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Systematic Risk Profiling

A Novel Approach with Applications to Kenya, Rwanda, and Malawi

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Abstract

This paper uses machine learning, simulation, and data mining methods to develop Systematic Risk Profiles of three developing economies: Kenya, Rwanda, and Malawi. We focus on three exogenous shocks with implications for economic performance: world market prices, capital flows, and climate-driven sectoral productivity. In these and other developing countries, recent decades have been characterized by increased risks associated with all these factors, and there is a demand for instruments that can help to disentangle them. For each country, we utilize historical data to develop multi-variate distributions of shocks. We then sample from these distributions to obtain a series of shock vectors, which we label economic uncertainty scenarios. These scenarios are then entered into economywide computable general equilibrium (CGE) simulation models for the three countries, which allow us to quantify the impact of increased uncertainty on major economic indicators. Finally, we utilize importance metrics from the random forest machine learning algorithm and relative importance metrics from multiple linear regression models to quantify the importance of country-specific risk factors for country performance. We find that Malawi and Rwanda are more vulnerable to sectoral productivity shocks, and Kenya is more exposed to external risks. These findings suggest that a country's level of development and integration into the global economy are key driving forces defining their risk profiles. The methodology of Systematic Risk Profiling can be applied to many other countries, delineating country-specific risks and vulnerabilities.

Keywords: Risk profiling; climate uncertainty; world market uncertainty; CGE modeling.

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1. Analyzing the impacts of simultaneous variability of exogenous shocks

Both climatic shocks and world market shocks (macro trade imbalances and world commodity prices) are major concerns in development research and policymaking. Climate change has increased shocks to sectoral production in many countries and shocks to world prices and trade imbalances have a long history. While climatic and world market shocks are both important, they tend to be analyzed in isolation, without considering possible synergistic interactions between them.[1] Their impacts are complex, working through different channels, and it is natural that researchers have tended to focus on them separately. However, providing systematic risk mapping of all uncertainty factors is important, especially for low-income countries that have faced multiple overlapping shocks in recent years.

The methods and analyses presented here seek to answer the following two questions:

- What is a country's overall vulnerability to exogenous shocks?
- Which of these shocks are more important for the economy?

To answer these and related questions, we present a novel methodology for country systematic risk profiling (SRP). The method utilizes machine learning and data mining methods to dissect complex relationships between sampled exogenous shocks and outcome variables in an economywide computable general equilibrium (CGE) model. CGE models are a popular tool in policy analysis because their structural nature depicts heterogenous characteristics of sectors and households within a consistent accounting framework and captures both direct and indirect effects

[1] For example, Guivarch et al. (2009) investigate the resilience of the Indian economy to rising oil prices; Arndt et al. (2023) investigate the implications for developing countries of the Russian invasion of Ukraine and consequent rising commodity prices; Escalante and Mamboundou (2024) investigate the impact of energy and food price shocks on the economy of Portugal. Lal et al. (2011) investigates the socio-economic impacts of climate change on rural USA; Wiebelt et al. (2013) and Wiebelt et al. (2015) analyze the impact of climate change on the economies of Tunisia and Yemen, respectively; Sandhani et al. (2023) analyze the impact of weather shocks on economic growth in India.

of shocks and/or policy interventions (Dervis et al., 1982; Robinson, 1991; Taylor, 1990, 2016). The CGE models deployed here follow good practice views that models should be built to be context-specific and answer specific research questions (EPA, 2017; Taylor, 2016). Following this philosophy, the CGE models used in our analysis are designed to capture the key linkages between the exogenous variables and economic outcomes of particular interest: GDP, consumption, poverty, and undernourishment.

When investigating simultaneous exogenous shocks such as world markets and climate, it is not possible to construct a reliable fixed reference/baseline scenario, which means that standard counterfactual scenario analysis is not feasible. To address the problem, some modern CGE-based studies use the method of systematic sensitivity Analysis (SSA), the essence of which lies in sampling influential model parameters from assumed or estimated distributions and extending classic deterministic CGE model results into a stochastic setting. Under this setup, outcomes are represented as random variables, rather than constants, with respective 'uncertainties' (distributions). The use of SSA is gaining momentum, and many modern CGE-based studies focus explicitly on modeling uncertainty (e.g., Abler et al. 1999; Arndt and Thurlow, 2014; Phimister and Roberts, 2017). Some studies go further and attempt to *understand* drivers of resulting uncertainty through the use of partial rank correlations between sampled model parameters and CGE outcomes (e.g., Hope, 2006) or by interpreting standardized linear regression coefficients between sampled model parameters and CGE outcome variables (Anthoff and Tol, 2013; Chatzivasileiadis et al., 2019). While simple and elegant, this approach cannot be applied to our parameters of interest (climate-associated yields and world market shocks), which have common fundamental driving forces and are highly correlated (see e.g., Ray et al. 2015 for climate-associated yields; Erten and Ocampo, 2013 for world prices of commodities). In this context, our suggested SRP approach uses uncertainty decomposition methods that allow us to sample correlated shocks.

Without delving into the argument that machine learning and data mining methods are just glorified (math) statistics (see e.g., Wlodarczak, 2020), the goal of this paper is to *understand* uncertainty. We use two specific tools: random forest (RF, part of the machine learning field) and the relative importance metric developed by Lindeman, Merenda, and Gold (LMG, part of the data mining field). While the technical details of the methodology are presented in subsection 3.3, the key idea of using these two tools stems from our intention to utilize importance metrics produced by both methods, which quantify the contribution of each shock to the variance of outcome variables given an imposed correlation structure among the shocks.

Our SRP approach consists of three sequential steps: (1) world market and climatic shocks are sampled so that scenarios sufficiently and realistically represent the parameter space of the potential exogenous shocks; (2) the sampled shock scenarios are imposed on country CGE models that estimate the economic outcomes corresponding to shocks; and (3) RF and LMG methods are used to quantify the importance of each shock for various outcomes. Each of the SRP's three steps generates distinct outcomes of interest.

The essential feature of our first step of SRP is the use of historical data on world market prices and flows of foreign exchange (FX) capital to the country (realm of world market uncertainty) as well as agricultural yields and electricity production (realm of domestic climate-associated uncertainty). This data set is then used to estimate a history-based variance-covariance of multivariate normal distribution, from which we sample 10,000 scenarios. As a result, the first stage of the SRP allows for uncertainty/risk comparisons of the input shocks (e.g., identification of the domestic crop sectors with the highest yield volatility). In turn, as a result of the second step of the SRP (CGE simulations in response to sampled shocks), it is possible to measure the scale of uncertainty of the outcomes. The third step of the SRP (RF and LMG uncertainty decomposition) elucidates uncertainty, generating a map of risks from the most to least important for each outcome.

Application of all three SRP steps to Kenya, Rwanda, and Malawi reveals interesting findings. First, historical volatility suggests that Malawi has remarkably high yield uncertainty amongst its major crops (much higher than in Kenya and Rwanda). This fact, as well as the high importance of primary agriculture in the Malawian economy, defines the country's high economic vulnerability to climatic shocks. For GDP, consumption, poverty, and undernourishment, climatic shocks are more important than world market shocks. Rwanda, being at a similar stage of development as Malawi, has a similar risk profile, with domestic productivity volatility dominating the country risk profile. Kenya, the most developed of these three countries, not only has lower total risk/uncertainty but also has a different structure of uncertainty. We find that for consumption and poverty risks in Kenya, world markets play a more significant role than domestic productivity volatility. For GDP and undernourishment, domestic productivity volatility factors dominate Kenya's risk profile, but their importance is the lowest among the three countries.

The remainder of this paper is organized as follows: Section 2 presents a contextual overview of relevant literature that addresses the problem of modeling uncertainty with SSA and explains the necessity of expanding to SRP; Section 3 describes in detail the steps of SRP; Section 4 demonstrates the application of SRP to Kenya, Rwanda, and Malawi; and Section 5 concludes.

2. Quest to quantify and understand uncertainty

CGE models, like many other economic simulation models, have been criticized for their sensitivity to influential model parameterization and assumptions (e.g., Olekseyuk and Schürenberg-Frosch, 2016, Ho et al., 2020). In response, there has been a recent and growing tendency to leave the standard deterministic setup and augment CGE modeling with SSA to essentially transform 'classic' deterministic results to a stochastic setting where outcomes are represented as random variables. The use of SSA is gaining momentum, and some CGE-based studies explicitly focus on modeling uncertainty.

For example, Arndt and Thurlow (2014) apply a probabilistic approach to assess the economic impacts of climate change on Mozambique. The authors provide a range of potential economic outcomes, showing that while large GDP losses in Mozambique are possible, they are unlikely. Similarly, Arndt et al. (2014) explicitly focus on uncertainty in climate forecasts in evaluating economic growth prospects for Malawi. The authors find that although climate change is unlikely to slow economic growth over the next couple of decades, its impacts become more pronounced over time. Phimister and Roberts (2017) model uncertainty of the size of the new onshore wind sector in Northeast Scotland and contrast these results with a CGE model where the sector size is assumed to be known, ultimately demonstrating that modeling uncertainty can significantly influence the modeling results.

These and other similar studies utilizing SSA principles usually focus on proper modeling of the scale of uncertainty, as it can be influential in interpreting both qualitative and quantitative results of simulations. At the same time, some of the more advanced studies that use SSA take one step further and decompose total uncertainty. Three studies in this regard are distinctive. First, Hope (2006) utilizes PAGE2002 integrated assessment model (IAM) to estimate marginal impacts of various greenhouse gases. As a sensitivity analysis, the author constructs a set of partial rank correlations between estimated marginal impacts and influential model parameters. Although it is not clear from the paper how model parameters are sampled, the author concludes that a parameter of equilibrium warming for a doubling of CO2 concentration has highest positive correlation with the marginal impact, while a scientific parameter of the half-life of global warming has highest negative correlation with the marginal impact. Anthoff and Tol (2013) also use an IAM to estimate the contribution of parameter uncertainty to the total uncertainty about the social cost of carbon. In doing so, the authors use two methods: (1) estimating correlation coefficients between the output (social cost of carbon) and individual inputs (parameters); and (2) running a linear regression of the outputs on inputs and computing the standardized regression coefficients. The authors then compare the importance of model parameters based on the two methodologies and conclude that parameters of curvature of the demand for cooling energy, climate sensitivity, and an agriculture quadratic level parameter in China are the most important parameters. Importantly, while Anthoff and Tol (2013) provide more information on parameter sampling, they remain silent about the possibility of the uncertain model parameters being correlated, which suggests that the authors sampled parameters independently. Finally, Chatzivasileiadis et al. (2019) use a similar SSA-based approach to address the problem of parameter uncertainty in CGE modeling of the effects of sea-level rise on the global economy. The uncertainty decomposition is done using a similar method as Anthoff and Tol (2013): by computing the standardized coefficients in linear regressions. The authors conclude that parameters defining land losses have a smaller importance compared to capital and seaport productivity loss parameters. Unlike Anthoff and Tol (2013), Chatzivasileiadis et al. (2019) explicitly recognize that their assumption of independent model parameters can be problematic. The key problem is that when model parameters are correlated, standardized coefficients no longer reflect contribution of covariates to the variance of the outcome variable.

In this context, there are many instances when correlations between certain model parameters must be considered, and when an independence assumption (zero correlations) is not feasible. For example, Webster et al. (2008) address the uncertainty in projections of emissions and costs of atmospheric stabilization for five climate scenarios. The authors explicitly acknowledge that, after assuming distributions of individual parameters, the second-most critical assumption in uncertainty analysis is the correlation among sampled parameters. Acknowledging a lack of empirical data, the authors impose correlation coefficients based on expert elicitation (that are, in turn, based on theory) and assign correlations for parameters reflecting various technological aspects. In this context, Webster et al. (2008) focus on modeling the scale of uncertainty and do not decompose the uncertainty.

Given our interest in modeling uncertainty of exogenous shocks associated with climate-affected productivity and world markets, we cannot ignore correlations among sampled shocks. Unlike Webster et al. (2008), who lack empirical data, there is ample evidence about common fundamental driving forces behind both the operation of world markets and climate-affected yields. For instance, Erten and Ocampo (2013) analyze commodity prices and found four super cycles since 1865 that are driven by movements in global GDP, with non-oil commodity prices following economic growth patterns. Ray et al. (2015) investigate the influence of inter-annual climate variations on crop yields and find that a third of global crop yield variability is driven by climate variation. This empirical work indicates that the model parameters of exogenous shocks that we are analyzing cannot be sampled independently, and their corresponding correlations need to be taken into account in both modeling the total scale of uncertainty and understanding its nature.

3. Integrated analytical framework for Systematic Risk Profiling

3.1.Key characteristics of the core economywide model

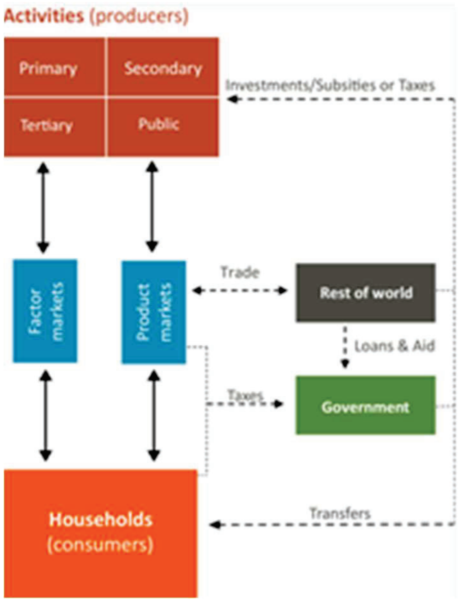
Our SRP approach is based on the standard single-country CGE model developed by the International Food Policy Research Institute (IFPRI), summarized in Table 1. This model has four key features: (1) a focus on the role of international trade including the roles of world prices and the balance of trade; (2) a prominent level of sectoral and household detail; (3) a macroeconomically consistent representation of economic linkages between activities, households, and the rest of the world; and (4) links to a network of poverty and undernourishment microsimulation modules that provide simulation results for variables of interest. The model has been a popular tool in simulating economy-wide adjustments in response to both climatic and world market price shocks in various countries (e.g., Arndt et al., 2023; Siddig et al., 2020; Wiebelt et al., 2013, 2015).

The theoretical properties of the IFPRI CGE model, and other related trade-focused CGE models, are well understood. Their links to standard international trade theory and their macro properties have been explored in numerous articles.[2] The underlying forces at work in CGE models when economies face world price and trade balance shocks are well described in this literature. What makes them complex is the extension to many sectors and households, which leads to empirically important indirect linkages that affect simulation results.

[2] See, for example, Devarajan, Lewis, and Robinson (1990) who use a simple theoretical model to explain how trade-focused CGE models can be seen as an extension of standard trade-theory models. Thierfelder and Robinson (2003) describe how the Stolper-Samuelson and Rybczynski Theorems linking international trade to factor markets operate in CGE models. Devarajan, Lewis, and Robinson (1993) explain how real exchange rates and trade balances work in these models.

Table 1. Specification of the CGE model

Schematic representation of flows



Functional forms

Block	Category	Form/closure
Production	Value-added (factors)	Constant Elasticity of Substitution (CES)
	Intermediates	Leontief
	Top nest	Leontief
Trade	Import	CES
	Export	Constant Elasticity of Transformation (CET)
Households	Consumption	Linear Expenditure System
Closures	Numeraire	Consumer Price Index
	Rest of the World	Current account and world prices are exogenous, exch. rate is endogenous
	Government	Fixed tax rates; (dis)savings adjust to available net revenues
	Savings-Investment	Neoclassical (Savings-Driven Investment)
	Factors	Fully employed & immobile except labor (fully employed & mobile)

Source: Own derivations based on Lofgren et al. (2002).
Note: The detailed explanation of the CGE model, including its equations, can be found in Lofgren et al. (2002). The description of poverty and undernourishment microsimulation modules linked to the CGE model can be found in Pauw and Thurlow (2011).

The application of the CGE model in an SRP analysis involves a number of steps. First, we define a parameter domain of all exogenous shocks that our model can handle (Table 2). This composition is attributed to several trade-offs, including: (1) our intention to provide as much detail as possible while maintaining a standardized approach that can be scaled to many countries; (2) computational intensity at the final stage of uncertainty decomposition which depends on number of shocks (see Subsection 3.3); and (3) availability of historical data. Our domain of shocks consists of 28 exogenous variables that can be broadly classified into 2 categories: external shocks (volatility of world prices and FX capital flows) and domestic shocks (climate-associated sectoral productivity volatility). To illustrate the approach, we explain key shock transmission mechanisms in the model by conducting a simple deterministic analysis of selected shock scenarios for the economy of Kenya.

Table 2. Domain of exogenous shocks

	Shock in CGE	Historical proxy	Units
External (world prices and current account)	1. Grains	Price index of grains	2019 USD
	2. Oilseeds	Price index of oilseeds	2019 USD
	3. Vegetables & fruits	Price index of fruits (average of bananas & oranges)	2019 USD
	4. Beverage crops	Price index of beverages (average of coffee, cocoa & tea)	2019 USD
	5. Other crops	Price index of other crops (average of cotton, rubber & tobacco)	2019 USD
	6. Meat	Price index of meat (average of beef, chicken, and lamb)	2019 USD
	7. Dairy	Price index of beef	2019 USD
	8. Forestry & wood	Price index of timber	2019 USD
	9. Fisheries	Price index of Mexican shrimps	2019 USD
	10. Energy	Price index of energy commodities	2019 USD
	11. Metals & minerals	Price index of metals & minerals	2019 USD
	12. Fertilizers	Price index of fertilizers	2019 USD
	13. Manufacturing	Manufactures unit value index	2019 USD
	14. Services	US CPI services less energy	2019 USD
	15. FX capital flows	Current account	Share of GDP
Domestic (productivity of activities)	16. Cereals	Yield of cereals	Index (2019=100)
	17. Pulses	Yield of pulses	Index (2019=100)
	18. Oilseeds	Yield of oilseeds	Index (2019=100)
	19. Roots	Yield of roots	Index (2019=100)
	20. Vegetables	Yield of vegetables	Index (2019=100)
	21. Fruits	Yield of fruits	Index (2019=100)
	22. Beverage crops	Yield of beverage crops	Index (2019=100)
	23. Nonfood crops	Yield of non-food crops	Index (2019=100)
	24. Livestock	Per capita production of livestock	Index (2019=100)
	25. Milk	Per capita production of milk	Index (2019=100)
	26. Forestry	Per capita production of roundwood	Index (2019=100)
	27. Fisheries	Per capita production of fish	Index (2019=100)
	28. Electricity	Per capita electricity generation	Index (2019=100)

Source: Own calculations based on World Bank, 2024a (price indices & manufactures unit value index); World Bank, 2024b (production of fish); IMF, 2024 (current account); FAO, 2024 (yields & production of livestock, milk & roundwood) and EIA, 2024 (electricity generation).

Kenya is a lower-middle income African country with GDP per capita of 1,970 USD (2019), a national poverty rate of 36.1% (2015) and a national undernourishment[3] rate of 23% (2019) (World Bank, 2024b). The structure of its economy (Table 3) is typical for a lower-middle income African country. Primary agriculture is a large share of economic activity (share of GDP is 22.73% and share of employment is 85.22%). The secondary sector is underdeveloped (share of manufacturing in GDP is 3.63% but the share of manufacturing goods in total demand is 15.96%). The country is a net importer, with a high share of imports of industrial products (81.86%). Exports

[3] Share of the population whose adult-equivalent daily consumption below the minimum calorie requirement defined by the Food and Agriculture Organization of the United Nations.

are mostly services and commodities, with beverage crops (coffee and tea) representing the most significant sector in terms of its export/output ratio (37.44%).

Table 3. Economic structure of Kenya, 2019

	% of total GDP	% of employment	% of total demand	Export % of sectoral output	Export % of total	Import % of sectoral demand	Import % of total
Crops	16.48	57.95	10.06	10.56	23.83	1.87	1.50
Cereals	3.72	10.48	2.09			9.00	1.50
Beverage crops	2.38	10.44	1.02	37.44	12.79		
Livestock	3.95	17.49	2.62				
Forestry	1.67	7.09	1.11				
Fishing	0.62	2.69	0.43				
Mining	1.58	0.61	0.97			3.99	0.34
Agroprocessing	4.98	0.37	9.40	12.12	23.04	11.31	7.42
Other manufacturing	3.63	0.24	15.96	11.27	13.91	66.58	81.86
Utilities	2.36	0.10	1.50				
Construction	6.13	0.94	7.94				
Food services	1.27	0.56	1.68	5.85	2.19		
Social services	12.57	2.35	9.89				
Other services	44.74	9.62	38.43	4.50	37.03	2.30	8.88
Total	**100.00**	**100.00**	**100.00**	**5.07**	**100.00**	**12.80**	**100.00**

Source: Own calculations based on the 2019 Social Accounting Matrix (SAM)[4] for Kenya. Available at Harward Dataverse (for details, see IFPRI, 2021 and Thurlow, 2021).

In this context, we consider three types of shocks that could be particularly relevant for Kenya: (1) volatility of FX capital flows (measured by the current account, see model closures in Table 1), which affects the real exchange rate with impacts that reverberate across the economy; (2) volatility of the world market price of beverage crops given their export importance and linkages to farmers; and (3) climate-induced volatility of cereal yields, which are important crops for poor farmers and play a significant role in levels of undernourishment.

For each of these three types of shocks, we consider both positive and negative scenarios and arbitrarily select two possible realizations. For FX capital flows, we increase/decrease the current account deficit by +/- 2% of GDP relative to the base level of 5.11% of GDP (in the last 20 years, Kenya's current account deficit ranged from -0.6% of GDP to -9.3% of GDP, see IMF, 2024).

[4] A SAM is a detailed snapshot of all transactions between agents of an economy (e.g., activities, households, the rest of the world) and is used as a primary data input for a CGE model (for a detailed explanation, see Pyatt and Round, 1985).

For world market prices of beverages and yield of cereals, we select scenarios of +/- 20% relative to base levels. According to our estimates based on World Bank (2024a) and FAO (2024) data, over the last 20 years, year-to-year changes of world market price of beverages ranged from -21.74% to 20.22%, and year-to-year change of the yield for cereals in Kenya ranged from -21.98% to 37.60%). Key simulation results for these shock scenarios are outlined below and in Table 4.

Table 4. Deterministic analysis of shocks that could impact the Kenyan economy

Outcome	Base (2019 levels)	Shocks scenarios (% difference versus base)					
		FX capital flows (current account)		WP of beverages		Yields of cereals	
		↑ by 2% of GDP	↓ by 2% of GDP	+20%	-20%	+20%	-20%
GDP at factor costs	91.97	-0.33	0.12	-0.04	0.03	0.99	-1.41
Agriculture	20.90	-0.47	0.43	0.09	-0.30	2.60	-3.31
Industry	17.18	0.80	-1.71	-0.14	0.14	0.78	-1.23
Services	53.88	-0.63	0.58	-0.06	0.12	0.44	-0.73
Private consumption	78.33	0.37	-0.37	0.61	-0.46	0.94	-1.48
Urban	47.85	0.77	-0.79	0.27	-0.08	1.10	-1.79
Rural	30.47	-0.26	0.28	1.13	-1.05	0.70	-1.00
Fixed investment	18.64	5.30	-7.79	0.08	0.02	0.57	-0.77
Export	8.58	-9.97	10.71	-2.07	0.63	0.52	-0.06
Imports	17.93	3.49	-4.12	1.73	-1.32	-0.02	0.35
Nominal exch. rate	100.00	-7.13	7.56	-8.37	9.05	0.64	-0.79
Real exch. rate	76.85	-7.94	8.36	-7.11	7.37	0.30	-0.27
Poverty (%)	36.07	-0.24	0.37	-1.13	0.94	-1.00	1.50
Urban (%)	29.04	-0.82	1.35	-0.47	0.68	-0.95	2.09
Rural (%)	39.99	0.09	-0.17	-1.49	1.08	-1.03	1.18
Undernourishment (%)	23.01	-0.19	0.22	-0.50	0.41	-1.73	2.11
Urban (%)	14.23	-0.38	0.54	-0.08	0.08	-1.50	2.22
Rural (%)	27.91	-0.09	0.05	-0.73	0.59	-1.86	2.05

Note: For poverty and undernourishment, shock scenarios as difference versus base.

Volatility of FX capital flows. We assume that foreign FX flows enter the economy as foreign savings denominated in FX currency (see Savings-Investment Closure in Table 1). As a result, changes in FX capital flows directly affect two aspects of the economy: the available foreign currency in the country, which influences both the real exchange rate and trade volumes, and investment demand (primarily in construction). Richer urban households have a higher share of imports in their consumption and are more exposed to fluctuations in FX flows than rural households. Consequently, urban poverty is more sensitive to FX flows than rural poverty. At the same time, the impact on sectoral GDP is dependent on the trade orientation of the sectors. Nontradable construction (the largest part of the industrial sector) reacts to the investment balance and is the most sensitive sector, while more trade-oriented agriculture and services sectors depend on nominal exchange rates (which grow when FX flows decrease and the exchange rate weakens, and vice-versa).

Volatility of world market price of beverages. The impact of these scenarios resemble FX capital flow shocks in that they affect the availability of FX as well as relative prices. Given the importance of beverage crops in total exports, changes in the world market price of beverage crops affects the real exchange rate. At the same time, unlike FX flows, the impacts of world market price fluctuations are very unevenly distributed, and mostly affect producers of these crops: rural households whose incomes are directly affected. Because most of the poor in Kenya are rural farmers, national poverty is more sensitive to beverage price fluctuations compared to FX flows.

Volatility of domestic yields of cereals. Unlike the other two shocks, these scenarios are associated with domestic climate factors. Given the direct linkage to production, domestic yield shocks significantly affect agricultural GDP and total GDP. In terms of the consumption effect, net consumers (urban households) are more sensitive to shocks than rural households. Finally, given the importance of this sector in defining calorie availability, volatility of domestic yields of cereals has a particularly pronounced effect on undernourishment rates.

A major problem is that realization of each of these and other shock scenarios (e.g., world market price of energy, domestic yields of pulses, etc.) as well as their combinations is not certain, meaning that proper identification of important risks is not possible without drawing on the uncertainty approach of SSA.

3.2. Utilizing historical data to characterize uncertain shocks

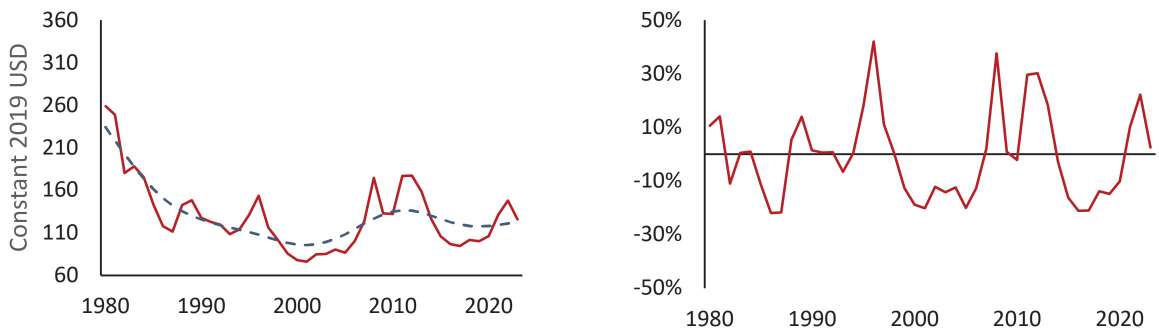
Unlike many SSA-focused studies (e.g., Webster et al., 2008; Anthoff and Tol, 2013; Chatzivasileiadis et al. 2019), uncertain model parameters of interest have available historical data. This availability allows us to utilize a straightforward approach to analysis commonly used in macroeconomic and finance models.

For each of the parameters in the defined domain of exogenous shocks (Table 2), we construct historical levels and use a Hodrick–Prescott (HP) filter for yearly data (see Hodrick and Prescott, 1997). We then extract a long-term trend component and assume that (relative) deviations from the trend reflect short-term volatility/risk. Figure 1 represents the world market prices of beverage crops and grains from 1980 to 2023 (with a blue dashed line representing the long-term trend and a red line representing short-term volatility around that trend). Figures to the right show the relative deviation from the respective trends.

Figure 1. Historical data of world market prices

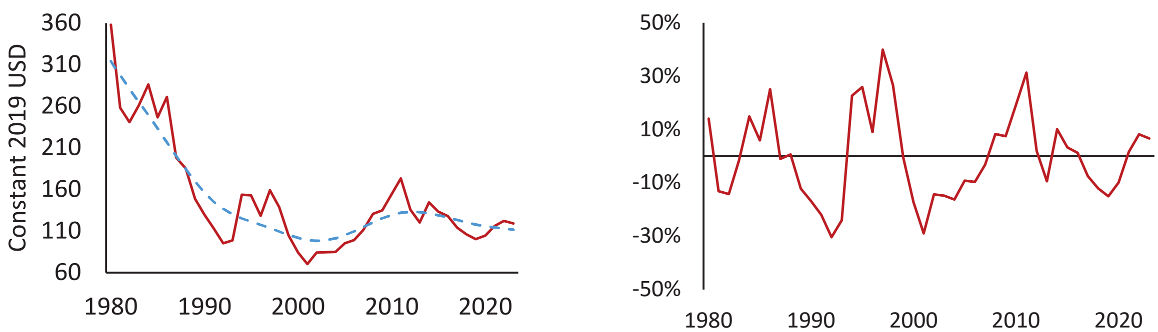
Beverage crops

Historical price index & HP filter trend (dashed) | Relative deviation from HP filter trend



Grains

Historical price index & HP filter trend (dashed) | Relative deviation from HP filter trend



Note: HP filter trend: Long-term trend based on the Hodrick–Prescott filter for yearly data (λ = 100, for details, see Hodrick and Prescott, 1997).

Source: Own calculations based on World Bank, 2024a.

As can be seen from Figure 1, this approach allows us to calculate not only respective variances of the two shocks (e.g., % deviations for beverage crops and grains respectively, standard deviations are 16.34% and 16.39%), but also estimate the covariance between the two. Both trends and short-term volatility factors of the two commodity prices have been mostly codirectional, and in 30 of 44 years, signs of the shocks (relative deviation from trends) are the same, with the correlation coefficient between the two equal to 0.38. This value is relatively high, meaning that an independence assumption is not valid (at least for these two shocks). Moreover, some of the correlations calculated using this method suggest that, in some instances, the economies are likely to be vulnerable to simultaneous shocks (for example, world market prices of manufacturing, energy, fertilizers, and metals are highly correlated). The same historical approach is used to consider volatility of domestic productivity. Long term HP trends are treated as long-term fundamental factors that drive long-term yields (mechanization and education, among others), while variations around long-term trends are considered to be climate-associated volatility factors. In this context, we combine the two domains (world market and domestic sectoral productivity risks) and fully specify the variance-covariance matrix, and, together with our assumption of zero means, sample all shocks from a multivariate Gaussian distribution. We follow the standard SSA approach and use the method of Latin Hypercube Sampling. Because our goal is to decompose the final resulting uncertainty using data-demanding LMG and RF methods, we select a relatively large sample size of 10,000.[5]

The approach of utilizing historical data to estimate a variance-covariance matrix might be considered overly simplistic from the perspective of modern macroeconometrics (see Hamilton, 2018). It is, however, sufficient for our purpose of roughly estimating the structure of variances and correlations of our shocks. Compared to previous studies that utilize expert elicitation to assign both variances and covariances, this approach represents an advance and is flexible enough for further modifications and improvements. History-based estimates of shock volatility can be further improved or refined and combined with expert elicitations or other models to define the future volatility of shocks, individual variances, and estimated correlations. These can be adjusted, for example, if there is an indication or belief that an unprecedented scale of some shocks is expected or that certain shocks in the future will be more highly correlated than in the past.

[5] In sampling, we utilize the R software and package 'EnvStats' by Millard (2013).

3.3.Machine learning and data mining methods used in post simulation processing

After 10,000 shocks scenarios are sampled, they are supplied to the CGE model, which produces corresponding outcomes (10,000 results of GDP, consumption, poverty, undernourishment per country). While many standard SSA-based studies stop at this point (because they produced outcomes that are no longer fixed and characterized by uncertainty), our goal is to make an additional step to understand this uncertainty.

In this context, the key step of the SRP post-simulation stage is utilization of metamodeling concepts (see e.g., Villa-Vialaneix et al. 2012; Ziesmer et al. 2023). Its essence is emulation of relationships captured by our CGE model (e.g., dependence of GDP, consumption, poverty, and undernourishment on *all* sampled shocks) such that we can quantify the contribution of each shock to the resulting uncertainty of each outcome. Given this specific goal, we utilize two metamodeling methods and employ corresponding importance quantification methods: (1) multiple linear regression and the Lindeman, Merenda, and Gold (1980) importance metric and (2) random forest based on the classification and regression tree (CART) algorithm by Breiman et al. (1984) and Breiman (2001) (RF-CART). These methods both use marginal variance decomposition, and unlike their alternative (conditional variance decomposition), are more appropriate for our purposes of explaining and understanding uncertainty relationships (for more details, see Grömping, 2015).

3.3.1. *Multiple linear regression and Lindeman, Merenda, and Gold importance metric*

Following Grömping (2006, 2009) who popularized the Lindeman, Merenda, and Gold (LMG) importance metric, denote the linear regression model of outcome Y and its variance $Var(Y)$ as:

$$Y = \beta_0 + X_1\beta_1 + \cdots + X_p\beta_p + \epsilon$$

$$Var(Y) = \sum_{j=1}^{p} \beta_j^2 v_j + 2\sum_{j=1}^{p-1}\sum_{k=j+1}^{p} \beta_j \beta_k \sqrt{v_j v_k}\, \rho_{jk} + \sigma^2$$

where $X_j, j = 1, \dots, p$, is sampled shocks (regressor variables); ε is an error term (uncorrelated to the regressors with mean zero and variance $\sigma^2 > 0$); v_j are variances of sampled shocks; and ρ_{jk} are the correlations between sampled shocks (the $p \times p$ covariance matrix between shocks is positive definite).

Importance methods based on linear regressions are designed to decompose the explained variance part of $Var(Y)$ (first two terms except σ^2), which can also be rewritten as R^2 (the ratio of the model sum of squares to the total sum of squares). In the case of uncorrelated regressors (as in Anthoff and Tol, 2013 and Chatzivasileiadis et al., 2019), R^2 can be uniquely decomposed. However, for correlated regressors, the decomposition is more complicated as the increase of R^2 attributed to a certain regressor X_j depends on which regressors are already present in the model, and a unique decomposition is defined for any particular order of regressors.

In this context, LMG averages order-dependent allocations over all *p!* orderings.

$$LMG(x_k) = \frac{1}{p!} \sum_{r\, permutation} seq\, R^2 (\{x_k\}/r)$$

$$seq\, R^2\big(\{x_k\} \big| S_k(r)\big) = R^2\big(\{x_k\} \cup S_k(r)\big) - R^2\big(S_k(r)\big)$$

where permutation of the available regressors $x_1, \dots, x_p$ is denoted by the tuple of indices $r = (r_1, \dots, r_p)$, and $S_k(r)$ is the set of regressors entered the model before regressor x_k in the order *r*.

In our calculations of LMG relative importance metrics, we utilize the R-package 'relaimpo' by Grömping (2006). The LMG metric in our case is (relatively) computationally intensive. Given the number of exogenous shocks of interest (28, see Table 2), per one outcome Y, the number of LMG permutations required for 28 covariates is 28! (about 3×10^{28}).[6]

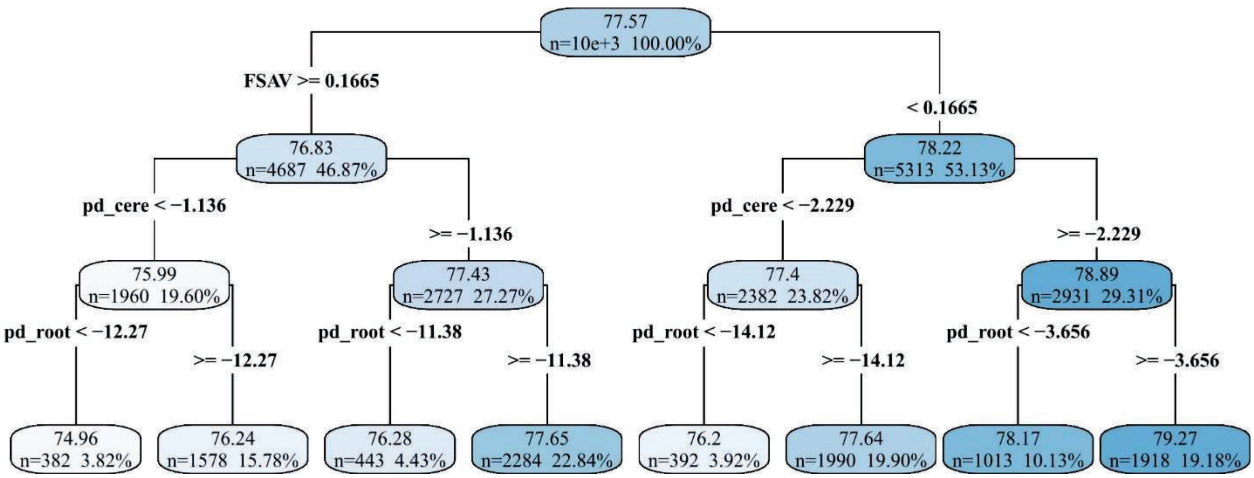
3.3.2. *Random Forest regression and its importance metric*

Unlike multiple linear regression, importance metrics produced by Random Forest require an explanation of underlying concepts of the modeling approach. In what follows, we provide simplified explanations of the key elements of the random forest machine learning algorithm for regression tasks (for detailed explanations, see Breiman, 1984, 2001; Grömping, 2009, 2015).

Random Forest is a machine learning algorithm that builds and combines multiple decision trees to produce a prediction model. In turn, a decision tree can be thought of as a multidimensional step function that recursively splits the feature space into increasingly homogeneous regions. Figure 2 represents a simplified CART by Breiman et al. (1984) for total consumption in Kenya (billions of 2019 USD). The tree is based on three shocks: FSAV (FX capital flows), pd_cere (yield of cereals), and pd_root (yield of roots). Each node shows the predicted value of consumption and the number of observations. The branch labels show the criteria used to split the nodes. For each node, the predicted value is the average of the target variable (consumption) for all observations that fall into that node, and the splitting criterion is overall node impurity (measured as the total sum of squared deviations from node centers) and the split for each node is aimed at its maximum reduction.

[6] It takes about 6 hours to calculate LMG for one outcome Y (64 GB RAM, 6.00GHz processor, with parallelization of calculations for 2 outcomes at the time)

Figure 2. Example of CART tree to predict total consumption in Kenya (billions of 2019 USD)



Note: Simplified tree based on 3 shocks: FSAV (FX capital flows), pd_cere and pd_root (yields of cerals and roots).
Source: Own derivations using R-packages `rpart' (R Foundation, 2024a) and `rpart.plot' (R Foundation, 2024b).

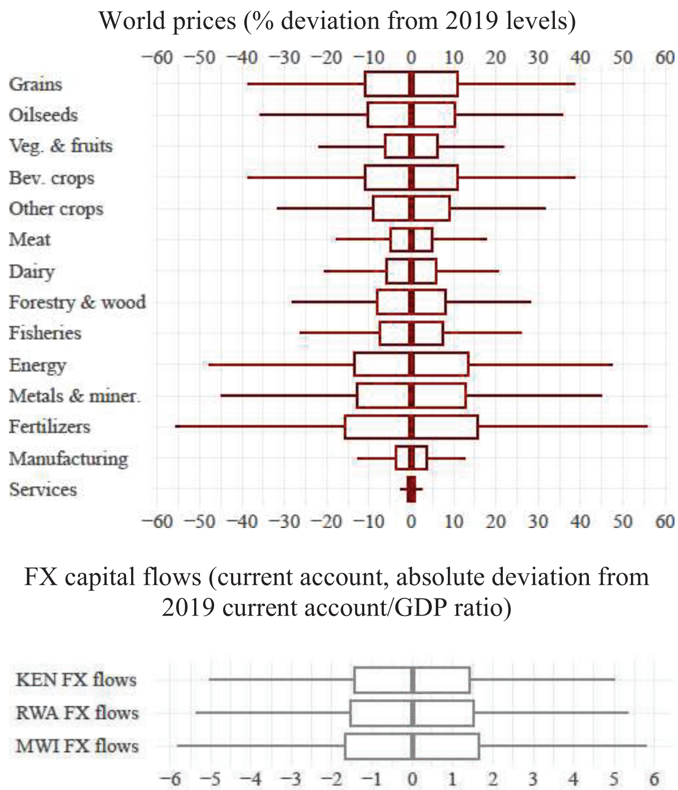
In the illustrative single-tree example in Figure 2, we limit the tree's growth to only three shocks, and the CART algorithm selected the three most informative features (of 28 shocks) to split the data. A random forest, however, consists of many trees, that can include many shocks, and final forest predictions are averages across trees. A random forest is random because (1) each tree is based on a random subset of the observations and (2) each split within each tree is created based on a random subset of candidate variables (Grömping, 2009). In our case, we utilize the R-package ‘random forest’ (R Foundation, 2024c) with specifications based on recommendations given by Breiman (2001 and 2003) for regressions with many covariates. The number of variables randomly sampled as candidates at each split equals 9 (p/3=28/3≈9) and trees are grown to the maximum possible number of trees (equal to 1,000). As a measure of variable importance, we use ‘standard average node impurity reduction’ which we normalize to 100% for comparison with LMG metrics.

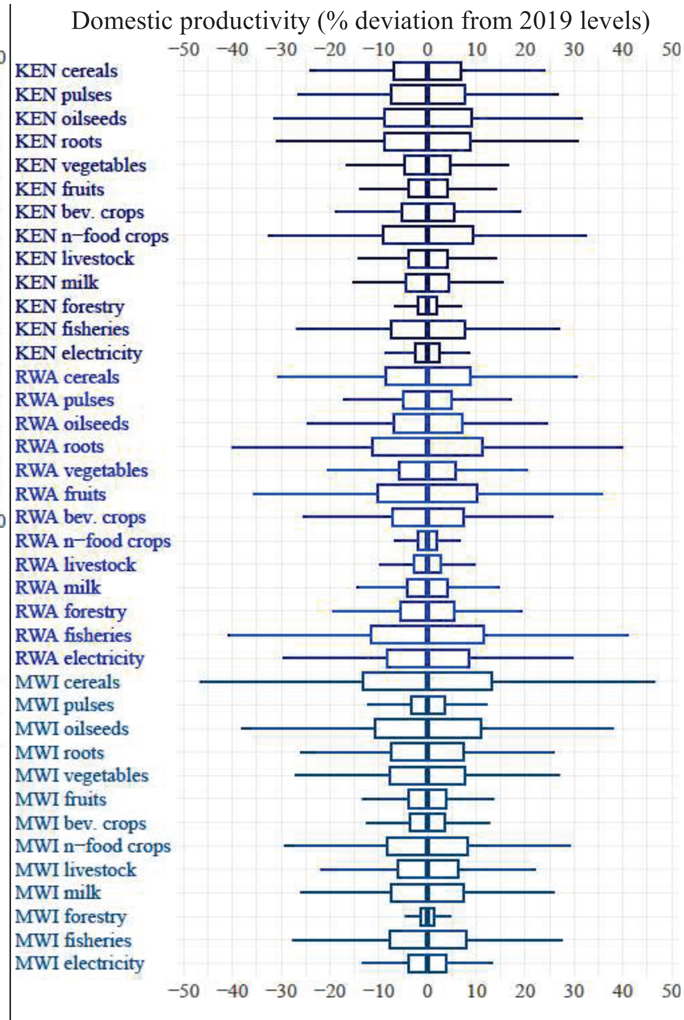
4. Model lessons from Kenya, Rwanda, and Malawi

4.1.Measuring shock uncertainty

The first step of SRP, estimating historical volatility of shocks, delineates the scale of potential shocks to these economies. Figures 3 and 4 represent characteristics of shocks for Kenya, Rwanda, and Malawi: world price changes are the same for all countries, but FX capital flows and domestic productivity shocks are country specific.

Figure 3. Marginal distributions[7] of shocks sampled for Kenya, Rwanda, and Malawi





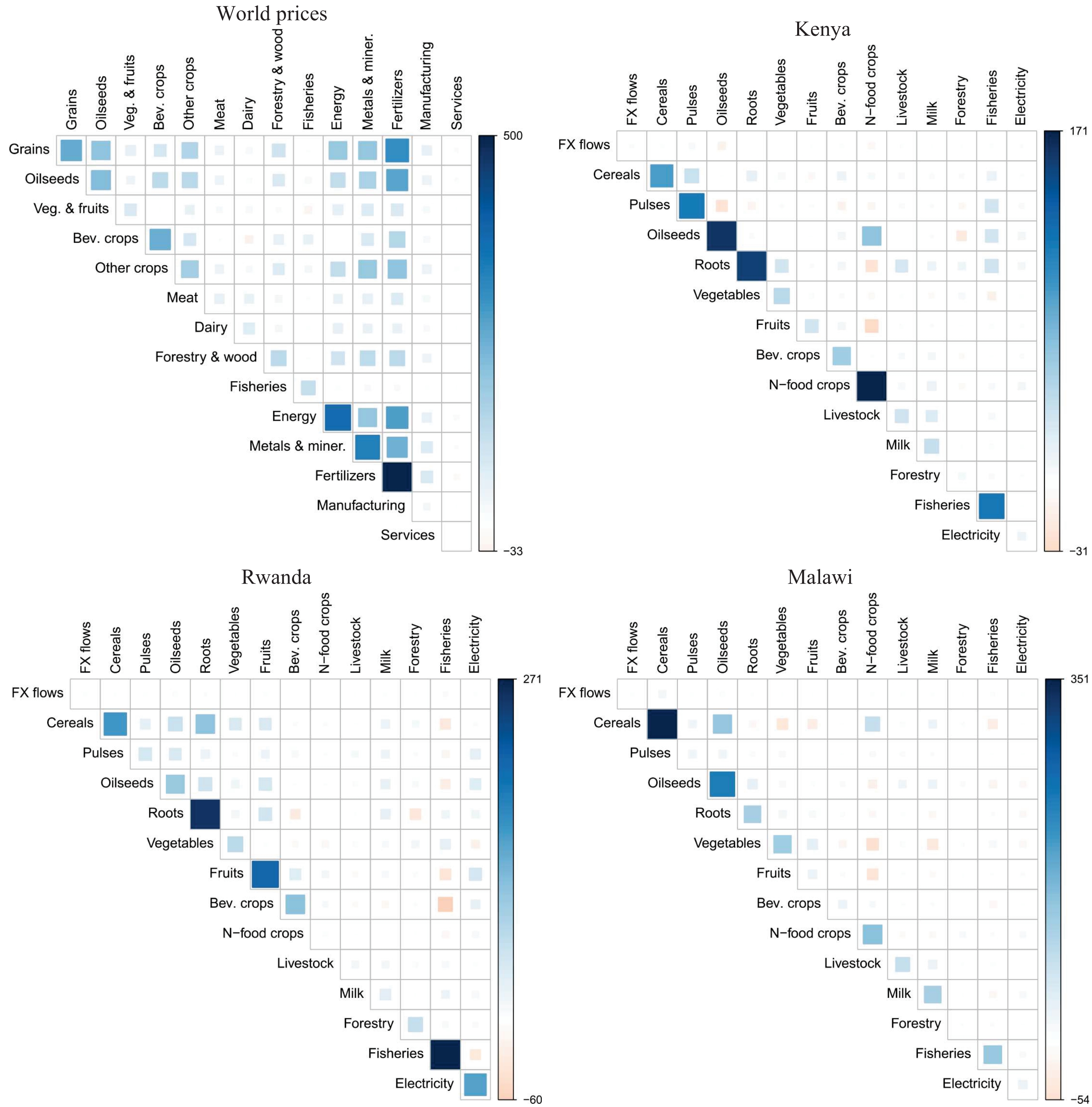
Note 1: KEN=Kenya, RWA=Rwanda, MWI=Malawi.

Note 2: Although some shocks' variation around trends were not symmetric, and the averages are not strictly 0, we do not believe that these patterns will repeat themselves; therefore, we assume zero means and zero skewness across all shocks' distributions.

Source: Own derivations based on historical data (sample size of shocks scenarios for each country: 10,000).

[7] The figure represents stacked boxplots of sampled shocks. A boxplot is a graphical representation of data that shows the distribution (the box represents the 2nd and 3rd quartiles (with the median in between), while the 'whiskers' extend to the 1st and 4th quartiles).

Figure 4. Variance-covariance structure of sampled shocks



Note 1: Each cell of the matrix represents the covariance between two variables: the cell sizes range from empty (zero covariance) to full squares (maximum covariance), and the cell colors range from red (negative) to blue (positive).
Note 2: Covariances between world prices and country specific shocks are low and not shown here.
Source: Own derivations based on historical data (sample size of shocks scenarios for each country: 10,000).

External shocks: world prices. World prices of primary commodities are the most volatile, followed by manufacturing and then services. In turn, within agricultural commodities, the price of beverage crops is the most volatile, followed by grains. Moreover, world prices of primary commodities are highly positively correlated, which suggests that, *ceteris paribus*, countries that are highly dependent on the import/export of volatile commodities such as energy, metals, fertilizers, beverage crops, and grains should be more exposed to turbulences on world markets.

External shocks: FX capital flows. All three countries are characterized by high volatility of the current account (e.g., in Rwanda in 1993 the current account was -6 % of GDP and moved to +7% of GDP in 1994). Most of the sharp movements of the trade balance were associated with some sort of domestic or international macroeconomic or political instability that led to panic sales of local currencies and FX capital withdrawal. Although similar in size, FX capital flows to Kenya are less uncertain, followed by Rwanda and Malawi.

Domestic productivity. Depending on climatic conditions, some sectors and countries have higher productivity volatility than others. Most notably, volatility of agricultural productivity in Malawi is remarkably high across all sectors. As evident from variance-covariance presented in Figure 4, it is about 1.5 times more uncertain then in Rwanda, and about 2 times more uncertain then in Kenya. These differences are due either to varying climatic exposure, geographical factors, or differences in levels of development between the countries (e.g., more developed countries could have better irrigation and drought management), but our crude historical estimates do not support more refined analysis.

4.2.Measuring economic uncertainty

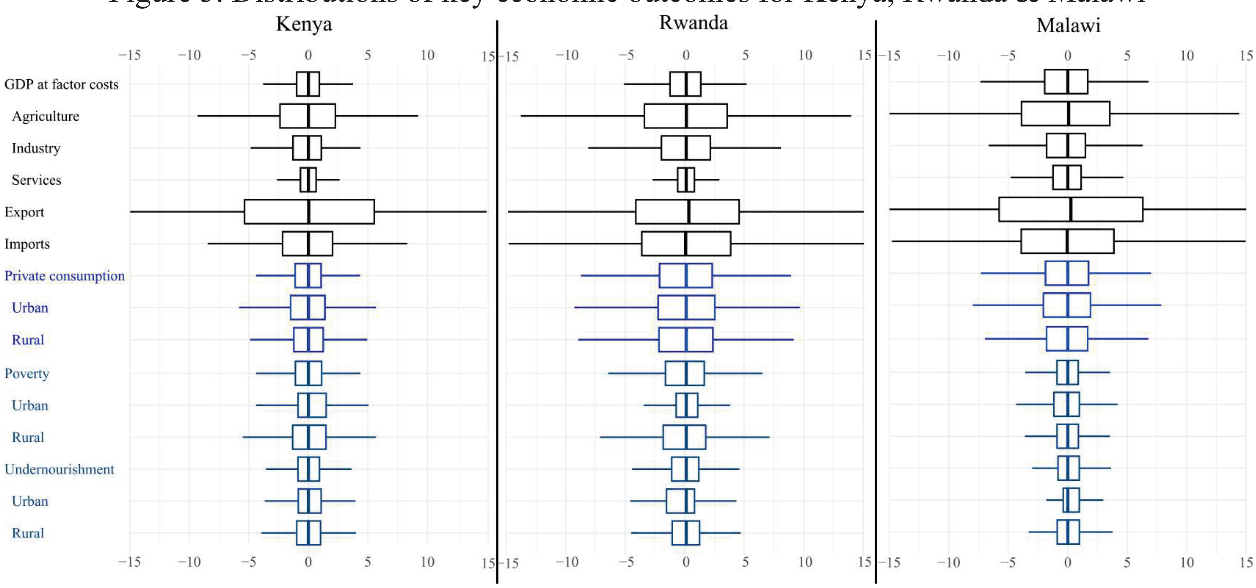
The second stage of the SRP models the economic uncertainty resulting from the shock scenarios using CGE models of Kenya, Rwanda, and Malawi. Core country characteristics within the CGE models are outlined in Table 1. In considering model results, we focus on key characteristics of the different countries (Table 5) and distributions of key outcomes resulting from the simulations (Figure 5 and Table 6).

Table 5. Key economic characteristics of Kenya, Rwanda & Malawi

	Kenya	Rwanda	Malawi
Agriculture (% of GDP)	22.73	25.73	24.47
Industry (% of GDP)	18.68	20.63	19.71
Services (% of GDP)	58.59	53.64	55.82
Export (% of output)	5.07	12.94	5.77
Import (% of consumption)	12.80	24.72	17.24
Current account (% of GDP)	-5.11	-10.57	-13.58
Per capita consumption, USD	1,711	596	478
Poverty rate - national	36.1	38.2	50.7
Urban	29.0	15.6	18.9
Rural	40.0	43.1	56.6
Undernourishment rate - national	23.0	32.7	16.5
Urban	14.2	19.8	8.2
Rural	27.9	35.5	18.0

Source: Own derivations based on constructed country SAMs for 2019 and World Bank (2024b).

Figure 5. Distributions of key economic outcomes for Kenya, Rwanda & Malawi



Note: Boxplots (without outliers) are based on normalized outcome variables (for poverty and undernourishment, as absolute deviations from base 2019 levels, for all other variables as % deviation from base 2019 levels;).
Source: Own derivations based on simulations data.

Table 6. Standard deviations (STD), minimum (min) and maximum (max) values of key economic outcomes for Kenya, Rwanda & Malawi

	Kenya			Rwanda			Malawi		
	STD	Min	Max	STD	Min	Max	STD	Min	Max
GDP at factor costs	1.40	-5.79	4.84	2.00	-8.61	5.53	2.80	-13.22	6.77
Agriculture	3.40	-13.04	12.26	5.22	-19.59	18.13	5.53	-21.59	15.56
Industry	1.81	-10.36	4.66	3.10	-12.71	9.36	2.75	-14.34	6.68
Services	0.98	-3.50	3.44	1.10	-5.08	3.58	1.92	-9.30	4.96
Export	8.96	-34.07	31.85	6.72	-28.77	16.21	10.37	-41.38	27.75
Imports	3.21	-13.54	12.60	5.45	-15.60	20.00	5.73	-16.00	23.53
Private consumption	1.60	-5.80	5.23	3.29	-12.38	13.00	2.87	-13.85	8.84
Urban	2.16	-9.08	6.80	3.46	-11.60	12.95	3.25	-16.13	10.78
Rural	1.82	-6.29	7.57	3.39	-13.03	13.15	2.67	-12.25	7.47
Poverty	1.58	-5.41	6.87	2.57	-9.33	10.63	1.25	-4.71	4.62
Urban	1.98	-5.56	8.77	1.54	-4.81	6.65	1.52	-4.35	11.56
Rural	1.97	-7.97	7.08	2.81	-10.31	11.49	1.27	-5.23	4.44
Undernourishment	1.36	-4.30	5.21	1.76	-5.97	7.26	1.46	-3.00	7.63
Urban	1.48	-3.82	6.26	1.56	-5.31	5.36	1.34	-1.81	8.93
Rural	1.52	-5.31	5.74	1.82	-6.12	7.67	1.49	-3.29	7.40

Note: Similar to boxplots, for poverty and undernourishment, calculations are based on absolute deviations from base 2019 levels, for all other variables as % deviation from base 2019 levels.
Source: Own derivations based on simulations data.

The Kenyan economy is the least vulnerable to shocks. The volatility of its three broad sectors (agriculture, industry, and services) and private consumption are the lowest among the three countries. Malawi has the highest GDP volatility, and Rwanda is in between. Besides varying uncertainty of degrees of shocks (Figures 3 and 4), the differences in economic structures of the countries (Table 5) plays a key role in how these shocks are propagated. Agriculture is the most volatile sector in all three economies, given its direct exposure to climate-affected productivity shocks, and its volatility and importance in the economy significantly defines economy-wide propagation of its risks. In Kenya, the share of agriculture in the economy is 22.73% (lowest), and so is the scale of most of the productivity shocks. Malawi has the highest scale of productivity shocks and high importance of agriculture in GDP. Uncertainty in consumption in all three countries has similar patterns. In general, it is more volatile than GDP, and consumption of urban households is more volatile than that of rural households.

For variation of poverty and undernourishment rates, the initial base rates play a significant role in defining a country's vulnerability. The densities of people who could be pushed above or below poverty lines and undernourishment (calorie) thresholds in response to positive or negative shocks depend on starting rates. Variation in poverty and undernourishment rates in Kenya and Malawi is asymmetric and skewed towards negative outcomes (increases in poverty and undernourishment). Furthermore, according to World Bank (2024b), Rwanda has the highest undernourishment rate among the three countries (32.7 %), and according to our model, is the most vulnerable to shocks (highest standard deviations and maximum values). This result could signal that either the country is distinctly vulnerable to shocks, or that the national undernourishment rates that we used to calibrate the undernourishment microsimulation module have some data problems.

4.3. Understanding economic uncertainty

Comparison of the importance metrics (LMG versus RF-CART) is not our primary goal, and in presenting the uncertainty decomposition, we use a simple ad hoc rule. For each variable, we present the uncertainty decomposition based on either LMG or RF-CART, and the selection depends on the higher explained variance in the underlying metamodel (R^2). The logic behind this approach is simple: variable importance decomposition should be based on the metamodel that better mimics the CGE model. In this context, we also omit discussion about why the linear or random forest metamodel better approximates the CGE model outcomes and why uncertainty decomposition between the two methods sometimes differs. For our analysis, we find that, broadly, the two methods do not differ qualitatively, especially in defining the more important shocks (for methodological discussion, see Grömping, 2009 and 2015).

Table 7. Risk decomposition of GDP and private consumption for Kenya, Rwanda, and Malawi

	Shock	Kenya Total GDP LM, R^2 = 97.4	Kenya Private consumption Total LM, R^2 = 98.3	Kenya Private consumption Urban LM, R^2 = 95.9	Kenya Private consumption Rural LM, R^2 = 96.5	Rwanda Total GDP LM, R^2 = 96.1	Rwanda Private consumption Total LM, R^2 = 97.0	Rwanda Private consumption Urban LM, R^2 = 97.4	Rwanda Private consumption Rural LM, R^2 = 97.0	Malawi Total GDP RF, R^2 = 93.1	Malawi Private consumption Total LM, R^2 = 91.6	Malawi Private consumption Urban LM, R^2 = 88.9	Malawi Private consumption Rural LM, R^2 = 93.8
External (world prices and current account)	Grains	1.19	3.08	2.25	3.34	0.63	2.93	4.76	1.45	1.36	1.18	1.26	1.12
	Oilseeds	1.66	3.02	4.99	2.83	0.95	1.92	3.18	1.07	0.76	0.63	0.65	0.64
	Veg. & fruits	1.12	1.04	1.59	1.35	2.48	2.16	2.34	1.78	2.46	5.46	6.40	4.48
	Bev. crops	0.60	6.27	1.37	19.81	0.85	2.57	1.14	4.53	0.36	1.14	1.35	0.98
	Other crops	1.13	1.26	1.52	2.06	0.75	1.37	2.11	0.90	0.34	1.03	1.50	0.79
	Meat	0.87	1.67	1.39	2.15	0.71	2.25	2.06	2.19	0.40	2.14	2.19	2.02
	Dairy	1.92	1.09	1.71	5.84	0.62	2.21	1.81	2.35	0.38	1.99	2.44	1.60
	For. & wood	1.98	0.78	0.68	1.58	1.37	2.26	2.65	1.75	0.53	0.76	0.80	0.75
	Fisheries	1.27	1.33	0.96	2.54	0.97	0.96	0.69	1.16	1.40	3.03	3.56	2.52
	Energy	1.30	16.52	9.31	14.13	0.51	16.75	23.69	9.48	1.62	7.36	9.34	5.53
	Met. & min.	2.07	0.82	0.86	1.35	2.40	2.54	3.15	1.82	0.49	0.71	0.77	0.75
	Fertilizers	1.19	3.74	2.13	5.07	0.78	4.03	6.24	2.12	0.95	0.84	0.79	0.97
	Manufactur.	1.41	1.20	0.83	2.65	0.89	1.97	2.63	1.35	0.46	1.03	1.07	0.99
	Services	2.57	8.73	7.14	4.15	0.91	6.28	10.80	2.88	1.60	2.41	2.89	1.95
	FX cap. flow	2.61	1.25	2.46	5.19	2.07	6.86	6.87	5.96	1.18	2.76	2.91	2.98
	Total	**22.90**	**51.80**	**39.18**	**74.04**	**16.88**	**57.09**	**74.13**	**40.80**	**14.30**	**32.47**	**37.90**	**28.05**
Domestic (productivity of activities)	Cereals	21.50	17.10	14.94	5.50	14.54	7.78	3.87	11.40	59.17	37.91	36.12	37.44
	Pulses	3.94	3.49	3.46	1.11	2.49	1.17	0.56	2.01	5.18	4.99	3.64	6.03
	Oilseeds	0.40	0.37	0.85	1.97	6.52	3.22	2.13	4.10	10.80	13.36	10.35	15.52
	Roots	20.30	5.98	12.51	2.30	36.72	13.81	7.04	19.68	0.96	0.95	0.91	1.36
	Vegetables	7.65	1.48	3.99	2.47	2.01	0.52	0.60	0.76	4.47	3.57	1.96	5.17
	Fruits	1.10	3.68	3.24	1.66	11.21	4.51	2.55	6.14	0.74	0.61	0.59	0.80
	Bev. crops	4.83	5.94	3.55	4.65	0.48	3.75	3.93	3.15	0.36	0.42	0.33	0.56
	N-food crop	0.50	0.53	0.62	0.62	0.57	1.47	1.50	1.41	0.61	1.55	1.45	1.60
	Livestock	7.84	4.11	9.86	1.96	1.25	0.53	0.28	0.84	1.07	1.41	2.90	0.73
	Milk	3.28	1.47	3.21	0.91	3.40	0.79	0.55	1.09	0.46	0.71	0.64	0.99
	Forestry	0.90	0.79	1.01	1.11	2.34	3.56	1.08	6.91	0.40	0.57	0.71	0.54
	Fisheries	3.45	1.80	2.33	0.89	0.83	0.66	0.77	0.55	1.10	1.05	2.11	0.54
	Electricity	1.41	1.44	1.24	0.80	0.76	1.15	1.03	1.14	0.39	0.43	0.40	0.66
	Total	**77.10**	**48.20**	**60.82**	**25.96**	**83.12**	**42.91**	**25.87**	**59.20**	**85.70**	**67.53**	**62.10**	**71.95**

Source: Own derivations based on simulations data.

Table 7 presents the risk decomposition of total GDP and consumption outcomes. Most importantly, climate-driven domestic productivity factors dominate GDP uncertainty in all three countries. Given the direct impact of productivity on GDP, this result is not surprising. In Kenya, the total sum of domestic factors is 77.1%, but in Rwanda and Malawi it is higher (83.12% and 85.7%, respectively). At the sectoral level, cereal productivity volatility is the greatest risk factor for GDP uncertainty in Kenya and Malawi; in Rwanda, it is the second greatest risk (cereal yield volatility accounts for 14.54% of GDP risks), with the top risk being root yield uncertainty, which makes up 36.72% of GDP risks. Other factors that notably affect GDP uncertainty include root yield volatility in Kenya and oilseed yield volatility in Malawi (although in Malawi cereals yield volatility dominates GDP uncertainty with 59.17%).

Consumption uncertainty varies across the three countries. For total consumption, external uncertainty factors are more significant in Kenya and Rwanda, while domestic productivity volatility is the dominant risk in Malawi. However, there are notable differences within household types. In Kenya, for rural households, external uncertainty is more important (74.04% of total risk), with the world price of export beverage crops being the key factor (19.81%). In contrast, for urban households, domestic production uncertainty plays a larger role (60.82% of total risk), with cereal yield volatility being the most important risk factor (14.94%). In Rwanda, urban households, who are wealthier and consume more imported products, are more affected by external factors (74.13% of total risk), with world energy prices being the main contributor to their consumption uncertainty (23.69%). Rural households, on the other hand, are more exposed to domestic risks (59.2% of total risk), with root and cereal yield volatility being the most significant factors (19.68% and 11.4%, respectively). Finally, in Malawi, domestic risks are more critical for both urban and rural households (62.1% and 71.95%, respectively), with cereal yield volatility being the most significant risk (36.12% and 37.44%, respectively).

Table 8. Risk decomposition of poverty outcomes for Kenya, Rwanda, and Malawi

		Kenya			Rwanda			Malawi		
	Shock	Total LM, R^2 = 97.9	Urban LM, R^2 = 93.6	Rural LM, R^2 = 96.2	Total LM, R^2 = 97.5	Urban LM, R^2 = 95.8	Rural LM, R^2 = 97.5	Total LM, R^2 = 96.4	Urban RF, R^2 = 83.7	Rural LM, R^2 = 96.9
External (world prices and current account)	Grains	3.29	2.11	3.22	1.71	3.05	1.58	1.63	1.13	1.70
	Oilseeds	1.98	4.85	2.79	1.07	1.98	0.99	2.00	0.66	2.25
	Veg. & fruit	1.01	2.54	1.25	1.23	1.86	1.17	2.20	4.02	1.62
	Bev. crops	18.75	3.69	20.82	3.45	2.42	3.58	4.45	1.06	4.96
	Other crops	1.87	0.89	2.42	0.95	1.28	0.94	1.22	1.35	1.11
	Meat	1.61	1.14	1.79	0.87	1.21	0.84	1.46	0.72	1.35
	Dairy	3.30	1.11	5.76	1.22	1.28	1.20	1.53	1.41	1.42
	For. & wood	1.16	0.64	1.74	1.28	1.75	1.23	1.10	0.75	1.24
	Fisheries	3.92	1.42	4.21	1.12	1.00	1.13	1.60	3.03	1.48
	Energy	12.15	6.67	9.36	6.20	9.64	5.81	6.83	10.30	6.41
	Met. & min.	0.75	1.04	1.02	2.15	2.72	2.09	0.98	0.77	1.03
	Fertilizers	4.65	1.87	4.94	1.41	2.61	1.30	2.39	1.09	2.79
	Manufactur.	1.19	1.00	1.86	0.98	1.40	0.94	1.98	0.85	2.23
	Services	4.45	4.66	2.64	1.94	3.35	1.81	2.14	2.03	2.06
	FX cap flow	1.21	6.38	2.84	6.22	9.82	5.81	1.88	1.20	1.70
	Total	**61.29**	**40.01**	**66.67**	**31.80**	**45.37**	**30.42**	**33.39**	**30.35**	**33.36**
Domestic (productivity of activities)	Cereals	18.73	19.43	9.31	25.50	18.35	26.25	21.67	40.47	17.87
	Pulses	3.18	4.28	1.48	2.66	1.72	2.77	6.86	4.44	6.75
	Oilseeds	0.86	0.77	1.88	3.90	2.95	4.00	15.27	10.55	14.87
	Roots	0.99	10.91	4.57	23.59	20.87	23.76	1.08	0.85	1.07
	Vegetables	1.34	2.64	3.60	1.45	0.89	1.53	7.95	4.13	8.12
	Fruits	2.34	3.14	1.25	3.21	2.29	3.31	1.09	0.72	1.14
	Bev. crops	6.03	4.39	3.93	2.14	2.63	2.08	0.82	0.63	0.89
	N-food crop	0.57	0.47	0.75	0.88	1.02	0.86	2.51	1.38	2.55
	Livestock	0.48	5.69	3.01	0.51	0.44	0.52	4.63	1.19	7.25
	Milk	0.48	1.74	1.17	1.36	1.00	1.41	2.39	0.62	3.04
	Forestry	0.93	1.03	0.98	1.59	0.87	1.71	0.97	0.64	1.16
	Fisheries	1.60	3.75	0.79	0.61	0.54	0.62	0.66	3.34	1.15
	Electricity	1.19	1.75	0.62	0.79	1.05	0.76	0.72	0.68	0.78
	Total	**38.71**	**59.99**	**33.33**	**68.20**	**54.63**	**69.58**	**66.61**	**69.65**	**66.64**

Source: Own derivations based on simulations data.

Table 8 presents the risk decomposition of poverty outcomes, and these results resemble the uncertainty decomposition of consumption. For Kenya, the higher-income country better integrated in world markets, 61.29% of its deviations in the poverty rate depends on external factors, and world price volatility of beverage crops is the most important risk (20.82 % in rural poverty and 18.75% in national poverty). In Rwanda and Malawi, about two-thirds of poverty uncertainty is due to domestic factors associated with climate-associated productivity volatility. At the sectoral level, productivity volatility of staples is important for poverty variation in all three countries (cereals in Kenya, cereals and roots in Rwanda, cereals and oilseeds in Malawi).

Table 9. Risk decomposition of undernourishment for Kenya, Rwanda, and Malawi

	Shock	Kenya			Rwanda			Malawi		
		Total LM, R^2 = 98.9	Urban LM, R^2 = 96.5	Rural LM, R^2 = 98.0	Total LM, R^2 = 97.7	Urban LM, R^2 = 96.2	Rural LM, R^2 = 97.5	Total RF, R^2 = 95.2	Urban RF, R^2 = 93.8	Rural RF, R^2 = 95.2
External (world prices and current account)	Grains	4.28	3.24	4.34	1.81	3.47	1.57	0.87	1.10	0.83
	Oilseeds	3.55	6.87	2.37	1.06	2.08	0.93	0.43	0.52	0.44
	Veg. & fruit	1.16	1.84	1.15	0.66	0.79	0.64	1.73	2.37	1.44
	Bev. crops	4.23	1.48	6.62	2.47	1.83	2.61	0.49	0.37	0.53
	Other crops	1.14	1.19	1.31	0.94	1.02	0.95	0.30	0.28	0.27
	Meat	0.84	0.82	1.01	0.52	0.56	0.51	0.48	0.51	0.45
	Dairy	0.74	1.13	1.67	0.58	0.52	0.60	0.27	0.30	0.30
	For. & wood	1.27	0.63	1.76	0.78	0.81	0.78	0.76	0.89	0.70
	Fisheries	3.23	1.51	3.95	0.93	0.76	0.96	0.43	0.54	0.37
	Energy	6.40	3.76	6.76	3.55	5.23	3.26	1.31	1.40	1.40
	Met. & min.	0.75	0.87	0.86	1.85	2.15	1.80	0.54	0.52	0.51
	Fertilizers	6.56	3.54	7.36	0.99	1.73	0.90	1.15	1.05	1.10
	Manufactur.	1.00	0.86	1.36	1.05	1.13	1.05	0.48	0.45	0.44
	Services	4.74	4.59	4.01	1.32	2.31	1.20	0.62	0.83	0.59
	FX cap flow	1.01	4.40	1.18	3.90	5.03	3.68	2.52	2.71	3.22
	Total	**40.92**	**36.72**	**45.71**	**22.40**	**29.42**	**21.41**	**12.38**	**13.84**	**12.60**
Domestic (productivity of activities)	Cereals	39.98	32.44	35.40	36.48	34.94	36.54	66.63	69.53	66.56
	Pulses	7.39	7.39	5.93	3.16	2.61	3.25	2.28	1.81	2.24
	Oilseeds	0.36	0.69	0.74	4.06	3.20	4.21	11.96	9.91	11.40
	Roots	0.94	6.32	1.46	22.25	18.96	22.75	0.45	0.54	0.42
	Vegetables	0.49	2.01	1.11	1.92	1.53	1.99	1.09	0.65	1.20
	Fruits	0.65	0.89	0.64	3.12	2.62	3.20	0.33	0.41	0.38
	Bev. crops	3.90	2.93	3.65	1.27	1.53	1.22	0.30	0.31	0.28
	N-food crop	0.36	0.29	0.50	0.68	0.82	0.66	1.57	1.09	1.37
	Livestock	0.28	3.04	1.04	0.65	0.72	0.64	1.37	0.33	1.83
	Milk	0.44	1.15	0.65	1.75	1.50	1.80	0.74	0.42	0.81
	Forestry	1.26	1.56	1.06	0.87	0.68	0.97	0.32	0.43	0.32
	Fisheries	2.20	3.49	1.44	0.88	0.85	0.88	0.28	0.45	0.29
	Electricity	0.85	1.06	0.66	0.51	0.62	0.49	0.30	0.30	0.29
	Total	**59.08**	**63.28**	**54.29**	**77.60**	**70.58**	**78.59**	**87.62**	**86.16**	**87.40**

Source: Own derivations based on simulations data.

Finally, Table 9 concludes with the risk decomposition of undernourishment rates. Domestic productivity uncertainty factors dominate undernourishment risks in all three countries, but more trade-dependent Kenya has the lowest importance of domestic factors (59.08%). Malawi depends on domestic agricultural productivity almost entirely (87.62%), while Rwanda falls between the two countries with domestic risk factors contributing to 77.60 % of undernourishment variation. At the sectoral level, productivity volatility of staple cereals, which largely defines calorie availability in the three countries, is the most important uncertainty factor.

5. Conclusion

This paper introduces a novel methodology for Systematic Risk Profiling of various exogenous economywide shocks. First, by using historical data, we derive a historically consistent parameter space of both world market and domestic productivity volatility and sample realistic shock scenarios that can hit the economies of Kenya, Rwanda, and Malawi. Then sampled scenarios are supplied into respective country CGE models that produce resulting economic uncertainty, and RF and LMG importance decomposition methods are used to trace back to the most important exogenous sources of uncertainty.

Our application of SRP to Kenya, Rwanda, and Malawi provides important insights into their different economic vulnerabilities. Malawi and Rwanda are more vulnerable than Kenya, primarily due to domestic climate-driven productivity volatility factors. Kenya's risk profile is largely influenced by world market volatility, reflecting its greater level of development and integration into the global economy.

These findings emphasize the need to consider both climate and world market uncertainties together rather than in isolation. The ability of the SRP methodology to produce detailed, context-specific risk assessments offers valuable insights for policymakers seeking to enhance economic resilience. The results can inform targeted interventions and policy adjustments to mitigate the adverse effects of these shocks, particularly on vulnerable populations.

Given the flexibility of the SRP method, it can be applied to other developing countries, broadening the understanding of their risk profiles. As economic systems grow more complex and interdependent, methodologies like SRP are crucial to inform policymaking. Adopting these advanced analytical techniques allows us to better understand and address the multifaceted risks faced by countries, contributing to their more effective and sustainable economic development.

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