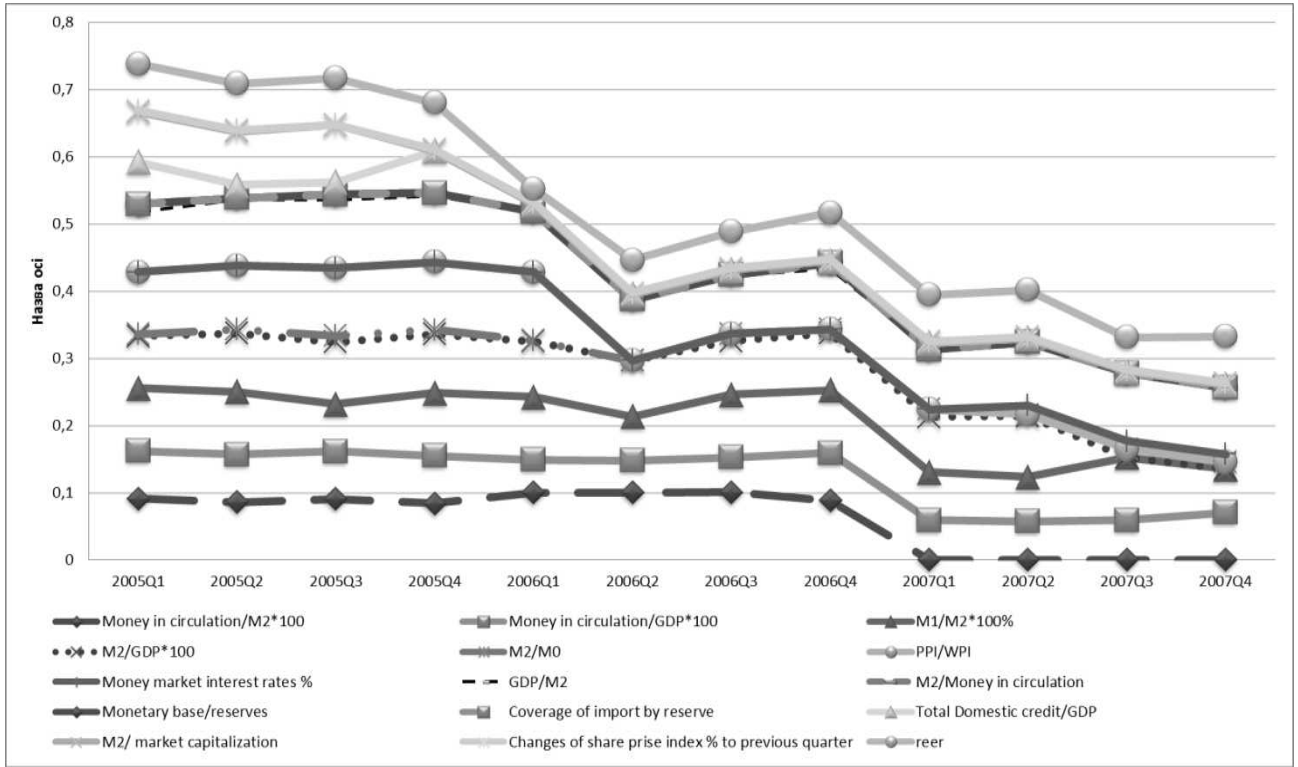
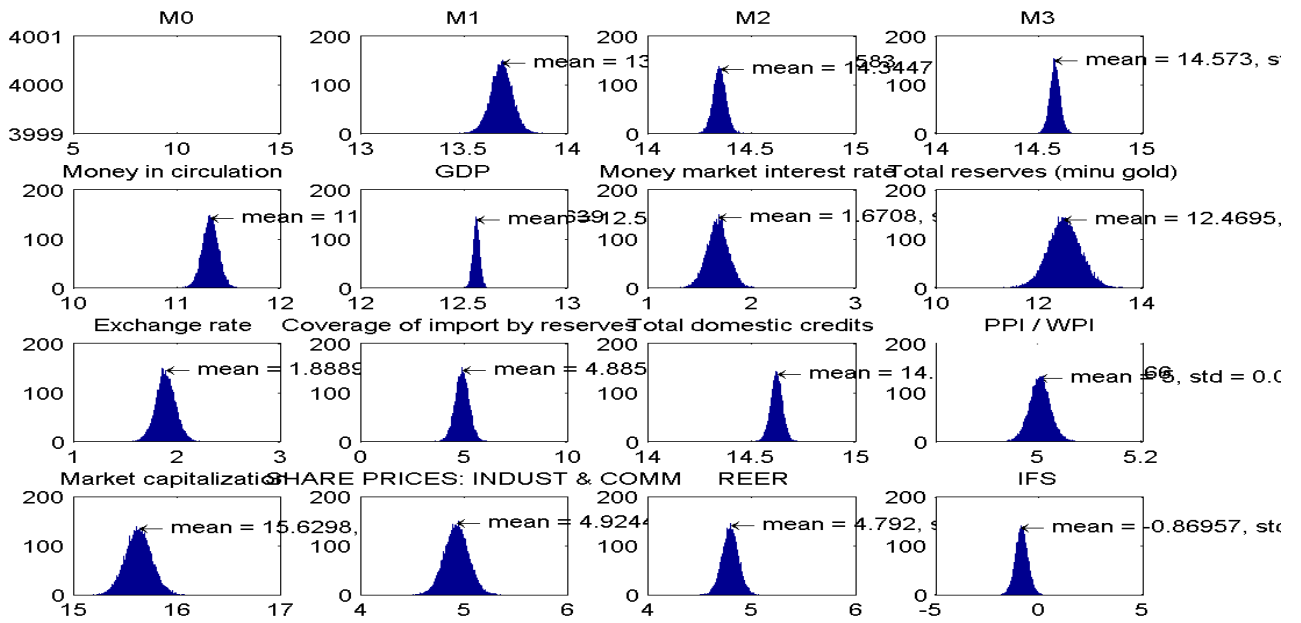*Figure 3: Graphs of posterior predictive*

Table 6: Test of the forecast accuracy of the IFS of South Africa with the three variables with the highest correlation

Priors	lags	MSFE	
		Iterated forecasts	**Direct forecasts**
Natural conjugate	1	0,0003288	0,0026896
Minnesota	1	0,0002869	0,0026571
Non-informative	1	0,0002435	0,0025435
Independent Normal-Wishart (Gibbs sampler)	1	0,0004234	0,0028440
SSVS in mean-Wishart (Gibbs sampler)	1	0,0007205	0,0015723
Natural conjugate	2	0,0001019	0,00384702
Minnesota	**2**	**0,0000090**	0,00320996
Non-informative	2	0,0000728	0,00343087
Independent Normal-Wishart (Gibbs sampler)	2	0,0000751	0,00386924
SSVS in mean-Wishart (Gibbs sampler)	2	0,0335782	0,02887436

Figure 4: Graph of the IFS of South Africa responses to the factors (period =24 quarters)
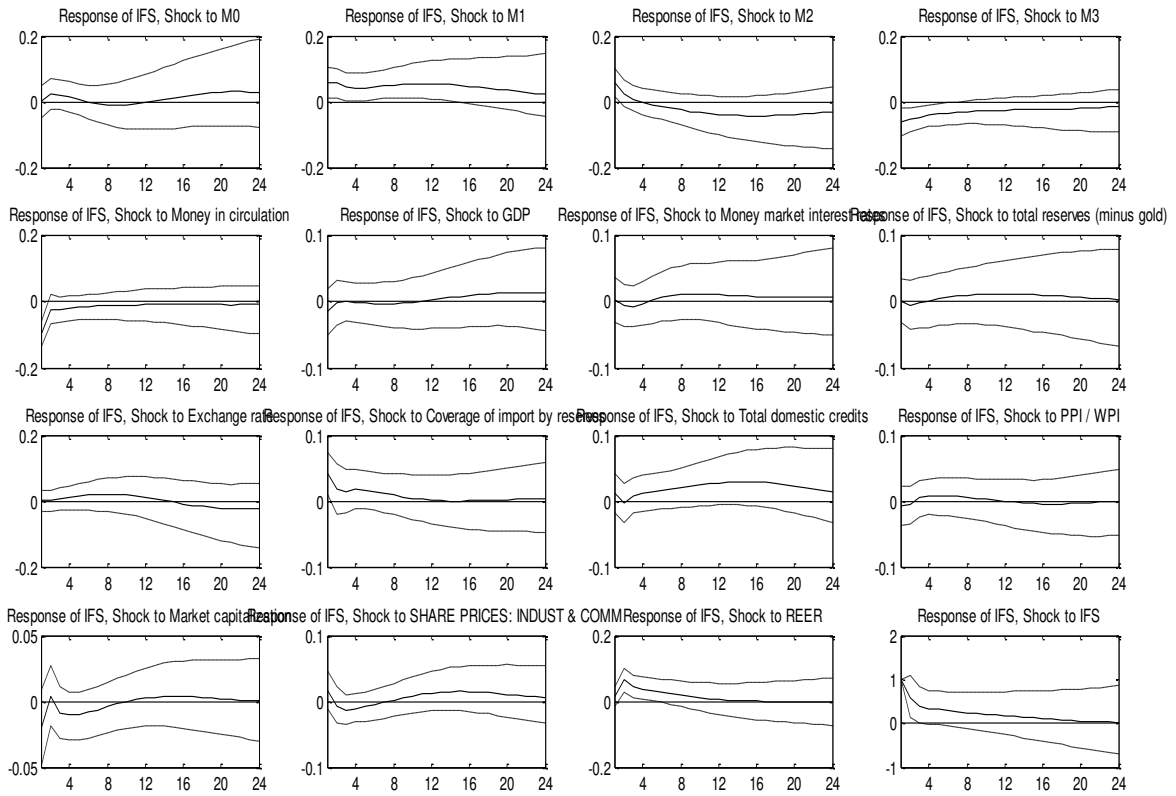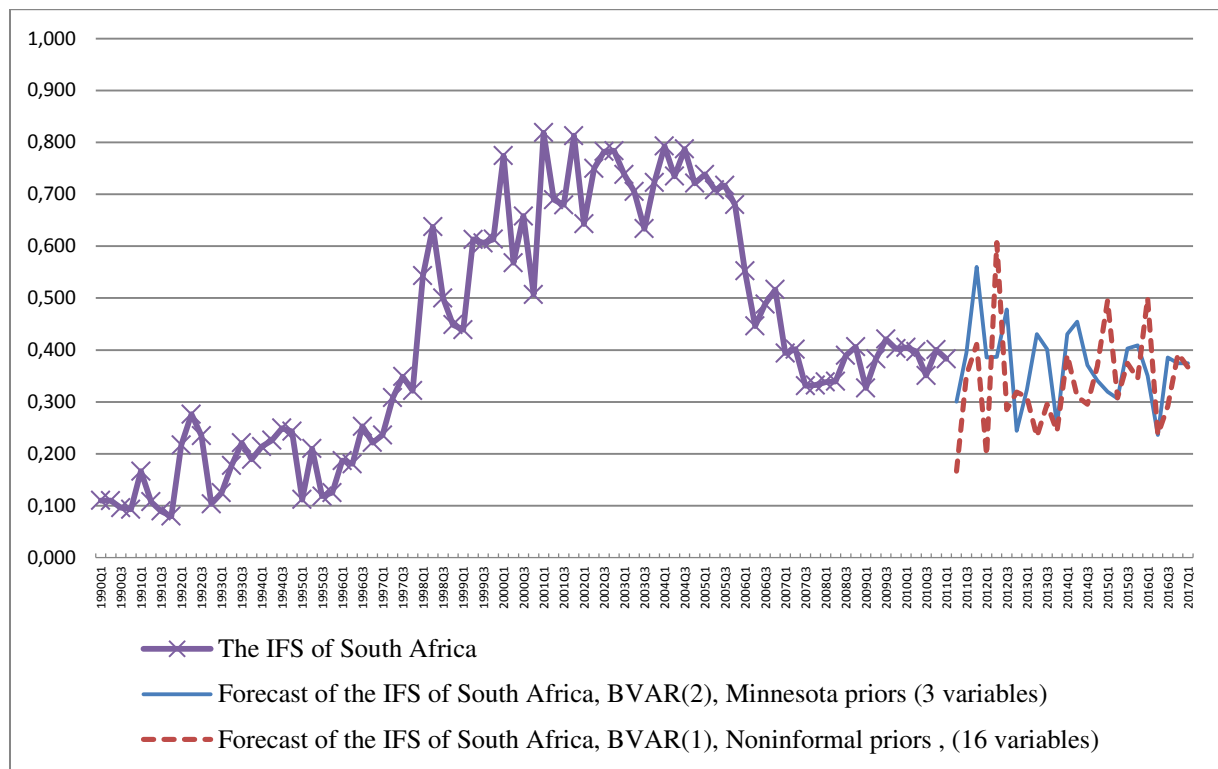
Figure 5: The real and forecasted values of IFS of South Africa until 2017Q1

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