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Identifying key sectors of sustainable development: A Bayesian framework estimating policy-impacts in a general equilibrium

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Abstract

Transformation of the previous centrally growth-oriented economic systems to a sustainable bio-economy is a global political trend, where public policy is a key factor in making this successful. Designing effective and efficient policies requires understanding the linkages between policy choices and outcomes. Most existing studies are missing a direct link to policy choices and ignore fundamental model uncertainty present in policy analysis. We empirically estimate a sector-specific, nested two-stage policy impact function to address these shortcomings. We apply a Bayesian estimation approach that combines existing statistical data with a priori information from political experts, thus reducing data and estimation problems. This is linked with a Computable General Equilibrium to model the entire link from policies to outcomes. We derive a theoretical framework that allows the definition of indicators for key sectors of an efficient Pro-Poor-Growth strategy. In our generalized framework, we show that indicators based only on growth-poverty linkages might be

Abbreviations: AU, African union; CAADP, Comprehensive Africa Agriculture Development Programme; CES, constant elasticity of substitution; CGE, computable general equilibrium; CGPE, computable general political economy equilibrium; DE-MC, differential evolution Markov chain; DSGE, dynamic stochastic general equilibrium; FOC, first order condition; HPD, highest posterior density; IFPRI, International Food Policy Research Institute; MCMC, Markov chain Monte Carlo; PEBAP, Promoting Participatory and Evidence-Based Agricultural Policy Processes in Africa; PIF, policy impact function; PPG, pro-poor-growth; SDG, sustainable development goal; TFP, total factor productivity.

misleading. To deal with model uncertainty inherent in the application, we derive a set of metamodels via simulations conducted under different model parameter settings and apply Markov Chain Monte Carlo sampling. Applying Bayesian model selection allows drawing statistical inferences on competing models to generate relatively robust policy-relevant messages even under model uncertainty. The approach is empirically applied to Ghana, Senegal, and Uganda, analyzing the allocation of public spending on agriculture under the Comprehensive Africa Agriculture Development Programme. [EconLit Citations: C11—Bayesian Analysis: General; C63—Computational Techniques, Simulation Modeling; D58—Computable and Other Applied General Equilibrium Models; O55—Africa; Q01—Sustainable Development; Q18—Agricultural Policy].

1 | INTRODUCTION

The transformation of the previous centrally growth-oriented economic systems to a sustainable bio-economy is a global political trend. Examples include initiatives like the Comprehensive Africa Agriculture Development Programme (CAADP) (NEPAD, 2010; Ostermann, 2017) or the European Green Deal. Additionally, there is a broad agreement in the development literature that sustainable economic growth is the only successful strategy to lead developing countries out of poverty and even beyond into middle-income status (Diao et al., 2012; Fan et al., 2000; Gaiha, 1989; Saith, 1981; Sen, 1997). The objective of the African-led and African-owned CAADP is to assist member nations in reforming and executing their agricultural policies to find effective and efficient Pro-Poor-Growth (PPG)-strategies. Among its core pillars are improving natural resource usage, better market access, and boosting agricultural research, aligning directly with several Sustainable Development Goals (SDGs) such as Zero Hunger (SDG 2) and No Poverty (SDG 1). The initiatives and activities in the different regions have interaction effects.

These challenges need solutions for complex collective action problems at all levels, that is, regional, national, and global levels. Government policy is crucial in achieving the SDGs. Therefore, understanding how effective and efficient policies can be identified and implemented in political practice is high on the political agenda. Promoting evidence-based policies is key, where policy impact evaluation is an important prerequisite. Policy impact evaluation encompasses ex post analysis of policy impacts and ex-ante predictions of future outcomes (Manski, 2018). Quantitative policy analysis plays a prominent role in impact evaluation. However, its application faces fundamental model uncertainty, that is, there exists a set of different model specifications that partly lead to conflicting policy impacts. Due to limited data, no empirical inference between different model specifications can be drawn. Accordingly, model uncertainty is mostly ignored in the scientific realm and political practice (Manski, 2018; Marinacci, 2015).

Applied policy analysis has for a long-time used and still uses Computable General Equilibrium models (CGEs) for ex ante evaluation of policy interventions as they comprehensively represent economy-wide effects (Arndt & Davies, 2016; Boysen et al., 2015; de Melo, 1988; Dixon & Jorgenson, 2013; Shoven & Whalley, 1984). CGEs have been widely used to assess the impacts of policies in the area of international trade (Caliendo & Parro, 2014; Hertel et al., 2007; Hertel, 1997), migration (Fan et al., 2018; Stifel & Thorbecke, 2003), agricultural policies (Benfica et al., 2019; Boulanger et al., 2018; Milczarek-Andrzejewska et al., 2018; Taylor et al., 1999), and energy (Burniaux & Chateau, 2014) or climate policies (Böhringer et al., 2014, 2021; Fujimori et al., 2016). Most existing studies ignore the inherent model uncertainty. Furthermore, longstanding criticisms of CGE models include that they are deterministic and provide only point estimates of impacts of an exogenous shock to an economy (Phimister & Roberts, 2017) and that they have weak econometric foundations (Jorgenson, 1984; McKitrick, 1998). Economic adaptation to shocks depends on specific behavioral parameters of CGEs, where parameters and functional forms are usually specified in a combination of estimation and calibration to replicate a base year (Ziesmer et al., 2023). In comparison, modern Dynamic Stochastic General Equilibrium models (DSGEs) are estimated using Bayesian approaches. Their system-wide estimation procedure not only delivers a more efficient estimate of the structural model parameters but also provides a consistent estimate of the structural shock processes driving recent economic developments (Hashimzade & Thornton, 2013; Smets & Wouters, 2003).

Furthermore, CGEs often do not directly model the transformation of policy instruments controlled by a government into policy shocks but focus on modeling the adaptation to policy shocks, while the shock itself is exogenously assumed or weakly estimated based on limited data. A policy impact function (PIF) models the transformation of policies into shocks, where the shocks are modeled as exogenous parameters to the CGE. A good case in point is modeling the impact of public infrastructure or human capital investments. Since the intervention logic of these investments corresponds to induced technical progress, CGE-studies often translate public investments into technical progress based on ad hoc assumptions and focus on modeling economic adaptation to exogenously assumed Total Factor Productivity (TFP) (see e.g., Dorosh & Thurlow, 2018). Löfgren and Robinson (2008) suggest combining an econometric approach estimating policy-growth linkages with a recursive dynamic general equilibrium model analyzing growth-poverty linkages. Looking at different policy options for the growth and transformation of the agricultural sector in Kenya, Boulanger et al. (2018) at least implicitly use the concept of a PIF. Similarly, Benfica et al. (2019) look at the effect of agricultural investments on poverty in Mozambique and also employ the concept of a PIF. Beyond widely accepted randomized control trial literature, a few studies target estimations of policy effects on the macro/national scale, for example, Benin et al. (2012) estimate multiple elasticities of different government investments on agricultural output and productivity for many countries. For the case of India, Fan et al. (2000) estimate elasticities for poverty and TFP of different interventions, and for example, find a much higher elasticity for research and development compared to health (−0.060 vs. −0.001). Focusing on food security, Kamenya et al. (2022) estimate that a one-unit increase in agricultural spending leads to a 0.2% reduction in undernourishment.

Therefore two main challenges arise: First, the specification of PIFs to complete the transformation (in combination with a CGE) of a policy decision into final policy outcomes (the economy-wide effects), and second the explicit integration of model uncertainty into the analysis. Specifying relevant PIFs is challenging due to limited adequate observational data, implying high model uncertainty. Econometric estimations of PIFs are plagued by severe estimation problems, for example, endogeneity or spurious correlation (see Fan & Rosegrant [2008] for a detailed discussion).

To tackle and solve these challenges, we derive a model framework combining different computational techniques, models, and data sources in this paper. This paper provides a novel estimation approach of PIFs, where statistical (historical) data is combined with expert information (future perspective) in a Bayesian estimation procedure (Durlauf et al., 2005; Eicher et al., 2018). On a technical level, we apply metamodeling to reduce the computational load and facilitate Bayesian estimation by combining historical data with expert knowledge. Following Löfgren and Robinson (2008), the PIFs are linked with a recursive dynamic CGE to an integrated approach. This framework allows the explicit incorporation of model uncertainty into the policy analysis.

We operationalize our framework to the case of CAADP in three African countries, Ghana, Senegal, and Uganda. Even though we focus our analysis on PPG-strategies, the framework is not specific to this case. We derive a set of metamodels via simulations conducted under different model parameter settings to deal with inherent model uncertainty in applying the CGE. These parameter settings correspond to different stylized macroeconomic adaptation behavior of the economy to exogenous economic shocks, for example, how savings and investments are modeled or the mobility of capital. We estimate corresponding PIF-parameters conditional on each specific metamodel.

Hence, in contrast to existing approaches, we can draw statistical inferences on competing models of growth-poverty linkages that allow us to generate relatively robust policy-relevant messages even in the presence of model uncertainty. In particular, based on our approach, we derive indicators to identify key sectors of an efficient PPG-strategy and show that indicators solely based on a CGE-analysis can be misleading. Furthermore, this modeling approach paves the way to integrate multiple different models into the analysis and to integrate modeling of the policy choice into the analysis. Finally, using available statistical data and a priori information collected from political experts, the Bayesian estimation approach significantly reduces data and estimation problems inherent in existing econometric approaches estimating PIFs.

We derive the general framework underlying our approach in the following Section 2. Section 3 provides some background information on our empirical case, CAADP, and details the specification of the derived framework: The derivation of metamodels from the CGEs, using statistical data to fit a first PIF, and finally integrating expert information gathered from personal interviews to estimate a second PIF in a Bayesian way. In Section 4, we show the impact of model uncertainty on the estimated models and highlight that ignoring policy-growth linkages can be misleading. The final section provides a summary and points for further linkages with, for example, legislative bargaining models.

2 | FRAMEWORK

This section presents the general framework underlying our approach. The framework is developed with the goal of quantitative, model-based ex ante policy analysis, meaning aiding in the policy choice problem, like helping select which sectors to promote. We combine complex simulation models, like CGEs, with PIFs to fully model the transformation from a policy decision into policy outcomes.

Formally, let F denote a model, which implicitly determines outputs, $\boldsymbol{z}$, as a function of a set of policies, $\boldsymbol{\gamma}$, and a set of model parameters, $\boldsymbol{\omega}$:

$$F(\boldsymbol{z}, \boldsymbol{\gamma}, \boldsymbol{\omega}) \equiv 0. \tag{1}$$

F is an I-dimensional vector-valued function, $\boldsymbol{z}$ an I-dimensional vector of endogenous output variables, $\boldsymbol{\gamma}$ is a J-dimensional vector of policy dimensions, and $\boldsymbol{\omega}$ a K-dimensional vector of exogenous model parameters. F defines an intervention logic of transforming $\boldsymbol{\gamma}$ into $\boldsymbol{z}$ and could correspond to any scientific model.

CGEs are the work-horse model in policy analysis capturing the effects of policy shocks $\boldsymbol{\beta}$ on an economy. Policies, such as budget allocations to different instruments, are often not at all, only partially or indirectly modeled in CGEs (Bourguignon et al., 2008; Henning et al., 2018). Therefore we follow Fan et al. (2000); Löfgren and Robinson (2008) and formulate F as a nested function comprised of two elements, 1) PIF $H(\boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\chi})$ and 2) an economic model $E(\boldsymbol{z}, \boldsymbol{\beta}, \boldsymbol{\theta})$. This approach allows analyzing policies ($\boldsymbol{\gamma}$) by transforming them into policy shocks ($\boldsymbol{\beta}$), which are modeled as exogenous parameters in E. Accordingly, we specify F, with $\boldsymbol{\omega} = (\boldsymbol{\theta}, \boldsymbol{\chi})$, as follows:

$$F : (\boldsymbol{\gamma}, \boldsymbol{\omega}) \;\rightarrow\; \boldsymbol{z}, E(\boldsymbol{z}, \boldsymbol{\beta}, \boldsymbol{\theta}) \equiv 0 \wedge H(\boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\chi}) \equiv 0. \tag{2}$$

The outcomes $\boldsymbol{z}$ are an indirect effect of policies defined through policy shocks $\boldsymbol{\beta}$ induced by policies. For example, public investment policy programs might induce technical progress defined by the PIF, while technical progress, in turn, is modeled as an exogenous parameter, $\boldsymbol{\beta}$, in the CGE implying a change in poverty or economic growth defined by the economic model. $\boldsymbol{\chi}$ denotes a vector of parameters determining the relationship between policies and induced shocks, for example, the effectiveness of public investment in specific policy programs.

Implementing the framework faces several challenges beyond specifying it as a nested function. Even though CGEs have been widely used to assess the impacts of policies, the results derived from them are driven by many assumptions of model structure, functional forms, and parameter values. Integrating model uncertainty into CGE-based analysis is increasingly used, but still limited (Chatzivasileiadis et al., 2019; Hertel et al., 2007; Phimister & Roberts, 2017; Webster et al., 2008). Therefore the first challenge is the integration of this uncertainty into the analysis.

In a pure modeling framework, policies $\boldsymbol{\gamma}$ are chosen that maximize an evaluation function (social welfare function) $S(\boldsymbol{z})$:

$$\begin{aligned} \max_{\boldsymbol{\gamma}} \quad & S(\boldsymbol{z}) \\ E(\boldsymbol{z}, \boldsymbol{\beta}, \boldsymbol{\theta}) \quad & \equiv 0 \\ H(\boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\chi}) \quad & \equiv 0. \end{aligned} \tag{3}$$

Given specifications for S, E, and H, Equation (3) can be solved, and the corresponding optimal policy is obtained. However, the solution of Equation (3) is driven by a lot of model assumptions, for example, functional forms, parameter values, and model structure. In particular, fundamental model uncertainty can be separated into parametric and nonparametric uncertainty (Chatfield, 1995; Draper, 1995; Marinacci, 2015). Non-parametric or structural uncertainty corresponds to different model structures and functional forms within the same model structure. This form of uncertainty stems from a lack of consensus on valid theoretical foundations. Economic theories can provide multiple perspectives on the relationships between variables, resulting in different possible model structures and functional forms. Furthermore, the abstraction of real-world heterogeneity, in which complex economic behaviors and patterns are simplified for modeling purposes, often leads to alternate model structures or functional forms. In contrast, parametric uncertainty corresponds to different parameter specifications within the same model structure and functional forms. Parametric uncertainty can originate from several sources, including the limited availability of data, which may lead to incomplete or imprecise estimations of parameters. Additionally, real-world data often contain measurement errors or noise, which can introduce further uncertainty to the estimated parameters. Disagreements or variability in empirical estimates across different studies or methodologies can also contribute to parametric uncertainty.

Furthermore, the solution can become computationally challenging, as CGEs (represented by E) often only define an implicit transformation from inputs to outputs, which is especially true for recursive dynamic CGEs. In this regard, we metamodel the CGE to derive an explicit function $\boldsymbol{z} = M^F(\boldsymbol{\omega}, \boldsymbol{\gamma})$ approximating the implicit function F. This approximation implies that the first-order conditions (FOCs) can be explicitly formulated and easily solved by applying standard numerical solution algorithms. Additionally, metamodeling allows the explicit integration of model uncertainty into the framework. To specify PIFs (H), we apply a Bayesian estimation procedure combining statistical and expert data. A detailed description of the implementation of the framework is given in Section 3.3 and the approach to handling model uncertainty in Section 3.4.

3 | APPLICATION

This section will show how to operationalize the derived policy analysis framework to the case of CAADP in Ghana, Senegal, and Uganda.

3.1 | CAADP

The 2003 Maputo Declaration on Agriculture and Food Security in Africa marked the starting point for CAADP (New Partnership for Africa's Development, 2003). Since then, over 40 countries have joined the CAADP process. The declaration included the prominent goal of a shared commitment of allocating at least 10% of the national budget to agriculture to achieve a 6% annual sector growth rate and improvements in food and nutrition security. In 2014 the African Heads of State and the African Union (AU) reasserted and recommitted to the principles and values of the CAADP process with the "Malabo Declaration" (African Union, 2014; Ostermann, 2017). The countries develop national agriculture investment plans inside the CAADP process. The national agriculture investment plans share a similar implementation, at least for the three countries, Ghana, Senegal, and Uganda.

3.2 | Data

The used CGE models are single country models and are International Food Policy Research Institute (IFPRI) Type II standard CGE models Löfgren et al. (2002). The CGE model has been linked to a micro-level poverty module based on household surveys for all three countries. The Senegalese and Ghanaian CGE have regionalized agricultural sectors, while the Ugandan CGE is not regionally disaggregated. We augment that with available data on production and public budget expenditure (International Food Policy Research Institute [IFPRI], 2017).

Furthermore, we use data from a policy network survey that was conducted in all three countries as part of the Promoting Participatory and Evidence-Based Agricultural Policy Processes in Africa (pebap) project.[1] The project duration was between 2012 and 2015 and was jointly implemented by IFPRI and the Universities of Kiel and Hohenheim in collaboration with local research institutions in Ghana, Uganda, and Senegal: The Institute of Statistical Social and Economic Research (ISSER), the Institut Sénégalais de Recherches Agricoles (ISRA), and the African Institute for Strategic Resource Services and Development, respectively. The interviews with key policymakers (e.g., political parties, ministries) and stakeholder organizations (e.g., donor or research organizations) from the general policy nexus of agriculture were mostly conducted in 2013. The organizations were asked about political interactions (see Henning et al. [2019] for a detailed analysis), preferred policy positions regarding the most appropriate state budget allocations to different policy programs under the CAADP agenda and what realistically can be achieved for different policy goals like poverty reduction in the next 10 years. In all three countries, about 45 organizations were interviewed.

3.3 | Specification of framework

We focus on investment policies since these are crucial in solving the poverty goal. We derive an intervention logic for CAADP, as shown in Figure 1. The intervention logic provides the framework to help understand how money spent on different programs transforms into goal achievements. Similar to the derived nested structure in Section 2, the impact mechanism follows a two-step process.

In the first step, money allocated to different policy programs leads to economic growth in different sectors. In this study, we focus on generated TFP by the policy programs as the impact mechanism. This growth, in turn, is then transformed into different goal achievements. Beyond poverty (Z_2), six more outputs are displayed in the intervention logic:

[1] https://pebap.agrarpol.uni-kiel.de/

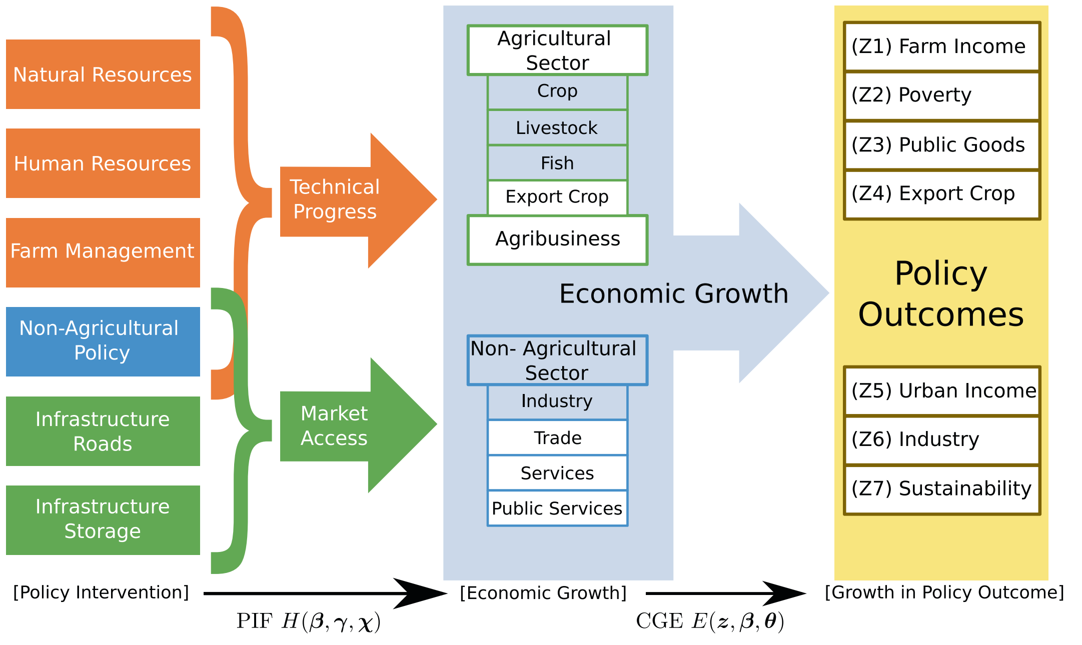

FIGURE 1 Comprehensive Africa Agriculture Development Programme intervention logic.

Z_1 Small-Scale Farm Income
Z_3 Public Goods Provision
Z_4 Welfare of Agricultural Export Sector
Z_5 Welfare of Urban Consumers
Z_6 Welfare of Industrial Sector
Z_7 Sustainability.

The different goals represent the interests of society in general and also of special interest groups. The third goal (Z_3) captures the provision of public goods, that is, schools, health care, military, and so forth. About 70% of the total state budget is allocated to the provision of public goods. The final output, sustainability, is not modeled. The CGE model could be extended to include measures for CO_2 emissions or linked with another micro-level model that captures local sustainability indicators. As described in the general framework, the transformation of a budget allocation ($\boldsymbol{\gamma}$) into economic (TFP) shocks ($\boldsymbol{\beta}$) is handled by the PIF H, while the transformation of economic shocks ($\boldsymbol{\beta}$) into policy outcomes ($\boldsymbol{z}$) is captured by the economic model E, the country-specific CGEs.

3.3.1 | Economic model E

Integrating a recursive-dynamic CGE in its original form into the estimation procedure for the PIF is, at the very least, very tedious, if not impossible. Therefore we apply metamodeling to derive an explicit analytical form of it (see Ziesmer et al. [2023] for an introduction in the context of CGEs).

For the sectors $a \in A$ of the CGE, we model the average linear growth rates $w_{a,j}$ over a time period T of goal achievements/outcomes ($\boldsymbol{z}$), dependent on policy-induced shocks ($\boldsymbol{\beta} = [\Delta tp_a]$). We will derive a simple linear metamodel of the main effects:

$$\boldsymbol{w} = \boldsymbol{\xi}^0 + \boldsymbol{\xi} \cdot \boldsymbol{\beta}. \tag{4}$$

The values for ξ^0 and ξ are derived from a simulation study. To derive ξ^0, we simulate a baseline run with all parameters set to default values. To derive ξ, we run the following simulations: A run is generated and calculated for each sector a, where $\beta_a = 4$, and $\beta_{k|k \neq a} = 0$. This allows us to compute ξ^0 and ξ as follows:

$$\begin{aligned} \xi_j^0 &= \frac{Z_{j,t_1}^0 - Z_{j,t_0}^0}{Z_{j,t_0}^0 \cdot T} \\ \xi_{a,j} &= \left(\frac{Z_{j,t_1}^a - Z_{j,t_0}^0}{Z_{j,t_0}^0 \cdot T} - \xi_j^0 \right) \frac{1}{\beta_a}, \end{aligned} \tag{5}$$

with t_0, t_1 denoting the starting and end period of the simulation and $T = t_1 - t_0 = 10$. Z_j^0 denotes the achievement levels reached in the baseline scenario. Z_j^a denotes the achievement levels reached in the respective scenario.

With this we can define $M^E(\boldsymbol{\beta}) = \boldsymbol{w} = \boldsymbol{\xi}^0 + \boldsymbol{\xi} \cdot \boldsymbol{\beta}$. This is a linear approximation, a metamodel, of the full CGE model. It only captures the relationship between Δtp and w, but it includes the general equilibrium effects that led to the derived coefficients. The derivation of the metamodel involves three steps: First, define and calibrate the CGE, second run the simulations, and last, derive the metamodel based on the simulation results. This metamodel can now be applied to estimate the PIF.

3.3.2 | Policy impact function H

To complete our theoretically derived framework, we also need to estimate the PIFs, which is done in two steps. We want to derive sector specific PIFs, relating policy instruments $\boldsymbol{\gamma} = [\gamma_i]$ to $\boldsymbol{\beta}$, with $i \in I$. The first step uses historically observed data to find a first good fit for the parameters. The model is calibrated to replicate past observations; it learns the past relationship. This is what we call the historical PIF. The goal is not to replicate the past but to predict the future. To find parameters that match expected future developments, the parameters are adapted in a second step using expert opinions. This results in the expert PIF.

We use a nested function for the PIF, a Constant Elasticity of Substitution (CES)-function transforming $\boldsymbol{\gamma}$ into the effective budget for each sector Be_a (Arrow et al., 1961), and a logistic function transforming Be_a into a change in TFP ($\beta_a = \Delta tp_a$, the policy shock). While many functional forms are possible for the PIF, we chose the logistic and CES functions for practical reasons. In detail, the logistic function captures the idea of (1) needing a certain amount of budget to have an effect, (2) a part where more budget is effective, and (3) after a certain point, more budget has only very little effect. The CES-function is rather flexible and allows, for example, γ_i to become zero without turning into a corner solution.

$$\begin{aligned} H(\boldsymbol{\gamma}) &= {tp^{max}}_a \frac{1}{1 + e^{-(a_a Be_a + b_a)}}, \\ Be_a(\boldsymbol{\gamma}) &= \eta_a \left(\sum_{i \in I} \mu_{a,i} \gamma_i^{-\rho} \right)^{\frac{-1}{\rho}}. \end{aligned} \tag{6}$$

The ${tp^{max}}_a$ parameter defines the maximal achievable TFP shock, while a_a and b_a control the shape of the sigmoid function. The substitution parameter ρ is set to 0.5. The interdependencies between the different policies are captured in the lower stage parameter $\mu_{a,i}$, the share parameter. The higher $\mu_{a,i}$ is compared with $\mu_{a,i'}$, the higher the impact of policy program i compared with i' is on technical progress in sector a. For example, some sectors might not benefit much/at all from spending on water policies, and therefore if much money is spent on water policies, the effective budget for that sector is low. The scaling parameter η_a could be used to incorporate the implementation efficiency of policy programs. Given the lack of data for this, we choose η_a, so that the upper limit of Be_a equals B:

$$\eta_a = \left(\sum_i \mu_{s,i}^{\frac{1}{1+\rho}}\right)^{\frac{1+\rho}{\rho}}. \tag{7}$$

Now $Be_a = B$ if the allocation for that sector equals the optimal allocation. The optimal shares $\alpha_{a,i}$ can be calculated as follows:

$$\frac{\alpha_{a,i}}{\alpha_{a,j}} = \left(\frac{\mu_i}{\mu_j}\right)^{\frac{1}{1+\rho}}, \tag{8}$$

$$1 = \sum_i \alpha_{a,i}. \tag{9}$$

The optimal amount of budget for policy program i, when only looking at a specific sector s, follows then as $\gamma_i = \alpha_{a,i} B$.

Given the chosen nested two-stage form, this leads to a large number of required parameters. We need $|A| \times 3$ parameters for the upper stage, this being the tp_a^{max}, a_a, b_a parameters. For the lower stage we need $|I| \times |A|$ parameters, $\mu_{i,a}$. So in total we have $(|I| + 3) \times |A| \approx 600$ parameters. Estimating these with a classical estimation approach is hardly possible because of limited data availability and inherent estimation problems.

We combine prior information gained from a literature review and previous studies with statistical/historical data and expert information (future perspective) in a Bayesian estimation procedure to estimate these parameters.

Historical PIF

We want to calibrate PIF parameters so that they replicate the past development of total factor productivity and budget.

In particular, following Fan (2008); Fan et al. (2000); Sene (2015), we use available production and public budget expenditure data to estimate PIF-parameters. Defining $TFP_{a,t}$ as a TFP index for the sector a in the year t and defining $\gamma_{i,t}$ the amount of total public expenditure allocated to a policy program i in year t implies:

$$\begin{aligned} TFP_{a,t} &= tp_{a,t}^0 + \Delta tp_{s,t} \\ \Delta tp_{a,t} &= tp^{max}{}_a \frac{1}{1 + e^{-(a_a Be_a + b_a)}} \\ Be_{a,t} &= \eta_a \left[\sum_i \mu_{a,i} \gamma_{i,t}^{-\rho}\right]^{-\frac{1}{\rho}} \\ \eta_a &= \left(\sum_i \mu_{a,i}^{\frac{1}{1+\rho}}\right)^{\frac{1+\rho}{\rho}} \\ \text{with:} &\quad \sum_i \mu_{a,i} = 1 \end{aligned} \tag{10}$$

tp_{st}^0 denotes the technical progress realized in sector s in the year t without any policy impact. In general, given sufficient observations for $TFP_{s,t}$ and $\boldsymbol{\gamma}_t$ PIF parameters could be estimated by applying standard econometric estimation methods. However, as has been pointed out (e.g., Fan et al., 2000; Fan & Rosegrant, 2008), adequate data is not available for most countries. In particular, panel data on detailed budget allocation across specific policy programs are hardly available.

Assuming prior information on parameters is encapsulated in normal prior distribution, $pr(\boldsymbol{\chi}^{hist})$, while the data information follows from the equation system (Equation 10).

In the Bayesian framework, missing data is considered as additional further parameters, which can be estimated assuming corresponding prior distributions.

Denoting by $y1$ the matrix of available empirical panel data, that is, the panel data on TFP and on budget expenditure, and let $RES(y1, \boldsymbol{\chi}^{\text{hist}})$ denote additional restrictions on parameters and unobserved variables, the Bayesian estimation approach corresponds to the following minimization problem:

$$\begin{aligned}
\boldsymbol{\chi}^{\text{hist}*} &= arg \min_{\chi^{\text{hist}}} [\boldsymbol{\chi}^{\text{hist}} - \bar{\boldsymbol{\chi}}^{\text{hist}}]\ \Omega^{-1}\ [\boldsymbol{\chi}^{\text{hist}} - \bar{\boldsymbol{\chi}}^{\text{hist}}] + v'v \\
&\textbf{s.t.} \\
TFP_{a,t} &= tp_a^0 + \Delta tp_{a,t} + v_{a,t} \\
\Delta tp_{a,t} &= tp^{max}{}_a \frac{1}{1 + e^{-(a_a Be_{a,t} + b_a)}} \\
Be_{a,t} &= \eta_a \left[\sum_i \mu_{a,i} \gamma_{i,t}^{-\rho}\right]^{-\frac{1}{\rho}} \\
\eta_a &= \left(\sum_i \mu_{a,i}^{\frac{1}{1+\rho}}\right)^{\frac{1+\rho}{\rho}} \\
\forall\ a \in A : \sum_i \mu_{a,i} &= 1 \\
RES(y1, \boldsymbol{\chi}^{\text{hist}}) &\equiv 0
\end{aligned} \tag{11}$$

Please note that we assumed that the TFP index could only be measured with some error, v, where we assume that for each sector and each year, errors are drawn iid from $N(0, 1)$. Further, the exogenous technical progress tp_s^0 is included in the parameter vector $\boldsymbol{\chi}^{\text{hist}}$. Additionally, since we are mainly interested in the general underlying trend in the TFP index, we applied the Hodrick–Prescott filter.

Expert PIF

Given the calibrated parameters from the historical PIF, we want to adapt those to match the expectations for the future of political experts. Let G denote the set of political experts, with $g \in G$ denoting the index of a specific expert. Expert surveys were undertaken with relevant governmental and nongovernmental organizations. Interviewed organizations are considered experts in development and agricultural policy. We are looking for a parameter specification of the PIF, where inserting the policy positions ($\boldsymbol{\gamma}_g$) into the combination of PIF and (metamodel of the) CGE will result in their desired achievement levels.

From the interviews, data on desired achievement levels for the policy goals ($\boldsymbol{z}_g$), preferred policy positions ($\boldsymbol{\gamma}_g$), and relative interests ($\boldsymbol{x}_g$) in the achievement of policy goals were gathered. Based on the interview data, we could calculate the average annual linear growth rate experts desire to achieve, that is, $\hat{w}_{g,j} = \frac{1}{10}\frac{Z_{g,j} - Z_{g,j}^0}{Z_{g,j}^0}$.

Assuming that each expert evaluates future development of policy goals based on the following inter-temporal Cobb-Douglas-function $S_g(\psi)$:

$$S_g(\psi) = \sum_t^T \prod_j \delta^t (1 + \psi_{j,t})^{X_{g,j}}. \tag{12}$$

Assuming policies ($\boldsymbol{\gamma}$) are constant over time and induce a constant linear growth rate $\psi_j(\boldsymbol{\gamma})$ for each policy goal, it holds:

$$\psi_{j,t} = \psi_j^0(\boldsymbol{\gamma}) + \psi_j(\boldsymbol{\gamma}) \cdot t, \tag{13}$$

where $\psi_j^0(\boldsymbol{\gamma})$ is the in-period, direct effect of a policy shock in period t. $\psi_j(\boldsymbol{\gamma})$ is the growth rate induced by a policy shock in period $t - 1$.

Given our intervention logic, policies impact policy goals via induced changes in technical progress. The metamodel M^E of the CGE is used to transform the change in technical progress into the growth rates of policy goals, where the change in technical progress is the result of the PIF. Inserting the derived metamodel into eq. (13) results in

$$\psi_j(\boldsymbol{\gamma}) = \xi_j^0 + \xi_j \cdot H(\boldsymbol{\gamma}). \tag{14}$$

Public spending in economic policy programs promoting TFP has opportunity costs; for example, assuming a constant state budget, these opportunity costs correspond to a reduction of state expenditures for public services. The provision of public services is an important policy goal. The level of the state budget not spent on investment policies measures the achievement level for j_{ps}. Without a policy, we achieve $Z_3^{\text{no-policy}} = B_0$, with B_0 being the total state budget in the base period. Let us now spend money on investment policies. We have the direct, in-period effect of less money available for the provision of public services and an additional effect in the following period. This means that for the base period, we have the following:

$$Z_{3,0} = B_0 - \sum_i \gamma_i. \tag{15}$$

For the following period, if we keep investing, we have the following level:

$$Z_{3,1} = B_0 - \sum_i \gamma_i + B_0 \cdot \psi_3(\boldsymbol{\gamma}) \cdot 1 = B_0 \cdot \left(1 + \psi_3(\gamma) - \frac{\sum_i \gamma_i}{B_0}\right). \tag{16}$$

Generalizing this to period t, the following achievement level results:

$$Z_{3,t} = B_0 - \sum_i \gamma_i + B_0 \cdot \psi_3(\boldsymbol{\gamma}) \cdot t = B_0 \cdot \left(1 + \psi_3(\boldsymbol{\gamma}) \cdot t - \frac{\sum_i \gamma_i}{B_0}\right). \tag{17}$$

We have no direct, in-period policy effect for the other policy goals. In addition, the investment policies are paid in part by donors. Let α_{donor} denote the donor share, therefore Z_3 is only reduced by $1 - \alpha_{\text{donor}}$. Now we can define the direct policy effect as follows:

$$\begin{aligned} \psi_j^0 &= -\Delta_j^{\text{ps}} \frac{\sum_i \gamma_i}{B_0}, \\ \Delta_j^{\text{ps}} &= \begin{cases} 0 & j \neq 3, \\ 1 - \alpha_{\text{donor}} & j = 3. \end{cases} \end{aligned} \tag{18}$$

Assuming political experts know the policy-growth (PIF) and growth-outcome relations (CGE), they can derive their optimal policy interventions, $\boldsymbol{\gamma}_g$, and desired future policy goal achievements $\boldsymbol{Z}_g$ from maximizing their evaluation function $S_g(\psi) = \sum_t^T \prod_j \delta^t (1 + \psi_{j,t}(\gamma))^{X_{g,j}}$. Therefore given an optimal allocation $\hat{\gamma}$, it has to fulfill the first-order conditions of Equation (19). The CGE is included through the metamodel of it in the red line, while the PIF is highlighted in blue.

$$\begin{aligned} \hat{\gamma}_g &= arg \max_{\gamma} \quad \sum_t^T \prod_j \delta^t (1 + \psi_{j,t})^{X_{g,j}} \\ &\textbf{s.t.} \\ \psi_{j,t} &= \psi_j^0(\gamma) + \psi_j(\gamma) \cdot t \\ \psi_j^0(\gamma) &= -\Delta_j^{\text{ps}} \frac{\sum_j \gamma_j}{B_0} \\ \psi_j(\gamma) &= \xi_j^{\text{base}} + \xi_j \cdot \Delta tp(\gamma) \\ \Delta tp_a(\gamma) &= tp^{max}{}_a \frac{1}{1 + e^{-(a_a Be_a + b_a)}} \\ Be_a(\gamma) &= \eta_a \left[\sum_i \mu_{a,i} \gamma_i^{-\rho}\right]^{-\frac{1}{\rho}}. \end{aligned} \tag{19}$$

The PIF parameters could be estimated econometrically by using the observed optimal policy positions and the preferred policy outcomes of a set of political actors. Given a large number of parameters, a large set of relevant actors would be needed, while the sets are relatively small in the three countries, with about 45 organizations each (Henning et al., 2019). The limited data makes a direct estimation of the PIF impossible because the econometric model is underdetermined. Therefore we will again apply a Bayesian estimation approach.

Let χ denote the parameters of the PIF. We can then denote the first-order conditions of the support maximization problem as $FOC(\boldsymbol{\chi})$, with $RES(\boldsymbol{\chi})$ denoting additional restrictions on the parameters. The prior values $\bar{\boldsymbol{\chi}}$ are taken from the results of the historical PIF, $\boldsymbol{\chi}^{hist*}$. The covariance matrix Ω for the PIF parameters can be derived from the hessian of the historical PIF estimation.[2] Following Heckelei and Mittelhammer (2008), we can derive $\boldsymbol{\chi}^*$ solving the optimization problem in the following equation:

$$\begin{aligned} \boldsymbol{\chi}^* &= arg \min_{\chi} \, [\boldsymbol{\chi} - \bar{\boldsymbol{\chi}}] \, \Omega^{-1} \, [\boldsymbol{\chi} - \bar{\boldsymbol{\chi}}] + \boldsymbol{\epsilon}'\boldsymbol{\epsilon} \\ \textbf{s.t.} & \\ FOC(\boldsymbol{\chi}) + \boldsymbol{\epsilon} &= 0 \\ RES(\boldsymbol{\chi}) &= 0. \end{aligned} \tag{20}$$

Given the specification of the PIF one can now simulate the effects of any policy specification ($\boldsymbol{\gamma}$) within our intervention logic. This is done by first calculating the changes in TFP (the policy shocks $\boldsymbol{\beta}$) and then inserting those either directly into the metamodel M^E or into the CGE and running the corresponding simulation.

3.4 | Model uncertainty

The derived estimation approach provides a good solution to the complex problem of estimating sector-specific PIFs. It consists of two main parts, the derivation of the metamodels M^E and the PIF. In both parts, we have sources of uncertainty. In the derivation of the metamodels, the results depend on the model assumptions for the used CGE model. These assumptions include the choice of closure rules and the value of trade, import and export, and production elasticities. The closure rules are a combination of a Savings/Investment rule and a Government Savings rule (see Tables A1 and A2).

As a very first brute force step to capture the uncertainty around elasticities, the original model's elasticities have been multiplied separately by a factor of either 0.5, 1, or 1.5. This approach follows and extends what Breisinger et al. (2011) did as a sensitivity analysis, resulting in $3^3 = 27$ combinations of elasticity scenarios.

We have 25 different closure rule scenarios and 27 elasticity scenarios, resulting in 675 different structural assumptions for the CGE. Therefore we have to compute $675 \cdot |A| \approx 35,000$ runs for each country. Therefore we will estimate PIFs, which are conditional on the assumptions. The Bayesian estimation procedure allows a relative ranking of those PIFs and, in turn, the selection of the most probable model under the selected specifications.

The estimation approach used for the PIF results in the highest posterior density (HPD) estimate, a point estimate. We want to derive a representative sample of the posterior distribution. Given the complex form, we can not directly sample from it. Metropolis/Metropolis-Hastings (Hastings, 1970; Metropolis et al., 1953) algorithms solve this problem. Many variants are available nowadays that build upon the basic variant.[3] We will use the Differential Evolution Markov Chain (DE-MC) algorithm by Braak (2006); ter Braak and Vrugt (2008). As the sample generation is time-consuming, we will only apply it to the most probable model.

[2]Please note that we set the covariance matrix to the diagonal matrix with the elements $\Omega = [(\bar{\chi})^2]$
[3]see https://m-clark.github.io/docs/ld_mcmc/for an overview of different algorithms

From the model's viewpoint, we can see the first part as structural uncertainty and the second as parameter uncertainty. We can think of the steps to handle the different sources of uncertainty as an algorithm to apply. In our specific case, this relates to the following steps:

Algorithm 1 Model uncertainty steps.

for $c \in \{\text{Ghana}, \text{Senegal}, \text{Uganda}\}$ **do**
estimate historical PIF_c
Start Structural Uncertainty
for $e \in$ elasticity scenarios **do**
for $l \in$ closure scenarios **do**
calibrate CGE model
derive $M_c^{E^{e,l}}$ based on CGE simulations
estimate expert $PIF_c^{e,l}$
end for
end for
End
Start Parameter Uncertainty
select most probable model specification PIF_c^*
generate a representative sample for PIF_c^*
End
end for

For each country, we estimate a historical PIF (PIF_c), derive the different metamodels $M_c^{E^{e,l}}$ based on the different structural assumptions, and use that to estimate the expert PIF ($PIF_c^{e,l}$) conditional on those assumptions. The applied steps are shown with the application to the estimation of the PIF. However, the general approach of doing a sensitivity analysis of model assumptions and estimated parameter values can also be applied to many other problems.

4 | RESULTS

We will first look at more technical results regarding the estimation process and showcase the complexity and importance of model uncertainty. As a first empirical application of the derived framework, we will look at a key sector indicator that tries to answer the question: Which sectors should one promote growth in to improve a specific goal?

4.1 | Estimation

Given the successfully applied estimation procedure, an interesting question is how different the two PIFs are. Meaning which impact did the experts' opinion have on the estimated parameters? In Figure 2, we see the predicted

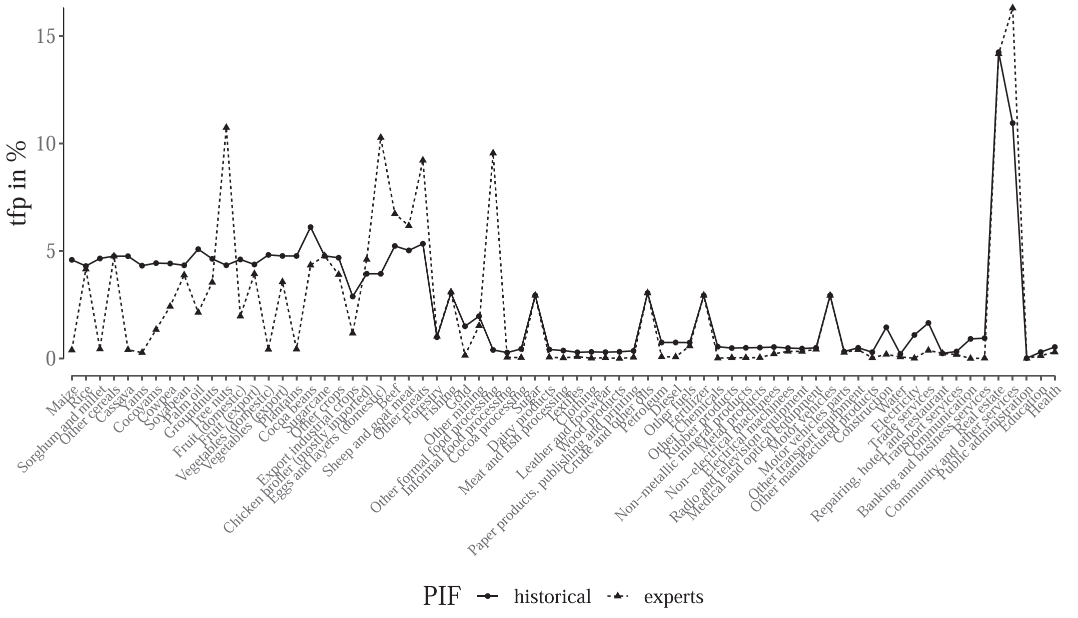

FIGURE 2 Δtp under status quo budget allocation.

policy shocks under the status quo budget allocation for Ghana. We notice larger differences in the agricultural sectors (on the left side of the chart) and mostly only small differences in the nonagricultural sectors. Given the captured technology beliefs of the experts, they would expect a lot less technical progress for the agricultural sector.

Figure 2 only shows a single model specification, but we are also interested in how dependent the results are on model assumptions, the structural uncertainty. We again calculated the policy shocks generated by the status quo policy, but this time aggregated the individual sectors to meso sectors and simply took their average. In Figure 3, we can see the different achieved levels for the three countries, with the dots denoting the median value, the outer bars the lower and upper quartiles, and the space between the dots and the bars the inner quartiles. We observe rather high variances. For example, the crop sector in Senegal has an interquartile range between 1% and 10% TFP and a median value of about 3%. For most sectors, the interquartile range is not very large, but the values of the observations in the lower 25% and upper 25% ranges cover a broad range. At a technical level, this already hints at model specifications being an important factor and the need for model uncertainty to be incorporated into policy analysis.

Let M_m with $m \in \{1, ..., 675\}$ denote the PIF estimation derived based on the different assumptions on closure rules and elasticities. Assuming we have no further prior information about the probability for a model to be the true one, we assign $P(M_m) = \frac{1}{675}$. The objective function (see Equation 20) used in the estimation is the negative log of the posterior density, with constants having been dropped. Given the assumption of normally distributed priors and errors, it is reduced to quadratic distances. Let t denote the objective function. Given the derivation and assumptions of the objective function and the $P(M_m)$, we can calculate the posterior odds ratios (a ranking) for models M_{m1}, M_{m2} as follows:

$$\frac{P(M_{m1}|y)}{P(M_{m2}|y)} = \frac{e^{-0.5t(M_{m1})}}{e^{-0.5t(M_{m2})}}\frac{P(M_{m1})}{P(M_{m2})}. \tag{21}$$

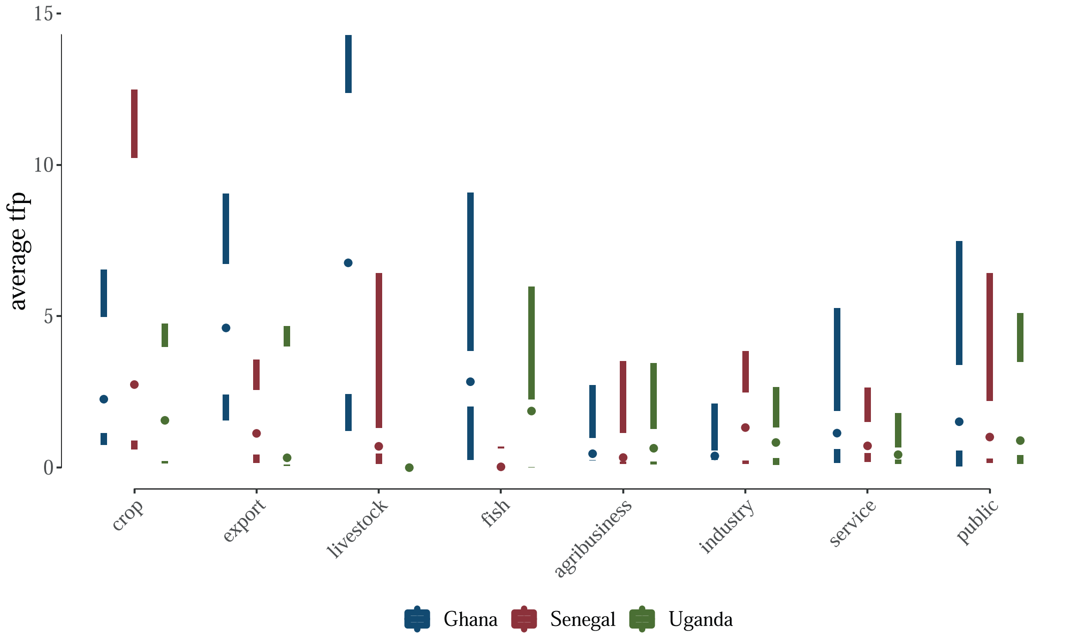

FIGURE 3 Structural uncertainty: Meso sector average Total Factor Productivity (TFP).

Further normalizing the derived odds ratios by the most probable model, we see exemplary results for Ghana in Figure 4. Please note that this is the most probable model given our set of specifications; there might be other specifications that would even better match the expert's positions and preferences. In this case, we can see that there is one specification clearly preferred over the others. For the other countries, there is no such dominance of one specification. Some closure rule combinations better match the collected data (e.g., 3-1 and 3-2 for Uganda), but there is no clear preference for a certain elasticity scenario (see Figures B1 and B2).

Finally, we also looked at parameter uncertainty by generating representative samples of the estimated PIF parameters. Due to computational limitations, we only do this for the best-fit model for each country. The generated samples are based on eight chains with 25, 000 thinned iterations per chain, resulting in a total sample size of 200, 000. Figure 5 shows the posterior values of the accepted draws for Uganda. Even though the posterior values of the accepted draws are quite distant from the posterior value of the HPD estimate, the posterior value of the mean and the median is quite close to the HPD estimate.

Looking again at the average TFP per meso-sector predicted under the status quo budget allocation, we note in Figure 6 that Uganda has the lowest variance in the agricultural sectors, except for the fisheries sector. Senegal has rather large variances for the crop and livestock sectors. Ghana falls in between those two countries, with usually lower variances than Senegal but higher than Uganda. The nonagricultural sectors are very similar across all three countries, both in the median value and the interquartile ranges being rather small. The service sector in Ghana is an exception, as well as the public services sector in Senegal.

We see that both structural and parameter uncertainty are present, and the ranges of possible values are broad in both cases. Handling model uncertainty is, therefore, an important but complex task. The required computational resources increase by a significant factor. For each country, instead of about 45 simulations, ≈35, 000 simulations had to be calculated. Moreover, based on the set of different assumptions, 675 PIF estimations had to be done. Manually running all the simulations and estimations is no longer feasible. The whole process needs to be structured appropriately and automated.

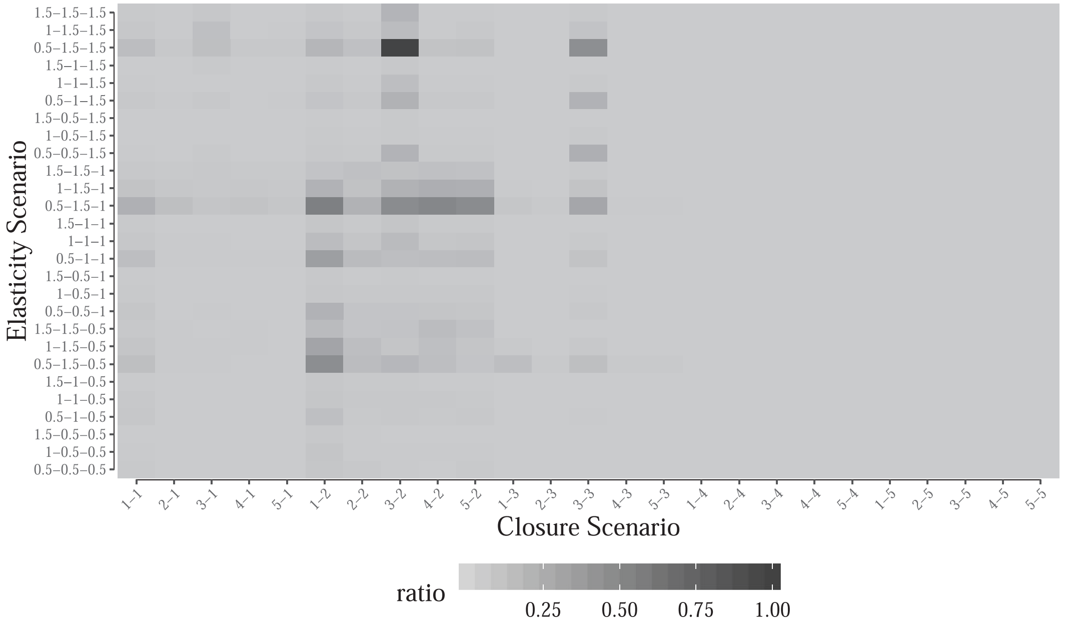

FIGURE 4 Ghana: Odds ratios.

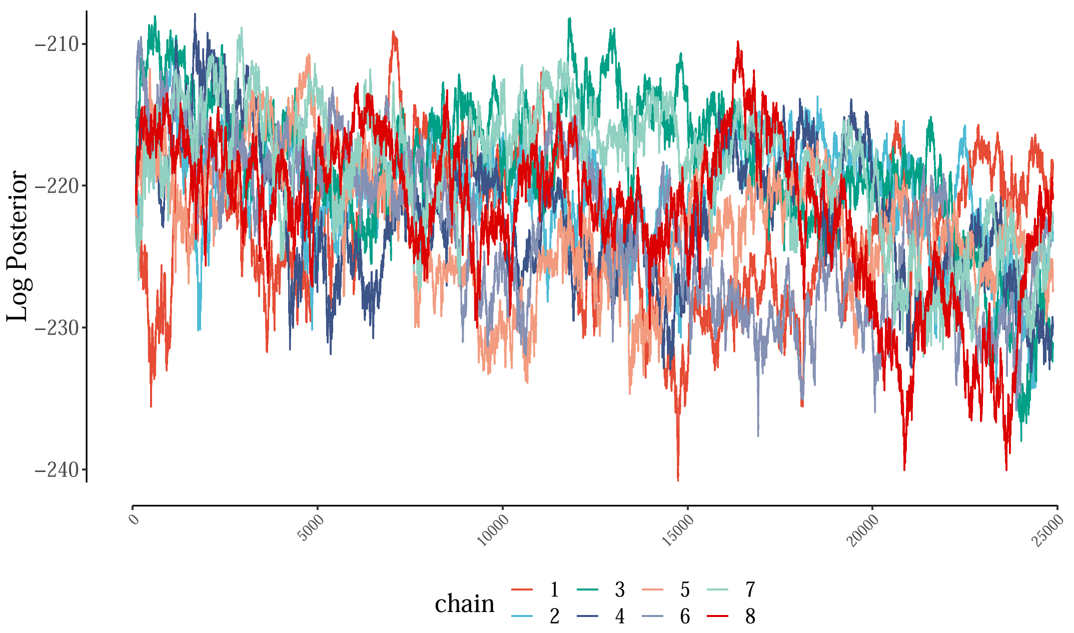

FIGURE 5 Uganda: Log posterior.

4.2 | Key sectors

Standard CGE-concepts, that is, CGE-elasticities and -multipliers, as derived, for example, by (Christiaensen et al., 2006; Diao et al., 2006; Dorosh & Thurlow, 2018), capture only the growth-outcome relations. The CGE-elasticity measures

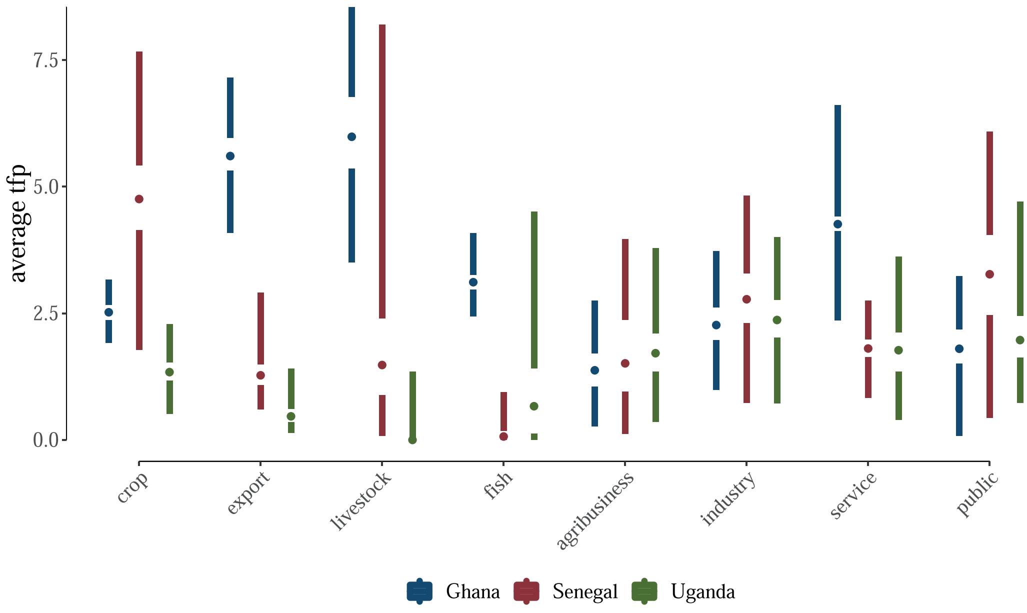

FIGURE 6 Parameter uncertainty: Meso sector average Total Factor Productivity (TFP).

how much additional goal achievement one would get if the technical progress in one sector is increased by 1%, while the CGE-multiplier measures how much additional goal achievement one would get if the GDP grows by 1% solely driven by one sector. As shown in the intervention logic and motivated in the framework (see Figure 1 and Section 2), this is only one part of the question, and another important aspect is how that growth is generated by policy programs. Therefore we combine the CGE-elasticities $\xi_a^{CGE} = \frac{\partial Z}{\partial \beta_a} = \frac{\partial CGE(\boldsymbol{\beta})}{\partial \beta_a} \approx \frac{\partial M^E(\boldsymbol{\beta})}{\partial \beta_a}$ (growth—outcome elasticities) with PIF-elasticities $\xi^{PIF} = \frac{\partial \beta_a(Be_a)}{\partial Be_a} \frac{\partial Be_a(\gamma)}{\partial B}$ (policy—growth elasticities) into policy—outcome elasticities: The marginal impact of total budget B on policy shocks $\boldsymbol{\beta}$ with the marginal impact of a factor change β_a on growth.

$$\xi^{PGE} = \xi^{CGE} \xi^{PIF}. \tag{22}$$

We will focus on key sectors of a PPG-strategy and name the indicator for poverty reduction (ξ_2^{PGE}) PPG-elasticity. This indicator combines the questions of how cheap/expensive it is to generate growth in a sector and how much poverty reduction one gets if that sector grows.

Figure 7 shows an exemplary comparison of the different indicators for Senegal. All indicators are given relative to the maize sector, and to further highlight the impact of the expert opinions on the derived PIF-parameters, we calculated the PPG-elasticities for both PIF variants. The PPG-elasticities for the historical PIF are denoted by *HIST Elasticity* and for the expert PIF as *PPG Elasticity*. As can be seen from Figure 7, identified key sectors crucially depend on the applied concept. In particular, standard CGE-concepts imply that especially growth in nonagricultural sectors has the potential to reduce poverty. In contrast, applying the concept of PPG-elasticities, taking both growth-poverty and policy-growth linkages into account, implies that, at least in Senegal, by far the highest potential to reduce poverty can be found in agriculture, especially the food sector. This result can be observed for both PIF variants. This shows that both the historical/statistical data, as well as the combination with the expert views, result in very similar marginal costs across sectors to promote TFP. The elasticities derived from the expert PIF are mostly lower, indicating that the experts, at least implicitly, think it is more costly to generate TFP than the historical data suggests.

Please note that PPG-potentials of nonagricultural sectors like telecommunication, chemistry, or trading, as well as the high potential of the agricultural export sector, that are indicated by standard CGE-concepts,

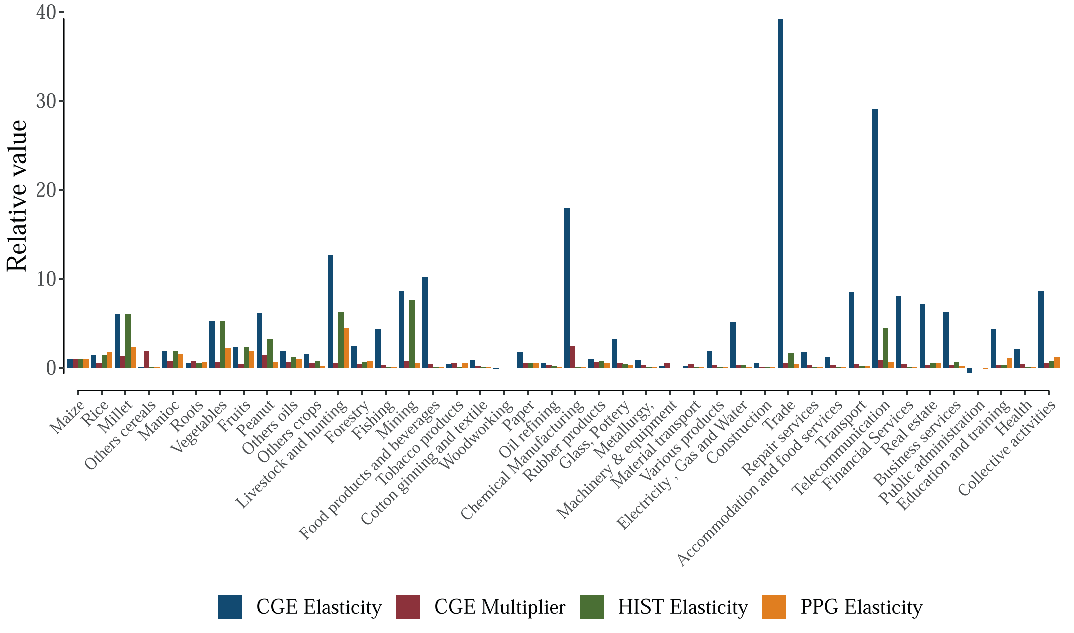

FIGURE 7 Senegal: Key sectors.

are finally not confirmed by the PPG-concept because the marginal costs to promote TFP in these sectors are incredibly high. This fact, however, does not necessarily imply that TFP is low in these sectors. For example, a very high TFP of over 7% on average could be observed over the last decade in Senegal for telecommunication. However, given the already high level of achieved TFP, it appears extremely costly to promote TFP even further in telecommunication. In contrast, for the trading sector, a very low level of TFP could be observed over the last decade in Senegal, and the PIF estimation also implies that it is generally extremely costly to promote TFP in this sector. Given the fact that the trade sector in Senegal, as in many other African countries, includes, to no small extent, the informal sector, this conclusion appears very much conceivable. Finally, interpreting PPG- or CGE-elasticities, one has to be aware of the fact that these elasticities are local indicators. They depend on the amount of public resources invested in promoting TFP and the level of TFP that has been realized in a sector.

So far, we have only looked at the results from the best-fit model for Senegal. As a next step, it is interesting to see if we can find blueprints or patterns that are the same between the three countries. Can we replicate the finding for macro-economic policies that have some clear blueprints to apply (Taylor, 1993)? As seen in the technical results, model uncertainty plays an important role, and the results might change. Starting with the structural uncertainty, the uncertainty from the model assumptions, Figure 8 shows the relative PPG elasticity for the meso-sectors across the countries, again normalized to the crop meso-sector. The model variance, depicted by the 100% scenario, and the best-fit models' variance with 50% of the cumulative density, depicted by the 50% scenario, are shown. If we take the full model variance, there is no clear-cut dominance of the crop meso-sector for Ghana and Senegal. Models, which have not been selected by the estimation process as good fit models, are also taken into account. Therefore it is more interesting to look at the 50% scenario. We can see that the high model variance is strongly reduced, and the dominance of the crop meso-sector is reproduced. In Uganda, we notice that the intervals for the different meso-sectors do not overlap. Therefore the relative ordering of the sectors is stable. In Senegal and Ghana, the different meso-sector intervals mostly overlap, and no clear investment priorities can be derived from these results.

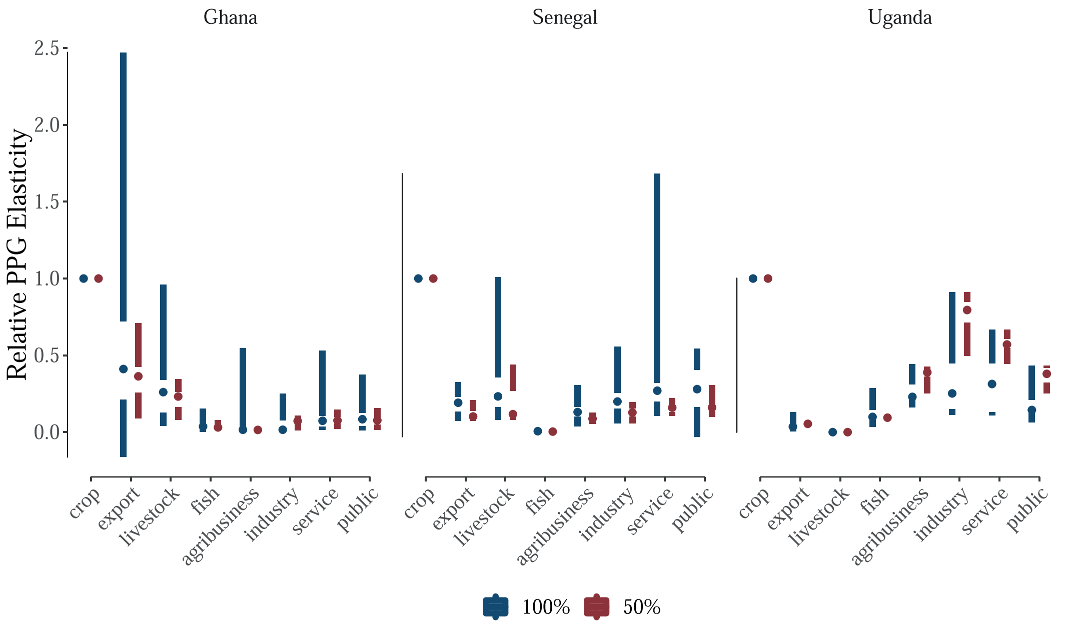

FIGURE 8 Pro-Poor-Growth key sectors.

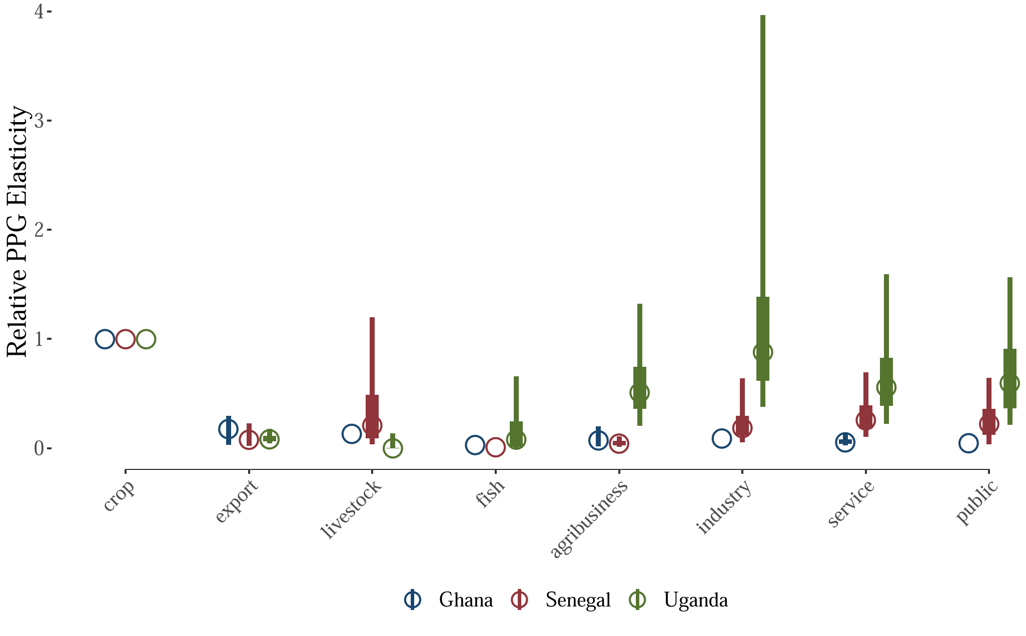

FIGURE 9 Markov Chain Monte Carlo sample: Pro-Poor-Growth (PPG) key sectors.

As a final step, we also check for the influence of the uncertainty in the parameter estimates by using the generated Markov Chain Monte Carlo (MCMC) sample. For each sample point, we calculated the PPG elasticity.

Figure 9 shows the relative PPG elasticity for the different meso-sectors. Ghana has relatively small variances across all meso-sectors, while for Uganda, relatively large variances can be observed. Senegal is in the middle of both countries, with larger variances for some meso-sectors (e.g., livestock) and small ones for the other sectors. The apparent dominance of the crop meso-sector is only confirmed for Ghana, while for Senegal, the 90% credible interval of the livestock meso-sector overlaps with the crop meso-sector. In Uganda, the 50% or 90% credible intervals of multiple meso-sectors intersect with the crop meso-sector. The crop meso-sector keeps dominating the other agricultural sectors, though, with an exception for Senegal (90% credible interval for livestock).

5 | CONCLUSION

Starting from the broadly agreed fact that, nowadays, evidence-based policies are the backbone of good governance, the paper tackles model uncertainty as a major challenge of model-based policy analysis. In particular, modeling the transformation process of a policy into outcomes faces fundamental model uncertainty. First, adaption to policy shocks is often captured in model parameters which are only weakly estimated due to data limitations (Ziesmer et al., 2023). Second, the transformation of policy instruments controlled by a government into policy shocks that are explicitly integrated into applied model frameworks is often rather ad hoc assumed or weakly estimated based on limited data.

This paper provides an innovative approach to derive and estimate an integrated model framework combining a CGE with a PIF approach. The latter translates specific policy interventions controlled by the government into policy shocks, while the former explicitly models economic adaptions to these policy shocks. In detail, we combine metamodeling with Bayesian estimation techniques to simultaneously estimate CGE- and PIF-parameters using statistical and expert data. Moreover, since we are able to identify the posterior parameter distribution, we can explicitly include model uncertainty in our policy analysis via simulating policy impacts by drawing parameters from this distribution.

We apply the framework for the case of CAADP in three African countries: Ghana, Senegal, and Uganda. In all three countries, we combined expert data collected via stakeholder surveys (future perspective) with statistical (historical) data to estimate PIFs in two versions, namely a historical PIF using only statistical data and an expert PIF. Overall, we derive the following results from our application:

1. The PIF estimations systematically differ using only statistical data or a combination of statistical and expert data. In particular, in Ghana, experts have a more pessimistic view of the positive impact of CAADP policies on TFP in agricultural sectors.
2. We identified significant structural uncertainty inherent in the applied CGEs. Especially in Uganda and Senegal, we identify a larger set of alternative structural CGEs with similar high posterior probabilities. At the same time, for Ghana, expert data clearly favor a specific structural model.
3. Overall, structural and parameter uncertainty implies significant variances in relevant policy indicators, for example, in all countries and for all mesosectors, a high variance of both, TFP induced by CAADP-policies as well as of relative PPG-elasticities could be observed. However, beyond these variances, some stable patterns could also be observed. For example, in all three countries, for almost all structural models, the highest PPG-elasticity can be observed for the crop sector. A comparatively low PPG-elasticity is observed for fishing in Ghana and Senegal and livestock in Uganda. Meaning the crop sector has a higher potential to reduce poverty than the fishing/livestock sectors, respectively.
4. Beyond structural uncertainty of the CGEs also parameter uncertainty of the PIFs has a significant impact on derived policy indicators. In particular, MCMC simulations imply high uncertainty for relative PPG-elasticities in Uganda.
5. Finally, comparing PPG-elasticities with CGE-elasticities and CGE-multipliers, respectively, clearly shows that classical indicators identifying key sectors of pro-poor growth used in the literature are misleading. In particular, in Senegal, standard CGE-concepts indicate high PPG-potentials for nonagricultural sectors like

telecommunication, chemistry, or trading, as well as the agricultural export sector. These potentials are not confirmed by our PPG-elasticity concept since these classical indicators focus only on growth-poverty linkages induced by TFP in these sectors and neglect the high cost to promote TFP in these sectors.

Our results show that advice for political practitioners based on ex ante simulation analysis needs to communicate the inherent uncertainty in the results. Furthermore, there are no simple cross-country blueprints, but a close investigation of each country's case is needed. Even though this analysis is only the first step, the improved key sector indicator (PPG-elasticity) indicates that the focus of CAADP on agriculture to promote PPG is correct. While CAADP offers guidance with the broad pillars for selecting policies and investments, this analysis allows a more detailed investigation of investment priorities, meaning which sectors to focus on with policies.

Our innovative framework provides a promising first step toward a model-based advanced policy analysis. However, despite the strength of the results of our analyses, it is also essential to recognize the limitations of the present study.

First, in the application presented in this paper, the suggested Bayesian approach allows us to sample model parameters from a corresponding posterior distribution by applying the DE-MC algorithm integrating available empirical data and expert information. However, to simplify computation, we assume a specific multivariate normal distribution for CGE- and PIF-parameters as the prior. Obviously, this specific assumption impacts the estimation results. Thus, in future research, it will be interesting to analyze how results change assuming different prior distributions. Nevertheless, we consider our framework as a first step to explicitly capture model uncertainty and estimate potential policy impacts resulting from the ignorance of model uncertainty. Second, in this paper, our policy analysis focuses on how specific policy indicators, namely PPG-elasticities, vary, taking structural and parameter model uncertainty into account. However, we still need to provide an analysis of how policy choices have to be optimally adapted while taking model uncertainty explicitly into account. A first way to integrate policy choice under fundamental uncertainty into our analysis would be to consider the individual choice of a benevolent dictator maximizing expected social welfare. In reality, however, political decision-making corresponds to a collective choice problem involving multiple actors with heterogenous evaluations of policy outcomes. Accordingly, a comprehensive analysis of policy choices made in real political systems needs to incorporate political bargaining among political actors explicitly. A possible way to extend our modeling approach would be to incorporate a political bargaining model, where spatial policy preferences of individual actors are derived as a second-order Taylor approximation of the expected welfare maximization problem using individual evaluation functions and individual beliefs regarding the probability distribution of metamodels. Finally, our approach is also a promising first step toward a transdisciplinary research design allowing interactive communication between scientific models and stakeholders as practical political experts.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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APPENDIX A: CLOSURE RULES

Tables A1 and A2 show the possibilities for the closure rules in the applied CGEs along with the explanation taken from the original model implementation.

TABLE A1 Savings/investment rules.

SICLOS	Explanation
1	inv-driven sav—uniform mps rate point change for selected ins
2	inv-driven sav—scaled mps for for selected ins
3	inv is sav-driven
4	inv and gov are fixed abs share—uniform mps rate point change (cf. 1)
5	inv is fixed abs share—scaled mps (cf. 2)

TABLE A2 Government savings rules.

GOVCLOS	Explanation
1	gov savings are flexible, dir tax rate is fixed
2	gov savings are fixed, uniform dir tax rate point change for selected ins
3	gov savings are fixed, scaled dir tax rate for selected institutions
4	gov savings are fixed, uniform sales tax rate point change for selected commodities
5	gov savings are fixed, scaled sales tax rate for selected commodities

APPENDIX B: ADDITIONAL GRAPHICS

Figure B1

Figure B2

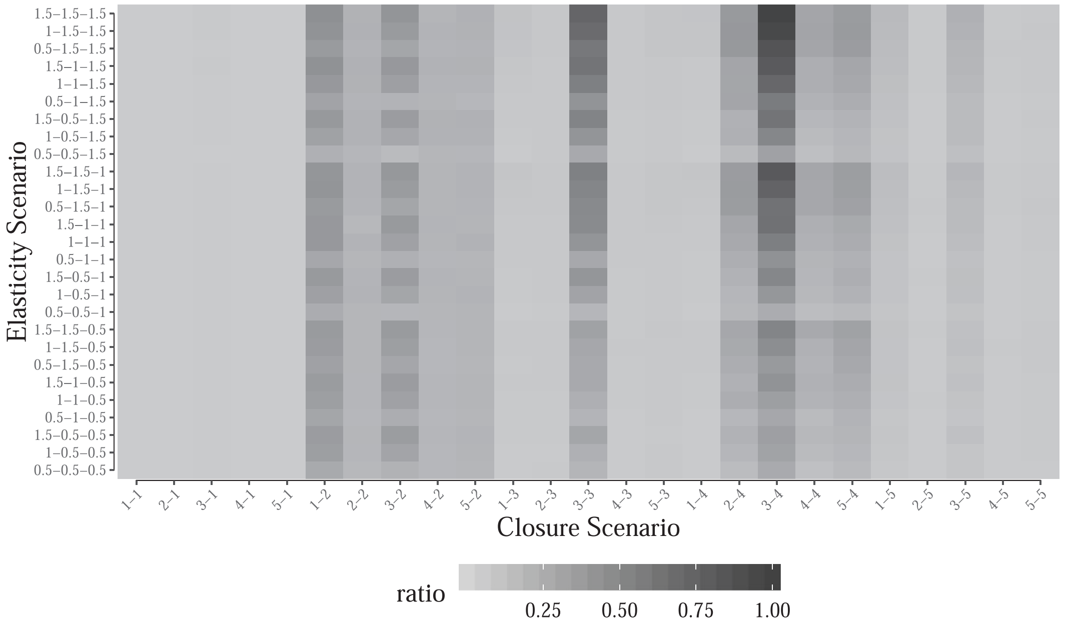

FIGURE B1 Senegal: Odds ratios.

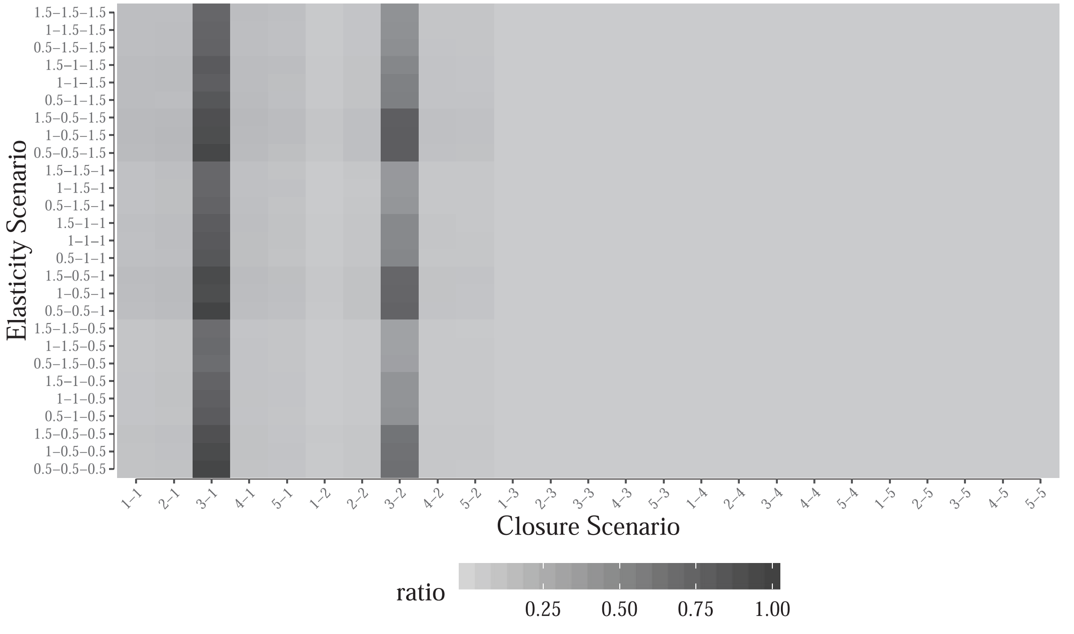

FIGURE B2 Uganda: Odds ratios.

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