Chapter 3

Research methodology

3.1. Introduction

In chapter 1, research methodology was defined as being the how of collecting data and the processing thereof within the framework of the research process (Brynard, 1997). As such, research methodology deals with research methods and techniques to be used. According to Jankowicz (2000), research methods deal with *what* is being done while research techniques concern the *how* it will be done. To avoid confusion at this early stage, specific methods and techniques are discussed in corresponding chapters in appropriate ways. Indeed, each specific method or technique is designed to verify at least one of the hypotheses formulated in the thesis and for most of the cases they emerge from a model specification itself. In this chapter, the attention is focused on a class of estimators, used in this thesis, called Generalized Method of Moments (GMM) estimators. However, before discussing the GMM approach, the study provides an overview on the Hodrick-Prescott Filter used to detrend some series.

3.2. The Hodrick-Prescott Filter

The Hodrick-Prescott (1997) filter has been used to separate the cyclical component of some time series such as coincident business cycle and industrial production from their potential levels. Hodrick and Prescott (1997) consider that a series y is composed of a trend s and cyclical component c. As such, the Hodrick-Prescott (HP) filter is a filter that computes the smoothed component s by minimizing the variance of y around s, subject to a penalty that constrains the second difference of s. The illustration is given by

$$\min \sum_{t=1}^{T}(y_t - s_t)^2 + \lambda \sum_{t=2}^{T-1}((s_{t+1} - s_t) - (s_t - s_{t-1}))^2$$

where T is the number of observations and λ is the penalty parameter. The value of λ depends on the frequency of the data and the larger the value of λ, the higher is the penalty. Hodrick and Prescott (1997) suggest that λ = 14 400 for monthly data is reasonable.

To tackle the end-point problem in calculating the HP trend (see Mise *et al*, 2005a&b), the sample has to be expended on both starting and ending points. With regards to the starting points, this study considers actual data for twelve months prior to 2000. With regard to the ending points, an autoregressive (AR(*n*)) estimation has been applied to the series under decomposition and the AR model is in turn used to forecast additional observations that have to be added to each of the series before applying the HP filter. The method is applied to the output measure and the components of the financial index (with n set at 4 to eliminate serial correlation). The obtained smoothed representation s (trend) of a given time series is considered to be its potential level. The cyclical component s represents the fluctuations around the long-run pattern. A negative value of the cyclical component indicates that the short-term level of the series is below its potential level, while a positive value indicates that the short-term level is above the potential one.

3.3. Generalized Method of Moments (GMM)

According to Johnston and DiNardo (1997), since Hansen's seminal paper (1982), there has been an extensive use of GMM estimators for two main reasons:

1. *"GMM nests many common estimators, and provides a useful framework for their comparison and evaluation.*
2. *GMM provides a 'simple' alternative to other estimators, especially when it is difficult to write down the maximum likelihood estimator."*

For the specific case of monetary policy rules, GMM is also useful for the estimation of forward-looking reaction function which contains expected values not observable at the moment the central bank makes the decision with respect to interest rate. Furthermore, the method can eliminate a potential simultaneity bias between the instrument and the explanatory variables (see Vdovichenko and Voronina, 2006).

3.3.1. GMM and the traditional Method of Moments (MOM)

The traditional Method of Moments (MOM) is the starting point of GMM estimation. The Method of Moments is based on the idea of estimating a population moment by using corresponding sample moment. The vector of L moment conditions that the true parameters β should satisfy may be written as

$$E[m(y_t, \beta)] = 0\,; \tag{3.1}$$

where y_t is a vector of variables observed at time t and β is the unique value of a set of parameters that makes the expectation equal to zero. Equation (3.1) should usually satisfy orthogonality conditions between a set of instrumental variables Z_t and the residuals of the equation, $u_t(\beta) = u(y_t, X_t, \beta)$ as follows:

$$E[Z_t \mu_t(\beta)] = 0\,; \tag{3.2}$$

where X_t refers to explanatory variables observed at time t. By replacing the moment conditions in equation (3.1) by its sample analogue, the following traditional MOM estimator is found

$$m_T(\beta) = \frac{1}{T}\sum_{t=1}^{T} Z_t u_t(\beta) = \frac{1}{T} Z' u_t(\beta) = 0\,; \tag{3.3}$$

where T is the sample size. The MOM can only yield an exact solution to this equation if the L number of moment conditions is equal to K number of parameter estimates.

However, in general, there are more moment conditions than the number of unknown parameters; $(L > K)$. Under such conditions, the alternative approach to deal with the so-called overidentified system is the GMM. Indeed, GMM procedure is an extension of the traditional MOM approach able to deal with the case in which there are more estimating equations moment conditions L than unknown parameters β (Mittelhammer *et al.*, 2000). Though there is generally no exact solution for an overidentified system, GMM is deemed to reformulate the problem by choosing a β that makes the sample moment as close to zero vector as possible. In pursuit of this objective the following quadratic function is used:

$$\begin{aligned} J\left(\beta, \hat{W}_T\right) &= T\, m_T(\beta)' \hat{W}_T^{-1} m_T(\beta) \\ &= \frac{1}{T} u(\beta)' Z \hat{W}_T^{-1} Z' u(\beta) \end{aligned} \tag{3.4}$$

where W_T is an $(m \text{ x } m)$ weighting matrix which minimizes the weighted distance between the theoretical and actual values. At this stage, it worth mentioning two other benefits of using GMM: first, it produces consistent estimates with any positive definite weighting matrix. For instance, Mittelhammer *et al.* (2000) insist that the GMM approach defines an entire family of consistent and asymptotically normally distributed estimators as a function of the weighting matrix. Another benefit arise in the presence of heteroscedastic errors in that GMM is asymptotically more efficient than its special cases (for example 2SLS).

3.3.2. Testing the validity of a GMM in Eviews

3.3.2.1. Instrument orthogonality test

For the orthogonality condition $E(Z'u(\beta)) = 0$, Eviews uses the C-test also known as Eichenbaum, Hansen and Singleton (EHS) Test to test whether the orthogonality conditions are satisfied by a subset of the instruments Z_1 but not satisfied by the remaining instruments Z_2 (see Eichenbaum *et al.*, 1988 for further discussion on the test).

$$E(Z_1' u(\beta)) = 0$$
$$E(Z_1' u(\beta)) \neq 0 \tag{3.5}$$

The orthogonality test, C_T, is calculated as the difference between the *J-statistic* (see equation (3.4)) of the original model that uses the entire set of instruments Z and the *J-statistic* of the secondary model which considers Z_1 only.

$$C_T = J(\beta, \hat{W}_T)_Z - J(\beta, \hat{W}_T)_{Z_1} \tag{3.6}$$

where the subscripts Z and Z_1 respectively stand for the entire set of instruments and the subset of instruments for which the condition is assumed to hold. The test statistic should be less than χ^2 degrees of freedom equal to the number of instruments Z_2 for which the condition of orthogonality is assumed not to hold.

3.3.2.2. Regressor Endogeneity Test

In Eviews, the Durbin-Wu-Hausman test is used to perform the regressor endogeneity test. A regressor is exogenous if it is not explained by the listed instruments, while an endogenous regressor is the one explained by such instruments. Candidate variables for endogeneity test are those which are specified in the regressor list but not appearing in the instrument list. By this test, the researcher identifies endogenous regressors and then evaluate whether the endogeneity has any effect on the consistency of β.

The test is performed by comparing the *J-statistic* of the original estimation to the *J-statistic* of the secondary estimation. As such, the endogeneity test, H_T, is calculated as the difference between the two *J-statistics*. The instruments in the secondary estimation are those of the original estimation augmented by the variables which are being tested for endogeneity.

$$H_T = J\left(\beta, \hat{W}_T\right)_2 - J\left(\beta, \hat{W}_T\right)_1 \qquad (3.7)$$

where subscripts 1 and 2 respectively stand for original and secondary equation. The test statistic should be less than χ^2 with degrees of freedom equal to the number of regressors being tested for endogeneity.

3.3.2.3. Weak Instrument Diagnostic

As proposed by Eviews, Moment Selection Criteria (MSC) that can provide a comparison of different sets of instruments is one way to have diagnostic information on whether the instruments are weak or not. There are three different MSCs in Eviews: the *Schwarz criterion* based and the *Hannan-Quin criterion* based proposed by Andrews (1999), and the *Relevant Moment Selection criterion* proposed by Hall *et al.* (2007). These three tests are respectively calculated as follows:

$$SIC-\text{based}=J_T-(c-k)\ln(T)$$

$$HQIQ-\text{based}=J_T-2.01(c-k)\ln(\ln(T))$$

$$\text{Relevant } MSC=\ln(/T\Omega)(1/\tau)(c-k)\ln(\tau)$$

where c is the number of instruments, k is the number of explanatory variables, T is the number of observations, Ω is the estimation covariance matrix, $\tau=\left(\frac{T}{b}\right)^{1/2}$, and b is the bandwidth used (for Weighting Matrix: Times series (HAC)) to estimate GMM.

3.3.4. Application of GMM on the Taylor monetary policy rule

To estimate an equation by GMM, one need to consider a set of instrumental variables (IV) and their number must be at least as many as there are unknown parameters for identification purpose (Eviews 7 user's guide, 2009). Another proposal is that such instrumental variables have to be highly correlated with explanatory variables but uncorrelated with the residuals.

For illustration purpose we consider the reduced form of the original Taylor rule (equation (2.10)) augmented with the financial conditions index f_t.

$$\hat{i}_t = \rho_0 + \rho_\pi \pi_t + \rho_y y_t + \rho_f f_t \tag{3.5}$$

for which the following orthogonality conditions in the system of equations (3.6) has to be satisfied.

$$
\begin{aligned}
&\sum \left(\hat{i} - \rho_0 - \rho_\pi \pi_t - \rho_y y_t - \rho_f f_t - \rho_i i_{t-1}\right) = 0 \\
&\sum \left(\hat{i} - \rho_0 - \rho_\pi \pi_t - \rho_y y_t - \rho_f f_t - \rho_i i_{t-1}\right) Z_{t-1} = 0 \\
&\sum \left(\hat{i} - \rho_0 - \rho_\pi \pi_t - \rho_y y_t - \rho_f f_t - \rho_i i_{t-1}\right) Z_{t-2} = 0 \\
&\sum \left(\hat{i} - \rho_0 - \rho_\pi \pi_t - \rho_y y_t - \rho_f f_t - \rho_i i_{t-1}\right) Z_{t-3} = 0 \\
&\sum \left(\hat{i} - \rho_0 - \rho_\pi \pi_t - \rho_y y_t - \rho_f f_t - \rho_i i_{t-1}\right) Z_{t-4} = 0 \\
&\sum \left(\hat{i} - \rho_0 - \rho_\pi \pi_t - \rho_y y_t - \rho_f f_t - \rho_i i_{t-1}\right) Z_{t-5} = 0 \\
&\sum \left(\hat{i} - \rho_0 - \rho_\pi \pi_t - \rho_y y_t - \rho_f f_t - \rho_i i_{t-1}\right) Z_{t-6} = 0
\end{aligned} \tag{3.6}
$$

In the system of equations (3.6), the instrumental variables are assumed to have the lags ranging from 1 to 6 ($t-1$, $t-2$, $t-3$, $t-4$, $t-5$, $t-6$).

3.4. Conclusion

Chapter 3 deals with research econometric methods to be used. As such, the chapter provides an overview on the Hodrick-Prescott Filter used to detrend some series. However, more focus is oriented on a class of estimators called Generalized Method of Moments (GMM) estimators. GMM is important in that it can be applied to several estimation contexts besides the linear model. In fact, GMM provides a useful framework for the comparison and evaluation of nested estimators. Furthermore, GMM can provide a simple alternative to other estimators, especially when it is difficult to write down the maximum likelihood estimator. For the specific case of monetary policy rules, GMM is also useful for the estimation of forward-looking reaction function which contains expected values not observable at the moment the central bank makes the decision with respect to interest rate. The method can also eliminate a potential simultaneity bias between the instrument and the explanatory variables.

Chapter 4

Data analysis and preliminary results

4.1. Introduction

In addition to this introduction and the conclusion, chapter 4 is composed of two sections. Section 4.2 is aimed to provide better understanding of the data used in the thesis. The section is composed of three subsections; namely data transformation, time series plot and descriptive statistics, and unit root test. Section 4.3 reports the results for monetary policy rules that take into account interest rate smoothing together with backward and forward looking versions. In the section, two measures of output gap and three measures of financial conditions index are explored with the aim to maintain the ones with better results for further investigations in subsequent chapters.

4.2. Data source and analysis

We use South African monthly seasonally adjusted data mainly sourced from the SARB database. The sample ranges from 2000:01 to 2010:12, which covers the inflation targeting regime in South Africa. The raw data and their sources are listed in Table 1 in alphabetical order.

Table 1: List of monthly raw data and source

No	Series name	Source	Code
1.	All share index	SARB	JFIA001E
2.	Coincident business cycle indicator	SARB	DIFN002A
3.	Consumer price index	SARB	VPI1000A + KBP7170N
4.	Corporate bonds* (most traded):		
	4(a) AB06 – Absa	SARB	BEYJ296M
	4(b) ABS3 – Absa	SARB	BEYJ271M
	4(c) CAL01 – Calyon	SARB	BEYJ251M
	4(d) FRB03 – FirstRand	SARB	BEYJ279M
	4(e) IV01 – Investec	SARB	BEYJ051M
	4(f) NED5 – Nedbank	SARB	BEYJ302M
	4(g) SBK5 - Standard Bank	SARB	BEYJ217M
	4(h) Eskom bonds	SARB	KBP2004M
5.	Government bonds - 10 years and over	SARB	KBP2003M
6.	House price index	ABSA	ABSAHPI
7.	Industrial production	SARB	DIFN033B
8.	Johannesburg Inter Bank Agreed Rate (JIBAR/JIBA rate) : 3 months	SARB	KBP1450W
9.	Monetary aggregate/Money supply	SARB	KBP1374N
10.	Real effective exchange rate (15 trading partners)	SARB	KBP5378M
11.	Repo rate	SARB	MMSM009E

*Corporate bond = $\frac{1}{n}\sum_{i=1}^{n} cb_i$, where cb_i is an individual corporate bond defined as 4(a) to 4(h).

4.2.1. Data transformation

This sub section shows the process followed to convert data from their status of raw data to the final status for modelling use. In fact, some of the series are slightly transformed (e.g. percent change) but some others are combined to compose one index after substantial transformations.

4.2.1.1. The measure of price stability

The computations of new data include inflation which is measured as the annual change of the consumer price index. Until December 2008, the latter is defined as the consumer price index (CPI) for metropolitan and other urban areas, with the exclusion of the interest rate cost on mortgage bonds. This exclusion was to limit the effects of interest rates on inflation targets. However, since the beginning of 2009, the CPI for all urban areas became the new measure of inflation-target. The latter includes owners' equivalent rent considered to be positively related to interest rate changes (SARB, 2011e).

4.2.1.2. The measurement of economic activity

In this thesis, two alternative measures of economic activity have initially been considered: namely, the coincident business cycle indicator and industrial production. The advantage the two measurements have over GDP is the availability of monthly data and the fact that they are not subject to major alterations like the GDP does. But still, industrial production is used with some caution. For instance, Bernanke *et al.* (2004) argue that the concept of "economic activity" may not be perfectly represented by industrial production or real GDP. The authors suggest an alternative to treat "economic activity" as an unobserved factor with multiple observable indicators. Therefore, coincident business cycle indicator which is the reference cycle for aggregate economic activity is expected to provide a more comprehensive image than industrial production. Coincident business cycle indicator is in fact the average of many specific cycles, among them the industrial production.

The choice of the method of measurement of economic activity is based on the information according to which the interest rate decision of the SARB considers among other factors, expected output gap between actual and potential output (SARB, 2011f). This study assumes that the level of output deviations from its potential captures the output objective of the SARB adequately. Walsh (2002) suggests using the growth in output relative to the growth in potential rather than the output gap itself (the level of output relative to potential). Accordingly, the thesis considers output gap measured as a percentage deviation of actual output from its Hodrick-Prescott (1997) trend.

4.2.1.3. The measurement of financial conditions index

Major transformation of the data concerns the measurement of the financial conditions index. In fact, although financial stability is one of the SARB objectives, the bank does not give an idea about variables that go into play in pursuing the objective of financial stability. In this study we are guided by views from different economic figures and institutions (see Castro, 2008 and 2010; Luüs, 2007; Montagnoli and Napolitano, 2005; Gerlach-Kristen, 2004; Castelnuovo, 2003, Goodhart and Hoofmann, 2001; and

Dudley, 1999) to develop a financial condition index composed of the following five variables:

(i) the real effective exchange rate $(REER_t)$ where the rand appreciation increases the index;

(ii) the real house price index (RH_t) where the house price index is an average price of all houses compiled by the ABSA bank, deflated by the consumer price index;

(iii) the real stock price (RS_t) which is measured by the Johannesburg Stock Exchange All Share index, deflated by the consumer price index;

(iv) the credit spread (CS_t) which is the spread between the yield on the 10-year government bond and the yield on A rated corporate bonds[2]; and

(v) the future interest spread which is the change of spread between the 3-month interest rate futures contracts (F_t) in the previous quarter and the current short-term interest rate.

First, the inclusion of asset prices, explicitly property and share prices, within the model is motivated by the fact that some economists (e.g. Montagnoli and Napolitano, 2005) consider that change in interest rate modifies the set of discount factors economic agents apply to their profit expectations or the future stream of services or revenues from the asset they hold. Furthermore, central banks would like to respond to asset

[2] For instance Burger (2008) argued that the spread between the mortgage rate and the and 10-year government bond rate is very much like an intermediate monetary target since its change leads to an opposite change in output or price level.

prices as they play an important role in the transmission of monetary policy. As noted by Montagnoli and Napolitano (2005), a rise in asset prices may have direct impact on aggregate demand and may, therefore, be associated with growing inflationary pressures. They emphasize that asset prices also influence the collateral values and bank's willingness to lend.

Second, the inclusion of real effective exchange rate is motivated by the fact that it is perceived as being the most important determinant (beside the interest rate) of aggregate demand and channel of monetary policy transmission in open economies. For example, external factors may cause the currency to depreciate and so stimulate higher exports that will in turn cause GDP growth to accelerate (see Luüs, 2007). Some banks, such as the Bank of Canada and the Reserve bank of New Zealand consider exchange rate as an operating target while others such as the Bank of Finland and the bank of Norway consider the former as an indicator for monetary policy (see Montagnoli and Napolitano, 2005).

Third, credit spread enters the model. Some economists such as Castelnuovo (2003) and Gerlach-Kristen (2004) advocated in favour of the credit spread within the interest rule and few years later, Driffill *et al* (2006) report empirical evidence of its overwhelming importance. To support the view, Castro (2010) states that credit spread is considered a leading indicator of the business cycle and of financial stress. The last variable is futures interest rate spread. As noted by Castro (2010) the futures interest rate spread provides an indication of the degree of volatility in economic agents' expectations that the central bank aims to reduce.

The constructed financial index is expressed in standardized form, relative to the mean value of 2000 and where the vertical scale measures deviations in terms of standard deviations; therefore, a value of 1 represents a 1-standard deviation difference from the mean. The construction of the index is in the spirit of the UK financial conditions index provided by the Bank of England's *Financial Stability Report* (Bank of England, 2007). Having motivated the choice of variables to compose the FCI, the remaining issue is to determine the weight attached to each of them. In fact, it would be easier to model the Taylor rule augmented with all the 5 additional regressors but unfortunately, such inclusion can severely affect the degrees-of-freedom. To avoid such degrees-of-freedom problems, all these 5 variables are compressed in a single index called financial conditions index (FCI). However, the determination of their weights is not straightforward since there is not a widely accepted definition of financial stability indicator (see Akram and Eitrheim, 2008; and references herein). This study explores 3 alternative measurements of the FCI.

The first option of constructing the FCI is to assume that it is an equal weight average of the five variables composing the index. By using this easy option, we keep in mind that the approach can be subjected to criticism *per se* as the components of the FCI do not have equal impact on the economic activity. However, the aim of this exercise is not to provide tips of how the FCI is ought to be computed. We are rather motivated to tackle the best measurement of the FCI in describing the behaviour of the SARB. Therefore, the financial conditions index resulting from equal weights average (FCI_{EW_t}) is also evaluated alongside other methods. FCI_{EW_t} can be described as follow:

$$FCI_{EW_t} = \frac{1}{n}\sum_{i=1}^{n} x_i \text{ , where } x_i \text{ is an individual component.} \tag{4.1}$$

The second option proposed in this paper amounts to choosing the optimal weights obtained from OLS estimation of the output gap on assets prices and financial variables composing the financial conditions index. By this approach, the weight of each variable depends on the importance it has in explaining the economic activity. The equation is given by

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 rir_{t-1} + \beta_1 reer_{t-1} + \beta_2 rh_{t-1} + \beta_3 rs_{t-1} + \beta_4 CS_{t-1} + \beta_5 F_{t-1} + \varepsilon_t \tag{4.2}$$

where rir, $reer$, rh and rs are respectively the deviations from the long run equilibrium path of real interest rate, real effective exchange rate $(REER_t)$, real house price (RH_t) and real stock price (RS_t). The weight attached to each variable is measured as

$$w_i = \frac{|\beta_i|}{\sum_{k=1}^{5} |\beta_k|}$$

Therefore, the FCI obtained from the OLS estimation is given by

$$FCI_{OLS} = w'_x . \sum_{k=1}^{5} x .$$

Where x is the matrix of financial variables $reer, rh, rs, CS$ and F. This logic of drawing the weights from the OLS estimation of the IS equation produces constant parameters and so constant weights. However, as discussed in Castro (2010) weights might depend on the relative economic importance of each variable at each particular moment in time. As such, the third option is to follow the methodology suggested by Montagnoli and Napolitano (2005) and Castro (2010) in determining the weights of the components of the financial conditions index. By this approach, financial conditions index is constructed as a weighted average of the series composing the index; where the weight of each variable depends on the importance it has in explaining the economic activity at particular moment. Therefore, time varying estimates of a state space are provided by applying Kalman filter approach on the assumed economy's backward-looking IS curve (see Castro, 2010).

$$y_t = b_0 + \sum_{k=1}^{p} b_k y_{t-k} + \sum_{l=1}^{q} b_l rir_{t-l} + \sum_{i=1}^{5} \sum_{j=1}^{n_i} b_{ij} x_{i,t-j} + \mu_t^d \tag{4.3}$$

Where rir and (x) are as defined above. Equation (4.3) is estimated using the Kalman filter over the following state-space form:

$y_t = X\beta_t + \mu_t$ (Measurement equation)

$\beta_t = F\beta_{t-1} + \omega_t$ (Transition equation)

where X is the matrix of regressors plus the constant, β_t is the state vector composed of time varying coefficients and F is an identity matrix. The weight of each variable is measured as

$$w_{x_{i,t}} = \frac{\left|\beta_{x_{i,t}}\right|}{\sum_{k=1}^{5}\left|\beta_{x_{k,t}}\right|},$$

where $\beta_{x_{i,t}}$ is the coefficient of variable x_i at time t. The FCI obtained from the Kalman-Filter algorithm is given by

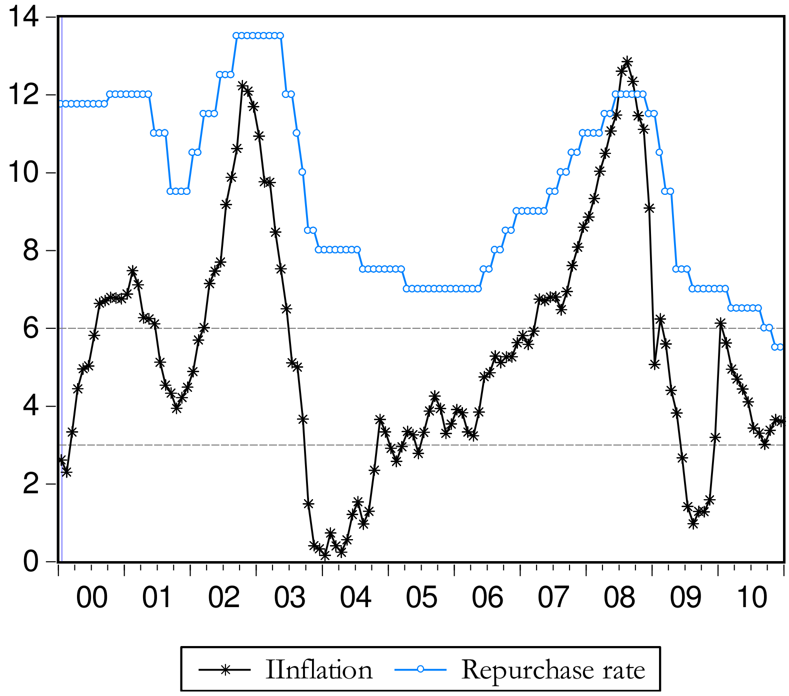
$$FCI_{KAL_t} = w'_{x_t}.x_t$$

Having the above three alternatives of measurement, they are alternatively included in the modified Taylor rule with the aim to obtain the most accurate FCI in describing the behaviour of the SARB.

4.2.2. Time series plot and descriptive statistics

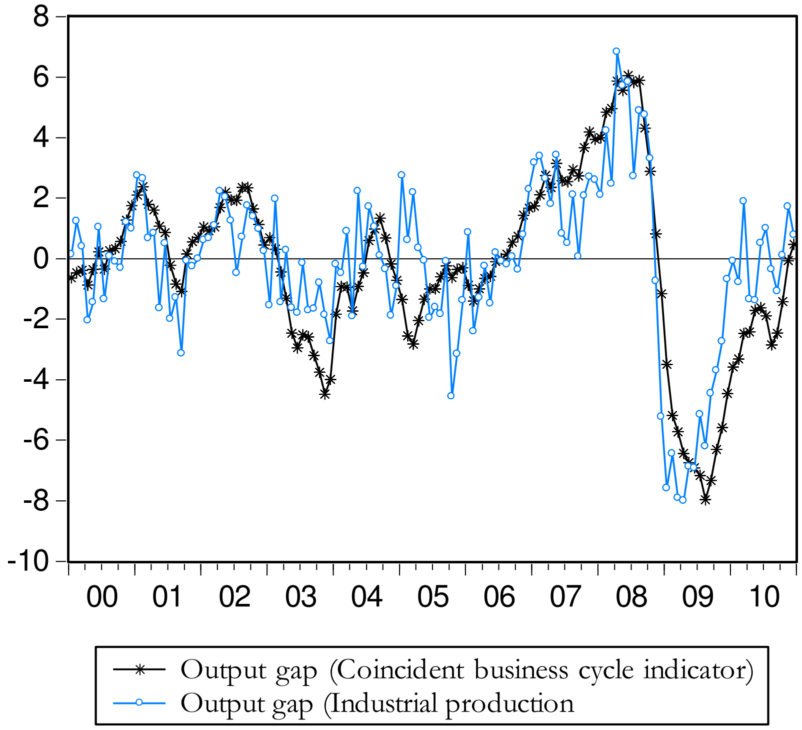
The evolution of the main variables is shown in Figures 1 to 3. The inflation rate (Figure 1) is showing significant fluctuations with an accompanying pattern of the interest rate; indicating the close link between the two variables.

Figure 1: Interest rate and inflation



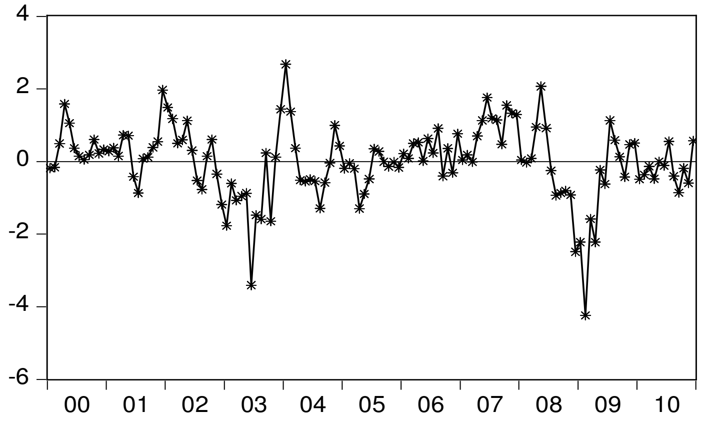
The output gap (Figure 2) is showing a severe downturn by the end of 2008 and a recovery is observed by the end of 2010. Movements in the two measures of output gap have a similar and close pattern showing the importance the industrial production has among other indexes composing the coincident business cycle indicator.

Figure 2: Output measures

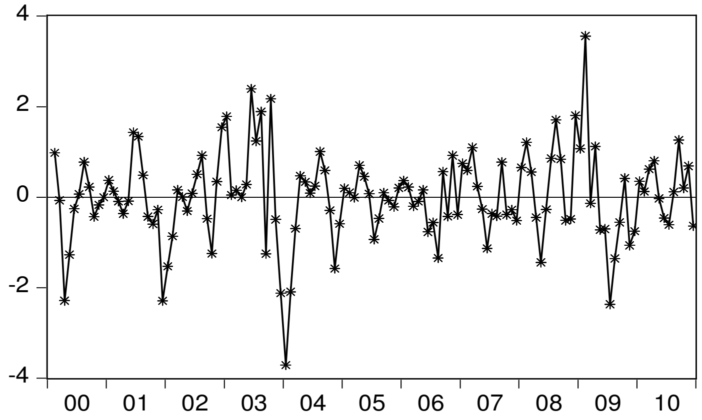


The financial conditions index (Figure 3) is showing a high level of volatility compared to Figures 1 and 2. The high level of volatility is indeed the concern of Bernanke and Gertler (1999) and Filardo (2001) about the potential costs of responding to asset price given its volatility relative to their information content while Mishkin and White (2002) suggest that monetary authorities should only be concerned by asset price misalignments when they affect financial stability. Descriptive statistics are reported in Table 2.

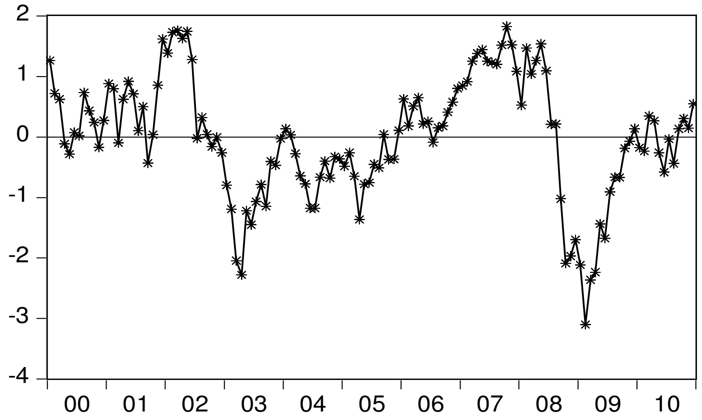
Figure 3: Financial conditions index



Financial conditions index (Equal weight)



Financial conditions index (Kalman filter)



Financial conditions index (OLS)

Table 2: Descriptive statistics of the main variables

	i_t	π_t	y_t (BC)*	y_t (IP)*	FCI_{EW}	FCI_{KAL}	FCI_{OLS}
Mean	9.52	5.43	-0.21	-0.12	10.70	0.00	-0.01
Median	9.50	5.03	-0.18	0.07	10.66	0.00	0.04
Maximum	13.50	12.85	6.05	6.82	53.12	3.56	1.83
Minimum	5.50	0.16	-7.96	-8.00	-29.48	-3.71	-3.10
Std. Dev.	2.30	3.07	2.90	2.67	11.44	1.00	1.00
Skewness	0.13	0.53	-0.34	-0.63	-0.05	-0.14	-0.44
Kurtosis	1.65	2.75	3.32	4.26	5.10	4.97	3.13
Jarque-Bera	10.36	6.40	3.06	17.45	24.15	21.69	4.24
Probability	0.01	0.04	0.22	0.00	0.00	0.00	0.12

*BC is coincident business cycle indicator and IP is industrial production.

4.2.3. Unit root test

This subsection carries out the unit root tests aimed to investigate whether the series to be used in the subsequent econometric modelling are stationary in their levels or in their first or second differences. The study uses the Augmented Dickey-Fuller (Dickey and Fuller, 1979; and MacKinnon 1991 and 1996), Phillips-Perron (1988), GLS-detrended Dickey-Fuller (Elliot *et al.*, 1996) and Kwiatkowski *et al.* (KPSS, 1992). In the next paragraphs, the tests are respectively abbreviated as ADF, PP, DFGLS and KPSS. The testing procedure has also tested the joint hypothesis of non existence of the trend (or constant) and the presence of unit root, using the non-standard *F*-statistic ϕ_3 (or ϕ_1) reported in Dickey and Fuller (1981). Failing to reject the joint hypothesis implies that the trend (or constant) is significant under the null of a unit root. As such, the asymptotic normality of the t-statistic follows and so, the standard *t*-statistic is used instead of the ADF critical values. Given that the literature suggests using such standard *t*-statistic with caution, the series were subjected to further testing steps.

In performing the unit root test, we keep in mind that it is rare to find an inflation series which follows a stationary process but that it can be treated as stationary in line with common practice (see Fuhrer and Moore 1995, for discussion of similar issues). The unit root tests reported in Table 3 below suggest that all the series follow a stationary process.

Table 3: Unit root test

Series	Model	ADF			PP Test	DFGLS	KPSS	Conclusion
		$\tau_\tau, \tau_\mu, \tau$	ϕ_3, ϕ_1	$t-stat$				
Repo rate	Intercept & Trend	-4.84***	15.89***	-4.84***	-2.30	-4.67***	0.11^{+}	I(0)
	Intercept	-4.57***	18.13***	-4.57***	-1.54	-1.91*	0.53	
	None	-3.28***	-	-	-1.27	-		
Inflation	Intercept & Trend	-3.31*	10.33***	-3.31***	-2.53	-2.98*	0.08^{+}	I(0)
	Intercept	-3.34**	12.98***	-3.34***	-2.54	-0.77	0.08^{+}	
	None	-0.78	-	-	-.116	-	-	
Output gap (Coincident business cycle indicator)	Intercept & Trend	-2.68	21.73***	-2.68***	-2.47	-2.70*	0.08^{+}	I(0)
	Intercept	-2.67*	32.75***	-2.67***	-2.45	-2.68***	0.12^{+}	
	None	-2.68***	-	-	-2.45**	-	-	
Output gap (Industrial production)	Intercept & Trend	-2.84	8.54***	-2.84***	-4.15***	-2.87*	0.05^{+}	I(0)
	Intercept	-2.84*	12.88***	-2.84***	-4.14***	-2.86***	0.07^{+}	
	None	-2.86***	-	-	-4.15***	-	-	
FCI_{AV}	Intercept & Trend	-5.99***	17.13***	-5.99***	-6.95***	-4.10***	0.02^{+}	I(0)
	Intercept	-6.02***	20.14***	-6.02***	-7.00***	-2.81***	0.02^{+}	
	None	-2.43**	-	-	-5.12***	-	-	
FCI_{KAL}	Intercept & Trend	-5.73***	14.73***	-5.73***	-7.13***	-4.32***	0.02^{+}	I(0)
	Intercept	-5.75***	17.30***	-5.75***	-7.23***	-3.36***	0.05^{+}	
	None	-5.77***	-	-	-7.17***	-	-	
FCI_{OLS}	Intercept & Trend	-2.74	3.95	-	-2.99	-2.48	0.07^{+}	I(0)
	Intercept	-2.81*	7.94***	-2.81***	-3.05**	-1.98**	0.11^{+}	
	None	-2.82***	-	-	-3.06***	-	-	

*(**)[***] Unit root is rejected at a 10(5)[1] % level of significance. $^{+}$ Stationarity is not rejected at 10% level of significance.

4.3. Preliminary results

The Taylor (1993) rule and its extensions seem to be the most popular model in its field. Modified or not, the Taylor rule (1993) enjoys such popularity because it can describe not only the inflation targeting regime's component, but also certain other characteristics, such as monetary policy response to business cycles. As it has been noticed in chapter 2, the trial modifications of the Taylor rule include interest rate smoothing, backward and forward looking versions. Early versions of the Taylor rule that allowed inclusion of lagged interest rate include Clarida *et al.* (1998, 2000), Amato and Laubach (1999), Goodhart (1999), Levin *et al.* (1999) and Woodford (1999, 2003). Examples of estimation including both backward and forward looking versions include Rudebusch (2002); Orphanides (2002); Osborn *et al.* (2005), and Dolado *et al.* (2005). See Rudebusch & Svensson (1999), Batini and Nelson (1999); Clarida *et al.* (2000), Orphanides (2001, 2003) and Huang *et al.* (2001) for forward looking versions.

Table 4 reports the results for rules that take into account interest rate smoothing together with backward and forward looking versions. In this section, two measures of output gap are explored but the one with better results will be maintained for further investigations in subsequent chapters. A forward looking version as defined in the Table's notes performs quite well especially when coincident business cycle indicator is concerned.

Table 4: GMM estimates of a non extended linear Taylor rule (2000-2010)

Model	ρ_i	ρ_π	ρ_y	AIC	S.E	$\bar{R}^2$	J-statistic (p value)
Panel A: Using coincident business cycle indicator							
1. Backward-looking	0.93***	0.24*	1.00***	1.01	0.39	0.97	0.16
	(0.01)	(0.14)	(0.22)				
2. Forward-looking	0.93***	0.94***	0.58***	0.87	0.37	0.97	0.15
	(0.01)	(0.09)	(0.12)				
3. Within-month	0.93***	0.38***	0.94***	0.97	0.39	0.97	0.15
	(0.01)	(0.09)	(0.16)				
Panel B: Using industrial production as output measure							
4. Backward-looking	0.93***	0.40***	0.98***	1.08	0.41	0.97	0.16
	(0.01)	(0.10)	(0.24)				
5. Forward-looking	0.91***	1.08***	0.06	0.88	0.37	0.97	0.18
	(0.01)	(0.08)	(0.09)				
6. Within-month	0.94***	0.50***	1.10***	1.03	0.40	0.97	0.17
	(0.01)	(0.10)	(0.22)				

Notes: Numbers in parentheses are standard errors. S.E is the regression standard error. AIC is Akaike Information criterion. J-statistic is the p-value of a chi-square test of the model's over-identifying restrictions (Hansen, 1982). The set of instruments includes a constant, 1-6, 9, 12 lagged values of repo rate, the inflation, the output gap, the financial conditions index, the 10-year government bond, and money (M3) growth.

Even the forward looking version using industrial production as output measure is having lower AIC compared to its counterparts but the later is not statistically different from zero. All in all, a forward looking version is going to be used in the following models that consider the inclusion of financial conditions index. The forward looking version is in line with what the SARB does. In fact, Mminele (2010) stipulates that the regular consultation between the SARB and the Cabinet Minister responsible for national financial matters helps to anchor inflation expectations. He says that it requires forward-looking policy-decision making based on expected inflation which allows for flexibility to respond to shocks not offered by strict monetary policy rules and fixed exchange rates. Similarly, the SARB's governor Gill Marcus (2010) insists that the monetary policy always has to be implemented in a forward-looking manner, given the lags between a policy change and its full impact on the economy.

In concomitance with modifications regarding backward and forward looking versions, there has been increasing debate on whether central banks should respond to assert prices and financial variables. For example, Clarida *et al*, (2000) extend a forward looking Taylor rule by the inclusion of exchange rate within the model. Other examples include Knedlik (2006) who combines the estimation of the Monetary Conditions Index (MCI) with the theoretic modelling of monetary policy rules for South Africa with the assumption that monetary policy is not only interested in optimal monetary conditions but also in external stability. Table 5 proposes three options of computing the financial conditions index with the following objective: to investigate whether the inclusion of the financial conditions index can provide better understanding of the behaviour of the SARB or not. As reported in Table 5, empirical evidences show that the behaviour of the SARB is best described by a Taylor rule extended by the inclusion of the financial conditions index. In fact, the findings reveal that every option of FCI is better than the counterpart model which ignores such inclusion in Table 4. Surprisingly though, it is found that the SARB allocates equal weight to variables composing the index as opposed to any of the weighted averages. With regard to the output measurement, none of the three alternative models exhibits a significant industrial production. As expected, coincident business cycle indicator performs better than industrial production which is indeed a component of the former. As such, the remainder of the thesis chooses to use the business cycle indicator as the measure of economic activity. Furthermore, the remainder of the thesis considers the financial conditions index measured as an equal weight average (FCI_{EW}) as it is the one that has described the SARB's behaviour better than any other tested measurement.

Table 5: GMM estimates of the linear forward-looking Taylor rule extended with FCI (2000-2010)

Model	ρ_i	ρ_π	ρ_y	ρ_f	AIC	S.E	$\bar{R}^2$	J-statistic (p value)
Panel A: Using coincident business cycle indicator								
1. FCI_{AV}	0.93*** (0.01)	1.06*** (0.08)	0.49*** (0.12)	0.07*** (0.01)	0.84	0.36	0.97	0.18
2. FCI_{KAL}	0.93*** (0.01)	1.03*** (0.08)	0.45*** (0.11)	-0.72*** (0.20)	0.86	0.36	0.97	0.18
3. FCI_{OLS}	0.93*** (0.01)	0.96*** (0.07)	0.46*** (0.12)	-0.07 (0.36)	0.92	0.38	0.97	0.18
Panel B: Using industrial production as output measure								
4. FCI_{AV}	0.93*** (0.01)	1.24*** (0.10)	0.13 (0.09)	0.08*** (0.02)	0.83	0.36	0.97	0.19
5. FCI_{KAL}	0.92*** (0.01)	1.19*** (0.08)	0.09 (0.08)	-0.78*** (0.23)	0.86	0.36	0.97	0.18
6. FCI_{OLS}	0.92*** (0.01)	1.07*** (0.07)	-0.14 (0.09)	0.86** (0.35)	0.93	0.38	0.97	0.18

Notes: Numbers in parentheses are standard errors. S.E is the regression standard error. AIC is Akaike Information criterion. J-statistic is the p-value of a chi-square test of the model's over-identifying restrictions (Hansen, 1982). The set of instruments includes a constant, 1-6, 9, 12 lagged values of repo rate, the inflation, the output gap, the financial conditions index, the 10-year government bond, and money (M3) growth.

4.4. Conclusion

The chapter was aimed to provide the source of data, to show the transformation made to some of them and to explore the data for preliminary results. To perform unit root tests, the study has used the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), GLS transformed Dickey-Fuller (DFGLS) and Kwiatkowski, *et. al.* (KPSS). Overall, the unit root tests have suggested that all the series follow a stationary process.

In this chapter, the backward, current and forward looking versions of the Taylor rule have been modelled. The later has outperformed the others. As such, the forward looking version has been considered to investigate whether the inclusion of the financial conditions index improves the fit of the monetary policy rule model. With the aim to find the most appropriate specification of the financial conditions index, three alternatives have been computed. The findings have revealed that the models that do not include financial conditions index display higher AICs. Therefore, no matter the methodology used to compute the financial conditions index, the models that accommodate the index describe the behaviour of the SARB better than the ones that ignore the financial variables. The financial conditions index measured as an equal weight average of its components yields a smallest AIC and so is considered for further modelling in subsequent chapters. In concomitance of the evaluation of the role of financial conditions index, the two measurements of output gap have been evaluated. The models that consider coincident business cycle indicator, rather than industrial production, perform better in terms of goodness of fit. Similarly, the coincident business cycle indictor is maintained for subsequent chapters. In fact, as defined by the SARB, the industrial production is only one of many components of the coincident business cycle indicator.