Welfare impacts of introducing water pollution tax in the Olifants river basin in South Africa: A revisited analysis using a top-down micro-accounting approach

Clement Kweku Kyei* & Margaret Chitiga-Mabugu

School of Public Management and Administration, University of Pretoria, Pretoria, South Africa

*Contact: Clement Kweku Kyei. School of Public Management and Administration, University of Pretoria, Pretoria, 0002, South Africa. Email: margaret.chitiga@up.ac.za

ABSTRACT

Addressing the high levels of poverty and inequality in South Africa remains a central policy concern. In this regard, this paper uses a Computable General Equilibrium (CGE) microsimulation approach to revisit the effects of taxing water pollution on poverty and inequality at the level of a river basin. We combined the commodity and factor price changes from a regional environmental CGE model, after introducing the water pollution tax, with household survey data from the 2012 National Income Dynamics Survey (NIDS) to explain the welfare impacts. The result shows that the tax policy will in general have adverse impacts in terms of welfare, poverty, and inequality. However, the tax policy coupled with a supply-side compensatory measure such as subsidising water pollution abatement has the potential to reduce regional poverty and inequality as well as improve the ecological status of the river. Our finding has policy implications for national and regional water resource managers.

KEYWORDS: Poverty, inequality, microsimulation, water pollution tax

1. Introduction

The deterioration of water quality threatens the functioning of ecosystems and the sustainability of socio-economic development especially for a water-stressed country like South Africa (SA). The Olifants river basin, which is one of the nine water management areas in SA, faces serious water scarcity, with declining surface and groundwater quality due to pollution from mining activities, irrigation agriculture, and industrial waste disposal. For example, mining activities in the upper parts of the basin produce mine water, which is high in dissolved solids such as sulphate, calcium, and magnesium. This contributes to low pH and increased salinity and sediment load which affect in-stream biota as well as riparian habitat (Department of Water and Sanitation (DWS) 2011). In the upper parts also, industrial effluent containing various potential pollutants (such as hazardous chemicals and nutrients) has negative impacts on the quality of the river. Furthermore, irrigation return flows and seepage, which contains salts from fertilisers, other agrochemicals (such as herbicides and weedicides), and effluent from animal husbandry contribute to the contamination of the river. Consequently, there is great competition for water among different economic sectors and between upstream and downstream users in the basin. Improving water quality will hence reduce the demand for fresh water and pressure on the current scarcity situation (DWS 2003; Department of Environmental Affairs (DEA) 2011). For this reason, the government has implemented a series of pollution control measures (such as the waste discharge charge system which aims to internalise the costs associated with waste discharges in accordance with the polluter-pays-principle) with the view to mitigating pollution and water shortage in the basin (DWS 2003, 2016). However, the public acceptance for the pollution control measures will depend on their distributional impacts or crucially the perceived impact on the poor and vulnerable – a category that constitutes about 70% of the basin's population (Rausch and Schwarz 2016; Association for Water and Rural Development (AWARD) 2019; Kyei and Hassan 2021). It is therefore important for policymakers to be aware of the likely impacts of their policies on the poor and vulnerable populations.

Policies affect households' distributional outcomes, both between and within their groups. The literature on Computable General Equilibrium (CGE) microsimulation documents the importance of both between- and within-group variations for explaining the distributional impacts of policy interventions (see, e.g., Decaluwé, Dumont, and Savard 1999; Chen and Ravallion 2004; Bourguignon, Robilliard, and Robinson 2005; Bourguignon and Spadaro 2006; Savard 2003, 2005). The core concern is that ignoring within-group variation in distributional studies may bias results and subsequent policy recommendations. In this respect, a range of approaches has been proposed to endogenise the variance of income distribution in CGE models or account for the heterogeneity among individual households. These approaches include, fully integrated (where actual households obtained from a household survey are incorporated directly into the CGE model), top-down micro-accounting (where factor and commodity price changes from a CGE model are fed into a microsimulation household model), top-down with behaviour (which extends the top-down with micro-accounting approach with behavioural responses of individuals/households), bottom-up (where the impacts of policy reform are first modelled in a microsimulation and the relevant information are then aggregated and fed into a CGE model), and the iterative or top-down/bottom-up (where the CGE model and the microsimulation models are linked in a bidirectional way). The choice of an approach, however, depends on factors such as research question and data availability.

In this light, this paper revisits the distributive effects of taxing water pollution in the Olifants river basin. In previous work, we have used a CGE model with representative households and the Hicksian equivalent variation as a welfare indicator to explore the distributional impacts of a water pollution tax considering the income and spending-side effects (Kyei and Hassan 2021). Although the representative household approach has the advantage of being relatively easy to implement, it is limited in accounting for a within-group variation after a policy reform because information on the actual households (such as consumption patterns) are lost in the aggregation process. In addition, Savard (2005) found that the representative household approach to income distribution in a CGE model can bias the results of poverty and inequality analysis. Furthermore, our reconsideration is motivated by a number of reasons. Firstly, we seek to more adequately assess the poverty and inequality effects of the tax policy and also explore whether demand- and supply-side mitigation measures deliver the same benefit in terms of addressing the pollution problem as well as reducing poverty and inequality. Thus, the findings will provide empirical evidence to the government regarding its objective to reduce poverty and inequality (as outlined in the National Development Plan (NDP) 2012) while improving water quality, particularly given that about 42% of the basin lies in one of the poorest provinces in SA – i.e., the Limpopo province, (Stats SA 2017, 2018; AWARD 2019). Secondly, previous studies in the context of carbon and energy policies have shown that ignoring household heterogeneity can qualitatively bias incidence or reduce the capacity to address distributional questions (Labandeira, Labeaga, and Rodríguez 2006; Rausch, Metcalf, and Reilly 2011; Rausch and Schwarz 2016). Moreover, Boccanfuso, Estache, and Savard (2011) recommend the use of CGE-microsimulation for distributional analysis in developing economies given that it improves our understanding of distributional incidence. In effect, we seek to answer the question: Does ignoring within-group heterogeneity bias the distributional outcomes of a water pollution tax? In this connection, we use a CGE-microsimulation model specifically, the top-down micro-accounting (TD-MA) approach because it's well suited for the small price changes produced by our policy simulations and besides, it avoids the pre-judgment about aggregating households into categories. Though our paper is related to the literature that uses CGE-microsimulations to explore the distributional impacts of environmental taxes, to the best of our knowledge, it's the first to consider how within-group heterogeneity in incomes and preferences affects the incidence of a water pollution tax and at the level of a river basin. Understandably, it can be considered to be an extension of the work of Kyei and Hassan (2021).

The rest of the paper is organised as follows. Section two presents the empirical methodology including the data sets used for the analysis. We discuss the results in section three and provide some policy recommendations in section four.

2. Methodology

Our analysis follows the steps in the literature on CGE-microsimulation, particularly the top-down approaches (see, e.g., Vos and De Jong 2003; Chen and Ravallion 2004; Bourguignon, Robilliard, and Robinson 2005; Ravallion and Lokshin 2008). That is, we use a CGE model to derive price changes for different consumer goods and factors after introducing the water pollution tax and then calculate the tax incidence for households using household-level survey data. In what follows, we briefly present the microsimulation model and the data used.

2.1 Microsimulation model

In the top-down with micro-accounting (TD-MA) approach, the predicted commodity and factor price changes from the CGE model are fed into a microsimulation household model with information on household members' socio-economic characteristics such as income, expenditure, gender, and race. Theoretically, the approach assumes a household model with an indirect utility function specified in terms of product, commodity, and factor prices (for more details, see, Chen and Ravallion 2004). The main equation used to measure the household-level welfare impacts of price changes due to the tax policy is given below:

$$g_i = \sum_{j=1}^{m} \left[p^s_{ij} q^s_{ij} \frac{dp^s_{ij}}{p^s_{ij}} - p^d_{ij} \left(q^d_{ij} + z_{ij} \right) \frac{dp^d_{ij}}{p^d_{ij}} \right] + \sum_{k=1}^{n} \left(w_k L^s_{ik} \frac{dw_k}{w_k} \right) \tag{1}$$

where g_i is the gain or loss in welfare for household i, p^s_{ij} and q^s_{ij} are respectively m-dimensional vectors of supply prices and quantities supplied by household *i* and for good j, $j, \frac{dp^s_{ij}}{p^s_{ij}}$ is the predicted change in the *j*th selling price, $-p^d_{ij}\left(q^d_{ij} + z_{ij}\right)$ is the (negative) weight for the predicted change in the *j*th demand price (i.e., $\frac{dp^d_{ij}}{p^d_{ij}}$) with p^d_{ij} and q^d_{ij} respectively representing m-dimensional vectors of demand prices and quantities, z_{ij} is the intermediate commodity used by household *i* in producing good $j, w_k L^s_{ik}$ is the weight for changes in the wage rate for labour type *k* (i.e., $\frac{dw_k}{w_k}$). Note that $w_k L^s_{ik}$ is the share of income that household *i* receives from labour type *k*. In essence, equation (1) calculates the welfare impact of the water pollution tax as the weighted sum of income and expenditure shares multiplied by their respective predicted commodity and factor price changes arising from the CGE model.

2.2 Data

The analysis is based on two main data sources. The first source is the commodity and factor price changes predicted by the regional environmental CGE model (which was calibrated using a 2012 environmental SAM database) as a result of introducing the water pollution tax. We take the predicted price changes as given, however, to provide context, we present a brief description of the CGE model as well as the policy scenarios.[1] The second source is the 2012 National Income Dynamics Survey (NIDS) household survey data which we will describe further below.

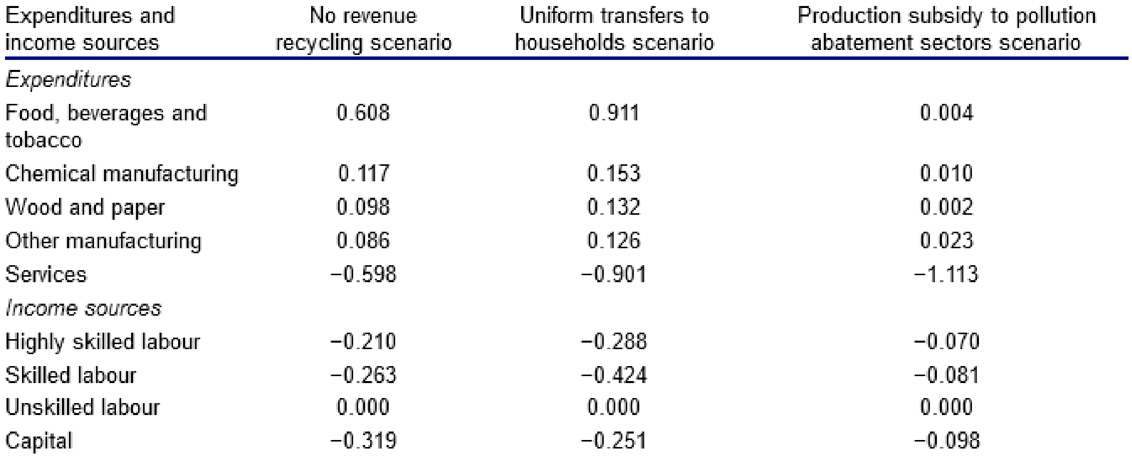
The core specification of the Olifants environmental CGE model follows that of the standard static model developed by the International Food Policy Research Institute (IFPRI) (Löfgren et al. 2002). However, the IFPRI model was extended to include a production function for pollution abatement activities with their "output" treated as special intermediate goods bought by polluters. The incorporated pollution abatement sectors have the responsibility of providing the best available purification services to help polluters meet prescribed environmental standards. Thus, the cost of production includes pollution-related costs in addition to the cost of intermediate inputs and primary factors. The model distinguishes 13 sectors: 10 producing sectors (namely field crops, horticulture crops, livestock, other agriculture, mining, chemical manufacturing, wood and paper, food, beverage, and tobacco, other manufacturing, and services) and 3 abatement sectors (salinity, nitrogen, and phosphorus). Also, the model incudes 3 labour types (namely highly skilled labour, skilled labour, and unskilled labour) in addition to capital.

We used the Johansen closure which combines fixed real government consumption, fixed foreign savings, and fixed real investment but implemented it in a manner where each of our scenarios represents a concern of the regional government. That is, each scenario mimics a different macro closure rule and captures our understanding of how the regional economy operates. For the factor market equilibrium constraint, we assumed that higher-skilled labour (highly skilled and skilled) and capital are fully employed with flexible real wages and capital rental price. Unskilled labour on the contrary is assumed to be perfectly elastic in supply with a fixed real wage to reflect the reality in the SA labour market. Furthermore, the CGE model employed 4 representative households based on income (namely poorest, vulnerable, middle-income, and high-income) to derive the price impacts.

In the first scenario which is labelled "no-revenue recycling" we assume that the regional government is more concerned about fiscal adjustments such as reducing the budget deficit. That is, all the revenue generated from the pollution tax is absorbed in the government budget balance. This represents an indirect subsidy to consumer demand in the form of an income tax break. Implicitly, the higher government savings leads to lower savings by households to maintain the economy-wide saving-investment balance. Under the second scenario, the revenue from the water pollution tax is returned to the economy as uniform government transfers to households. This is a direct subsidy to households in the form of cash grants. In the third scenario, the pollution tax revenue is returned to pollution abatement sectors in the form of a production subsidy. This is a supply-side subsidy that reduces the cost of production in pollution abatement sectors, thus reducing the prices of abatement goods. It should be noted that in each of the scenarios, it was assumed that the government arbitrarily raises the water pollution tax rate on nitrogen emission by 50% with reference to the base value.

Table 1 gives the results of price changes for the different scenarios. As expected, the prices of pollution-intensive goods (namely food, beverages and tobacco, chemical manufacturing, wood and paper, and other manufacturing) increased across all scenarios but to a greater degree under the lump-sum transfers to households. On the contrary, prices of non-polluting goods (such as services), as well as factor prices, fell across all scenarios.

Table 1. Predicted price changes due to a 50% increase in pollution tax on nitrogen emission under alternative revenue recycling scenarios (%age change relative to base run)



Expenditures and income sources	No revenue recycling scenario	Uniform transfers to households scenario	Production subsidy to pollution abatement sectors scenario
Expenditures			
Food, beverages and tobacco	0.608	0.911	0.004
Chemical manufacturing	0.117	0.153	0.010
Wood and paper	0.098	0.132	0.002
Other manufacturing	0.086	0.126	0.023
Services	−0.598	−0.901	−1.113
Income sources			
Highly skilled labour	−0.210	−0.288	−0.070
Skilled labour	−0.263	−0.424	−0.081
Unskilled labour	0.000	0.000	0.000
Capital	−0.319	−0.251	−0.098

Source: Authors' calculations based on Olifants environmental CGE model, (Kyei 2019).

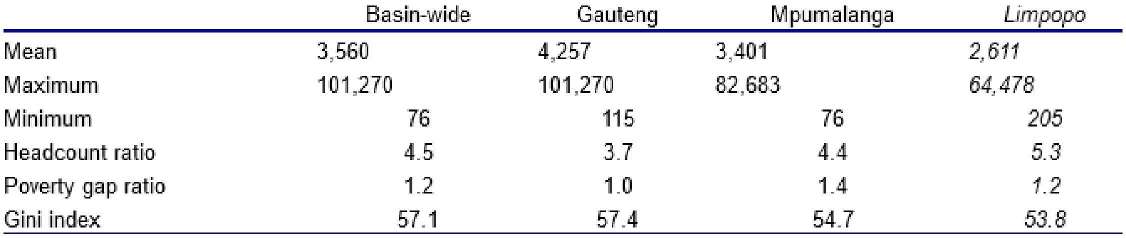
The second data source is the 2012 NIDS household survey data which consists of household size, income, expenditure, and other demographics (Southern Africa Labour and Development Research Unit (SALDRU) 2012). For comparability reasons, we used the 2012 NIDS data because it was collected around the same year as our reference SAM (i.e., the macro data).[2] NIDS is a nationally representative household survey that tracks a sample of South Africans and the people they reside with, at the time of the interview. However, for this study, we focus on the households and individuals residing in the Olifants river basin (these come from households in the Gauteng, Mpumalanga, and Limpopo provinces). There were over 7000 households in the full sample but were reduced to 2317 after subsetting and data cleaning. That is, there were 2317 households located in the basin.

As mentioned above, there are 13 sectors in the CGE model. The micro-data, on the other hand, have over 100 items/variables for consumption. The variables from the micro-data are matched to the closest category in the CGE model. For example, all food items such as grains, meat, fish, and potatoes in addition to tobacco and "non-alcoholic" beverages are placed in the food, beverages, and tobacco category. The items in the micro-data matched into five categories/commodities in the macro-data (i.e., chemical manufacturing, wood and paper, food, beverage, and tobacco, other manufacturing, and services). In like manner, there are 3 labour types in the CGE model. The classification of an individual into a given labour type (say highly skilled) in the micro-data was done using their education level. For example, individuals with diplomas, honours, bachelor's, master's, and PhDs are placed in the highly skilled labour category. Implicitly, this assumes that individuals with high-education and training have the knowledge and skills of managers and administrators, professionals, and para-professionals as per the ILO's (International Labour Organisation) definition. It suffices to say that the ideal classification should have been based on education and occupational skill but data limitations did not permit so. Finally, we used household expenditure as a welfare measure to assess the impact of the tax policy on poverty and inequality.

3. Results and discussion

Using the predicted commodity and factor price changes from the CGE model and the commodity and factor shares from the micro-data, equation (1) was used to assess the aggregate impact of the tax policy on poverty and inequality. That is, for each household the gain (loss) in welfare (i.e., g_i) was added to their pre-reform consumption expenditure to obtain the post-reform expenditure distribution. Table 2 reports the baseline monthly expenditure characteristics as well as the poverty and inequality indices for the basin and its constituent provinces. For poverty, we used two measures of the Foster, Greer, and Thorbecke family while the Gini coefficient was used for inequality. The poverty and inequality indices were estimated using the Distributive Analysis Stata Package (DASP) developed by Araar and Duclos (2013). The estimated poverty headcount was 4.5% of the basin's population using the 2012 national lower-bound poverty line of R541.[3] The Gini coefficient of 0.571 is relatively high in international comparison but is reflective of the situation in South Africa. On average, households in Limpopo had the lowest mean expenditure when compared with households in Gauteng and Mpumalanga. However, the estimated poverty headcount was higher for Limpopo than the other provinces though its inequality rate is the lowest. In addition, Mpumalanga had the highest poverty gap at 1.4% which implies that households in Mpumalanga are relatively far from the poverty line compared with those in the other provinces. It's worth mentioning that these findings are qualitatively similar to those reported by Stats SA (see Stats SA 2017, 2018). That is, poverty is more prevalent in Limpopo than in Gauteng and Mpumalanga.

Table 2. Baseline expenditure characteristics and distribution

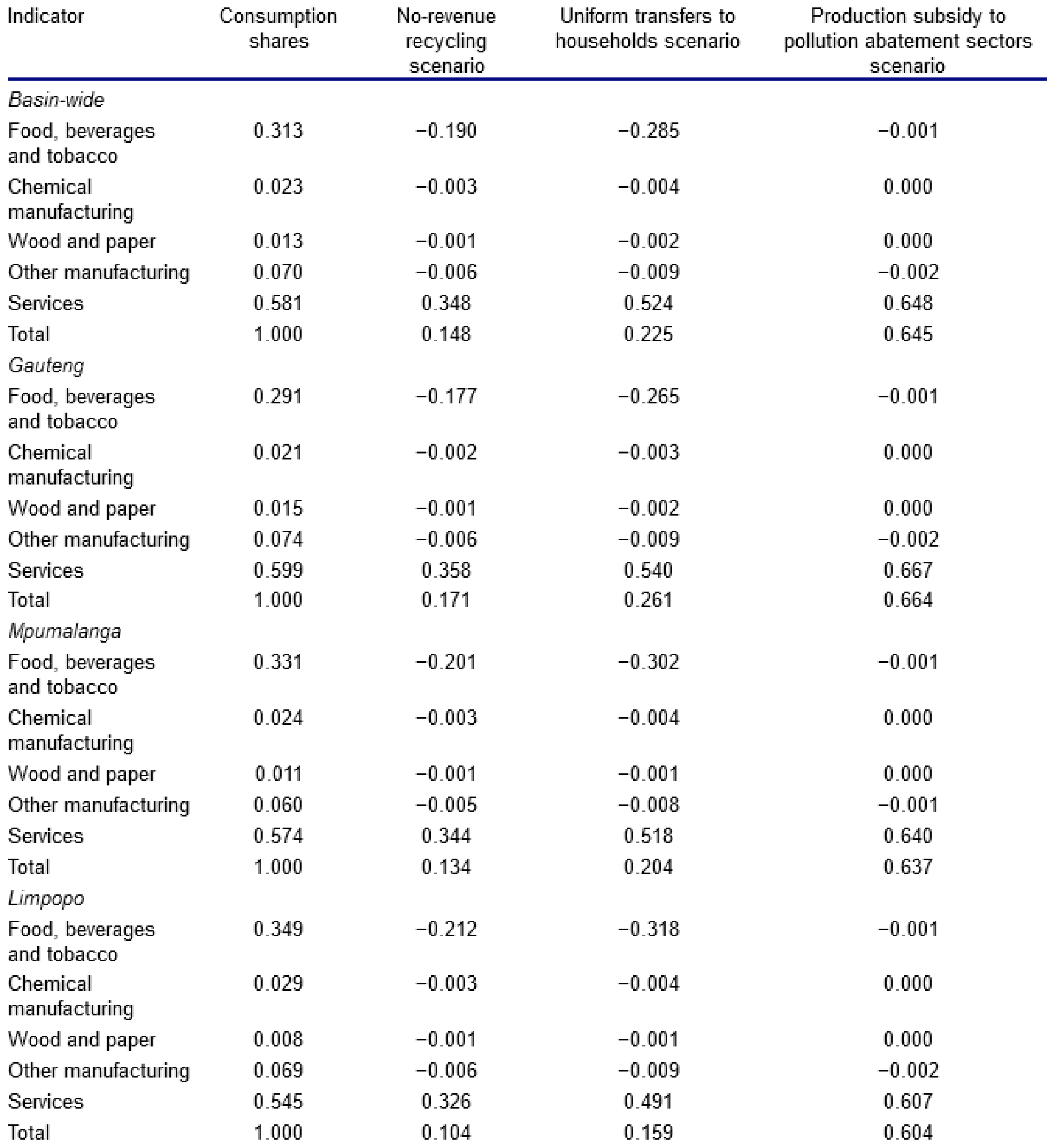


	Basin-wide	Gauteng	Mpumalanga	*Limpopo*
Mean	3,560	4,257	3,401	*2,611*
Maximum	101,270	101,270	82,683	*64,478*
Minimum	76	115	76	*205*
Headcount ratio	4.5	3.7	4.4	*5.3*
Poverty gap ratio	1.2	1.0	1.4	*1.2*
Gini index	57.1	57.4	54.7	*53.8*

Source: Authors' estimations based on NIDS data (2012); Note: Poverty and inequality indices are multiplied by 100 for ease of exposition.

Table 3 reports the consumption shares and the mean welfare impacts, disaggregated by commodity for the three policy scenarios. It indicates that households in the basin spend a larger fraction of their income on services followed by food, beverages, and tobacco. Together, the two commodities constitute about 90% of total household expenditure in the basin. Spending patterns, however, differ across provinces. For example, households in Limpopo spend more on food, beverages, and tobacco and less on services compared with their counterparts in Gauteng who spend more on services and less on food, beverages, and tobacco. This confirms the conventional finding that poor households spend a greater share of their income on core needs. It should be noted that the estimated welfare effects reported below depend on these commodity shares and the predicted price changes from the CGE model. Thus, for a given price change, the greater the share of pollution-intensive goods in a province's consumption basket the bigger the loss in mean consumption.

Table 3. Consumption shares and mean consumption impacts under alternative revenue recycling scenarios

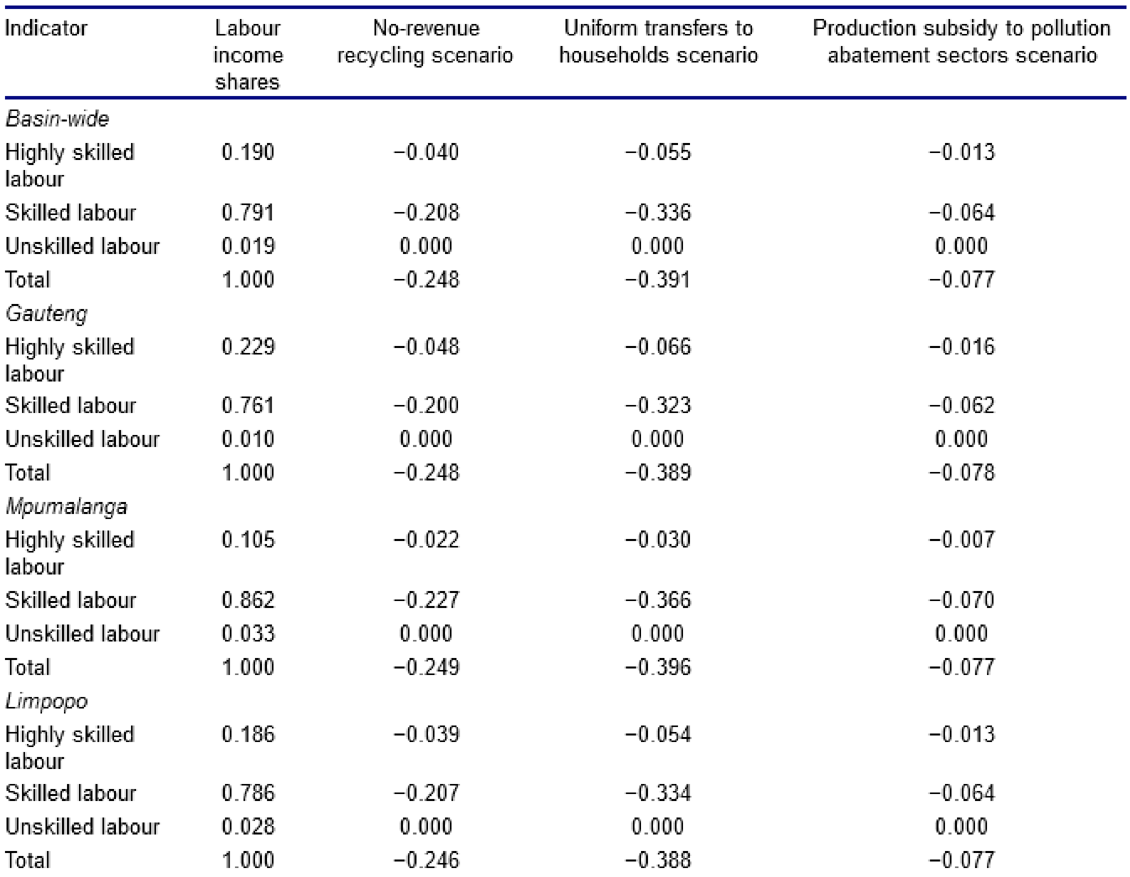


Indicator	Consumption shares	No-revenue recycling scenario	Uniform transfers to households scenario	Production subsidy to pollution abatement sectors scenario
Basin-wide				
Food, beverages and tobacco	0.313	−0.190	−0.285	−0.001
Chemical manufacturing	0.023	−0.003	−0.004	0.000
Wood and paper	0.013	−0.001	−0.002	0.000
Other manufacturing	0.070	−0.006	−0.009	−0.002
Services	0.581	0.348	0.524	0.648
Total	1.000	0.148	0.225	0.645
Gauteng				
Food, beverages and tobacco	0.291	−0.177	−0.265	−0.001
Chemical manufacturing	0.021	−0.002	−0.003	0.000
Wood and paper	0.015	−0.001	−0.002	0.000
Other manufacturing	0.074	−0.006	−0.009	−0.002
Services	0.599	0.358	0.540	0.667
Total	1.000	0.171	0.261	0.664
Mpumalanga				
Food, beverages and tobacco	0.331	−0.201	−0.302	−0.001
Chemical manufacturing	0.024	−0.003	−0.004	0.000
Wood and paper	0.011	−0.001	−0.001	0.000
Other manufacturing	0.060	−0.005	−0.008	−0.001
Services	0.574	0.344	0.518	0.640
Total	1.000	0.134	0.204	0.637
Limpopo				
Food, beverages and tobacco	0.349	−0.212	−0.318	−0.001
Chemical manufacturing	0.029	−0.003	−0.004	0.000
Wood and paper	0.008	−0.001	−0.001	0.000
Other manufacturing	0.069	−0.006	−0.009	−0.002
Services	0.545	0.326	0.491	0.607
Total	1.000	0.104	0.159	0.604

Source: Authors' estimations

By reporting the gain (loss) in mean consumption per commodity in Table 3, we can estimate the net impact of the tax policy on the basin's consumers under each policy scenario. As can be seen, net mean consumption is higher under the revenue recycling scenarios relative to the no-revenue recycling scenario. For instance, it increases from 0.148% under the no-revenue recycling scenario to 0.225% under the lump-sum transfers to households with the biggest net gain recorded under the production subsidy to pollution abatement sectors. This is because revenue recycling compensates for the losses in income due to the tax policy. On the contrary, demand for non-polluting goods (such as services) increased. Thus, the positive impact on net mean consumption is a result of the large share of services in the basins' consumption basket. It's also noticeable that pollution-intensive goods recorded their biggest loss in mean consumption under the lump-sum transfers to households' scenario. This is because though consumption demand is boosted, there is upward pressure on the prices of pollution-intensive goods due to their limited domestic supply. As a result, this revenue recycling option may impinge on domestic demand for pollution-intensive goods as consumers are likely to substitute in favour of cheap imports. In this regard, it's palliative in nature because it boosts consumption demand but at the expense of shifting the pollution problem outside the basin's borders. This corroborates the finding of Williams et al. (2015) who in the context of carbon and energy taxes found that lump-sum transfers are more progressive but less efficient. The result by province shows that consumers' in Limpopo recorded the lowest net gain in mean consumption due to the bigger share of pollution-intensive goods in their consumption basket.

Table 4. Labour income shares and mean income impacts under alternative revenue recycling scenarios



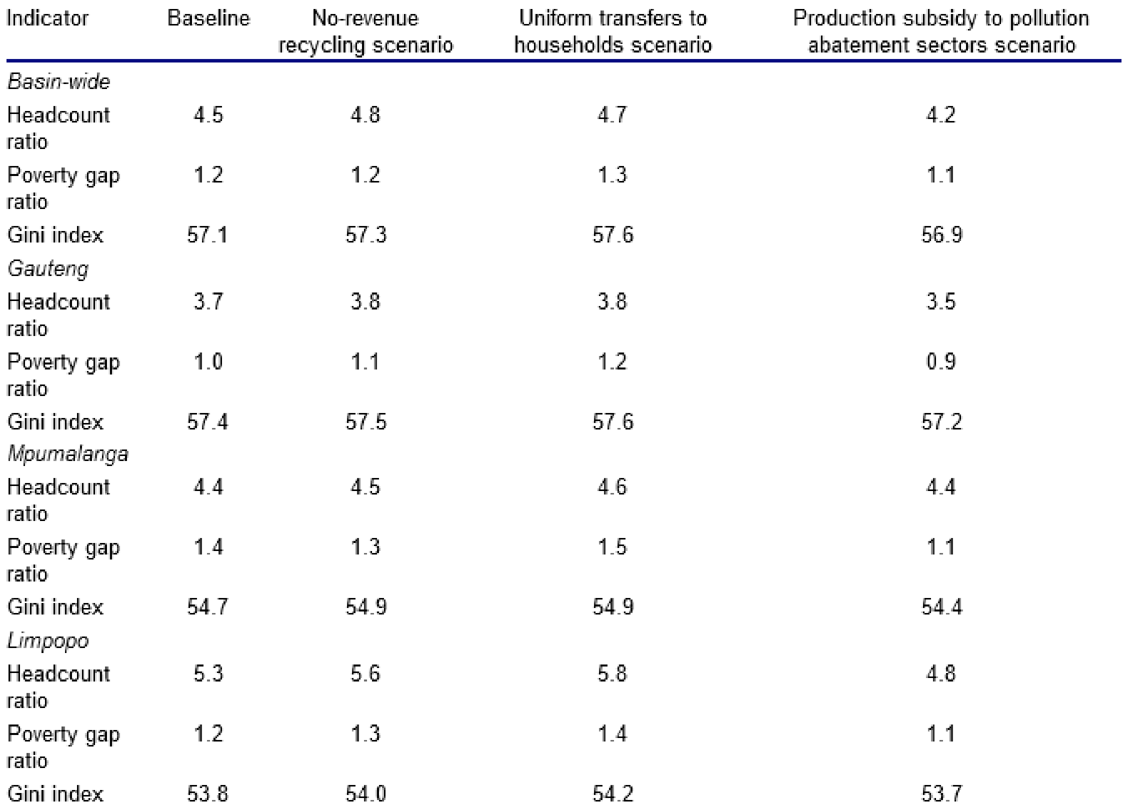
Indicator	Labour income shares	No-revenue recycling scenario	Uniform transfers to households scenario	Production subsidy to pollution abatement sectors scenario
Basin-wide				
Highly skilled labour	0.190	−0.040	−0.055	−0.013
Skilled labour	0.791	−0.208	−0.336	−0.064
Unskilled labour	0.019	0.000	0.000	0.000
Total	1.000	−0.248	−0.391	−0.077
Gauteng				
Highly skilled labour	0.229	−0.048	−0.066	−0.016
Skilled labour	0.761	−0.200	−0.323	−0.062
Unskilled labour	0.010	0.000	0.000	0.000
Total	1.000	−0.248	−0.389	−0.078
Mpumalanga				
Highly skilled labour	0.105	−0.022	−0.030	−0.007
Skilled labour	0.862	−0.227	−0.366	−0.070
Unskilled labour	0.033	0.000	0.000	0.000
Total	1.000	−0.249	−0.396	−0.077
Limpopo				
Highly skilled labour	0.186	−0.039	−0.054	−0.013
Skilled labour	0.786	−0.207	−0.334	−0.064
Unskilled labour	0.028	0.000	0.000	0.000
Total	1.000	−0.246	−0.388	−0.077

Source: Authors' estimations

Table 4 reports the welfare impacts of the three scenarios on mean income. Firstly, it shows that households in the basin derive a significant share of their income from skilled and highly skilled labour. Secondly, it reveals the net loss to wage earners across scenarios with the magnitude being higher under the lump-sum transfer to households' revenue recycling option. As discussed previously, transferring the tax revenue in a lump-sum fashion per household stimulates demand for imported commodities at the expense of domestic supply chiefly because of higher domestic prices and the fact that polluting sectors are more trade-exposed. As a result, wages were severely impacted by this scenario (see Table 1). On the contrary, recycling the tax revenue through a production subsidy to pollution abatement sectors lowers the net loss in mean income. For the reason that pollution abatement goods become relatively cheap thus, increasing their demand and boosting the capacity of the regional economy to clean up its pollution. This stimulates domestic production with benign welfare impacts. A comparable finding was observed in Van Heerden et al. (2016) who showed that recycling carbon tax revenue in the form of a production subsidy to all industries mitigates the adverse impact of the tax on economic growth. It should be noted that the weak impact of the production subsidy recycling option is due to rigidities on the production side of our CGE model. That is, we assumed a Leontief production function for activities which implies no substitution between abatement goods and other inputs to production. Therefore, the supply of pollutants in our model moves in direct proportion to the level of economic activity.

Table 5 shows that the water pollution tax policy will marginally increase poverty and inequality in the basin. Relative to the baseline, the estimated poverty headcount increase from 4.5% to 4.8% under the no-revenue recycling scenario. Similarly, inequality increases under the no-revenue recycling option relative to the baseline from 57.1% to 57.3%. This is because, without revenue recycling, the tax policy depresses domestic activity by increasing the cost of production and prices of pollution-intensive goods. As a result, both the functional and size distribution of income is impacted.

Table 5. Household welfare impacts of the water pollution tax policy under alternative revenue recycling scenarios



Indicator	Baseline	No-revenue recycling scenario	Uniform transfers to households scenario	Production subsidy to pollution abatement sectors scenario
Basin-wide				
Headcount ratio	4.5	4.8	4.7	4.2
Poverty gap ratio	1.2	1.2	1.3	1.1
Gini index	57.1	57.3	57.6	56.9
Gauteng				
Headcount ratio	3.7	3.8	3.8	3.5
Poverty gap ratio	1.0	1.1	1.2	0.9
Gini index	57.4	57.5	57.6	57.2
Mpumalanga				
Headcount ratio	4.4	4.5	4.6	4.4
Poverty gap ratio	1.4	1.3	1.5	1.1
Gini index	54.7	54.9	54.9	54.4
Limpopo				
Headcount ratio	5.3	5.6	5.8	4.8
Poverty gap ratio	1.2	1.3	1.4	1.1
Gini index	53.8	54.0	54.2	53.7

Source: Authors' estimations; Note: Poverty and inequality indices are multiplied by 100 for ease of exposition.

Recycling the tax revenue, on the other hand, compensates for the losses in income but, our finding reveals that regional poverty and inequality increases under the demand-side scenario. This is because, though income is boosted, the fall in factor incomes offset the gains due to consumers substituting in favour of cheap imported goods. Nonetheless, the finding that recycling the tax revenue has the potential to reduce poverty is similar to that of Van Heerden et al. (2006) who showed that a triple dividend (i.e., decreased carbon dioxide emissions and poverty while increasing domestic income) is possible when the revenues from environmental taxes are recycled through a reduction in food prices. In terms of the core aim of this paper, the findings reported here qualitatively corroborate those of Kyei and Hassan (2021) which highlights that both the representative household and CGE-microsimulation approaches may produce similar results in the incidence impacts of a water pollution tax, particularly when the derived price impacts on commodities and factors are small. However, unlike Kyei and Hassan (2021) who ignored the within-group income distribution after the tax policy, this paper by using the CGE-microsimulation approach overcomes that limitation and thus, has more adequately assessed the poverty and inequality effects of the water pollution tax. Consequently, we recommend that where data permits, the CGE-microsimulation approach should be used to study the incidence impacts of a water pollution tax especially when the focus is on poverty and inequality. More importantly, our finding shows that subsidising water pollution reduction technologies has the potential to improve regional income distribution in the presence of a water pollution tax. We do not find a significant difference in welfare effects between male and female-headed households but the differences due to race are reflective of the South African story.[4]

4. Conclusion

In this paper, we provide empirical evidence of the effects of taxing water pollution on poverty and inequality in the third most water-stressed and most polluted basin in South Africa – the Olifants river basin. We employed a Computable General Equilibrium (CGE) microsimulation model that accounts for both between- and within-group changes after a policy intervention. The analysis was based on two data sets. The first data came from a regional environmental CGE model and includes predicted changes in factor and commodity prices after introducing the water pollution tax. The second was a household survey data sourced from the 2012 NIDS. We also analysed the potential of mitigating the adverse welfare effects of the tax policy through two revenue recycling options.

Our analysis shows that without revenue recycling, the water pollution tax will marginally increase poverty and inequality in the basin. However, the poverty and inequality reducing effects of the revenue recycling options differ. A demand-side compensatory measure such as a lump-sum transfer to households has the potential to worsen regional poverty and inequality if the fall in factor incomes offset the gains due to consumers substituting in favour of cheap imported goods. In contrast, a supply-side compensatory measure such as subsidising water pollution abatement may reduce regional poverty and inequality. As a result, we recommend that redistribution of the tax revenue should be done in a way that advances the supply of water pollution reduction technologies or the development of wastewater treatment technologies. In a nutshell, our result shows that a water pollution tax coupled with a supply-side compensatory measure has the potential to improve the welfare of the basin's population, particularly for the poor and vulnerable that rely on the river for their livelihood and various ecosystem goods and services.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Notes

1 For a detailed description of the Olifants environmental CGE model, see Kyei (2019).

2 The 2012 NIDS data is used to ensure similarity in the value of the consumer baskets between the SAM for 2012 and micro-data. It is, however, likely that using any of the subsequent NIDS datasets (i.e. wave 4 or 5) would yield qualitatively similar findings.

3 Please note that three poverty lines namely food, lower-bound and upper-bound are provided by Stats SA. However, we chose the lower-bound poverty line because we believe it's a good indicator of general wellbeing and hence represent moderate poverty. Moreover, it's the preferred poverty line that is commonly used for SA's poverty reduction targets such as those outlined in the NDP and the Medium Term Strategic Framework (MTSF) (Stats SA 2017).

4 That is, the proportions of black African and Coloured below the poverty line are higher than that of Indian/Asian and White (Stats SA 2017). Results are available upon request.

References

Araar, A., and J.Y. Duclos. 2013. User manual DASP version 2.3. *DASP: Distributive Analysis Stata Package, Université Laval, PEP, CIRPÉE and World Bank*.

Association for Water and Rural Development (AWARD). 2019. The Olifants River Catchment: A User's Guide. Retrieved from http://award.org.za/wp/wp-content/uploads/2019/01/The-Olifants-River-Catchment-User-Guide.pdf.

Boccanfuso, D., A. Estache, and L. Savard. 2011. The intra-country distributional impact of policies to fight climate change: A survey. *The Journal of Development Studies* 47, no. 1: 97–117.

Bourguignon, F., and A. Spadaro. 2006. Microsimulation as a tool for evaluating redistribution policies. *The Journal of Economic Inequality* 4, no. 1: 77–106.

Bourguignon, F., A. Robilliard, and S. Robinson. 2005. Representative versus Real Households in the Macroeconomic Modeling of Inequality. In Kehoe, T., T. Srinivasan, and J. Whalley (Eds.), *Frontiers in Applied General Equilibrium Modeling: In Honor of Herbert Scarf* (pp. 219-254). Cambridge: Cambridge University Press. doi:10.1017/CBO9780511614330.011

Chen, S., and M. Ravallion. 2004. Welfare impacts of China's accession to the World trade organization. *The World Bank Economic Review* 18, no. 1: 29–57.

Decaluwé, B., J.C. Dumont, and L. Savard. 1999. How to measure poverty and inequality in general equilibrium framework. *Laval University, CREFA Working Paper*, 9920.

Department of Environmental Affairs (DEA). 2011. State of the environment: inland water. https://www.environment.gov.za/sites/default/files/reports/environmentoutlook_chapter8.pdf (accessed 10 July 2018).

Department of Water and Sanitation (DWS). 2003. Water Quality Management Series. Sub-Series No. MS11. Towards a Strategy for a Waste Discharge Charge System, 1st edn. Department of Water and Sanitation, Pretoria, South Africa.

Department of Water and Sanitation (DWS). 2011. Water Quality Report: Development of a reconciliation strategy for the Olifants river water supply system. Report number: P WMA 04/B50/00/8310/2. Retrieved from http://www6.dwa.gov.za/OlifantsRecon/Documents/Supporting%20Reports/ORRS%20Summary%20Report.pdf.

Department of Water and Sanitation (DWS). 2016. *Water Quality Management Policies and Strategies for South Africa. Report No. 1.2.3: A Review of Water Quality Management Instruments for South Africa. Inaugural Report*. Water Resource Planning Systems Series, DWS Report No.: 000/00/21715/4. Pretoria, South Africa.

Kyei, C., and R. Hassan. 2021. Distributional impacts of taxing water pollution in the Olifants river basin of South Africa. Manuscript submitted for publication.

Kyei, C.K. 2019. *Economy-wide implications of water quality management policies: a case of the Olifants river basin, South Africa*. Ph.D Thesis. University of Pretoria, Pretoria, South Africa.

Labandeira, X., J.M. Labeaga, and M. Rodríguez. 2006. A macro and microeconomic integrated approach to assessing the effects of public policies. Working Papers 22, ECINEQ, Society for the study of economic inequality.

Löfgren, H., R.L. Harris, S. Robinson, M. El-Said, and M. Thomas. 2002. *A standard Computable General Equilibrium (CGE) model in GAMS. microcomputers in Policy Research, Vol. 5*. Washington, D.C: IFPRI.

National Planning Commission (NPC). 2012. National Development Plan 2030: Our future – make it work. Pretoria, SA: The Presidency. Retrieved from https://www.nationalplanningcommission.org.za/assets/Documents/ndp-2030-our-future-make-it-work.pdf.

Rausch, S., and G.A. Schwarz. 2016. Household heterogeneity, aggregation, and the distributional impacts of environmental taxes. *Journal of Public Economics* 138: 43–57.

Rausch, S., G.E. Metcalf, and J.M. Reilly. 2011. Distributional impacts of carbon pricing: A general equilibrium approach with micro-data for households. *Energy Economics* 33: S20–S33.

Ravallion, M., and M. Lokshin. 2008. Winners and losers from trade reform in Morocco. In Bourguignon, F., M. Bussolo, and L.A. Pereira da Silva (Eds.), *The Impact of Macroeconomic Policies on Poverty and Income Distribution: Macro-Micro Evaluation Techniques and Tools* (pp. 27-60). Oxford: Oxford University Press.

Savard, L. 2003. Poverty and income distribution in a CGE-household micro-simulation model: Top-down/bottom up approach.

Savard, L. 2005. Poverty and inequality analysis within a CGE framework: A comparative analysis of the representative agent and microsimulation approaches. *Development Policy Review* 23, no. 3: 313–31.

Southern Africa Labour and Development Research Unit (SALDRU). 2012. National Income Dynamics Study Wave 2, 2010-2011 [dataset]. Version 4.0.0. Pretoria: SA Presidency [funding agency]. Cape Town: Southern Africa Labour and Development Research Unit [implementer], 2018. Cape Town: DataFirst [distributor], 2018. https://doi.org/10.25828/j1h1-5m16.

Statistics South Africa (Stats SA). 2017. Poverty trends in South Africa: An examination of absolute poverty between 2006 and 2015. *Pretoria: statistics south. Africa*.

Statistics South Africa (Stats SA). 2017. *Men, women and children. Findings of the Living Conditions Survey, 2014/15* (Vol. 15). Report No. 03-10-02 2014.

Van Heerden, J., J. Blignaut, H. Bohlmann, A. Cartwright, N. Diederichs, and M. Mander. 2016. The economic and environmental effects of a carbon tax in South Africa: A dynamic CGE modelling approach. *South African Journal of Economic and Management Sciences* 19, no. 5: 714–32.

Van Heerden, J., R. Gerlagh, J. Blignaut, M. Horridge, S. Hess, R. Mabugu, and M. Mabugu. 2006. Searching for triple dividends in South Africa: fighting CO_2 pollution and poverty while promoting growth. *The Energy Journal* 27, no. 2: 113–41.

Vos, R., and N. De Jong. 2003. Trade liberalization and poverty in Ecuador: A CGE macro-microsimulation analysis. *Economic Systems Research* 15, no. 2: 211–232.

Williams III, R.C., H. Gordon, D. Burtraw, J.C. Carbone, and R.D. Morgenstern. 2015. The initial incidence of a carbon tax across income groups. *National Tax Journal* 68, no. 1: 195–214.