ADRS' DYNAMICALLY INTEGRATED MACRO-MICRO SIMULATION MODEL OF SOUTH AFRICA (DIMMSIM)

A TECHNICAL REPORT

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ADRS offers expertise in economic modelling, policy research, advisory services, training and capacity building to assist our clients in government, non-governmental organizations, development agencies, and the private sector. ADRS services in economic analysis, policy analysis, economic modelling, innovative web-based modelling interface, and capacity building equip policymakers and others with the tools to design policies that go to the heart of development challenges. To date, ADRS has built economic models for more than 60 countries, exemplifying expertise that enables users to design and test the effectiveness of wide-ranging policy choices.

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1. INTRODUCTION

During the last 30 years, poverty analysis and the challenge of designing "pro-poor" policies have gradually occupied the central attention of development research.[1] This is partly attributed to worsening inequality and the persistence of high rates of poverty in many parts of the world. An important dimension of the current research, which has received particular attention from economic modellers, is increased recognition of the need for a better understanding of the interactions between macroeconomics dynamics and household level poverty and inequality. As Bourguignon *et al.* (2008) point out, macro models do not account for the poverty and distribution effects of policy changes at the household level, and micro models cannot explain the impact of macroeconomic policy changes on poverty.

While new techniques have been developed to use economic modelling as a tool for designing concrete and country specific pro-poor policies, awareness is mounting that the effects of policies need to be traced to changes in the income and expenditure of individuals and households, *and* that changes in household welfare has an important bearing on economic growth. Thus, economic models have been developed to capture the interactions between the macroeconomy and household poverty and inequality. This improvement has paved the way for a more holistic approach to the design of anti-poverty policies. Pioneering works in the early 1980s by Dervis, de Melo and Robinson (1982), and Gunning (1983) paved the way for a significant leap in linking household level poverty-distribution analysis and the dynamics of the macroeconomy to what is now known as linked macro-micro modelling.[2]

The range of linked macro-micro techniques is varied and has expanded in recent time.[3]There are at least four categories of linked macro-micro models. The main distinction between the four rests on the technique used to either represent households in the model or to extend the scope and nature of dynamic interactions between macroeconomics and households.[4]The first approach is the traditional CGE modelling technique that utilises a small number of representative households[5] to capture households in their design. Though it is widely used, the main shortcomings of this approach are generally found to be that it assumes no intra-group income distribution changes or imposes restrictions on the distribution. The second type of model is a variation of the first with the incorporation of a larger number of representative households into the CGE. This is an attempt to better represent the existing socioeconomic stratification within the population.[6]Examples of this approach are found in the work of Decaluwe *et al.* (1999) and Cockburn (2001). This approach clearly avoids the problem of selecting 'representative households' and, furthermore, allows for detailed analyses of distribution and poverty. However, as Piggot and Whalley (1985) point out, there are important intra-group heterogeneities that a high number of representative households do not capture. The third approach combines microsimulation modelling techniques, pioneered by Orcutt *et al.*

[1] Kakwani and Pernia (2000) define pro-poor policies as policies that are deliberately biased in favour of the poor so that the poor benefit proportionately more than the non-poor.

[2] The idea of linking micro and macroeconomic simulation models goes back to Orcutt (1967). The next set of important contributions in this area include Thorbecke (1991), Bourguignon *et al.* (1991), de Janvry*et al.* (1991) and Morrisson (1991). More recent contributions include Decaluwe *et al.* (1999), Cogneau and Robilliard (2000), Agenor *et al.* (2003), Cockburn (2001), Bourguignon, Robilliard and Robinson (2003), Bourguignon *et al.* (2003), and Savard (2003).

[3] Estrades (2013) reviews the different linked macro-micro techniques and presents a brief description of their pros and cons.

[4] The following review uses Savard (2003).

[5] See for example Dervis *et al.* (1982), de Janvry *et al.* (1991) and Agenor *et al.* (2003).

[6] The three commonly used criteria to disaggregate households in a social accounting matrix are geographical location, household resources, and occupation of the head of household (Thorbecke 2000).

(1961), with CGE modelling to further enhance the rigor and flexibility of household behaviour in the overall model. Examples of this approach include Bourguignon, Robilliard, and Robinson (2003).

Traditional CGE models with "representative households" allow a feedback effect of household behaviour but given the exiting heterogeneity among households, its usefulness for the purpose of pro-poor policy design is severely limited. On the other hand, most CGE models that incorporate large household surveys do not capture two-way interactions between the economy and households. This clearly weakens their overall appeal within the current development discourse since they fall into the traditional approach of allowing the macroeconomy to influence income distribution and poverty, but do not allow changes in income distribution and poverty to influence macroeconomic performance.

Savard (2003) represents a fourth approach within the CGE framework. His work aims to overcome some of the shortcomings of the previously described approaches in as much as his model is designed to keep the feedback mechanism between households and the economy while using microsimulation techniques for households. He addresses some of the issues related to the coherence between the household model and the CGE model, introduces two-way links between the two, and develops an approach to achieve convergence between the results from the two models.

In practice, international applications of linked macro-micro modelling techniques have predominantly relied on empirical CGE approaches to represent the working of the economy. Similarly, in South Africa, CGE based linked macro-micro techniques have been used for policy analyses. These models have relied on CGE techniques to produce projections of employment, wages and prices that are transmitted to the micro component of the model to estimate the poverty and distribution impact.[7]

Yet, empirical CGE models have been extensively criticised in the literature from analytical, functional and numerical perspectives. The analytical criticisms centre on the theoretical foundation of CGE models which informs the specification of variables used in the models and their causal relationships. Since CGE models are quantitative expressions of neo-classical general equilibrium theory, they embody strong theoretical assumptions about the working of the economy that do not necessarily reflect the reality of market economies, especially those in developing economies. These assumptions include perfect competition and flexible markets with inherent tendencies to self-correct and achieve full employment general equilibrium, i.e., to simultaneously clear all goods and factor markets. These assumptions are among CGE's highly debatable depiction of the working of the economy. De Canio (2003) and Ackerman (2002) review these assumptions, Barker (2004) examines their influence on the development of CGE models, and Taylor *et al.* (2006) provides a critique of CGE models as used in studies of impact of trade liberalisation.

Another set of criticisms of CGE models centres on the calibration method used to develop the model's parameters (i.e., elasticities). The method is a deterministic approach to calculating parameter values from a bench-mark equilibrium data set. Shoven and Whalley (1992) point out that the techniques are less than ideal and undermine the reliability of the results derived from the model since the parameters are either based on the empirical literature, arbitrary or are a set of values that "force the model to replicate the data of a chosen benchmark year." Similarly, Jorgensen (1984), Lau (1984), Jorgensen *et al.* (1992), and Diewert and Lawrence (1994), among others, point out flaws they have found in the parameter setting techniques in CGE models. This includes the use of industry or commodity level elasticities that are methodologically inconsistent, and/or are from other countries, and/or are old and obsolete estimates, and/or are outright

[7] Pauw and Leibbrandt (2012) use a linked CGE micro model to study the impact of minimum wage in South Africa. The Treasury Department, MacLeod (2015), has also used the CGE based linked macro-micro model that was developed by Pauw (2007) and Alton *et al.* (2012) to examine the impact of the NMW. Bhorat *et al.* (2015) refers to the use of a CGE model for its examination of the feasibility of a NMW for South Africa. However, the specifics of the model have not been provided.

guesses.[8] They correctly point out that without reliable or credible parameter values, the utility of the empirical CGE models is compromised.

Since calibration is a process through which a model's parameters are adjusted until the model reproduces the national account for the benchmark year, the quality of the data is critical. Yet, one year data, which empirical CGE models are usually built upon, provides insufficient grounds upon which to base generalized results. Thus, an important criticism regarding the inherently limited scope of CGE models hinges on the calibration technique itself, which causes the quality of the model to be at least partly dependent on the quality of the data for an arbitrarily chosen benchmark year. Critics also note that the calibration techniques are susceptible to errors and biases as a result of subjecting the data matrices to various scaling processes to force micro-consistency. These errors and biases will directly influence the parameters of a calibrated model.[9]

Another important criticism of the CGE model's calibration approach is that it tends to be based on a "one-size-fits-all" approach to all industries by using the Constant Elasticity of Substitution (CES) class of functions. Utilising restrictive assumptions about the industry elasticities not only have a bearing on the way in which industries are incorporated into the model but also on the validity of the results derived. McKitrick (1998) demonstrates that changing from CES functions to flexible forms modifies the performance of a CGE model so much that the two models seem to represent entirely distinct descriptions of the economy. He finds that the choice of functional forms influences both industry-specific results and aggregate results, even for small policy shocks.

McKitrick (1998) calls the above critique of the functional and numerical structure of calibrated CGE models the 'econometric critique' of CGE modelling, which is separate from criticisms directed at the analytical structure of these models. These critiques raise serious doubts about the validity of the functional and numerical structures of calibrated CGE models that are currently being used, including the CGE models used in South Africa. The econometric critique of CGE modelling provides a priori reasons for doubting the validity of the functional and numerical structures of many CGE models used in South Africa and raise serious questions about both their industry-specific and aggregate results.

It is the combination of both the underlying theoretical assumptions of CGE models, e.g., perfect competition and general equilibrium, and their functional and empirical shortcomings that raises serious questions about the utility of empirical CGE models for policy analyses in South Africa.

In this paper, we utilise a linked macro-micro model of South Africa that is neither based on the neo-classical theory of perfect competition and general equilibrium nor uses calibration methods to develop the model's parameters. The Dynamically Integrated Macro-Micro Simulation Model (DIMMSIM) links a multi-sector macroeconometric model of South Africa with a household microsimulation model of the country to capture the dynamic two-way interactions between the macroeconomic performance and household level poverty and income distribution. DIMMSIM's analytical approach is in the tradition of pluralism of heterodox economics and uses modern time series specification and estimation methods to estimate the parameters of the model's behavioural equations.

[8] The "expediencies" they identify include the use of "elasticities estimated for commodity and/or industry classifications which are inconsistent with those maintained in the model, and/or for countries other than the one(s) represented by the model, and/or obsolete estimates from past literature, not to mention outright guesses when no published figures are available."

[9] See Mansur and Whalley (1984) and Lau (1984) for an extensive review of the calibration method.

2. BASIC STRUCTURE AND FEATURES OF DIMMSIM

Over the last 15 years, ADRS has built a suite of 10 South African economic models which include two core models and eight specialised models. The two distinct core models were built using fundamentally different modelling techniques. The ADRS multi-sector Macroeconomic Model of South Africa (MEMSA) is a large multi-sector macroeconometric model built as a tool for designing, forecasting and conducting impact analyses of macroeconomic and industry policy scenarios. Its construction utilised time-series data and analysis. The ADRS South African Tax and Transfer Model (SATTSIM) is a microsimulation model built using household-level survey data. It is a tool for designing, forecasting and conducting impact analyses of policies related to direct and indirect taxes, social security, public works, poverty and inequality.

DIMMSIM integrates MEMSA and SATTSIM to capture the dynamic interactions between the macroeconomic performance and the poverty and income distribution at household level and is available at the ADRS website through its user-friendly web-platforms. Following is a brief technical introduction to the DIMMSIM and its features.

2.1. DIMMSIM's Macroeconomic Component

One of the two economic models that underlie DIMMSIM is a non-linear Macroeconometric Model of South Africa (MEMSA) that captures the structure and the working of the South African economy. It allows design and analyses of macroeconomics and industrial policies and produces projections of the paths of key indicators related to the economy and its economic sectors under various domestic and international contexts and policy options.

2.1.1. Basic Model Structure

MEMSA is a bottom-up model with more than 3200 equations that captures the structure of the National Income and Product Account (NIPA) at sector and aggregate levels and produces projections that are consistent with various national account identities in nominal and real terms. The model includes more than 400 estimated equations that analytically and empirically capture the behaviour of the private and household sectors as part of capturing the working and the dynamic of the economy from its production, expenditure and income perspectives. DIMMSIM's equation system (Figures 1 and 2) can be broken down into a number of blocks that include:

- **Final Demand Block**: This block encompasses 769 equations. It includes sets of estimated equations that capture the behaviours of the private sector as they relate to 45 sector level investments, exports, and imports; households in terms of expenditure on 27 categories of consumption goods and services; and the public sector in terms of final consumption expenditure and investment. The expenditure block of equations therefore produces projections of various components of aggregate demand in the economy that facilitate the model's projection of real and nominal GDP from the expenditure side.[10]

- **The Production Block** includes 712 equations that represent sector and aggregate production related activities in the economy. It includes sets of equations that produce projections of sector outputs, potential outputs, capital stock, and capital productivity, all in nominal and real terms. Private sector

[10] GDP from the expenditure side is the sum of final consumption expenditure by households and general government, gross investment, exports and imports of goods and services, and the GDP residual item.

decisions on how much to produce in various sectors of the economy are captured through 40 estimated equations that link the decisions to various demand, supply and price factors in the economy. Therefore, equations of the production block generate consistent projections of nominal and real values for sector and aggregate outputs, i.e., value added at basic prices. The aggregate of sectoral value added at basic prices plus the net taxes and subsidies on products provide the model's annual projections of GDP from the production side.[11]

- **Price and Wage Block** is comprised of 413 equations that include time series estimated behavioural equations for sector output prices (45), consumer prices (30), and investment prices (45). It also includes equations for sector import and export prices, sector and economy-wide inflation rates, and 45 estimated equations for the sector level real wage rate (i.e., average remuneration rates) and 45 calculated sectoral level nominal wage rates.

- **Labour Market Block** is comprised of 186 equations that include 40 estimated equations that capture factors that determine short and long term demand for sector level employment. In addition, this block includes equations for sectoral labour productivity, labour force, unemployment rate, and other labour market indicators.

- **Income, Expenditure, and Saving Block** includes 569 equations that capture a detailed breakdown of income, expenditure, and saving of households, incorporated business and government, in both nominal and real terms. A combination of variables from this block, the labour market block, the price and wage block, and the production block provide forecasts of the real and nominal GDP from the income side.[12]

- **Financial Block** embodies 88 equations for indicators related to the financial and monetary side of the economy, such as the interest rate, exchange rates, money supply, credit extensions, households financial assets and liabilities, and foreign direct and portfolio investments. The financial block variables are especially important determinants of variables in other equation blocks and include policy variables and time series estimated variables.

- **National Account Block** incorporates more than 470 equations. This block of equations is responsible for ensuring consistency and enforcing national income and product account relationships within the economic system captured by the model. For example, it ensures that in the model, the calculation of GDP, both real and nominal, from income, production and expenditure sides are comprised of relevant NIPA components and are consistent with each other at aggregate and sector levels, in nominal and real terms.

The model's list of exogenous variables includes a number of domestic and international variables. Among exogenous inputs to the model are:

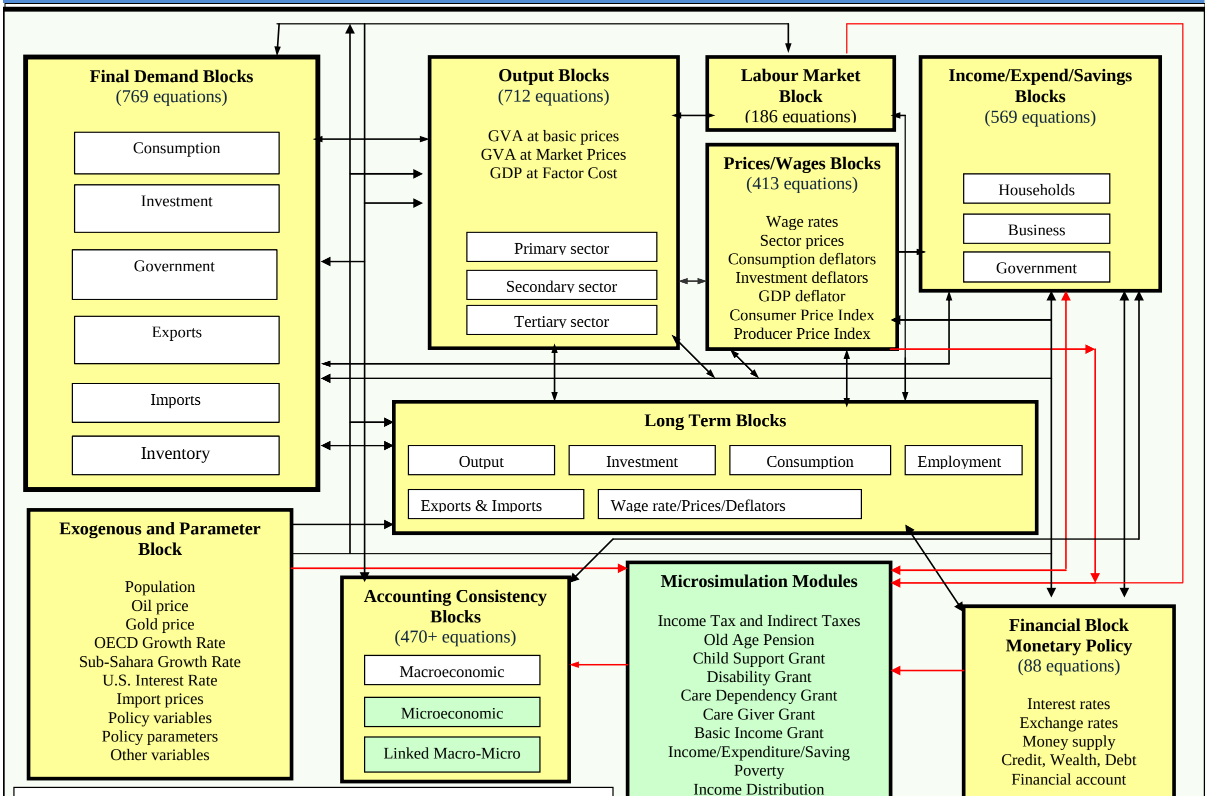
- General government and public corporation investment
- Monetary and fiscal policy rules
- Government current spending
- Tax and subsidy rates
- Population
- Oil price
- Gold price
- Import demand growth from Asia
- Import demand growth from Europe

[11] GDP from the production side is equal to the sum of sectoral value added at basic prices and net taxes on products.

[12] GDP from the income side is calculated as the sum of gross value added at factor cost plus net taxes on production and products.

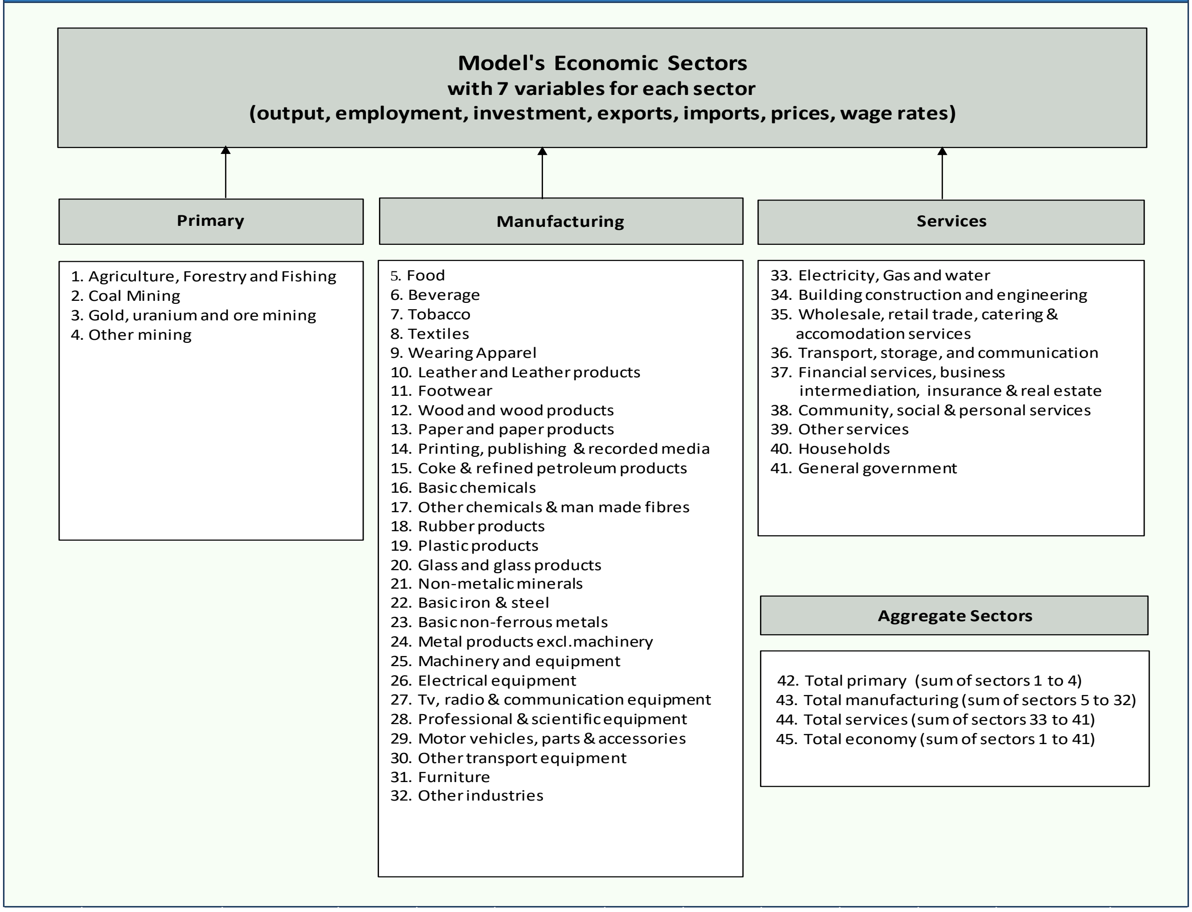
- Import demand growth from Middle East and Africa (excluding South Africa)
- Import demand growth from America
- Import demand growth from the World
- Net foreign direct investment
- U.S. interest rate
- U.S. inflation rate

Figure 1: Dynamically Integrated Macro-Micro Model of South Africa (DIMMSIM)



Source: Adelzadeh, A.. Applied Development Research Solutions (ADRS), www.adrs-global.com

Figure 2: Macro-Econometric Model of South Africa (MEMSA) Sectors



The macroeconomic module of DIMMSIM generates annual forecasts of a relatively large number of aggregate, sector level, nominal and real variables and indictors. It includes indicators related to production, labour market, prices, wages, financial variables, and incomes and expenditures of households, business and government. The model projections are consistent across aggregation levels both in nominal and real terms. Key outputs of the model include projections of:

- Key macroeconomic indicators
- Demand for employment and the real and nominal average wage rates for 45 economic sectors
- Output, investment, exports, imports, wages, and prices for 45 economic sectors
- Financial indicators such as the interest rate, credit extensions, and money supply
- Trade indicators
- Income and expenditure indicators
- Sustainability indicators
- Labour market indicators
- Production indicators
- Demand (expenditure) indicators

2.1.2. Model Specification

Specification refers to the selection of a model's functional form, that is, specifying the perceived nature of relations between variables in the economy. In the case of macroeconomic models, model specification generally is based on a good theoretical and empirical knowledge of how an economy functions and evolves over time. A model's specification therefore must include sufficient structural detail to approximate the system and its multiple interactions while ensuring conformity between economic theory and econometric test criteria. Finally, model specification should provide sufficient detail to generate forecasts and should include relevant policy variables and their transmission channels.

The Specification of MEMSA can be described in terms of the specification of its time-series estimated behavioural equations and a large number of real and nominal accounting and other relationships that together constitute the overall model.

Specification of MEMSA's Behavioural Equations: The latest version of MEMSA includes more than 400 estimated behavioural equations. It is composed of industry level specification of output, employment, investment, wage rate, export and import, investment prices, sector prices, and export and import prices. The rest of the model's estimated equations include detailed specification of real private household consumption expenditure, consumption prices, credit extension, money supply, exchange rates and other behavioural equations of the model.

Given the heterogeneity among sectors of the economy, for the specification of each sector level variable (e.g., employment, investment), we considered the broad theoretical and empirical literature on the subject. Therefore, the specification of the model's behavioural equations avoids *a priori* imposition of one theoretical stand on the determination of a given sector level variable. The adapted broad specification approach is especially appropriate since the focus of MEMSA is not to test or assert the validity of a particular theoretical proposition, but to capture the potential differences in the law of motion (i.e., behavioural differences) among sectors of the economy, using a combination of econometric test criteria and economic theory.[13]

The model therefore has used the theoretical and empirical literature to identify a range of sector and economy-wide variables that are found significant in explaining the long-term trend and short-term fluctuations of the model's behavioural equations. In general form, the specification of the model's behavioural variables includes demand-side (*d*), supply-side (*s*), price and expectation variables:

$$Y_v^t = f_v(s_h, d_j, p_k, e_q, x_u) \qquad [1]$$

Where:

Y_v^t represents estimated variables in MEMSA with $v=1,2,..,V$;

s_h represents supply side variables with h = 0,1,2,..,H;

d_j represents demand side variables with j = 1,2,..,J;

p_k represents various aggregate and sector level prices with k=0,1,…,K;

e_q represents various expressions of expectations with e=0,1,…, E; and

x_u represents other variables with u=0,1,…,U.

Space limitation does not allow presentation of specification of MEMSA's large number of estimated equations. Table 1 provides a summary list of variables used in the specification and estimation process and their classification as demand side, supply side, prices, expectation, and other variables. It is important to note that the classification of variables is for ease of presentation.

[13] At the same time, the adopted approach reduces the risk of working with mis-specified regression equations.

Table 1: Classification of Sample of Variables Used in Specification of

Supply Side	Demand Side	Prices	Expectations	Others
Productivity	Exports	Consumption prices	Price expectations	Employment
Capital labour ratio	Imports	Sector prices	Profit expectations	Output
Tax rates	Consumption	Investment prices	Output expectations	Deficit/GDP
	Income	Exchange rates		Debt/GDP
	Investment	Export prices		
	Government Expenditure	Import prices		

To provide an example of the procedure that was followed to specify and estimate particular blocks of economic variables, section 2.1.5 describes the processes for the model's 41 sector employments.

Specification of MEMSA's Non-behavioural Equations: A significant number of MEMSA equations are designed to capture a wide range of nominal-real conversions and accounting relationships at sector and aggregate levels and to ensure inter-temporal consistency. The specification of this considerable part of the model is concerned with enforcing the necessary accounting relationships at aggregate and sector levels to ensure model results are consistent, meaningful and reliable. MEMSA's iterative process of generating each period's forecast ensures that the accepted simulation results for each period satisfies all the specified accounting relationships. For example, within MEMSA, the components of the product account add up, and the income and product sides of the accounts are equal. Moreover, the price-quantity relationships are consistent.

2.1.3. MEMSA Data Sources and Preparation

The specification of the model equations informed the range and the details of its data requirements. MEMSA as a multi-sectoral macroeconometric model uses extensive amounts of data as input. The model's main sources of data for its endogenous variables include the Reserve Bank's electronic historical National Income and Product Account dataset and Quantec's industry database, which is based on Statistics South Africa data. The model's datasets start from 1970. As part of building the model's database, the process included cross checking industry time series data with the Reserve Bank time series data in order to ensure data consistency. The Standard Industrial Classification (SIC) for agriculture, mining (comprising three sectors) and services (comprising seven sectors) is aggregated at the 2-digit SIC level. Manufacturing (comprising 28 sectors) is aggregated at the 3-digit level. The data for the model's aggregate sectors, primary, manufacturing, services and total economy, are the sum of data from relevant sectors.

The model's database of exogenous variables includes domestic and international economic and policy indicators whose values are not determined within the model but are either a necessary part of the national accounting of the South African open economy or found to have statistically significant impact on particular endogenous variable(s) of the economy. This includes, for example, the growth rates of OECD countries and Sub-Saharan countries, oil prices, metal prices, the U.S. interest rate, foreign investment, population growth, etc. For these and other similar data, MEMSA uses various international databases, such as the electronic databases and publications of the International Monetary Fund, the World Bank, the OECD, the European Union, the African and Asian Development Banks, OPEC, and other similar sources.

2.1.4. Parameter Estimation Method

The parameter estimation process refers to the utilisation of historical data and suitable econometric techniques to establish the explicit forms of the model's behavioural equations. The process is expected to yield theoretically acceptable and statistically significant values for the parameters of the model equations.

The range of available regression techniques has expanded with the evolution of econometrics and the availability of more and more data. Empirical literature has also expanded the choices that are available for estimating parameters of an economic model. For the specific functional form of its estimated equations, MEMSA uses the cointegration technique, in which relationships among a set of economic variables are specified in terms of error correction models (ECM) that allow dynamic convergence to a long-term outcome.[14]The independent variables of the estimated equation act as the 'long run forcing' variables for the explanation of the dependent variable.[15] The cointegration technique has been the preferred method used globally to build national macroeconometric models.

Among the several such techniques available, MEMSA uses the Autoregressive Distributed Lag (ARDL) estimation procedure, developed by Pesaran (1997) and Pesaran, Shin and Smith (1996, 1999). The advantages of this technique are that it offers explicit tests for the existence of a unique cointegrating vector, and since the existence of a long run relationship is independent of whether the explanatory variables are integrated of order one, I(1), or of order zero, I(0), the ARDL remains valid irrespective of the order of integration of the explanatory variables.[16]

The ARDL approach hinges on the existence of a co-integrating vector among the chosen variables, selected on the basis of economic theory and a priori reasoning. If a cointegrating relationship exists, then the second stage regression is known as the error-correction representation and involves a dynamic, first-difference, regression of all the variables from the first stage, along with the lagged difference in the dependent variable, and the error-correction term (the lagged residual from the first stage regression).[17]

The following equation represents the relevant ARDL formula used for the estimation of the model's behavioural equations such as y_t with a range of explanatory variables $x_{i,t-j}$. It includes the computation of the long run coefficients and the associated error correction model (ECM).

$$\Delta \ln y_t = \beta_0 + \sum_{j=1}^{l_1} \eta_j \Delta \ln y_{t-j} + \sum_{i=1}^{n} \sum_{j=0}^{l_2} \gamma_{i,j} \Delta \ln x_{i,t-j} + \rho(\ln y_{t-1} + \sum_{i=1}^{n} \beta_n \ln x_{i,t-1}) + \varepsilon_t \qquad [2]$$

A successful single equation estimation of the above model includes acceptable theoretical relationships among the estimated variables and values for parameters $\beta_0, \eta_j, \gamma_{i,j} \beta_n, \rho$ that are statistically significant and can be used to write the specific functional form of y_t in MEMSA. Moreover, each estimated ARDL equation that has been integrated into the MEMSA's system of equations had to pass all the diagnostic tests.[18] For example, the coefficient of the lagged error correction term had to be negative and statistically significant, as a confirmation of a cointegrating relationship existed among the variables in the estimated equation. It signifies the rate of adjustment to the long run tendency of the dependent variable after a disturbance. F-Stat was used to test whether the overall regression was significant, that is, whether the

[14] Engle *et al.* (1987).

[15] Pesaran and Pesaran (1997), p.306.

[16] Another advantage of the technique is that the endogenous variables are valid explanatory variables.

[17] The existence of a CV is tested by the variable addition test, a technique that utilises the F tests developed by Perron. Where a CV existed, both short and long run estimates of the regression model are computed. It is an established fact that wherever there is a long-run relationship, there must exist a valid error correction mechanism that depicts the adjustment process towards this long run relationship. The critical test for the validity test of this adjustment process is that the coefficient of adjustment must be negative, between 0 and 1, and statistically significant.

[18] Hansen (1992) provided the rational for parameter testing.

explanatory variables in the model are good predictors of the dependent variable. The cumulative sum of recursive residuals (CUSUM) and CUSUMSQ of recursive residuals stability tests have been used to check the stability of the coefficients of the model, as suggested by Pesaran and Pesaran (1997). The Lagrange Multiplier was used to test for residual serial correlation, Ramsey's RESET test was used for Functional Form misspecification. Normality was tested based on a test of skewness and kurtosis of residuals, and heteroscedasticity was tested based on the regression of squared residuals on squared fitted values.

In order to provide a more concrete understanding of the procedures that were used to specify and estimate each of more than 400 behavioural equations of MEMSA, the next section presents the process of estimating the model's 41 employment equations.[19]

2.1.5. Application of Empirical Method: Employment

In MEMSA, the block of behavioural equations that capture the working of the labour market includes 41 sector level estimated equations for employment and 45 estimated equations for the real wage rates.[20] Since industry level employment is one of the main channels that link the DIMMSIM's macroeconomic module to the microsimulation component, this section focuses on specifications and estimations of the employment equations of MEMSA.

First, in MEMSA, employment in the total economy is broken down into three aggregate categories (i.e., Primary, Manufacturing and Services) that have been further disaggregated into 41 sectors composed of 4 primary, 28 manufacturing, and 9 services. There is significant diversity within the 41 economic sectors in terms of economic activity (e.g., agriculture versus banking sectors), size, production techniques (i.e., their utilisation of different mix of factors of production), links and dependency to other sectors, the rest of the economy, and the rest of the world.

As explained earlier, given the diversity of economic sectors, at the specification stage, MEMSA uses a broad theoretical perspective to define, compile and process a number of variables which have been proposed to explain long-term trends and short-term fluctuations in employment. This allows the estimation process, which is the next step, to capture the differences in factors that determine employment of various sectors. The list of explanatory variables for the estimation of sector employment includes sector specific and macroeconomic variables. The hypothesised relationships are consistent with a pluralism in labour market theory and empirical research, such as Neoclassical supply side determination of employment, Keynesian consideration of the direct relationship between employment and aggregate demand, and Phillips curve depiction of the negative relationship between the inflation and unemployment rates. Therefore, on the supply side, the specification of employment equations include: the real average remuneration rate, the technique of production represented by a sector's capital labour ratio, a sector's labour productivity represented by the real output per unit of labour. On the demand side, we have included: sectoral real output, imports, exports, and the real gross domestic expenditure. Finally, the specification of this group of endogenous variables includes economy-wide price levels represented by the GDP deflator.[21]

Overall, the following equation presents the broad specification of the sector employment equations in MEMSA in a general form.

[19] We have chosen to present a detailed discussion of estimation of sectoral employment since the project committee has been especially interested in employment wage elasticities. In the main part of the report, these elasticities are presented for all the sectors we used for the estimation purpose.

[20] The model includes 45 employment equations, 41 of which are estimated equations consisting of 4 primary, 28 manufacturing and 9 services. Four employment equations are for total primary, total manufacturing, total services, and total economy. Each aggregate variable is the sum of employment of its subsectors.

[21] Ashworth, MacNulty and Adelzadeh (2002) and Adelzadeh (2020) provide explanation of the theoretical propositions that underlie the inclusion of different independent variables in the specification of employment equations of MEMSA.

$$L_i = f_i(\overset{-}{rw_i}, \overset{-}{rw_{tot}}, \overset{-}{cl_i}, \overset{-}{lp_i}, \overset{+}{ex_i}, \overset{+/-}{im_i}, \overset{-}{I_i}, \overset{+}{GDE}, \overset{+}{GDP}, \overset{+}{REER}, \overset{+}{q_i^e}, \overset{-}{P}) \qquad [3]$$

Where L_i represents employment in sector i where i=1,2,…,41, and the signs above the independent variables reflect the hypothesised relationship between the variables and the sector employment. The variables are:

- rw_i represents real wage rate in sector i
- cl_i represents capital-labour ratio in sector *i*
- lp_i represents labour productivity in sector *i*
- ex_i represents real export (in 2010 prices) of sector *i*
- im_i represents real import (in 2010 prices) of sector *i*
- I_i represents real investment (in 2010 prices) of sector *i*
- GDE_i represents real gross domestic expenditure (in 2010 prices)
- GDP_i represents real gross domestic product (in 2010 prices)
- $REER$ represents the real effective exchange rate
- q_i^e represents one period ahead expectation of the real output of sector *i*
- P represents economy-wide general price index

After visual inspection of the plots of each data set to assess whether the data should be run in logs or levels, two separate regressions were run, one in log form and one in level form. Using the Schwartz-Bayesian Criterion, it was possible to draw a final conclusion about each variable's level of transformation. The results highlighted the fact that almost all variables used in the regressions should be run in log form.

Next a combination of Augmented Dickey Fuller tests, auto-correlation functions and Box-Pierce statistics were used to test for the existence of unit roots (i.e. the stationarity of data) and the order of integration of each variable. The results indicated that all the variables used in the specification of employment were integrated of order one, implying that the data series had to be differenced once, in order to render them stationary. Since one of the major advantages of the ARDL technique is that the exact order of integration is not important when running co-integration tests (see Pesaran *et. al.* 1996, 2001), the above information was used specifically to ensure the careful choice of variables for the application of the OLS technique where co-integrating vectors did not exist. Needless to say, the employment data (the dependent variable in all our estimations) was found to be integrated of order one, I(1), at all levels of aggregation.

The specification equation [3] and above data analysis were used to formulate, run and diagnose sector specific ARDL models using Microfit 5.0 software. Since the ARDL approach involves multiple steps that include diagnostic information, the following provides an example of the process and the outcome for the Metal Products Excluding Machinery (Metal Products) sector.

The ARDL approach involves two stages. At the first stage, the existence of the long run relation between the variables under investigation is tested by computing the F-statistic for testing the significance of the lagged levels of the variable in the error correction form of the underlying ARDL model. The F-statistics for testing the joint null hypothesis that the coefficients of the level variables used in the equation are zero (i.e., there exists no long run relationship between them) is 6.9918 in Table 2. The critical value bounds for the F-test are computed by Pesaran *et al.* (1996) and are provided in Table 2. The relevant critical value bounds for the present application are also given in Table 2, and at the 95 percent level are given by 2.9346 to 4.2868. Since the F-statistic of 6.9918 exceeds the upper bound of the critical value band, we can reject the null hypothesis of no long-run relationship between the variables in the equation, irrespective of the order of their integration. Therefore, the test results suggest that there exists a long run relationship between all selected variables, and that the explanatory variables can be treated as the 'long run forcing' variables for the explanation of the employment in the Metal Products sector.

The estimation of the long run coefficients and the associated error correction model could then be accomplished using the ARDL. The Schwarz Bayesian (SBC) criterion was used to select the ARDL(2,0,1,0) specification, and the estimates of the long run coefficients based on this model is provided in Table 3. The point estimates include expected signs and magnitudes with acceptable estimated standard errors.

Table 2: Testing for existence of a level relationship among the variables in the ARDL model

****
*

F-statistic	95% Lower Bound	95% Upper Bound	90% Lower Bound	90% Upper Bound
6.9918	2.9346	4.2868	2.4839	3.6694

W-statistic	95% Lower Bound	95% Upper Bound	90% Lower Bound	90% Upper Bound
41.9510	17.6075	25.7210	14.9032	22.0164

****
*

If the statistic lies between the bounds, the test is inconclusive. If it is above the upper bound, the null hypothesis of no level effect is rejected. If it is below the lower bound, the null hypothesis of no level effect can't be rejected. The critical value bounds are computed by stochastic simulations using 20000 replications.

Table 3: Estimated Long Run Coefficients using the ARDL Approach
ARDL(2,1,0,0,0,0) selected based on Schwarz Bayesian Criterion

****

Dependent variable is LE447ME
42 observations used for estimation from 1972 to 2013

****

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
LRW494MP	-0.36529	0.089335	-4.0890[.000]
LVA541MP	0.49840	0.10185	4.8936[.000]
LFI353MP	0.096780	0.036150	2.6772[.011]
LGDE11	0.23965	0.048622	4.9288[.000]
LRM635ME	-0.11681	0.032709	-3.5711[.001]
C	3.0384	1.3841	2.1953[.035]

****

Testing for existence of a level relationship among the variables in the ARDL model

****

F-statistic	95% Lower Bound	95% Upper Bound	90% Lower Bound	90% Upper Bound
6.9918	2.9346	4.2868	2.4839	3.6694

W-statistic	95% Lower Bound	95% Upper Bound	90% Lower Bound	90% Upper Bound
41.9510	17.6075	25.7210	14.9032	22.0164

****

If the statistic lies between the bounds, the test is inconclusive. If it is above the upper bound, the null hypothesis of no level effect is rejected. If it is below the lower bound, the null hypothesis of no level effect can't be rejected. The critical value bounds are computed by stochastic simulations using 20000 replications.

Table 4: Error Correction Representation for the Selected ARDL Model
ARDL(2,1,0,0,0,0) selected based on Schwarz Bayesian Criterion

****

Dependent variable is dLE447ME
42 observations used for estimation from 1972 to 2013

****

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
dLE447ME1	0.18683	0.10336	1.8076[.080]
dLRW494MP	-0.59903	0.096409	-6.2134[.000]
dLVA541MP	0.33417	0.067121	4.9786[.000]
dLFI353MP	0.064889	0.024748	2.6220[.013]
dLGDE11	0.16068	0.042716	3.7616[.001]
dLRM635ME	-0.078318	0.026322	-2.9754[.005]
ecm(-1)	-0.67048	0.087384	-7.6727[.000]

****

List of additional temporary variables created:
dLE447ME = LE447ME-LE447ME(-1)

dLE447ME1 = LE447ME(-1)-LE447ME(-2)
dLRW494MP = LRW494MP-LRW494MP(-1)
dLVA541MP = LVA541MP-LVA541MP(-1)
dLFI353MP = LFI353MP-LFI353MP(-1)
dLGDE11 = LGDE11-LGDE11(-1)
dLRM635ME = LRM635ME-LRM635ME(-1)
ecm = LE447ME + .36529*LRW494MP -.49840*LVA541MP -
.096780*LFI353MP -.23
965*LGDE11 + .11681*LRM635ME -3.0384*C
****
****
R-Squared 0.73716 R-Bar-Squared 0.67345
S.E. of Regression 0.030567 F-Stat. F(7,34) 13.2220[.000]
Mean of Dependent Variable 0.005909S.D. of Dependent Variable 0.053491
Residual Sum of Squares 0.030834 Equation Log-likelihood 91.9578
Akaike Info. Criterion 82.9578 Schwarz Bayesian Criterion 75.1382
DW-statistic 2.0934
****
****
R-Squared and R-Bar-Squared measures refer to the dependent variable dLE447ME and in cases where the error correction model is highly restricted, these measures could become negative.

The estimate of the error correction model associated with the above long-run estimate is given in Table 4. All the estimated coefficients are statistically significant and have the expected signs and reasonable magnitudes. The error correction coefficient, estimated at -0.67048 is statistically significant, has the correct sign, and suggest a relatively high speed of convergence to the long run. Moreover, the underlying ARDL equation also passes all the diagnostic tests. Table 4 shows that the overall regression is significant at one percent (F-Stat (7, 34) =13.2220[.000]), which implies that the explanatory variables in the model are good predictors of employment in the Metal Products sector. Furthermore, the test statistics for serial correlation (Table 4) shows that there is no evidence of spurious regression. Also, Table 4 indicates that the errors are normally distributed and the model passes the Ramsey's RESET for correct specification of the model as well as the white hetroskedasticity test.

Finally, to check the stability of the coefficients of the model, we employed the CUSUM and CUSUMSQ of recursive residuals stability tests as suggested by Pesaran and Pesaran (1997). According to Bahmani-Oskooee (2004), the null hypothesis for this test is that the coefficient vector is the same in every period. The plot of the CUSUM and CUSUMSQ of recursive residual stability test in Figures 3 and 4 indicates that all the coefficients of the estimated model are stable over the estimation period since they are within acceptable critical bounds.

Figure 3

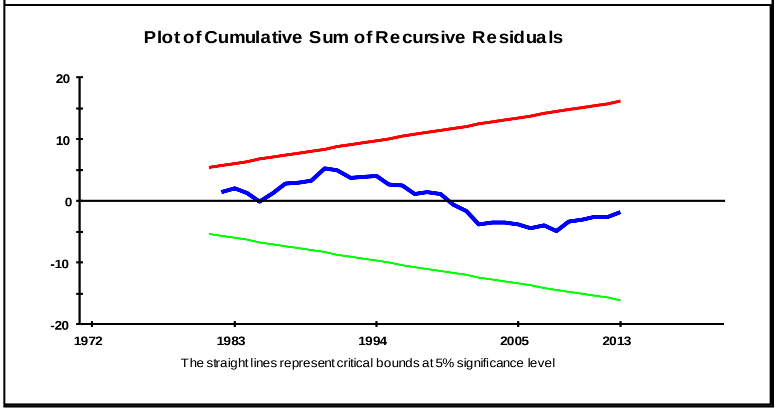


Figure 4

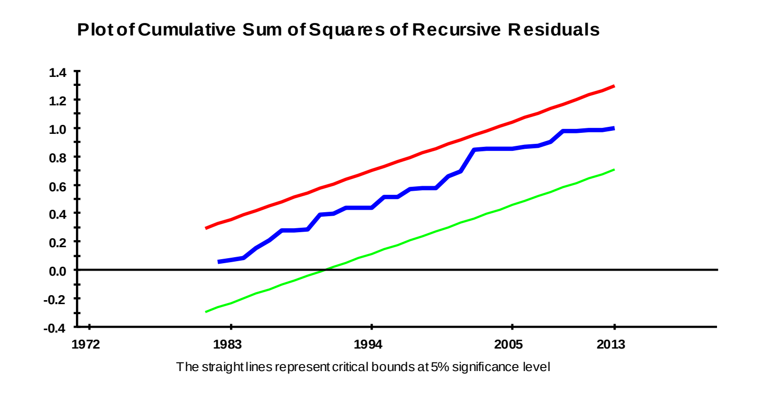
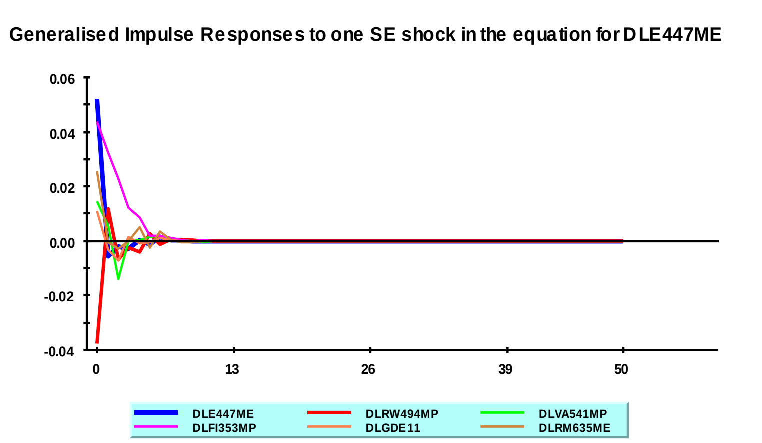


Figure 5



Finally, we have used the generalized impulse response function (Koop, Pesaran, and Potter 1996; Pesaran and Shin 1998, and Potter 1998) to examine the responses of employment in the Metal Product sector to one standard deviation shock in independent variables in the ARDL equation for employment in the Metal Products. It captures how quickly the long run relations in sector employment converge to their steady state values. Figure 5 shows that near-complete adjustments are achieved after approximately (or less than) 10 years.

Figures 6 and 7 show the statistical tests of the estimated error correction model's forecast performance conducted by splitting the data set into an in-sample period, used for the initial parameter estimation and model selection, and an out-of-sample period, used to evaluate forecasting performance. The root mean squares of forecast errors of around 0.67 percent per year compares favourably with the value of the same criterion computed over the estimation period.

The estimated ARDL equation for the Metal Product sector shows that employment in this sector is determined by several demand and supply factors. For example, *ceteris paribus*, one percent increase in the sector real wage rate is expected to reduce sector employment by 0.6 percent. And, one percent increase in the Gross Domestic Expenditure (GDE) is expected to lead to an increase in employment in the Metal Products sector of 0.16 percent in the short run and 0.24 percent in the long run. Moreover, a one percent increase in the real imports of Metal Products is expected to reduce the sector employment by 0.08 percent in the short run and 0.12 percent in the long run.

Figure 6

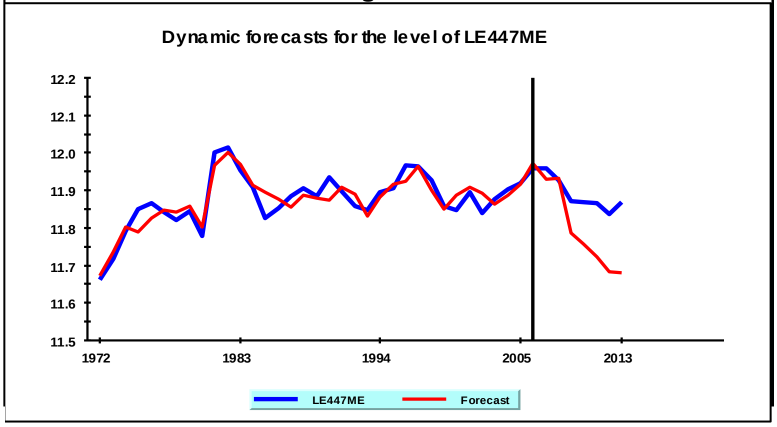
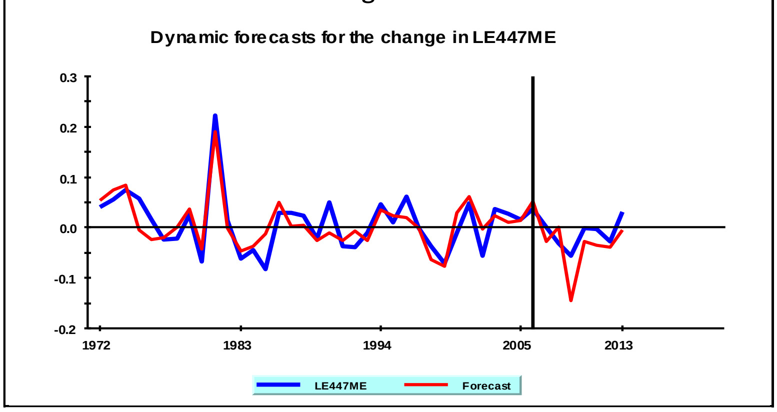


Figure 7



Overall, the econometric estimation of MEMSA's employment equations captures the short and long term responsiveness of sector demands for labour to various independent variables, including the real wage rate. Out of 40 estimated employment equations, employment in 36 sectors was found to have a statistically significant negative relationship with the sector real wage rate. The values of all the short term wage elasticities are between minus one and zero. The estimated employment equation for the Rubber Product sector has the lowest estimated wage elasticity of -0.11028 and the Households sector has the largest wage elasticity of -0.84953. The wage elasticities of the remaining 34 sectors fall between the above two values. At the same time, the results show consistency between short and long wage elasticities within the sectors. That is, the sizes of the short run elasticities are in line with the corresponding long run elasticities in terms of when the latter is relatively high in a sector, the short run elasticity is relatively high as well.

The above procedure was followed for the specification and estimation of the rest of the MEMSA equations associated with production, prices, labour market, trade sector, financial market, and others. The sectoral estimations were conducted for 40 sectors of the economy.

2.2. DIMMSIM's Microsimulation Component

The modelling principle employed to build the South African household model is the microsimulation modelling technique, whose application to socio-economic modelling was pioneered by Guy Orcutt in the United States in the late 50's and early 60's (Orcutt, 1957; Orcutt *et al.*, 1961). The South African model which was originally built as a static model (Adelzadeh, 2001) has been expanded and complemented with dynamic properties for the purpose of building DIMMSIM.

The main components of the model are its database and its tax and social policy modules that have been regularly updated and upgraded over the last 15 years. The South African model has used a micro-database of individuals and households using official annual General Household Survey (since 2002), Community Survey (2016), the Income Expenditure Survey (1995, 2000, 2010/2011), the Census (1996, 2001 and 2011), and the Labour Market Dynamics in South Africa 2014, which are key sources of countrywide individual and household microdata. The model's database is prepared in terms of family units, because it relates closely to the definition of the financial unit used by many of the government tax and transfer programmes. The model's database includes 125 830 individuals, making up 61 684 families or 29 800 households. The database includes weights for individuals, families and households, which are used to translate each of the three samples to their corresponding populations for a given year. Each unit record includes more than 400 columns of information for each individual in the family – including demographic, labour force, marital status, housing, education, and income and expenditure information.

The data ageing is obtained by 'reweighting' and 'uprating' each record. Reweighting is used to modify the demographic, family and labour force characteristics of the model's population. Uprating, on the other hand, is used to update individual and family income and expenditure. CALMAR (*cal*iberation of *mar*gins) is a reweighting algorithm that has been used to alter weights in a sample dataset to reflect a new population of reference. It applies given marginal totals to a set of initial weights on a survey record file. DIMMSIM endogenously uprates various categories of income and expenditure of individuals and families, using more than 50 deflators.

The South African microsimulation model includes three government taxation policies (i.e., personal income tax, excise tax, and value added tax), government's expanded public work programme (EPWP), and six transfer programmes (i.e., old age grant, child support, disability grant, care dependency grant, care giver support, and the basic income grant). Four of the programs constitute government's main social security programmes.

2.3. Accounting Consistency within DIMMSIM

Technically, two important distinguishing features of DIMMSIM relate to establishing two-way interactions between its underlying models and generating the model's macro and household level results that embody the necessary accounting requirements related to linked macro-micro models for each period.

A considerable part of the model is concerned with enforcing the necessary accounting relationships both within and between the two models to ensure simulation results are consistent, meaningful and reliable. DIMMSIM's iterative process of generating each period's forecast ensures that the accepted simulation results for each period satisfies all the specified accounting relationships. For example, with regard to the macroeconomic model, the components of the product account add up, and the income and product sides of the accounts are equal. Moreover, the price/quantity relationships are consistent. Some of these relationships include:

- The income tax module of the microsimulation part of DIMMSIM estimates family level income tax for each period, and feeds the information to the equation for the calculation of household disposable income, and the equation that captures sources of government current income, where the government's overall revenue from taxes on income and wealth is made up of household and business enterprise contributions.

- Similarly, the VAT module of the microsimulation component of the DIMMSIM uses detailed household level expenditure to calculate the contribution of households to the government's revenue from the VAT and excise taxes, where n3 represents the number of goods and services covered by the VAT payment.

- The social security modules of the microsimulation model provide for the estimation of households income from government's direct transfers. For each year of the forecast, the model's policy modules that capture the current government's old age pension, child support, disability, care dependency, and war veteran grants estimates total number of eligible persons for each grant and the required budget allocation. Changes to the eligibility and entitlement conditions of either of these policies and changes in the overall poverty rate in the country (e.g., due to a rise in the unemployment rate) implies changes in the budgetary requirements of these programs. In turn, the estimated budgetary requirement of the above government programs feed into the households' income accounts and government's expenditure account in the macroeconomic model.

3. MACRO-MICRO INTERACTIONS IN DIMMSIM

The model establishes two-way interactions between its macro and micro components such that (a) changes in macroeconomic variables (e.g., changes in prices, employment, and wage rates) influence welfare of individuals and families, and (b) changes in household level economic conditions (e.g., poverty, inequality, consumption, taxes, eligibility for social grant, etc.) influence macroeconomic outcomes. The Gauss-Seidel's iterative method is used to solve the overall system. The procedure runs the two models for a number of interactions, allowing interactions between the macro and micro parts of the model, before it converges and generates the final results for each year of the forecast period. This ensures that each period's results reflect convergence of the macroeconomic variables and household level variables at the aggregate level. Therefore, the two models are dynamically integrated and generate time-based results that reflect the actual process of policymaking and evaluation. For example, the above interaction between the macro and micro parts of the model helps explain how a National Minimum Wage ultimately affects households (Adelzadeh and Alvillar, 2016).

4. MODEL VERIFICATION AND VALIDATION

Model verification and validation are essential parts of the model development process. Verification concerns with whether the model's computer codes correctly represent the model's conceptual framework, and validation concerns whether the model represents and correctly reproduces the behaviour of the real world system. The two are iterative processes that are carried out throughout the model building process (Banks et al., 2010, Sargent, 2011).

Verification, therefore, is concerned with building the model right. It refers to the comparison of the conceptual model to the computer representation that implements that conception and asks whether the model's computer codes correctly represent the model's conceptual framework. That is, has the model been constructed correctly? Are the input parameters and logical structure of the model correctly represented?

Verification is therefore the process of checking whether (a) the model is programmed correctly; (b) the algorithms have been implemented properly; and (c) the model does not contain errors, oversights, or bugs. The process ensures that mistakes have not been made in implementing the model's specification. However, since no computational model will ever be fully verified, guaranteeing 100 percent error-free implementation, model verification continues as more tests are performed, errors are identified, and corrections are made to the underlying model, often resulting in retesting requirements to ensure code integrity. Technically, the aim of the verification process is to have a model that has passed all the verification tests.

ADRS' multi-sector macro-econometric model, that is the foundation upon which DIMMSIM is built on, has gone through a rigorous verification process over the last twelve years. In addition, as an integrated model, the DIMMSIM has gone through its own verification process. Among measures used to verify the model are:

- the model outputs have been closely examined for reasonableness under a variety of settings of the input parameters. The model codes include a wide variety of output statistics that are used to verify the working of each module of the model and the model as a whole.

- The desktop version of the model was directed to print the input parameters at the end of the simulation, to make sure that these parameter values are not changed inadvertently during the simulation process.

- The model’s computer codes are written as self-documenting as possible by giving a precise definition of every variable used, and a general description of the purpose of each major section of code.

The validation process concerns with building the right model. It concerns determining whether a model is an accurate representation of the real system. Validation is usually achieved through an iterative process of comparing the model to actual system behaviour and using the discrepancies between the two, and the insights gained, to improve the model. This process is repeated until model accuracy is judged to be acceptable. Therefore, the ultimate goal of model validation is to make the model useable through establishing that the model is able to address specific problems. Validation also provides accurate information about the real system that it represents. To validate the DIMMSIM, the model was subjected to a series of exercises that included:

- Using historical data on the exogenous variables to obtain predicted values of endogenous variables in the model. These predicted values were then compared with actual values of the variables to find whether the predicted and actual values are close.

- Testing the DIMMSIM on whether other properties of the models are consistent with the actual properties of the South African economy. For example, we mapped out the model’s “response” functions for specific shocks and compare it to “stylized facts” from historical experience or from experience of comparable countries.

- Testing whether the model “explains” history by conducting controlled experiments, that is, by using the model to produce values for the endogenous variables for the latest year(s) for which actual values for some or all endogenous variables exist.

- Testing whether all model results are explainable, usually with simple economics.

The current version of the model has passed all the validation tests. Moreover, the validation process provided the modelling team with a good understanding of the model’s capabilities, limitations, and appropriateness for addressing a range of important questions.

We have therefore concluded that the current version of the model, that is reported here, performs well and can be used for policy evaluation exercises.

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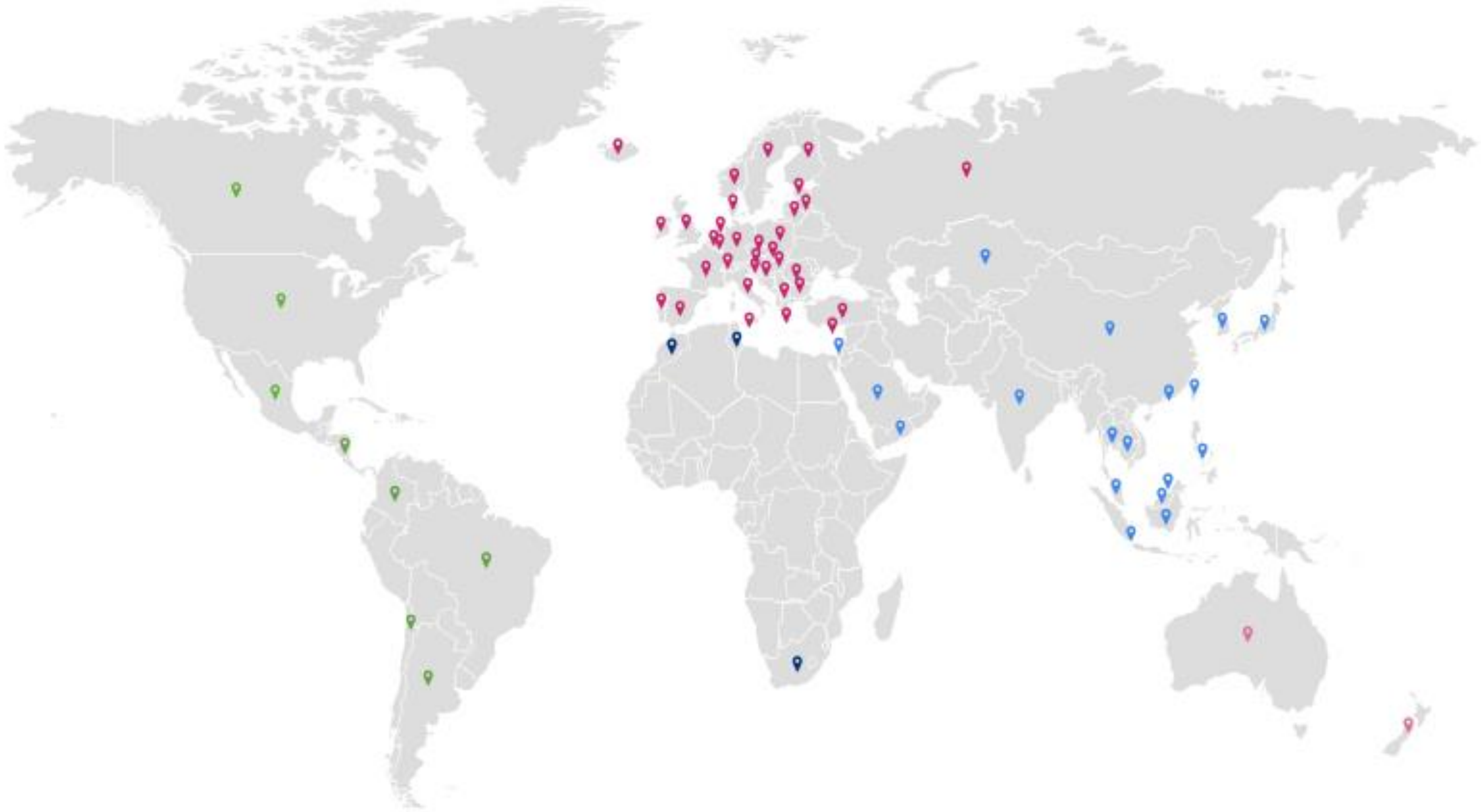
ADRS Country Models



ADRS Country Models

AFRICA

Morocco | Tunisia | South Africa (Suite of Macro and Micro Models)

ASIA

Brunei | Cambodia | China | Hong Kong | India | Indonesia | Israel | Japan | Kazakhstan | South Korea | Malaysia | Philippines | Saudi Arabia | Singapore | Taiwan | Thailand | Yemen

EUROPE

Austria | Belgium | Bulgaria | Croatia | Cyprus | Czech Republic | Denmark | Estonia | Finland | France | Germany | Greece | Hungary | Iceland | Ireland | Italy | Latvia | Lithuania | Luxembourg | Macedonia | Malta | Netherlands | Norway | Poland | Portugal | Romania | Russian | Federation | Slovakia | Slovenia | Spain | Sweden | Switzerland | Turkey | United Kingdom

NORTH & CENTRAL AMERICA

Canada | Mexico | United States of America

SOUTH AMERICA

Argentina | Brazil | Chile | Colombia | Costa Rica

OCEANIA

Australia | New Zealand