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Structural Equation Models: An Application to Namibian Macroeconomics

Mathematical Statistics MSc Research

School of Statistics and Actuarial Science

University of Witwatersrand

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Declaration

I, Stetson Homateni Hufiku declare that this Thesis (Structural Equation Models: An Application to Namibian Macroeconomics) is my own work, aided by my supervisor Mr. Charles Chimedza. It is being submitted in partial fulfillment of the requirement for the **Masters of Science degree** in Mathematical Statistics at the University of the Witwatersrand, Johannesburg. It has not been submitted for any degree or examination at any other University.



17 September 2012

Abstract

Structural Equations Models (SEMs) are now widely used almost in every discipline of research. Most of the existing materials for the Namibian macroeconomic models are studies of the well documented time series approach. In this study, we provided a statistical approach on modelling the Namibian macroeconomics for the real and fiscal economic sectors using SEMs. The approach is based on testing the theoretical specification laid down by the Namibian Macroeconometrics Model (NAMEX) of 2004. The economic structure and relationships among the variables is evaluated by means of exploratory and confirmatory analysis and the results are congruent to the existing theory in terms of loading patterns. Between Maximum Likelihood (ML) and Generalized Least Square (GLS) estimation methods, we compared the discrepancy of parameter estimates under the commonly encountered problems of sample size, violation of underlying assumptions in the data as well as model misspecifications. GLS estimation methods seem to provide better goodness of fit indices under those conditions. We have also shown that the fiscal sector is not well represented by our SEM. We recommend further studies to employ sufficiently larger samples so that models are correctly specified.

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List of Acronyms

AGFI	Adjusted Goodness of FIT Index
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BON	Bank of Namibia
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CMA	Common Monetary Area
EFA	Exploratory Factor Analysis
FA	Factor Analysis
FRED	Federal reserve Bank of St. Louis
GDP	Gross Domestic Produces
GFI	Goodness of Fit Index
GLS	Generalalized Least Square
IFS	International Financial Statistics
IMF	International Monetary Fund
MEMWOG	Macroeconomic Modelling Working Group
ML	Maximum Likelihood
NAMAF	Namibian Macroeconomics Framework
NAMMAC	Namibian Macroeconomics Model
NAMEX	Namibian Macroeconmetrics Model
NDP1	First National Development Plan
NFI	Normed Fit Index
NNFI	Non-Normed Fit Index
NPC	national Planning Commissions
OLS	Ordinal Least Square
PCA	Principal Component Analysis
PNFI	Parsimony Normed Fit Index
PR	Rparsimony Ratio
RMSEA	Root Mean Square Error of Approximation
RMSM-X	Revised Minimum Standard Model-Extended
RMSR	Root Mean Square Residuals
RPFI	Relative Parsimony Fit Index
RPR	Relative Parsimony Ratio
SACU	Southern Africa Custom Union
SEM	Structural Equation Model
SMC	Squared Multiple Correlation
SRMSR	Standardised Root Mean Square Residual
SVAR	Structural Vector Autoregressive

Chapter 1

Introduction

1.0 Introduction

In the behavioural, educational, medical and social sciences, substantive theory usually involves two kinds of variables, namely observed and latent variables (Lee, 2007). Observed variables are those that can be measured directly from observed data while latent variables are those that cannot be measured directly from a single variable but are created hypothetically from the observed data. Hence, when one is working with such variables, it is most important to substantively establish an appropriate model to evaluate a series of simultaneous hypotheses about the impact of latent variables on the other variables, while taking the measurement error into account (Lee, 2007).

Fox (2002) stipulates that Structural Equation Models (SEMs) are well recognized as the most important statistical methods to serve the above mentioned purpose. They specify the process underlying the joint distribution of a set of observed variables. Fox (2002) defines SEMs as multivariate regression models with multiple equations in which the response variables can also appear as explanatory variables in other equations in the model.

Unlike other multivariate models, their usage has a wide general approach ranging from the analyses of covariance, estimation of models, to studying causal relationship among the variables. Therefore, they are also known as Covariance Structure, Causal Modeling or Path Analysis. The name SEMs is preferred because it does not intend to impose any specific hypothetical definition of cause but as a heuristic view that the meaning of cause resides in the mechanism embodied in an equation system (Bielby and Hauser, 1977).

SEMs share some commonalities with Structural Vector Autoregressive (SVAR) models widely used in econometrics. SVARs are multivariate linear models of observable variables on their own lags and other variables (Fernandez-Villaverde and Rubio-Ramirez, 2008). Both SVAR and SEM models facilitate translating theories into data analysis and vice versa.

Theory may be formal, for example an economic theory, or may depend on a set of predefined objectives which a researcher is aiming to achieve among a set of variables. Arranging variables

according to a prior specification of the relationships among the variables is referred to as ordering. In SVARs, ordering is important because of the economic importance attached to it. However, a statistical researcher is often faced with nothing but a set of data from which inferences should be based upon. Therefore ordering is of less importance in general approaches to SEMs unless a prior set of problems which require a certain ordering is specified.

Another important difference between SEMs and other traditional multivariate models is the causality relationship. In multivariate regression the term correlation is widely used, which indicates how the variables are related. On the other hand, SEMs are often classified by how they evaluate the causal relationship among variables of interest, which refers to the influence one variable has on the dynamic path of another. This influence can either be direct or indirect. Direct influence refers to the influence of variables on the same current values of other variables. Indirect influence is where the lagged value of one variable affects the current values of the other variables. This is a common trend often found in time series data.

SEM analysts prefer using terms such as exogenous and endogenous in place of independent and dependent variables in multivariate statistics respectively. Exogenous and endogenous variables have slightly different and relaxed meanings compared to the latter. Their definitions relate to the causality they embed on one another. In SEMs, variables can be used interchangeably as exogenous or endogenous in different model equations. It is therefore important to have some common definition for the variables and how they relate to each other.

In a system of equations or in a model, exogenous variables are not causally influenced by other variables in the model and their values are measured directly from the population. On the other hand, endogenous variables account for all the causal relations in the model. Their values are determined by the state of other variables which are the exogenous and sometimes other endogenous variables in that system (Engle, Hendry & Richard, 1983).

The focus of this study is to peer into the key Namibian macroeconomic variables and study their evolvement, as well as their influence on one another. This would be accomplished from a perception different from the widely used time series analysis. We would rely on the hypothesized theory for the specification of the estimating models when necessary.

Specification is a component which enables researchers in econometrics to intuitively choose among the competing models. It is basically the hypothesized linkage of variables into a system of equations to be estimated.

1.1 Problem Statements

In econometrics there are numerous model approaches that can be used to perform specification, identification and estimation of time series models. Different models can perform equally well for the same set of variables and it depends solely on the researcher which one to choose, depending on their assumptions and what they are aiming to achieve. Such models can be tested for adequacy by different model fit tests or information criteria for specific objectives and whether prior assumptions hold.

One problem common in economics and econometrics is the non stationarity of the macroeconomic variables. In simple terms, a time series is stationary if it does not change over time. Modelling these non stationary variables leads to what is called the spurious regression. Spurious regression is a situation whereby the results of regression do not hold due to regressing unrelated concepts.

To combat this, economists and econometricians use several methods such as cointegration. The idea with cointegration is that for non stationary variables of the same order, there might be a linear combination of those variables which is stationary.

This approach performs well in econometric models. However, our approach in this context would solely depend on the statistical approach of transformation of variables. Since these methods of cointegration and differencing sometimes results in loss of key information in the data, the objective is to ascertain whether theory would still transpire and whether presentable models fit to represent specific economies are obtainable without cointegration or differencing.

Another problem which this application would like to identify is the discrepancy of different types of estimation methods related to data assumptions. Several estimation methods perform differently under the conditions of assumption violation and model misspecifications which are problems often encountered in practice.

It is desirable however, to test the durability of the SEMs and compare different methods of estimation. Therefore the overall aim is to conceptualize the Namibian macroeconomics into a comprehensive SEM that would enable:

- Understanding the structure and causal relationships among the variables that make up the Namibian economy
- Understanding economic responses to shocks
- Forecasting

1.2 Aim and Objectives

The aim of this application is to construct a structural equation model for the Namibian macroeconomic system. There has been little done in the Namibian context as the economy is still very young and there has been an information deficiency with regard to availability of data. Furthermore, since Namibia attained independence only in 1990, there was not enough data available for the purpose of a complete model evaluation. This is highlighted by models that have been discussed in the previous section which are dated as early as the mid 1990's with the latest in the first quarter of 2004. This means that the series are not long enough to cover all the shocks and fluctuations of the processes that affected the economy.

This study aims to address three objectives in the context of macroeconomic data:

1.2.1 Study the relationships among the Namibian macroeconomics by means of Exploratory Factor Analysis (EFA).

1.2.2 Test the congruency of model specification amenable for the Namibian economy based on the theoretical framework of Namibian Macroeconomics Model (NAMEX) by means of Confirmatory Factor Analysis (CFA).

1.2.3 Estimate the derived SEM model and compare different methods of estimations under conditions of assumption violation and model misspecification.

The first objective will preclude theory. This would allow the studying of the macroeconomic variables and how they are related to one another. The approach for this first objective would be to perform EFA in order to develop an understanding of the relationships vested in the Namibian macroeconomics and build a specification with regard to derived results.

The second objective would perform akin to what has been addressed as theory driven causal research questions at the observed variable level of macroeconomics data. The approach is to perform CFA based on the prior economic specification attributed to models such as NAMEX. This would enable the researcher to verify whether theory is congruent in the Namibian context for the two sectors.

The third objective is to estimate the derived specification of the SEM by two estimation methods namely, the Maximum Likelihood (ML) and the Generalized Least Square (GLS), and compare the results for fit of models and discrepancy of estimated parameters. It is well understood that the ML estimation method provides more realistic indexes of fit and less biased parameters than the GLS estimation method when models are correctly specified (Olsson *et al*., 2000).

1.3 Limitation of the Application

Perhaps the biggest challenge this application is faced with is the availability of long span data. There exists a problem with the small sample of available data. In most SEM applications, the sample size deemed sufficient for capturing the relationships by several methods of estimation based on their asymptotic properties is 200 observations. In this application, there exists only a sample size of 27 observations.

However, several estimation procedures that we wish to employ such as ML and GLS estimation are consistent even in situations of small sample size if prior assumptions are met (Olsson *et al*., 2000). Therefore, we assume that there is consistence of parameter estimator by these methods.

Another shortfall of the small sample problem is the consumption of degrees of freedom by the estimation models. To develop a fully fledged SEM, one needs many variables. Since it is impossible to develop a model with many variables that can make the number of parameters exceed the number of observations, we further assume that the variables used are exogenous even though they are constructs of some other variables. This simply implies that, we assume that the variables that influence our selected exogenous variables were measured without errors. This assumption will avoid having too many parameters in the model.

1.4 Organization of the Application

This study is organized in five chapters. The first chapter introduces SEMs, states the statement of the problem as well as the limitations of the study. The second chapter concentrates on the literature review which incorporates the origins of SEMs and their usage in many other disciplines. The third chapter presents the methodology of this study. The fourth chapter constitutes of the analysis carried out in the study as well as the presentation of the results. Finally, chapter five concludes the main results and provides the necessary recommendations.

Chapter 2

Literature Review

2.1 Origins of SEMs

SEMs have been in existence, although not in the same sense as the modern SEMs, since the early 20th century. Lawley and Maxwell (1962) state that the most prominent work was done by Charles Spearman in 1904, followed by Thurstone in 1935 and in 1947, both psychologists who pioneered what is called Factor Analysis (FA). Both Spearman and Thurston were concerned primarily with hypotheses about the organization of mental ability suggested by the examination of matrices of correlation between cognitive tests (tests for mental functioning and attentiveness). As a consequence, a large number of approximate and sometimes confusing techniques for dealing with these problems appeared in psychological journals and factor analysis became the black sheep of statistical theory (Lawley and Maxwell, 1962).

Kimble and Wertheimer (2002) state that Thurstone, in particular with regard to factor analysis, developed a variety of models ranging from tests of intelligence, clerical skills, engineering aptitude and ingenuity. Thurston's work on physiological examination for high school graduates and college freshmen was later converted to the scholastic aptitude tests administered by the Education Testing Services, an organization that was founded primarily for that purpose.

According to Kimble and Wertheimer (2002), the method Thurstone used was to extract factors from a correlation matrix and support the use of estimates of common test variance rather than total test variance in the analysis. This allows the transformation from a larger dimension to a smaller and more meaningful dimension.

By definition, common test variance or just common variance is the variance accounted for by more than one variable in performing factor analysis and total test variance is the variance produced as a result of Principal Component Analysis (PCA), components conceptualized as being linear combinations of variables (Suhr, 2005). Both FA and PCA are discussed in Section 2.2.

Bulmer (1998) pointed out that models that were able to draw inferences from cross-cultural data were developed as early as 1883 by Francis Galton. Using what is today known as

autocorrelation, correlation of a variable with itself, Galton (1983) developed the law of ancestral heredity which states that '*the two parents contribute between them on average one-half of the total heritage of the offspring, the four grandparents, one-quarter and so on*'. Galton interpreted the results both as a representation of separate contributions of each ancestor to the heritage of the offspring and as a multiple regression formula for predicting the value of a trait from ancestral values (Bulmer, 1998).

In biology, Provine (1986) states that Wright, in 1934, introduced what is called path modelling by quantifying and synthesizing at the same time the basic variables of evolution in nature into a compelling view of the entire process. Wright's work was based on the assumption that selection of variables occur on unmeasured size and shape of factors that summarize linear relations among sets of observed variables he was working with. These unmeasured factors are referred to as latent variables.

More recent publications in biology, particularly morphology (a study of the structure of organisms), have focused on using path analysis in attaining a general size of factors that summarize these linear relations among a sets of observed variables. The attained magnitude of factors is then coupled with a hypothesis of biological explanation (Crespi and Bookstein, 1989).

In economics, SEMs were first highlighted by Haavelmo in 1944. Trygve Magnus Haavelmo was an influential economist with a specific research interest in the field of econometrics and economic theory. He introduced the probability approach to econometrics. Haavelmo argued that '*we should envision existing economic data series as being a sample selected by nature, that is randomly derived from a hypothetical series of distributions which governed reality by which it was unobserved'* (Haavelmo, 1944). This he claimed would facilitate the validity of economic theories.

Relative to SEM, Haavelmo developed a model which links income, consumption and investments in which he addressed for the first time the issue of identification of the covariance matrix in simultaneous equation modeling. Haavelmo's model was of the following nature:

$$\boldsymbol{Y = C + I} \tag{2.1}$$

$$\boldsymbol{C = a + bY + \varepsilon} \tag{2.2}$$

The model has characteristics of causal effects. Hypothetically, income $\boldsymbol{Y}$ causes consumption $\boldsymbol{C}$ (Equation 2.2). According to Streissler (2010), Haavelmo argues that if $\boldsymbol{Y}$ is varied independently of $\boldsymbol{C}$ in Equation 2.2, an Ordinary Least Square (OLS) estimation would result in bias based on some economic theory which we would not discuss here. Haavelmo was more concerned with identification thus provides the basis for his argument by representing income in Equation 2.2 with the identity, Equation 2.1. Equation 2.1 is called an identity equation because of the absence of the random error term that regardless, income is a sum of consumptions and investments $\boldsymbol{I}$.

Identification, as discussed in detail in Section 2.4, allows for testing model fit in any model approach where there exist causal effects among variables. Bartels (1985) defines identification as the problem of relating the structural parameters of a simultaneous equations model to the reduced form parameters that summarize all relevant information available in the sample data. The reduced form implies that in Equations 2.1 and 2.2 there is a need to find parameters that can be equated to the two variables on the left hand side and at the same time incorporating the effect or causal relationships of the other observed variables.

Bergstrom (1988) cited further work relative to SEMs in economics done by Koopmans in 1953. Koopmans was first concerned with theoretical econometrics. Acknowledging Haavelmo's probability approach, Koopmans suggested that models are necessary to give meaning to any significance assertion present in any phenomena and in observations.

Secondly, Koopmans proposed a confidence interval by using ML estimates for models containing error terms. He suggested that the presence of error terms on independent variables vitiates the coefficients of a multiple regression that neglects them (Bergstrom, 1988). His achievements in the field of econometrics include the development and identification of models with multiple equations, derivation of workable inference procedures based on logical assumptions and the theoretical study of properties of those procedures (Malinvaud, 1972).

ML estimates have become an integral part in model estimation including SEMs. There are other approaches as suggested by several theories and in different fields such as the Generalized Least Square (GLS) estimates. However, ML estimates characteristics of selecting values of model parameters that give observed data greater probability might be an advantage over other

estimation procedures in SEMs. Working with models that have many parameters has consequences that can prove fatal if not properly evaluated.

The causal influences among the variables to be used in any estimation have to be relevantly accounted for and any error elements in them have to be highlighted. This should not only be based on assumptions or theory but also on model approaches, for example factor analysis, regression analysis, path modelling and estimation procedures such as ML. The researcher has to take into account the fact that every situation has unique characteristics. Therefore, developing models and evaluating them has to be based on careful selection of procedures.

Although the above mentioned approaches are not specifically SEM procedures, they have some commonality with the modern SEMs. In the following sections, we continue with a more detailed discussion of those procedures that are more related to SEM.

2.2 Factor and Principal Component Analyses

One of the characteristics of SEMs is identifying the nature of the underlying factors that are responsible for covariation in the data. If a researcher is confronted with several variables, then those variables or some of them are often correlated, not only with the endogenous variables, but within the exogenous variables as well. FA is therefore appropriate in identifying the co-variation among the variables.

Another task which FA can perform is to reduce the number of variables. For example, a researcher may administer a questionnaire containing over a hundred questions. However, those questions may only measure three concepts. FA is then an approach which can reduce those questions into the three concepts that can satisfactorily explain the amount of variation or co-variation among the variables.

There are two types of FA: EFA and CFA. EFA attempts to discover the nature of the constructs influencing a set of measured variables without a pre-specified or hypothesised structure and CFA tests whether a specific set of constructs is influencing responses in a predicted way (DeCoster, 1998).

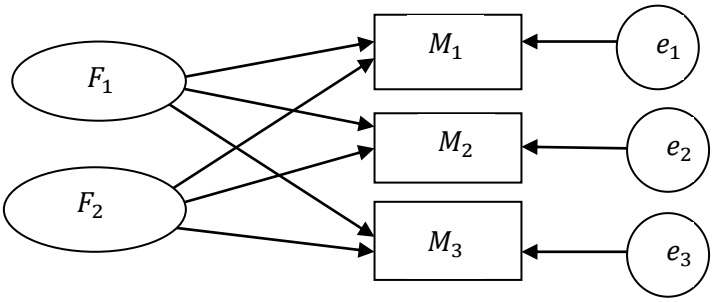


Figure 2.1 Factor analysis

This basic diagram (**Figure 2.1**) illustrates a simple factor analysis model. $\boldsymbol{M_i}$ denotes the measured variables, $\boldsymbol{F_i}$ denotes the Factors and $\boldsymbol{e_i}$ denotes the errors terms. This model purports that the three measured variables ($\boldsymbol{M_1}$, $\boldsymbol{M_2}$ and $\boldsymbol{M_3}$) are functions of the underlying factors $\boldsymbol{F_1}$ and $\boldsymbol{F_2}$. Each $\boldsymbol{M}$ variable is linearly related to the two factors as follows:

$$\begin{aligned} \boldsymbol{M_1} &= \boldsymbol{\beta_{10} + \beta_{11}F_1 + \beta_{12}F_2 + e_1} \\ \boldsymbol{M_2} &= \boldsymbol{\beta_{20} + \beta_{21}F_1 + \beta_{22}F_2 + e_2} \\ \boldsymbol{M_3} &= \boldsymbol{\beta_{30} + \beta_{31}F_1 + \beta_{32}F_2 + e_3} \end{aligned} \qquad (2.3)$$

The error terms indicate that the relationships are not exact. The parameters $\boldsymbol{\beta_{ij}}$ are referred to as the loadings. For example, $\boldsymbol{\beta_{12}}$ is the loading of variable $\mathbf{M_1}$ on factor $\mathbf{F_2}$.

FA is based on two assumptions concerning the relationships in Equation 2.3. The first assumption is that the error terms are independent of one another such that $\mathbf{E(e_i) = 0}$ and $\mathbf{Var(e_i) = \sigma_i^2}$. That is $\mathbf{e_i}$'s are the outcome of a random draw from a population having mean **0** and variance $\boldsymbol{\sigma_i^2}$. The second assumption stipulates that the unobserved factors, $\mathbf{F_j}$'s are independent of one another and the error terms are such that $\mathbf{E(F_j) = 0}$ and $\mathbf{Var(F_j) = 1}$ (DeCoster, 1998).

For mathematical convenience these assumptions imply that the factors are independent of one another. However, it can be relaxed in more advanced models. As for factor means and variances, the assumption is that the factors are standardised based on the fact that they are unobservable (DeCoster, 1998).

To illustrate the consequences of making such assumptions, DeCoster (1998) considered a specific observable variable. Each observed variable is a linear combination of independent factors and error terms;

$$\boldsymbol{M_i = \beta_{i0} + \beta_{i1} F_1 + \beta_{i2} F_2 + (1) e_i} \quad (2.4)$$

The variance of M_i can be calculated as;

$$\begin{aligned} \boldsymbol{Var(M_i)} &= \boldsymbol{\beta_{i1}^2 Var(F_1) + \beta_{i2}^2 Var(F_2) + (1)^2 Var(e_i)} \\ &= \boldsymbol{\beta_{i1}^2 + \beta_{i2}^2 + \sigma_i^2} \end{aligned} \quad (2.5)$$

Therefore, the variance of $\boldsymbol{M_i}$ consists of the communality of the variables ($\boldsymbol{\beta_{i1}^2 + \beta_{i2}^2}$); which is the part that is explained by the common factors and the specific variance ($\boldsymbol{\sigma_i^2}$); which is not accounted for by the common factors.

The covariance of any two measured variables is given by:

$$\begin{aligned} \boldsymbol{Cov(M_i, M_j)} &= \boldsymbol{\beta_{i1}\beta_{j1} Var(F_1) + \beta_{i2}\beta_{j2} Var(F_2) + (1) Var(e_i) + (0)(1) Var(e_j)} \\ &= \boldsymbol{\beta_{i1}\beta_{j1} + \beta_{i2}\beta_{j2}} \end{aligned} \quad (2.6)$$

These expressions are important for the interpretation of the models. Specifically, the factor loadings are deemed to be unique (DeCoster, 1998). Different models can have different factor loadings with the same variance and covariance. This is done by rotating the axes of the loading matrix. For ease of exposition, imagine that there is a prior expectation of the loadings.

First, an analyst would obtain the first loadings which yield the theoretical variance and covariance. These loadings are not necessarily in agreement with the prior expectation. Thus, the loadings are rotated in an effort to arrive at another set of factors that fits the observed variance and covariance satisfactorily, and are also more consistent with the prior expectations. This makes interpretation easy (DeCoster, 1998). This practice could be cumbersome, but with the modern computer technology, life has been made easier. Most software can perform various rotation methods.

Sometimes there exists data redundancy; variables are correlated with one another possibly because they are measuring the same construct and the objective is to reduce the number of variables. Another way to explore the data is what is known as PCA (Hatcher, 1994).

PCA aims to produce constructs, also referred to as components that account for most of the variation in the data, for instance 80%. A researcher would then decide whether to discard the remaining components, which explains the minimal variation or retain them. In this form the components are created to reflect what is being estimated by the model.

Formally, PCA is defined as the linear combination of optimally weighted observed variables (Suhr, 2005). The reason behind the definition is that the variables, which are used to measure the same construct, are grouped together linearly to form that component. The process involves the calculation of regression weights on all the variables and producing the equation called the Eigen-equation. Therefore, the weights produced by these Eigen-equations are optimal weights for a given set of data and no other set of weights could produce a set of components that are more successful in accounting for the variation in the observed variables (Hatcher, 1994).

PCA and FA can both be used as variables reduction methods. Nonetheless, their differences deal mostly with the assumptions of the underlying causal structure.

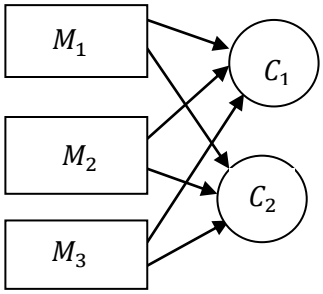


Figure 2.2 Principal component analysis

By comparing **Figure 2.1** and **Figure 2.2**, one can see the exact difference between FA and PCA. The obvious difference between the two is that the direction of the influence is reversed. FA assumes that the measured responses are based on the underlying factors while the components, $\boldsymbol{C_1}$ and $\boldsymbol{C_2}$, are based on the measured variables $\boldsymbol{M_1}$, $\boldsymbol{M_2}$ and $\boldsymbol{M_3}$. Another difference worth noting is the presence of the error terms in the FA.

PCA can also be thought as the first stage for determining a set of loadings that bring the estimate of the total communality as close as possible to the total of the observed variance. However, PCA is not FA even though there are several similarities in the sense that they are both data reduction methods. Nonetheless, their difference deals mostly with the assumptions of the underlying causal structure. Consider Equations 2.7 and 2.8 by Lawley and Maxwell (1962):

$$\boldsymbol{z_r = \sum_{r=1} w_{ir} x_i \ (i, r = 1, 2, \dots, p)} \quad (2.7)$$

$$\boldsymbol{x_i = \sum_{r=1}^{k} l_{ir} f_r + e_i \ (i = 1, 2, \dots, p)} \quad (2.8)$$

Where x_i denotes the observed variables, $\boldsymbol{z_r}$ is the $\boldsymbol{r^{th}}$ component where $\boldsymbol{r}$ is less than or equal $\boldsymbol{p}$, $\boldsymbol{w_{ir}}$ is the weight of the $\boldsymbol{r^{th}}$ component in the $\boldsymbol{i^{th}}$ variate, $\boldsymbol{f_r}$ is the $\boldsymbol{r^{th}}$ common factor, $\boldsymbol{l}$ is the loading factor and $\boldsymbol{p}$ is defined as the observed variate denoted by $\boldsymbol{x_i}$'s. Therefore the underlying assumptions are such that each $\boldsymbol{x_i}$ is transformed into some components such that they account for maximum variance and those components are uncorrelated. In Equation 2.8, the random errors are supposed to be independent of one another and also to be independent of the factors. Factors are necessarily uncorrelated (Lawley and Maxwell, 1962). Equations 2.7 and 2.8 denote PCA and FA, respectively.

FA assumes that the co-variation in the observed variables is due to the presence of one or more latent variables that exert causal influence on these observed variables. Latent variables are those that cannot be directly observed or measured from raw data. FA is appropriate for testing hypothetical theories. On the contrary, PCA makes no assumptions about an underlying causal model (Hatcher, 1994). It is a process of absolute extraction and is appropriate for understanding the nature of the observed variables based on their correlation with each other.

2.3 Path Analysis and Model Specification

Path analysis is an approach used to test theoretical models that specify the causal relationships between a number of observed variables. It determines whether the theoretical model, as often found in practice for different disciplines, successfully accounts for the actual relationships observed in the sample data (Hatcher, 1994). They are often represented with path diagrams.

Path diagrams continue to be a significant aid in model specification. A path diagram is a representation of causal influences between variables. It constitutes an arrow pointing in the direction of that influence. The direction of the arrow illustrates that the two variables are expected to co-vary. Causality can either be one variable influencing the other or both variables asserting causal influence on one another, in which case the arrow would point in both directions.

It is important to formally define the type of variables at this stage. The variables whose variability is predicted to be causally affected by other variables in a model are called the endogenous variables. These variables cannot necessarily influence any other variable unless it is a mediator variable or if one is dealing with what is known as a recursive model. A recursive

model has one or more than one endogenous variables, that are expected to have a reciprocal causal influence on each other (Hatcher, 1994). Often the causal effect between endogenous variables is dealt with separately.

In contrast, exogenous variables are those that only influence others. The only causal effect they can experience is between one another. Therefore mediator variables are endogenous variables as well. Technically, endogenous variables have direct arrows pointing to them but no arrow points towards an exogenous variable unless it is a curved arrow which represents that there exist a causal effect between those exogenous variables.

Path analysis allows complicated models to be estimated. In a simple analysis, based on the underlying theory, there is only a direct causal effect among the variables. However, often one experiences indirect effects in which there are some variables acting as mediators or through some lagged values of other variables. That means some variables exert causal influence not directly to some endogenous variable but through other variables that are called the mediator variables.

The objective of the path analysis is to evaluate and account for the variation among all the variables at all levels, either directly or through the mediator variables. The path that leads from the exogenous variable to the endogenous variable is called the coefficient path and it is this path which constitutes the equation to be estimated. The analysis may contain several coefficient paths and that could result in a model of multiple equations for estimation.

The model depicted in **Figure 2.3** state that the exogenous variables $\boldsymbol{v_3}$, $\boldsymbol{v_4}$ and $\boldsymbol{v_5}$ are correlated. Variable $\boldsymbol{v_2}$ is a mediator variable as its causation on the endogenous variable $\boldsymbol{v_1}$ is a result of linear combination of two exogenous variables $\boldsymbol{v_3}$ and $\boldsymbol{v_4}$,. This variable $\boldsymbol{v_2}$ has a direct causal effect on $\boldsymbol{v_1}$, but also conveys the indirect effect of $\boldsymbol{v_3}$ and $\boldsymbol{v_4}$ on $\boldsymbol{v_1}$. The short arrows pointing to variables $\boldsymbol{v_1}$ and $\boldsymbol{v_2}$ represent the random errors. It is noticeable that the only variables which have error terms are the endogenous variables, $\boldsymbol{v_1}$ and $\boldsymbol{v_2}$, which makes sense because they are the ones being predicted in the model. The straight arrows between variables represent the path coefficients. The covariance terms between the exogenous variables are represented by the curved double arrows.

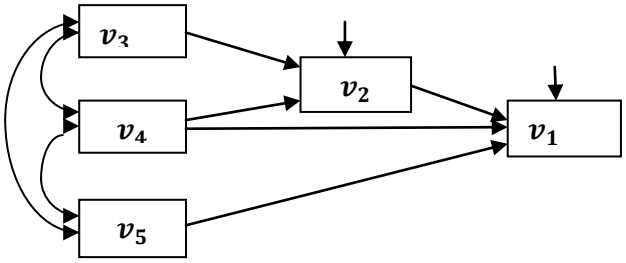


Figure 2.3 Path analysis

Even though path diagrams are the first step in identifying relationships among observed variables, it is highly desirable for a researcher not to unnecessarily hypothesize about causality among the variables because of the danger of spurious correlation that may occur between the variables due to influence exerted by some shared but unmeasured variables. So to infer about causality, one needs association (presence of statistical significance), non spuriousness, direction of influence and causal mechanism (Cao, Mokhtarian & Handy, 2008).

By virtue of nature most models suggest, especially in social science, the inclusion of latent variables. As previously defined, latent variables are hypothetically constructed. They are not directly observed and their data are not directly available. Going back to the data reduction procedures, PCA and EFA are explanatory, unlike CFA or SEMs as we shall see later, that are driven by theory. In the former the underlying structure is identified and the dimension is derived thereby suggesting the theoretical design or mechanism, whereas the later is a model based on a theoretical framework which if fitted to the data.

2.4 Model Identification

In the modelling approach, one of the confounding obstacles is the evaluation of how well the estimated models can properly approximate the actual data generating process. Competing models can sufficiently represent the underlying process just as much as they can completely fail to represent the theoretical structure.

Investigating which model sufficiently fits the available data is dealt with by an identification mechanism. Identification allows for testing the durability of such models and whether they actually represent the true data generating process.

In path analysis, likewise in many other model approach processes including SEM, a researcher is faced with several interrelated variables, resulting in a system of multiple equations. Each of

those equations represents a path with coefficients that have to be estimated. Let us consider **Figure 2.4** below for illustrative purpose.

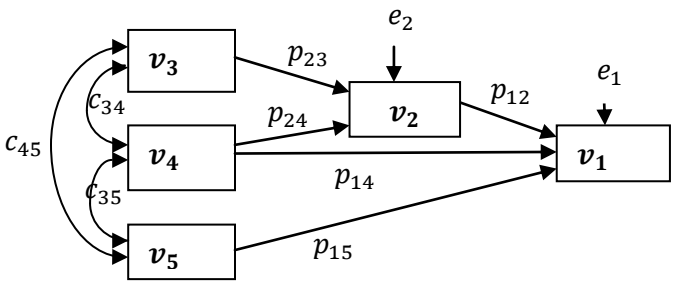


Figure 2.4 Path diagram

Causal models represent a system of functional equations in a way that the arrows connecting endogenous to exogenous variables (a path) represents some coefficients and parameters which are unknown as shown in **Figure 2.4.** It is predetermined that the endogenous variable will be causally determined by the exogenous variable plus the error terms. For the endogenous variables $\boldsymbol{v_1}$ and $\boldsymbol{v_2}$, specific functional equations represented in **Figure 2.4** takes the following form:

$$\boldsymbol{v_2} = \boldsymbol{P_{23}}\,\boldsymbol{v_3} + \boldsymbol{P_{24}}\,\boldsymbol{v_4} + \boldsymbol{e_2} \quad (2.9)$$

$$\boldsymbol{v_1} = \boldsymbol{P_{12}}\,\boldsymbol{v_2} + \boldsymbol{P_{14}}\,\boldsymbol{v_4} + \boldsymbol{P_{15}}\,\boldsymbol{v_5} + \boldsymbol{e_1} \quad (2.10)$$

The two equations represent the model illustrated in **Figure 2.4**. $\boldsymbol{v_1}$ is the endogenous variable predicted by exogenous variables $\boldsymbol{v_3}$, $\boldsymbol{v_4}$ and $\boldsymbol{v_5}$. $\boldsymbol{v_2}$ is the mediator variable linking $\boldsymbol{v_3}$ and $\boldsymbol{v_4}$ to $\boldsymbol{v_1}$. The P's in the equations represent the paths or more generally the model coefficients. For example, $\boldsymbol{P_{12}}$ is the path from $\boldsymbol{v_2}$ to $\boldsymbol{v_1}$. The arrows directly pointing to $\boldsymbol{v_1}$ and $\boldsymbol{v_2}$ represent the residuals $\boldsymbol{e_1}$ and $\boldsymbol{e_2}$ respectively. It is assumed that $\boldsymbol{v_1}$ and $\boldsymbol{v_2}$ have error terms because they are being explained by other variables. Note that in such a model, there should be five variances to be estimated, each for all the exogenous variables and the residual terms. Furthermore the covariance terms between the exogenous variables are captured by $\boldsymbol{c_{34}}$, $\boldsymbol{c_{35}}$ and $\boldsymbol{c_{45}}$.

It is highly desirable that a model should not be under-identified (when the model includes fewer linearly independent equations than the unknowns). For example, the model in **Figure 2.4** is under-identified by Equations 2.9 and 2.10 as there are more unknowns than equations. Under-identification can produce an infinite number of solutions for the parameters. Parameter estimates are meaningful only if they are obtained from the estimation of an identified model. Here an identified model means a model which is just-identified or over-identified models (Hatcher, 1994).

Just identified models have exactly as many equations as parameters. These models have the disadvantage of not allowing for any test for goodness of fit. This implies that the empirical observation is a firm indicator of the specified structural function. Hence no any other model would compete with that specification (Cicchetti, Smith, Knetsch & Patton, 1972). This is the reason why researchers typically prefer to work with an over-identified model where there are more equations than parameters so that different competing models can be tested for the goodness of fit for the data.

There are several technical procedures that can be used to determine if a model is identified. Hatcher (1994) noted that one common procedure is by checking whether the number of data points in the analysis is larger than the number of parameters to be estimated. This procedure suggests the threshold test of model identification. According to Hatcher (1994), the number of data points is calculated by the following formula:

$$\boldsymbol{Number\ of\ data\ points} = \frac{\boldsymbol{p}(\boldsymbol{p}+\mathbf{1})}{\mathbf{2}} \qquad (2.11)$$

Where $\boldsymbol{p}$ represents the number of the variables in the system and the number of parameters in the model is the sum of all the coefficients to be estimated including the variance and the covariance. Let us use the model represented in **Figure 2.4** to illustrate the procedure. There are five observed variables in the model, $\boldsymbol{v_1}$ to $\boldsymbol{v_5}$. Therefore, the number of data points as given by Equation 2.11 is 15. The number of parameters to be estimated is the sum of two variances ($\boldsymbol{e_1}$ and $\boldsymbol{e_2}$), three covariance terms between $\boldsymbol{v_3}$, $\boldsymbol{v_4}$ and $\boldsymbol{v_6}$, and the five path coefficients.

The total number of parameters to be estimated is therefore equal to 10. Since the number of data points exceeds the total number of parameters to be estimated, one may conclude that the model

might be identifiable. By using this method to check for identification as in Equation 2.11, it is however recommended that other approaches need to be employed too. Equation 2.11 is only conclusive in a way that if the test fails, that the number of data points does not exceed the total number of parameters, then the model is under-identified. Therefore it is not testable. However, if the model passes the test, it does not necessarily imply that the model is identified or over-identified (Hatcher, 1994).

There are several methods in the literature on to test for identification. Many approaches are well documented in Duncan (1975), Brito and Pearl (2002a, 2002b), as well as Tian (2007).

2.5 Structural Equation Models

So far the preceding sections have been an introduction into some techniques which are more closely related to SEMs. Several approaches to these techniques such as the causal relationships, model specification using path diagrams and model identification described are what make up SEMs. The origin of SEMs emanates from these different techniques and their practical applicability in the different fields.

Modelling with SEMs is a cumbersome procedure. Modern SEMs have advanced into their unique inter-disciplines within statistics and social science. In SEMs, the structural parameters of a theoretical model which has a distinct structure for its effect do not coincide with coefficients of regression among the observable variables, but the model does impose constraints on the regression coefficients (Bielby and Hauser, 1977).

Constraints are imposed on some of the parameters so that identification is attainable. This is either based on a certain theory or simply on the researcher's intuition, most likely on those parameters deemed less relevant in the model.

The advancement of software to identify and to estimate SEMs is however also vastly growing which makes it easier to deal with the matrix algebra encountered especially in the covariance structure of the SEMs.

2.5.1 Structure of SEMs

In most research, it is important to establish an appropriate model to evaluate a series of simultaneous hypotheses about the impact of variables on each other in the model.

Usually standard SEMs are composed of two stages. The first stage relates corresponding variables to each other and takes the measurement errors into account. It involves a regression model which regresses the variables. It also involves a regression type structural equation which regresses the endogenous variable with the linear terms of some endogenous and exogenous variables (Lee, 2007). The second stage is the estimation stage, usually by estimation methods such as ML or GLS.

In most cases, some of these variables are latent variables and since they are unobserved, they cannot be directly analyzed by techniques in ordinary regression that are based on raw data observations. SEMs make it easy to apply formulated familiar regression type models to these variables.

A typically SEM is given by:

$$\begin{pmatrix} \Gamma_{11} & \cdots & \Gamma_{1L} \\ \vdots & \ddots & \vdots \\ \Gamma_{L1} & \cdots & \Gamma_{LL} \end{pmatrix} \begin{pmatrix} y_{1j} \\ \vdots \\ y_{Lj} \end{pmatrix} = \begin{pmatrix} \beta_{11} & \cdots & \beta_{1K} \\ \vdots & \ddots & \vdots \\ \beta_{L1} & \cdots & \beta_{Lk} \end{pmatrix} \begin{pmatrix} \eta_{1j} \\ \vdots \\ \eta_{kj} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1j} \\ \vdots \\ \varepsilon_{Lj} \end{pmatrix} \tag{2.12}$$

Or more compactly:

$$\Gamma \boldsymbol{y}_j = \boldsymbol{B}\boldsymbol{\eta}_j + \boldsymbol{\varepsilon}_j \tag{2.13}$$

Where $\boldsymbol{y}_j$ represents the true observed values of the L endogenous variable and $\boldsymbol{\eta}_j$ is the jth observation of K exogenous variables, $\boldsymbol{\varepsilon}_j$ is the structural disturbance for the jth observation in each of L structural equation and $\boldsymbol{r}$ and $\boldsymbol{B}$ are the structural coefficients. The $\boldsymbol{\varepsilon}_j$'s are assumed to have a zero mean and they are serially uncorrelated with each other or the observed variables. All the terms in the equation are matrices, $\boldsymbol{r}$ is $(\boldsymbol{L} * \boldsymbol{L})$, $\boldsymbol{y}_j$ is $(\boldsymbol{L} * \boldsymbol{1})$, $\boldsymbol{B}$ is $(\boldsymbol{L} * \boldsymbol{K})$, $\boldsymbol{\eta}_j$ is $(\boldsymbol{K} * \boldsymbol{1})$ and $\boldsymbol{\varepsilon}_j$ is $(\boldsymbol{L} * \boldsymbol{1})$.

Measurement errors are usually specified with continuous latent variables. Such models are called factor models when the observed measures are continuous. A basic assumption of a measurement model is that the measurements are conditionally independent. That is, the dependence among the measurements is solely due to the common association with the latent variable (Skrondal and Rabe-Hesketh, 2004).

In SEMs, the parameters are the structural coefficients, for example gamma and $\boldsymbol{B}$ in the equation and they are called the moments of the exogenous variables in the case where there is correlation among them as well as the structural disturbance (Skrondal and Rabe-Hesketh, 2004). These are the parameters to be estimated after they have been properly identified.

Let us examine the simple SEM illustrated by **Figure 2.5** below. The figure is a path diagram illustrating a model either derived by theory or by an explanatory technique such as EFA. Variable $\boldsymbol{v_1}$ is taken as a latent variable, $\boldsymbol{v_2}$ and $\boldsymbol{v_3}$ are mediator variable and $\boldsymbol{v_4}$ is an exogenous variable. In this case, the two mediator variables can also be the endogenous variables of the model implying that they are constructs of some other variables outside the system. In Equation 2.1 we have $\boldsymbol{Y}$, income taken as the sum of consumptions $\boldsymbol{C}$ and investments $\boldsymbol{I}$. For illustrative purpose, income in Equation 2.2 can be represented by variable $\boldsymbol{v_3}$ in **Figure 2.5**.

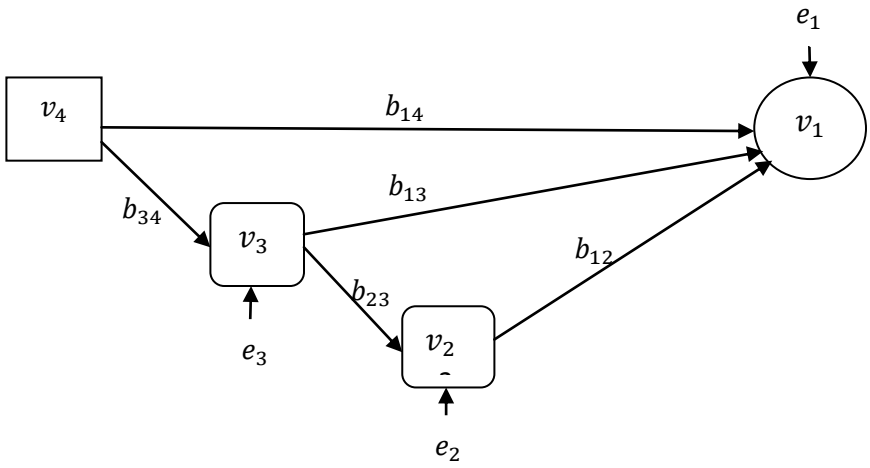


Figure2.5 Causal Representation

Equations 2.14 to 2.16 give the system of equations representing the path diagram in **Figure 2.5**.

$$\boldsymbol{v_1 = b_{14}\, v_4 + b_{13}\, v_3 + b_{12}\, v_2 + e_1} \quad (2.14)$$

$$\boldsymbol{v_2 = b_{23}\, v_3 + e_2} \quad (2.15)$$

$$\boldsymbol{v_3 = b_{34}\, v_4 + e_3} \quad (2.16)$$

Variable $\boldsymbol{v_1}$, is predicted by endogenous variables $\boldsymbol{v_2}$ and $\boldsymbol{v_3}$ and by exogenous variable $\boldsymbol{v_4}$ in Equation 2.14. In Equation 2.15, $\boldsymbol{v_2}$ is predicted by $\boldsymbol{v_3}$. $\boldsymbol{v_3}$ in turn is predicted only by $\boldsymbol{v_4}$ in the system. The disturbance terms are represented by $\boldsymbol{e_1}$, $\boldsymbol{e_2}$ and $\boldsymbol{e_3}$, the vertical arrows pointing to $\boldsymbol{v_1}$ $\boldsymbol{v_2}$ and $\boldsymbol{v_3}$.

Such a specification can be viewed as the theoretical framework of the model to be estimated. Therefore, identification would then imply that all the parameters of the model are incorporated and if necessary, some of the coefficients could be constrained by theory as discussed in Section 2.4. With reference to Equation 2.12 the betas and epsilons are represented by $\boldsymbol{b}$'s and $\boldsymbol{e}$'s respectively in Equations 2.14 to 2.16.

In practice, Hatcher (1994) stated that models with latent variables are often referred to as SEMs, covariance structure models, latent variable models or causal models with unmeasured variables. Evidently, PCA and EFA can be viewed as the processes of building models that can be substantially tested by CFA or SEMs. On the other hand, path analysis, CFA and SEM are one and the same technique. Hatcher's (1994) discussion to distinguish between a CFA and a SEM was based only on whether the path analysis was specified with manifest (observed) or latent variables respectively.

2.6 Estimations of SEMs

There are several methods that are used to estimate SEMs. In literature, perhaps the most popular approaches are the ML and the GLS estimation methods. These methods are believed to produce consistent estimators of the model parameters under some specified assumptions observed in the data (Olsson, Foss, Troye & Howell, 2000).

Applied researchers often have difficulty in determining which method is best applicable. However, there are general approaches that may guide researchers in determining the most appropriate model for the data. The following section is the discussion of the two methods of estimation in more details. The guidelines used for the evaluation of model fit are discussed in Section 2.7 and 2.8.

2.6.1 Maximum Likelihood

The whole idea of estimation is to produce model parameters that best fit the observed data. ML is one of the most widely used parameter estimation methods. The method leads to estimates of the parameters that maximize the likelihood that the empirical covariance matrix is drawn from the population from which the model implied covariance is a valid matrix (Schermelleh-Engel, Moosbrugger & Muller, 2003). This basically implies that the discrepancy between the model covariance matrix and the empirical covariance matrix is minimized.

The fit function of the ML can be expressed as:

$$\boldsymbol{F_{ML} = log\,|\sum(\Theta)| - log\,|S| + tr\left[S\sum(\Theta)^{-1}\right] - p} \qquad (2.17)$$

Where

$\boldsymbol{Log}$ is the natural logarithm,

$\boldsymbol{S}$ is the empirical covariance matrix,

$\boldsymbol{\Theta}$ is the vector of parameters,

$\sum(\boldsymbol{\Theta})$ and $|\sum(\boldsymbol{\Theta})|$ are the model implied covariance matrix and its determinant respectively,

$\boldsymbol{tr}$ is the trace of matrix and

$\boldsymbol{p}$ is the number of observed variables.

ML maximizes a log-likelihood function which in principle is similar to minimizing the function in Equation 2.17.

Estimation using ML involves that certain assumptions are met. ML assumes that the sample size is sufficient. With large sample size, the distribution of the estimators approximates the normal distribution (Schermelleh-Engel *et al*., 2003). Another important assumption is that the variables are multivariate normal. That is, their joint distribution is normally distributed.

The advantage ML poses over other methods as Schermelleh-Engel *et al*. (2003) pointed out is that ML estimates are generally scale free. This simply means that the function in Equation 2.17

does not depend on whether the correlation or covariance matrix is used or whether the variables are transformed. Furthermore, Bollen (1986) illustrated that ML allows for formal statistical tests of overall model fit.

2.6.2 Generalized Least Square

Under the same assumption of multivariate normality and large sample size, another estimation method widely recommended is the GLS. Again, reserving the mathematics behind the intuition, the GLS fit function is expressed as:

$$\boldsymbol{F_{GLS}} = \frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{tr}\{[\boldsymbol{S} - \sum(\Theta)]\boldsymbol{S^{-1}}\}^{\mathbf{2}} \quad (2.18)$$

The parameters are defined as in Equation 2.17. Under the same assumption of multivariate normality, GLS minimize the fit function of Equation 2.18, thereby minimizing the discrepancy between the empirical and model implied covariance matrices.

Asymptotically, GLS is deemed to be equivalent to ML. However, their consistency in small samples is based on whether the models are well specified. Olsson et al. (2000) showed that in misspecified models, the estimates are no longer equivalent and hence GLS is somehow found to provide better empirical fit.

In practice, the violation of distributional assumption is often unavoidable. Furthermore, sufficient sample sizes adequate for estimating parameters using these methods are often lacking, which makes it difficult for researchers to choose among competing models. The issue of misspecification also plays a huge role in determining which estimation method is appropriate for a set of data.

Bollen (1986) demonstrated that efficiency, consistence and unbiasedness of these estimators are based on asymptotical properties. Therefore, considering those shortfalls and keeping in mind that different estimation methods have different distributional assumptions as well as different discrepancy functions to be minimized, it is highly recommended that models should be carefully evaluated for overall and descriptive goodness of fit (Schermelleh-Engel *et al*., 2003).

2.7 Evaluation of SEMs

The methods discussed above are all subjected to serious model evaluation strategies that determine whether those estimates truly fit the data. Once estimation is undertaken and

parameters are obtained and believed to converge to a reasonable solution, the process of evaluation begins. Hatcher (1994) illustrated that the first approach is to review the overall goodness of fit and then thereafter, the model indices for more detailed assessments of significance are evaluated.

There are numerous indices which are used to assess the suitability of the models. The most widely used is the chi-square test. The chi-square test is used for hypothesis testing to evaluate the appropriateness of the model (Schermelleh-Engel *et al*., 2003). Chi-square evaluates whether the population covariance matrix is equal to the model implied covariance matrix. That is basically testing the null hypothesis that the model fits the data.

Technically, Schermelleh-Engel *et al*. (2003) illustrated that a correct null hypothesis implies that the minimum fit function converges to the chi-square variates. That is:

$$(\boldsymbol{N-1})\boldsymbol{F}[\boldsymbol{S},\sum(\Theta)] \sim \boldsymbol{\chi^2}(\boldsymbol{df}) \qquad (2.19)$$

Where

$\boldsymbol{df}$ is the degrees of freedom,

$\boldsymbol{N}$ is the sample size,

$\boldsymbol{F}$ denotes the estimation method fit function,

$\boldsymbol{S}$ is the empirical covariance matrix and

$\sum\boldsymbol{(\Theta)}$ is the model implied covariance matrix.

The usefulness of the chi-square test depends on whether the distributional assumptions of the data are met. The test depends on the method of estimation and its values are derived from that specific method. When proper assumptions are met, that is large sample and multivariate normal, the chi-square test provides significant tests with regard to the estimation method (Hatcher, 1994).

Furthermore, this test depends on the degrees of freedom attached to it. If the model provides good fit to the data, then the chi-square statistic is expected to be equal to the degrees of freedom. However, since the test depends on the sample size as well, Schermelleh-Engel *et al*.

(2003) stated that it leads to the problem that plausible models might be rejected based on a significant chi-square statistic even though the discrepancy between the sample and model implied covariance matrix is actually irrelevant.

Another shortcoming with the chi-square statistics raised by Raykov, Tomer and Nesselroade (1991) is when researchers rely on the fact that the smaller the chi-square the better the models fits the data. The null is accepted when the chi-square is not significant with regard to the probability value. However, the decrease in the sample size decreases the chi-square statistics, leading to significant probability values even though the discrepancy might be considerable. Since the null is rejected when the probability value of the statistic is significant, the chi-square is also termed as a badness of fit measure (Hooper, Coughlan and Mullen, 2008)

Even though it is a common practice to seek a model with relatively small chi-square other than the significant model, Schermelleh-Engel *et al*. (2003) suggested that it is good practice to trade between the statistic itself and the degrees of freedom. As a rule of thumb, a ratio of chi-square and the degrees of freedom ($\boldsymbol{\chi^2/df}$) of two and three are indicative of good and acceptable model-data fit respectively.

Marsh, Hau and Wen (2004) warned against the complete reliance on the chi-square statistic. They emphasized that other alternatives should also be undertaken, in addition to the overall goodness of fit such as chi-square discussed in this section, for the overall conclusive inference about the model-data fit to be drawn. These methods are discussed in considerable details in the following sections.

Another overall goodness of fit index often reported in the literature is the Root Mean Square Error of Approximation (RMSEA), which is a measure of approximate fit in the population. RMSEA is bounded below by zero. A cutoff point for the RMSEA is generally considered as 0.6. That is the values less than 0.6 are considered to indicate a good fit of the model (Schermelleh *et al*., 2003).

Unlike the chi-square, RMSEA is considered to be relatively independent of the sample size. It is estimated by the square root of the estimated discrepancy due to approximation (Schermelleh *et al*., 2003) which is defined as:

$$\hat{\varepsilon}_a = \sqrt{max\left\{\left(\frac{F(S,\sum(\Theta))}{df} - \frac{1}{N-1}\right), 0\right\}} \quad (2.20)$$

Where

$\hat{\varepsilon}_a$ is the square root of the estimated discrepancy,

$F(S, \sum(\Theta))$ is the minimum of the fit function,

df is the number of degrees of freedom and

N is the sample size.

Other indices included the Root Mean Square Residual (RMSR) which is defined as:

$$RMSR = \sqrt{\frac{\sum_{i=1}^{p}\sum_{j=1}^{i}(s_{ij}-\sigma_{ij})^2}{p(p+1)/2}} \quad (2.21)$$

Where

s_{ij} is an element of the empirical covariance matrix

σ_{ij} is an element of the model-implied covariance matrix and

p is the number of observed variables.

There is also a standardised version of RMSR which measures the overall badness of fit based on fitted residuals. These residuals are the difference between the values of the sample covariance matrix and the population covariance matrix. The Standardised Root Mean Square Residual (SRMSR) should have a value less than 0.05 for a model to be considered a good fit. Detailed discussion of these indices is found in Schermelleh *et al*. (2003).

2.8 Descriptive Goodness of Fit Indices

Since researchers are urged not to completely rely on the chi-square as a result of the drawbacks pointed out in the last section, several descriptive fit indices are developed that are often assessed intuitively (Schermelleh-Engel *et al.* (2003). These indices are called descriptive since their sampling distributions of goodness of fit are unknown and hence the critical values are not

defined. Several computer software packages used by researchers to estimate models have these indices build in. They are distinguished as incremental and parsimony fit indices.

2.8.1 The Incremental Fit Indices

These indices described in further detail below are called incremental fit indices because of their nature in trading between different model restrictions of parameters. This basically implies that incremental fit indices are a comparison between different models with regard to parameter restriction. Often, a baseline model to which the target model is compared has to be defined.

The Normed Fit Index (NFI) developed by Bentler and Bonnet (1980) is the first of this kind in this discussion. NFI assess the model by comparing the chi-square value of the target model (a model under investigation) to the chi-square of the null or baseline model (Hooper *et al*., 2008). It is defined as:

$$\boldsymbol{NFI} = \frac{\chi_b^2 - \chi_t^2}{\chi_b^2} \qquad (2.22)$$

Where

$\boldsymbol{\chi_b^2}$ is the chi-square of the baseline model and

$\boldsymbol{\chi_t^2}$ is the chi-square of the target model.

The baseline model assumes that the observed variables are measured without errors. In a baseline model, there are no parameters to be estimated. Basically, all parameters are fixed to zero making it a very poor fitted or zero model. The target model is then compared to this bad fitted model to see if it is an improvement (Schermelleh *et al*., 2003). A less restricted baseline model is where only the variances of the variables are allowed to be freely estimated.

The values of the NFI range between zero and one. More recent studies suggested that an NFI greater than 0.95 indicates a good fit model (Hooper et al., 2008). However, a statistic of 0.9 is also widely accepted to represent an acceptable model fit.

The drawback as Hooper *et al*. (2008) pointed out is that the NFI suffers if you have a small sample size. To correct for this Bentler and Bonnett (1980) proposed the Nonnormerd Fit Index (NNFI). NNFI is believed to be less affected by the sample size because of the degrees of

freedom which, unlike in the NFI, are incorporated in the calculation of the statistic. It is defined as:

$$\boldsymbol{NNFI} = \frac{(\chi_b^2/df_b)-(\chi_t^2/df_t)}{(\chi_b^2/df_b)-\mathbf{1}} \quad (2.23)$$

Where all values are defined as in Equation 2.22 and ***df*** is the degrees of freedom.

Schermelleh *et al*. (2003) stated that since the NNFI is not normed, the values can sometimes exceed one. As a rule of thumb, a value of 0.97 is indicative of a good fit and 0.95 as an acceptable fit.

The problem with the NNFI is that, although it is believed to perform better than the NFI in small samples, it can indicate a poor fit despite other statistics pointing towards a good fit (Hooper et al., 2008).

Another widely reported fit index of this kind and included in most SEM programs due to its nature of being least affected by sample size is the Comparative Fit Index (CFI). CFI is believed to avoid the underestimation of model fit often noted in small samples for the NFI. It assumes that the latent variables in the model are uncorrelated and it compares the sample covariance matrix with the one of the baseline model (Hooper *et al*., 2008). Schermelleh *et al*. (2003) indicated that the cut-off point of 0.97 is indicative of the good fit relative to the baseline model. CFI is defined as:

$$\boldsymbol{CFI} = \mathbf{1} - \frac{max[(\chi_t^2-df_t),\mathbf{0}]}{max[(\chi_t^2-df_t),(\chi_b^2-df_b),\mathbf{0}]} \quad (2.24)$$

All terms in Equation 2.22 are as defined previously in Equation 2.22 and 2.23.

2.8.2 Parsimony Fit Indices

Parsimony is the issue of dealing with the trade-off between over parameterization of the model and degrees of freedom in the model. Technically, Hooper *et al*. (2008) defined that complex models means that the estimation process is dependent on the sample data. Therefore, a less rigorous theoretical model should produce better fit. Researchers are urged to consider models with fewer parameters, resulting in more degrees of freedom.

As with the incremental Indices, these indices are based on comparison of a target model to a baseline model, which is often an over parameterized model. The target model seeks to improve from this baseline model which has all the parameters fixed to zero, which is the same as that there is no model at all.

The most reported index which is not described in detail here is the Goodness of Fit Index (GFI), which measures the amount of variance and covariance in the empirical covariance matrix that is predicted by the model implied covariance matrix (Schermelleh *et al*., 2003). A model that fits the data better is determined by having a GFI value over 0.95 but, Hooper *et al*. (2008) argued that since this index penalises for model complexity which results in values that are lower than the other goodness of fit indices, it is generally possible to obtain a perfectly fitting model with a GFI value in the region of 0.5. GFI is defined as:

$$\boldsymbol{GFI = 1 - \frac{\chi_t^2}{\chi_n^2}} \qquad (2.25)$$

Where

$\boldsymbol{\chi_t^2}$ is the chi-square of target model and

$\boldsymbol{\chi_n^2}$ is the chi-square of a null model.

Another version is the Adjusted GFI (AGFI) which adjusts for the bias implied by the model complexity. Schermelleh *et al*. (2003) stated that AGFI adjusts for the model degrees of freedom relative to the number of observed variables and therefore rewards less complex models with fewer parameters. The AGFI is defined by replacing the terms in the fraction of Equation 2.24 with their respective ratio of chi-square to the degrees of freedom.

Perhaps the most widely used Indices in this category are the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Hooper *et al*. (2008) state that these criteria are generally used when comparing models estimated with the same data and indicates to the researcher which model is the most parsimonious. AIC is defined as:

$$\boldsymbol{AIC = -2logL + 2(p)} \quad (2.26)$$

Where $\boldsymbol{log\ L}$ is the maximized value of the log likelihood function for the fitted model and $\boldsymbol{p}$ is the number of parameters estimated. It can also be measured in other forms as suggested by different software in which instead of the $\boldsymbol{log\ L}$ being used, the chi-square value of the model is used.

Shermelleh *et al*. (2003) pointed out that Bentler (1995) adopted a version of AIC defined as:

$$\boldsymbol{AIC_b = \chi^2 - 2(df)} \quad (2.27)$$

Equation 2.26 and 2.27, are one and the same. Both take into account the statistical goodness of fit, incorporated in the maximized likelihood in Equation 2.26 and in the chi-square value in Equation 2.27, as well as the number of parameters estimated.

The BIC on the other hand is defined as:

$$\boldsymbol{BIC = \chi^2 + pln(n)} \quad (2.28)$$

Notice that the BIC has taken into consideration the number of data points denoted by $\boldsymbol{n}$ in Equation 2.28. This is because it assumes that these data points are independently and identically distributed. Same as in the case of the AIC, given any two models, a model with lower value of the BIC is to be preferred.

Generally, the intuition behind these criteria is that they measure the difference between the true data distribution and the model distribution. Both criteria include a penalty that penalizes the free parameters in the model. These criteria are commonly used with the ML estimation method. Since ML maximizes the likelihood function, increasing the number of parameters would also maximize this likelihood. The penalties introduced by these criteria are there to correct for the case of over fitting the model (Liddle, 2008).

It should be recognized that these criteria are not to test for significance. The task is to select the model which serves as an approximation to reality, based not on the systematic discrepancy (induced by the population) or error of approximation but on the error of estimation of the model (Schermelleh *et al*., 2003). Therefore, the assumption of the estimation procedure must be

satisfied beforehand so that one can completely rely on these criteria in choosing a model among the competing models.

2.8.3 Variable transformation

The estimation methods discussed above are based on the assumption of multivariate normality of the data. Often this is a challenging task for researchers. However, there are several transformation methods that are employed in literature that ensure that one is working with normally distributed data. Transformation is necessary because as Osborne (2010) states that when the relevant theoretical assumptions relating to a selected method of estimation are satisfied, the usual procedures can be applied in order to make inferences about unknown parameters of interest.

Osborne (2010) further discussed that when the assumptions are violated, one of the options the researcher are left with is to design a model that has important aspects of the original and satisfy the assumptions by applying a proper transformation to the data. One of the widely used transformation methods is the Box-Cox transformation technique.

The Box-Cox transformation technique is a member of class of transformations called the power transformations. Power transformations are transformations that raise numbers to an iterative exponent that provide a range of opportunities for closely calibrating a transformation to the needs of the data (Osborne, 2010). This implies that a better transformation among that range of opportunities is the one which provide data that are as close as possible to being normally distributed. It is defined as:

$$y_i^{\lambda} = \begin{cases} y_i^{\lambda} - 1)/\lambda; & \lambda \neq 0 \\ log(y_i); & \lambda = 0 \end{cases} \qquad (2.29)$$

Where

y_i represents the observation in the variables of interest and

λ is the transformation parameter defined on a specific range.

The value of λ is found by maximizing a likelihood function and there are several approaches such as ML or Bayesian methods as discussed in Sakia (1992).

In this application, the method of interest is the maximizing normality function of the SAS Enterprise Miner. This method is similar in application to Box-Cox transformation in the sense that it also raises the numbers to an exponent. The advantage of this method is that it is a built in function within the SAS Enterprise Miner software and is accessible with the click of a button.

This type of transformation is defined as the best power transformation from among a range of available transformers such as the square root transformation, logarithm transformation and etc. To find the best transformation that maximizes normality, sample quantiles from each of the available transformations are compared with the theoretical quantile of a normal distribution and the transformation that yields quantiles closest to the normal distribution is chosen (Kattamuri, 2007).

However, before considering transforming the data, a test for normality should be undertaken. Park (2008) discussed several graphical and numerical methods for analyzing normality in the data.

2.8.4 The Scale Reliability

The use of latent variables in CFA or more generally in SEMs permits estimation of relationships among theoretically interesting constructs. Raykov, Tomer and Nesselroade, (1991) stated that the approach supports the development and testing of models concerning their relative fit to the collected data.

Prior to undertaking CFA, one may want to identify how well the observed variables measure those constructs or latent variables. In practice, the widely used procedure to test this is called the scale reliability. The scale reliability is the measure of how well the observed variables measure a certain construct when applying a CFA or a SEM to the data. Hatcher (1994) defined reliability as the percentage of variance in an observed variable that is accounted for by true scores on the underlying constructs and is measured by the alpha coefficient. That is;

$$\boldsymbol{\alpha} = \left(\frac{\boldsymbol{N}}{\boldsymbol{N-1}}\right)\left(\frac{\boldsymbol{s^2 - \sum s_i^2}}{\boldsymbol{s^2}}\right) \qquad (2.30)$$

$\boldsymbol{\alpha}$ is the alpha coefficient, $\boldsymbol{N}$ is the number of variables that measure that construct, $\boldsymbol{s_i}^{\boldsymbol{2}}$ is the variance of the individual variable in the construct and $\boldsymbol{s^2}$ is the summated scale score variance, which is the variance of all observations in that construct (Hatcher, 1994).

As a rule of thumb, an alpha coefficient of 0.7 is considered acceptable (Hatcher, 1994). That is, the observed variables are measuring the underlying construct if the alpha coefficient is over 0.7. To measure how well a specific observed variable compare with the others that are deemed to measure the same construct, an item-total correlations can also be calculated.

Item-total correlation is defined as the correlation between an individual variable and the sum of the remaining variables in that construct if that specific variable is removed. If an item-total correlation is small, this implies that such variable is not measuring that construct it is deemed to have been measuring. This suggests that it should be dropped (Hatcher, 1994).

2.8.5 The Model Modification Indices

Estimation of models is an iterative process. If the initial model does not fit the data, a researcher often considers re-specifying the model in order to arrive at a model which best fit the data. There are several indices which most computer software provides for easy modifications of the model.

These indices provide information whether certain parameter should be fixed by assigning to them a specific value or those that were fixed should be freed in the specification for estimation. The information for freeing parameters is provided by the Lagrange multiplier test while the information for the former is provided by the Wald test.

The basic intuition of these indices is based on the null hypothesis that the model fits the data. The Lagrange Multiplier starts with the null hypothesis that the model fits the data and identifies whether moving towards the alternative hypothesis is an improvement (Engle, 1984). The test is accompanied by a goodness of fit statistics such as the chi-square test. Therefore, the test determines whether adding parameters to the model would significantly improve the goodness of fit statistics or not.

On the hand, Engle (1984) stated that the Wald test begins at the alternative hypothesis and tries to improve the model by identifying which parameters would significantly improve the goodness of fit statistic if they are either removed or fixed to a specific value.

2.9 Overview of the Namibian economy

2.9.1 Geographic location

Namibia is situated in Southern Africa, neighboring five other countries namely Angola, Botswana, Zambia, Zimbabwe and South Africa. It is a middle income country with a total population of just over two million. Since gaining independence in 1990, Namibia recorded economic growth which fluctuates with the development of the regional and world economies.

Namibia's economy is heavily dependent on South Africa which is the major economy in the region. This is because Namibia is a member of the Common Monetary Area (CMA) where South Africa continues to set monetary and exchange rate policies. Also, the Namibian dollar which was issued in 1993 is pegged to the South African Rand. As a result the Rand is a legal tender in Namibia. This agreement ensures further that the Namibian Dollar is at par with the Rand.

The economy is structured in five sectors namely, real sector, fiscal sector, monetary sector, price sector and labour sector. Practically, the Real Sector determines the demand function. The Fiscal Sector deals with revenues and expenditures of the government. The monetary sector estimates the broad money aggregates functions and the price sector attempts to capture factors influencing the domestic price level. (Tjipe, Nielsen and Uangata, 2004). The labour sector deals with employment and unemployment issues.

2.9.2 Review of the Economic Models

The Namibian economy is very young, hence there have been relatively few attempts in modelling its macroeconomics. One of the first models was the Namibian Macroeconomics Framework (NAMAF), developed in 1993. This model was revised to what is called the Revised Minimum Standard Model-Extended (RMSM-X) of the World Bank. The former was structured mainly for the short and medium term planning in order to be used for public expenditure review in accordance with the first Namibian Development Plan (NDP1) (Tjipe *et al*., 2004).

However, with the intense involvement in the world economy and especially being a member of the regional and international monetary policy organizations such as the Southern African Custom Union (SACU), CMA and the International Monetary Fund (IMF), there exists a need to

develop a more complex model not only for the short and medium terms but for the long term as well.

The National Planning Commission (NPC), Bank of Namibia (BON) and the Ministry of Finance together with the Namibian Economic Policy Research formed the Macroeconomic Modelling Working Group (MEMWOG). According to Tjipe *et al*. (2004), this group was formed to facilitate the future course of action with regard to model development in Namibia. This new development, having acknowledged the groundwork of the NAMAF, extended its usefulness in to the RMSM-X in early 1995, resulting in the Namibian Macroeconomics Model (NAMMAC).

As earlier stated, the Namibia economy is relatively young, and these models customarily suffered from what faces all the developing economies. Timely available data and information deficiency are some of the daunting tasks many developing countries are faced with. Such limitation of data has dealt a heavy blow to sustainability of these models and hence formulations of concrete policies. Since most of the key macroeconomic variables were never available and if they were, they were limited and unreliable. This deficiency can be attributed to the previous administration in the country where data were gathered only to support their policy but were never really representative of the whole economy.

Generally, this is what constitutes the limitation which NAMMAC suffered. The failure to incorporate a labor market, the financing aspects related to fiscal deficits and the use of inflexible production on the supply side (Tjipe *et al*., 2004). One can only attribute such misspecifications to the lack of information or data in those aspects.

Another weakness identified by Tjipe *et al*. (2004) is the recursive nature of NAMMAC in solving macroeconomic variables. NAMMAC ignores the simultaneous nature of the key macroeconomic variables. It is generally believed that there is a strong co-movement in macroeconomic factors. And the nature of the model in dealing with individual macroeconomics was not a solution into studying the overall structure of the economy. The only way to understand the underlying mechanisms was to model all the economic sectors simultaneously.

As such, Tjipe *et al*. (2004) proposed the NAMEX in 2004. NAMEX is a well developed model which represents all the major sectors of the Namibian economy (real, fiscal, monetary, price and labour). In contrast with the past models in which the fiscal policy was understood to be the main

influence of the economic outcomes, this model represents and highlights all the influences of all these other sectors. Hence it attempts to model the Namibian economy, its evolvement, performance as well as perhaps forecasting the future which is necessary for policy formulation.

The NAMEX is a pure time series econometric model. This only suffices in a way that macroeconomic variables are captured as time series data. In estimating the model, several econometric approaches were considered such as cointegration and unit root tests. These approaches are done to understand the data generating mechanisms before any attempt is made to estimate the models. However, the resulting procedures especially differencing, is understood to carry a penalty of losing important information in the data.

2.9.3 The Real Sector

The Namibian real sector is distinguished by what is called the national identity or the national output, which is basically the Gross Domestic Product (GDP). The GDP is taken as a function of private consumption, private investments, total government expenditure and the trade balance. The government expenditure is the sum of public consumption and investments. Since Namibia is a foreign trading economy country, the trade balance which is the difference between the exports and the imports has also an influence on the national output and is hence included.

In reality, these variables that make up the national output cannot be viewed as exogenous variables. They are further influenced by other factors outside the system. For instance, private investment is further influenced by the change in capital stock and the world consumer price index taken as a weighted average consumer price index of the five major trading partners of Namibia (Tjipe *et al*., 2004).

2.9.4 The Fiscal Sector

The fiscal sector is identifiable by the budget deficit defined by Tjipe *et al.* (2004), as an excess of the total government expenditure over the total government revenues. As in the case of variable identifying the national output, the total government expenditures and the total government revenues are functions of other variables outside the system. The total government revenue is defined to be influenced by both taxes of the government. On the other hand, the total government expenditure is a function of all the government spending which includes the wages,

interest payments on debts, subsidies and transfers as well as the government expenditure on goods and services. Furthermore, the government expenditure of goods and services is defined as the function of nominal gross domestic produces and inflation rate. (Tjipe *et al*., 2004).

Assuming that the variables which make up the national output and the fiscal budget deficit are exogenous implies that those variables outside the system were measured without error or that their measurement errors are captured in the error of their respective functions.

2.9.5 NAMEX Representation of the Real and Fiscal Sectors

In the NAMEX, each sector represents a unique structural function. There are five and three structural functions for the real sector and the fiscal sector respectively. The NAMEX model in terms of the two sectors took the form:

(i) The Real Sector is defined as:

$$\boldsymbol{Y_t = CP_t + IP_t + G_t + (X_t - M_t)} \tag{2.31}$$

Where

$$\boldsymbol{CP_t = YD_t + \varepsilon_t}$$

$$\boldsymbol{IP_t = YD_t + CPIW_t + \Delta K_{t-1} + RIR_t + \varepsilon_t}$$

$$\boldsymbol{G_t = CG_t + IG_t + \varepsilon_t}$$

$$\boldsymbol{X_t = YW_t - RER_t + \varepsilon_t}$$

$$\boldsymbol{M_t = GDEN_t - (MPI_t - CPI_t) + \varepsilon_t}$$

(ii) The Fiscal sector is defined as:

$$\boldsymbol{GBD_t = TGE_t + TGR_t} \tag{2.32}$$

Where

$$TGE_t = TDT_t + TIDT_t + NTGR_t + \varepsilon_t$$

$$TGR_t = WS_t + GEGS_t + IPD_t + ST_t + GCN_t + \varepsilon_t$$

$$GEGS_t = YN_t + InfR_{t-1} + \varepsilon_t$$

Table 2.1 describe the variables in Equation 2.31 and 2.32.

Table 2.1 Variables description

Variable	Description	Variable	Description
CG	Public consumption	MPI	Import price index
CP	Private consumption	NTGR	Not tax government revenues
CPI	Consumer price index	RER	Real exchange rates
CPIW	World consumer price index	RIR	Real interest rates
G	Government expenditure	ST	Subsidies and transfers
GBD	Gross budget deficit	TDT	Total direct taxes
GCN	Government capital expenditure	TGE	Total government expenditures
GDEN	Nominal gross domestic expenditure	TGR	Total government revenues
GEGS	Government expenditure on goods and services	TIDT	Total indirect taxes
IG	Public investments	X	Exports of goods and services
InfR	Inflation rates	Y	Gross domestic produces
IP	Private investments	YD	Disposal income
IPD	Interest payment on debts	YN	Nominal GDP
K	Capital stock	YW	World GDP
M	Imports of goods and services	WS	Wages and salaries

The NAMEX model was developed to analyse different time periods which are, the period before independence and the period after independence. In most of the single equations estimated, dummy variables were included for those periods. The single equations which are proposed by the theory are indicating some contrasting results in the model. For example, the real interest which is proposed to be influencing the private consumptions was not significant in that specific single equation. Therefore, it was not included in Equation 2.31. Note that, Equation 2.31 and 2.32 are the resultant estimation of the two sectors.

However, the insignificance of variables in their single equations was not a problem in NAMEX because the cointegration approach that is used, as typically of time series analysis, proved to illustrate some relationships of linear combinations between the variables. Therefore, some of the NAMEX parameters significances in Equation 2.31 and 2.32 are based on the approach of cointegration. The justification of this approach is not based on the statistical parameter

significance but it is rather based on how the estimated model performs with regard to forecasting. In the NAMEX model, the significances of the single equations were interpreted with regard to how the forecast of that specific variable falls within the standard error bands.

Chapter 3

Methodology

3.1 Sources of Data

Data to be employed in this study constitute all the available macroeconomic data for the Namibian economy. Since most data started being readily available and independently collected only after the 1990's, it was initially stated that only that period would be studied. However, sufficient effort was made to obtain series of data from as early as 1983. The Bank of Namibia (BON) provided most of the data especially those that were used in the NAMEX model.

Previous studies have also obtained some series from the International Financial Statistics (IFS) of the IMF. The Research Department of the BON and the Economic Division of the NPC are the two bodies responsible for updating the Namibian profile at the international organizations. Those institutions are the other sources of the data employed in this study. The rest of the data, especially the international data for Namibia's major trading partners, was obtained from the Federal Reserve Bank of St. Louis (FRED) website (stlouisfed, n.d.).

3.2 Analytic techniques

3.2.1 Model specification

This stage firstly focuses on the development of the model. Since the first objective makes no hypothesis about the co-movement of the variables, it would be proper to start the specification stage by a well defined explanatory analysis and to intuitively draw up the path diagram depicting the relationships between the variables.

Secondly, relying on and acknowledging the specification of the NAMEX model, the Namibian economy was specified in this manner. There were 16 equations in total representing the four sectors, nine of those are stochastic and seven are identities. The NAMEX evaluated four of the five sectors of the Namibian economy. However, due to the data limitation stated earlier, our model would aim to evaluate and estimate only those sectors (real and fiscal) where data is deemed sufficient both in terms of sample size and availability.

As stated earlier, in the NAMEX, each sector represents a unique structural function. Those Equations can be represented in a path diagram as in **Figure 3.1.**

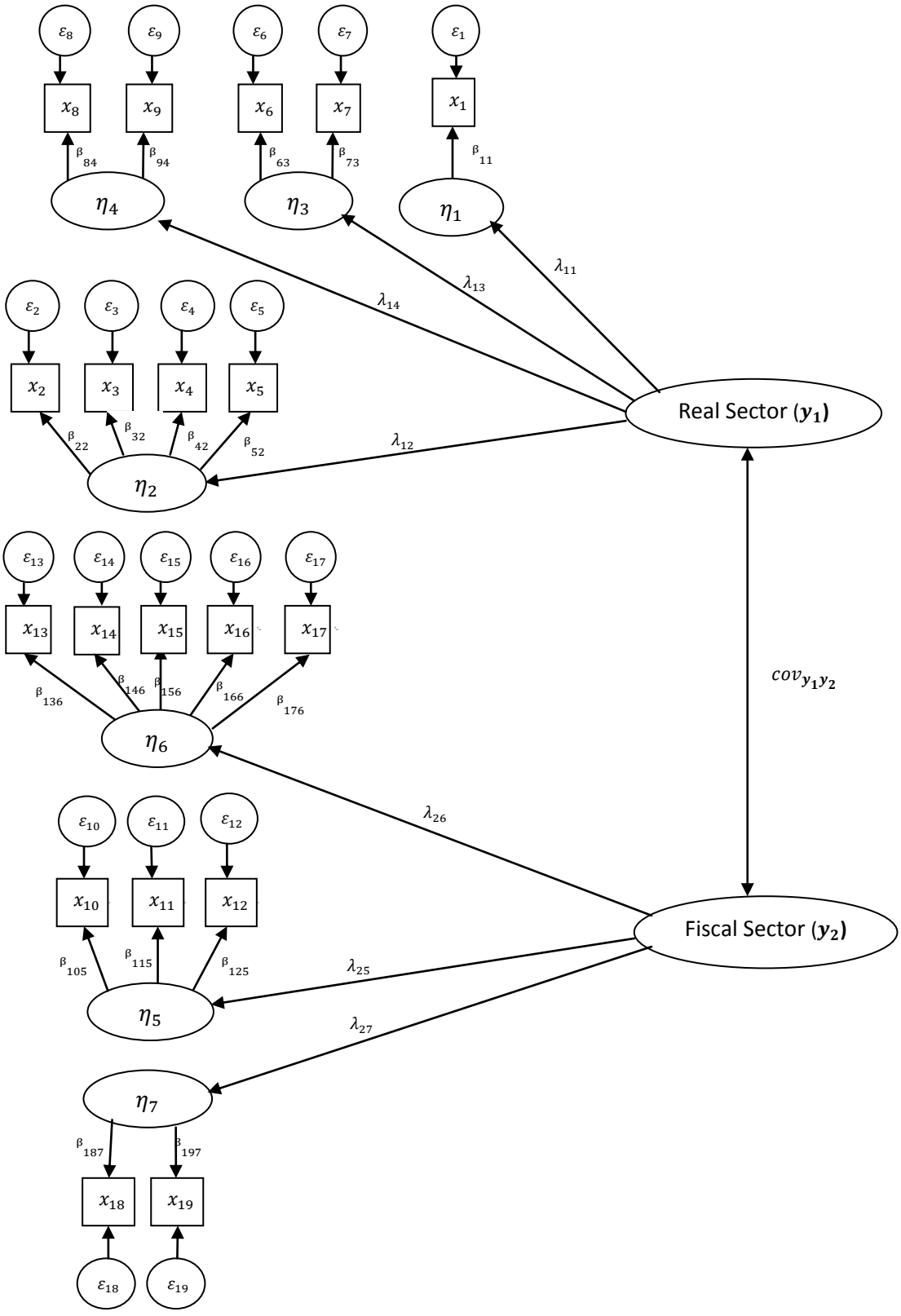


Figure3.1 NAMEX representation

Figure 3.1 can be viewed as a second-order confirmatory factor analysis model. Regardless of how NAMEX was identified, the justification of this limitation is only based on the methods of estimations in SEMs which requires that for identification, the number of observations should be larger than the number of parameters in the model as illustrated by Equation 2.11.

Equation 2.31 and 2.32 of Section 2.9.5 provided the theoretical specification for the model we considered to estimate for the Namibian economy with regard to the two sectors. However, note that this specification is based on the already estimated NAMEX model. We have indicated in Section 2.9.5 that there are variables such as interest rates for the private consumptions that are not significant in their single equations and therefore, are not included in that specification.

Note that **Figure 3.1** above is not a complete representation of the Namibian economy but only depicts the two sectors to which this application is of interest, due to the inevitable limitation of the small sample size. It shows how we intended to model the two sectors. The specification is drawn from the theoretical basis provided in the NAMEX concerning only the real and fiscal sectors. The two sectors are the latent variables in the model.

Table 3.1 NAMEX variable definitions

Variable	Description	Variable	Description
η_1	Private consumption	x_7	Public investments
η_2	Private investments	x_8	Exports of goods and services
η_3	Government expenditure	x_9	Imports of goods and services
η_4	Trade balance	x_{10}	Total direct taxes
η_5	Total government expenditures	x_{11}	Total indirect taxes
η_6	Total government revenues	x_{12}	Not tax government revenues
η_7	Government expenditure on goods and services	x_{13}	Wages and salaries
x_1	Disposal income	x_{14}	Government expenditure on goods and services
x_2	Disposal income	x_{15}	Interest payment on debts
x_3	World consumer price index	x_{16}	Subsidies and transfers
x_4	Capital stock	x_{17}	Government capital expenditure
x_5	Real interest rates	x_{18}	Nominal gross domestic produces
x_6	Public consumption	x_{19}	Inflation rates

The variables are as defined in **Table 3.1**. Note that disposable income is an exogenous variable in both private consumptions and investments. Also, government expenditures on goods and services, which is an endogenous variable is one of the exogenous variables in total government revenues. That is the reason why those variables, disposable income and government expenditure on goods and services appear twice in the table.

However, such a specification (**Figure 3.1**) would hardly work in our application because of the sample size we have. Defining such specification would result in 47 parameters (19 $\boldsymbol{\beta_i}$'s, 7 $\boldsymbol{\lambda_i}$'s, 19 error terms for each exogenous variable and two disturbance terms for the latent variables) to be estimated which is more than 27, the number of observations in our sample size. This is impossible for identification with reference to Equation 2.11.

The special objective of the specification above is to aid in understanding the two economic sectors. For us to identify variables that we should include in the model, we have to set assumptions with regard to how the variables would be used in our model and that theoretical specification is of such importance.

The most important adjustment we wish to make for our model is to utilize some of the endogenous variables in Equations 2.31 and 2.32 as our exogenous variables. This practice necessitates that the specification in **Figure 3.1** is broken down so that each exogenous variable is significant in the construction of our $\boldsymbol{\eta_j}$'s. One method we can employ is performing an OLS on the single Equations of 2.31 and 2.32.

However, since one of our objectives is to compare methods of estimations, we would simply specify our model with those variables as exogenous and check for consistency of parameter estimates between those estimation methods. There are two conditions under which the comparison of those estimation methods are brought into perception and one of them is the misspecification of the models (Olsson *et al*., 2000). The other as earlier discussed, is the multivariate normality assumption of the variables.

The latent variables comprise of different other variables. Therefore, performing the scale reliability would enable us to determine whether those variables that made up such constructs are indeed measuring that constructs with some degrees of significance. The variables which are not significant will be discarded from our application.

Such a process would enable us to construct our $\boldsymbol{\eta_j}$'s that we will use as our exogenous variables without losing the importance of the economic background incorporated in them and hence we will split the path diagram in **Figure 3.1** into two parts. The first part involving testing of significance of exogenous variables $\boldsymbol{x_i}$'s in making up the endogenous variables $\boldsymbol{\eta_j}$'s and the second and final model part with $\boldsymbol{\eta_j}$'s as exogenous variables.

This whole process of breaking down the model into two parts will be forced upon us due to the limited sample size. Therefore, splitting will be necessary so that we are remaining with a model adequate for our small sample size. This would prevent the number of parameters from becoming too overwhelming and consuming too many degrees of freedom from our model to the extent that the model becomes unidentifiable.

Therefore, the assumptions we wish to make are:

***Assumption 1*:** The exogenous variables $\boldsymbol{x_i}$'s were measured without error and they are indeed representing the economic theory in Equation 2.31 and 2.32. This assumption would allow us to use endogenous variables as exogenous variables in the model.

Assumption 2: The variables are multivariate normal. This assumption would enable our estimation methods to perform with consistency as it was discussed in Section 2.6

3.2.2 The Proposed Model

In the light of the limitation of this study, we propose a very simple model for estimation. We have indicated that there is no sufficient sample to estimate a full SEM for the Namibian two economic sectors that we have specified in **Figure 3.1**. Such limitation has forced us to set prior assumptions with regard to the model specification.

We will acknowledge the NAMEX specification that the real sector is caused by the Private Investment (IP), the Public Consumptions (CP) and the Government Expenditures (G). The Trade Balance (TB) is defined as the difference between the Exports (X) and Imports (M). The Government Expenditure comprises of Public Investments (IG) and Public Consumptions (CG).

The idea is therefore to utilize imports, exports and public investments, public consumptions instead, if they are significant in their respective estimation of the trade balance and the government expenditures respectively.

Therefore, if assumption 1 is satisfied, the real sector will be defined in our study as:

$$\boldsymbol{Real} = \boldsymbol{IP} + \boldsymbol{CP} + \boldsymbol{CG} + \boldsymbol{IG} + \boldsymbol{X} + \boldsymbol{M} + \varepsilon \quad (3.1)$$

On the other hand, we will specify the fiscal sector to be caused by the gross budget deficit which is defined as the difference between the Total Government Expenditures (TGE), the Total Government Revenues (TGR) and the Government Expenditures on Goods and Services (GEGS). Again, we are utilising the Nominal Gross Domestic Product (YN) as the measure of the government expenditure on goods and services. Therefore we will technically represent the fiscal sector as:

$$\boldsymbol{Fiscal} = \boldsymbol{TGE} - \boldsymbol{TGR} + \boldsymbol{YN} + \boldsymbol{\varepsilon} \quad (3.2)$$

Where $\boldsymbol{IP}$, $\boldsymbol{CP}$, $\boldsymbol{CG}$, $\boldsymbol{IG}$, $\boldsymbol{X}$, $\boldsymbol{M}$ $\boldsymbol{TGE}$, $\boldsymbol{TGR}$ and $\boldsymbol{YN}$ are our new exogenous variables justified by virtue of satisfying assumption one. In the event of this assumption not satisfied, we will continue with the estimations under the condition of misspecification.

Figure 3.2 represents a path diagram for the model which we deem sufficient for estimation under the circumstances of the small sample size. The model is specified with two latent variables representing the sectors.

The exogenous variables as described above are the private investments, private consumptions, public investments, public consumptions, imports and exports for the real sector and total government expenditures, total government revenues and nominal gross domestic products for the fiscal sector. The arrows from the latent variables to the endogenous variables represent the model coefficients which are the loadings in this simple specification. There are nine standard error terms for each exogenous variable.

Tjipe *et al*. (2004) highlighted that since the nominal output of the country is used as a scale in many fiscal sector equations, the two sectors are expected to co-vary. This is represented by the double arrow between real and fiscal in the diagram. Notice that, **Figure 3.2** is only the part that

consist of the link between the latent variables and the endogenous (now our exogenous) variables in **Figure 3.1**.

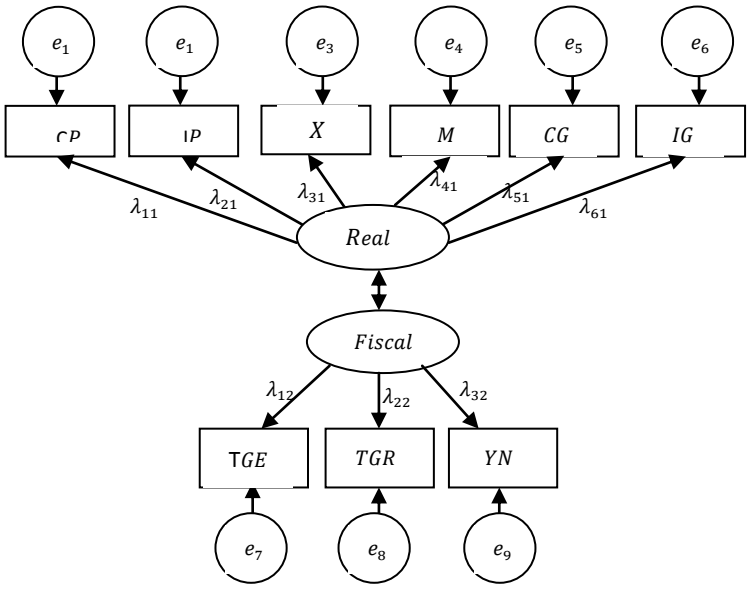


Figure 3.2 Model specification

Therefore the model is compactly defined as:

$$\boldsymbol{\eta_i} = \boldsymbol{\Gamma Y_i} + \boldsymbol{\varepsilon_i} \tag{3.3}$$

Where

$\boldsymbol{\eta_i} = (\boldsymbol{\eta_i}, \boldsymbol{\eta_2}, \dots\dots, \boldsymbol{\eta_9})'$ is a $(\mathbf{9} \times \mathbf{1})$ vector of exogenous variables,

$\boldsymbol{\Gamma}$ is a $(\mathbf{9} \times \mathbf{1})$ vector of $\boldsymbol{\lambda}$ coefficients,

$\boldsymbol{Y_i} = (\boldsymbol{y_1}, \boldsymbol{y_2})$ is a $(\mathbf{2} \times \mathbf{1})'$ vector of the latent variables and

$\boldsymbol{\varepsilon_i} = (\boldsymbol{\varepsilon_1}, \boldsymbol{\varepsilon_2}, \dots\dots, \boldsymbol{\varepsilon_i})$ is a $(\mathbf{9} \times \mathbf{1})$ vector of the error terms.

Furthermore, note that the specification in **Figure 3.2** is only for the proposed model to evaluate the structure and relationships among the variables (Proposed based on the available variables to be used in this study due to limited sample size). A thorough investigation will be conducted at the stage of model building where the model would be evaluated with the help of model modification indices and parameter significances.

3.2.3 Model Estimation

Perhaps the most important stage of the application is the estimations of the models that will enable the comparison of model parameters for this analysis. This stage is where we would evaluate the model adequacy. Theory purports that under assumption of multivariate normality of SEMs, ML and GLS produce consistent estimates of parameters (Olsson et al., 2000).

Therefore, the study wishes to compare results between the ML and GLS estimations methods under conditions of such violation of normality assumptions and model misspecifications as stipulated in the study objectives. Note that **Figure 3.1** and **Figure 3.2** are the graphic representation of the prior information contained in the NAMEX model. **Figure 3.1** is the NAMEX model and **Figure 3.2** is the proposed model for this application under the limitation of the study (limited sample size) as discussed in Section 1.3. This application intent to develop a SEM in light of the information contained in those models.

3.2.4 Statistical Software

Ranging from the now available *sem* library in R, there are other software such as, SAS Enterprise Miner as well as the SAS Enterprise Guide which are highly fluent especially in our specification and identification stages. However, we intend to utilize SAS for this study particularly, for estimating the models.

Chapter 4

Analysis and Results

4.1 Introduction

This chapter provides the analysis and the results of this application. The chapter is divided in two sections based on the objectives of the application. The first section (Section 4.2 to 4.4) deals with data management and the study of relationships among the variables as well as their structures. It also contains the development of the measurement model. The second section (Section 4.5) deals with the estimation of the SEM. It also provides the comparison of different methods of estimations under conditions specified in the objective.

4.2 Description of Data

This section begins by studying the raw data of the variables used in this study. The variables included in the application are those specified in the NAMEX specification of **Figure 3.1**. **Appendix A.1** provides the graphical representation of the variables over the period from 1983 to 2009. As it is always a trend in macroeconomic variables, the plots seems to show an increasing patterns over time. However, some series display some unusual trends either a sudden drop or a rise during some periods included the study.

These patterns are better explained in econometrics as either variable are stationary, which imply that there are no changes in their evolvement, or the variable are not stationary, which in simple terms means that they meander over the time. Stationarity is essential in time series analysis. In this study, we observe this variables and determine whether they are normally distributed or not by using formal statistical normality tests such as graphical or numerical methods.

One of the variables that display an unusual pattern is the Trade Balance (TB). The plot displays two steep drops. The first drop was experienced during the period from 1991 to 2000 and the second steep drop was experienced in 2004. By definition, the trade balance is the difference between the exports and the imports. Therefore, in those periods, the trend illustrated by the plot depicts that there was more imports coming into the country than the country was able to export.

The other variable which causes concerns is the Gross Budget Deficit (GBD) which is defined as the difference between the Total Government Expenditures (TGE) and the Total Government

Revenues (TGR). The plot shows that the deficit was consistent and positive during the period from 1983 to 1995 and starts to increase slightly during 1995 to 2003. The biggest concern is shown by a very steep drop around 2006. This implies that the government was spending more than it was receiving during that period.

Another concern was highlighted by the Public Investments (IP) which displays two sudden rises in 1999 and 2001. Interest Payments on Debts (IPD) displays what perhaps an econometrician would describe as a policy change by seeming to have started over from 1993. However, it displayed the rising pattern from there again which is the same as it was before 1993.

Inflation Rates (InfR) have a sharp high peak in 1992 and lower peak in 2005. Beside an economic explanation for the 1992 peak, it is possible this observation could be an outlying observation because it is not consistent with the whole pattern depicted by the plot. Furthermore, the sample started only from 1990 for inflation rates, Subsidies and Transfers (ST) as well as Real Interest Rates (RIR). Fortunately, these variables were not used extensively in this study other than checking for their significances in their single equation by OLS in which case only that period was used for all the involved variables.

The most anticipated plot was displayed by the Non Tax Government Revenues (NTGR). It shows what looks like a definite policy change in periods before and after 1990. We expected this display for most of the variables because of the change in government in 1990. However, no other variables displayed such trend.

There exist many economic explanations such as changes in relative price levels which affects the gross domestic expenditures on the side of imports or changes in the exchange rates, which affects the exports. However, the economic explanations of such theories are beyond the scope of this study. This study only necessitate that the variables that are dealt with are normally distributed and attemps to explain the resulting trends from the estimated models. The rest is left to the policy analysts, economists and econometricians to deduce what might have happened in those concerned periods.

4.3 The Normality Assumption check

In this section we formally test whether the variables are normally distributed. We begin by checking whether the normality assumptions are satisfied in the data. The test is conducted using

the Shapiro-Wilk test, which only requires that the sample size be greater than seven. **Table 4.1** below provides the significance tests for the Sapiro-Wilk statistic for the variables under consideration. The procedure tests the null hypothesis that the data are from a normal distribution against the alternative that they are not from the normal distribution.

Table 4.1 Normality significance test

Variable	W-Statistic	P-value	Variable	W-Statistic	P-value
CP	0.8714	0.0073	CG	0.9444	0.1563
IP	0.8636	0.0022	IG	0.9117	0.0250
G	0.9353	0.0931	X	0.9438	0.1508
TB	0.8038	0.0002	M	0.8492	0.0010
TGE	0.8669	0.0025	TDT	0.8437	0.0009
TGR	0.8442	0.0009	TIDT	0.8330	0.0005
GEGS	0.9008	0.0140	NTGR	0.8765	0.0040
Y	0.9026	0.0154	WS	0.9040	0.0166
GBD	0.8956	0.0106	IPD	0.8390	0.0007
YD	0.9217	0.0433	ST	0.8861	0.0275
CPIW	0.9554	0.2895	GEC	0.7531	0.0001
K	0.8156	0.0003	YN	0.8585	0.0017
RIR	0.9421	0.2876	INFR	0.9398	0.2614

The variables that have a distribution significantly different from the normal distribution are highlighted. This implies that, at 95% confidence level, there exist 13 variables that have a distribution significantly different from a normal distribution.

These are the variables that need to be transformed. Before one considers transforming the variables, a thorough investigation of the variables should be undertaken. In this study, the distributions of those variables found not normally distributed are further investigated for discrepancies such as skewness. **Appendix A.2.1** at the end of the study provides the plots of the variables probability density functions for the normal distribution. The R code used in computing the probability density functions is provided in **Appendix A.2.2**.

Skewness and kurtosis statistics which show how the distributions of the variables deviate from the normal distributions are provided in **Table 4.2**. The table includes only those variables which are found not to be normally distributed at 95% confidence level by the W-statistics test performed earlier. For the rest of this study, only the 95% confidence level for normality test is considered.

Table 4.2 Variables normality deviation and transformations

Variable	Skewness	Kurtosis	Transformation
CP	0.8713	-0.3312	log (CP)
IP	1.0431	0.1386	log (IP)
TB	-1.9903	4.7688	$(TB + 12450)^2$
TGE	1.1288	0.5913	log(TGE)
TGR	1.1321	0.2384	log(TGR)
K	1.1684	0.3287	log(K)
M	1.2543	0.9460	log(M)
TDT	0.9720	-0.3062	log(TDT)
TIDT	1.2562	0.6828	$\sqrt[4]{TIDT}$
NTGR	0.9387	-0.2671	log$(NTGR)$
IPD	0.6886	-1.0852	log(IPD)
GCE	1.8816	3.2191	log(GCE)
YN	1.1139	0.3159	log(YN)

A variable may be considered normally distributed if the skewness and kurtosis are around zero and three respectively. In **Table 4.2** above, only Government Capital Expenditure (GCE) has kurtosis statistic relatively close to three (3.2191) however, its skeweness statistic is far from zero at 1.8816. Furthermore, the kurtosis statistics of all the variables indicates distributions of thicker tails and lower peaks than a normally distributed variable with the exception of Trade Balance (TB) which has a higher peak and thinner tail than a normally distributed variable.

On the other hand, skewness statistic indicates that most of the variables have distributions skewed to the right except the Trade Balance (TB). This implies that, they have more observations on the left side while the trade balance has more observations on the right side than a normally distributed variable.

In the study, all the variables in **Table 4.2** were subjected to the SAS Enterprise Miner function (discussed in Section 2.8.3) of maximizing normality and all but Trade Balance (TB) and the Total Indirect Taxes (TIDT) were transformed by the logarithmic function.

The variables are entered and a maximizing normality command was issued that provides the maximum normality that can be attained with every variable. TIDT which is the total indirect taxes was transformed as it is fourth root while the TB, the trade balance, a constant is added to it and then it is squared. The reason why a constant is added is because of the negative values found in the trade balance which is the difference between the exports and the imports illustrating that Namibia imports more goods than she exports at certain periods.

4.4 Correlation and Regression

First and foremost, we wish to establish whether the variables at hand are related because it does not make sense to use factor analysis or principal component analysis if the different variables are unrelated. One should not attempt to model for common factors if they have nothing in common. As a rule of thumb, variables should have a correlation coefficient of at least 0.3 (Habing, 2003).

Table 4.3 indicates that all the variables are highly correlated with one another with the lowest correlation being 0.881 between Public Investments (IG) and Exports (X).

Table 4.3 The variables correlation matrix

Pearson Correlation Coefficients, N = 27									
	IP	CP	X	M	CG	IG	TGE	TGR	YN
IP	1.0000								
CP	0.9580	1.0000							
X	0.9480	0.9180	1.0000						
M	0.9640	0.9670	0.9520	1.0000					
CG	0.9520	0.9310	0.9370	0.9750	1.0000				
IG	0.9180	0.9140	0.8810	0.9520	0.9560	1.0000			
TGE	0.9120	0.9090	0.9370	0.9640	0.9600	0.9290	1.0000		
TGR	0.9100	0.8980	0.9380	0.9570	0.9520	0.9160	0.9960	1.0000	
YN	0.9100	0.8940	0.9390	0.9570	0.9550	0.9190	0.9980	0.9980	1.000

Secondly, it was stated that due to the limitation of the data, some of the endogenous variables in the study will be used as exogenous variables. To control for this, we set an assumptions (Assumption 1) in Section 3.2.1 which stipulates that those variables that are deemed to be

influencing the entered variables but not included in the models were measured without errors, a problem we would attribute to misspecification in this study.

To prove this misspecification if there is any, we have conducted regression analysis using OLS so that we are able to identify those relationships and whether those relationships are significant. This approach also serves as justification of the assumption we set with regard to the chosen exogenous variables.

This could be viewed in the sense that if those variables not included in the model are significant in estimating the endogenous variables (which are the model exogenous variables) then, we are able to draw conclusions that the entered exogenous variables were measured without or with minimum errors. In that way, the model is then able to capture the theoretical structure as stipulated in much more complex specification such as **Figure 3.1,** with only few variables. Significances of these variables in their single OLS regression equations would also enable us to place some statistical confidence in using them as exogenous variables or otherwise the model is misspecified.

Table 4.4 below is the SAS output of the regression analysis performed on the relevant endogenous variables that were entered as exogenous variables in this study. The dependent variables are listed in the left column. Indeed, there seems to be evidence of misspecification with regard to some variables which bring into question if we can rely on that theoretical specification of Equation 2.31 and 2.32 for our own specification. Accordingly, only Capital Stock (K) is significant in estimating the value of the Private Investments (IP).

With regard to the Total Government Expenditures (TGE), the Non Tax Government Revenues (NTGR) is not significant while Total Government Revenues (TGR) has only the Government Capital Expenditure (GCE) and Interest Payment on Debts (IPD) which are significant. Nonetheless, that is what this study is trying to evaluate, i.e., the performance of the estimating methods under conditions which are often encountered in practice such as misspecification of models or seldom met assumptions.

Table 4.4 Regression coefficients

	Parameter Estimates				
Dependent variable	Independent variables	Estimate	Standard Error	t Value	Pr > |t|
CP	Intercept	-26134	5685.8043	-4.6000	0.0003
	YD	1.7311	0.2006	8.6300	<0.0001
IP	Intercept	-178386	45820	-3.8900	0.0016
	YD	-0.0817	0.1254	-0.6500	0.5253
	CPIW	-37.6841	37.4743	-1.0100	0.3317
	K	16774	4437.5894	3.7800	0.0020
	RIR	51.2010	70.1811	0.7300	0.4777
TGE	Intercept	3.9414	0.4131	9.5400	<0.0001
	TDT	0.6336	0.1052	6.0200	<0.0001
	TIDT	0.1655	0.0402	4.1100	0.0009
	NTGR	-0.1804	0.1545	-1.1700	0.2612
TGR	Intercept	2.5794	1.2685	2.0300	0.0614
	WS	$-2.957 * 10^{-5}$	$2.49 * 10^{-5}$	-1.1800	0.2560
	IPD	0.1671	0.0611	2.7400	0.0161
	ST	$-5.517 * 10^{-5}$	$8.98 * 10^{-5}$	-0.61	0.5490
	GCE	0.78483	0.18642	4.21	0.0009

Since the model specification used in this study is based on the NAMEX which only evaluated a period up to 2004, we are adamant to conclude that Equation 2.31 and 2.32 where we based our specification are a result of model misspecification. With reference to **Appendix A.1**, we have seen radical changes in variables after 2004 for example the discussed Gross Budget Deficit (GBD). Other variables such as Government Expenditures (G), Public Consumptions (CP), Government Expenditure on Goods and Services (GEGS) and Inflation Rates (InfR) also seems to display a different pattern after 2004. This could affect the relationships among the variables in the light of the new observation since 2004.

There may be other factors which could not be overlooked such as change in economic policies which may result in different specification in the light of new information. Other factors such as world financial depressions may have contributed to the evolution of the data in this context which could also significantly change the relationships among the variables.

Nonetheless, for this study, there is sufficient evidence that **Assumption 1** that we set as a priori is not satisfied. Therefore, the rest of the study concentrates on the fact that, we have a serious

misspecification. In light of this information, the study proceeds with evaluating the performance of the estimating methods under such conditions which can never be ignored in practice.

4.5 Model Development

One of our objectives is to study the relationships among the Namibian macroeconomic variables. This objective can be constituted in two parts. The first is to identify the factor structure underlying the macroeconomic variables of the Namibian economy. The second part is to analyze whether that structure conforms to the theoretical structure as already specified in the context of the Namibian economy by studies such as NAMEX. These are two different applications in factor analysis. The first part is formally undertaken by the earlier discussed Exploratory Factor Analysis (EFA) and the second is evaluated using the Confirmatory Factor Analysis (CFA).

4.5.1 Exploratory Factor Analysis

It was highlighted that Principal Component Analysis (PCA) can be used as a first stage for FA. In addition it can be used as the data reduction mechanism. Its main purpose is to derive a relatively smaller number of components that can account for a large number of variables. In this study, the objective is to study the factor structure underlying the Namibian macroeconomics specifically those selected to represent the two economic sectors as specified in **Figure 3.2**. The attested variables are the exogenous variables of the model. **Table 4.5** below provides the summary statistics of the variables.

Table 4.5 Descriptive statistics

Means and Standard Deviations		
Variable	Mean	Std Dev
CP	20718.2630	5633.2703
IP	3924.1560	2419.1957
X	12902.7040	4081.6339
M	9.5390	0.3857
CG	7218.3300	1961.9968
IG	1914.3960	993.1701
TGE	8.5160	0.9537
TGR	8.3520	1.0507
YN	9.6520	1.0320

Table 4.5 shows that the scale of measurement is very different as shown by some means having larger values and other having relatively smaller values. This information is relevant so that during interpretation, one should use the standardised results or the results provided by estimating the models using the covariance matrices rather than the correlation matrices. To preserve the metric in this regard, this study used the covariance matrices as well as standardised results. However, in this section (Section 4.5.1) the correlation matrix was used as a result of the specified method of Squared Multiple Correlation (SMC) for extracting prior communality estimates. See for example **Table 4.6**.

EFA on the nine exogenous variables yields one factor accounting for 97% of the total variance proportion as shown in **Table 4.6** below. This indicates that the Namibian real and fiscal economic sectors can be estimated as one factor. However, we do not wish to make such conclusion because of the economic theory behind the sectors. We have stated that we will preclude such theory in the mean time such that we try to simply understand the structure within the raw data.

Another reason for not making any conclusions that the Namibian real and fiscal economic sectors can be represented as one factor is the earlier stated limitation of the sample size. With sufficient sample size the pattern might be very different and the misspecification we have encountered here might not exist.

Table 4.6 Factor analysis eigenvalues

Eigenvalues of the Reduced Correlation Matrix: Total = 8.77339148 Average = 0.97482128				
	Eigenvalue	Difference	Proportion	Cumulative
1	8.5030	8.3083	0.9692	0.9692
2	0.1947	0.1229	0.0222	0.9914
3	0.0717	0.0413	0.0082	0.9996
4	0.0303	0.0289	0.0035	1.0030
5	0.0014	0.0018	0.0002	1.0032
6	-0.0004	0.0010	-0.0001	1.0031
7	-0.0015	0.0074	-0.0002	1.0030
8	-0.0089	0.0080	-0.0010	1.0019
9	-0.0170		-0.0019	1.0000

Table 4.6 provides the output of the eigenvalues of the analysis. Notice that the program provides nine eigenvalues equal to the number of variables entered. However, the criterion that

only components, in this case the factors, with eigenvalue greater than one are retained implies we can only retain the first factor which is the only one with the eigenvalue greater than one.

An eigenvalue greater than one criterion implies that the observed variables contributed one unit of variance to the total variance in the data. That is, those components that are accounting for a greater amount of variance.

One implication of this eigenvalue greater than one criterion is retaining wrong number of components under circumstances when the communalities are small. **Table 4.7** below shows the communalities among the variables which are relatively high, justifying our decision to retain only one component.

Table 4.7 Communality estimates

Final Communality Estimates: Total = 8.697787								
CP	IP	X	M	CG	IG	TGE	TGR	YN
0.9595	0.9678	0.9213	0.9877	0.9642	0.9069	0.9971	0.9941	0.9991

The above results are typically of PCA. Without interpreting these results further, we proceed with FA which is more of interest in the study. This is because, due to the limited number of observations and therefore having limited variables to build the model, there is no need to reduce the number of variables, which is the main purpose of PCA.

The immediate objective is to examine whether the available variables conform to the theory. In terms of EFA, this is simply to see whether the variables that are entered would show a pattern reflecting that they are measuring the two sectors. This would be reflected in their factor loadings pattern. That is, those deemed to be measuring a specific sector should load highly on that respective sector.

In this study so far, it is highlighted that only the real and fiscal sectors are appropriate for evaluation due to the nature of data at hand. Therefore, according to our specification, the nine variables entered, have made up those two sectors. The main purpose here is to determine whether the number of constructs, in this case sectors, are two and whether the variables are loading significantly on their respective sectors as suggested by theory.

Like in PCA, determining the number of meaningful factors is the challenging task. One can simply not use the eigenvalue greater than one criterion in determining the number of factors. The reason why this is the case is because, each variable does not contribute one unit of variance, but instead contributes its prior communality estimates which will be less than one. This is also the difference between PCA and EFA. That is, they are either based on the priori assumption of whether retaining components or factors based on variance contribution or communality estimates.

An appropriate and widely used criterion is examining the scree plot. This is the plot of the eigenvalues against the number of possible factors which is always equal to the number of variables entered. The factors that appear below the elbow (the last big break) in the plot are usually deemed unimportant and hence they are normally not retained and only those above the elbows are retained (Hatcher, 1994).

Examining the scree plot below seems to confirm that in our analysis only one factor is sufficient for our data.

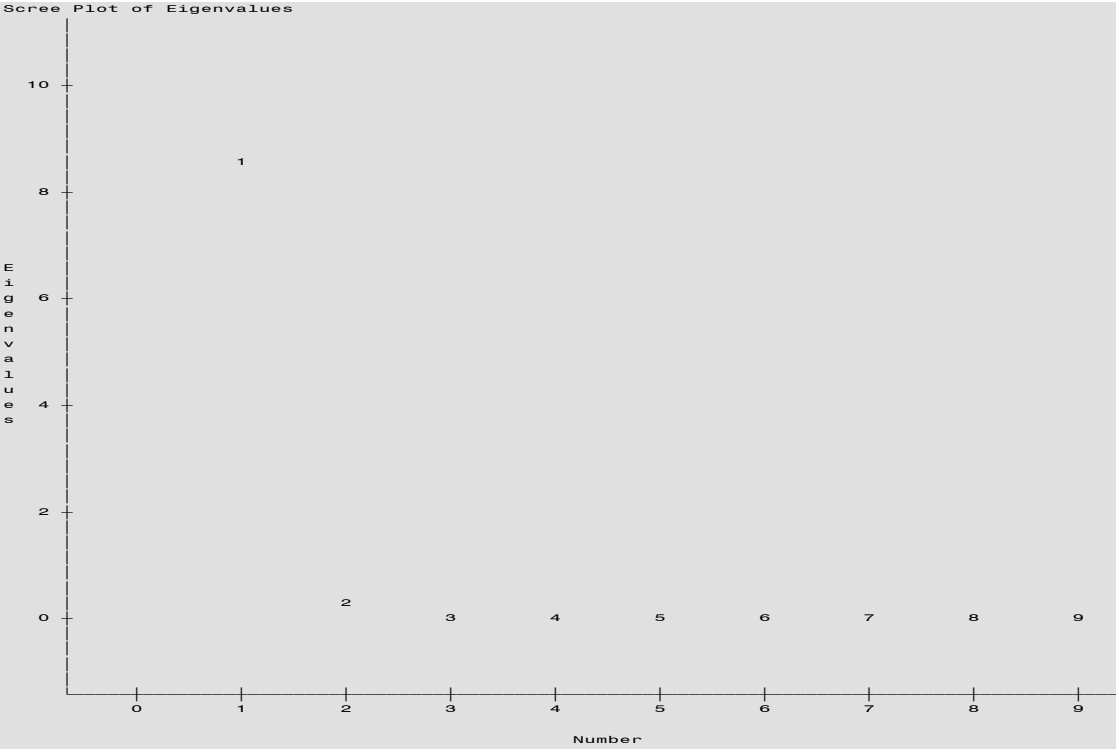


Figure 4.1 Scree plot of the eigenvalues

This method is based on the analyst intuition. One can also argue that two factors can be retained because looking at the diagram, the rest of the factors appear to have straightened out in a line but one and two. Notice that there is a big break between one and two implying once more that only the first factor should be retained for this analysis. The proportion of variance accounted for by factors is another criterion that can be used to determine the meaningful number of factors. This criterion is based on prior set percentage of the common variance. For example, factors that account for at least 5% or 10% of the common variance.

Table 4.6 provides the information needed for this criterion. According to this criterion, the proportions suggest that only one factor should be retained from this analysis at 5% of the common variance. This is shown by the first factor accounting for 96.92% of the common variance.

One can see how the proportions diminish right after the first factor. These proportions are calculated using the following formula.

$$\boldsymbol{proportion} = \frac{\boldsymbol{Eigenvalue\ for\ the\ factor\ of\ interest}}{\boldsymbol{Total\ eigenvalue\ of\ the\ correlation\ matrix}} \quad (4.1)$$

The SAS program that produced the results in this section is provided in **Appendix A.3.1**. Basically, the program requests simple descriptive statistics followed by Principal Factor (PF) as a method of initial factor extractions. Other methods such as ML can also be used. The method of prior communality estimate is specified as SMC between a given variable and the other observed variable, Hatcher (1994).

Since there are no assumptions made with regard to whether the factors are correlated, a varimax rotation method was employed. The coefficients are rounded off to the nearest integer by the round command so that they are easy to read. The nfact command specify how many factors should be retained and the flag command marks any factor loading whose absolute values is greater than a specified value, in this case 0.70. This value is set this high because of the nature of our sample size and hence limited number of variables.

For the rest of this section we would be attesting two different solutions for comparison. These solutions are based on the method of prior extraction of the factors whether is PF or ML. The models are specified with number of factors to be extracted as two and in each instance they are flagged with 0.70.

Table 4.8 below reproduces the eigenvalue of the two methods of factor extraction, ML and PF. The results coincide but according to ML method, four factors should be retained based on eigenvalue greater than one criterion. However, the proportion of total variance shows that one factor accounts for most of total variance in both cases whether the method used is PF or ML. The proportions of variance accounted for the first factor equals to 96.92% and 99.03% for PF and ML methods respectively.

Table 4.8 Eigenvalues and propotion of variances

	Principal component		Maximum Likelihood	
	Eigenvalue	Proportion	Eigenvalue	Proportion
1	8.5030	0.9692	1932.1636	0.9903
2	0.1947	0.0222	16.7107	0.0086
3	0.0717	0.0082	2.1942	0.0011
4	0.0303	0.0035	1.3331	0.0007
5	0.0014	0.0002	0.1413	0.0001
6	-0.0004	-0.0001	-0.0598	0
7	-0.0015	-0.0002	-0.2845	-0.0001
8	-0.0089	-0.0010	-0.4249	-0.0002
9	-0.0170	-0.0019	-0.6799	-0.0003

Let us now formally interpret the results of the two solutions. **Table 4.9** below shows the factor patterns of the PF method solutions. The table only contains the rotated factor patterns as the final solutions. The specification was set in a way that only factor loadings which are greater than 0.7 in absolute value are highlighted as significant. This makes it easier for interpretation.

There appears to be an indication that Private Investments (IP), Private Consumptions (CP), Exports (X), Imports (M), Public Consumptions (CG) and Public Investments (IG) are measuring the same construct. This is because they load highly and significantly on the first factor. On the other hand, the second factor has Total Government Expenditures (TGE), Total Government Revenues and Nominal GDP (YN) loading highly and significantly on it.

Table 4.9 Rotated factor patterns

Rotated Factor Pattern				
Principal component method				
	Factor1		Factor2	
CP	83	*	52	
IP	82	*	54	
X	70	*	66	
M	75	*	65	
CG	71	*	67	
IG	71	*	63	
TGE	58		81	*
TGR	56		82	*
YN	56		83	*
Printed values are multiplied by 100 and rounded to the nearest integer. Values greater than 0.70 are flagged by an '*'.				

Generally, one could easily form two constructs made up of those variables. In theory and according to the specification in **Figure 3.2**, one can easily see that the first factor represents the real sector while the second could be regarded as the fiscal sector of the Namibian economy. With these results, the Namibian economic structure in terms of the two economic sectors is sufficiently explored and hence the theory based on our specification hold in the Namibian context.

At this stage, one would proceed in estimating such factor models. We have established that without making any assumptions with regard to how the raw variables are expected to interact with one another, the exploratory stage of this application has given enough reason to believe that the specification can be estimated and be checked for model-data fit.

Also, one can see that the real sector dominates the fiscal sector with regard to how the model is specified. There are six variables loading highly and significantly on the real sector in comparison to the only three variables on the fiscal sector. This is true of the economy because the real sector is a generalization of the whole country economy as proposed by the theory. That is, it is defined by the national identity or aggregate demand for domestic consumptions which also include the government activities on which the fiscal sector is centralized.

The next stage constitutes estimating the model as specified in **Figure 3.2**. It would be interesting to compare how the different methods of estimation such as those discussed in Section 6.2 would perform. This process is carried out by the already discussed CFA.

4.5.2 Determining the model variables within their constructs

We have indicated in the methodology that due to the limited sample size, we would be utilizing variables as exogenous variables that in fact are endogenous variables. For example, in **Table 4.4**, Private Investments (IP) is a function of other variables such as Capital Stock (K), the World Consumer Price Index (CPIW) and etc.

For us to use them in the model as exogenous, we have set an assumption that the exogenous variables which made up those endogenous variables were measured without errors, an assumption which we were not able to satisfy in this study by virtue of OLS regression analysis performed in Section 4.4. This problem was later classified as model misspecification in this study. We have further indicated that we would be utilising the scale reliability discussed in Sections 2.8.3 to determine how well the exogenous variables as selected (whether they are indeed endogenous variables) measure those constructs. That is; their validity (as constructs) in our specification based on the **Assumption 1** we made in Section 3.2.1.

The specification in **Figure 3.2** has nine exogenous variables and two latent variables representing the two sectors.

Table 4.10 Factors alpha coefficients

Real Sector Alpha = 0.8720		
Variables	Correlation	Alpha
CP	0.9520	0.8490
IP	0.9760	0.8120
X	0.9420	0.7940
M	0.9870	0.9080
CG	0.9610	0.8290
IG	0.9320	0.8670
Fiscal Sector Alpha = 0.9980		
TDT	0.9970	0.9980
TIDT	0.9970	0.9970
YN	0.9980	0.9950

The alpha coefficient is calculated for a group of variables that are deemed to be measuring the same construct. **Table 4.10** above shows how the variables are arranged. The real sector is measured by Private Investments (IP), Private Consumptions (CP), Exports (X), Imports (M), Public Consumption (CG) and Public Investments (IG). On the other hand, Total Government

Expenditures (TGE), Total Government Revenues (TGR) and Nominal Gross Domestic products (YN) are deemed to be measuring the fiscal sector.

The computed alpha coefficients are 0.8720 and 0.9980 for real and fiscal sectors respectively. They are shown in the rows heading each sector in the table. Since both our alpha coefficients exceed 0.7, we have a good reason that our variables are good measures of the two sectors. The correlations provided in the table are the item-total correlations. They are all very high which suggests that all the variables are truly measuring their constructs.

The alpha values in the table indicates what the alpha coefficient would be looking if any of those variables are dropped from their respective constructs. There seems to be no indication to delete any of the variables. However, if Imports (M) is deleted from the real sector, the alpha coefficient would improve from 0.8720 to 0.9080. Nonetheless, that is not necessary as the coefficient is already in the acceptable range by exceeding 0.7 as a rule of thumb cut-off point.

In conclusion, conventional interpretation of reliability scales implies that scale reliability was assessed by calculating coefficients alpha. Reliability estimates were 0.8720 and 0.9980 for the real and fiscal sector of the Namibian macroeconomics respectively.

4.5.3 Confirmatory Factor Analysis

CFA deals with underlying theory. Most of the economic specifications are based on the theory regarding the effects of several variables on one another. In this context, a structural relationship between a sector and its respective indicator variables represents a specific economic theory.

In the previous section we have established that the entered variables are subjects of only two factors which in principle can be termed as the two sectors we are dealing with. This prior knowledge is not always available to the researchers and that is the reason why we have performed the EFA. CFA is used to test the fit of the measurement model for example, the one specified in **Figure 3.1**.

There are several assumptions which are imposed to the data before a CFA can be undertaken. One of the most important assumptions is that the variables must be normally distributed. The reason behind this assumption is that, most statistical tests used to check the fit of the model such

as the chi-square test, assume multivariate normal data. Anderson and Gerbing (1988) suggested the use of ML or GLS in estimating models when such assumption is not satisfied in the data.

In this study, we considered transformation of the variables as shown in **Table 4.1** of Section 4.3. However, we will also estimate these models with variables which are not transformed and compare the results. The reason for this approach is to evaluate the discrepancy of parameter estimates between different estimation methods (ML and GLS) when assumptions of normality as often encountered in practice are not met.

The second most important assumption as suggested by Hatcher (1994) is that there should be an absence of multicollinearity of the variables. This is further discussed in Grewal, Cote & Baumgartner (2004) that when multicollinerity is extreme especially in small samples, several Monte Carlo simulations show that it can cause problems in SEM estimations. Multicollinearity is the condition where exogenous variables exhibit a very strong correlation with one another. In this study, the variables have exhibited a high correlation, exceeding the correlation coefficient of 0.8 suggested as the threshold.

However, as earlier stated the variables are not observable, they are nonetheless taken as exogenous variables in this study. Those other variables not reflected in our model or measurement error as Grewal *et al.* (2004) discusses may have caused causal effect on several of these variables resulting in such high correlations.

With regard to this problem imposed by the limitation of the sample size, we wish to estimate a non self-contained model anyway, i.e., some non-trivial causes are not included in the model attributing to multicollinearity among the variables or misspecification of the model. The idea is to scrutinize the performance of the different estimation methods under these conditions which are often encountered in practice. We hope that the methods of estimation would display some consistency regardless of failing to meet such assumptions as suggested by Anderson and Gerbing (1988) as well as Olsson *et al*. (2000).

The model we have estimated is one of the simplest ones. We have indicated that we have only nine exogenous variables that we are trying to model for the real and fiscal sector of the Namibian economy. **Figure 4.1** represents the path diagram of the initial model for this analysis.

Slightly modifying the specification in **Figure 3.1**, the Trade Balance (TB), Government Expenditures (G) and Government Expenditures on Goods and services (GEGS) are included as exogenous variables to capture some of the causal effect exhibited in the underlying theory of these variables. See SAS codes in **Appendix A.3.3**.

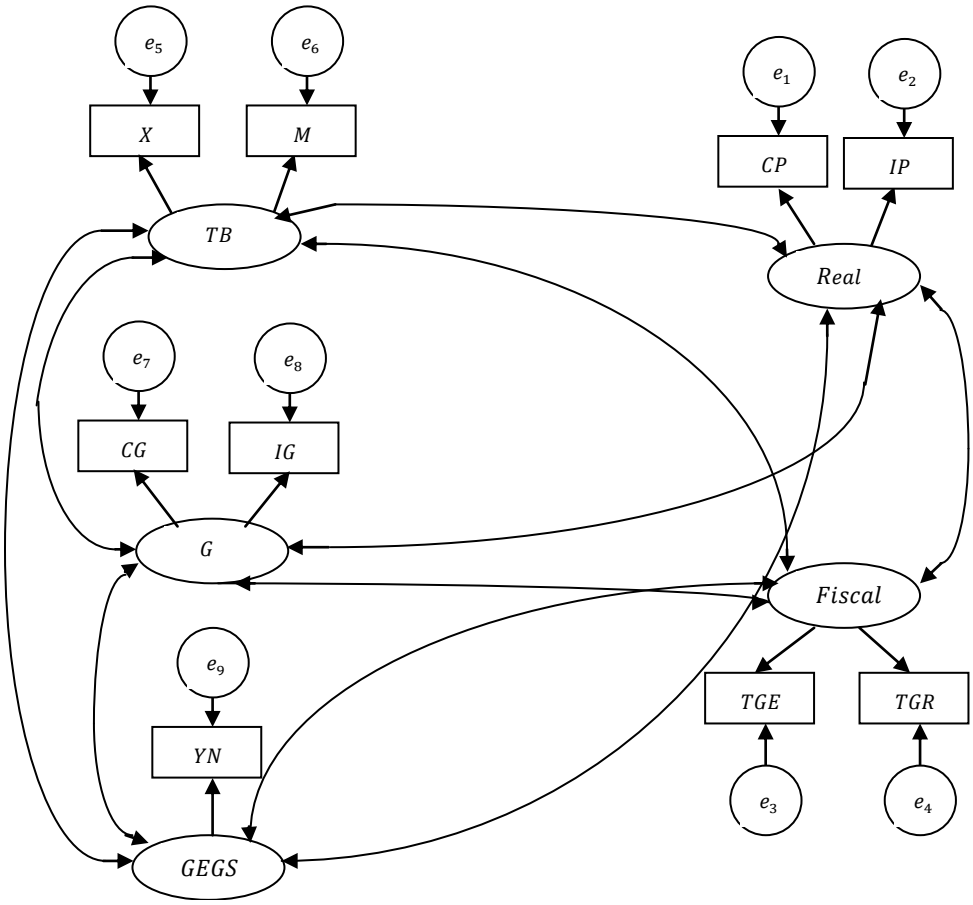


Figure 4.2 Initial model specification (Model 1)

The model is specified with five latent variables representing the sectors, since according to CFA, the endogenous variables are those that are being influenced by the constructs. In this case, the constructs are the exogenous variables. That is Private Investment and Private Consumptions by the Real sector, Total Government Expenditures and Total Government Revenues by the Fiscal sector, Exports and Imports by the Trade Balance, Public Investments and Public Consumptions on the Government Expenditures and Nominal Gross Domestic Produces by the Government Expenditure on Goods and Services.

The arrows from the constructs to the endogenous variables represent the model factor loadings. For example, the loading of Nominal Gross domestic Products (YN) on Government Expenditures on Goods and Services (GEGS) is represented by the straight arrow between them. This specification is what is called the null model whereby there is no specified causal direction among the constructs as indicated by the double curved arrows. The double curved arrow between Real, Fiscal, TB, G and GEGS simply suggest the covariance between the constructs. There are nine error terms for each endogenous variable.

Before interpreting the results of the analysis, the basic descriptive statistics of the model should be reviewed to verify that the SAS program ran correctly. **Table 4.11** above is the output of how the variables were entered in the model. The model has a total of 23 terms, nine endogenous variables which are the entered variables, five exogenous construct variables and nine error terms for each endogenous variable.

Table 4.11 Model variables confirmation

Variables in the Model		
Endogenous	Manifest	CG CP IG IP M TGE TGR X YN
	Latent	
Exogenous	Manifest	
	Latent	F_Fiscal F_G F_GEGS F_Real F_TB
	Error	e7 e1 e8 e2 e6 e3 e4 e5 e9
Number of Endogenous Variables = 9 Number of Exogenous Variables = 14		

Note that the program has specified Government Expenditures (F_G), Government Expenditures on Goods and Services (F_GEGS) and Trade Balance (F_TB) as latent variables in the same way as the original latent variables F_Real and F_Fiscal for the real and fiscal sector respectively.

This is typical of CFA in the sense that the underlying structure in the data is being identified by the constructs they represent. The program has only taken into consideration the fact that both of the F variables are influenced by other variables which are the endogenous variables regardless whether they were observed or not. F denotes a construct or a factor in a SAS program.

Table 4.12 below verifies that the SAS program did in fact analyse the intended model. It represents the linear equations as they were entered in the program. The loadings of each

variable on the latent variables are represented by ***a***'s and the ***b***'s represents loadings of endogenous variables on the other three exogenous variables which are F_TB, F_G and F_GEGS.

Table 4.12 Initial estimates of linear equations

Initial Estimates for Linear Equations				
CP	=	a1F_Real	+	e1
IP	=	a2F_Real	+	e2
TGE	=	a3F_Fiscal	+	e3
TGR	=	a4F_Fiscal	+	e4
X	=	b1F_TB	+	e5
M	=	b2F_TB	+	e6
CG	=	b3F_G	+	e7
IG	=	b4F_G	+	e8
YN	=	b5F_GEGS	+	e9

Table 4.13 below contains the model parameters and their standardised estimates of the two methods of estimation for the raw and transformed data. 28 parameters, more than 27 the number of observations were estimated. However, the results in the table are standardised and the SAS program has set the initial loading of Nominal Gross Domestic Products which is ***b5*** at one so that the model is identified (See **Appendix A.3.2** for the initial parameter estimates). This approach of setting some parameters at specific values is what is called parameter restrictions or more generally, identification.

Table 4.13 also serves as another confirmation of the prior settings. It contains the estimates of the loading coefficients denoted by ***a*** and ***b***, the variances of all the endogenous variables as indicated by the term *var* followed by the variable name as well as the covariance term between the latent variables.

Evidently, the parameter estimates of the loadings are almost identical for the two methods as well as whether the data was transformed or not. Also, there is not much difference between the estimates of the covariances regardless of the method of estimation or the type of data used. However, one could see there is a slight discrepancy on the estimates of the variances of the error terms between our attested models.

Also, **Table 4.13** below shows some negative variances which indicate that there might be a problem of multicollinearity between some of the variables. However, as Kolenikov and Bonnet (2007) pointed out that, there is not just a single cause for negative variances. Among these causes are outliers, non-convergence, under-identification, structurally misspecified models or sampling fluctuations.

Table 4.13 Standardised parameter estimates

	Raw Data		Transformed Data	
Loadings	ML1	GLS1	ML2	GLS2
a1	0.9781	0.9887	0.9817	0.9928
a2	0.9800	0.9908	0.9764	0.9971
a3	0.9949	0.9992	0.9980	0.9993
a4	0.9958	0.9980	0.9977	0.9980
b1	0.9498	0.9819	0.9586	0.9777
b2	0.9797	0.9897	0.9931	0.9967
b3	0.9986	1.0012	0.9934	0.9900
b4	0.9574	0.9628	0.9624	0.9734
b5	1.0025	0.9953	1.0108	1.0019
Variances				
varCP	0.0433	0.0225	0.0363	0.0143
varIP	0.0396	0.0183	0.0466	0.0056
varTGE	0.0101	0.0016	0.0039	0.0014
varTGR	0.0084	0.0039	0.0046	0.0040
varX	0.0979	0.0359	0.0810	0.0440
varM	0.0402	0.0204	0.0137	0.0066
varCG	0.0027	-0.0024	0.0131	0.0199
varIG	0.0834	0.0730	0.0738	0.0524
varYN	-0.0049	0.0093	-0.0216	-0.0037
Covariance				
CovReal_Fiscal	1.0072	1.0015	0.9282	0.9224
CovReal_TB	1.0099	0.9992	0.9926	0.9815
CovReal_G	0.9634	0.9842	0.9667	0.9694
CovReal_GEGS	1.0019	1.0049	0.9100	0.9150
CovFiscal_GEGS	0.9989	1.0048	0.9891	0.9981
CovFiscal_TB	1.0039	0.9957	0.9711	0.9697
CovFiscal_G	0.9670	0.9828	0.9642	0.9797
CovTB_G	0.9861	0.9902	0.9880	0.9941
CovTB_GEGS	0.9998	0.9993	0.9551	0.9643
CovG_GEGS	0.9614	0.9840	0.9504	0.9742

It is customary to perform further diagnostics to isolate the source the negative variances in the model. Normally, the estimates of those negative variances are never significant. Hence, the

most efficient way to deal with the negative variances is to eliminate them from the overall specification as we shall see later in Section 4.5.5.

Nonetheless, this indicates that the two methods are consistent with each other but one needs a formal test to make such conclusion as we shall see in the later sections. The SAS code for the initial model (Model 1) is provided in **Appendix A.3.3.**

Hatcher (1994) pointed out that, to solve the problem of scale indeterminacy in a CFA (latent variables have no established metric or scale because they are not observed), all variances of the latent variables are fixed. This approach is to establish a scale for the latent variables and ensure that the model is identified. See **Appendix A.3.3**.

4.5.4 Assessing the Fit Between the Models and the Data

Hatcher (1994) illustrates that, to begin with the model assessments the overall goodness of fit has to be reviewed, for example the chi-square test. Thereafter, the model indices are analyzed for more detailed assessments for significance tests of the factor loadings etc. In our study, we might have violated several assumptions such as model misspecification that would make these significance tests unviable. Nevertheless, we proceed with the tests and compare different approaches such as ML and GLS and see how well they each perform despite such short falls.

Table 4.14 below contains those fit indices that were used in reviewing the model fit to the data. There are several tests that are undertaken to test whether a CFA model is adequate. In this study we began with the overall goodness of fit for the model. That is whether the model fits the data at all. We fitted two models using ML and GLS estimation methods. The table summarises only a few of the indices used for model comparison.

In **Table 4.14**, the model provides contrasting results for the two estimation procedures. The reported chi-square for the ML method is 39.0428 (0.0018) and 39.4519 (0.0015) for the untransformed (column ML1) and transformed (ML2) data respectively which are both significant at 5% significance level. This implies that the null hypothesis that the model fits the data is rejected and the conclusion that the model does not fit the data adequately.

Table 4.14 Model fit indices

Fit Summary		Raw Data		Transformed Data	
		ML1	GLS1	ML2	GLS2
Modeling Info	N Variables	9	9	9	9
	N Parameters	28	28	28	28
	Active Constraints	0	0	0	0
Absolute Index	Fit Function	1.5016	0.8705	1.5174	0.6774
	Chi-Square	39.0428	22.6333	39.4519	17.6115
	Chi-Square DF	17	17	17	17
	Pr > Chi-Square	0.0018	0.1616	0.0015	0.4137
	RMSR	0.0071	0.0179	0.0082	0.0208
	SRMSR	0.0071	0.0179	0.0082	0.0208
	GFI	0.8000	0.8066	0.7709	0.8495
	AGFI	0.4706	0.4879	0.3936	0.6015
Parsimony Index	A IC	95.0428	78.6333	95.4519	73.6115
	BIC	131.3260	114.9160	131.735	109.8940
Incremental Index	CFI	0.9704	0.5751	0.9685	0.9374
	NNFI	0.9372	0.1003	0.9333	0.8674

The GLS test chi-square values are 22.6333(0.1616) and 17.6115(0.4137) for raw data (GLS1) and transformed (GLS2) data respectively which are both insignificant at 5% significance level, there by accepting the null hypothesis that the model fits the data. According to the chi-square, the GLS estimation method with transformed data produces model estimates that best fits the data. The chi-square probability level is 0.4137.

Although, both chi-square values of the GLS method are significant, the discrepancy is wide with the raw data significant at probability level of 0.1616. This could be explained by the fact that the GLS method does not assume the distribution of the data. On the contrary, the margin between the probability levels of the ML methods is relatively small.

In several applications of SEM, the chi-square is often found significant even if the model fits the data. An intuitive practice frequently used is to associate the chi-square statistic with the degrees of freedom as discussed in Section 2.7. In both cases for the ML method, there is still no indication that the model fits the data. In both cases, the ratios of chi-square statistic to the degrees of freedom are 2.2966 and 2.3207 for the raw and transformed data respectively. Both of them exceeded 2 which is the accepted cut-off point to indicate a good model fit to the data. Therefore, ML method is again suggesting a poor fit. However, if the ratio is compared to a

value of 3, (Schermelleh-Engel *et al*., 2003), the models are considered to fit the data at an acceptable level.

On the other hand, the ratio for the GLS method are suggesting a good model fit to the data with ratios of chi-square to the degrees of freedom (1.3314 and 1.036 for the raw and transformed data respectively) which are both less than 2.

The Standardised root Mean Square Residuals (SRMR) indicates that both estimation methods provides a good model fit with all indices in both instances less than the cut-off point of 0.05. This implies that the model implied covariance matrix approximates the actual covariance matrix of the data well.

Even though the Goodness of Fit Index (GFI) and Adjusted Goodness of Fit Index (AGFI) are lower than 0.95 (regarded as indicative of good model-data fit) in both cases of the estimation methods, it is a widely acceptable practice to accept models with the GFI and AGFI indices in the region of 0.5. In this case, both GFI are over 0.5. However, only the AGFI of the transformed GLS method is over that value at 0.6015, again suggesting that that GLS is a better estimation method for the data.

The parsimonious indices are in the favour of the GLS. Both AIC and BIC are lower for the GLS method than the ML method. However, in the transformed case, the GLS is again regarded as the best fit to the data with the lowest values of 73.6115 and 109.894 for AIC and BIC respectively.

For the incremental indexes which measure the deviation of the observed covariance matrix from the covariance matrix implied by the parameter estimates for the model, the NonNormed Fit Index (NNFI) and Comparative Fit Index (CFI) which are believed to be less affected by small samples like in our situation were considered. These indices seem to be in favour of the ML method with both (ML1 and ML2) having a CFI relatively close to 0.97. According to Schermelleh *et al.* (2003), 0.97 should be considered as a cut-off point.

For the ML method on the raw and transformed data, the NNFI values are 0.9372 and 0.9333 respectively. Although they are not within the range of the cut-off point of 0.97, they are relatively close compared to those of the GLS method (0.1003 and 0.8674 respectively). On the

other hand, only the version of raw data for ML method has a CFI value (0.9704) exceeding the cut-off point.

One explanation for the CFI to display contrasting results to those displayed by the chi-square statistics with regard to favouring different estimation methods as Hooper *et al*. (2008) noted, is that it avoids the underestimation of fit of model often noted in small samples by assuming that the latent variables are uncorrelated. This is hardly a case in CFA because there is no such assumption made especially with initial models, like in this situation, where all the exogenous variables are expected to covary.

Furthermore, the smaller indices such as the CFI and NNFI displayed by the GLS estimation methods for the raw data could be linked to the way the weight matrices used are calculated. Olsson *et al*. Olsson *et al*. (2000) discussed this problem that for the ML method, the weight matrix is a function of the model whereas for the GLS method, the elements in the weight matrix are functions of the second order moments of the observed variables. Since the observed variables used in the model are different (whether transformed or not transformed) for the GLS method, the indices are expected to be different.

Although the NNFI is also believed to suffer less in the case of the small sample size, it can indicate a poor fit despite other statistics pointing towards a good fit. This is evident in the sense that it is favouring the ML method while almost every other statistic is in the favour of the GLS method. The reason behind this as stated earlier is based on the assumption that the ML method makes assumptions with regard to the distribution of the data. If the models are misspecified for example as we have noted in this study, those assumptions may not hold and hence the results may not be accurate.

The assessments reviewed above generally test for the discrepancies the elements of sample covariance matrix and that of the model implied covariance matrix. So far it is illustrated that reviewing the covariance between the real and fiscal sector and the variances of the endogenous variables, the GLS estimation method performs better than the ML method with the available data especially with the transformed data. This is perhaps as a result of the distributional assumption on which the ML fit function relies.

4.5.4 Reviewing the model parameters

In practice there is often contrasting results as we have seen above, especially in the case of incremental indices which is the only one seems to be in favour of the ML estimation method while all the other indices are favouring the GLS estimation method. When such contrasting results occur, it is necessary to proceed by reviewing the significance of the factor loadings themselves.

Generally, the output would indicate whether there are some loadings which are not significant in the initial specification. If any loadings are not significant, the model has to be modified either by removing the variable associated with that loading or fix the loading to a specific value. A non-significant loading implies that the involved variable is not well representing the underlying factor.

Table 4.15 below presents the model factor loadings for the ML method of estimation (Only the ML method is reviewed because there is sufficient evidence that the GLS method provide parameters which sufficiently fits the data. Also, it is only with the ML estimation method that the parameter could be tested for significance. That is one of the reasons why ML is widely used). It is conventionally preferred to review the standardised loadings. Therefore, any modifications we may consider in this study are based on the method of ML estimation.

There is no indication of an estimation problem according to values provided in **Table 4.15**. There are no near-zero standard errors for example, less than 0.0003 (Hatcher, 1994). The factor loadings are very large and their t-value statistics are significant at probability level 0.001[1].

As for the model variances of the error terms, two terms namely, the variance the Public Consumptions (varCG) (*t*-value of 0.20 and 0.99 for the raw and transformed data respectively) and the absolute variance of Nominal Gross Domestic Products (varYN) (0.16 and 0.75 for the raw and transformed data respectively) are found to be insignificant at 5%[2] significance level because their t-value statistics are less than 1.96. Also, the variance of Imports (M) (1.49) is also not significant at $p<0.05$ when the data is transformed. All the covariance terms are significant in **Table 4.15**.

[1] A *t*-value greater than 3.291 is significant at $p<0.001$ (Hatcher, 1994)
[2] A *t*-value greater than 1.960 is significant at $p<0.05$ (5%) (Hatcher, 1994)

Table 4.15 Reviewing the model parameter estimates

	Standardised Results ML1			Standardised Results ML2		
Loadings	Estimate	std error	t-value	Estimate	std error	t-value
a1	0.9781	0.0090	109.1000	0.9817	0.0090	108.8000
a2	0.9800	0.0083	118.3000	0.9764	0.0107	91.4300
a3	0.9949	0.0021	483.5000	0.9980	0.0009	1137.7000
a4	0.9958	0.0017	571.7000	0.9977	0.0010	1001.2000
b1	0.9498	0.0198	47.9400	0.9586	0.0163	58.7600
b2	0.9797	0.0094	104.8000	0.9931	0.0047	213.6000
b3	0.9986	0.0069	145.1000	0.9934	0.0067	149.2000
b4	0.9574	0.0176	54.2600	0.9624	0.0157	61.4700
b5	1.0025	0.0152	65.9300	1.0108	0.0143	70.7400
Variances						
varCP	0.0433	0.0175	2.4700	0.0363	0.0177	2.0500
varIP	0.0397	0.0162	2.4400	0.0467	0.0209	2.2400
varTGE	0.0102	0.0041	2.4800	0.0040	0.0018	2.2600
varTGR	0.0085	0.0035	2.4400	0.0046	0.0020	2.3300
varX	0.0979	0.0376	2.6000	0.0811	0.0313	2.5900
varM	0.0402	0.0183	2.1900	0.0138	0.0092	1.4900
varCG	0.0027	0.0138	0.2000	0.0131	0.0132	0.9900
varIG	0.0835	0.0338	2.4700	0.0738	0.0301	2.4500
varYN	-0.0050	0.0305	-0.1600	-0.0217	0.0289	-0.7500
Covariance						
CovReal_Fiscal	1.0073	0.0041	248.5300	0.9283	0.0296	31.3200
CovReal_TB	1.0099	0.0077	130.2800	0.9926	0.0082	120.4700
CovReal_G	0.9634	0.0180	53.5900	0.9667	0.0172	56.1900
CovReal_GEGS	1.0020	0.0143	70.1400	0.9101	0.0384	23.7300
CovFiscal_GEGS	0.9990	0.0148	67.6400	0.9892	0.0140	70.5800
CovFiscal_TB	1.0039	0.0062	161.3200	0.9712	0.0130	74.7500
CovFiscal_G	0.9670	0.0149	65.08	0.9643	0.0158	60.9800
CovTB_G	0.9861	0.0121	81.2800	0.9881	0.0092	107.1200
CovTB_GEGS	0.9998	0.0154	64.9400	0.9552	0.0233	41.0700
CovG_GEGS	0.9615	0.0263	36.5000	0.9505	0.0252	37.7000

For further analysis, we investigated the residuals of the models. The results are shown in **Appendix A.4.1** and **Appendix A.4.2.** There is no indication of problematic residuals (problematic when they are greater than two which is a situation considered as under-predicting the relationships between the involved variables). The distributions of standardised residuals are relatively centered on zero in both raw and transformed data for the ML estimation method. They also appear to be somewhat symmetric although, a little skeweed to the negative values.

At this point of the study, we have demonstrated that the GLS estimation method seems to be favoured by the data more specifically with the transformed data. Furthermore, the models with transformed data seem to fit better than those with raw data. However, several descriptive indices are indicating that ML model fits the data better when they are not transformed.

With the results so far, one can easily conclude that the GLS method produces better model parameters estimates that best fits the data used in this application. However, it is necessary to consider modifying the model by re-specifying and re-estimate it for evidence of better fit especially in the case of ML estimation method. Furthermore, researchers rarely proceed with their initial models because they invariably fail to provide an acceptable fit (Anderson and Gerbing, 1988).

In this study, there is an insufficient sample size to add more parameters to the model. Furthermore, when the loadings are found to be significant, the models are always considered adequate. Nonetheless, we proceeded by reviewing the modification indices to the ML estimation method analysed above and checked for evidence of model improvements.

4.5.5 Reviewing and Modifying the Model

So far, there is strong evidence in support of the GLS estimation method. Therefore, the following evaluation would mainly focus on the ML method to illustrate how the model could be modified.

Table 4.16 The Wald test

Stepwise Multivariate Wald Test					
ML1					
Parameter	Cumulative Statistics			Univariate Increment	
	Chi-Square	DF	Pr > Chi-Square	Chi-Square	Pr > Chi-Square
varYN	0.0292	1.0000	0.8643	0.0292	0.8643
varCG	0.0654	2.0000	0.9678	0.0362	0.8492
ML2					
Parameter	Cumulative Statistics			Univariate Increment	
	Chi-Square	DF	Pr > Chi-Square	Chi-Square	Pr > Chi-Square
varYN	0.8676	1.0000	0.3516	0.8676	0.3516
varCG	1.8488	2.0000	0.3968	0.9811	0.3219
varM	4.4441	3.0000	0.2173	2.5953	0.1072

The null hypothesis of the Wald test stipulates that the model chi-square statistic would remain the same if some of the parameters are removed. The test in **Table 4.16** indicates that two parameters could be removed to improve the model of the ML1 estimation method when the data is not transformed. However, there is no indication of an improvement in the chi-square of the model. Both cumulative statistics and univariate increment probability for the chi-square are not significant. Those parameters are the variance of the Nominal Gross Domestic Product (varYN) as well as the variance of Public Consumptions (varCG).

This is the same situation with the ML2 estimation when the data is transformed but an additional parameter (variance of Imports (varM)) was identified. These are also the parameters that were identified to be not significant with their *t*-value statistics less than 1.960 in **Table 4.15**.

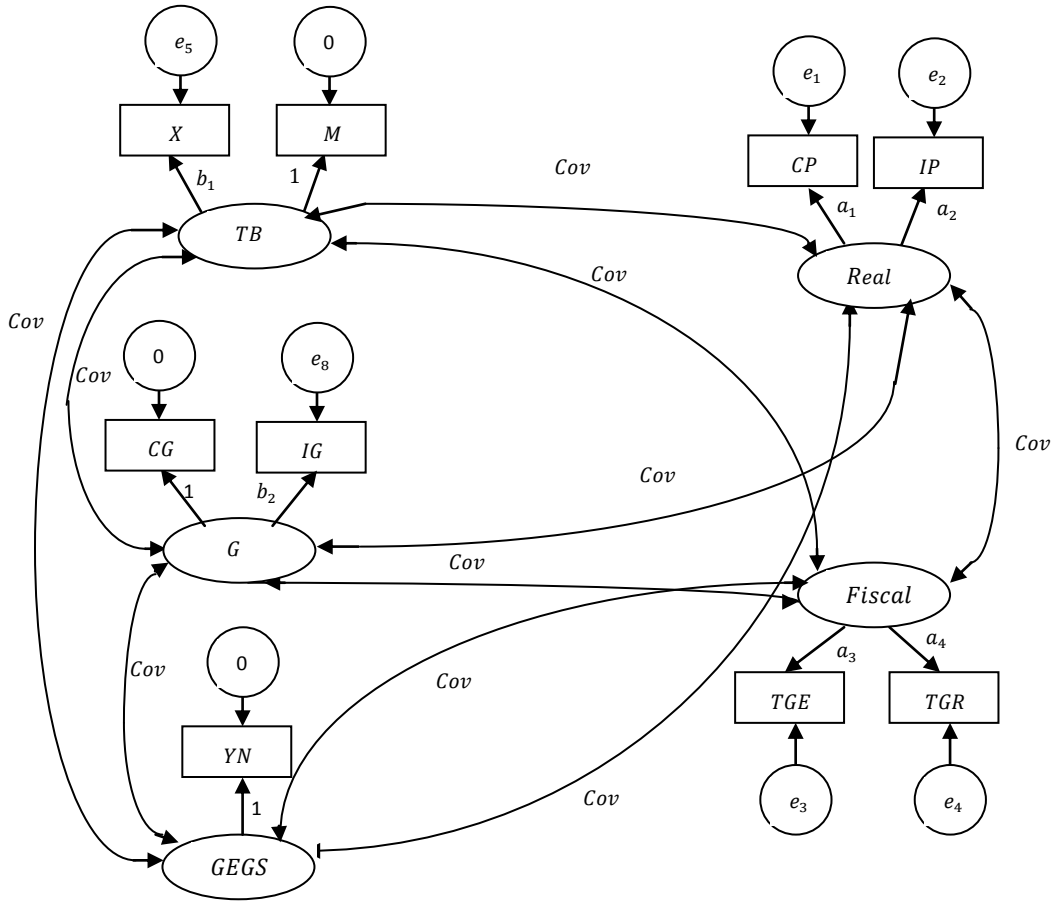


Figure 4.3 Measurement model specification (Model 2)

In this situation, there is no point in dropping those parameters. The null hypothesis that the chi-square statistic is remaining the same if those parameters are removed cannot be rejected. However, Hatcher (1994) indicated that, a substantial reduction in the degrees of freedom may have significant impact on the ratio of chi-square to the degree of freedom, which is one of the indices we used to test the fit of the model.

Furthermore, Anderson and Gerbing (1988) pointed out that, when a construct has only a single indicator, it is highly unlikely that it could perfectly estimate the construct. As we have experienced during the course of model specification, GEGS has YN as the only indicator. This could be classified as a misspecification of the model which is regarded by Kolenikov and Bonnet (2007) as one of the causes of negative variances encountered in Section 4.5.3.

Like we stated, we have GEGS which only has YN as an indicator. YN is one of the variables with a non significant variance term. Hence based on that, we would modify the model by fixing the loading of YN on GEGS to unity. In addition, we would apply the same to M and CG loadings, as well as dropping the variances of YN, M and CG as they are not significant. We would then investigate and compare this new model, specified in **Figure 4.3,** with the former to check if there is an improvement in the fit indices. Fixing and dropping some of these parameters is simply a model identification procedure.

Notice the adjustments done to the model. The loadings of M, YN and CG are fixed to unity as suggested above. Also, the error terms of YN, M and CG do not appear any more in the current specification. It is necessary to remind that it is the variances of those error terms which are constrained to zero. All endogenous variables of a CFA model are accompanied by an error term of which their variances are expected to be estimated. *Cov* in **Figure 4.2** represents the covariance between all the exogenous variables of the model. See **Appendix A.3.4** for the SAS program.

Table 4.17 below contains indices of the ML estimation method for this new model with raw data (ML3) and transformed data (ML4). We have also included the previous model indices for ease of comparison as well as the results of the same specification estimated by the GLS method. There are in total eight models for comparison.

The model has gained more chi-square degrees of freedom compared to the previous one. That is, eight more degrees of freedom from 17 to 25. The new models are contained in the columns headed ML3 and GLS3 for the untransformed data and ML4 and GLS4 for the transformed data. As in the previous model, the chi-squares for the ML estimation method are significant. On the other, the probability levels of the GLS method went from 0.41 to 0.84 for the transformed data implying that the null hypothesis is still not rejected. The AIC and the BIC are also in favour of the modified GLS model as well.

Table 4.17 Fit indices for the initial and modified models

	Raw data				Transformed data			
	ML1	GLS1	ML3	GLS3	ML2	GLS2	ML4	GLS4
N Variables	9	9	10	10	9	9	10	10
N Parameters	28	28	30	30	28	28	30	30
Fit Function	1.5000	0.8700	3.0223	1.0515	1.5200	0.6800	2.7523	0.9983
Chi-Square	39.0400	22.6300	54.4010	18.9270	39.4500	17.6100	49.5420	17.9690
Chi-Square DF	17	17	25	25	17	17	25	25
Pr > Chi-Square	0.00	0.1600	0.0006	0.8006	0.0000	0.4100	0.0024	0.8437
RMSR	0.0100	0.0200	0.0286	0.3913	0.0100	0.0200	0.0365	0.6009
SRMSR	0.0100	0.0200	0.0286	0.3913	0.0100	0.0200	0.0365	0.6009
GFI	0.8000	0.8100	0.6660	0.7897	0.7700	0.8500	0.6899	0.8003
AGFI	0.4700	0.4900	0.2652	0.5373	0.3900	0.6000	0.3179	0.5608
AIC	95.0400	78.6300	114.400	78.9270	95.4500	73.6100	109.5400	77.9690
BIC	131.3300	114.9200	142.730	107.260	131.740	109.890	137.8800	106.300
CFI	0.9700	0.5800	0.9420	.	0.9700	0.9400	0.9492	.
NFI	0.9500	0.5400	0.9015	0.5386	0.9500	0.6200	0.9062	0.4921
NNFI	0.9400	0.1000	0.8957	-1.7480	0.9300	0.8700	0.9086	-0.3150

Although the results of the modified model have improved, there is no contrasting evidence between the corresponding models. Overall results indicate that the transformed data performs better with both estimation methods and even better in the modified model. The chi-square statistics are not significant in any of the evaluated models for the GLS method but very significant in both instances for the ML indicating that GLS is the method of preference for the data at hand. **Appendix A.3.4** provides the SAS code used in this section.

4.6 Estimation of the Structural Equation Model

We have so far confirmed the underlying structure which involves the Namibian macroeconomics related to the two economic sectors under investigation. The selected exogenous variables seem to load on their respective sectors as attested by EFA in the previous

section. Furthermore, the theory behind those variables and how they are related to the sectors was confirmed by the CFA. This brought the application at the stage where the confirmed model could be estimated.

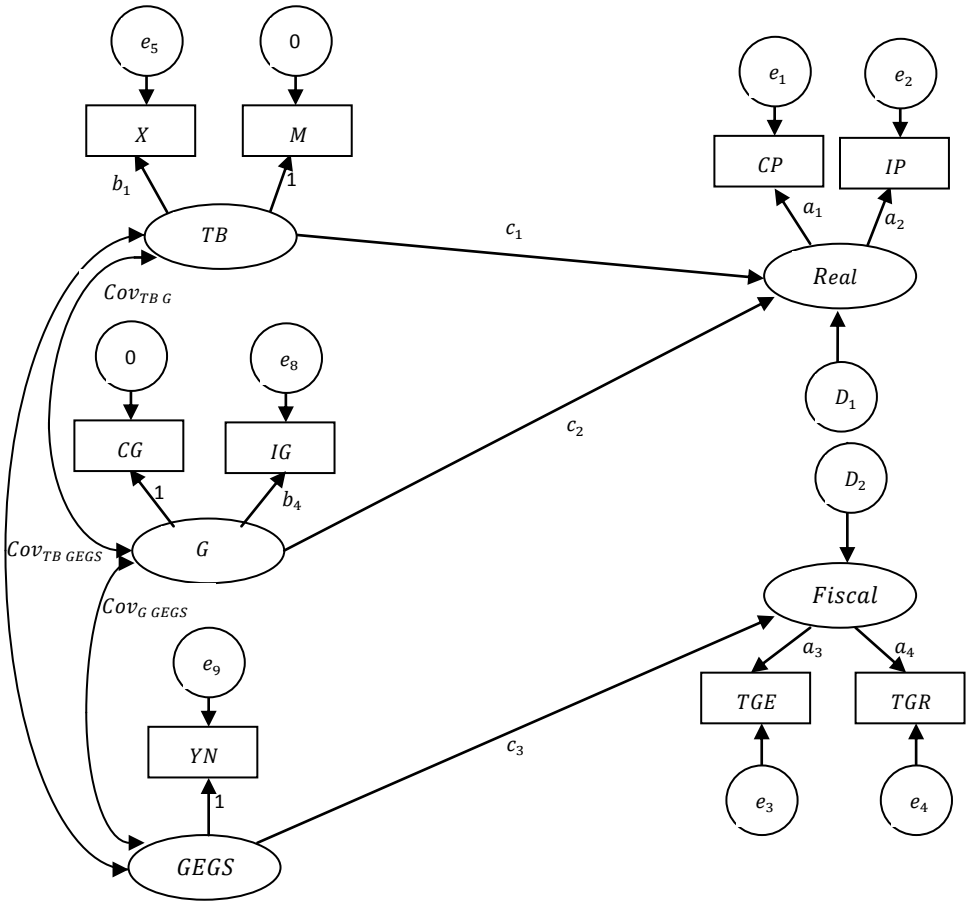


Figure 4.4 Theoretical model specification (Model 3)

Although it was identified in the previous section that GLS estimation method seems to favour the model fit to the data compared to the ML method, we still wish to compare the two methods in the present section with the transformed data. **Figure 4.3** shows the specification of the theoretical model estimated in this section.

Notice that the double curved arrows are now replaced by the unidirectional single arrows. This adjustment indicates that the causal relationships are now hypothesized in the model and the arrows are now representing the path coefficients ($\boldsymbol{C_i}$'s) showing the direction of causal

relationships. The model suggests that the Trade Balance (TB) and the Government Expenditures (G) have causal influence on the real sector. On the other hand, the Government Expenditure on Goods and Services (GEGS) has a causal influence on the fiscal sector, in addition to the Total Government Expenditure (TGE) and the Total Government Revenue (TGR).

Notice also there is no longer covariance terms between the latent variables and other variables in the model. This is because the real and fiscal are now endogenous variables which are caused by other variables as defined above. For example, variables which have direct arrows pointing to them are never expected to have covariances (Hatcher, 1994). Therefore, following this convention, real and fiscal sectors are specified to have the disturbance terms ($\boldsymbol{D_i}$'s). See **Appendix A.3.5** for the SAS code used to estimate the theoretical model.

Table 4.18 contains the model fit indices necessary to interpret the results of the two estimation methods with transformed data and whereby the initial model is modified as discussed above. Hatcher (1994) stipulated some basic steps to follow when interpreting the result of the SEM. In this study, we follow these steps;

Table 4.18 Fit summary for the theoretical model (Model 3)

Fit Summary	ML	GLS
Chi-Square	54.1140	27.5080
Chi-Square DF	22	22
Pr > Chi-Square	0.0002	0.1926
Bentler Comparative Fit Index	0.9550	0.4359
Bentler-Bonett NFI	0.9278	0.3989
Bentler-Bonett Non-normed Index	0.9263	0.0770

Step 1: Reviewing the model chi-square test. The first step involves reviewing the model chi-squares statistics. The estimated model chi-square statistics are 54.114 (0.0002) and 27.5080 (0.1926) for the ML and GLS methods respectively. The values in brackets are the probability significant values for the statistics. Evidently, the GLS is not able to reject the null hypothesis that the model fits the data. These results go in hand with the previous results at the stage of model development.

The ratios of chi-square to the degrees of freedom are 2.4597 and 1.2503 for ML and GLS estimation methods respectively. Again, this result supports the GLS estimation method. The ratio for the ML exceeds the acceptable value of two.

Step 2: Reviewing the normed fit index and Comparative fit index. The CFIs of the two models are 0.9550 and 0.4359 for the ML and GLS estimation methods respectively. Since the acceptable fit level is 0.97, the ML method is indicating almost a good model fit for the data than the GLS method. However, as discussed in Section 4.5.4, one should be careful to rely on these indices in a situation of small samples.

The same results are obtained by the NFI and the NNFI values which exceeded the acceptable level of 0.97 for the ML estimation method but again very short for the GLS method. The values for the ML method again support a relatively better model fit at 0.9278 and 0.9263 of NFI and NNFI respectively. One should rely on these values with cautious because they are believed to be affected by a small sample size as in this situation.

Step 3: Reviewing the significance test for the factor loadings and the path coefficients. The factor loadings and the path coefficients between the variables are the most important components of a SEM. Therefore, it is a good practice to review them in this step. **Table 4.19** provides these parameter estimates, their standard errors as well as their t-value statistics.

Table 4.19 Theoretical model (Model 3) parameter estimates

	Standardised results ML			**Standardised results GLS**		
Loadings	Estimate	std error	t-value	Estimate	std error	t-value
a1	0.9806	0.0098	99.5560	0.9903	0.0062	158.1000
a2	0.9774	0.0108	90.6007	0.9981	0.0049	203.3000
a3	0.9979	0.0009	1046.0000	0.9993	0.0004	2161.4000
a4	0.9978	0.0010	1040.6000	0.9978	0.0009	1051.0000
b1	0.9520	0.0184	51.7746	0.9780	0.0104	94.0032
b2	1.0000			1.0000		
b3	1.0000			1.0000		
b4	0.9560	0.0169	56.7045	0.9690	0.0142	68.1897
b5	1.0000			1.0000		1023.3000
Path coefficient						
c1	1.0059	0.1910	5.2655	1.1391	0.2736	4.1637
c2	-0.0204	0.1959	-0.1042	-0.1551	0.2787	-0.5565
c3	0.9999	0.0005	2197.9000	1.0002	0.0002	3542.2000

As in the case of the CFA, one must watch out for the near zero standard error as this may indicate an estimation problem. 0.0003 or less is the value considered enough to be near zero (Hatcher, 1994). For the ML estimation method, only the standard errors of loading ***a3*** and ***c3*** are quite small but yet still not considered close enough to zero. In addition to ***a3*** and ***c3***, ***a4*** also has a relatively smaller standard error for the GLS estimation method. Therefore, there is no indication of any estimation problem in this instance.

All the factor loadings have a t-value greater than 1.96 (significant at probability less than 0.05). This implies that the factor loadings are significantly different from zero. The path coefficients of the structural portion of the model are all significantly different from zero except for ***c2*** which is the path from Government Expenditure to the Real sector. It has an absolute t-value of 0.1042 and 0.5565 for ML and GLS estimation methods respectively. This indicates that, the estimates of these coefficients are not significantly different from zero. One may consider removing those paths.

Step 4: Reviewing the R^2 for the latent variables. One particular interest of this study is the amount of variance in the latent variables explained by their respective exogenous variables. **Table 4.20** below provides the values of the two sectors. It seems that 97% and 99% of the total variance in the Real sector and Fiscal sector respectively is explained by their exogenous variables when the method of estimation is ML.

On the other hand, GLS method shows that only the Real sector has its total variance explained by its exogenous variables at 97%. There is no value for R^2 provided by the SAS output for the fiscal sector by the GLS method as well as the presence of negative error variances.

The only way to obtain an R^2 value for this study is by constraining the negative error variance of F_Fiscal to a positive value between of 0.3 and 0.9. In fact, 0.9 yielded a maximum R^2 value of only 0.2941. This implies that only 29% of the total variance in the Fiscal sector is explained by its exogenous variables.

However, since we do not know the exact economic value, we avoided this process of constraining F_Fiscal error variance to a definite constant and hence relying on the basic model building approach as shown in Section 4.5.5. This approach entails fixing the non-significant parameters such as variances of YN, M and CG to zero.

Table 4.20 Variances accounted for by latent variables

Variable	Error Variance	Total Variance	R-Square
ML			
F_Real	0.0255	0.9201	0.9722
F_Fiscal	0.0003	1.0291	0.9997
GLS			
F_Real	0.0310	1.1820	0.9738
F_Fiscal	-0.0003	0.9954	

A result like that attained for the Fiscal sector when the method of estimation is GLS further illustrates the misspecification of this model. We have seen that the Government Expenditure on Goods and Services (GEGS) is uniquely indicated by the Nominal Gross Domestic Product (YN) as its endogenous variable. This is a problem in model estimation. Hatcher (1994) suggested that each construct should have at least three indicator variables.

Nonetheless, the total variance explained in the model by all the other endogenous variables is presented in **Appendix B.1**. The results show that all the endogenous variables explain over 90% of the total variance in the model.

Step 5: Reviewing the residual distributions. The models are considered to provide a good fit to the data if their distributions of the residuals are symmetric and centered on zero. The residuals are centered on zero in the case of the ML estimation method (**Table 4.21**).

However, the symmetric pattern of the residual distribution in the case of the GLS method seems to be distorted by one outlying residual. It also seems to be skewed to the right.

The Parsimony Ratio (PR) of the theoretical model is 0.611 for both the ML and GLS estimation methods. This indicates that in comparison to the measurement model, the theoretical model is less complex therefore, more desirable because as Hatcher (1994) states the principal of parsimony phenomenon that when several explanations are equally satisfactory in accounting for some phenomenon, the preferred explanation is the one that is less complicated and require fewer assumptions. However, as it can be seen, our model is a little more complicated than the uncorrelated model which makes no assumption on covariances among the variables.

Table 4.21 Theoretical model (Model 3) residuals distribution patterns

Distribution of Residuals			
Each * Represents 1 Residuals			
ML			
Range	**Freq**	**Percent**	
-0.0204	2	4.4400	**
-0.0102	3	6.6700	***
0.0000	6	13.3300	******
0.0102	25	55.5600	**************************
0.0204	4	8.8900	****
0.0307	4	8.8900	****
0.0409	1	2.2200	*
GLS			
Range	**Freq**	**Percent**	
0.02427	4	8.8900	****
0.05244	11	24.4400	**********
0.08061	20	44.4400	********************
0.10878	5	11.1100	*****
0.13695	4	8.8900	****
0.16512	0	0.0000	
0.19329	1	2.2200	*

Step 6: Reviewing the parsimony ratio and the parsimony normed fit index. **Table 4.22** contains the information necessary to review the rest of the model aspects. It contains the entire models that have been tested to arrive at the final structural model or the theoretical model as denoted by $\boldsymbol{M_t}$ (Model 3) in the table. $\boldsymbol{M_n}$, $\boldsymbol{M_u}$ and $\boldsymbol{M_m}$ (model 2) denote the null model, the uncorrelated model and the measurement model respectively. A measurement model is defined as the confirmatory model in which all the exogenous (including latent) variables are expected to covary. An uncorrelated model is identical to the measurement model except that none of the exogenous variables are allowed to covary. In the null model, all the paths and covariances between the variables have been deleted (Hatcher, 1994).

The model Parsimony Normed Fit Index (PNFI) is 0.5663 and 0.2431 for ML and GLS estimation methods respectively. The ML theoretical model passes the ad-hoc criterion of an acceptable fit of greater than 0.5. This shows that the desirable state of both fit and parsimony of the model is attained with the ML estimation method.

Table 4.22 Summary of all models fit indices

Goodness of Fit and Parsimony Indices for the Models											
Model		Combined Model							Structural Model		
		Chi-Square	DF	NFI	NNFI	CFI	PR	PNFI	RNFI	RPR	RPFI
M_n	ML	749.252	36								
	GLS	45.764	36								
M_u	ML	434.975	27	0.420	0.237	0.428	0.750	0.315	0.000	1.000	0.000
	GLS	41.885	27	0.085	-1.033	-0.524	0.750	0.064	0.000	1.000	0.000
M_t	ML	54.1143	22	0.927	0.926	0.955	0.611	0.5663	0.9752	0.500	0.4876
	GLS	27.5078	22	0.398	0.077	0.435	0.611	0.2431	0.7459	0.500	0.3729
M_m	ML	39.452	17	0.947	0.933	0.969	0.472	0.447	1.000	0.000	0.000
	GLS	17.612	17	0.615	0.867	0.937	0.472	0.291	1.000	0.000	0.000

Step 7: Reviewing the relative normed fit index. A SEM is composed of two parts. The first part constitutes the measurement model that describes the relationships between the endogenous variables (including the latent variables) and their indicators. The second part is the theoretical part which describes the relationships between the endogenous variables and the latent variables. So far the reviewed indices have to do with both of these parts combined. However, one would also like to review the specific structural part of the model. The remainder of the indices reviews this part.

For the model of interest, which is the theoretical model (**M_t** or Model 3**)**, the RNFI are 0.9752 and 0.7459 for the ML and GLS estimation methods respectively. This implies that, the ML method produces an outstanding fit of the structural portion of the model compared to GLS.

Step8: Reviewing the relative parsimony ratio and the relative parsimony fit index. The structural portion of the model Relative Parsimony Ratio (RPR) is 0.5 for both ML and GLS estimation method. RPRs are the same in both estimation methods because it relies on the degrees of freedom and the same model with same degrees of freedom is estimated with ML and GLS methods. Since there is only one theoretical model, these indices does not tell whether to accept or reject the fitness or parsimonious of the model. It is useful when there are competing models and preference is given to the one with the highest value.

However, it is also used in calculation of Relative Parsimony Fit index (RPFI). RPFI provides information that simultaneously reflects both the fit and the parsimony in the structural portion of the model. A model with higher RPFI value is more desirable (Hatcher, 1994).

The RPFI of the models are 0.4876 and 0.3729 for the ML and the GLS estimation methods respectively. In this case, the model fit and parsimony are explained better by the ML estimation method compared to the GLS method. Note that this index is used not necessarily for the model suitability but in aiding to choose among competing models with same parameters.

Step 9: Performing the chi-square difference test. This test is used to determine whether the theoretical model is significantly different from the measurement model. The chi-square for the theoretical model when the method of estimation used is ML is 54.1143 and 39.4520 for the theoretical and the measurement model respectively. Therefore, their absolute chi-square difference is 14.6623. The difference in the degrees of freedom is 5.

On the other hand, the statistics are 27.5078 and 17.612 for theoretical and measurement models respectively, with 9.8958 as the difference between them when GLS is used as the estimation method. The difference in degrees of freedom is also 5.

At probability level equal to 0.05, the test can not reject the null hypothesis that there is no difference between the fit provided by the structural parts of the theoretical model and the measurement model for the GLS estimation method. The chi-square critical value at 5% significance level is 11.070, which is greater than the chi-square differences observed when the GLS is used as the estimation method. This indicates that the theoretical model provides a fit that is not significantly different from the measurement model when predicting the relationships between the variables involved in the structural portion of the model.

On the contrary, there exists a significant difference between the fit provided by the structural parts of the theoretical model and that of the measurement model when the ML is used as the estimation method. The chi-square difference is 14.6623, which is greater than the 5% significance level value of 11.070. Therefore, this test indicates that the GLS estimation method is the better option for estimating the structural portion of the model parameters for our data.

Based on the available data used in this application, the Namibian real and fiscal sector could be structurally estimated by the following series of equations.

Table 4.23 Standardised Equations for the estimated model (Model 3)

Standardised Linear Equations - ML									Standardised Linear Equations - GLS								
CP	=	*0.9806*	*Real*	+	*e1*				*CP*	=	*0.9903*	*Real*	+	*e1*			
IP	=	*0.9774*	*Real*	+	*e2*				*IP*	=	*0.9981*	*Real*	+	*e2*			
TGE	=	*0.9979*	*Fiscal*	+	*e3*				*TGE*	=	*0.9993*	*Fiscal*	+	*e3*			
TGR	=	*0.9978*	*Fiscal*	+	*e4*				*TGR*	=	*0.9978*	*Fiscal*	+	*e4*			
X	=	*0.952*	*TB*	+	*e5*				*X*	=	*0.978*	*TB*	+	*e5*			
M	=	*1*	*TB*	+	*e6*				*M*	=	*1*	*TB*	+	*e6*			
CG	=	*1*	*G*	+	*e7*				*CG*	=	*1*	*G*	+	*e7*			
IG	=	*0.956*	*G*	+	*e8*				*IG*	=	*0.969*	*G*	+	*e8*			
YN	=	*1*	*GEGS*	+	*e9*				*YN*	=	*1*	*GEGS*	+	*e9*			
Real	=	*1.0059*	*TB*	-	*0.0204*	*G*	+	*d1*	*Real*	=	*1.1391*	*TB*	-	*0.1551*	*G*	+	*d1*
Fiscal	=	*0.9999*	*GEGS*	+	*d2*				*Fiscal*	=	*1.0002*	*GEGS*	+	*d2*			

Although there were so many contrasting results in the evaluation of goodness of fit as well as the fit indices between the two estimation methods, the overall model estimates are almost identical.

Chapter 5

Conclusion and Recommendations

5.1 Conclusion

There are several obstacles that are frequently encountered in model estimation. In this study we have seen how different methods of estimation perform under those problematic circumstances such as misspecification of models, underlying assumptions not met in the data and the required sample size. The Namibian economy in this application is dated from the year 1983 which shows how very young it is. However, one would wonder how reliable those variables are, especially under the instability which the country experienced before its independence in the early 1990's.

The primary contribution of this study is to present a comprehensive insight into how the Namibian macroeconomic sectors, specifically the two economic sectors evolved and analyze their structure from a statistical point of view other than the well documented time series approach.

Despite those short comings, we have demonstrated that, the two economic sectors could still be estimated and the persisting structure is confirmed in the exploratory section of the study. The variables that were selected to represent the two economic sectors conform to the economic structure by displaying highly and significant loadings on their respective sector.

Furthermore, we used a two-step approach in developing and estimating the SEM. With a slightly complex initial specification of the two economic sectors, a measurement model was first developed. This model symbolizes the key obstacles stated above.

The first obstacle is the misspecification of the model. The measurement model is deemed misspecified because there are other variables outside the system which are not included in the model. With such a problem of misspecification, the study was not able to compare the estimation methods thoroughly since the sample size is not adequate to correctly specify the models. Therefore, this problem is attributed to the main limitation of the study which is the small sample size.

Nonetheless, there is sufficient evidence that the GLS method of estimation suits the data better than the ML as anticipated under such conditions. In the literature, it is well represented that

under circumstances of misspecification, GLS provides better model fit to the data in comparison to the ML method. Throughout the measurement model development to the estimation of the SEM, GLS display better model fit chi-square statistics than the one displayed by the ML.

A logical explanation to this pattern as discussed earlier in Section 4.5.4 could be attributed to the elements of the weight matrix used in the calculations of the fit functions of these estimation methods. Since the weight matrices are directly involved in the calculations of the estimates, this could be the reason for the fit indices to display contrasting results between the two estimation methods, especially in small samples compared to large samples where they approximate each other asymptotically. This explanation is beyond the scope of this application further insight is found in Olsson *et al*. (2000).

In contrast to the overall goodness of fit favouring the GLS method, several model fit indices indicate that ML has a better model fit. However, one should be cautious to draw inferences based on the fit indices because they rely heavily on the sample size which again could be highlighted as the limitation of this application. Furthermore, there is no point on relying on fit indices when the overall goodness of fit is not attained. The conventional approach and desired result is to have these indices to support the overall goodness of fit so that one arrives at a reasonably model which fit the data.

The second obstacle advocated in this application has to deal with the issue of underlying assumptions. The first assumption violated is the absence of multicollinearity in the observed variables. Although the literature on SEMs seems to disagree with the fact that multicollinerity can pose a problem in SEMs, Grewal *et al*. (2004) pointed out some conditions under which multicollinearity may pose a problem in estimating SEMs. One of these conditions is the problem of small samples which we also encountered in this study.

This violation is (Presence of multicollinearity is depicted in this application by some negative variance estimates as seen in **Table 4.13** and **Table 4.15**) attributed to the misspecification that in turn is influenced by the sample size as discussed above. Since the model is specified in a very simple manner with only the available variables involved, the application found no any other alternative. We believe such multicollinearity would not persist under circumstances when the sample size is large enough and the models are correctly specified.

The second assumption dealt with in this application is the normality assumption. The models are attested with both raw and transformed data types. The methods of estimations display consistency in the sense that, the results attained by the raw data is very similar to the results displayed by the transformed data for ML and GLS estimation methods respectively. However, the application found out that, the transformed data had improved fit indices in both estimation methods, compared to the raw data.

Formally, the outlined procedure that is followed in this study is discussed below in more detail to accompany the discussion of the results. The analysis started with an iterative approach to study the nature and structure of the Namibian macroeconomic sectors with regard to the real and the fiscal sectors. Although, there is a strong suggestion of extracting just one factor representing the two sectors, further analysis by the CFA highlighted that with two factors, the entered exogenous variables display a pattern that points them towards their respective sectors as indicated by theory. Therefore, our first objective was sufficiently addressed.

Secondly, a measurement model is developed which describes the nature of the relationships among the exogenous variables as well as between exogenous variables and their respective indicators. The model has two latent exogenous variables representing the sectors. Three other constructs namely, the trade balance, the government expenditures and the government expenditures on goods and services are also specified. Each construct and latent variables were having at least two indicators.

This measurement model is estimated using the ML and GLS methods of estimations. The chi-square statistics suggests that only the GLS method seems to fit the data. On the contrary, the fit indices provided some contrasting results but such discrepancy was attributed to the limitation of the sample size. Furthermore, the results indicate that transformed data displays better estimates than the raw data.

The modification index, specifically the Wald test, was also evaluated in an attempt to improve the fit of the model. Although the index highlighted some parameters that could be adjusted, the test show that making such adjustments would not significantly improve the chi-square statistic. Were it made theoretical sense, some parameters were nonetheless constrained so that some degrees of freedom were gained.

The loadings of nominal gross domestic produces on the government expenditures on goods and services, public consumptions on the government expenditures and import on the trade balance are all constrained to unity in the application. This approach has an effect that those variables with the parameter constrained to unity explain total variance in their respective constructs. See discussion in Section 4.5.5.

In addition, the variances of import and public consumptions are constrained to zero, arriving at a less complex and therefore more parsimony (as displayed by the PR and PNFI especially in the case of the ML method) measurement model that could be estimated. This whole process of constraining parameter also ensured that the model was identified.

The measurement model is estimated as the final SEM, in this regard as the theoretical model, and the goodness of fit statistics and other fit indices for discrepancy and parsimony are reviewed in the conventional nine model reviewing steps. The results of the theoretical SEM (Model 3) points out that, GLS is the best estimation method for the data in this study, the same results as attained with the preceding models.

The parameters of the SEM are all significant, except for one path coefficient which depicts the relationship between the government expenditure and the real sectors. The $\boldsymbol{R^2}$ values for the two estimation methods indicated that the trade balance and the government expenditure accounted for 98% of the variance in the real sector. On the other hand, government expenditures on goods and services accounted for none of the variance in the fiscal sector.

In conclusion, although the data used in this study were able to represent the structure of the Namibian real and fiscal sector, that structure was not sufficiently estimated. A simple modified specification is required to represent what is otherwise a complex specification based on the sample used in this study. The discrepancy of the parameters estimates is highlighted under the conditions of misspecification and small sample as well as the violation of multivariate normal assumptions. The GLS estimation method provides overall better goodness of fit indices under those conditions for both the confirmatory model and the structural equation model.

5.2 Recommendations

Even though the Namibian real economic sector is sufficiently represented by the SEM, there is little evidence that the fiscal sector is well represented in this study. The specification needs to be

adjusted with regard to the fiscal sector. This is highlighted by government expenditure unable to account for any of the variance in the fiscal sector.

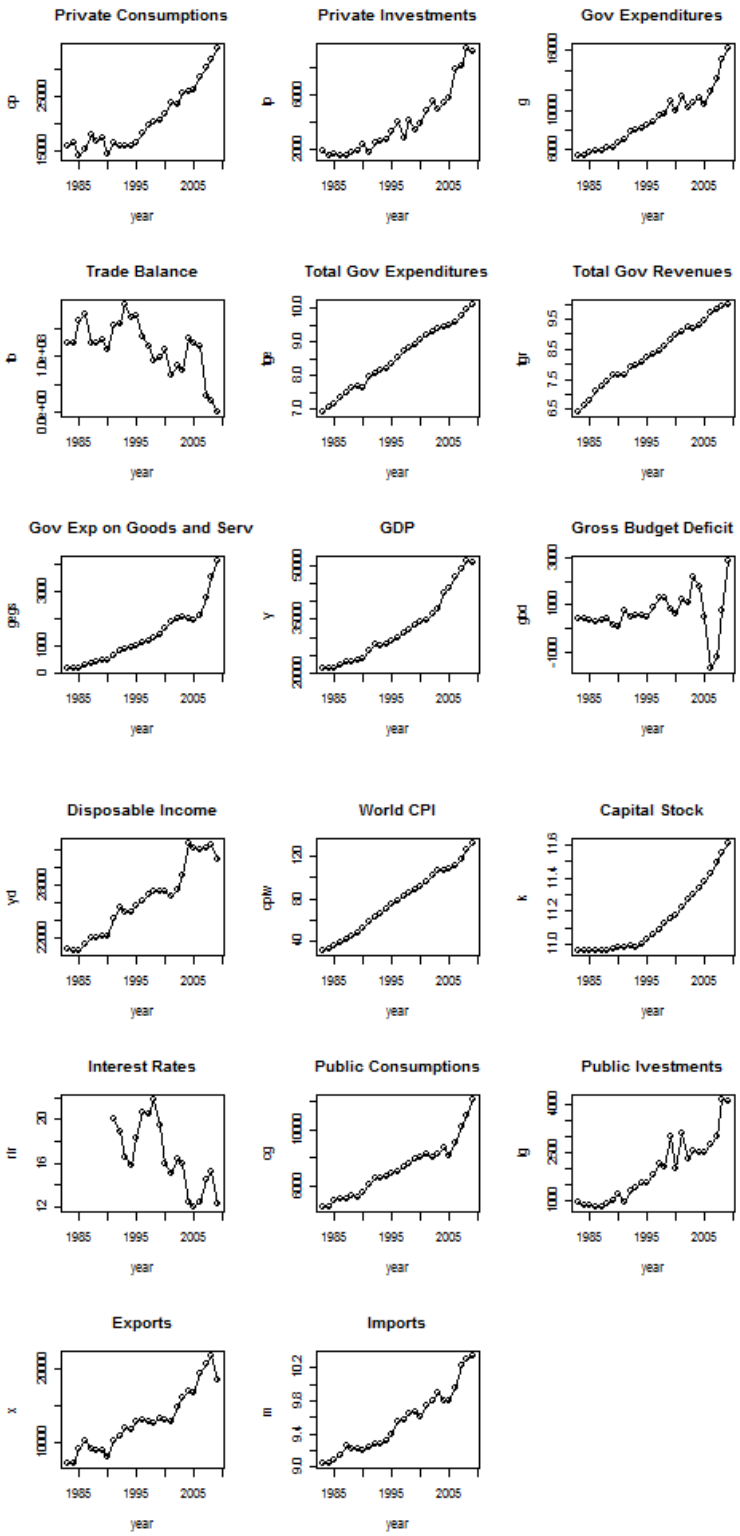
Note that all the obstacles highlighted in this application are attributed to the main limitation of the application which is the small sample size. It is well documented that the consistency of most of the existing estimation methods is based on their asymptotic properties. With this limitation, parameter estimates based on small sample sizes especially in this situation have to be dealt with carefully. To adequately represent an economy like Namibia where the sample size is very small, instead of using yearly observations, one needs to utilize quarterly or monthly data if its available.

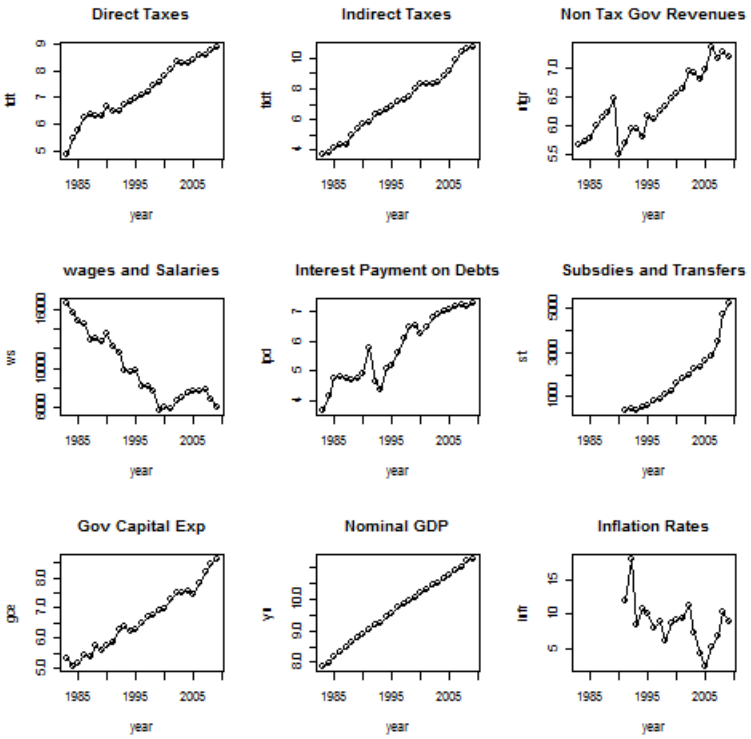
Another problem is the number of indicators which each construct should have for more proficient estimates. Hatcher (1994) suggests that, each construct should have at least three indicator variables. In this study, there are only two indicator variables for each constructs and hence a potential problem of that aspect. With a large enough sample size, the model would become more complex without the fear of consuming too many degrees of freedom. Also assumptions such as the absence of multicolinearity as violated in this study would be satisfied since there would be a wide variety of variables from which models could be specified.

Nonetheless, the study attained partly, its objectives. The structure as posited by the underlying theory is confirmed and discrepancies displayed by the estimation methods under the obstacles as often encountered in practice are highlighted. This would assist future researchers when trying to identify which estimation method will produce consistent, unbiased and valid parameters under certain conditions displayed by the data. However, several factors such as data needs need to be identified and rectified before a fully fledged macroeconomic model could be developed not only for the real and fiscal sector but, for the entire economy.

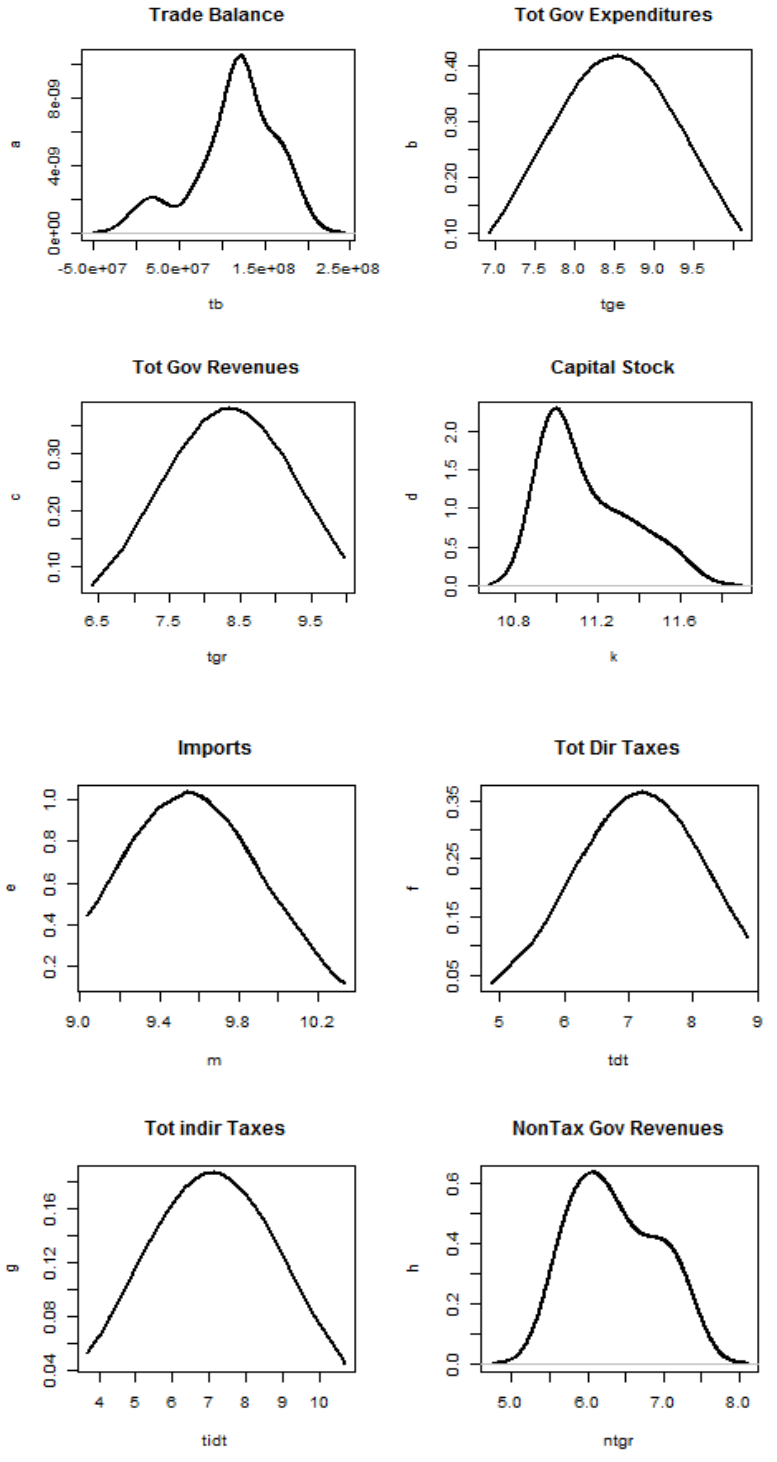
Appendices

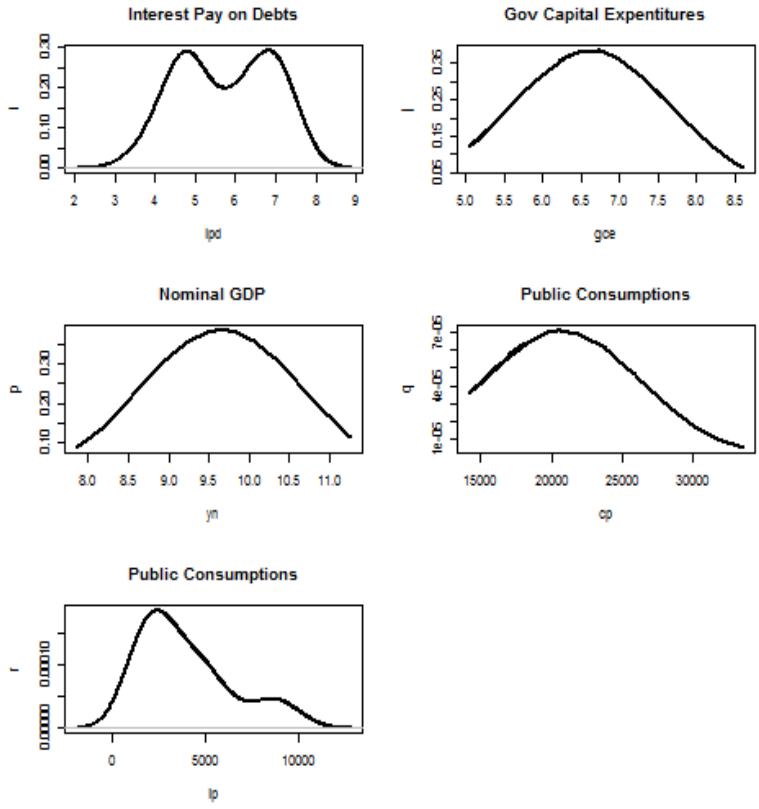
Appendix A.1: Raw data plots




Direct Taxes
dit
year
Indirect Taxes
idit
year
Non Tax Gov Revenues
ntgr
year
wages and Salaries
ws
year
Interest Payment on Debts
ipd
year
Subsdies and Transfers
st
year
Gov Capital Exp
gce
year
Nominal GDP
yd
year
Inflation Rates
infl
year

Appendix A.2.1: Distributions of non-normal variables




Interest Pay on Debts
l
lpd
Gov Capital Expentitures
l
goe
Nominal GDP
p
yn
Public Consumptions
q
cp
Public Consumptions
r
lp

Appendix A.2.2 Probability density function and the normal plots R codes

```
cp=data$CP

ip=data$IP

tb=data$TB

tge=data$TGE

tgr=data$TGR

k=data$K

m=data$M

tdt=data$TDT

tidt=data$TIDT

ntgr=data$NTGR

ipd=data$IPD

gce=data$GCE

yn=data$YN

a=dnorm(tb, mean=0,sd=1)

b=dnorm(tge, mean=mean(tge),sd= sd(tge))

c=dnorm(tgr, mean=mean(tgr),sd= sd(tgr))

d=dnorm(k, mean=0,sd=1)

e=dnorm(m, mean=mean(m),sd= sd(m))

f=dnorm(tdt, mean=mean(tdt),sd= sd(tdt))

g=dnorm(tidt, mean=mean(tidt),sd= sd(tidt))

h=dnorm(ntgr, mean=0,sd=1)

i=dnorm(ipd, mean=0,sd=1)

j=dnorm(gce, mean=mean(gce),sd= sd(gce))

p=dnorm(yn, mean=mean(yn),sd= sd(yn))

q=dnorm(cp, mean=mean(cp),sd= sd(cp))

r=dnorm(ip, mean=mean(ip),sd= sd(ip))


bmp(file="C:/Users/My/Desktop/Sep analysis/Distr/fig1.bmp")

par(mfrow=c(2,2))

plot(density(tb),type="l",lwd=2,main="Trade Balance", xlab= "tb", ylab = "a")

plot(tge,b,type="l",lwd=2,main="Tot Gov Expenditures")

plot(tgr,c,type="l",lwd=2,main="Tot Gov Revenues")

plot(density(k),type="l",lwd=2,main="Capital Stock", xlab= "k", ylab = "d")
```

```
bmp(file="C:/Users/My/Desktop/Sep analysis/Distr/fig2.bmp")
par(mfrow=c(2,2))
plot(m,e,type="l",lwd=2,main="Imports")
plot(tdt,f,type="l",lwd=2,main="Tot Dir Taxes")
plot(tidt,g,type="l",lwd=2,main="Tot indir Taxes")
plot(density(ntgr),type="l",lwd=2,main="NonTax Gov Revenues", xlab= "ntgr", ylab = "h")

bmp(file="C:/Users/My/Desktop/Sep analysis/Distr/fig3.bmp")
par(mfrow=c(3,2))
plot(density(ipd),type="l",lwd=2,main="Interest Pay on Debts", xlab= "ipd", ylab = "i")
plot(gce,j,type="l",lwd=2,main="Gov Capital Expentitures")
plot(yn,p,type="l",lwd=2,main="Nominal GDP")
plot(cp,q,type="l",lwd=2,main="Public Consumptions")
plot(density(ip), type = "l", lwd = 2, main = "Public Consumptions", xlab = "ip", ylab = "r")
```

Appendix A.3.1: Exploratory factor analysis SAS program

```
proc factor data = efa.efadata
simple
method = prin
priors smc
nfact = 2
scree
rotate = varimax
round
flag = 0.7;
var CP IP X M CG IG TGE TGR YN;
Run;
```

Appendix A.3.2 The initial parameter estimates (Model 1)

Parameter Estimates					
N	Parameter	ML1	GLS1	ML2	GLS2
1	a1	0.9854	0.98543	0.9818	0.9818
2	a2	0.9936	0.99367	0.9971	0.9971
3	a3	0.9964	0.99641	1.0019	1.0019
4	a4	0.9989	0.99893	0.9959	0.9959
5	b1	0.9618	0.96183	0.9730	0.9730
6	b2	1.0022	1.00229	1.0023	1.0023
7	b3	1.0072	1.00724	1.0071	1.0071
8	b4	0.9699	0.96997	0.9700	0.9700
9	b5	1.0000	1.0000	1.0000	1.0000
10	varCP	0.0289	0.0289	0.0358	0.0358
11	varIP	0.0126	0.0126	0.0100	0.0100
12	varTGE	0.0100	0.0100	0.0100	0.0100
13	varTGR	0.0100	0.0100	0.0100	0.0100
14	varX	0.0748	0.0748	0.0531	0.0531
15	varM	0.0100	0.0100	0.0100	0.0100
16	varCG	0.0100	0.0100	0.0100	0.0001
17	varIG	0.0591	0.0591	0.0590	0.0590
18	varYN	0.0100	0.0100	0.0100	0.0100
19	CovReal_Fiscal	0.9940	0.9940	0.9179	0.9179
20	CovReal_TB	0.9795	0.9795	0.9712	0.9712
21	CovReal_G	0.9490	0.9490	0.9490	0.9490
22	CovReal_GEGS	0.9936	0.9936	0.9114	0.9114
23	CovFiscal_GEGS	0.9990	0.9990	0.9987	0.9987
24	CovFiscal_TB	0.9809	0.9809	0.9619	0.9619
25	CovFiscal_G	0.9588	0.9588	0.9510	0.9510
26	CovTB_G	0.957	0.9573	0.9590	0.9590
27	CovTB_GEGS	0.9834	0.9834	0.9593	0.9593
28	CovG_GEGS	0.9565	0.9565	0.9481	0.9481

Appendix A.3.3: Confirmatory factor analysis SAS program (Model 1)

```
PROC CALIS data = cfa.cfadata
        COVARIANCE CORR RESIDUAL MODIFICATION;
         Var CP IP TGE TGR X M CG IG YN;
         LINEQS
                CP      =    a1  F_Real      +    e1,
                IP      =    a2  F_Real      +    e2,
                TGE     =    a3  F_Fiscal    +    e3,
                TGR     =    a4  F_Fiscal    +    e4,
                X       =    b1  F_TB        +    e5,
                M       =    b2  F_TB        +    e6,
                CG      =    b3  F_G         +    e7,
                G       =    b4  F_G         +    e8,
                YN      =    b5  F_GEGS      +    e9;
         STD

                F_Real                          =    1,
                F_Fiscal                        =    1,
                F_TB                            =    1,
                F_G                             =    1,
                F_GEGS                          =    1,
                e1 e2 e3 e4 e5 e6 e7 e8 e9      =    varCP varIP varTGE varTGR varX varM varCG
                                                     varIG varYN;
        Cov

                F_Real F_Fiscal     =    CovReal_Fiscal,
                F_Real F_TB         =    CovReal_TB,
                F_Real F_G          =    CovReal_G,
                F_Real F_GEGS       =    CovReal_GEGS,
                F_Fiscal F_GEGS     =    CovFiscal_GEGS,
                F_Fiscal F_TB       =    CovFiscal_TB,
                F_Fiscal F_G        =    CovFiscal_G,
                F_TB F_G            =    CovTB_G,
                F_TB F_GEGS         =    CovTB_GEGS
                F_G F_GEGS          =    CovG_GEGS;
Run;
```

Appendix A.3.4: Measurement model SAS program (Model 2)

```
PROC CALIS data = stetty.madala
  COVARIANCE CORR RESIDUAL MODIFICATION;
  Var CP IP TGE TGR X M CG IG YN;
  LINEQS

      CP    =  a1   F_Real          +   e1,
      IP    =  a2    F_Real         +   e2,
      TGE   =  a3   F_Fiscal        +   e3,
      TGR   =  a4   F_Fiscal        +   e4,
      X     =  b1   F_TB            +   e5,
      M     =       F_TB            +   e6,
      CG    =       F_G             +   e7,
      G     =  b2   F_G             +   e8,
      YN    =       F_GEGS          +   e9;
  STD

      F_Real      =   1,
      F_Fiscal    =   1,
      F_TB        =   1,
      F_G         =   1,
      F_GEGS      =   1,
      e1          =   varCP,
      e2          =   varIP,
      e3          =   varTGE,
      e4          =   varTGR,
      e5          =   varX,
      e6          =   0,
      e7          =   0,
      e8          =   varIG,
      e9          =   varYN;
  Cov

      F_Real F_Fiscal     =   CovReal_Fiscal,
      F_Real F_TB         =   CovReal_TB,
      F_Real F_G          =   CovReal_G,
      F_Real F_GEGS       =   CovReal_GEGS,
      F_Fiscal F_GEGS     =   CovFiscal_GEGS,
      F_Fiscal F_TB       =   CovFiscal_TB,
      F_Fiscal F_G        =   CovFiscal_G,
      F_TB F_G            =   CovTB_G,
      F_TB F_GEGS         =   CovTB_GEGS
      F_G F_GEGS          =   CovG_GEGS;
Run;
```

Appendix A.3.5: Theoretical model SAS program (Model 3)

```
PROC CALIS data = sem.semdata
  COVARIANCE CORR RESIDUAL MODIFICATION method =GLS;
  Var CP IP TGE TGR X M CG IG YN;
  LINEQS

        CP      =   a1   F_Real     +   e1,
        IP      =   a2    F_Real    +   e2,
        TGE     =   a3   F_Fiscal   +   e3,
        TGR     =   a4   F_Fiscal   +   e4,
        X       =   b1   F_TB       +   e5,
        M       =        F_TB       +   e6,
        CG      =        F_G        +   e7,
        G       =   b4   F_G        +   e8,
        YN      =        F_GEGS     +   e9,
        F_Real  =   c1   F_TB       +   c2   +   d1,
        F_Fiscal =  c3   F_GEGS     +   d2;

  STD

        e1      =   varCP,
        e2      =   varIP,
        e3      =   varTGE,
        e4      =   varTGR,
        e5      =   varX,
        e6      =   0,
        e7      =   0,
        e8      =   varIG,
        e9      =   varYN,
        F_TB    =   varTB,
        F_G     =   0,
        F_GEGS  =   varGEGS,
        d1      =   varReal,
        d2      =   varFiscal;
  Cov

      F_TB F_G      =   CovTB_G,
      F_TB F_GEGS   =   CovTB_GEGS
      F_G F_GEGS    =   CovG_GEGS;
Run;
```

Appendix B.1 Variances explained by the endogenous variables in the model (Model 3)

Squared Multiple Correlations ML			
Variable	*Error Variance*	*Total Variance*	*R-Square*
CP	*0.0384*	*1.0000*	*0.9615*
IP	*0.0446*	*1.0000*	*0.9554*
TGE	*0.0042*	*1.0000*	*0.9957*
TGR	*0.0043*	*1.0000*	*0.9957*
X	*0.0937*	*1.0000*	*0.9062*
M	*0.0000*	*1.0000*	*1.0000*
CG	*0.0000*	*1.0000*	*1.0000*
IG	*0.0859*	*1.0000*	*0.9140*
YN	*0.0000*	*1.0000*	*1.0000*
F_Real	*0.0255*	*0.9201*	*0.9722*
F_Fiscal	*0.0003*	*1.0291*	*0.9997*
Squared Multiple Correlations GLS			
Variable	*Error Variance*	*Total Variance*	*R-Square*
CP	*0.0157*	*0.8208*	*0.9808*
IP	*0.0036*	*0.9378*	*0.9961*
TGE	*0.0013*	*0.9250*	*0.9986*
TGR	*0.0040*	*0.9382*	*0.9956*
X	*0.0420*	*0.9663*	*0.9565*
M	*0.0000*	*0.9006*	*1.0000*
CG	*0.0000*	*0.9371*	*1.0000*
IG	*0.0527*	*0.8649*	*0.9390*
YN	*0.0000*	*0.9437*	*1.0000*
F_Real	*0.0310*	*1.1820*	*0.9738*
F_Fiscal	*-0.0003*	*0.9954*	.

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