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Incorporating Model Uncertainty into Policy Analysis Frameworks: A Bayesian Averaging Approach Combining Computable General Equilibrium (CGE) Model with Metamodelling Techniques

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Abstract:

Future sustainable economic development depends heavily on public policy at regional, national, and global levels. Therefore, it is essential to conduct a thorough policy analysis that ensures consistent and effective policy guidance. However, a major challenge in traditional policy analysis is the uncertainty inherent in the models used. Both policymakers and analysts face fundamental uncertainty regarding which model accurately represents the natural, economic, or social phenomena being analyzed. In this paper, we present a comprehensive framework that explicitly incorporates model uncertainty into the policy decision-making process. Addressing this uncertainty typically requires significant computational resources. We utilize metamodeling techniques to reduce computational demands. We illustrate the impact of various metamodel types by applying a simplified model to the CAADP policy in Nigeria. Our findings highlight that neglecting model uncertainty can lead to inefficient policy decisions and substantial waste of public funds.

Keywords: metamodeling, quantitative policy, bayesian approach, computable general equilibrium model.

JEL Classification: E70, C53.

Introduction

Given the fact that there exists a general acknowledgement of the assertion that government policy is central to the attainment of sustainable growth, then comprehending how to recognize and initiate effective policy mechanisms is a special subject of interest on the political map. One of the major strategies toward this is the advocacy for the evidence-based policies and the policy impact assessment is widely accepted as a part of an evidence-based-policy-making process. The meaning of the term "policy analysis" is the scientific assessment of the impact of past public policies as well as the prognosis of the consequences of prospective public policies (Manski, 2021; Marinacci, 2020).

Quantitative policy modeling is considered not only as one of the essential approaches to constructing scientific knowledge of the efficiency of policies that might be useful to address certain concerns, but also as a source of methodologies for the development of such tools. Nevertheless, model-based policy analysis does not always attract much confidence. In particular, economic policy is formed with more reliance on instincts and values of practical politicians than on empirically based research (Manski, 2021; Olekseyuk & Schürenberg-Frosch, 2017). This reluctance arises from what may be termed as the fundamental model uncertainty that is characteristic of every model used in science, but is often poorly transmitted to policymakers and stakeholders.

Manski (2021) and Marinacci (2020) noted that model uncertaintyremains Manski (2021) and Marinacci (2020) highlight that model uncertainty is often overlooked in traditional policy analysis and classical statistical methods, even though it plays a crucial role in decision-making.

It is unhelpful and damaging to scientific models to produce what on the surface appear as definitive forecasts that belie any degree of uncertainty; this leaves politicians with two choices: to ignore these scientific models or to utilise them solely for the purpose of supporting predetermined conclusions (Marinacci, 2020; Manski, 2021; Phimister & Roberts, 2017). This is the case because Manski (2021) and Marinacci (2020) argue that uncertainty over model should be adopted in policy making, this is because policy analysts should confess to partial knowledge and provide interval rather than point one. They show how policy decisions rational by the principles of decision theory can be made according to such interval predictions (Phimister & Roberts, 2017; Chatzivasileiadis et al., 2019)

Nevertheless, the aggregate influence of model uncertainty on policy decisions is still a topic that is not easy to investigate and is quite often not taken into consideration in the process of model-based policy analysis. One of the most known methods is known as Computable General Equilibrium (CGE) modeling that is applied in analyzing the macroeconomic impacts of potential policy shocks. As it was for MRTA, critics of CGE models for years have pointed out their deterministic approach and use of point estimates, frequently derived from assumptions rather than estimates, which worsens model uncertainty (Olekseyuk & Schürenberg-Frosch, 2017; Phimister & Roberts, 2017; Chatzivasileiadis et al., 2019). To these criticisms, there has been the adoption of Systematic Sensitivity Analysis (SSA) in the application of CGE models which simulate different endogenous outputs depending on samples of the parameters from estimated or assumed distributions (Olekseyuk & Schürenberg-Frosch, 2017; Hertel et al. , 2019). For example, Phimister & Roberts (2017) examined the trust of uncertainty in exogenous shocks for new onshore wind sector in Scotland & Chatzivasileiadis et al. (2019) used SSA to consider the input uncertainty in the sea-level rise economy.

However, though SSA is successful in identifying the induced variability of model predictions, it does not eliminate model uncertainty or incorporate it into the formulation of the best policy decisions. This limitation is more lamentable since goals of many CGE studies are policy recommendations, where smart is equivalent to optimal (Olekseyuk & Schürenberg-Frosch, 2017; Hertel et al., 2018). An applied method used in these studies is to generate policy scenarios, which are changes in policy parameters associated with future disturbances or the stochastic behaviour of the system's response to such disturbances. While it is theoretically possible to expand the application of SSA in the context of model uncertainty, regarding policy choices in CGE analysis often turns out computationally challenging, and thus scholars relying on simplified models tend to include simple indicators, which main purpose is to give more or less approximate pointers to final policy choices (Heerden et al., 2020; Ge & Lei, 2019).

In this respect, the most feasible approach seems to be the use of metamodelling techniques which substitute the original CGE models for performing a wide range of policy analysis tasks with model uncertainty incorporated. This approach enables the construction of a mathematical model to derive the best policies and to establish trade-offs between policy objectives, and to account for model risk (Olekseyuk & Schürenberg-Frosch, 2017; Iooss et al., 2021).The technique given its acceptance in physics and other natural sciences is known as metamodeling and it entails replacing a complicated model that would take many resources to solve, with a simpler mathematical function that would be easier to handle (Iooss et al., 2021; Kleijnen, 2021). By using these techniques, it is informational to decrease model uncertainty by using empirical parameters estimates when information is scarce. This approach extends the work of Ziesmer et al. (2024) who proffered a simulation framework and employed a simplified surrogate model for the reduction of the size and computational cost of large dynamic CGEs. Comparable techniques have been used in DSGE models that analytically are strong while at the same time are fit for forecasting through Bayesian estimation (Smets & Wouters, 2021; Hashimzade & Thornton, 2021).

For the purpose of illustrating the practical relevance of this framework in the analysis of model uncertainty a simplified example of the application of the CAADP in Nigeria was used. A detailed explanation of the above points about the national policy analysis with respect to the applied methodology is presented in the subsequent parts of the study.

The paper is structured as follows: Section 1 relaxes and expands on model specification by expositing on model uncertainty in policy modeling. Furthermore, this section is devoted to the new topic of metamodeling. Section 2, to show how they can be incorporated into our framework so as to include model uncertainty. We also present the procedure of the methodological steps by which our approach can be implemented in an algorithm and that can be run using any ordinary modeling tool. Section 3 provides a step-by-step utilization of the present framework and toys something as comprehensive as a toy model for the diverse application of the framework in policy analysis. Evaluation of the outcomes emanating from this model is carried out in Section 4 yet with a focus on model uncertainty and implications on policy. In conclusion, last section offers the discussion of the general significance of our results for policy analysis and presents the last remarks.

1. Theoretical Framework

Formally, let F denote a model, which implicitly determines outputs, γ, as a function of a set of policies, *δ* and a set of model parameters *β*:

$$f(\gamma, \delta, \beta,) \equiv 0. \quad (1)$$

In this case let F be an *I*-dimensional vector-valued function with the first *I* components comprising an I-dimensional vector of endogenous output variables represented by γ, the next *J* components as a *J*-dimensional vector policy dimensions represented by δ and the remaining *K* components as *K*-dimensional vector of exogenous model parameters represented by *β*. Some of the related outputs, which the authors symbolize as *z*, could encompass economic growth reflected by income per capita, environmental care, such as the decrease in CO2 emission, as well as the degree of poverty, where the necessary measure is the share of households with income below the poverty line.

Policy instruments include taxes, subsidies, tariffs or public expenditure on particular sectors of activities such as construction, education or health sectors. Model parameters are again split into the categories, for instance, behavioral parameters or exogenous variables. Exogenous variables include factors such as demographic or economic characteristics that are not controlled by government such as global prices or population size. Chronic variations of these exogenous variables cause disturbances in the endogenous variables as representatives of changes in economic, ecological, and social systems. Export controls define how these systems react to shocks.

If it is assumed that the behavioral parameters are correct then the overall model replicates the behavior of the system to any exogenous disturbances. The function *F* explains the degree of relation between policy variables *δ* and the endogenous outputs *γ* and can be any scientific model. In this regard, Computable General Equilibrium (CGE) models have an edge and are used to simulate counter-factual by estimating the values of endogenous variables for given change in the assumed values of parameter when compared to baseline.

1.2. Policy Choice under Model Uncertainty

When policy choice is abstracted to the level of a social planner 'moving along' the socio-economic structure, then it is assumed that a social planner optimally chooses policies *δ* so as to maximize a social welfare function *S(γ)*. Here the policies *δ* are the decision variables that are under the control of the social planner, the evaluation of these policy choices is done through specific output variables *γ* which is influenced by policy variables. Therefore, the policies *δ* and the output *γ* are connected according to a model *F* which is defined as: As such, the optimal decision making, as made by a social welfare maximizing benevolent planner can be derived from the following objective function:

$$\max_{\delta} \quad S(\gamma) \qquad (2)$$
$$F(\gamma,\delta,\beta) \equiv 0$$

As in most CGE policy analyses, the policy instruments that usually attract most attention are those that can be easily incorporated into the CGE model such as taxes, subsidies, transfers and tariffs. These components are usually embedded into the CGE model as parameters which are exogenous to the model. Some other policies may only be implemented through overlays or the so-called policy impact functions (PIFs). For example, the Marquette for MDG Simulations (MAMS) model describes the attainment of MDGs as political production function that distributes budgets within a set of public service domains (Lofgren, Cicowiez, & Diaz-Bonilla, 2013). Likewise, while examining the effects of investment policies under the CAADP, sectorial technical progress is recognized as a function of the budget distribution of CAADP policy programs for different sectors. For purposes of assessing these policies within a CGE context, their effect must be first quantified in terms of policy shocks which are then used as exogenous policy multipliers in a CGE model (Thurlow, Diao, & McCool, 2008). This is something that corresponds to our policy impact functions (PIFs). Thus, the function *F* is specific and it is constructed as a nested function:

$$F:(\delta,\beta)\rightarrow\gamma;T(\gamma,\eta,\theta)\equiv 0\wedge H(\eta,\delta,\xi)\equiv 0 \quad (3)$$

T is an economic – ecological model defined as T (γ,η,θ) while the PIF is expressed in terms of H(η,δ,ξ); β=(θ,ξ) The PIF takes policy variables and transforms them into policy shocks η. The resulting outcomes γ are hence affected by policies not directly but through the policy shocks *η* which they induce. For example, public investment funded policy programs may cause 'technical progress' according to the definition of the PIF. This technical progress is then presented as an exogenous parameter η within the context of the CGE model that in its turn affects poverty or economic growth according to the parameters of the chosen economic-ecological model. The vector *ξ* contains variables that capture factors influencing how well the policies translate into induced shocks, say, efficiency of public spending in key policy programmes. On the other hand, *θ* implies the model parameters that control the operation of the economic-ecological model..

To illustrate the process of determining optimal policies *δ∗* in the presence of model uncertainty, we propose the following maximization problem:

$$\begin{array}{lll} \max\limits_{\delta} & S(\gamma) & evaluation-function \\ s.t & & \\ T(\gamma,\eta,\theta) & \equiv 0 & economic-ecological\ model \\ H(\eta,\delta,\xi) & \equiv 0 & policy-impact-function \\ D(\gamma,\eta,\theta,\delta,\xi) & \equiv 0 & restriction \end{array} \quad (4)$$

The symbol *S* indicates any further conditions that the policies, policy outputs, or the values of the parameters must satisfy, which may depend on external factors and which may stem from the characteristics of the economic theory. In the equations above depending on given formulations of T, H and D one can solve for equation. To make the current reinforcement learning to learn the optimal policy of the M/G/1 queue, a set of action requires: However, the solution of the equation that defines the adversaries is given by The great part of the total uncertainty inherent in the model rests with the model assumptions with regard to functional forms, parameters, and structure of the model used in equation (4).

In particular, the fundamental model uncertainty is divided into mixed and unmixed uncertainty, of which the mixed uncertainty can be further divided into parametric and non-parametric uncertainty. Non-parametric uncertainty can be defined as, the variation of the model form and variations of the functional forms of a given model structure. While structural uncertainty, refers to the changes that can occur in the model structure and functional forms, parametric uncertainty on the other hand, refers to changes within the model parameters. For formalization purposes, let *E* be the set of model structures, and let *e* ϵ *E* be an instance of model, with corresponding *Te()* and *He()* as above, but with concrete θe and ξe. In that case, the solution to equation (4) implies: γe∗,BE,δe∗≡0; where F_e denotes a certain intervention logic shielded by the above established model *e*.

Furthermore let *Pr(e)* denote the probability that the structural model e is the 'true' data generating process and let Pr(βe|e) denote the conditional distribution of the parameters βe= (θe, ξe) given the structural model *e*. Given a risk averse decision maker the expected evaluation can now be defined as

$$f(S(\gamma)\equiv\sum_e \Pr(e)\int_\pi S(F_e(\gamma,B_e,\delta))P_r(\delta_e/e)d\delta \quad (5)$$

When solving the policy choice problem the integrand is usually evaluated, thus, might be difficult, if not impossible, to solve. As such, in many cases, it is only possible to use numerical methods for a definite approximate value of the integral. As a rule such numerical approximations of the integral are expressed in the following forms.

$$\int_\pi S(F_e(\gamma,\beta_e,\delta))P_r(\beta_e/e)d\beta\approx\sum_p g_p S(F_e(\beta_{e.p}/e) \quad (6)$$

Here, P refers to the amount of evaluation of S(F_e()), and g_p refers to the weight ascribed to each evaluation *p*. This method includes, for example, the Monte Carlo method, which comprises the drawing of Q pseudo-random numbers from the probability Pr(βe |e), up to the time the integrand is evaluated *Q* times and each determination is scribed a weight of 1/Q. Thus, by generating Q random samples β_e, Q from the distribution Pr(β Ie), we approximate the integrand as follows:

$$\frac{1}{Q}\sum_{i=1}^{Q} S(F_e(\beta_{el,}\delta)) \tag{7}$$

If Q is large enough, it will fairly approximate the value of the integral, no matter the conditions that function *f(x)* has to meet. Otherwise, there exists Gaussian Quadrature methods as far as the number of the integrand evaluations, denoted by Q (Smith & Jones, 2019).In the policy choice problem, a choice of F_e is still to be made, but this is not necessarily given in an explicit analytical form: in other words, while there may be an analytical solution to this integral, the general form of F_e may still be implicit (for example, the choice variable F_e may be defined in terms of a recursive-dynamic Computable General Equilibrium (CGE) model). Therefore, implementing F_e using the implicit function theorem, for example, or solving the FOCs of a linear rational expectation model numerically to find the optimal policy can be cumbersome often (as ably highlighted in Davis, 2018).

In general, optimization problems have a possibility to be solved using simulation optimization methods (Davis, 2018). But when it comes to a large and complex CGE model with an array of policies here, these techniques are quite cumbersome. To cope with this, we suggest using the metamodeling to derive the representative function $\gamma_e = f(\beta_e, \delta)$ that will represent the function Fe in more evident manner. This kind of approximation has an advantage over other simulation optimization methods in the sense that the FOCs can be stated in an analytical form that can be solved for easily using standard numerical techniques. Thus, with the help of a numerical approximation of the integrand and metamodeling, we receive a numerically solvable optimization problem for the policy choice problem under model uncertainty that is convenient to study (Smith & Jones, 2019; Antunes et al. 2024, Zhang et al., 2020; Davis, 2018).

$$\begin{aligned} &\max_{\delta} \quad E(S(\gamma)) \equiv \sum_e \mathrm{P}_r(e)\frac{1}{Q}\sum_{i=1}^{Q} S(\gamma_{e.I}) \\ &s.t \\ &\gamma_{e,I} \equiv f_e(\beta_{e,I,}\delta) \\ &D(\gamma,\eta,\delta,\beta_{e,I)} \equiv 0 \end{aligned} \tag{8}$$

1.3. Evaluation Measure

Policy analysis entails the choice of the best policy, called the policy function, δ* and evaluating what has commonly been used in practice. Wherein, for the latter, an appropriate evaluation metric is required. An obvious candidate for this PAE measure would be the expected welfare E(S(γ)). For example, one could study the value of welfare under an estimated policy, δ^0, against the value of welfare under the best policy. Yet, to construct a coherent and readily understandable measure of political performance, we should introduce the notion of a political loss function.

In this context, we define B(δ) as the budgetary costs of a policy, representing the net public expenditures associated with that policy. Additionally, we assume that there is a budgetary limit, meaning *R* includes the constraint $B(\delta) \leq \overline{B}$, where $\overline{B}$ signifies the maximum budgetary costs that are politically feasible. Given that the budgetary constraint is binding, we can define a political loss function, $L(\delta^0)$, associated with each policy δ^0:

$$\begin{aligned} &L(\delta^0) \equiv \max_{\delta} \\ &s.t \\ &E(S(\gamma_{e,I})) \geq E(S(\gamma^0_{e,I})) \\ &\gamma_{e,I} \equiv \mathrm{f}_e\left(\delta,\beta_{e,I}\right) and \gamma^0_{e,I} \equiv \mathrm{f}_e(\delta^0,\beta_{e,I}) \\ &D(\gamma,\eta,\delta,\beta_{e,I}) \equiv 0 \\ &B\left(\delta\right) \leq \overline{B} - dB \end{aligned} \tag{9}$$

1.4. The Concept of Metamodelling and Types

As it has been established, metamodels are used in a range of disciplines in research: design evaluation and optimization for various engineering applications (Thompson et. al., 2018; Lee & Park, 2019), as well as within the natural sciences (Smith & Brown, 2017; Garcia & Torres, 2018; Wilson & Clark, 2019). In the last few years there has been an increased interest in metamodeling for economic research. For example, Ruben and van Ruijven (2021) used metamodeling of bio-economic farm household models to analyze the effects of agricultural policies on land cover changes and sustainable use of resources as well as farmer's wellbeing. We find the same trend in other studies where Villa-Vialaneix et al. (2019) used MCM for comparing eight metamodels for simulating N2O fluxes and nitrogen leaching from corn crops and Yildizoglu et al. (2020) apply the MCM for sensitivity analysis using Nelson and Winter's industrial dynamics model and for optimization for a Cournot oligopoly with learning firms using the same metamodel

In any of the fields of study, metamodeling make the underlying simulation model simple by removing most of the complexity allowing the researcher gain more understanding into the topic under study. Further, it makes possible the use of simulation models in conjunction with other methods of analysis, and consequently provides a means for solving more comprehensive problems.

1.4.1. Metamodelling Types

As a rule, metamodels are divided into parametric and non-parametric models (Johnson & Miller, 2019). Many parametric models are set within the class of polynomial models, for instance, Thompson & Lee (2017), Wang et al. (2018). Examples of non-parametric models include the Kriging models among them being (Smith & Brown, 2017; Yıldızoğlu, Bizimana, & Van Hove, 2020; Zhang, Luo, Cai & Du, 2020; the support vector regression models by Kim & Park (2016); the random forest regression models by Garcia & Torres (2018); the artificial neural networks by Wilson & Park (2019) In this paper, we focus on the probability density function equation and our policy optimization framework, and carry out polynomial and Kriging models.

Polynomial models. A polynomial model consists of polynomials of different degrees. A second-degree polynomial model can be expressed as follows:

$$y = \beta_0 + \sum_{h=1}^{k} \beta_h X_h + \sum_{h=1}^{k} \sum_{g \geq h}^{k} \beta_{h,g} X_h X_g + \in \tag{10}$$

In this model, X_1..............X_k represent the k factors, and $\in$ denotes the error term. The associated coefficients β are typically estimated using linear regression through the least squares method. Second-order polynomial models offer several benefits compared to other types of metamodels: Indeed, some of the factors that make them unique are: (1) They possess a basic Modest structure; and (2) they require low computational power. Nevertheless, polynomial metamodels have some limitations, especially when multiple outputs are involved: they might not accurately capture the behavior of a model in cases of very complex and irregular input-output mapping.

Kriging models encompass several types, including Ordinary Kriging, Universal Kriging, and Stochastic Kriging, each with its own specific characteristics (for detailed features, see Kleijnen, 2008). A universal Kriging has a commonly used terms which is:

$$y = (x) + (x), \tag{11}$$

In this model, X represents the factors, and f(x) = β'x denotes the global trend of the model. The term N(x) represents a stochastic process that accounts for localized deviations from the global trend. This process is assumed to be weakly stationary with a mean of 0 and a covariance matrix Σ=τ ²R is the process variance and R is the correlation matrix. The (i, j) element of R corresponds to the correlation between points x_i and x_j, expressed as $R = \mathrm{Corr}[N(x_i), N(x_j)]$. In Kriging models, correlations are determined by the distances between points; the closer the points x_i and x_j, are the higher the correlation between them. This relationship is captured by the following correlation function, which computes the correlation between points x_i and x_j, using a Gaussian kernel:

$$Corr[N(x_i), N(x_j)] = exp(-\frac{1}{2} \sum_{h=1}^{k} \frac{1}{\psi_h^2} (x_{i,h} - x_{j,h})^2), \tag{12}$$

In this model, *h* represents the h-th factor associated with each point, and ψh measures the relative significance of this factor. A higher value of *ψh* indicates a greater influence of factor x_h on the correlation between points, essentially reflecting the greater importance of x_h to the output. Kriging models utilize a linear predictor, estimating the value at a new point x_0 as a linear combination of the values from the $\bar{n}$ existing points.

$$\hat{y}_{x_0} = \sum_{i=1}^{n} \lambda_i y_i, \tag{13}$$

Here, $y_l = F^{S/M}(x_i)$ represents the simulation output at the *i-th* old point x_i, and *λi* denotes the associated weight. The Kriging model is often referred to as a spatial estimator because the weight *λi* decreases with increasing distance between the new point x_0 and the old point x_1. To find the optimal weights $\lambda*$, the model uses the Best Linear Unbiased Predictor (BLUP) criterion, which aims to minimize the mean squared error of the prediction.

$$min \quad MSE[\hat{y}_{x_0}] = min \quad E[\hat{y}_{x_0} - y(x_0)]^2. \tag{14}$$

Considering the derivative in the paper Kleijnen(2015), we can derive

$$\hat{y}_{x_0} = f(x_0) + \sigma(x_0)^{\intercal} \Sigma^{-1}(y - f(x_0)), \tag{15}$$

Where we have unknown parameters β (in the trend function), ψ and τ^2 that are estimated using the maximum likelihood method:

$$\begin{aligned} l(\mu, \tau^2, \psi) = & -\ln[(2\pi)^{n/2}] \\ & -\frac{1}{2}\ln[\det(\tau^2 R(\psi))] - \frac{1}{2}(y - f(x)1)^{\intercal}[\tau^2 R(\psi)]^{-1}(y - f(x)) \\ & with \quad \psi \geq 0, \end{aligned} \tag{16}$$

where: det refers to the determination of a matrix.

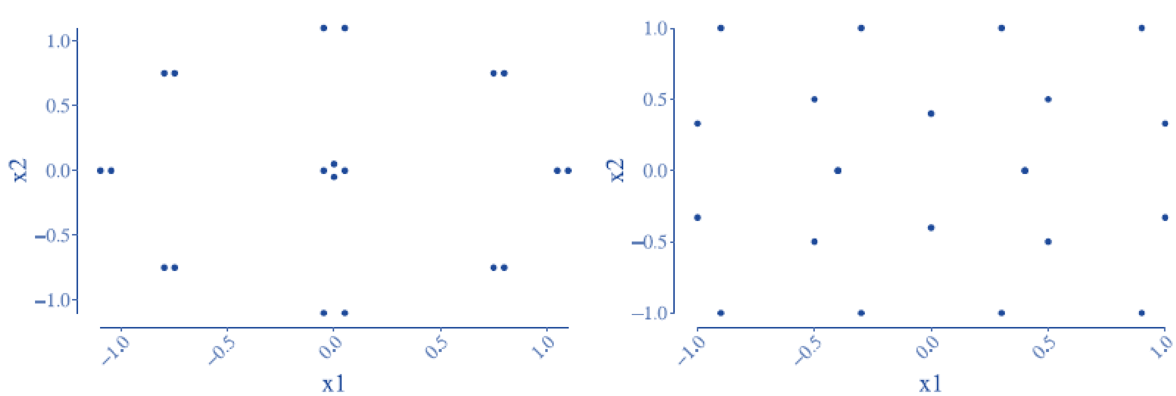
Kriging models are generally more effective than second-order polynomials for approximating nonlinear and irregular relationships. They are designed to provide exact predictions for the training data. However, fitting Kriging models can be challenging and time-consuming due to the need to optimize a complex maximum likelihood function (Kleijnen, 2015).

1.4.2. Design of Experiment

In order to apply metamodels in practice, one has to estimate the coefficients pertinent to the metamodel at hand. This entails create simulation sample using a technique known as Design of Experiments (DoE), which is the process of sampling in computer experiments (Johnson et al., 2021). The estimation of this percentage is made by feeding this simulation sample into the simulation model.

DoE can be implemented in two primary ways: There are two types of experimental methods, basic experimental design and experimental design that occupies the entire space (refer to Figure 1).

Figure 1. Classical and space-filling design



Source: Adapted from Simpson et al. (2009)

Sample points are located at the vertices and the center of the hypercube so that the variance of random errors of stochastic simulation models is minimized. However, Sacks et al., (1989) has pointed out the fact that this type of approach is not very useful while working with fundamentally deterministic simulation models in which systemized error proportions are usually encountered. Therefore, space-filling experimental designs have been suggested for use in place of the traditional design. Of them, the so-called Latin Hypercube design is preferred since it is capable of producing sample points with a uniform distribution pattern and offering good including propagation of the sample points in parameter space, as well as its flexibility in regards to the number of sample points (Morris & Mitchell, 1995).

1.5. Bayesian Averaging of CGE-Models Applying Metamodeling

Expected utility maximization in order to obtain the best policies entails having knowledge of the probability distribution functions Pr(e) and Pr(βe|e). Ziesmer et al. (2020) proposed a Bayesian estimation method most suitable in scaling up a giant number of and intricate dynamic CGE models. One development of this method is the use of Bayesian estimation in combination with metamodels (see Morris and Mitchell 1995) which replaces the detailed CGE model with a surrogate model. This helps to greatly decreasing the complexity and the computational costs of the overall system.

We propose using this framework to minimize model uncertainty and derive the posterior distributions Pr(e) and Pr(βe|e) by utilizing available statistical data, forecasts of selected output variables, and insights from theoretical and practical experts. In the general Bayesian framework, observed variables are noisy, i.e., data $\gamma_0 = \{\gamma^0_1, \ldots, \gamma_n\}$ correspond to true variable values, $\gamma = \{\gamma_1, \ldots, \gamma_n\}$ and noises $\alpha = \{\alpha_1, \ldots, \alpha_N, \}$. The posterior results as:

$$\begin{aligned} & pr(\beta / \gamma^0) \qquad \sigma\, pr(\beta)\, pr(\in) \\ & \quad with \quad (\beta(\alpha) \in \psi := (\beta, \alpha) / \alpha = \gamma^o - \gamma \,\&\, \mathrm{f}\left(\gamma, \delta, \beta\right) \equiv 0 \end{aligned} \tag{17}$$

Building upon this general Bayesian framework, we develop a procedure to derive the posterior parameter distribution for a quasi-dynamic CGE model and a corresponding PIF function. Assuming normal distributions for $\boldsymbol{\epsilon} \propto N(0, \Sigma\boldsymbol{\epsilon})$ and $\beta \propto N(\beta, \Sigma\beta)$ with the co-variance matrices $\Sigma\boldsymbol{\epsilon}$, Σ_β as diagonal matrices with elements $\sigma 2\epsilon$, $\sigma 2\omega$, we can derive the following optimization problem for the Highest Posterior Density (HPD)-estimator:

$$\begin{aligned} \beta^* \quad & = \arg \min_{\beta} (\beta - \vec{\beta})^i \sum\nolimits^{-1} (\beta - \vec{\beta}) + \in^1 \sum\nolimits_{\in}^{-1} \in \\ \in \quad & = \gamma^o - \gamma \\ T(\gamma, \eta, \theta) \quad & \equiv 0 \\ H(\eta, \delta, \xi) \quad & \equiv 0 \\ D(\gamma^0, \eta, \theta, \delta, \xi) \quad & \equiv 0 \end{aligned} \tag{18}$$

In general, when working with observed or forecasted outputs γ, the option of the Highest Posterior Density (HPD) estimation is formulated as an optimization problem as described by the following system: Some other distributions or extremum measures can be chosen retaining the essence of the approach. Further, this approach see (18) enables the case where some of the variables or parameters are fixed. In such cases, those specific variables or parameters are said to be 'constrained' to their prior values and are hence omitted in the prior density function.

1.6. Implementation of the Framework

We derived these steps in R (see R Core Team, 2021) and the General Algebraic Modeling System (GAMS). (see Brooke et al., 2022). As for the utilization of Multiple CPU cores and HPC resource, GAMS is mostly used in single-threaded mode for the optimization models, thus our code was developed accounting for the multi-threaded parallel processing. This parallelization is made possible by the fact that, in the second phase, the simulations are independent of each other. Additionally, it is important to generate two distinct samples: The first one is concerned with building the metamodels which have been discussed in the first part of the paper while the second one is for implementing the policy analysis which was discussed in the second part of the paper.

2. Regional Dynamic Computable General Equilibrium for Nigeria

We began our analysis with the modified SAM structure of the year 2015 for Nigeria elaborated earlier by Randriamamonjy and Thurlow (2016) which encompasses more than 70 sectors in five regions with a distinction in the urban and rural households. To this, our revised SAM narrows it to six sectors and five regions. Based on the binary recursive-dynamic Computable General Equilibrium (CGE) model of the International Food Policy Research Institute (IFPRI), Robinson et al. (2016), the present model assesses the effect of CAADP on sustainable development in Nigeria. This CGE model builds from the assumption that regional goods move in the national market, in turn there are six specific commodities: a sector for each.

The sectors incorporated into our model are:
- Crop Production (crop);
- Other Agriculture (including forestry, fishing, and livestock) (oagr);
- Agricultural Product Processing (agrib);
- Other Industrial Production (oind);
- Public Goods and Services (pub);
- Private Sector Services (prserv).

Our model employs three primary production factors: In other words, the classic factors of production, that are capital, labor, and land. Capital in this scheme is split into agricultural and non- agricultural and land is only associated with a strictly agricultural category. Labor and land are bought and sold in regional markets while capital is 'sold' in the national markets with the agricultural capital and the nonagricultural capital being sold in different markets. In the application of specified sectors, a nested production function is used. This function combines the first level primary factors into the value-added by means of a constant elasticity of substitution (CES) production function. The intermediate inputs from all the other sectors are added together in a fashion that is postulated in the Leontief technology and the total of this input is used to produce the final commodity through another Leontief technology.

On the demand side, the model estimates the per-household type of commodity demand for each region using the linear expenditure system (LES). For imports, the so-called sector-specific CES functions are employed, while for exports the constant elasticity of transformation (CET) functions are used. For the present work, the regional CGE model includes 68 different activities. In parallel with the model developed by Randriamamonjy and Thurlow (2016), our model also includes a micro-poverty module that estimates poverty rates for all of the CGE model's equilibrium conditions.

We identified three key outputs from the model as critical policy objectives: *γ* income (in the form of GDP per capita, *γ* poverty (as captured by the national poverty headcount rate, *γGDP*, *γ* pollution (in the form of CO2 emissions *γCO2*). They paint a picture of a nation's medium-term trade-offs captured by the three dimensions of the sustainable development goals (SDGs) agenda (United Nations, 2021). Since the extent of change in the CGE model is always in a constant flux, the three selected goals are measured in terms of linear growth rates.

$$\gamma_I = \frac{\gamma_K^{2025} - \gamma_K^{2016}}{\gamma_K^{2016}}, I \in \text{(GDP, POVERTY, CO}_2\text{)} \quad (19)$$

Where analysis is based on ten years timeline between 2016 till 2025.

2.1. Policy Impact Function

The following Cobb Douglas function is assumed to change the policy choice vector *γ* into policy impacts $\boldsymbol{\eta}$:

$$\begin{aligned} &H(\boldsymbol{\eta}, \boldsymbol{\gamma}, \xi) \\ &\eta_j && = \xi_j^0 \gamma_j^{\xi_j} \\ &\bar{B} = 1 && \geq \sum_j \gamma_j \end{aligned} \quad (20)$$

where: γj represent the investment of the public in one of the sectors with ∈ {$crop$, $oagr$, $agrib$, $oind$, pub, $presev$}.

Considering the theoretical background, we will assume the base parameter variable for ξ_j which means that the necessity to induce an increase in the technical progress which is the public expenditure is proportional to the magnitude of the sector. Additionally, we set ξj = 0.6. Let s_j denote the share of sector j in total GDP. Then, we assume:

$$\xi_j^0 = \bar{\xi}^0 \left[\frac{1}{\bar{B} \cdot s_j} \right]^{\xi_j} \tag{21}$$

Which then means that for every sector the equal improvement in the technical progress, $\bar{\xi}0$, is real if the portion of the investment of the public share is equivalent to the share of the gross domestic product of the sector. In other words, it means that if we have $\frac{y_i}{B} = S_j$ then with Eq. (20) and Eq. (21), we have $\eta_j = \xi^0 \left\{ \frac{1}{B_{sj}} \right\} Y_j$, thus $\eta_j = \xi^0$.

Certainly, the formulation of the Policy Impact Function (PIF) is inherently ad hoc. Nonetheless, since our primary goal is to illustrate methods for addressing fundamental model uncertainty, we do not view this assumption as a constraint on our analysis. In practical empirical applications, the parameters ξj and ξ0j can typically be estimated within a Bayesian framework that integrates sparse statistical data with insights obtained from stakeholders and expert opinions.

2.2. Model Uncertainty and Metamodelling

Model Uncertainty

To deal with the model uncertainty we are interested in a proper subset of computable general equilibrium (CGE) parameters, θ which is precipitated with some level of imprecision. Here we are talking about the behavior parameters based on production and demand, and the parameters concerning the responses to trade internationalization, which all contribute to the model's uncertainty parameters. Furthermore, structural uncertainty - closure rules and functional forms, for instance - is also present, but is not the main concern here.

With regard to this demonstration we focus on the parameter uncertainty and consider only the 27 parameters while the structure of the model closure rules and functional forms which are described in the Appendix section is kept fixed. Hence our analysis consists of six production elasticities derived from CES production functions, five Armington and CET trade elasticities and international import and export prices. We also consider some doubts concerning the total national factor endowments and foreign savings.

To some extent parameter uncertainty in aggregate demand is mitigated by calculating changes in the number of households in urban and rural areas, nevertheless we retain parameters affecting demands for specific commodities fixed and in so doing are guilty of oversimplification, given the inherent uncertainty in such parameters. This approach assists in echoing down the process of analysis and concentrate only on those uncertainties that influence policy measures.

Forms of Meta Models

As enumerated in the previous section, this research implement he polynomial and kringing model to estimate the possible impact of technical progress which are exogenous shock on important policy goals deriving from the CGE, T (z, $\boldsymbol{\eta}$, θ). The below five meta model types are estimated for more details ,

$$LM1: z = \beta_0 + \sum_{h=1}^{k} \beta_h x_h + \varepsilon;$$

$$LM2: z = \beta_0 + \sum_{h=1}^{k} \beta_h x_h + \sum_{g \geq h}^{k} \beta_{h.g} x_h x_g + \varepsilon;$$

$$OK: z = f(x) + N(x), where f(x) is a constant$$

$$UK1: z = f(x) + N(x), where f(x) is same as LM1$$

$$UK2: z = f(x) + N(x) where f(x) is same as LM2$$

x in the equation above represent and $\theta 1$ in T (z, θ, $\boldsymbol{\eta}$). LM1 only contains the important effect of sampled parameters in the polynomial model LM1 and LM2, while the LM2 contains the main effect and self-quadratic effect and also some subset of double interaction which are selected between multiple parameters. The kringing models included OK, UK1 and UK2.

2.3. Calculation of Optimal Policies and Policy Loss

Considering the computed Metamodels and the Monte carlo sample L, We estimate the optimal policy (δ^*) taking the uncertainty in the model into consideration in eq. (22):

$$\delta^* = \arg\max_{\delta} \ \frac{1}{L}\sum_{I=1}^{L}\prod_{K}\gamma_{i,k}^{ak} \tag{22}$$

$$\begin{array}{ll} s.t & \\ \gamma_i = & f^e(\eta_i, \theta_i \\ \eta_{i,j} = & \xi_1^0 \delta_j^{\xi_{i,j}} \\ \overline{B} = 1 & \geq \sum_j \gamma_j \end{array}$$

The estimated metamodel of the CGE model, denoted as ($\boldsymbol{\eta}l$, θl) is derived for the CGE parameters θl = ($\theta 1$, $\theta - 1$), where $\theta - 1$ represents all fixed CGE parameters - essentially θ.excluding the sampled parameters $\theta 1$. Similarly, we can address the problem outlined in Equation (22) by solving it for a single chosen parameter specification I∈L. This approach yields the optimal policies (δ_l^*) corresponding to the specific parameter specification I∈L.

$$\delta_l^* = \arg\max_{\delta} \ \frac{1}{L}\sum_{I=1}^{L}\prod_{K}\gamma_{i,k}^{ak} \tag{23}$$

$$\begin{array}{ll} s.t & \\ \gamma_i = & f^e(\eta_i, \theta_i \\ \eta_{i,j} = & \xi_1^0 \delta_j^{\xi_{i,j}} \\ \overline{B} = 1 & \geq \sum_j \gamma_j \end{array}$$

Table 1. Validation result across metamodel types

Goal	Measure	LM1	LM2	UK1	UK2	OK
γ_{GDP}	RMSE	0.0475	0.0413	0.0323	0.0219	0.0439
	ER	0.1457	0.0356	0.0462	0.0369	0.0282
$\gamma_{POVERTY}$	RMSE	0.0456	0.0373	0.0452	0.0622	0.0376
	ER	0.1244	0.0164	0.0348	0.0340	0.0625
γ_{CO_2}	RMSE	0.0243	0.0817	0.0410	0.0511	0.0135
	ER	0.3570	0.2036	0.1962	0.1269	0.1715
Total	AER	0.3214	0.1100	0.0611	0.0606	0.0747

Source: Author

To estimate how the optimal policy obtained base on a specific chosen specification of parameter δ_l^* differs from the optimal policy derived under uncertainty in model, we estimate the distance measured; $D(\gamma_i^*, \gamma^*) = \Sigma_j \left|\gamma_j^* - , \gamma^*_{i,j}\right|$. More so, we derive a performance political gap for individual optimal policy δ_l^* relating to the loss of policy L(δ_l^*) as defined in eq. (9).

3. Research Results

3.1. Validation of Metamodel

Our chosen modeling framework requires the estimated metamodels to capture the policy impact well as that done by the original CGE model. The results of validation are given in the form of a comparison between various metamodel types. The polynomial models shown that the Kriging models obtained a better fit than the polynomial metamodels. In particular, it is possible to observe that the RMSE of the degree 1 polynomial model (LM1) is higher and statistically different from the RMSE of the Kriging models. However, the values of RMSE obtained from the quadratic model (LM2) are highly competitive with those of the Kriging models.

These differences in degree as Table 1 reveals indicate that metamodels can be rather accurate in predicting policy outcomes, although their level of accuracy may fluctuate depending on the goal in question. The following table provides validation data for several metamodel types: the linear trend models LM1 and LM2, and the Kriging models UK1, UK2 and Ordinary Kriging (OK). RMSE and ER were calculated and used as measures of performance as they gave the best results out of the available methods.

The relative prediction errors for most models are less than 7% for the development of GDP per capita and poverty reduction; the relative prediction errors of L1M have reached 12% and 15%, respectively. This suggests that linear trend model has relatively a lower prediction accuracy or power in these goals. It is, however, markedly higher for the prediction errors for the reduction rate of GHG emissions across all models. The next model, the quadratic Kriging model, has been referred to as the UK2 and it has the lowest error 13%.

In general, the AER varies from 0.32 to 0.36 with different errors being more frequent in different articles depending on their type and goal. It dropped to 1% for LM1, a significantly worse 11% for LM2, and just 6. 1% and 6. It is zero percent for the Kriging models UK1 and UK2 respectively. This implies that of all the metamodels except LM1, the impact of policy on the policy outcomes as estimated by the original CGE model was approximated fairly well. Of these, the best approximations are given by the universal Kriging models, namely the UK1 and the UK2, although the latter requires high computational power. Especially, it is found that solving the expected utility maximization problem with Kriging models costs approximately 50GB RAM, and takes approximately 30 minutes CPU time, which suggests that these models are quite computationally expensive.

3.2. Policy Choice

The Table 2 presents the optimal budget allocations across various economic sectors as determined by different metamodel types, highlighting the emphasis on technical progress (TFP) within specific sectors. The table details the distribution of budget shares among six sectors: Crop Production, Other Agriculture (Oagr), Agribusiness (Agrib), Other Industrial Production (Oind), Public Goods and Services (Pub), and Private Services (Prserv).

Table 2. Optimal budget allocation

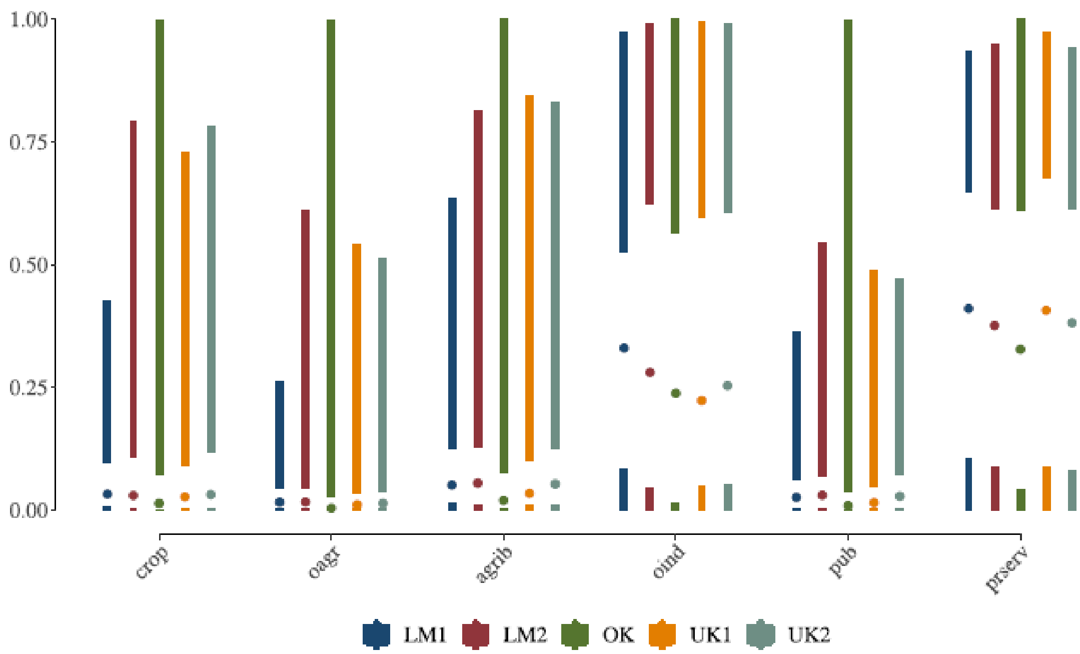
Type	Crop	Oagr	Agrib	Oind	Pub	Prserv
LM1	0.02	0.05	0.38	0.08	0.33	0.04
LM2	0.03	0.04	0.49	0.04	0.42	0.04
OK	0.01	0.05	0.47	0.42	0.02	0.32
UK1	0.49	0.02	0.02	0.37	0.04	0.02
UK2	0.43	0.04	0.37	0.05	0.02	0.08

Source: Author

This work revealed that the decisions of metamodels can affect essentially the optimal budget allocations decided. Remarkably, all developed metamodels recommend pointing to the private service sector, and the proportion in the budget shares ranging from 42% in the quadratic trend model, LM2, to 49% in the Kriging model, UK1. The industrial sector also takes its large shares of the budget; it ranges from 37% for the Kriging models to 42% for the OK – ordinary Kriging. On the other hand, the agriculture and its related agribusiness lines have always been awarded low budget means across all the metamodels. This shows that in these sectors, irrespective of the type of metamodel that is being followed, the emphasis for enhancing TFP, is given lesser importance.

Also, as indicated in Figure 2, it is evident that the budget optimality of all the various metamodel types shifts slightly as we tweak the various parameters of the budget allocation problem. Especially, it is possible to point out the instability in the shares of budget specifying the industrial and private service sectors, varying from zero to one. For Other Agriculture (Oagr) and Public Services (Pub), the growth of max bud share is generally stabilised under 0.75, although majority are below 0.5. These patterns are true for all the metamodel types, with an exception of the basic Kriging model which predicts a full spectrum of budget share for all the sectors.

Figure 2. Budget allocation distribution



The identification of the most suitable policy outcomes, feasible for implementation by the government, highly depends with the specified model parameters (βl, ξl) especially on the way PIF is constructed. For example, Henning et al. (2018) performed a Bayesian sectoral estimation of PIFs in Malawi and discover that fostering TFP in industrial and private service producing subsectors is extremely costly. Their research therefore implies that the Malawi agriculture based sectors should be allocated more proportion of the CAADP funding than the industrial and privatized service domains despite the evidential GDP ratio. This tells us that the assignment of policy where uncertainty prevails should be done cautiously so as to consider the effect of model parameters. To eliminate uncertainty it is necessary to use all the information available, including opinions of experts, to calculate the posterior distribution of appropriate parameters. Nonetheless, in this study, emphasis is on portraying how model uncertainty affects policies rather than prescribing ways of dealing with model uncertainty. Hence the current study does not use empirical studies or knowledge from experts to fine-tune these theoretical assumptions about model parameters. However, the metamodeling approach adopted in this study also has application in Bayesian estimation of other PIF parameters from expert as well as statistical data.

3.3. Policy Loss Induced by Neglecting Model Uncertainty

To show the potential consequences of model uncertainty neglect, policy losses were estimated assuming that 10,000 metamodels have been developed with the aid of Monte Carlo simulations presupposing a certain preselected model specification. This analysis has been performed only for the LM2 metamodel because for the Kriging models the computational load is particularly high. The LM2 metamodel was used instead because we find its AAE to be comparable to the AAE of the Kriging metamodels and, moreover, gives the same policy optimal values regardless of the metamodel type. Hence, by concentrating our analysis on the LM2 model, the study is not particularly limited because this metamodel captures the overall trends and does not impose a high level of computational costs compared to other metamodels.

Figure 3. Density of simulated policy loss

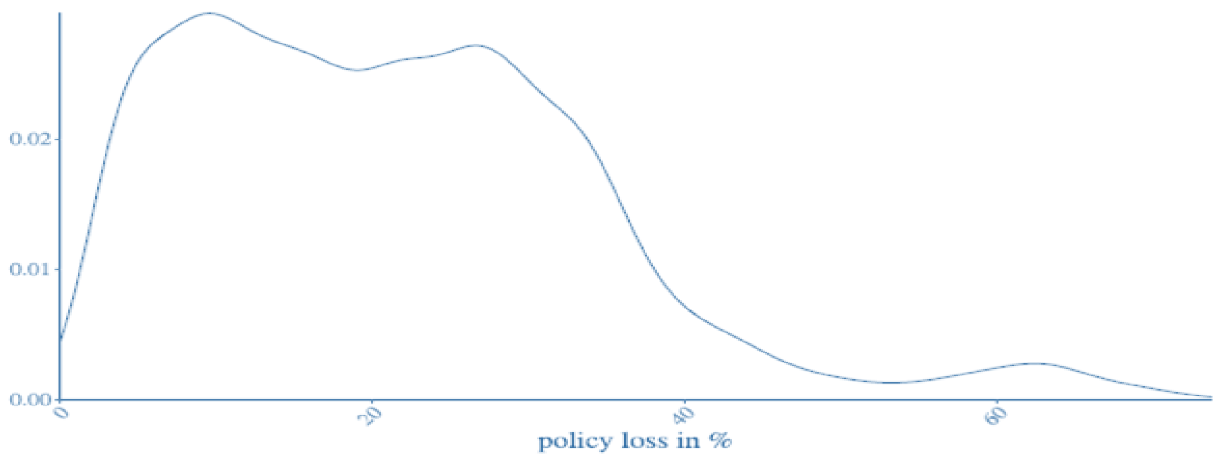


Figure 3 shows separate histograms for each parameter specification indicates the normalized policy losses of the LM2 metamodel type. It is the pure policy loss expressed in the number of actual policy losses divided through by the maximal budget that could have been 'saved' if the welfare level with the same expected value could have been reached by applying an 'ideal' policy. These lost, obtained from simulation made from a sample of parameters to 10,000; varies from 1% to 74% of total budget expenditure. The policy loss mean is 20% while the standard deviation is 8%; for the interquartile range the data is 11% to 30%. This implies that failure to consider model uncertainty results in inefficiency this is because if one randomizes there is always a 50% chance of wasting more than 11% of the budget and a 25% chance of wasting more than 30%.

In light of the study's outcomes, there is evidence that Manuski's theory has it right; vagueness in policy models can lead to considerable bias in predictions and subsequent policy implications. Moreover, policy losses rise even more steeply with the separations of the policies deduced from various models and the ones achieved by Bayesian model averaging. This analysis shows that changes in parameters of CGE models and the parameters of the Policy Impact Function (PIF) create considerable influence on policy losses, assuming that there are strong difficulties in estimating the PIF functions.

Conclusions

This paper responds to the major policy problem of model uncertainty that, while not considered in basic policy analysis, brings about policy failure. The paper introduces a methodological approach by using Bayesian Averaging with metamodeling for model uncertainty in policy analysis. This framework enables one to compute a policy loss function that describes the policy's loss when model uncertainty is not considered. Also, the Bayesian approach helps in minimizing the problem of model uncertainty by estimating the posterior probability distribution of models employing existing data and stakeholder knowledge. This method can be used for solving various public policy problems, in which the use of one or another policy instrument or the achievement of one or another policy goal presupposes certain input-output relations, which are described by complex models.

The application of the framework for evaluating policies under model uncertainty involves the expected welfare maximization where integrals over model based partial derivatives of input-output relations need to be computed. Metamodeling therefore makes this process easier by linking the policies and the model parameters to the output through simulation analysis. In this regard, and to illustrate this approach, the paper is devoted to Nigeria's sustainable development policies, which raises the questions of how the government should distribute public funds across agricultural and, particularly, non-agricultural sectors. To do so, the study employs Latin Hypercube Sampling (LHS), simulating a CGE model to produce policy impacts, estimating multiple metamodels, as well as measuring the political costs of omitting model risk. The key findings from our simulation analyses are as follows:

- The validation of metamodels proves that virtually all selected metamodels well approximate the parameters of policy scenarios in the framework of the original CGE model, and the mean absolute percentage error ranges from 7% to 22%. As expected, again, kringing models are more accurate than polynomial models albeit needing much more computation time.

- When optimal policy choices are obtained from the expected welfare maxima with respect to the different classes of metamodels, the results turn out to be comparable. Nonetheless, investment shares in the in all the sectors demonstrates that model parameters affect policy choices and it may therefore be concluded that parameter specification influences policy choices.
- For the 10,000 Monte Carlo simulations the policy loss ranges from 1% to 74% of the total budget expenditures under CAADP. The median policy loss is 20% so you might choose random parameters for your model and achieve inefficiencies in access of 20% of the budget. These results decisively back the case that failure to address model uncertainty can result in costly policy mistakes.

However, it is pertinent to note some of the limitations that have been noted in our study Biases, The study has some of the following sources of biases – the exclusion of participants who may have reported stress during screening can be referred to as a selection bias. First, the simulation analyses are, in fact, derived from a simple toy CGE model while practical policies are modelled using far more complicated models, for instance the original CGE model for Nigeria comprising 70 production sectors across five regions. This complexity raises the difficulty of effectiveness sampling and estimation of metamodels and especially for polynomial models the number of simulations needed increases as the square of the number of parameters. Nevertheless, the proposed framework can handle metamodels with more than one thousand parameters, using parallel computing or cluster system to share the computational burden. Third, they model a third person's choices, but in reality, there are multiple decision-makers with their answers and preferences. Maybe, extending our approach towards the political bargaining models would provide more realistic view of the situation. Further, examining the process of formation of policy beliefs and their place in political decision-making might contribute to the reduction of biases and enhancement of science-society relationships. Presumably, our framework could be developed into computational tools that would enable interaction between scientific models and stakeholders.

Credit Authorship

Authorship credit is attributed to Paul Gabriel Ekpeyong for his work on incorporating model uncertainty into policy analysis frameworks. His research introduces a Bayesian Averaging Approach that combines Computable General Equilibrium (CGE) models with metamodelling techniques, enhancing the accuracy and robustness of policy analysis under uncertainty.

Conflict of Interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix

Standard deviation

Standard deviations.

flab	flnd	fcap_e	hhd_u	hhd_r	Ecrop	Icrop	Eoagr	Ioagr	Eagrib	Iagrib	Eoind	Ioind	prserv	fsav
0.51	0.99	1.25	0.33	0.24	2.94	4.31	3.09	2.74	2.44	2.31	6.16	4.21	1.35	7.98

Correlation

Correlations.

	flab	flnd	fcap_e	hhd_u	hhd_r	Ecrop	Icrop	Eoagr	Ioagr	Eagrib	Iagrib	Eoind	Ioind	prserv	fsav
flab	1														
flnd	0.43	1													
fcap_e	0.38	0.62	1												
hhd_u	0.70	0.00	−0.05	1											
hhd_r	−0.29	−0.62	−0.90	−0.01	1										
Ecrop	0.42	0.57	0.74	0.16	−0.81	1									
Icrop	0.54	0.54	0.67	0.26	−0.68	0.89	1								
Eoagr	−0.20	−0.01	0.09	0.01	−0.06	0.15	0.10	1							
Ioagr	−0.24	−0.15	−0.19	0.05	0.22	−0.06	−0.06	0.93	1						
Eagrib	0.10	0.22	0.30	0.17	−0.31	0.53	0.50	0.87	0.79	1					
Iagrib	0.45	0.53	0.69	0.31	−0.74	0.92	0.84	0.38	0.19	0.71	1				
Eoind	0.17	0.59	0.87	−0.11	−0.94	0.80	0.69	0.05	−0.23	0.28	0.71	1			
Ioind	0.18	0.59	0.85	−0.06	−0.94	0.80	0.69	0.11	−0.17	0.32	0.75	0.99	1		
prserv	0.16	−0.27	−0.78	0.45	0.64	−0.39	−0.23	−0.22	0.02	−0.19	−0.33	−0.68	−0.66	1	
fsav	0.43	0.43	0.75	0.31	−0.86	0.72	0.63	−0.01	−0.25	0.21	0.66	0.85	0.85	−0.49	1