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CHAPTER 12

Economywide and Distributional Impact of an Oil Price Shock on the South African Economy

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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 effect should be modeled and anticipated. The links between the two aspects—macroeconomics and poverty/income distribution—surely have 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 sets from microeconometric modeling of individual or household behaviors about income and employment opportunities with the more aggregative behavior in a macroeconomic model.

A promising approach for researchers is to employ computable general equilibrium (CGE) modeling as a meso framework because CGE models generate from macroeconomic changes a set of consistent relative prices, wages, and profits at the sectoral level that provides the vital sources and changes of household incomes and expenditures for further analysis of poverty impact and income distribution (see figure 12.1). There have been several ways of utilizing CGE models and household analysis to establish the links between macroeconomic changes and poverty analysis, depending on the level of simplification and the level of information retained for both macroeconomic and microeconomic components. 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

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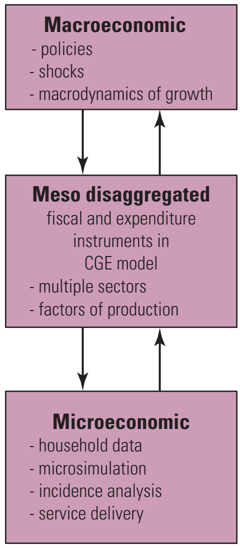
FIGURE 12.1

Disaggregated Framework Linking Macroeconomic Events to Poverty Reduction Issues



Source: Authors' illustration.

Note: CGE = computable general equilibrium.

the CGE framework into an 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, and those movements are then mapped to the expenditure and income sources of various household groups (for example, income deciles). Growth impact is derived from either short-term vector autoregressive analysis or long-term growth regression of various determinants. More information is provided in CGE models with higher levels of disaggregation, such as the South Africa model in Go et al. (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 then can easily be linked to macroeconomic models to examine policy and external shocks.

The approach provides the flexibility of choosing the macroeconomic framework from among simple macroeconomic consistency models (like the World Bank's RMSM-X or the International Monetary Fund's financial programming model) to more sophisticated econometric or CGE models.

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

Although the various approaches of combining CGE models and household data are distinguished by the level of sophistication and information retained in either the macroeconomic or microeconomic component, there is one drawback. The integration of the macroeconomic and microeconomic 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 Robilliard (2000) implemented a version for Madagascar. However, the general equilibrium macroeconomic framework has very few sectors. Heckman and Lochner (1998) did an overlapping-generations general equilibrium model of labor earnings with heterogeneous agents; but to present both integration and dynamics, the macroeconomic part is aggregative. A classic econometric method for the integration of a CGE model with detailed household analysis is provided by the work of Jorgenson, Lau, and Stoker (1980), whereby exact aggregation of the representative consumer from heterogeneous households is econometrically estimated from survey data; and whereby, under certain demand restrictions, demand functions of heterogeneous groups are recoverable from the representative consumer. Given an overall representative household, however, stable or fixed household distribution underlying the econometric results is implicitly assumed. A promising and practical link between the macroeconomic and the microeconomic has been provided by Savard (2003, 2006), who uses a recursive iteration between the two approaches without the need to simplify each of them. A similar approach has been adopted in this chapter and will be described below.

The purpose of this chapter 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 microsimulation 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 heterogeneous households. We implement a recursive two-way feedback mechanism similar to Savard (2003, 2006) and devise an efficient reconciliation between the CGE and microsimulation models to derive a consistent or integrated analysis of the shocks from the two approaches while retaining the particular advantages provided by each approach—that is, the detailed structure of an economy in the CGE model and the full heterogeneity of households and labor in the microsimulation. At the end, we draw some possible lessons about where the multilayered analysis may be 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 Roy's method in Ravallion and Lokshin (2004); and a simpler summary of the household characteristics by income deciles or a parameterized Lorenz curve.

The outline of the rest of the chapter is as follows. The second section 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 microsimulation models of household welfare and occupational choice. The third section analyzes the distributional implications of a large oil price shock to the economy. A summary and conclusions are presented in the fourth section.

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* among stabilization, structural, and distributional issues, but also for the *heterogeneity* of the stakeholders that underpins distributional concerns. This section describes the macro-microsimulation framework used to track the macroeconomic, structural, and distributional implications of a sizable oil price shock for the economy

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of South Africa. A disaggregated CGE model is used for the macroeconomic and structural implications whereas the microsimulation component accounts for agent heterogeneity and the impact on distribution.

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 12.1 for the composition of the aggregate categories). As seen in figure 12.2, agriculture accounts for 4 percent of value added, industry accounts for 27 percent, and services accounts for 69 percent.

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; the same is true for informal labor.[5]

TABLE 12.1
CGE Model Sectors

I. Agriculture	II. Industry (cont'd)	III. Services
Agriculture	Basic chemicals	Electricity, gas, and steam
II. Industry	Other chemicals and man-made fibers	Water supply
Coal mining	Rubber products	Construction and civil engineering
Gold and uranium ore mining	Plastic products	Catering and accommodation
Other mining	Glass and glass products	Wholesale and retail trade
Food	Nonmetallic minerals	Transportation and storage
Beverages and tobacco	Basic iron and steel	Communication
Textiles	Basic nonferrous metals	Financial services
Wearing apparel	Metal products excluding machinery	Business services
Leather and leather products	Electrical machinery	Health, community, social, and personal services
Footwear	TV, radio, and communication equip	
Wood and wood products	Professional and scientific equipment	Other producers
Paper and paper products	Motor vehicles parts and accessories	Government services
Printing and publishing and recorded media	Other transport equipment	
Coke and refined petroleum products	Furniture	

Source: South Africa SAM 2003 Database.

Note: CGE = computable general equilibrium.

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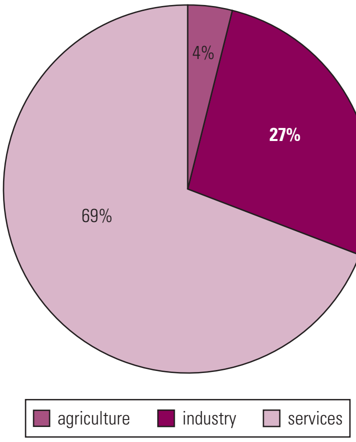
FIGURE 12.2
Aggregate Activity Share of Value Added



Source: South Africa SAM 2003 Database.

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 (that is, 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]

Structural unemployment is specified for low-skilled and semi-skilled formal workers, with sticky real wages. There is full employment in the other labor markets. The peculiarities of the labor markets in South Africa are treated in a fashion similar to that 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 detail (Essama-Nssah et al. forthcoming).

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.

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TABLE 12.2
Value-Added Shares

Factor	Agriculture	Industry	Services
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.

Value added is allocated to primary factors according to the shares shown in table 12.2.

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.[7]

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 crude oil, the region is heavily dependent on 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.[8] Direct household purchases of petroleum are quite low, with expenditure ranging from 4 percent to 6 percent, depending on household; for basic chemicals, the household expenditure shares are 1 percent or less.

Given the structure of the economy, the effects of an oil price shock (which is modeled as an 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 that use refined petroleum and basic chemicals as intermediate inputs (see table 12.3). Note that

TABLE 12.3

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

Final product/service	Rand	Final product/service	Rand
Coke and refined petroleum products	1.16	Nonmetallic 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 nonferrous metals	0.14	Wood and wood products	0.06
Other chemicals and man-made fibers	0.11	TV, radio, and communication equipment	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 equipment	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.

production of electricity and gas does not depend heavily on refined petroleum. Instead, coal is a more important intermediate input.

Modeling Household Response to Macroeconomic 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) noted 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

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types of effects on the distribution of economic welfare: (1) *endowment effects* due to changes in the amount of resources available to individuals, (2) *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 to 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 the second approach relies on a data set that combines information from the 2000 Labor Force Survey (LFS) with data from the 2000 Income and Expenditure Survey (IES).[9] Given that both surveys are based mostly on the same sample of households, the combined data set provides comprehensive information on household expenditures, labor and nonlabor income, labor supply, employment, and several socioeconomic 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 data sets 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.

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

$$v_h(p^s_h, p^d_h, w_h) = \max_{q^s_{h}, L_h}[u_h(q^d_h, L_h) \,|\, p^d_h q^d_h = w_h L_h + \pi_h(p^s_h)] \quad (12.1)$$

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 of its arguments 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:

$$g_h = \sum_{j=1}^{m}\left[p_{hj}^s q_{hj}^s \frac{dp_{hj}^s}{p_{hj}^s} - p_{hj}^d q_{hj}^d \frac{dp_{hj}^d}{p_{hj}^d}\right] + \sum_{i=1}^{n}\left[w_i L_{hi} \frac{dw_i}{w_i}\right] \tag{12.2}$$

Equation (12.2) says that a first-order approximation of 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 sociodemographic characteristics of households and because 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 therefore also consider a model of earnings generation that would allow for such effects.

Household Earnings-Generation Model

To account for endowment and occupational effects, we need a framework that links both earnings and occupational choice to sociodemographic 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

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and Ferreira (2005). The model has three components: (1) a multinomial logit model of the allocation of individuals across occupational states, (2) a model of the determinants of earnings, and (3) 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 workers, 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 workers, agriculture; (15) self-employed workers, industry; and (16) self-employed workers, services.

Table 12.4 shows the distribution of employment by sector and occupation. These results show that about six people out of ten are employed in the services (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 employed people are highly skilled. Furthermore, the highest

TABLE 12.4

Distribution of Employment by Sector and Occupation

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

Source: Authors' calculations.

TABLE 12.5

Distribution of Employment by Sector and Skill Level

Percent

Sector	Low-skilled workers	Semi-skilled workers	High-skilled workers	All workers
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.

percentage of people at any skill level is found in the tertiary sector (table 12.5).

Now, let 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

$$P_{ij} = \frac{\exp(z_i\gamma_j)}{\left[1 + \sum_{j=2}^{16} (\exp(z_i\gamma_j)\right]} \tag{12.3}$$

where 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 aged 9 or less, 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 terms of utility-maximizing behavior, the utility[10] 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 (12.3) of the earnings generation model should be estimated jointly with the earnings equations defined in the next subsection of this chapter. For 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 nonlabor

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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 earnings 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 12.6.

Overall results show that gender has significant impact on the 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 the services sector. Among formal workers, people in the industry and services sectors are more likely to be living in the urban areas than are people in the agriculture sector, as expected. It is also true for the informal and self-employed sectors. Similarly, the number of children (aged 9 years or less) has a significant impact on the choice to participate in the labor force. People with children aged 0 through 9 years 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 to be paid workers. Being head of the household also plays a significant role for participating in the labor force. Furthermore, married people are more likely to be active in the labor force than are unmarried couples.

Earnings

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

$$\log w_i = x_i\beta_w + u_{iw} \tag{12.4}$$

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 ordinary least squares (OLS).[11] The results are presented in table 12.7.

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TABLE 12.6

Occupational Choice Models for Individuals

Variable	Formal employees									Informal employees			Self-employeed		
	Agriculture			Industry			Services			Agriculture	Industry	Services	Agriculture	Industry	Services
	Low-skilled	Semi-skilled	High-skilled	Low-skilled	Semi-skilled	High-skilled	Low-skilled	Semi-skilled	High-skilled						
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]**
Eduyear	−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]**
Eduyear2	−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]**
Expyear	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]**
Expyear2	−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]**
Fambusiness	−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]**
Eduyearhd	−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]
Headd	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

Source: Authors' calculations.

Note: For descriptions of the variables, see table 12A.1 in the annex to this chapter. Absolute value of *z*-statistic appears in brackets.

* Significant at 5%.

** Significant at 1%.

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TABLE 12.7

OLS Estimates of the Formal Wage Equation

	Agriculture sector			Industry sector			Services sector		
Variable	Low-skilled	Semi-skilled	High-skilled	Low-skilled	Semi-skilled	High-skilled	Low-skilled	Semi-skilled	High-skilled
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	1,665	1,713	123	804	2,412	368	1,588	4,544	2,649
R^2	0.26	0.42	0.41	0.29	0.31	0.37	0.28	0.32	0.24

Source: Authors' calculations.

Note: OLS = ordinary least squares. For descriptions of the variables, see table 12A.1 in the annex to this chapter. Absolute value of *t*-statistic appear in brackets.

* Significant at 5%.

** Significant at 1%.

These results indicate that variables such as education and experience have expected signs and are consistent with the standard human capital approach and economic theory. Estimate coefficients for education (eduyear2) are statistically significant at 1 percent, except in the primary high-skill group. The relationship between the education variable and wage is mostly nonlinear. In the agriculture low-skill segment, an additional three years of schooling increase formal wage income by 5.7 percent for formal wage earners.

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

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

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 finding may be due partly to a relatively higher cost of living in urban areas as well as to the structure of the labor markets—for example, higher skills in urban and nonagricultural sectors. We draw on empirical literature in selecting a 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 wages.

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

$$\log iw_i = x_i \beta_{iw} + u_{iiw} \tag{12.5}$$

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TABLE 12.8
OLS Estimates of the Informal Wage Equation

Variable	Agriculture	Industry	Services
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	3,860
R^2	0.21	0.22	0.28

Source: Authors' calculations.

Note: OLS = ordinary least squares. For descriptions of the variables, see table 12A.1 in the annex to this chapter. Absolute value of *t*-statistic appears in brackets.

* Significant at 5%.

** Significant at 1%.

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, and a dummy for married. Table 12.8 contains the results of the OLS estimation of this equation.

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:

$$\log \pi_i = x_i\beta_\pi + u_{i\pi} \tag{12.6}$$

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

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TABLE 12.9
OLS Estimates of Self-Employed Earning Equation

Variable	Agriculture	Industry	Services
Gender	0.146 [3.52]**	0.605 [7.40]**	0.45 [10.81]**
Eduyear	−0.059 [4.12]**	0.027 [1.02]	−0.024 [1.79]
Eduyear2	0.011 [10.44]**	0.004 [2.60]**	0.007 [8.66]**
Expyear	0.042 [8.62]**	0.049 [4.06]**	0.078 [13.74]**
Expyear2	0 [3.83]**	−0.001 [3.35]**	−0.001 [12.52]**
Headd	0.352 [7.00]**	0.065 [0.74]	0.182 [4.20]**
Urban	0.131 [1.91]	0.158 [1.96]*	0.27 [6.78]**
SkillH	0.361 [1.85]	0.811 [5.92]**	0.556 [10.42]**
Formallab	1.451 [17.45]**	0.798 [7.05]**	0.703 [13.58]**
Constant	6.926 [83.49]**	7.215 [34.98]**	6.982 [72.40]**
Sample size	2,544	776	3,217
R^2	0.44	0.42	0.42

Source: Authors' calculations.

Note: For descriptions of the variables, see table 12A.1 in the annex to this chapter.

* Significant at 5%.

** Significant at 1%.

for working in the formal sector. Table 12.9 contains the results of the OLS estimation of equation (12.6).

We observe many patterns for self-employment that are similar to the case of wage employment. For instance, in the primary sector, heads of household earn 35 percent more from self-employment than those who are not heads of household. This is much higher than the 20 percent premium they earn as wage employees 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 than 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. The findings are similar for people engaged in the formal sector of the economy.

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AGGREGATION

Given individuals' earnings, household income is aggregated according to the following formula:

$$y_h = \sum_{i \in h} w_i L_{iw} + \sum_{i \in h} iw_i L_{iiw} + \sum_{i \in h} \pi_i L_{i\pi} + y_{0h} \tag{12.7}$$

As equation (12.7) 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, whereas the last element is an exogenous unearned income, such as transfers and capital income (see table 12.10). Real income is obtained by deflating total income by a household-specific consumer price index CPI_h. This is a weighted sum of the prices of various commodities purchased by the household. The weights are given by the budget shares, which vary across households.

Household's annual total income is defined as total annual income including wage income, self-employed income, and all other income.[12] Average values vary significantly among income deciles. On average, 9 percent of the household income is coming from other sources of income—nonwage income for laborers and non-self-employed income for self-employed people. When compared among income deciles, the ratio of other income to the total income varies between 12 percent in the lowest decile and 9 percent in the richest decile of the income distribution.

TABLE 12.10

Household Income Distribution between Labor and Nonlabor Income

Population decile	Nonlabor income/total annual income (ratio)	Total annual household nonlabor income (rand/year)	Total annual household income (rand/year)	Annual nonlabor income per capita (rand/year)	Annual total income per capita (rand/year)
1	0.12	720.35	6,025.79	107.24	723.94
2	0.13	949.01	7,164.21	133.37	990.21
3	0.13	1,258.22	9,519.38	182.21	1,420.86
4	0.12	1,467.23	12,381.75	233.49	1,801.05
5	0.11	1,637.85	15,365.86	299.38	2,443.36
6	0.10	2,256.26	22,175.89	429.49	3,795.05
7	0.08	2,497.54	31,152.63	543.68	6,044.95
8	0.09	3,414.77	39,702.75	817.71	9,067.07
9	0.08	5,650.85	67,829.13	1,498.38	16,997.32
10	0.09	15,061.66	159,162.60	5,589.73	53,806.32
Total	0.09	3,491.71	37,050.35	983.65	9,710.38

Source: Authors' calculations from Income and Expenditure Survey (2000) and Labor Force Survey (2000).

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Linking the Microsimulation Components to the CGE Model

Assessing the *endowment, price,* and *occupational* effects of an oil price shock in a way that fully accounts for heterogeneity at both individual and household levels requires appropriate channels of communication between the CGE model and the microsimulation components. This communication works in the following way. The CGE model translates the impact of the shocks and policies through changes in relative prices of commodities and factors and through levels of employment. The microsimulation module takes these changes as exogenous and translates them into change in household behavior, which underpins changes in earnings, occupational status, and welfare.

To obtain meaningful results from the simulation framework, one must ensure that outcomes from the microsimulation 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, which requires that the observed occupational choices predicted by the microsimulation module match the employment shares in the CGE model. Similarly, simulated earnings at the microeconomic level must match macroeconomic predictions.[13] A key consideration here stems from the fact that occupational choice depends on the random utility function, which is a *latent variable.* For example, a shock might cause unemployed or inactive individuals to become employed in one of the segments of the labor market. Implementation of the consistency constraints, therefore, requires information on both the observable and nonobservable components of the occupational choice and earning models. The observable components of these models are calculated on the basis of estimated parameters and data on observable characteristics. For those showing zero earnings, counterfactual earnings are computed on the basis of 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 microeconomic and macroeconomic data (sampling weights, coverage, imputed values, and so forth) make it very difficult to enforce fully the consistency constraints described above. Therefore, we adopt several steps to achieve the consistency. First, because of the importance of the labor market structure in South Africa, we ensure that the occupational choices in the microsimulation have the

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same classification as the labor categories in the CGE model and capture the appropriate taxonomy, structural, and unemployment issues in South Africa. Second, the base years for the social accounting matrix (SAM) (2003) and the survey data (2000) in our study of South Africa are different. To retain the more recent numbers in the macroeconomic accounts as well as the familiar poverty and inequality measurements of the microeconomic data, we employ percent changes to communicate changes in employment, wages, and prices from the CGE to the microsimulation.[14]

As noted by Bourguignon, Robilliard, and Robinson (2002), reconciliation in the postshock microsimulation 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.

Impact of a Large Oil Price Shock

The nominal price of crude oil increased by about 125 percent during the period from 2003 to 2006. In May 2007, for example, the global oil price averaged over $65 a barrel. 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 those for metal and minerals (for example, gold and other metals), also have 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 so far has not risen as sharply as it did for oil-importing countries, when compared with the previous shock of 1999–2000. The trend of rising prices, however, is 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 6 percent increase in the world price of all other imported goods.

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TABLE 12.11
Macroeconomic Results for South Africa

Real variables	Oil price shock (% change)	Oil and general price shock (% change)
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
Consumer price index	1.9	2.7

Source: Authors' calculations.

Note: GDP = gross domestic product.

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

Macroeconomic Results

The macroeconomic results are shown in table 12.11. 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 percent to 22.4 percent, depending on the magnitude of the price shock (that is, an oil price increase alone or an oil price increase plus a general price increase). In effect, the currency depreciates to shift resources into exports, increasing export earnings to pay for the more expensive but essential crude oil imports.[15] Total absorption and real gross domestic product (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 of crude oil imported—a commodity with no domestic substitute—declines slightly by approximately 1 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 12.3–12.6 for output results by activity and price shock.

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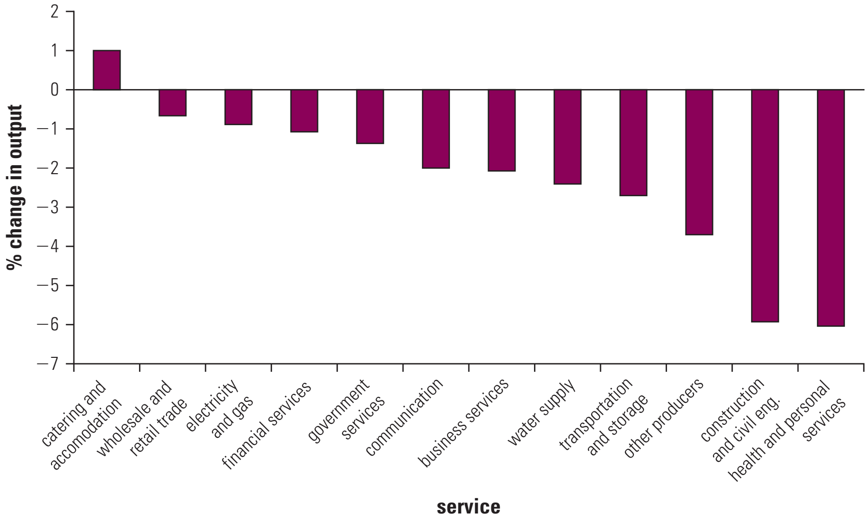
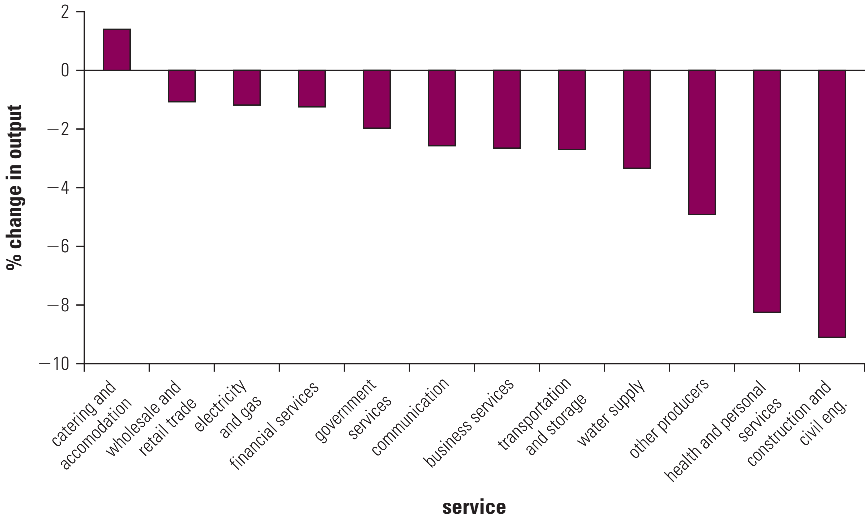
FIGURE 12.3
Output Adjustment in the Services Activities: Oil Price Shock



Source: Authors' calculations.

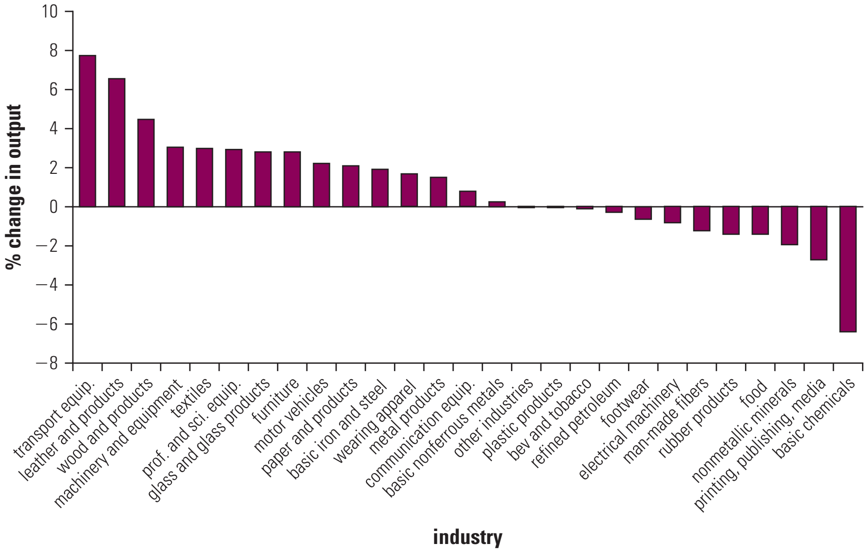
FIGURE 12.4
Output Adjustment in the Services Activities: Oil and General Price Shock



Source: Authors' calculations.

FIGURE 12.5

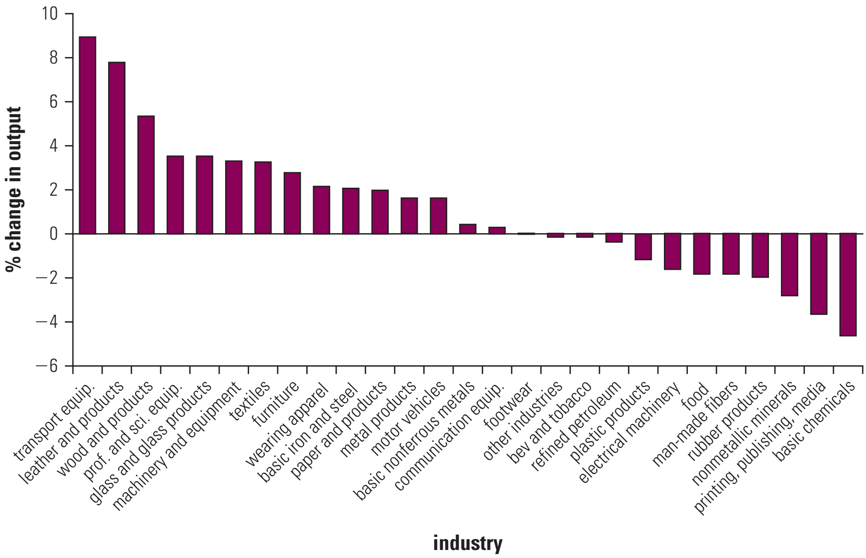
Output Adjustment in the Industry Activities: Oil Price Shock



Source: Authors' calculations.

FIGURE 12.6

Output Adjustment in the Industry Activities: Oil and General Price Shock



Source: Authors' calculations.

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For price shock, refined petroleum and basic chemicals—the sole users of crude oil—contract when the price of imported oil increases because the input cost increases. Other sectors with strong indirect intermediate input use of petroleum (such as printing and publishing, rubber products, transportation and storage, and food) also contract. (See table 12.3 for a ranking of intermediate input demand for refined petroleum, accounting for direct and indirect effects.) Output also responds to economywide changes induced by the world price shocks. As a result of the depreciation, output of services activities—which are primarily nontraded (with the exception of catering and accommodations)—decline.

Consistent with the output changes, employment in services activities declines 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 presented in table 12.12. (Note that there is movement of resources within the industry and services activities, but here we report only the aggregate changes.)

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 the price shocks considered here (table 12.13).

As wages decline, household demand for goods and services also declines. The commodity price changes result from shifts in both the demand and the supply curves for each activity. The net effect of an increase in oil prices (as well as for oil and a general price shock) is a dramatic increase in the price of fuel (see table 12.14). Prices also increase for food and transportation.

Welfare and Distributional Implications of the Oil Price Shock

Having identified the macroeconomic effects of an oil price increase, we now address the poverty and distributional implications. We measure poverty with members of the Foster, Greer, and Thorbecke (1984) family of decomposable indexes. Our analysis of inequality is based on the Gini coefficient and general entropy indexes. We discuss, respectively, the baseline distribution of welfare and the distributional implications of a severe oil price shock.[16]

TABLE 12.12
Employment Changes

Workers, by sector	Oil price shock (% change)	Oil and general price shock (% change)
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
Economywide 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.

TABLE 12.13
Wage Changes

Workers, by wage type	Oil price shock (% change)	Oil and general price shock (% change)
Real		
Formal high-skilled workers	–11.3	–15.2
Formal semi-skilled workers	0	0
Formal low-skilled workers	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.

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TABLE 12.14
Price Changes

Expenditure category	Oil price shock (% change)	Oil and general price shock (% change)
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 and 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.

Baseline Distribution of Economic Welfare

The available survey data provide information on both household income and consumption expenditures. Figure 12.7 and table 12.15 describe the distribution of these two variables by decile. 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 was a little more than R 10,000 and per capita income was about R 9,700 in 2000.

Moreover, the average values of income and expenditures vary significantly by decile and locality. Comparing average consumption levels across rural and urban South Africa shows disparities between rural and urban sectors (table 12.15). Similar disparities exist in per capita expenditure levels among deciles and between urban and rural locations.

Figure 12.8 and table 12.16 provide a poverty profile for South Africa in 2000, based on a poverty line set at $1 per day, which amounts in South Africa to R 2,533 per capita per year. Figure 12.8 contains a set of TIP[17] curves, one based on the distribution of per capita expenditure and the other one based on that of per capita income. TIP curves offer an alternative way to test for unanimous poverty comparisons across time and across

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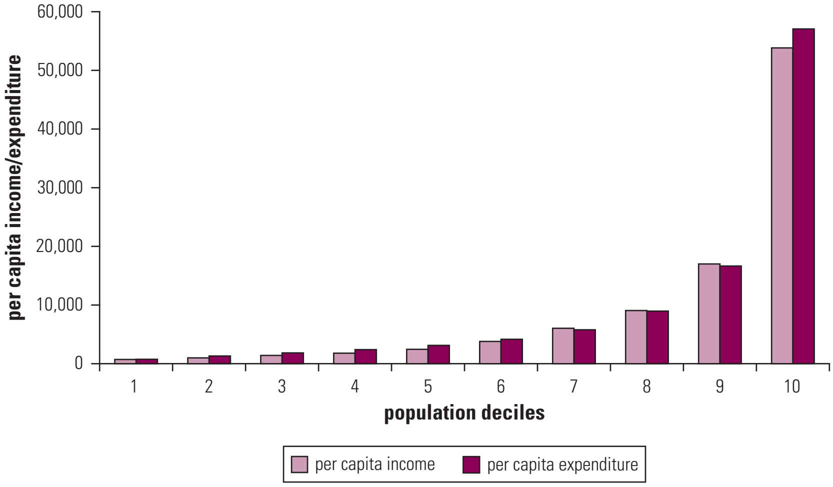
FIGURE 12.7
Distribution of Income and Expenditure, by Decile



Source: Authors' calculations.

TABLE 12.15
Per Capita Household Expenditures and Income, by Decile
Rand

Income decile	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	1,346.4	1,321.2	992.7	989.1	1.02	1.00
3	1,842.2	1,827.9	1,604.2	1,312.2	1.01	1.22
4	2,399.6	2,389.6	1,980.5	1,643.0	1.00	1.21
5	3,129.6	3,102.7	2,757.1	2,093.1	1.01	1.32
6	4,174.7	4,115.0	3,853.8	3,685.0	1.01	1.05
7	5,794.8	5,733.5	6,385.0	5,151.1	1.01	1.24
8	8,984.7	8,917.5	9,232.4	8,436.0	1.01	1.09
9	16,744.7	15,807.2	16,528.3	21,353.3	1.06	0.77
Richest	56,017.3	72,562.9	53,167.3	63,415.5	0.77	0.84

Source: Authors' calculations.

regions and countries, based on a wide class of poverty indexes. The TIP curve provides a graphical summary of incidence, intensity, and inequality dimensions of aggregate poverty, based on the distribution of poverty gaps (Jenkins and Lambert 1997). On the basis of this poverty profile, we note that about 37 percent or 49 percent of the population was poor in 2000, as welfare is measured by expenditure or income.

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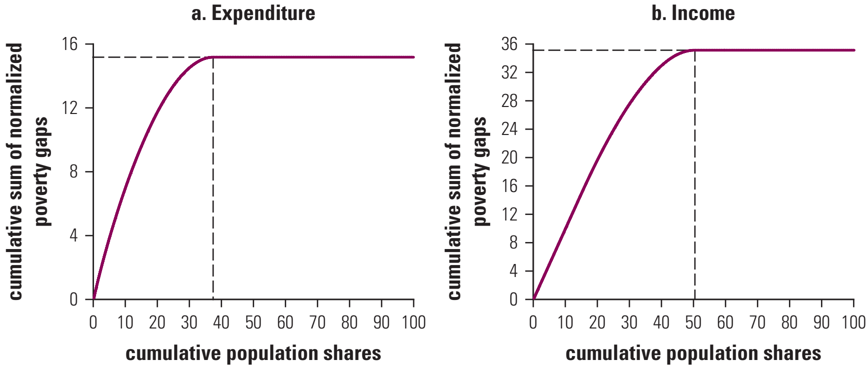
FIGURE 12.8

A Picture of Poverty in South Africa, 2000



Source: Authors' calculations.

TABLE 12.16

Poverty Profiles, 2000

a. Expenditure-based profile

Measure	Estimate	Scale-elasticity	Gini elasticity	Trade-off
Head count	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

b. Income-based profile

Measure	Estimate	Scale elasticity	Gini elasticity	Trade-off
Head count	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. Using the distribution of expenditure by decile, we find that the richest 20 percent of the population, on average, spends 35 times more than the poorest 20 percent of the population in 2000 prices. The Gini coefficient associated with the distribution of expenditure is about 67 percent and that for the distribution of income is about 72 percent. These baseline case results are in line with other studies of South Africa (for example, Jenkins and Thomas 2000). The high level of inequality is certainly a constraint to the responsiveness of poverty to economic growth. Table 12.16 presents information on two types of poverty elasticities computed according to the Kakwani (1993) method.

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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 rate is the rate at which income needs to grow to compensate for an increase of 1 percent in the Gini coefficient to keep poverty constant. Thus, the information presented in table 12.16 reveals 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 on 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 microsimulation 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 the multilogit model is set to zero).

The microsimulation calculates the formal wages, informal wages, self-employment incomes, and occupational choices at the microeconomic units (that is, for each individual) that are consistent with the post-shock relative prices, wages, and employment levels by broad categories generated from the CGE model. After aggregating all incomes within the households, per capita income and expenditures are deflated by a 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 the consumer basket.

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TABLE 12.17
Household Expenditure Shares, by Income Quintile

Quintile	Food	Beverage	Alcoholic beverage	Cigarette and tobacco	Personal 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	0.20	0.06	0.03	0.01	0.05
4	0.02	0.20	0.06	0.03	0.02	0.07
Richest	0.01	0.21	0.04	0.03	0.04	0.10
Average	0.03	0.21	0.05	0.02	0.02	0.06

Quintile	Communication	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	0.0010	0.004	0.10

Source: Authors' calculations.

The survey shows that households' budget allocation on different types of consumer goods and services varies significantly (table 12.17). For example, the poorer households spent a larger share of their incomes on food and 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 has affected prices of other goods and services through second-round effects. Although the 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 prices for many other goods and services have declined slightly. Consequently, households had been affected differently, depending on their spending patterns. Because

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TABLE 12.18

Wage Impact of Oil Shock on Formal Workers, by Decile

Rand, 2000 prices

Income decile	Formal wage, postshock	Formal wage, preshock	Ratio of postshock to preshock wage
Poorest	3,824.85	4,101.92	0.93
2	7,724.03	8,157.37	0.95
3	11,895.97	12,409.63	0.96
4	16,163.26	16,540.06	0.98
5	21,572.56	21,915.76	0.98
6	27,394.34	27,768.17	0.99
7	33,806.99	34,605.13	0.98
8	44,793.30	46,425.38	0.96
9	65,200.57	68,435.89	0.95
Richest	180,520.80	194,553.30	0.93
Overall average	32,967.42	34,511.12	0.96

Source: Authors' calculations.

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 Labor Sector

The adverse impact of the 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 preshock earnings (table 12.18). Although, the wage loss varies by income decile, the differences are significant only for the poorest and the richest deciles of formal workers.

In addition to a decline in wages, formal sector labor also experienced increased unemployment in the tertiary sector. Most of those who became unemployed were low- and medium-skill workers of the tertiary sector. These unemployed workers lost their earnings completely following the shock (table 12.19). Almost 70 percent of these newly unemployed formal wage earners belong to the bottom three deciles (based on preshock per capita incomes).

Welfare Impact on Low-Skill Households

As noted above, the poorest deciles were disproportionately adversely affected by the shock because they tend to have low skills. Figure 12.9

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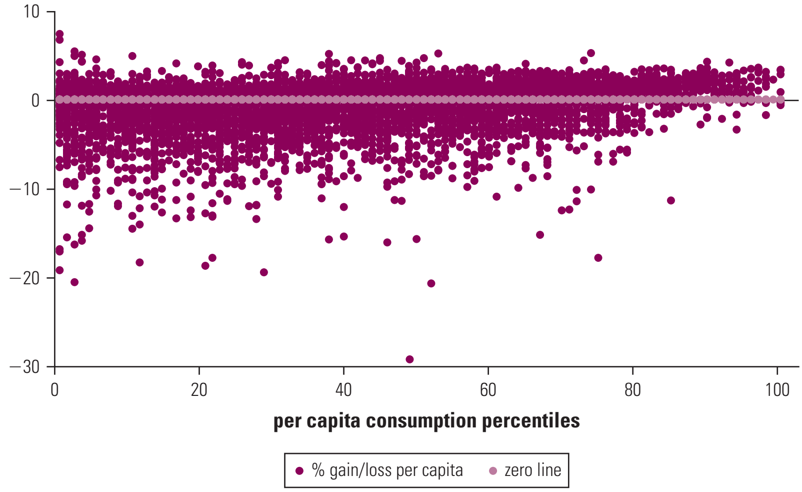
TABLE 12.19
Unemployment Impact of Oil Shock on Formal Workers, by Decile

Income decile	Percentage of people	Average annual wage, preshock	Average annual wage, postshock	Loss (%)
Poorest	31.07	3,742.64	0	–100
2	19.11	8,253.35	0	–100
3	18.39	12,127.46	0	–100
4	9.11	16,562.43	0	–100
5	10.18	21,893.82	0	–100
6	4.46	27,403.68	0	–100
7	3.39	33,850.42	0	–100
8	2.50	45,794.71	0	–100
9	1.25	70,534.29	0	–100
Richest	0.54	97,081.67	0	–100
Overall average	n.a.	18,306.53	0	–100

Source: Authors' calculations.

Note: n.a. = not applicable.

FIGURE 12.9
Gains and Losses from Oil Price Shock for Low-Skill Households



Source: Authors' calculations.

shows that households with low skill levels 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 households with low skill levels).

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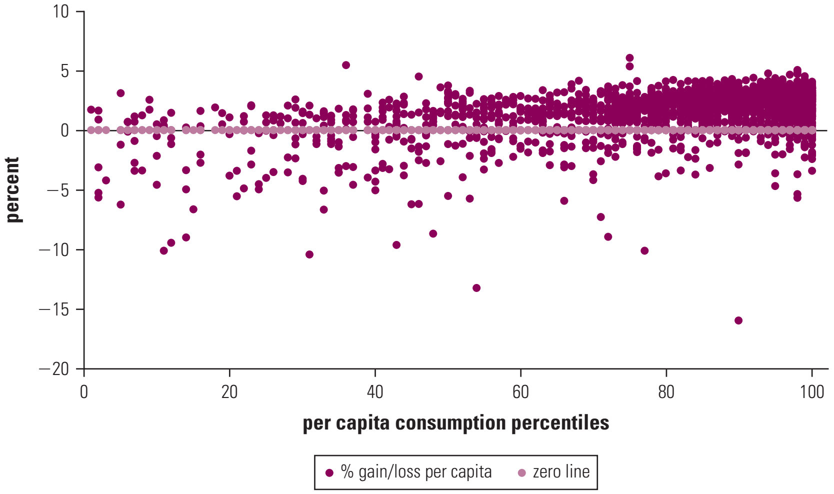
FIGURE 12.10

Gains and Losses from Oil Price Shock for High-Skill Households



Source: Authors' calculations.

Welfare Impact of the Oil Price Shock on High-Skill Households

In contrast to low-skill households, those with a high skill level are, on average, gaining from the shock. As figure 12.10 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 increases as a result of an oil price 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 by the price changes following the oil price shocks. To start with, they are richer and spend relatively less on food and other goods affected most by the changes in oil prices.

Overall Welfare Impact of the Oil Price Shock

Figure 12.11 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 by this shock. For instance, households below the seventh decile of income per capita are losing and becoming poorer, whereas 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.

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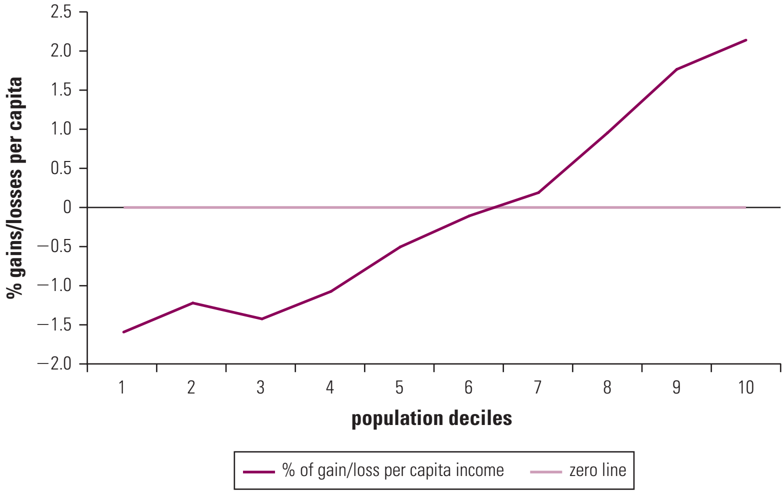
FIGURE 12.11
Distribution of Gains and Losses to Households, by Decile



Source: Authors' calculations.

Following the shock, not only did the extent of poverty increase slightly but also the distribution of household welfare became less equal.

Table 12.20 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, whereas only 33 percent of urban population had income below the poverty line (the equivalent of $1 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 $1 a day poverty line and the income measure of welfare) increases slightly less, from 49.0 percent to 49.5 percent (it increases 37 percent to 38 percent if we consider expenditure per capita as a welfare measure). Poverty rates also increased at the regional level. The poverty gap index increased from 15 percent to 16 percent (result not reported), which indicates that there is a 1 percent increase in the difference between actual income and income required to sustain a minimum standard of living.

As far as inequality is concerned, we use both general entropy indexes 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 1 percent, the same increase as the Gini coefficient for the urban and rural sectors. Thus, following the oil price shock, income distribution worsened slightly. The

TABLE 12.20
Impact of Oil Shock on Poverty and Income Distribution

Indicator	Base case			Simulation 1: oil price shock		
	National	Urban	Rural	National	Urban	Rural
Poverty indicator, 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
Poverty indicator, using income						
Head count ratio	0.49	0.33	0.72	0.49	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 Indicator, 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
Inequality Indicator, 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.

distributional impact, as measured by changes in the Gini coefficient, deteriorated both for rural and urban areas. These results suggest that the impact on heterogeneous households tends to average out when the households are collected by income groups. The separation of impact by household would be meaningful for the macroeconomic-microeconomic linking if the household classification were based on characteristics other than income, and if the data were rich enough in such characteristics for the construction of the SAM underlying the CGE model. However, aggregative poverty and income inequality measures do not vary much. The oil price shock tends to increase the disparity between rich and poor—that is, the mean welfare or consumption of various household groups. This finding means that the impact on different household types will tend to be the same if they have more or less the same mean welfare or income prior to the shock—that 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. Members of this class are defined by the following expression:

$$GE(\theta) = \frac{1}{\theta^2 - \theta}\left[\frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i}{\mu}\right)^{\theta} - 1\right] \tag{12.8}$$

When the focal parameter θ is equal to 1, we get Theil's measure; and when the parameter is equal to 0, we get the MLD defined as follows:

$$GE(0) = \frac{1}{n}\sum_{i=1}^{n}\log\left(\frac{\mu}{x_i}\right) \tag{12.9}$$

To see clearly what the decomposition entails, let y_i and x_i stand, respectively, for the post- and prereform welfare per person in household i, and let g_i stand for the gain (or loss) to household i as a result of the shock. Thus, $y_i = x_i + g_i$. The vertical component relates to inequality among people at different preshock welfare levels, whereas the horizontal component measures inequality between people at the same preshock welfare level. The decomposition involved here requires an estimate of the average impact for the distribution of gains at given preshock welfare (x). In other terms, we need an estimate of the conditional mean impact defined by $g_i^c = E(g_i | x = x_i)$. It would be difficult to observe significant dispersion in impact at given prereform welfare within a data set from a household survey. This conditional expectation can be estimated using a nonparametric regression of the gains on x (for example, locally estimated scatter plot smooth). On the basis of the MLD, it can be shown that the overall change in inequality can be written as

$$\Delta I = \frac{1}{n}\sum_{i=1}^{n}\ln\left(\frac{1 + \bar{g}/\bar{x}}{1 + g_i^c/x_i}\right) + \frac{1}{n}\sum_{i=1}^{n}\ln\left(\frac{1 + g_i^c/x_i}{1 + g_i/x_i}\right) \tag{12.10}$$

The first term on the right-hand side of equation (12.10) measures the contribution to the change in total inequality of the way conditional mean impacts vary with prereform welfare levels, and is called the vertical component. The horizontal component, the second term, measures the contribution of the deviations in impacts from their conditional means.

Table 12.21 shows the decomposition of the impact on inequality. In the case of a shock produced by increased oil prices, aggregate results show that the horizontal component is inequality reducing whereas the vertical impact is inequality enhancing. A closer look at the components of this

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TABLE 12.21
Decomposition of the Impact on Inequality

Decomposition	Vertical component	Horizontal component	Total
Gains from consumption[a]	137.0	−37.0	100.0
Gains from changes in formal wages[a]	120.4	−20.4	100.0
Gains from changes in informal wages[a]	104.1	−4.1	100.0
Gains from changes in self-employed income[a]	77.0	23.0	100.0
Aggregate gains[a]	135.0	−35.0	100.0
Aggregate gains[b]	119.0	−19.0	100.0

Source: Authors' calculations.

a. Using per capita consumption as an explanatory variable in the locally weighted scatter plot smooth regression.

b. Using per capita income as an explanatory variable in the locally weighted scatter plot smooth regression.

aggregate result reveals (except in the case of self-employment income), that the horizontal impact is inequality decreasing, whereas the vertical effect is inequality enhancing. Because self-employed individuals are a relatively smaller share of the total employed population (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-employment income will change the sign of the horizontal impact.

Summary and Conclusions

This chapter has developed a macroeconomic-microeconomic framework for examining the macroeconomic and distributional consequences of an oil price shock for the South African economy. In so doing, it gave simultaneous quantitative expressions to the impact of an external shock on macroeconomic aggregates such as GDP, real exchange rate, total absorption, exports, imports, various subsectors 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 framework was accomplished by implementing and merging (1) a highly disaggregative CGE model that captures important economywide consequences of relative price and income effects, as well as labor market adjustment arising from a significant external shock or policy change; and (2) a microsimulation component linking both earnings and occupational choice to sociodemographic characteristics of the household, as in Bourguignon and Ferreira (2005).

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We emphasize that the application to the oil price shock should be taken as illustrative because offsetting factors are not considered. Although the magnitude of the shock would be similar to that of 2003–06, there were several other factors at play in South Africa—like the strong macroeconomic policy in place, the overall favorable terms of trade, the relative strength of the South African rand, and strong investment programs in the public sector.[18] 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—that is, a conservative case. It also assumes that the labor market structure and rigidities, particularly about the real wages of the low- to medium-skill workers, will continue to be operating along the shocks. Under those circumstances, the two scenarios indicate that total absorption would fall between 5 and 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 more than 20 percent. The impact on industries can vary widely, with most of the negative impact falling 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 a lot numerically. However, a look beyond these aggregate results enables 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 those workers belonged to the bottom three deciles of the formal labor force.

Our findings show that losses are more pronounced in the low-skill group than are the gains. On the other hand, high-skill households, on average, gained from the oil price shock. Most high-skill households 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 is 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 toward food and other goods affected most by the changes in oil prices.

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Evidence also suggests that high-skill workers are less likely to be laid off when unemployment increases as a result of the oil price shock, or they can move relatively easily and quickly 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 quickly will seek 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 are low-skill individuals. Thus, an adverse shock is like a poverty trap for low-skill workers unless there are polices and institutional arrangements to mitigate the adverse impact of the shock on this group of households.

The overall welfare impact shows that the poorer, and generally low-skill, segment of the population is more adversely affected by 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 to be the same if they have more or less the same mean welfare or income prior to the shock—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 microsimulation module. If the distributional effects collected and pulled together from the microsimulation 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 macroeconomic model was found to be necessary. In the end, what constitutes an appropriate or meaningful classification of the households for a two-way feedback likely would depend on the policy issue and external shock under investigation. The trade-offs between greater sophistication and simplification also will depend on data constraints as well as the needs and capacity of policy makers.

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Annex

TABLE 12A.1
Description of Variables

Variable name	Description
Demographic variables, individual-level data	
Gender	Dummy variable:1 male, 0 female
Age	Years of age
Nchild09	Number of children aged 0–9 in household
Nchild01	Number of children aged 0–1 in household
Headd	Dummy variable: 1 household head, 0 otherwise
Married	Dummy variable: 1 married couple, 0 otherwise
Urban	Dummy variable: 1 urban, 0 rural
Prov	Regional province variable
Hhsize	Household size
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 $(=\text{age-eduyear-5})^2$
Eduyearhd	Years of schooling of head of the household
SkillH	Professional, semiprofessionals, technical occupations, managerial, executive administrative occupations, and certain transport occupations, such as 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
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 someone in the household owns family business, 0 otherwise

(*Continued on the following page*)

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TABLE 12A.1

(continued)

Variable name	Description
Occhoice1	Dummy variables: 0 unemployed and 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 workers, 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
Economic sectors	
Primary sector	Includes agriculture, forestry, and fishing, mining and quarrying
Secondary sector	Includes manufacturing, electricity, other utilities, and construction
Tertiary sector	Includes trade, transport, financial, and business services; and social, personal, and community services
Formallab	Dummy variable for formal labor: based on question asked in labor force survey
Informallab	Dummy variable for Informal labor: based on question asked in labor force survey
Household aggregate expenditures and income variables, household-level data from income and expenditure survey 2000	
Household expenditures and consumer price index for 17 household expenditure categories	Food; nonalcoholic 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	Includes formal wage income, informal wage income, and self-employed income from labor force survey, and other income from income and expenditure survey .

Sources: Labor Force Survey (2000) and Income and Expenditure Survey (2000).

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Notes

This paper is issued simultaneously as a working paper at the World Bank and the Institute of Development Studies (IDS), Sussex University. The framework used in the paper is based on a World Bank technical assistance to develop a computatble general equilibrium-microsimulation model for South Africa's National Treasury in a collaborative effort with IDS and the U.S. 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, and James Thurlow for helpful comments on an earlier version of this paper.

1. See, for example, Bourguignon and Pereira da Silva (2003) or Essama-Nssah (2006) for a compilation and evaluation of various approaches, techniques, and tools.
2. There are also other issues, such as introducing dynamics and growth, incorporating individual firm behavior, and so forth. See, for example, the conclusion chapter in Bourguignon and Pereira da Silva (2003).
3. Full details of the South Africa CGE model can be found in Kearney (2004); for a version of the model used to analyze value-added taxes, see Go et al. (2005). In this description, we comment on features of the model important for an analysis of the oil price shock.
4. More specifically, the employment data in the CGE have been calibrated to match the employment share data from the household survey in which there are five labor types (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 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).
7. McDonald and van Schoor (2005) also adjusted the "other mining" category to properly account for crude oil. They supplemented the social accounting matrix with data on imported crude oil. In this chapter, we assert that all inputs of other mining into refined petroleum are actually imports of crude oil.
8. By construction, crude oil is used only as an intermediate to the refined petroleum sector and it is not produced domestically.

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9. These surveys are published by Statistics South Africa, and are available at http://www.statssa.gov.za.
10. 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) noted that such an interpretation would not be valid in cases where occupational choices are constrained by the demand side of the market.
11. 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 subsamples of individuals with observed earnings in the given activity. There was no significant difference in the results. We therefore stick with OLS.
12. "All other income" is 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.
13. Bourguignon, Robilliard, and Robinson (2002) explained that benchmark consistency could be achieved by ensuring that the calibration of the CGE is compatible with the consistency constraints.
14. Savard (2006) discussed a way to achieve consistency in a case where the SAM of the CGE model and the survey data of the microsimulation have the same base year.
15. The elasticity of substitution between imports and the domestic variety in consumption for refined petroleum is 0.73; for basic chemicals, it is 0.677. Crude oil is not produced domestically. A value less than 1 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.
16. We also estimate poverty indicators at sectoral levels (urban, rural) and by provinces, but the latter are not reported.
17. TIP stands for "three 'I's of poverty"—that is, incidence, intensity, and inequality. The length of the nonhorizontal section reveals poverty incidence, intensity is represented by the height of the curve, and the concavity of the nonhorizontal section translates the degree of inequality among the poor.
18. The increase in the dollar price of crude oil was counterbalanced significantly by the strong South African rand during much of the recent trend in crude oil prices. The nominal rand per dollar, for example, appreciated by about 20.0 percent from end-2002 to end-2006 and by as much as 42.5 percent from end-2001 to end-2006.

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