WPS4354

POLICY RESEARCH WORKING PAPER 4354

Economy-wide and Distributional Impacts of an Oil Price Shock on the South African Economy

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The World Bank
Africa Region
Office of the Chief Economist
September 2007

Abstract

As crude oil prices reach new highs, there is renewed concern about how external shocks will affect growth and poverty in developing countries. This paper describes a macro-micro framework for examining the structural and distributional consequences of a significant external shock—an increase in the world price of oil—on the South African economy. The authors merge results from a highly disaggregative computable general equilibrium model and a micro-simulation analysis of earnings and occupational choice based on socio-demographic characteristics of the household. The model provides changes in employment, wages, and prices that are used in the micro-simulation. The analysis finds that a 125 percent increase in the price of crude oil and refined petroleum reduces employment and GDP by approximately 2 percent, and reduces household consumption by approximately 7 percent. The oil price shock tends to increase the disparity between rich and poor. The adverse impact of the oil price shock is felt by the poorer segment of the formal labor market in the form of declining wages and increased unemployment. Unemployment hits mostly low and medium-skilled workers in the services sector. High-skilled households, on average, gain from the oil price shock. Their income rises and their spending basket is less skewed toward food and other goods that are most affected by changes in oil prices.

This paper—a product of the the Office of the Chief Economist, Africa Region, in collaboration with the country team for South Africa—is part of a larger effort in the Africa Region to improve the macro-micro economic framework for policy analysis. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at dgo@worldbank.org.

Economy-wide and Distributional Impacts of an Oil Price Shock on the South African Economy[♦]

By

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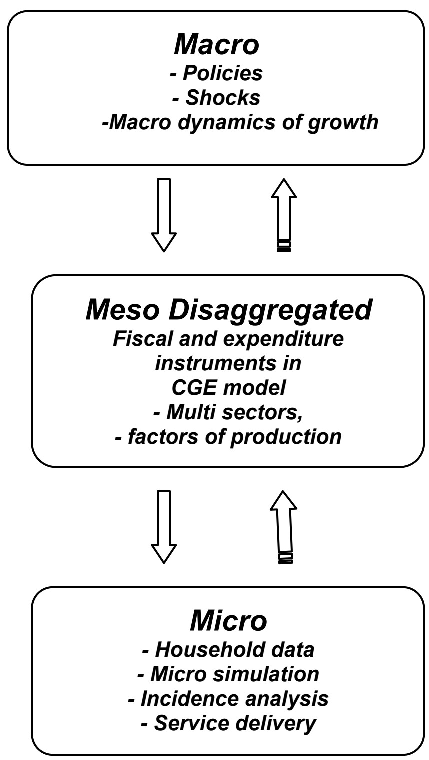
[♦] This paper is issued simultaneously as a working paper at the World Bank and Institute of Development Studies (IDS), Sussex University. The framework used in the paper is based on a World Bank technical assistance to develop a CGE-micro simulation model for South Africa National Treasury in a collaborative effort with IDS and US Naval Academy. The work is jointly managed by Delfin Go at the World Bank and Marna Kearney at the South Africa National Treasury. The purpose of the exercise is to illustrate the potential use of the framework for analysis of policy and external shocks. The views expressed are those of the authors and do not necessarily reflect those of their respective institutions or affiliated organizations. The authors would like to thank Maurizio Bussolo, David Coady, Alan Gelb, Jeffrey Lewis, Hans Lofgren, John Page, James Thurlow and Rogier van den Brink for helpful comments on an earlier version of this paper.

1. Introduction

As crude oil prices reach new highs, there is a renewed concern about how external shocks will affect growth and poverty in developing countries and how this should be modeled and anticipated. The linkages between the two aspects - macroeconomics and poverty/income distribution - have indeed become a major focus of economic research and modeling in recent years.[1] However, the main challenge has been the reconciliation of potentially very detailed and large information set from micro econometric modeling of individual or household behaviors about income and employment opportunities with the more aggregative behavior in a macroeconomic model.

Figure 1
A Disaggregated Framework Linking Macro Events to Poverty Reduction Issues



A promising approach for researchers is to employ computable general equilibrium (CGE) modeling as a meso-framework because CGE models generate from macroeconomic

[1] See, for example, Bourguignon and Pereira da Silva (2003) or Essama-Nssah (2006) for a recent compilation and evaluation of various approaches, techniques and tools.

changes a set of consistent relative prices, wages and profits at the sectoral level that provide the vital sources and changes of household incomes and expenditures for further analysis of poverty impact and income distribution (see Figure 1). Depending on the level of simplification and the level of information retained for both macro and micro components, there have been several ways of utilizing CGE models and household analysis to establish the links between macroeconomic changes and poverty analysis. At one end of the spectrum, where data constraints and technical capacity of policy analysts are issues, the "123PRSP Model" in Devarajan and Go (2003) simplifies the CGE framework into aggregative distinction of tradable and nontradable goods. Effects of external shocks are first derived in terms of movements of the real exchange rate between tradable and nontradable goods, which are then mapped to the expenditure and income sources of various household groups (e.g. income deciles). Growth impact is derived from either short-term vector autoregressive analysis (VAR) or long-term growth regression of various determinants. More information is provided in CGE models with higher level of disaggregation, such as the South Africa model in Go, Kearney, Robinson, and Thierfelder (2005), which combines a rich structure of the economy and a good number of household groupings – 49 industries, 3 labor categories, and 13 household groups.

Another type of simplification is found in Essama-Nssah (2005), which distills the income distribution from household surveys into a parameterized Lorenz model of income distribution and which can then be easily linked to macro models to examine policy and external shocks. The approach provides the flexibility of choosing the macroeconomic framework from simple macro consistency models like the World Bank's RMSM-X or the IMF financial programming model to more sophisticated econometric or CGE models.

However, none of these selected models mentioned so far make full use of household information, which is a significant feature in micro-simulation models. As an example at the other end of the spectrum, Bourguignon, Robilliard, and Robinson (2002) merge a disaggregative macroeconomic framework in a CGE model with a micro-simulation model that make full use of the entire household data, with explicit treatment and full individual heterogeneity of labor skills, preferences and characteristics at the individual and household levels.

While the various approaches of combining CGE models and household data are distinguished by the level of sophistication and information retained in either the macro or micro component, there is nonetheless one drawback. The integration of the macro and micro components is often a one-way, top-down approach because of the inherent complexities of a full integration.[2] To be sure, there are attempts at full integration. Cogneau and Robillard (2000) implement a version for Madagascar. However, the general equilibrium macro framework has very few sectors. Heckman and Lochner (1998) construct an overlapping generations general equilibrium model of labor earnings with heterogeneous agents but in order to present both integration and dynamics the macro part is aggregative. A classic econometric method to the integration of a CGE model with detailed household analysis is provided by the works of Jorgenson, Lau and Stoker (1980) where exact aggregation of the representative consumer from heterogeneous households is econometrically estimated from survey data and under certain demand restrictions, demand functions of heterogeneous groups are recoverable from the representative consumer. Given an overall representative household, stable or fixed household distribution underlying the econometric results is however implicitly assumed. A promising and practical link between the macro and the micro is provided recently in Savard (2003, 2006), which uses a recursive iteration between the two approaches without the need to simplify each. A similar approach is adopted in this paper and will be described below.

The purpose of this paper is to assess the potential impact of a large oil price shock on the economy, poverty, and income inequality in South Africa using a combination of a disaggregative CGE model and micro simulation analysis of household surveys. The framework employed is a valuable tool to sort out the wide-ranging impact of an external shock on the economy as well as on the various sectors, industries, and the heterogeneous households. We implement a recursive two-way feedback mechanism similar to Savard (2003, 2006) and devise an efficient reconciliation between the CGE and micro-simulation models in order to derive a consistent or integrated analysis of the shocks from the two approaches while retaining the particular advantages provided by each approach – i.e., the detailed structure of an economy in the CGE model and the full heterogeneity of households

[2] There are also other issues such as introducing dynamics and growth, incorporating individual firm behavior etc. See for example the conclusion chapter in Bourguignon and Pereira da Silva (2003).

and labor in the micro simulation. At the end, we draw some possible lessons where the multi-layered analysis maybe most useful and where simpler approaches would be sufficient, including – a one way top-down approach; a more clear-cut decomposition of the vertical and horizontal impact on inequality such as the Roy's method in Ravallion and Lokshin (2004); a simpler summary of the household characteristics by income deciles or a parameterized Lorenz curve.

The outline of the rest of the paper is as follows. Section 2 describes the simulation framework used to analyze the issues raised in this introduction. Basically, the framework links a CGE model for South Africa to two types of micro-simulation models of household welfare and occupational choice. Section 3 analyzes the distributional implications of a large oil price shock to the economy. A summary and conclusions are presented in section 4.

2. The Simulation Framework

For an oil-importing country, a significant increase in the price of this commodity not only will have consequences on various macroeconomic aggregates but also will have structural and distributional implications because of changes in relative prices of goods and factor costs due to the pass through of oil costs throughout the economy. Thus we need a framework that accounts not only for the *interdependence* between stabilization, structural, and distributional issues, but also for the *heterogeneity* of the stakeholders which underpins distributional concerns. This section describes the macro-micro simulation framework used to track the macro, structural, and distributional implications of a sizeable oil price shock to the economy of South Africa. A disaggregated CGE model is used for the macro and structural implications while the micro simulation component accounts for agent heterogeneity and the impact on distribution.

2.1. A CGE Model of the South African Economy

The CGE model has 43 production activities.[3] For reporting purposes, the output results by activity are aggregated into three categories: agriculture, industry, and services (see Table 1 for the composition of the aggregate categories).

Table 1: CGE Model Sectors

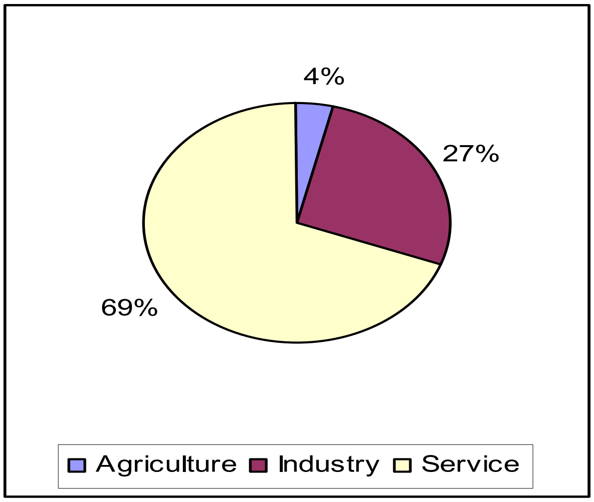
I. AGRICULTURE	**II. INDUSTRY (cont'd)**	**III. SERVICES**
Agriculture	Basic Chemicals	Electricity & Gas & Steam
II. INDUSTRY	Other Chemicals & Man-Made Fibers	Water Supply
Coal Mining	Rubber Products	Construction & Civil Engineering
Gold & Uranium Ore Mining	Plastic Products	Catering & Accommodation
Other Mining	Glass & Glass Products	Wholesale & Retail Trade
Food	Non-metallic Minerals	Transportation & Storage
Beverages & Tobacco	Basic Iron & Steel	Communication
Textiles	Basic Non-ferrous Metals	Financial Services
Wearing Apparel	Metal Products Excluding Machinery	Business Services
Leather & Leather Products	Electrical Machinery	Health & Community & Social & Personal Services
Footwear	TV & Radio & Communication Equip	Other Producers
Wood & Wood Products	Professional & Scientific Equip	Government Services
Paper & Paper Products	Motor Vehicles Parts & Accessories	
Printing & Publishing & Recorded Media	Other Transport Equipment	
Coke & Refined Petroleum Products	Furniture	

Source: South Africa SAM 2003 Database

As seen in Figure 2, agriculture accounts for 4 percent of value added, industry accounts for 27 percent, and service accounts for 69 percent.

[3] Full detail of the South Africa CGE model can be found in Kearney (2004); for a version of the model used to analyze Value Added Taxes (VAT) see Go et al. (2005). In this description we comment on features of the model important for an analysis of the oil price shock.

Figure 2: Aggregate Activity Share of Value Added



Source: South Africa SAM 2003 Database

Labor categories are combinations of labor types (formal, self-employed, and informal), and skill levels (high-skilled, semi-skilled, and low-skilled).[4] Each activity can use these labor categories and capital in production. For reporting purposes, all skill levels of self-employed are aggregated into a single input, self-employed labor; likewise for informal labor.[5]

In the production technology, it is assumed that substitution possibilities among inputs differ and the following structure is used: (1) it is difficult to substitute low-skilled labor for high-skilled labor in any of the three labor categories; (2) it is easy to substitute across labor categories for the same skill (i.e. a high-skilled formal worker is a good substitute for a high-skilled informal worker or a high-skilled self-employed worker); and (3) as the skill level of labor increases, it is more difficult to substitute capital for labor.[6]

[4] More specifically, the employment data in the CGE has been calibrated to match the employment share data from the household survey in which there are five labor types in the household survey (high-skilled formal, semi-skilled formal, low-skilled formal, self-employed, and informal) and three activities (agriculture, industry, and services).

[5] To match the 15 occupational choices in the household data, we report results for five labor categories, and aggregate economic activities (agriculture, industry, and services).

[6] All activities except coal, gold, other mining, and refined petroleum use a translog production function; coal, gold, other mining, and refined petroleum use a constant elasticity of substitution (CES) production function with the assumption that it is difficult to substitute among inputs so the elasticity of substitution is low, less than 0.5 in each activity.

Structural unemployment is specified for low-skilled and semi-skilled formal workers, with sticky real wages, while the other labor markets clear in equilibrium. The peculiarities of the labor markets in South Africa are treated in a similar fashion as in Go et al. (2005) and Lewis (2001). In a separate analysis of the possible impact of a wage subsidy scheme contemplated by the South African authorities, we examine the labor market structure and markets in much more details.[7]

It is assumed that all resources in coal, gold, and other mining are activity specific, consistent with the notion that the supply of these mineral products is relatively inelastic. For the other activities, we assume that capital is activity specific.

Value added is allocated to primary factors according to the following shares:

Table 2: Value Added Shares

	Agriculture	Industry	Service
Capital	0.76	0.54	0.45
High-skilled formal labor	0.03	0.12	0.25
Semi-skilled formal labor	0.02	0.12	0.18
Low-skilled formal labor	0.11	0.15	0.04
Self-employed labor	0.04	0.03	0.04
Informal labor	0.04	0.04	0.04

Source: South Africa SAM 2003 Database

In the base data, the category other mining includes crude oil as well as diverse mineral inputs such as diamonds and iron ore. To focus on the impact of an oil price shock, we create an additional category, crude or unrefined oil, which is the amount of other mining inputs used in the production of refined petroleum and basic chemicals. It is assumed that all crude oil is imported and that there is no tariff on crude oil.[8]

As noted above, crude oil imports account for 100 percent of crude oil consumption. Refined petroleum imports account for 17 percent of oil consumption, and basic chemical imports account for 29 percent of basic chemical consumption in South Africa. In addition to

[7] See Essama-Nssah, Go, Kearney, Robinson, and Thierfelder (forthcoming).

[8] McDonald and van Schoor (2005) also adjust the other mining category to properly account for crude oil. They supplement the Social Accounting Matrix with data on imported crude oil. In this paper, we assert that all inputs of other mining into refined petroleum are actually imports of crude oil.

crude oil, the region is heavily dependent upon imports of commodities such as communication equipment (70 percent of consumption), other transportation equipment (65 percent of consumption), and machinery and equipment (56 percent of consumption).

Crude oil, petroleum, and basic chemicals are primarily purchased as intermediate inputs.[9] Direct household purchases of petroleum is quite low, with expenditure ranging from 4-6 percent depending on household; for basic chemicals the household expenditure shares are one percent or less.

Table 3: Direct and Indirect Input Requirements of Refined Petroleum per Rand Spent on Final Demand

Final Product	Rand	Final Product	Rand
Coke and Refined Petroleum Products	1.16	Non-metallic Minerals	0.07
Basic Chemicals	0.18	Footwear	0.07
Transportation and Storage	0.18	Health, Community, Social, and Personal Services	0.06
Rubber Products	0.14	Furniture	0.06
Basic Non-ferrous Metals	0.14	Wood and Wood Products	0.06
Other Chemicals and Man-Made Fibers	0.11	TV, Radio, and Communication Equip	0.06
Plastic Products	0.11	Other Industries	0.06
Agriculture, Forestry, and Fisheries	0.11	Beverages and Tobacco	0.06
Electrical Machinery	0.10	Other Transport Equipment	0.05
Construction and Civil Engineering	0.09	Wearing Apparel	0.05
Basic Iron and Steel	0.09	Glass and Glass Products	0.05
Food	0.09	Catering and Accommodation	0.05
Textiles	0.08	Printing, Publishing, and Recorded Media	0.05
Machinery and Equipment	0.08	Business Services	0.04
Motor Vehicles Parts and Accessories	0.08	Wholesale and Retail Trade	0.04
Leather and Leather Products	0.07	Water Supply	0.04
Professional and Scientific Equip	0.07	Electricity, Gas, and Steam	0.04
Other Mining	0.07	Other Producers	0.04
Metal Products Excluding Machinery	0.07	Government Services	0.03
Coal Mining	0.07	Gold and Uranium Ore Mining	0.03
Paper and Paper Products	0.07	Financial Services	0.02
Communication	0.07		

Source: South Africa SAM 2003 Database

[9] By construction, crude oil is only used as an intermediate to the refined petroleum sector and it is not produced domestically.

Given the structure of the economy, the effects of an oil price shock (which is modeled as increase in the world price of imported crude oil, refined petroleum, and basic chemicals) on households will be felt primarily through the effects on prices of final goods which use refined petroleum and basic chemicals as intermediate inputs (see Table 3). Note that production of electricity and gas does not depend heavily on refined petroleum. Instead coal is a more important intermediate input.

2.2. Modeling Household Response to Macro-economic Events

Fundamentally, we can think of the observed poverty and inequality in a given society as an outcome of individual behavior subject to endowments and the institutions that govern social interaction. Indeed, Bourguignon and Ferreira (2005) note three groups of determinants of the size distribution of economic welfare: (1) the distribution of factor *endowments* and socioeconomic characteristics among the population, (2) the *returns* to these assets, and (3) the *behavior* of socioeconomic agents with respect to resource allocation subject to institutional constraints. Thus, we would expect the distributional impact of macroeconomic events to have three types of effects on the distribution of economic welfare: (1) *endowment effects* due to changes in the amount of resources available to individuals, (2) the *price effects* reflecting changes in the reward of these resources, and (3) *occupational effects* linked to changes in resource allocation.

For the purpose of our study we consider two alternative approaches of simulating these effects at the household level. The first approach, as applied by Ravallion and Lokshin (2004) to the case of a trade reform in Morocco, relies on the *envelope theorem* to downplay the endowment and occupational effects and focus on the welfare implications of price effects. The second approach, explained in Bourguignon and Ferreira (2005) tries to account for the endowment and occupational effects through a *model of earnings generation*

Our empirical implementation of this approach relies on a dataset which combines information from the 2000 Labor Force Survey (LFS) with data from the 2000 Income and

Expenditure Survey (IES)[10]. Given that both surveys are based mostly on the same sample of households, the combined dataset provides comprehensive information on household expenditures, labor and non-labor income, labor supply, employment, and several socio-economic characteristics of individuals and households. The IES sample contains 26,687 households and 104,153 individuals. The LFS sample consists of 105,792 individuals. When the two datasets are combined and observations with missing sampling weights are dropped, the remaining number of individuals in our combined database drops to 103,732 from 26,214 households.

The Envelope Model of Household Welfare

Just as in the context of the general equilibrium model, we rely on the optimization principle to model economic welfare at the household level. Following Ravallion and Lokshin (2004), we assume that each household's preferences can be represented by a utility function of the quantities of commodities demanded and labor supplied to both external and own production activities. In addition, the household earns a profit from a productive activity. The optimal behavior of household **h** can be represented by an envelope function known as the *indirect utility function*. This is the maximum attainable welfare given the level of resources and prevailing prices. Formally, we write:

$$v_h(p_h^s, p_h^d, w_h) = \max_{q_h^s, L_h} [u_h(q_h^d, L_h) \mid p_h^d q_h^d = w_h L_h + \pi_h(p_h^s)] \qquad (2.1)$$

In the above expression, q_h^d stands for a vector of commodities demanded by the household, L_h is the vector of labor supplies by activity and w_h is the corresponding vector of wages. In addition, p_h^d and p_h^s stand for vectors of consumption and production prices respectively while $\pi_h(p_h^s)$ is the maximum profit achievable from own production given prevailing prices.

The indirect utility is a function of prices. According to the envelope theorem, as manifested by Roy's identity, the change in the maximum utility induced by a change in one

[10] These surveys are published by Statistics South Africa.

of its arguments while the underlying choice variable adjust optimally is equal to the partial derivative of the indirect utility with respect to the argument. The money metric of this change is obtained by normalizing the partial derivative on the basis of the marginal utility of income. The following expression of the overall welfare change induced by price changes provides a framework for assessing the impact of shock or policy reform on a household.

$$g_h = \sum_{j=1}^{m}[p_{hj}^{s} q_{hj}^{s} \frac{dp_{hj}^{s}}{p_{hj}^{s}} - p_{hj}^{d} q_{hj}^{d} \frac{dp_{hj}^{d}}{p_{hj}^{d}}] + \sum_{i=1}^{n}[w_i L_{hi} \frac{dw_i}{w_i}] \tag{2.2}$$

The above equation says that a first-order approximation to the welfare impact in a neighborhood of the optimal behavior of the household is equal to a weighted sum of proportionate changes in prices. The weights are the initial patterns of demand or supply as revealed by expenditure and sales patterns. These patterns help us account for heterogeneity to the extent that they are based on socio-demographic characteristics of households and the fact that households may face different prices for the same commodity.

Depending on the application, the benefit of being able to derive an elegant closed-form approximation from the envelope approach must be weighed against the limitation stemming from the fact that it assumes away endowments and occupational effects. In what follows, we also consider therefore a model of earnings generation that would allow for such effects.

The Household Earnings-Generation Model

To also account for endowment and occupational effects, we need a framework that links both earnings and occupational choice to socio-demographic characteristics of the household. That is, we need a model of the income-generation process at the individual or household level. We base the specification of our model on the general framework described in Bourguignon and Ferreira (2005). The model has three components: (a) a multinomial logit model of the allocation of individuals across occupational states, (b) a model of the determinants of earnings, and (c) an aggregation rule for computing household income from the contribution of its employed members.

Occupational Component. The occupational component contains 16 categories: (1) inactive and unemployed, (2) formal sector workers-low skilled in agriculture, (3) formal sector workers-semi skilled in agriculture, (4) formal sector workers- high skilled in agriculture, (5) formal sector workers-low skilled in industry, (6) formal sector workers-semi skilled in industry, (7) formal sector workers- high skilled in industry, (8) formal sector workers-low skilled in services, (9) formal sector worker-semi skilled in services, (10) formal sector workers- high skilled in services, (11) informal sector workers-agriculture, (12) informal sector workers-industry, (13) informal sector workers-services, (14) self-employed-agriculture, (15) self-employed-industry, and (16) self-employed-services.

Table 4: Distribution of Employment by Sector and Occupation

	Agriculture	Industry	Services	Total
Formal Sector Workers				
Low -Skill	6.0	2.9	5.7	14.6
Semi -Skill	6.2	8.7	16.5	31.3
High- Skill	0.7	1.3	9.6	11.6
Informal Sector Workers	2.7	2.5	13.9	19.2
Self Employees	9.1	2.8	11.5	23.4
Total	24.6	18.2	57.2	100.0

Source: Authors' calculations.

Table 4 shows the distribution of employment by sector and occupation. These results show that about 6 people out of ten are employed in the service (or tertiary) sector. About the same ratio represents those engaged in formal sector work. About 24 percent of working individuals are self-employed. Although, the data are available for disaggregating informal and self-employment sectors by skill types, analysis was performed by economic sectors for informal and self-employed categories.

With respect to the distribution of skills, the results show that about 15 percent of the employed are highly skilled. Furthermore, the highest percentage of people of any skill level is found in the tertiary sector (Table 5).

Table 5: Distribution of Employment by Sector and Skill Level

	Low -Skilled	Semi -Skilled	High- Skilled	All
Agriculture	8.9%	14.9%	0.6%	24.4%
Industry	3.5%	13.0%	1.7%	18.2%
Services	19.9%	25.0%	12.4%	57.4%
All	32.4%	52.9%	14.7%	100.0%

Source: Authors' calculations.

Now, let $\mathbf{P_{ij}}$ stand for the probability of observing individual **i** engaged in activity **j**. Then selecting one category as a reference (here inactive and unemployed), we can express this probability as:

$$P_{ij} = \frac{\exp(z_i \gamma_j)}{\left[1 + \sum_{j=2}^{16} (\exp(z_i \gamma_j)\right]} \qquad (2.3)$$

where $\mathbf{z_i}$ is a vector of observable characteristics of individual **i**. In our case, **z** includes the following variables: a constant, gender, years of education, education squared, experience, experience squared, a dummy for residence in the urban area, the number of children who are at most nine years old, a dummy for marital status, a dummy indicating whether a member of the household owns a family business, years of schooling for the head of household, and a dummy indicating whether the individual is head of household.

When the multinomial logit model is motivated in term of utility maximizing behavior, the utility[11] associated with activity **j** is given by: $z_i \gamma_j + \varepsilon_{ij}$, where the second term represents the unobserved determinants of the utility of activity **j**. The utility of the reference activity is arbitrarily set to zero. It is usually assumed that the random component of the activity-utility follows the law of extreme values and is independently distributed across individuals and activities.

In principle, the participation component (2.3) of the earnings-generation model should be estimated jointly with the earnings equations defined in the next sub-section. For

[11] This is the latent variable that governs occupational choice to the extent that people are believed to move to the activity with the highest level of utility. However, Bourguignon and Ferreira (2005) note that such an interpretation would not be valid in cases where occupational choices are constrained by the demand side of the market.

the occupational model to be considered as a structural model of labor supply its specification must include the wage rate, the productivity of self-employment and non-labor income. To avoid the difficulties associated with joint estimation, we follow Bourguignon and Ferreira (2005) in their reduced-form interpretation of the framework. Thus the components can be estimated separately with the possibility of testing for selection bias at the level of earning equations. This interpretation precludes any causal inference, and the resulting parameter estimates are simply statistical descriptions of conditional distributions based on the chosen functional forms. The reduced-form estimates for the occupational model are presented in Table 6.

Table 6: Occupational Choice Models for Individuals

	Formal Employees									Informal Employees			Self Employees		
	Agriculture			Industry			Services			Agriculture	Industry	Services	Agriculture	Industry	Services
Variables	Low-Skill	Semi-Skill	High-Skill	Low-Skill	Semi-Skill	High-Skill	Low-Skill	Semi-Skill	High-Skill						
Gender	0.82	2.442	1.563	0.909	1.192	1.043	-0.057	0.583	-0.102	0.993	1.762	-0.78	0.123	0.25	-0.321
	[14.06]**	[24.12]**	[7.22]**	[11.31]**	[22.85]**	[7.31]**	[1.01]	[15.74]**	[1.75]	[11.88]**	[17.31]**	[19.00]**	[2.70]**	[2.88]**	[6.24]**
Education (years)	-0.01	-0.086	-0.222	0.062	0.07	-0.055	0.071	0.002	0.221	-0.072	0.035	-0.038	-0.073	-0.144	-0.143
	[0.43]	[3.40]**	[3.16]**	[1.85]	[3.22]**	[0.77]	[2.99]**	[0.14]	[3.68]**	[2.25]*	[1.02]	[2.60]**	[4.18]**	[4.81]**	[7.78]**
Education-squared	-0.009	0.003	0.029	-0.003	0.002	0.023	-0.002	0.011	0.021	-0.003	-0.004	0.001	0.009	0.015	0.015
	[4.44]**	[2.11]*	[8.67]**	[1.29]	[1.31]	[7.45]**	[0.95]	[10.82]**	[8.74]**	[1.04]	[1.57]	[0.78]	[6.92]**	[8.02]**	[12.76]**
Experience (years)	0.124	0.221	0.215	0.18	0.214	0.219	0.19	0.167	0.254	0.132	0.212	0.184	0.032	0.205	0.168
	[14.39]**	[20.72]**	[7.62]**	[15.19]**	[27.79]**	[10.63]**	[22.19]**	[30.57]**	[26.83]**	[10.93]**	[16.12]**	[32.38]**	[5.37]**	[15.69]**	[24.11]**
Experience-squared	-0.003	-0.004	-0.004	-0.003	-0.004	-0.004	-0.003	-0.003	-0.005	-0.003	-0.004	-0.003	0	-0.003	-0.003
	[18.58]**	[23.53]**	[7.30]**	[15.48]**	[27.53]**	[9.77]**	[21.48]**	[29.52]**	[23.27]**	[12.93]**	[16.53]**	[32.70]**	[0.53]	[14.91]**	[22.26]**
Urban	-2.181	-1.119	-0.366	0.781	0.891	1.549	0.691	0.816	0.449	-1.91	-0.237	0.408	-2.468	-0.108	0.128
	[26.83]**	[18.97]**	[2.21]*	[9.13]**	[16.14]**	[7.57]**	[11.37]**	[18.94]**	[6.95]**	[17.41]**	[2.91]**	[10.41]**	[33.99]**	[1.29]	[2.51]*
Nchild09	-0.292	-0.485	-0.332	-0.08	-0.084	-0.129	-0.07	-0.107	-0.049	-0.172	-0.063	-0.204	0.107	-0.159	-0.071
	[12.96]**	[16.55]**	[4.04]**	[2.69]**	[4.45]**	[2.35]*	[3.31]**	[7.10]**	[2.11]*	[5.91]**	[2.04]*	[13.49]**	[8.39]**	[5.00]**	[4.06]**
Married	0.903	1.282	1.297	0.526	0.711	1.248	0.283	0.663	0.656	0.657	0.222	0.236	0.274	0.488	0.503
	[14.45]**	[18.18]**	[6.55]**	[6.37]**	[13.80]**	[9.03]**	[4.91]**	[16.85]**	[11.29]**	[7.53]**	[2.45]*	[5.98]**	[5.41]**	[5.48]**	[9.46]**
Own family business	-1.081	-0.624	-0.567	-0.333	-0.197	-0.223	-0.242	0.004	-0.427	-0.661	-0.135	-0.08	0.685	4.088	4.845
	[7.42]**	[5.05]**	[1.98]*	[2.47]*	[2.55]*	[1.26]	[2.51]*	[0.07]	[5.01]**	[3.80]**	[0.98]	[1.28]	[12.03]**	[38.58]**	[66.28]**
Education for head	-0.026	0.04	0.058	-0.025	-0.01	0.05	-0.03	0.035	0.045	-0.036	-0.006	-0.013	0.003	-0.005	0.005
	[2.64]**	[2.62]**	[1.75]	[2.02]*	[1.22]	[2.10]*	[3.31]**	[6.22]**	[5.12]**	[2.53]*	[0.43]	[2.11]*	[0.43]	[0.35]	[0.70]
Dummy for head	1.44	2.11	1.27	1.073	1.279	1.316	1.349	1.237	1.292	1.26	1.294	1.342	0.708	1.946	1.976
	[21.86]**	[23.83]**	[5.89]**	[12.12]**	[22.83]**	[8.76]**	[21.47]**	[29.83]**	[20.11]**	[13.47]**	[13.05]**	[32.23]**	[12.89]**	[19.72]**	[33.48]**
Constant	-3.485	-7.37	-10.084	-6.969	-7.324	-11.818	-6.223	-6.268	-11.408	-4.552	-7.326	-4.059	-3.474	-8.943	-7.735
	[26.98]**	[41.28]**	[20.77]**	[35.02]**	[54.59]**	[24.27]**	[43.17]**	[59.43]**	[29.90]**	[24.12]**	[33.54]**	[44.72]**	[34.49]**	[38.92]**	[57.81]**
Sample Size	65113	65113	65113	65113	65113	65113	65113	65113	65113	65113	65113	65113	65113	65113	65113

Notes:Absolute value of z statistics in brackets. * significant at 5%; ** significant at 1%

Source: Authors' calculations

Overall results show that gender has significant impact on probability of being employed in different sectors. However, gender is not a statistically significant explanatory variable for being employed for the formal low-skilled and formal high-skilled individuals in service sector. Among formal workers, people in the industry and services sectors are more likely to be living in the urban areas than people in the agriculture sector as expected. It is also true for informal and self-employed sector as well. Similarly, the number of children (9 years at most) has a significant impact of the choice participating to the labor force. People are less likely to participate as formal workers. They are more likely to be self-employed. Similarly, individuals living in households owning a family business are more likely to be self-employed than paid workers. Being head of the household also plays a significant role for participating in the labor force. It is also case for married people being active in the labor force than non-married couples.

Earnings. The earnings block of the micro-simulation model consists of three equations explaining formal wages, informal wages, and self-employment income in terms of observable and non-observable individual characteristics. The specification of these equations follows the Mincerian model. The wage equation is written as:

$$\log w_i = x_i \beta_w + u_{iw} \tag{2.4}$$

The set of observable characteristics used as explanatory variables includes: a constant, gender, years of education, education squared, experience, experience squared, a dummy indicating whether the individual is head of household, a dummy for residence in the urban area, a dummy for union membership, and a dummy for marital status. We estimate this equation separately for the primary, secondary and tertiary sectors using OLS[12]. The results are presented in Table 7.

These results indicate variables such as education and experience have expected signs and are consistent with standard human capital approach and economic theory. Estimate coefficients for education (eduyear squared) are statistically significant at 1 percent except in

[12] We also tried the Heckman method on both the wage and self-employment equations to account for possible selection bias due to the fact that estimation is based on sub-samples of individuals with observed earnings in the given activity. There was no significant difference in the results. We therefore stick with OLS.

primary-high skill group. The relationship between education variable and wage is mostly non-linear. In agriculture-low skill segment, additional three years of schooling increase formal wage income by 5.7 percent for formal wage earners in that segment.

Table 7: OLS Estimates of the Formal Wage Equation

	Agriculture Sector			Industry Sector			Services Sector		
Variables	Low Skill	Medium Skill	High Skill	Low Skill	Medium Skill	High Skill	Low Skill	Medium Skill	High Skill
gender	0.227	0.154	0.512	0.298	0.29	0.233	0.245	0.142	0.092
	[6.34]**	[2.08]*	[1.99]*	[5.83]**	[8.69]**	[1.97]*	[5.89]**	[5.76]**	[2.70]**
eduyear	0.007	-0.03	0.107	-0.01	-0.077	-0.002	-0.015	0.014	-0.047
	[0.57]	[2.15]*	[1.20]	[0.46]	[5.83]**	[0.04]	[0.95]	[1.27]	[2.26]*
eduyear2	0.004	0.01	0.001	0.006	0.011	0.007	0.005	0.006	0.007
	[3.59]**	[8.96]**	[0.24]	[3.81]**	[12.97]**	[3.14]**	[4.23]**	[9.01]**	[8.10]**
expyear	0.033	0.065	0.009	0.032	0.038	0.051	0.038	0.031	0.034
	[6.06]**	[8.72]**	[0.31]	[4.06]**	[7.45]**	[3.15]**	[5.50]**	[8.13]**	[6.11]**
expyear2	0	-0.001	0	0	0	-0.001	0	0	-0.001
	[5.30]**	[7.74]**	[0.00]	[2.33]*	[4.76]**	[2.13]*	[4.06]**	[5.04]**	[4.55]**
headd	0.056	0.112	0.216	0.051	0.058	0.189	0.149	0.117	0.218
	[1.49]	[1.83]	[0.88]	[0.97]	[1.77]	[1.60]	[3.44]**	[4.60]**	[6.31]**
urban	0.408	0.362	0.658	0.31	0.295	0.395	0.273	0.303	0.309
	[8.35]**	[9.82]**	[4.53]**	[5.92]**	[8.80]**	[2.43]*	[6.47]**	[10.86]**	[8.17]**
union	0.569	0.556	-0.033	0.408	0.272	-0.108	0.624	0.404	0.056
	[11.83]**	[15.51]**	[0.22]	[8.59]**	[9.85]**	[1.18]	[15.32]**	[17.82]**	[1.89]
married	0.033	0.094	-0.077	0.089	0.193	0.018	0.038	0.253	0.173
	[1.00]	[2.16]*	[0.35]	[1.78]	[6.32]**	[0.18]	[0.93]	[10.70]**	[5.27]**
Constant	7.792	7.674	8.368	8.039	8.229	8.41	7.943	8.031	9.174
	[97.87]**	[62.41]**	[13.84]**	[60.69]**	[98.18]**	[22.51]**	[71.85]**	[115.94]**	[62.64]**
Sample Size	1665	1713	123	804	2412	368	1588	4544	2649
R-squared	0.26	0.42	0.41	0.29	0.31	0.37	0.28	0.32	0.24

Notes: Absolute value of t statistics in bracket. Significance level * significant at 5%; ** significant at 1%

Source: Authors' calculations.

In the manufacturing sector, three years of additional schooling will bring 2.4 percent more additional wage income for the low skill formal workers. The returns to education are the highest in the tertiary sector-medium skill segment with 9.6 percent increase in wage income for additional three years of schooling.

Empirical literature suggests that union membership is an important determinant of wages, labor market behavior, and unemployment rate in South Africa. Our results show that union membership has a strong positive impact on income of members except for high skill individuals cross economic sectors. The associated coefficient is very significant statistically (at 1 percent level). In agriculture, membership to a labor union brings about 60 percent more income than non-membership (low skill in tertiary sector and 37 percent for medium skill formal workers), other things being equal in the same sectors with similar characteristics. The pattern is similar in the other sectors (e.g., about 40 percent in manufacturing-low skill and 28 percent for manufacturing medium skill, and 62 in the tertiary sector-low skill).

Another interesting result relates to the effect of urbanization on wages. People living in the urban areas are earning on average 30 percent higher wages. This may be partly due to relatively higher cost of living in urban areas as well as the structure of the labor markets, e.g., higher skills in urban and non-agricultural sectors. We draw on empirical literature in selecting model specification for the wage function. Another important determinant of wages is gender differences. Everything else being equal, male employees are paid on average 9 percent to 51 percent higher in wages.

Next, we specify informal wage equation *(iw)* which is analogous to the formal wage equation.

$$\log iw_i = x_i \beta_{iw} + u_{iiw} \qquad (2.5)$$

The explanatory variables in this equation include: a constant, gender, years of education, education squared, experience, experience squared, a dummy indicating whether the individual is head of household, a dummy for residence in the urban area, a dummy for married. Table 8 contains the results of the OLS estimation of this equation.

Table 8: OLS Estimates of the Informal Wage Equation

Variables	Agriculture Sector	Industry Sector	Service Sector
gender	0.095	0.347	0.254
	[1.34]	[3.88]**	[8.43]**
eduyear	-0.01	0.041	-0.045
	[0.49]	[1.44]	[4.73]**
eduyear2	0.007	0.002	0.011
	[4.00]**	[1.08]	[14.53]**
expyear	0.029	0.023	0.043
	[3.01]**	[1.86]	[9.33]**
expyear2	0	0	-0.001
	[3.12]**	[1.39]	[7.68]**
headd	0.153	0.11	0.121
	[2.05]*	[1.47]	[4.36]**
urban	0.311	0.397	0.177
	[3.68]**	[5.84]**	[6.55]**
married	0.124	0.184	0.055
	[1.99]*	[2.59]**	[1.99]*
Constant	7.665	7.594	7.331
	[52.30]**	[37.71]**	[98.81]**
Sample Size	758	693	3860
R-squared	0.21	0.22	0.28

Notes: Absolute value of t statistics in brackets
Significance level * significant at 5%; ** significant at 1%

Source: Authors' calculations

As noted earlier, the specification of the equation explaining self-employment earnings (π) is entirely analogous to that of the wage equation. We express that equation as follows.

$$\log \pi_i = x_i \beta_\pi + u_{i\pi} \qquad (2.6)$$

The explanatory variables in this equation include: a constant, gender, years of education, education squared, experience, experience squared, a dummy indicating whether the individual is head of household, a dummy for residence in the urban area, a dummy for high skill level, and a dummy for working in the formal sector. Table 9 contains the results of the OLS estimation of this equation.

We observe many patterns similar to the case of wage employment. For instance, in the primary sector, heads of households earn 35 percent more from self-employment than non-head. This is much higher than the 20 percent premium they earn as wage employee in the same sector. Similarly, self-employment pays more (15 to 30 percent) in the urban area than in the rural area. However, this premium is lower that the one estimated for formal wage employment. Finally, we observe that self-employment pays much more for highly skilled individuals than for the other skill categories. Similarly for people engaged in the formal sector of the economy.

Table 9: OLS Estimates of Self-Employed Earning Equation

Variables	Agriculture Sector	Industry Sector	Service Sector
Gender	0.146	0.605	0.45
	[3.52]**	[7.40]**	[10.81]**
Eduyear	-0.059	0.027	-0.024
	[4.12]**	[1.02]	[1.79]
eduyear2	0.011	0.004	0.007
	[10.44]**	[2.60]**	[8.66]**
Expyear	0.042	0.049	0.078
	[8.62]**	[4.06]**	[13.74]**
expyear2	0	-0.001	-0.001
	[3.83]**	[3.35]**	[12.52]**
Headd	0.352	0.065	0.182
	[7.00]**	[0.74]	[4.20]**
Urban	0.131	0.158	0.27
	[1.91]	[1.96]*	[6.78]**
skillH	0.361	0.811	0.556
	[1.85]	[5.92]**	[10.42]**
Formallab	1.451	0.798	0.703
	[17.45]**	[7.05]**	[13.58]**
Constant	6.926	7.215	6.982
	[83.49]**	[34.98]**	[72.40]**
Sample Size	2544	776	3217
R-squared	0.44	0.42	0.42

Note; Significance level * significant at 5%; ** significant at 1%

Source: Authors' calculations

Aggregation. Given individuals earnings, household income is aggregated according to the following formula.

$$y_h = \sum_{i \in h} w_i L_{iw} + \sum_{ieh} iw_i L_{iiw} + \sum_{i \in h} \pi_i L_{i\pi} + y_{0h} \qquad (2.7)$$

As the above expression shows, total household income is a sum of three components. The first two components add all earnings (wage and self-employment) across individuals and activities, while the last element is an exogenous unearned income such as transfers and capital income (see Table 10). Real income is obtained by deflating total income by a household specific consumer price index $\mathbf{CPI_h}$. This is a weighted sum of prices of various commodities purchased by the household. The weights are given by the budget shares that vary across households.

Table 10: Household Income Distribution between Labor and Non-Labor Income

Population Deciles	**Other Income/Total Annual Income**	**Total Annual Household Other Income**	**Total Annual Household Income**	**Annual Non Labor (Other) Income per capita**	**Annual Total Income per capita**
	Ratio	Rand/year	Rand/Year	Rand/year	Rand/year
1	0.34	720.35	6025.79	107.24	723.94
2	0.32	949.01	7164.21	133.37	990.21
3	0.31	1258.22	9519.38	182.21	1420.86
4	0.26	1467.23	12381.75	233.49	1801.05
5	0.23	1637.85	15365.86	299.38	2443.36
6	0.20	2256.26	22175.89	429.49	3795.05
7	0.16	2497.54	31152.63	543.68	6044.95
8	0.14	3414.77	39702.75	817.71	9067.07
9	0.13	5650.85	67829.13	1498.38	16997.32
10	0.12	15061.66	159162.60	5589.73	53806.32
Total	0.21	3491.71	37050.35	983.65	9710.38

Source: Author's Calculations from Income and Expenditure Survey(2000) and Labor Force Survey (2000)

Household annual total income is defined as total annual income including wage income, self-employed income, and all other income[13]. Average values vary significantly between income deciles. On the average 21 percent of the household income is coming from other sources of income which is non-wage income for laborers and non-self-employed income for self-employed people. When compared between income deciles, the ratio of other income to the total income varies between 34 percent in the lowest decile to the 12 percent in the richest decile in the income distribution.

2.3. Linking the Micro-Simulation Component to the CGE Model

To be able to assess the endowment, price and occupational effects of an oil price shock in a way that fully account for heterogeneity at both individual and household levels requires appropriate channels of communication between the CGE model and the micro-simulation components. In this section, we briefly describe the approach followed here and the constraints that must respected in order to ensure consistency between the two blocks of the framework.

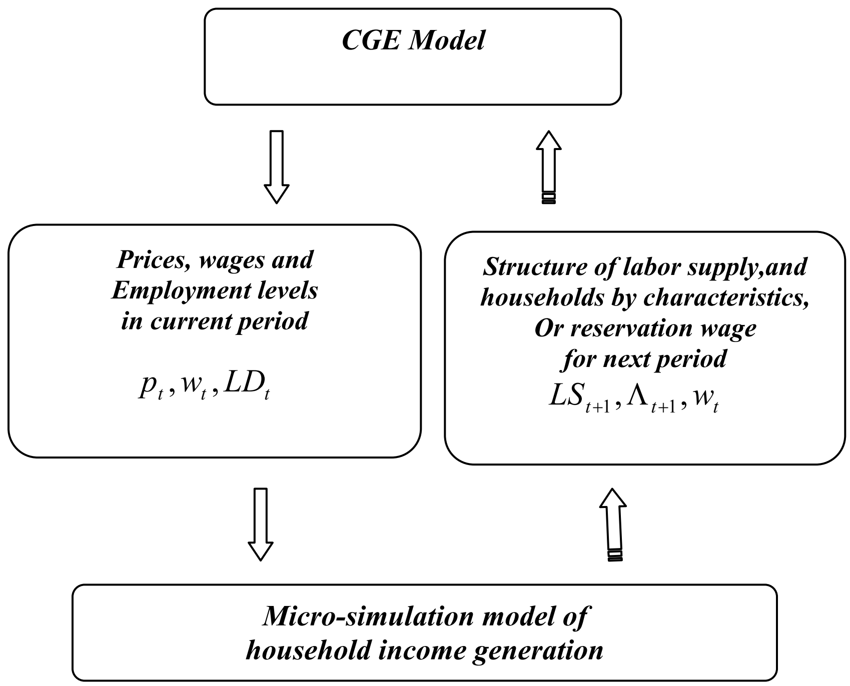
Approach

Figure 3 shows a possible way of framing the communication between the CGE model and the micro-simulation model. On the left hand side of the figure, the CGE model translates the impact of the macroeconomic shocks and policies through changes in relative prices (of commodities and factors), and levels of employment incomes. The micro-simulation module takes these changes as exogenous and translates them into change in household behavior which underpins changes in earnings, occupational status and welfare. In particular, we use equation (2.2) to predict the welfare effects associated with changes in

[13] All Other Income: Income derived from the sale of vehicles, fixed property, other property, rents collected, payments received from boarders and other members of the household, lump sums resulting from employment before retirement, gratuities and other lump sum payments received from pension, provident and other insurance or from private persons, life insurance and inheritances received, claims, grants, total withdrawals from savings, remittances, and other sources of income.

commodities and factor prices. We use the income generation model to predict changes in earnings and occupational status implied by the structural changed produced by the CGE model.

Figure 3: Macro-Micro Linkages with a Feedback Mechanism



The right hand side of the figure shows that, in addition to usual top-down link depicted by the left hand side, we may use a simple recursive feedback mechanism from the household level to the CGE model. Such a mechanism transmits back to the CGE the updated household behavior to generate new aggregate predictions. Behavioral updates are obtained in a manner analogous to the renewal of capital stocks by sectoral investments. The structure of final demand of private consumption by household group and the supply of labor by labor type are similarly updated in a recursive way but consistent with the micro results of the previous period (see Figure 3). Both modules will keep updating each other until convergence is achieved. However, the structure of household demand and labor characteristics was found to be relatively stable without a more dynamic setting that allows for structural changes in demography and household characteristics as well as human and physical capital accumulation etc. A more dynamic setting, which makes endogenous some of the determinants of the variables being exchanged – e.g. a human capital formation story to explain the behavior of education and skill acquisition - is currently beyond the scope of this study. Hence, for the comparative statics in this paper, it was not be necessary to conduct the bottom-up feedbacks from micro simulations to the macro framework.

Consistency

To obtain meaningful results from the simulation framework, one must ensure that outcomes from the micro-simulation model are consistent with the aggregate results from the CGE model both before and after the shock. This implies that the links between the two modules must respect a set of consistency constraints. The envelope method offers an easy way out of this requirement by assuming that choice variables at the household level adjust optimally to the impact of a shock. In the case of the earnings generation model, consistency requires that the observed occupational choices predicted by the micro-simulation module add up to the aggregate levels of employment solved by the CGE model. Similarly, simulated earnings at the micro level must match macro predictions. Bourguignon, Robilliard and Robinson (2002) explain that benchmark consistency could be achieved by ensuring that the calibration of the CGE is compatible with the consistency constraints.

A key consideration here stems from the following. *The random utility function is the latent variable that explains occupational choice*. Furthermore, a shock might cause individuals to move from unemployment to being employed in one of the segments of the labor market. Implementation of the consistency constraints therefore requires information on both the observable and non-observable components of the occupational and earnings models. The observable components of these models are calculated on the basis of estimated parameters and data on observable characteristics. For each individual, the random component of the utility function is drawn randomly from the law of extreme values. As far as earnings equations are concerned, we note that estimation of these equations is based on sub-samples of individuals with nonzero earnings in the corresponding occupation. This estimation readily yields residuals for these sub-samples. For those showing zero earnings, counterfactual earnings are computed on the basis their observable characteristics, estimates of the relevant coefficients, and residuals drawn from a normal distribution with the same standard deviation as the distribution of residuals for those individuals with nonzero earnings.

In practice, differences underlying the micro and macro data (sampling weights, coverage, imputed values etc.) make it very difficult to fully enforce the consistency constraints described above. We therefore adopt several steps to achieve the consistency.

Labor categories. Because of the importance of the labor market structure in South Africa, we ensure that the occupational choices in the micro simulation have the same classification as the labor categories in the CGE model and capture the appropriate taxonomy, structural and unemployment issues in South Africa. As mentioned previously - formal labor is divided into highly skilled labor, semi- (or medium-) skilled labor, and unskilled labor; in addition, there are self-employed earners, and informal labor. Structural unemployment is specified for unskilled and semi-skilled workers (with sticky real wages) while the other labor markets clear in the equilibrium.

Reconciling Base-year and Post-shock Numbers. Consistency between the CGE and micro simulation models basically means that the core information being communicated between the two modules are the same. This refers to the market wages and employment and unemployment structure (distribution shares) in the CGE model and the corresponding reservation wages and occupational-choice probabilities in the micro simulation. In a more dynamic setting, the structure of household demand and labor supply are also additional information to exchange. To achieve consistency in the base-year data or reference run as well as in the post-shock simulation, the following options are possible.

First, if the SAM of the CGE model and the survey data of the micro simulation have the same base year but there exist some discrepancies, consistency in the base-year numbers can be attained by feeding the reservation wages arising from the micro econometric estimation into the CGE model like Savard (2006). Then fixing wages, the employment and unemployment structure consistent with the reservation wages can be computed in the CGE model. If it is important to maintain the reservation wages that are empirically derived from micro econometrics, a single iteration should be sufficient. However, this will not necessarily guarantee convergence of both wages and employment shares in both modules. Hence, further iterations are possible with the caveat that the final numbers may not correspond to the original numbers in each module.

If the base years of the two modules are different, which is often the case, a second option is adopted. In many countries, household and labor force surveys are prepared less frequently than the SAM data underlying the CGE model. With techniques like the cross-entropy methods in Robinson, Cattaneo, and El-Said (2001), a SAM is easily updated to a more recent year to make it consistent with the national accounts and macro data available to policy analysts. At the time of implementation of our South Africa model, the base year of the SAM is 2003 while the survey data were based in 2000. In order to retain both structure - the more recent numbers in the macro accounts as well as the familiar poverty and inequality measurements of the micro data, we employ percent changes to communicate changes in employment and wages as the next best option. In the South Africa model, the labor categories and employment structure in the CGE module are also closely matched to the employment shares in the micro data.

In a post-shock simulation, reconciliation of both wages and employment shares are implemented as in the second option above.

Reconciliation Method. Like Bourguignon, Robilliard and Robinson (2002), reconciliation in the post-shock micro simulation means adjusting the intercepts (or constant terms) of the wage and occupational functions to ensure that changes predicted by the income generation model are consistent with those predicted by the CGE model. Traditionally, all the quantitative analysis and calculations of the micro information are all done with statistical packages designed for processing micro survey data like STATA.[14] The steps entail – i) the econometric estimation of wage and occupational choice functions; ii) the recalibration of the intercept or constant terms of these equations to achieve consistency as described above; and finally iii) the "regeneration" of the household and labor surveys to derive the impact on heterogeneous households of the shocks being introduced. However, to recalibrate the intercept terms in second step above, we find that programming packages like GAMS[15] for

[14] The statistical package STATA is the trade mark of STATA Corporation.
[15] GAMS (General Algebraic Modeling System) is the trade mark of GAMS Corporation.

CGE modeling to be much less sensitive to increasing the number of labor categories in the wage and occupational choice models and much more efficient (i.e. no convergence problems) in solving simultaneous equations necessary to calculate the new intercepts. For this reason, a GAMS program is used in the second step.

3. The Impact of a Large Oil Price Shock

The nominal price of crude oil increased by about 125 percent during the recent period from 2003 to 2006. In May 2007, for example, global oil price averaged over $65/bbl. In real terms however, the recent price increase is only a cyclical recovery and has yet to reach the peaks of 1979-80. Moreover, non-oil commodity prices such as metal and minerals (e.g. gold and other metals) have also risen significantly and have contributed very positively to the balance-of-payment positions of countries like South Africa. As a result, the ratio of oil and non-oil commodity prices has so far not risen as sharply as it did for oil importing countries when compared to the previous shock of 1999-2000. The trend of rising prices is however worrisome. In what follows, we analyze the marginal impact of a large increase in the price of oil similar to the price hike in 2003-06 (holding other things constant unless otherwise specified).

To analyze the effects of an oil price shock on prices and the structure of production in South Africa, we consider two experiments:

1. A 125 percent increase in the world price of imported crude and refined oil.
2. A 125 percent increase in the world price of imported crude and refined oil, a 30 percent increase in the world price of imported basic chemicals and a 6percent increase in the world price of all other imported goods.

The second experiment takes into account the spillover effects on other commodities of an oil price increase.

3.1. Macroeconomic Results

The macroeconomic results are shown in Table 11.

Table 11: Macroeconomic Results for South Africa

Real variables (percent change)	Oil Price Shock	Oil & General Price Shock
Real exchange rate	16.2	22.4
Total absorption	-5.6	-7.8
Exports	7.7	9.1
Imports	-6.2	-10.3
Household consumption	-6.5	-8.8
Total investment	-7.0	-10.8
GDP (at market prices)	-1.8	-2.5
Total employment	-2.1	-2.7
CPI	1.9	2.7

Source: Authors' calculations

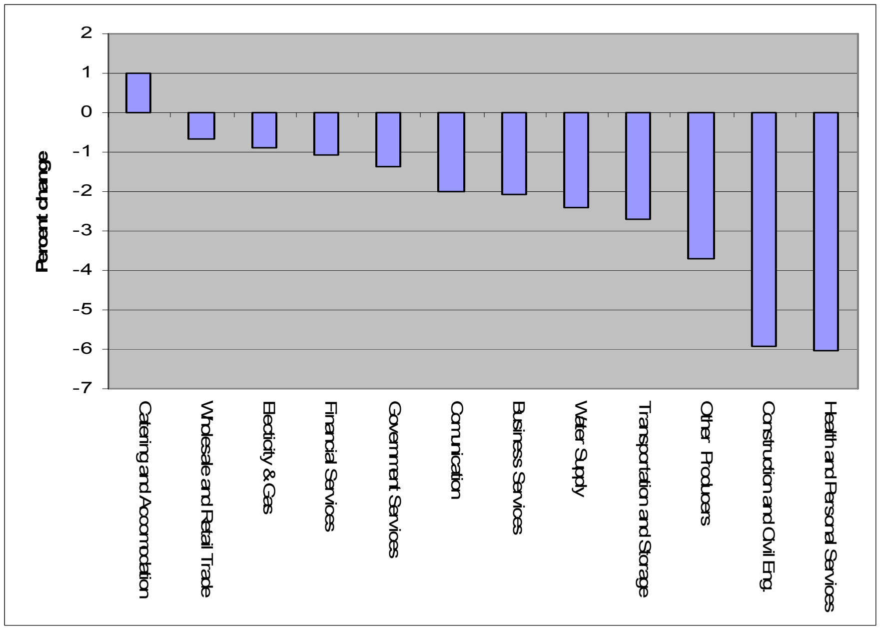
When world prices of imported goods increase, the currency depreciates; the real exchange rate, measured as local currency units per world currency unit, increases from 16.2 to 22.4 percent depending upon the magnitude of the price shock (i.e. an oil price increase alone or an oil price increase plus a general price increase). In effect, the currency depreciates in order to shift resources into exports, increasing export earnings in order to pay for the more expensive, but essential, crude oil imports[16]. Total absorption and real GDP at market prices decline as imported oil becomes more expensive. The world price shocks reduce employment, which also contributes to the decline in real GDP.

Despite a dramatic increase in the world price of crude oil imports, the quantity imported of crude oil, a commodity with no domestic substitute, declines slightly, by approximately one percent, in either price shock scenario. Imports of refined petroleum decline by approximately 20 percent. Imports of all other goods fall as a result of the currency depreciation.

Output responds to the direct effects of an increase in input costs as crude and refined petroleum prices increase. See Figures 4-7 for output results by activity and price shock.

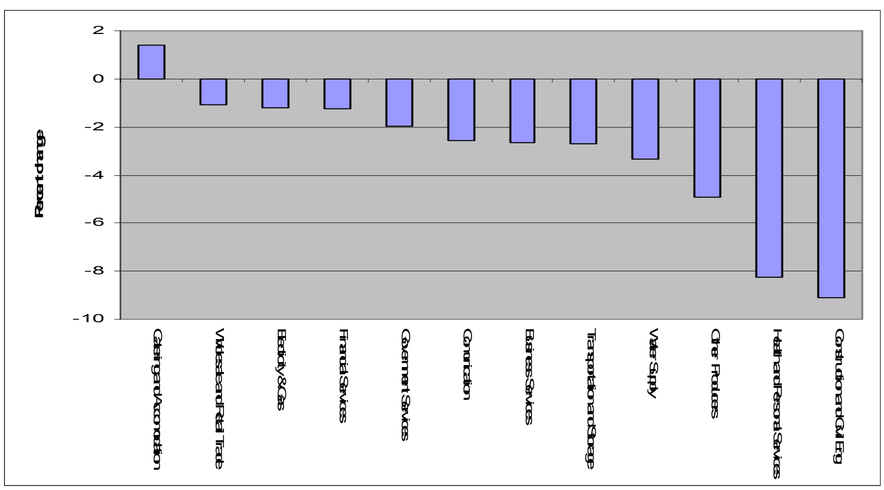
[16] The elasticity of substitution between imports and the domestic variety in consumption for refined petroleum is 0.73 and for basic chemicals is 0.677; crude oil is not produced domestically. A value less than one indicates that the imported variety is not a good substitute for the domestic variety. See Devarajan, Lewis, and Robinson (1993) for a more detailed discussion of the real exchange rate in CGE models.

Figure 4: Output Adjustment in the Service Activities
Oil Price Shock



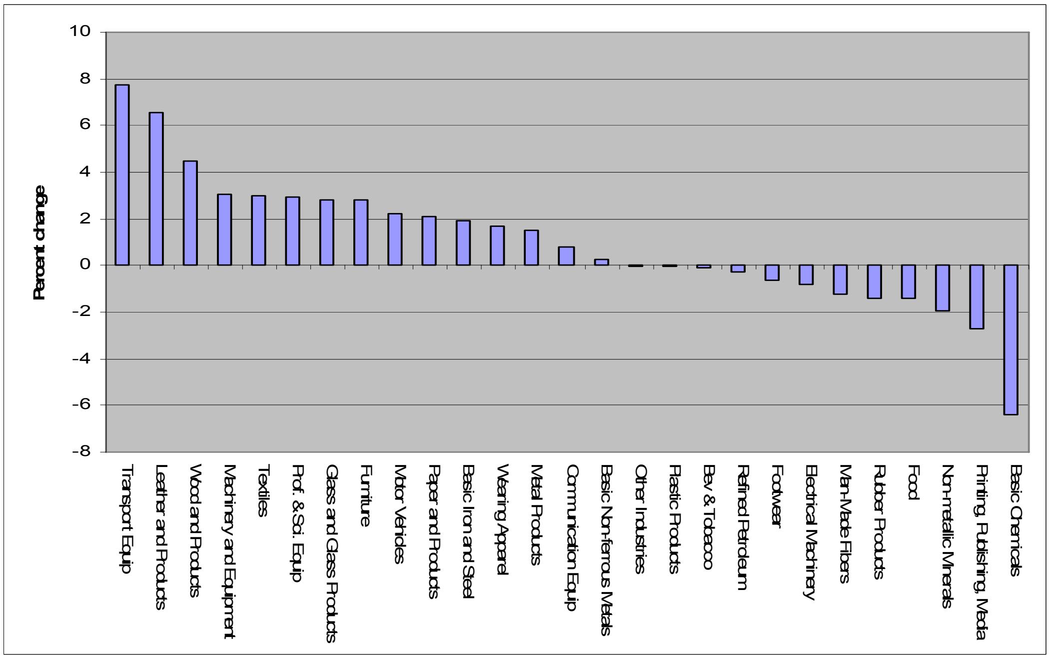
Source: CGE Model Simulation

Figure 5: Output adjustment in the Service Activities
Oil & General Price Shock



Source: CGE Model Simulation

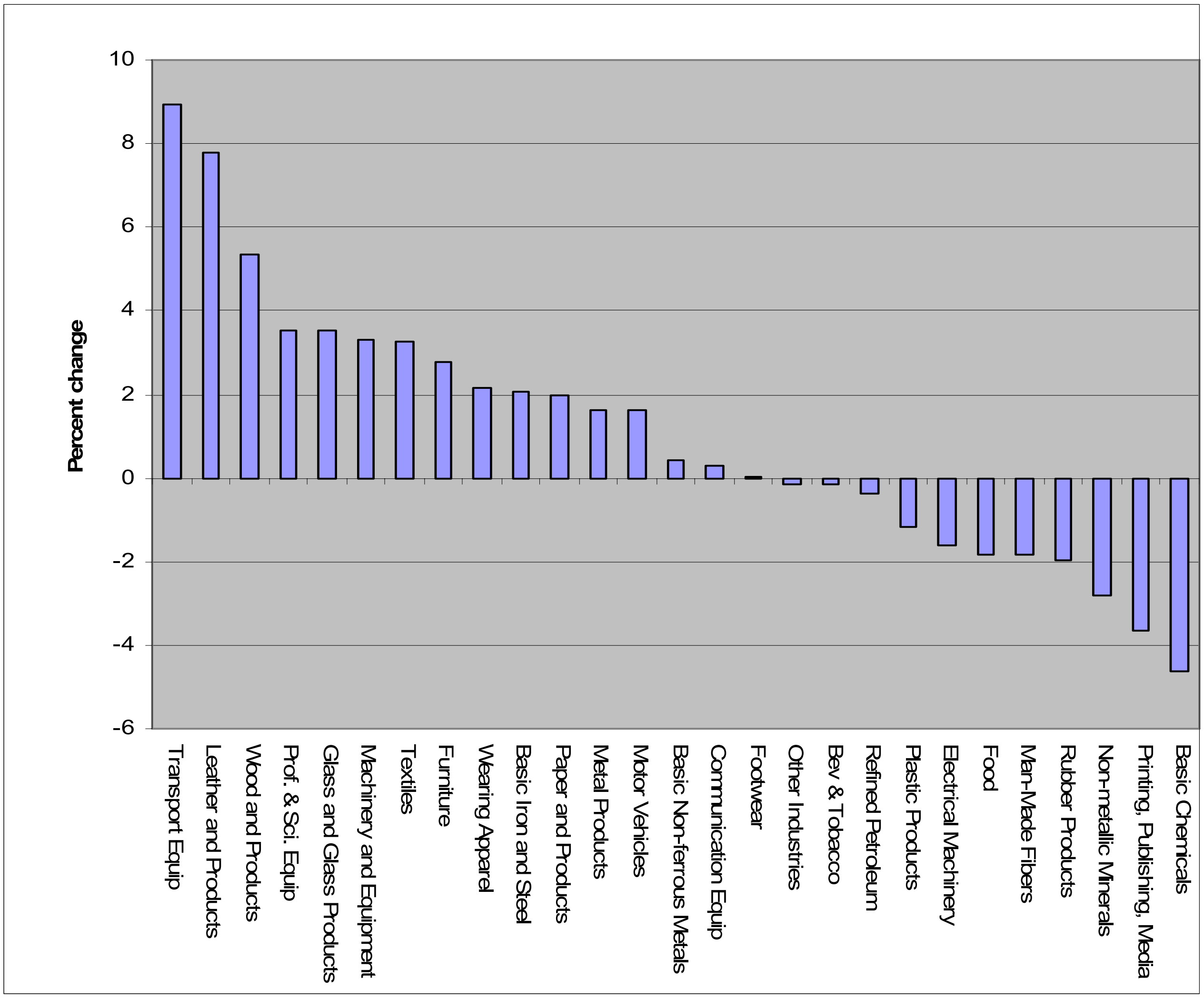
Figure 6: Output Adjustment in the Industry Activities
Oil Price Shock



Source: CGE Model Simulation

For price shock, refined petroleum and basic chemicals, the sole users of crude oil, contract when the price of imported oil increases, due to input cost increases. Other sectors with strong indirect intermediate input use of petroleum, such as printing & publishing, rubber products, transportation & storage, and food, also contract (See Table 3 for a ranking of intermediate input demand for refined petroleum, accounting for direct and indirect effects). Output also responds to economy-wide changes induced by the world price shocks. As a result of the depreciation, output of services activities which are primarily non-traded (with the exception of catering and accommodations) decline.

Figure 7: Output adjustment in the Industry Activities
Oil & General Price Shock



Source: CGE Model Simulation

Consistent with the output changes, employment in services activities decline and labor moves to agriculture and industry activities. Overall employment declines as the demand for semi-skilled and low-skilled labor declines following the import price shocks (the direction of the results is the same for either price shock, the magnitude of the shock is higher when there is an increase in oil and other commodity prices).The percent changes in employment are as follows (note that there is movement of resources within the industry and services activities, here we just report the aggregate changes).

Table 12: Employment Changes (percent change)

	Oil Price Shock	Oil & General Price Shock
Agriculture		
Formal high-skilled workers	3.5	4.9
Formal semi-skilled workers	-1.5	-1.4
Formal low-skilled workers	1.0	1.9
Self-employed	3.6	5.2
Informal workers	8.0	11.8
Industry		
Formal high-skilled workers	2.1	2.5
Formal semi-skilled workers	-1.7	-2.6
Formal low-skilled workers	0.5	0.1
Self-employed	2.6	2.8
Informal workers	4.2	5.2
Services		
Formal high-skilled workers	-0.5	-0.7
Formal semi-skilled workers	-8.6	-11.4
Formal low-skilled workers	-8.4	-11.6
Self-employed	-3.4	-4.8
Informal workers	-2.3	-3.3
Economy-wide employment		
Total	-2.1	-2.7
Formal semi-skilled workers	-5.3	-7.0
Formal low-skilled workers	-2.8	-3.7

Source: Authors' calculations

Real wages decline for all labor categories with the exception of semi-skilled and low-skilled formal workers who receive a constant real wage and the quantity employed adjusts (downward in price shocks considered here).

Table 13: Wage Changes (percent change)

	Oil Price Shock	Oil & General Price Shock
Real		
Formal high-skilled workers	-11.3	-15.2
Formal semi-skilled workers	0.0	0.0
Formal low-skilled workers	0.0	0.0
Self-employed	-10.5	-13.8
Informal workers	-9.6	-12.8
Nominal		
Formal high-skilled workers	-9.6	-13.0
Formal semi-skilled workers	1.9	2.7
Formal low-skilled workers	1.9	2.7
Self-employed	-8.8	-11.6
Informal workers	-7.9	-10.5

Source: Authors' calculations.

As wages decline, household demand for goods and services also decline. The commodity price changes result from shifts in both the demand and supply curves for each activity. The net effect of an increase in the oil prices (as well as for oil and a general price shock) is a dramatic increase in the price of fuel (see Table 14). Prices also increase for food and transportation.

Table 14: Price Changes (percent change)

	Oil Price Shock	Oil & General Price Shock
Food	0.6	1.6
Beverages	-1.7	-1.6
Alcoholic Beverages	-1.7	-1.6
Cigarette and Tobacco	-1.7	-1.6
Personal Care	-7.2	-9.2
Housing Operations	-3.8	-5.1
Fuel	65.9	68.1
Housing, Energy and Water	-3.1	-3.7
Clothing & Footwear	-0.9	0.3
Furniture	-0.2	1.4
Health	-7.2	-9.2
Transportation	4.5	7.3
Communication	-1.7	-1.5
Education	-7.2	-9.2
Reading	0.2	2.0
Entertainment	-7.2	-9.2
Miscellaneous	-3.8	-5.1

Source: Authors' calculations.

3.2. *The Welfare and Distributional Implications of the Oil Price Shock*

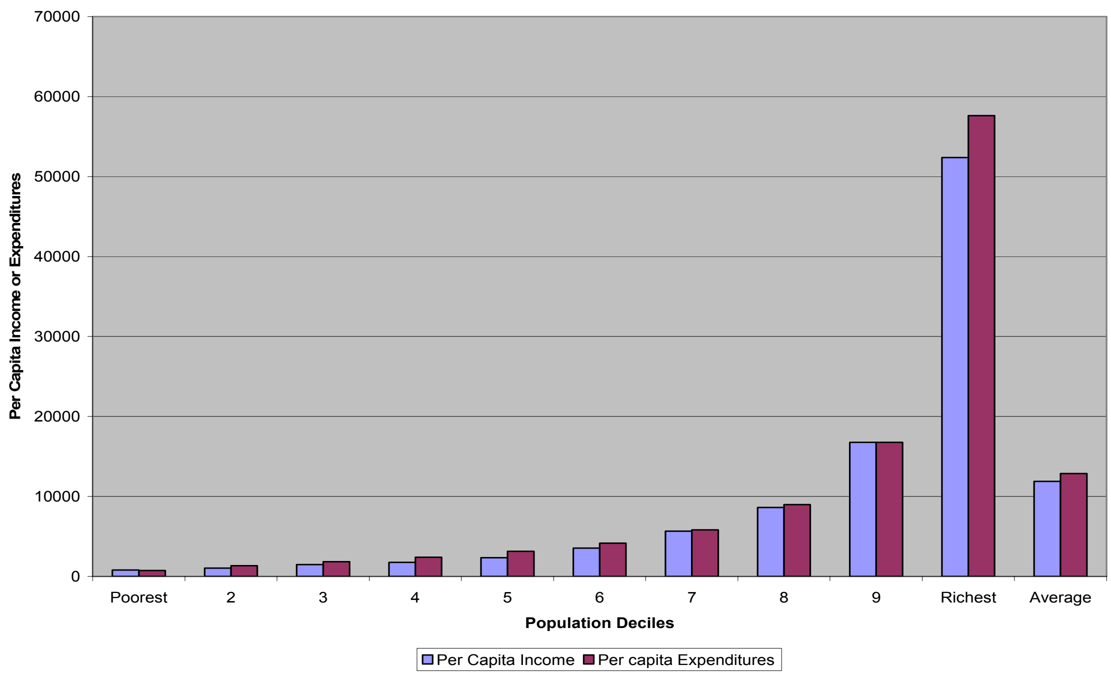
After identifying the macro effects of an oil price increase, this section addresses the poverty and distributional implications. We measure poverty with members of the Foster, Greer and Thorbecke (1984) family of decomposable indices. Our analysis of inequality is based on the Gini coefficient and General Entropy indices. We discuss respectively the baseline distribution of welfare, and the distributional implications of an oil price shock[17].

Baseline Distribution of Economic Welfare

The available survey data provides information on both household income and consumption expenditures. Figure 8 and Table 15 describe the distribution of these two variables by deciles. We combine information on household size and the sample household weights to estimate poverty and inequality at the population level. At the national level, average per capita consumption is little over Rand 10,000 and per capita income of about Rand 9,700 in 2000.

[17] We also estimate poverty indicators at sectoral levels (urban, rural) and by provinces, but the latter are not reported.

Figure 8: Distribution of Income and Expenditure by Deciles



Source: Authors' calculations

Table 15: Per Capita Household Expenditures and Income

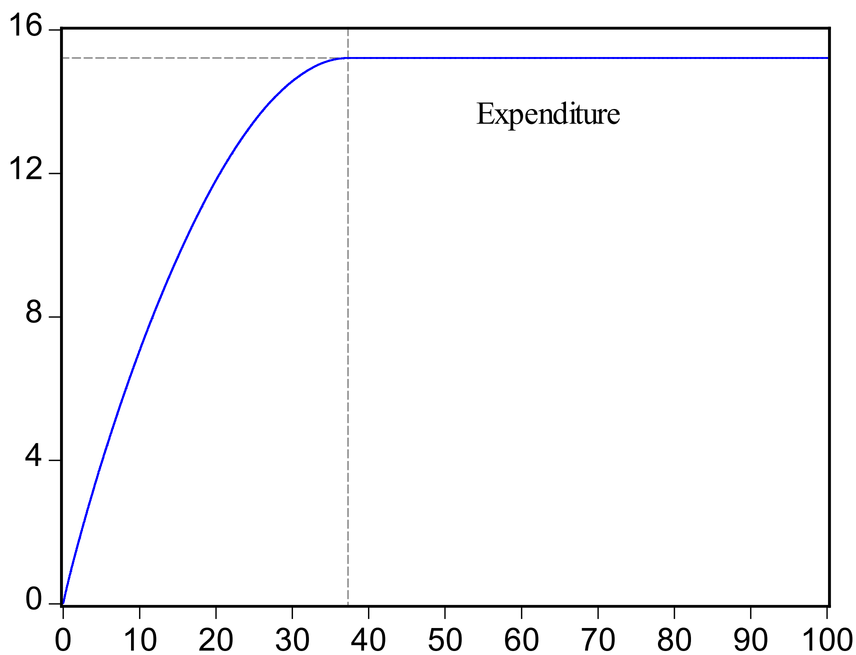
Population Deciles		Expenditure		Income		Urban/Rural Ratio	
		Urban	Rural	Urban	Rural	Expenditure	Income
Poorest		759.0	741.6	724.4	723.8	1.02	1.00
	2	1346.4	1321.2	992.7	989.1	1.02	1.00
	3	1842.2	1827.9	1604.2	1312.2	1.01	1.22
	4	2399.6	2389.6	1980.5	1643.0	1.00	1.21
	5	3129.6	3102.7	2757.1	2093.1	1.01	1.32
	6	4174.7	4115.0	3853.8	3685.0	1.01	1.05
	7	5794.8	5733.5	6385.0	5151.1	1.01	1.24
	8	8984.7	8917.5	9232.4	8436.0	1.01	1.09
	9	16744.7	15807.2	16528.3	21353.3	1.06	0.77
Richest		56017.3	72562.9	53167.3	63415.5	0.77	0.84
Total		14412.7	4018.1	13899.5	3553.0	3.59	3.91

Source: Authors' calculations.

Moreover, the average values of income and expenditures vary significantly by locality; comparing average consumption levels across rural and urban South Africa shows huge disparities between rural and urban sectors (Table 15). For instance, when compared with rural versus urban per capita incomes, people living in the urban areas have on average income that is more than four times the income earned in rural areas. A similar disparity exists in per capita expenditure levels between deciles as well as urban rural differences.

Figure 9 (a&b) and Table 16 (a&b) provide a poverty profile for South Africa in 2000 based on a poverty line set at US$1 per day, which amounts to South Africa is Rand 2533 per capita per year. Figure (9a&b) contains a set of TIP curves, one base on the distribution of per capita expenditure and the other one on that of per capita income. TIP curves offer an alternative way to test for unanimous poverty comparisons across time, across regions and countries based on a wide class of poverty indices. The TIP curve[18] provides a graphical summary of incidence, intensity and inequality dimensions of aggregate poverty based on the distribution of poverty gaps.[19] On the basis of this poverty profile, we note that about 37 or 49 percent of the population was poor in 2000 according as welfare is measured by expenditure or income.

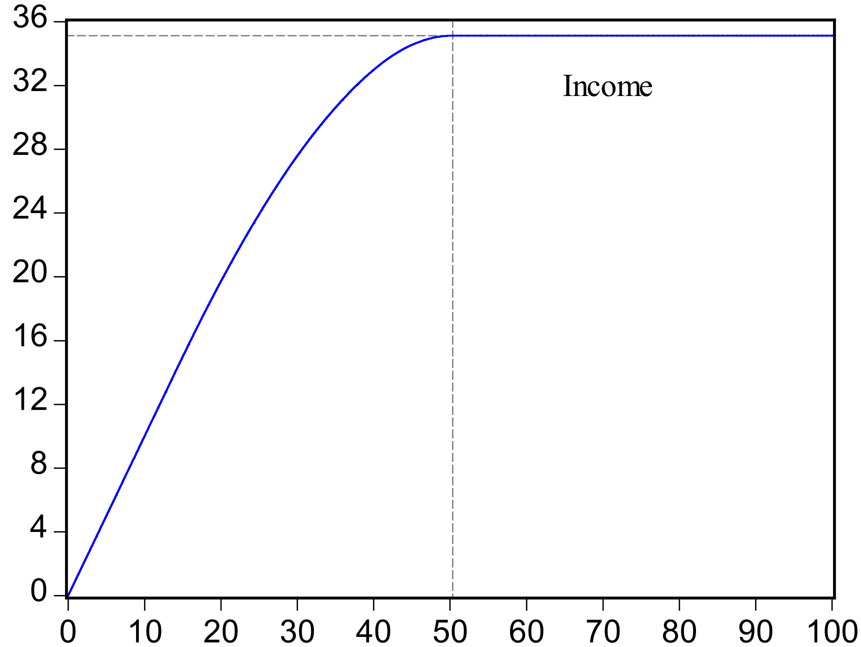
Figure 9a: A Picture of Poverty in South Africa, 2000 (Expenditure)



Source: Authors' calculations

[18] TIP stands for "three 'i's of poverty", that is incidence, intensity and inequality. The length of the non-horizontal section reveals poverty incidence, intensity is represented by the height of the curve while the concavity of the non-horizontal section translates the degree of inequality among the poor.
[19] Jenkins and Lambert (1997).

Figure 9b: A Picture of Poverty in South Africa, 2000 (Income)



Source: Authors' calculations

Table 16a: Expenditure-Based Poverty Profile for the Year 2000

Measure	Estimate	Scale-Elasticity	Gini-Elasticity	Trade-Off
Headcount	0.37	-0.95	2.88	3.03
Poverty Gap	0.15	-1.45	8.42	5.81
Squared Poverty Gap	0.08	-1.70	13.20	7.78

Source: Authors 'calculations

Table 16b: Income-Based Poverty Profile for the Year 2000

Measure	Estimate	Scale-Elasticity	Gini-Elasticity	Trade-Off
Headcount	0.49	-0.44	1.22	2.76
Poverty Gap	0.34	-0.43	4.96	11.45
Squared Poverty Gap	0.28	-0.40	8.64	21.48

Source: Authors' calculations

Inequality is also quite high in South Africa. Based on the distribution of expenditure by deciles, we find that the richest 20 percent of the population, on average spends 35 times more than the poorest 20 percent of the population. The Gini coefficient associated with the distribution of expenditure is about 67 percent and that for the distribution of income about

72 percent. These base case results are in line with other studies of South Africa.[20] The high level of inequality is certainly a constraint to the responsiveness of poverty to economic growth. Tables 16 a and b present information on two types of poverty elasticities computed according to Kakwani (1993) method. The scale elasticity measures the responsiveness of poverty to changes in the mean value of the welfare indicator (expenditure or income). The Gini elasticity indicates the extent to which poverty responds to changes in inequality as measured by the Gini coefficient. The trade-off indicator is known as the proportional rate of substitution (Marginal Proportional Rate of Substitution) between mean welfare and inequality. This is the rate at which income needs to grow to compensate for an increase of one percent in the Gini coefficient to keep poverty constant. Thus the information presented in Table 16 reveal that income would have to grow at least 3 percent to keep poverty incidence constant at the 2000 level.

Distributional Impact of the Severe Oil Price Shock

We now focus our attention to the case of the severe oil price shock. The distributional implications of this shock are obtained by comparing the baseline distribution of income or expenditures to the one that accounts for gains and losses arising from changes in wages, self-employment income, occupational choices, and consumer prices. To enforce the consistency constraint discussed earlier, we adjust the constants (or intercepts) of the set of equations estimated from the household and labor surveys so that the modified equations respect changes from the CGE model. Recall that the micro-simulation model has three economic sectors and three skill types for formal wage workers, 16 occupational choices (including a base category of inactive and unemployed) and three types of incomes (formal wages, informal wages, and self-employment income). Overall, the model has a total of 30 equations with 30 constants (15 constants for income equations and 15 constants for occupational choice equations (the constant for the base category in multi-logit model is set to zero).

[20] See, for example, Jenkins C, and Thomas L,(2000), The changing Nature of Inequality in South Africa, WIDER, Working Paper Series, October 2000.

The micro-simulation calculates the formal wages, informal wages, self-employed incomes and occupational choices at the micro units – i.e., for each individual - that are consistent with the post-shock relative prices, wages and employment levels by broad categories that are generated from the CGE model. After aggregating all incomes within the households, per capita income and expenditures are deflated by new household-specific consumer price index. As the price index reflects household-specific consumption baskets, changes in prices of consumer goods and services will have differential impact on individual households based on their allocation of budget to these components of consumer basket.

Table 17: Household Expenditure Shares by Quintile

Quintile	Food	Beverage	Alcoholic Beverage	Cigarette and tobacco	Person al Care	Housing operation
Poorest	0.45	0.01	0.01	0.01	0.05	0.03
2	0.42	0.01	0.01	0.01	0.05	0.03
3	0.38	0.01	0.02	0.01	0.05	0.03
4	0.31	0.01	0.02	0.02	0.05	0.03
Richest	0.17	0.01	0.01	0.01	0.03	0.04
Average	0.35	0.01	0.01	0.01	0.05	0.03

Quintile	Fuel	Housing, Energy and Water	Clothing and Footwear	Furniture	Health	Transportation
Poorest	0.05	0.23	0.05	0.01	0.01	0.03
2	0.04	0.21	0.06	0.02	0.01	0.03
3	0.03	0.2	0.06	0.03	0.01	0.05
4	0.02	0.2	0.06	0.03	0.02	0.07
Richest	0.01	0.21	0.04	0.03	0.04	0.1
Average	0.03	0.21	0.05	0.02	0.02	0.06

Quintile	Communic ation	Education	Reading	Entertainment	Miscellaneous
Poorest	0.01	0.03	0.0001	0.002	0.04
2	0.01	0.02	0.0002	0.002	0.06
3	0.01	0.02	0.0003	0.003	0.08
4	0.02	0.03	0.0007	0.004	0.12
Richest	0.03	0.03	0.0012	0.008	0.23
Average	0.02	0.03	0.001	0.004	0.1

Source: Authors' calculations

The survey shows that households' budget allocation on different types of consumer good and services varies significantly (Table 17). For example, the poorer households spent larger share of their incomes on food, utilities like water, energy and rent for housing. On the other hand, the richer households spent relatively more on health, transportation and communication, and other goods and services. The oil price shock has directly increased prices for energy and transport but also affected prices of other goods and services through second round effects. While overall price level has gone up slightly, we observed significant variation in prices within the consumer basket. For example, prices for food, fuel and transportation have gone up, but for many other goods and services have declined slightly. Consequently, households had been affected differently depending on their spending patterns. As poorer households spend relatively more on food, they are expected to be adversely affected by the oil price shock. This issue of changes in households' welfare is discussed next.

Impact on the Formal Wage Labor. The adverse impact of oil price shock was most obvious in the formal labor sector. Following the shock, formal workers' wages, on average, declined by 4 percent of their pre-shock earnings (Table 18). Although, the wage loss varies by income deciles, the differences are not significant except for the poorest and the richest deciles of formal workers.

Table 18: Impact of Oil Shock on Formal Wage Workers

Deciles	Formal Wage-Post Shock	Formal Wage-pre shock	Ratio: Post-shock/ Pre-shock
Poorest	3824.847	4101.92	0.93
2	7724.035	8157.375	0.95
3	11895.97	12409.63	0.96
4	16163.26	16540.06	0.98
5	21572.56	21915.76	0.98
6	27394.34	27768.17	0.99
7	33806.99	34605.13	0.98
8	44793.3	46425.38	0.96
9	65200.57	68435.89	0.95
Richest	180520.8	194553.3	0.93
Overall Average	32967.42	34511.12	0.96

Source: Authors' calculations

In addition to a decline in wages, formal sector labor also experiences increased unemployment in the tertiary sector. Most of those who became unemployed were from low and medium skill workers of tertiary sector. These unemployed workers lost their earnings completely following the shock (Table 19). Almost 70 percent of these newly unemployed formal wage earners belong to the bottom three deciles (based on pre-shock per capita incomes).

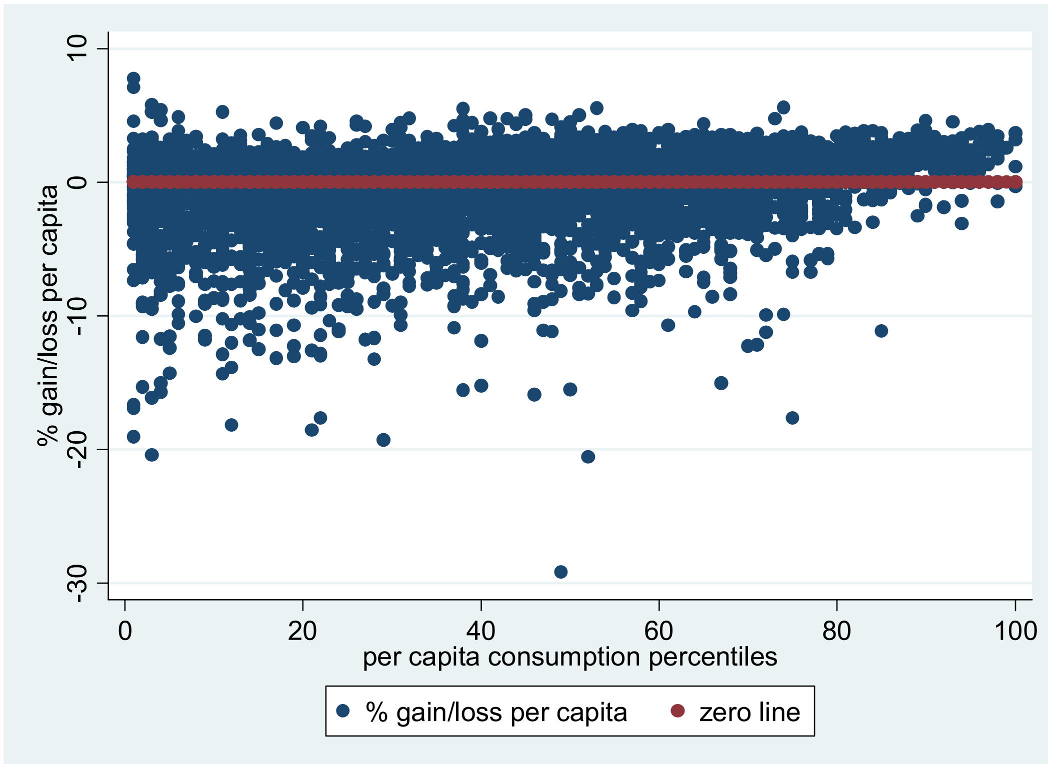
Table 19: Unemployment Impact of Oil Shock on Formal Workers

Income deciles	Percentage of People	Average Annual Wage-pre shock	Average Annual Wage-post shock	Percent of loss
Poorest	31.07	3742.644	0	-100
2	19.11	8253.346	0	-100
3	18.39	12127.46	0	-100
4	9.11	16562.43	0	-100
5	10.18	21893.82	0	-100
6	4.46	27403.68	0	-100
7	3.39	33850.42	0	-100
8	2.50	45794.71	0	-100
9	1.25	70534.29	0	-100
Richest	0.54	970816.7	0	-100
Overall Average	100	18306.53	0	-100

Source: Authors' calculations

Welfare Impact of the Oil Price Shock on Low-Skill Households. As noted above, poorest deciles were disproportionately adversely affected from the shock because they tend to have low skills. The following figure shows that household with low skill level tend to lose more than they gain from the shock. Losses are more pronounced than the gains; also, losses are more clustered around the lower end of the distribution (poorer household with low skill).

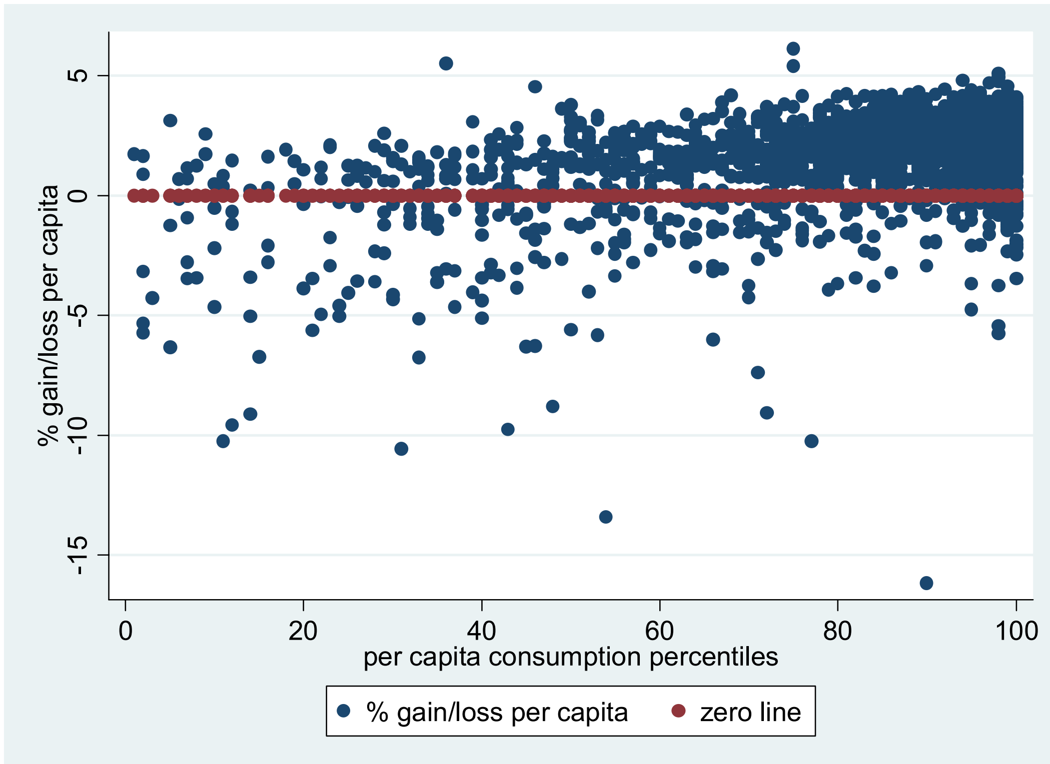
Figure 10 : Gains and Losses from Oil Price Shock for Low Skill Households



Source: Authors' calculations

Welfare Impact of the Oil Price Shock on High Skill Households. In contrast to low-skill households, those with high skill level are, on average, gaining from the shock (Figure 11). As the figure shows, there are relatively few households that are experiencing losses from the shock and they are scattered across the income deciles. However, most high-skill households have gained more income after the shock and these gainers are concentrated on the higher end of the income distribution. In our view, high-skill workers are less likely to be laid off when unemployment increase as a result of oil shock, or they can move relatively easily to different jobs. Moreover, these households, which are already mostly in higher income quintiles, are also less affected from the price changes following the oil price shocks. To start with they are richer and spending relatively less on food and other goods affected most from the changes in oil prices.

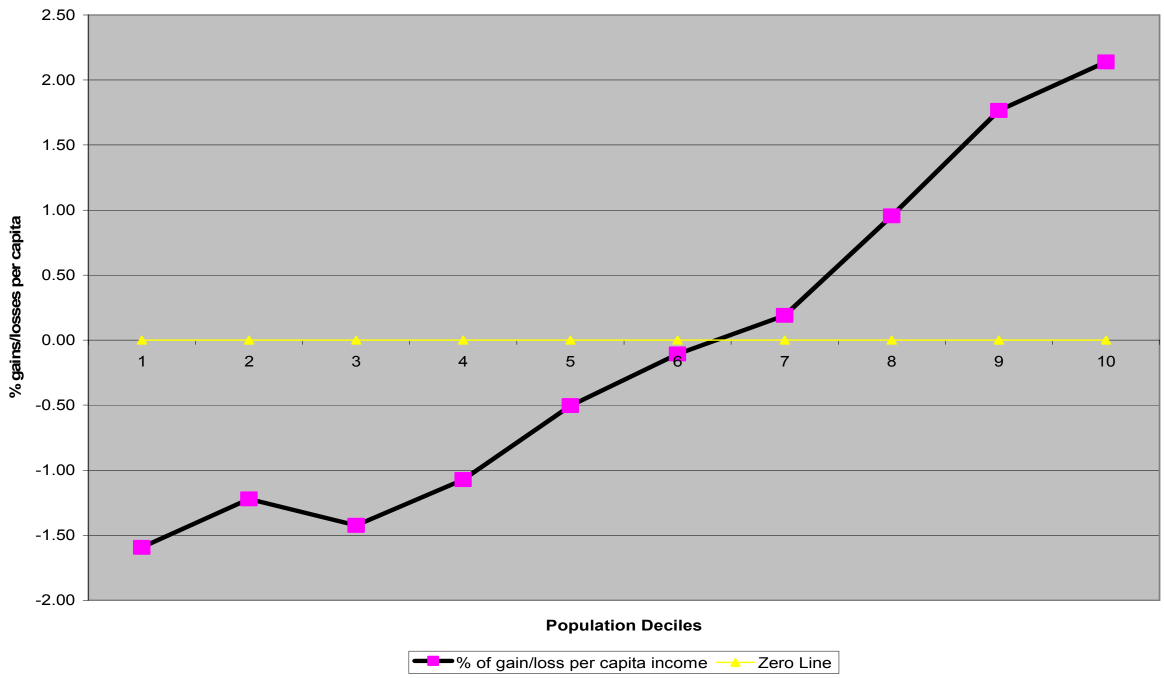
Figure 11: Gains and Losses from Oil Price Shock for High Skill Households



Source: Authors' calculations

Overall Welfare Impact of the Oil Price Shock. Figure 12 presents an overall picture of gainers and losers from the oil price shock. It is clear that the poorer segment of the population is more adversely affected from this shock. For instance, households below the 7th decile of income per capita are losing and becoming poorer, while the richest 35 percent of households are gaining even higher incomes as a result of the shock. On average, shock results in a decline of about 1.5 percent of initial per capita income for the poorer segments of the population. Following the shock, not only the extent of poverty increased slightly but also distribution of the welfare of the households became less equal.

Figure 12 : Distribution of Gains and Losses to Households by Deciles



Source: Authors' calculations

Table 20 presents our results on poverty and inequality indicators along with some disaggregations of the baseline profile. Thus, when regional disparities are considered, over 70 percent of people living in rural South Africa were poor, while only 33 percent of urban population had income below the poverty line (the equivalent of a dollar a day). The simulation results for oil price shock have an adverse impact on poverty. The proportion of individuals living under poverty (based on a dollar a day poverty line and the income measure of welfare) increases slightly less from 49 percent to 49.5 percent (increased 37 percent to 38 percent if we consider expenditure per capita as a welfare measure.) On the regional level, head count ratios again increased both in urban and rural areas experienced a relatively larger increase in poverty. The poverty gap index increased from 15 to 16 percent (result not reported), which indicates that there is a one percent increase in the difference between actual income and income required to sustain minimum standard of living.

Table 20: Impact of Oil Shock on Poverty and Income Distribution

	Base Case			Simulation 1: Oil Price Shock		
	National	*Urban*	*Rural*	*National*	*Urban*	*Rural*
Poverty Indicators						
Using Expenditure						
Head Count Ratio	0.37	0.21	0.60	0.38	0.22	0.61
Poverty Gap	0.15	0.08	0.26	0.16	0.08	0.27
Poverty Severity	0.08	0.04	0.15	0.08	0.04	0.15
Using Income						
Head Count Ratio	0.49	0.33	0.72	0.495	0.33	0.72
Poverty Gap	0.33	0.22	0.51	0.33	0.22	0.51
Poverty Severity	0.28	0.17	0.43	0.28	0.18	0.43
Inequality Indicators						
Using Expenditure						
General Entropy(0)	0.87	0.77	0.60	*0.89*	*0.78*	*0.61*
General Entropy(1)	0.98	0.80	1.04	*1.00*	*0.81*	*1.06*
Gini coefficient	0.67	0.63	0.58	*0.68*	*0.64*	*0.59*
Using Income						
General Entropy(0)	1.22	1.02	1.14	1.23	1.03	1.15
General Entropy(1)	1.20	1.00	1.46	1.21	1.02	1.48
Gini coefficient	0.71	0.67	0.71	0.72	0.68	0.72

Source: Authors' calculations

As far as inequality is concerned, we use both General Entropy indices and the Gini coefficient for the whole population and decomposition at the regional levels. The simulation results also show some increase in inequality. The overall Gini coefficient increases by about one percent, the same increase as the Gini coefficient for the urban and rural sector. Thus following the oil price shock, income distribution worsened slightly. The distributional impact, as measured by changes in the Gini coefficient, deteriorated both for rural as well urban areas. These results suggest that the impact on heterogeneous households tend to average out when they are collected by income groups. The separation of impact by household would be meaningful for the macro-micro linking if the household classification is based on characteristics other than income, and if the data are rich enough in such characteristics for the construction of both the SAM underlying the CGE model and the micro-simulation model. However, aggregative poverty and income inequality measures do not vary very much numerically. The oil price shock tends to increase the disparity between rich and poor – i.e the mean welfare or consumption of various household groups This means that the impact on different household types will tend be the same if they have more or less the same mean welfare or income prior to the shock - which is a significant finding.

Finally we decompose the overall change in inequality into its vertical and horizontal components. We follow Ravallion and Lokshin (2004) in using the mean log deviation (MLD) measure of inequality. This measure is a member of the Generalized Entropy class with the focal parameter set to zero. Member of this class are defined by the following expression.

$$GE(\theta) = \frac{1}{\theta^2 - \theta}\left[\frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i}{\mu}\right)^{\theta} - 1\right] \tag{3.1}$$

When the focal parameter θ=1, we get Theil's measure and when the parameter is equal to zero, we get the MLD defined as follows:

$$GE(0) = \frac{1}{n}\sum_{i=1}^{n}\log\left(\frac{\mu}{x_i}\right) \tag{3.2}$$

To see clearly what the decomposition entails, let $\mathbf{y_i}$ and $\mathbf{x_i}$ stand respectively for the post- and pre-reform welfare per person in household **i**, and $\mathbf{g_i}$ for the gain (or loss) to household **i** due to the shock. Thus, $y_i = x_i + g_i$. The *vertical* component relates to inequality among people at different pre-shock welfare levels, while the horizontal component measures inequality between people at the same pre-shock welfare. The decomposition involved here requires an estimate of the average impact for the distribution of gains at given pre-shock welfare (**x**). In other terms, we need an estimate of the conditional mean impact defined by: $g_i^c = E(g_i \mid x = x_i)$. It would be difficult to observe significant dispersion in impact at given pre-reform welfare within a data set from a household survey. This conditional expectation can be estimated using a non-parametric regression of the gains on **x** (e.g. LOESS[21]). On the basis of the MLD, it can be shown that the overall change in inequality can be written as:

[21] LOESS stands for Locally Estimated Scatter Plot Smooth, while LOWESS stands for Locally Weighted Scatter Plot Smooth.

$$\Delta I = \frac{1}{n}\sum_{i=1}^{n}\ln\left(\frac{1+\bar{g}/\bar{x}}{1+g_i^c/x_i}\right)+\frac{1}{n}\sum_{i=1}^{n}\ln\left(\frac{1+g_i^c/x_i}{1+g_i/x_i}\right) \tag{3.3}$$

The first term on the rhs of (3.3) measures the contribution to the change in total inequality of the way conditional mean impacts vary with pre-reform welfare levels. This is the vertical component. The horizontal component, the second term, measures the contribution of the deviations in impacts from their conditional means.

Table 21: Decomposition of the Impact on Inequality

	Vertical Component	Horizontal Component	Total
Gains from Consumption[1]	137.0	-37.0	100.0
Gains from changes in Formal Wages[1]	120.4	-20.4	100.0
Gains from changes in Informal Wages[1]	104.1	-4.1	100.0
Gains from Changes in Self-Employed Income [1]	77.0	23.0	100.0
Aggregate Gains[1]	135.0	-35.0	100.0
Aggregate Gains[2]	119.0	-19.0	100.0

Notes:

1. Using per capita consumption as an explanatory variable in the Lowess regression
2. Using per capita income as an explanatory variable in the Lowess regression

Source: Authors' calculations

Table 21 shows the decomposition of the impact on inequality. In the case of increase oil prices shock, aggregate results show that the horizontal component is inequality reducing whereas vertical impact is inequality enhancing. A closer look at the components of this aggregate result reveals except in the case of self-employed income, horizontal impact is inequality decreasing, while vertical effect is inequality enhancing. Since, self-employed individuals are relatively smaller share of the total employed individuals -about 23 percent- and their contribution to household income is not high enough (about 16 percent), it is unlikely that the impact of changes in the self-employed income will change the sign of the horizontal impact.

4. Summary and Conclusions

This paper has developed a macro-micro framework for examining the macroeconomic and distributional consequences of an oil price shock on the South African economy. In so doing, it gave simultaneous quantitative expressions to the impact of an external shock on macro aggregates such as GDP, real exchange rate, total absorption, exports, imports, various sub-sectors of interest to policy makers as well as the household distributional response to the shocks with the full heterogeneity of household and labor characteristics normally found only in household and labor surveys. This was accomplished by implementing and merging (i) a highly disaggregative computable general equilibrium model that captures important economy-wide consequences of relative price and income effects as well as labor market adjustment arising from a significant external shock or policy change, and (ii) a micro-simulation component with linking both earnings and occupational choice to socio-demographic characteristics of the household as in Bourguignon and Ferreira (2005).

We emphasize that the application to the oil price shock should be taken as illustrative since offsetting factors are not considered. While the magnitude of the shock would be similar to 2003-06, there were other several factors at play in South Africa like the strong macro and economic policy in place, the overall favorable terms of trade, the relative strength of the South Africa rand, and strong investment programs in the public sector.[22] In fact, economic growth in South Africa has been very high during that period. The scenarios should be taken as the marginal impact of a similar severe price hike without the benefit of offsetting factors – i.e. a conservative case. It also assumes that the labor market structure and rigidities, particularly the real wages of the low to medium skill workers, will continue to operate along the shocks. Under those circumstances, the two scenarios indicate that total absorption would fall between 5 to 8 percent. Real GDP would decline 1.8 to 2.5 percent. The real exchange rate depreciation that would be necessary ranges from 16 to over 20 percent. The impact on industries can vary widely with most of the negative impact falling

[22] The increase in the dollar price of crude oil was counterbalanced significantly by the strong South Africa rand during much as the recent trend of the crude oil prices. The nominal rand per dollar, for example, appreciated by about 20 percent from end 2002 to end 2006 and by as much as from 42.5 percent from end 2001 to end 2006.

on fuel-intensive sectors such as construction, rubber and plastic products, various chemicals, electrical machinery, and health services.

With respect to the distributional impact of these shocks, we find that aggregative poverty and income inequality measures do not vary very much numerically. However, a look beyond these aggregate results allows us to identify various groups of winners and losers. The adverse impact of the oil price shock was mostly felt by the poorer segment of the formal labor market in the form of declining wages and increased unemployment. Unemployment hit mostly low and medium-skill workers in the tertiary sector and about 70 percent of these workers belonged to the bottom three deciles of the formal labor work force.

Our findings show that losses are more pronounced in the low skill group than the gains. On the other hand, high skill households, on average, gained from the oil price shock. Most high skill households have gained more income after the shock. Moreover, the gainers are concentrated on the higher end of the income distribution, but the relatively small number of losers are scattered across the income deciles. In addition, the shock has a limited impact on high-skill households for another reason: the spending basket of these relatively rich households is less skewed towards food and other goods affected most from the changes in oil prices.

Evidence also suggests that high-skill workers are less likely to be laid off when unemployment increase as a result of the oil price shock, or they can move relatively easily and faster to different jobs. In fact, the opportunity cost of not working is typically higher for the highly skilled individuals. Therefore, in response to a job loss, high-skill workers will seek quickly another employment. Workers with more years of schooling and experience may also be better able to adapt to new jobs and have better access to information on vacancies and opportunities than low-skill individuals. Thus, an adverse shock is like a poverty trap for low-skill individuals unless there are polices and institutional arrangements to mitigate the adverse impact of the shock for this group of households.

The overall welfare impact shows that the poorer, and generally low-skill, segment of the population is more adversely affected from this shock. Thus, the oil price shock tends to increase the disparity between rich and poor. This conclusion is also supported by the observed changes in the mean welfare or consumption of various socioeconomic groups considered in this study. Furthermore, a decomposition of changes in inequality reveals that the horizontal component tends to decrease inequality. This comparison of aggregate and disaggregate results suggests that the impact on different household types will tend be the same if they have more or less the same mean welfare or income prior to the shock - which is a significant finding.

Finally, the relative stability of the aggregate measures of poverty and inequality also poses an issue for the recursive linking between the CGE model and the micro simulation module. If the distributional effects collected and pulled together from the micro simulation are aggregative in nature, such as the income groupings currently specified in the CGE model, the broadly defined structures of households and labor supplies for the bottom-up feedback are likely to be relatively stable. This is consistent with empirical findings that without long term economic growth, productivity change, and factor accumulation, as can be found in a more dynamic CGE setting, poverty and inequality measures will likely not vary significantly. Hence, in the static setting found in current implementation of the CGE model, no recursive feedback into the macro model was found necessary. In the end, what constitutes as an appropriate or meaningful classification of the households for a two-way feedback would likely depend on the policy issue and external shock under investigation. The trade-offs between greater sophistication and simplification will also depend on data constraints as well as the needs and capacity of policy makers.

References

Bourguignon, François., and F. H. G. Ferreira. 2005. "Decomposing Changes in the Distribution of Household Incomes: Methodological Aspects." In F. Bourguignon, F. H. G. Ferreira, and N. Lustig, eds., *The Microeconomics of Income Distribution Dynamics in East Asia and Latin America*. New York: Oxford University Press.

Bourguignon, François and Luiz A. Pereira da Silva. 2003. *The Impact of Economic Policies on Poverty and Income Distribution.* New York: Oxford University Press.

Bourguignon, François, Ann-Sophie Robillard, and Sherman Robinson. 2002. "Representative vs. Real Households in the Macroeconomic Modeling of Inequality." International Food Policy Research Institute, Washington, DC. Processed.

Cogneau, Denis and Ann-Sophie. Robillard. 2000. "Income Distribution, Poverty and Growth in Madagascar: Micro Simulations in a General Equilibrium Framework." IFPRI TMD Discussion Paper No. 61.

Devarajan, Shantayanan and Delfin S. Go. 2003. "The 123PRSP Model." In Francois Bourguignon and Luiz A. Pereirra da Silva. 2003.

Devarajan, Shantayanan, Jeffrey D. Lewis, and Sherman Robinson. 1993. "External Shocks, Purchasing Power Parity and Equilibrium Real Exchange Rate." *World Bank Economic Review* 7:45-63.

Essama-Nssah, B. 2006. "Macroeconomic Shocks and Policies." In *Analyzing the Distributional Impact of Reforms*, ed. Aline Coudouel and Stefano Paternostro, 355-435. Washington D.C: The World Bank.

Essama-Nssah, B. 2005. "Simulating the Poverty Impact of Macroeconomic Shocks and Policies." Policy Research Working Paper 3788, Washington, DC.: The World Bank.

Foster, J., J, Greer, and E. Thorbecke. 1984. "A Class of Decomposable Poverty Measures." *Econometrica* 52(3): 761-66.

Go, Delfin S., Marna Kearney, Sherman Robinson, and Karen Thierfelder. 2005. "An Analysis of South Africa's Value Added Tax." Policy Research Woprking Paper 3671, Washington, DC.: The World Bank.

Heckman, James and Lance Lochner. 1998. "Explaining Rising Wage Inequality: Explorations with a Dynamic General Equilibrium Model of Labor Earnings with Heterogeneous Agents." *Review of Economic Dynamics,* 1:1-58, January.

Jenkins C, and L. Thomas. 2000. "The changing Nature of Inequality in South Africa." WIDER, Working Paper Series, October 2000.

Jenkins, Stephen P. and Peter J. Lambert. 1997. "Three 'I's of Poverty Curves, with an Analysis of UK Poverty Trends." *Oxford Economic Papers.* July, 49:317-27.

Jorgenson, D.W., L.J. Lau, and T.M. Stoker (1980). "Welfare Comparison under Exact Aggregation." *American Economic Review,* Vol. 70, No. 2, May, pp. 268-72.

Kakwani, Nanak. 1993. "Poverty and Economic Growth with Application to Côte d'Ivoire." *Review of Income and Wealth* 39(2): 121-39.

Kearney, Marna. 2004. *Restructuring Value-Added Tax in South Africa, A Computable General Equilibrium Analysis,* Ph.D. Dissertation, University of Pretoria, Pretoria, South Africa.

Korman, Vijdan. 2006. "A Micro-simulation Model to Assess Poverty Impact of Oil Shock in South Africa." The World Bank. Processed.

Magnac, Thiery. 1991. Segmented Competitive Labor Markets. Econometrica, Vol. 59, No.1: 165-187.

McDonald, Scott and Melt van Schoor (2005). "A Computable General Equilibrium (CGE) Analysis of the Impact of an Oil Price Increase in South Africa," *PROVIDE Project Working Paper,* 2005:1.

Ravallion Martin and Lokshin Michael. 2004. Gainers and losers from Trade Reform in Morocco. *World Bank Policy Research Working Paper.* No. 3368, Washington, DC.: The World Bank.

Robinson, Sherman, Andrea Cattaneo, and Moataz El-Said. 2001. "Updating and Estimating a Social Accounting Matriz Using Cross Entropy Methoids." *Economic Systems Research,* 13(1): 47-64.

Roy, A. D. 1951. "Some Thoughts on the Distribution of Earnings." *Oxford Economic Papers*, Vol3, No.2: 135-146.

Savard, Luc. 2006. Analyse de la pauvreté et distribution des revenus dans le cadre de la modélisation en équilibre général calculable. Ph. D dissertation, Ecole des Hautes Etudes en Sciences Sociales.

Savard, Luc. 2003. « A Segmented Endogenous Labour Market for Poverty, Income Distribution Analysis in a CGE-Household MS Model: A Top-Down/Bottom-Up Approach." Working Paper CIRPEE, Université Laval #03-43.

Statistics South Africa. 2000. Income and Expenditure Survey.

Statistics South Africa. 2000. Labor Force Survey.

Annex A: Description of Variables

Variable Name	Description
1. Demographic Variables -Individual Level Data	
Gender	Dummy variable:1 male and 0 female
Age	Years of age
nchild09	number of children age between 0-9 in household
nchild01	number of children age between 0-1 in household
headd	Dummy variable: 1 for household head; 0 otherwise
married	Dummy variable: 1 for married couples; 0 otherwise
urban	Dummy variable: 1 for urban; 0 rural
prov	Regional Province variable
hhsize	Household size
2. Education and Experience-Individual Level Data	
eduyear	Number of years spent in school. Highest education completed.
eduyear2	Number of years spent in school-squared
expyear	Experience measured as (=Age-eduyear- 5)
expyear2	Experience-squared measured as (=Age-eduyear- 5)^2
eduyearhd	Years of schooling of head of the household
skillH	Professional, semi professionals, technical occupations, managerial, executive administrative occupations, and certain transport occupations, eg., pilot navigator
skillM	Clerical occupations, sales occupations, transport, delivery and communications occupations; Service occupations, farmer, farm manager, artisan, apprentice and related occupations, Production foreman production, supervisor
SkillL	Elementary occupations, and domestic workers
3. Income from employment and Occupational categories-Individual Level Data	
fwage	Yearly wage income in Rand-Formal workers
fwagelog	Log of yearly wage income-Formal workers
Iwage	Yearly wage income in Rand-Informal workers
iwagelog	Log of yearly wage income-Informal workers
selfincr	Yearly total self-employed income in Rand
seinclog	Log of yearly self-employed income
fambusiness	Dummy variable: 1 for someone in the household own family business;0 otherwise.
occhoice1	Dummy variables: 0=unemployed+inactive; 1=self-employed-agriculture; 2=informal wage employee;3=formal wage employee;
Occhoice2	Dummy Variables:(1) Inactive and unemployed, (2) formal sector workers-low skilled in agriculture, (3) formal sector workers-semi skilled in agriculture, (4) formal sector workers- high skilled in

	agriculture, (5) formal sector workers-low skilled in industry, (6) formal sector workers-semi skilled in industry, (7) formal sector workers- high skilled in industry, (8) formal sector workers-low skilled in services, (9) formal sector worker-semi skilled in services, (10) formal sector workers- high skilled in services, (11) informal sector workers-agriculture, (12) informal sector workers-industry, (13) informal sector workers-services, and (14) self-employed-agriculture, (15) self-employed-industry, and (16) self-employed-services
Economic Sectors	
Primary Sector	It include agriculture, forestry, and fishing, mining and quarrying
Secondary Sector	It include manufacturing, electricity, other utilities, and construction
Tertiary Sector	It include trade, transport, financial, business services, and social, personal and community services
Formallab	Dummy variable for formal labor: based on question asked in Labor force survey (sector=1(q4.19))
informallab	Dummy variable for Informal labor: based on question asked in Labor force survey(sector=2(q4.19))

4. Household Aggregate Expenditures and Income Variables (Household Level)- Data from Income &Expenditure 2000.

Household Expenditures and Consumer Price Index for 17 household expenditure categories

	Food; Non Alcoholic Beverages, Alcoholic beverages, Cigarettes, cigars, and tobacco, Clothing and footwear,
	Housing, Fuel and power, Furniture and equipment, Household operations, Health, Transport
	Communication, Recreation and entertainment, Education, Miscellaneous-personal care,
	Other miscellaneous goods and services.
Household Aggregate Income	It includes formal wage income, informal wage income, and self-employed income from Labor force Survey, and other income from Income and Expenditure Survey .

Source: The data is obtained both from Labor Force Survey 2000,and Income and Expenditure Survey 2000.