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Computational Modeling and Analytical Tools in  
Applied Policy Modeling

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## Abstract

Policy analysis, the scientific evaluation of policy impact, must include both the technical transformation and political decision process. This analysis is plagued by limited data that leads to model uncertainty. Not only the derived models are uncertain, but also political decision-makers have to deal with this. They form simple mental models, policy beliefs. Therefore, a political economy equilibrium framework, the Computable General Political Economy Equilibrium (CGPE) model, is developed. The CGPE models the political and economic system together and allows the disentanglement of political performance gaps into knowledge and incentive gaps. Structural model uncertainty is handled by a large simulation sample, while for parameter uncertainty, a MCMC sample is derived. A distributed simulation tool has been developed. A meta-modeling approach is applied to model the transformation of economic growth into outcomes. Sector-specific policy impact functions are estimated using observational and expert data in a Bayesian estimation framework. We applied this framework empirically to the case of the Comprehensive Africa Agriculture Development Programme (CAADP) in Ghana, Senegal, and Uganda. Indicators for key sectors, key policies, and optimal policies are derived, and the impact of model uncertainty on them is assessed. A theoretical framework for measurement and evaluation of participatory network structures is developed. The network generating process is estimated using exponential random graph models, and separate measures for lobbying and informational influence are derived. By combining this, individual policy beliefs are estimated, and their political performance gaps are measured and disentangled into knowledge and incentive gaps. The central results of these applications are: In the technical evaluation, model uncertainty is important, as derived messages can change dramatically. Designing efficient participation structures is hard. Beyond biased incentive gaps, biased beliefs are important for the observed political performance gaps. Using different constitutional and participation scenarios, we show that such a design does not solve the performance gaps. A way out are transdisciplinary research approaches, as they connect the science world with the society, and in doing so, new knowledge is generated.

## Zusammenfassung

Eine fundierte Politikanalyse, d.h. eine wissenschaftliche Bewertung von Politikauswirkungen, muss neben der technischen Transformation spezieller Politikinstrumente in relevante Politikergebnisse auch die Analyse des gesellschaftspolitischen Entscheidungsprozesses, in dem die letztendliche Politikauswahl erfolgt, umfassen. Das zentrale Problem einer umfassenden Politikanalyse ist die begrenzte Verfügbarkeit von Daten. Formal impliziert dies eine fundamentale Modellunsicherheit. In der bisherigen Praxis der wissenschaftlichen Politikanalyse wird diese fundamentale Modellunsicherheit bislang kaum berücksichtigt. Ebenso wird der Umgang mit fundamentaler Modellunsicherheit von realen politischen Akteuren und deren Implikationen in politische Entscheidungsprozesse bislang kaum berücksichtigt. Dies hat erhebliche Konsequenzen nicht nur für die Effizienz politischer Entscheidungen, sondern auch für die Bedeutung von wissenschaftlichen Politikanalysen in der Politikberatung, d.h. die praktische Bedeutung von evidence-based Politikprozessen. Letztere werden in der Literatur standardmäßig als ein institutioneller Garant von *Good Governance* hervorgehoben. Im Gegensatz dazu steht die Kritik des Ökonomen Manski, der in einem prominent publizierten Artikel in PNAS (Manski, 2018) klar herausstellt, dass die gängige Praxis der wissenschaftlichen Politikanalyse einer Ignoranz von fundamentaler Modellunsicherheit gleichkommt. Diese Ignoranz impliziert die Manifestation spezieller Mechanismen in der politischen Praxis - wie beispielsweise die systematische Selektion wissenschaftlicher Ergebnisse, die die eigene politische Meinung unterstützen -, die insgesamt nicht nur zu einer extrem ineffizienten Politikformulierung führen, sondern auch begründen, warum wissenschaftliche Politikanalysen kaum einen effektiven Einfluss auf reale politische Entscheidungsprozesse ausüben. Im Gegenteil reale politische Prozesse sind vielmehr durch naive Vorstellungen, Policy Beliefs, der relevanten politischen Akteure (Stakeholder und Wähler), die fachliche Laien sind, bestimmt. In diesem interessanten Bereich einer erweiterten wissenschaftlichen Politikanalyse unter expliziter Berücksichtigung von fundamentaler Modellunsicherheit leistet die vorgelegte Arbeit interessante Beiträge. Methodisch fallen diese in die innovative Schnittstelle von Informatik und Sozialwissenschaften.

Konkret liegen diese in dem sich gerade etablierenden Teilgebiet *Computational Analytics and Public Policy*. Inhaltlich werden die entwickelten *Computational Analytics* Methoden zur Analyse der CAADP-Reform in drei afrikanischen Staaten mit Hilfe eines Computable General Political Economy Equilibrium (CGPE) verwendet.





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# Chapter 1

## Introduction

The Millennium Development Goal (MDG) of halving the poverty ratio by 2015 has been achieved. As can be seen in fig. 1.1, many regions are still in the ‘Low income (L)’ and ‘Lower middle income (LM)’ categories (blue colored countries), with most of them located in Africa. Achieving the Sustainable Development Goal (SDG) #1 - No poverty: “End poverty in all its forms everywhere.” - remains an important and complex challenge (United Nations, 2015). In achieving this, there is a wide 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 (Saith, 1981; Gaiha, 1989; Sen, 1997; Fan, Hazell, and Thorat, 2000; Diao et al., 2012). Furthermore, scholars agree that public policy is a crucial determinant of growth and poverty reduction (Fan, Hazell, and Thorat, 2000). The political practice also echoes this agreement in the theoretical literature. For example, at the annual ReSAKSS Meeting in 2015 in Addis Abbaba Ousmane Badiane, IFPRI Director for Africa, highlighted the crucial role of governmental policy in promoting growth and reducing poverty in his opening address: “... policymakers need to continue to refine policies, improve institutions and increase investments to sustain and accelerate the pace of growth as well as its inclusivity or broadness and the outcomes of their decisions can be the difference between persistent poverty and future shared prosperity for many of Africa’s most vulnerable populations.”

However, while there is this broad agreement that government policy plays a crucial role in achieving sustainable growth, putting this policy into an ef-

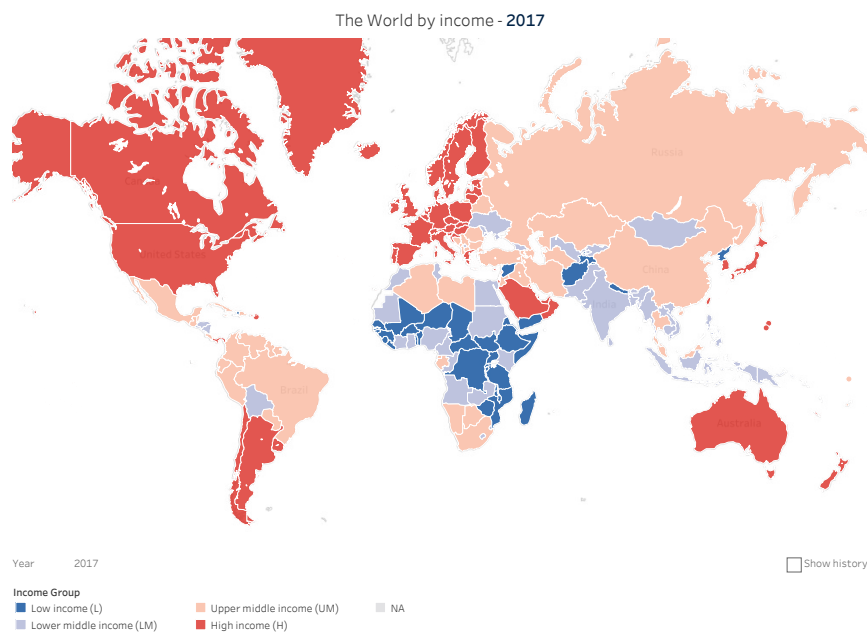


Figure 1.1: The World by income - 2017

Source: <https://data.worldbank.org/products/wdi-maps>

fective operation is a complicated task. Given the dynamic environment, in the economic and the political system, in which this transformation process happens, we need model-based policy analysis. As a first step, we need data to know what happened, and this means being descriptive. Building upon that, we need to understand why and how something happened, the model should help us in diagnosis. The next step is then to predict and understand what will happen, given some choices. The final step is then to also help in making a choice, further clarifying what one should do, i.e., develop a therapy.

Developing and empirically applying such a model is a complex task and needs to connect different worlds. It needs to connect economic with policy modeling, and in doing so, it needs to combine different disciplines like computer science, statistical learning, and economic and policy analysis.

This combination of different disciplines and approaches is the topic of this thesis. The thesis consists of two main parts, the first providing the theoretical and methodological framework and the second applying it empirically to the case of Comprehensive Africa Agriculture Development Programme (CAADP)

in three African countries.

Chapter 2 provides the background and explains the motivation behind the chosen modeling approach, while chapter 3 introduces the Computable General Political Economy Equilibrium (CGPE) and the techniques required in solving the challenges associated with it.

The second part focuses on the empirical application. Chapter 4 contains a short introduction to the empirical background and introduces the framework of the policy modeling problem. An explanation of the estimation approach for the empirical application follows. The next chapter introduces the chosen approach to deal with model uncertainty.

Three different applications around the CAADP policy nexus are described. The first application, described in chapter 7, focuses on the often considered problem of key sectors and key policies and compares the policy impact function (PIF) based approach with previous approaches. It also includes the derivation of technically optimal policies. The second application, chapter 8, looks at the lobbying and informational influence of stakeholders in the policy process. The last application applies the developed framework to look at possible reasons for persisting policy failure.

The final chapter 10 of the thesis is the summary and critical outlook.



Part I

Theoretical and Methodological  
Framework





## Chapter 2

# Policy Analysis: A theoretical framework and literature review

There is a broad agreement in the economic literature that public policy is a crucial determinant to enable future sustainable economic development. This applies to regional, national and global levels, for example regional and national development policies (Saith, 1981; Gaiha, 1989; Sen, 1997; Fan, Hazell, and Thorat, 2000; Diao et al., 2012), or international climate policy (Fan, Hazell, and Thorat, 2000; Obergassel, Mersmann, and Wang-Helmreich, 2017; Lofgren, Thurlow, and Robinson, 2004). This agreement in the theoretical literature is also echoed in political practice (New Partnership for Africa's Development, 2003; NEPAD, 2010; African Union, 2014). In light of the broad agreement that government policy plays a key role in achieving sustainable growth, putting this policy into an effective operation remains a complicated task. A key approach is the promotion of evidence-based policies, where it has been fully recognized that policy impact evaluation is an important prerequisite for evidence-based policy processes. In this regard, the term policy analysis describes the scientific evaluations of the impacts of past public policies and predictions of the outcomes of potential future policies (Manski, 2018).

However, linking scientific analysis to policy formulation and outcome evaluation is a very complex and tedious process. The problem is not just one of applying rigorous science to high-quality data in order to tackle relevant questions. This linking is difficult enough but may still be the easiest part. A second and even greater challenge is for the knowledge and insights generated

from policy research and analysis to find their way into the decision making process. Therefore, a comprehensive policy analysis goes beyond the classical technical analysis of policy impact but includes the analysis of the political process that determines the final policy choice.

## 2.1 Classical Economic Models of Policy Analysis

To illustrate these problems at an abstract level, let  $I$  denote a set of policy instruments, with  $\gamma$  being the chosen implementation. Policy analysis includes two different aspects. First, it is necessary to assess the technical transformation of a policy  $\gamma$  into relevant policy outcomes  $Z$ . This transformation is captured by the technical transformation function  $T(Z, \gamma)$ . Second, different policy outcomes have to be evaluated from the viewpoint of society. Formally, welfare analysis is a tool that provides an adequate evaluation criterion, an index function  $S(z)$ . This index function transforms each state of the world  $Z$  into an index number, and by doing so, allows for consistent ordering of states. Accordingly, if we were to know both functions,  $S(Z)$  and  $T(Z, \gamma)$ , evaluation would be a purely technical task. For a set of available, feasible policies, the policy with the maximal evaluation value  $S(Z)$  would be implemented.

There are many different ways to model the transformation of policies into outcomes. However, each model corresponds to an intervention logic. Any intervention logic for policy programs is based on theory. Generally, modeling approaches can be distinguished in qualitative and quantitative models. Qualitative models, for example, the logical framework matrix, only provide a qualitative description of the intervention logic. Quantitative modeling approaches are based on a quantitative specification of relevant cause-and-effect linkages. Following Henning and Hedtrich (2017) quantitative evaluation models can further be subdivided into model-based, and econometric policy evaluation approaches. Understanding that any model approach implicitly or explicitly determines a set of policy result functions  $\phi$  helps in the differentiation of quantitative modeling approaches. Let  $M$  denote a set of models determining the transformation of a policy  $\gamma$  into relevant outcomes  $Z$ , where  $m \in M$  denotes

a specific model. A policy result function is determined for each model  $m$ :

$$Z = \phi^m(\gamma) \tag{2.1}$$

Let  $\beta^m$  denote a vector of model parameters and variables explicitly considered in the model  $m$ . Then we can further specify the intervention logic by:

$$Z = \phi^m(\gamma, \beta^m) \tag{2.2}$$

### 2.1.1 Econometric Models

In this framework, a simple model corresponds to an econometric modeling approach that postulates a set of policy result functions  $\phi(\gamma, \beta)$ , where  $x$  denotes a set of control variables and uses observational data on  $Z$ ,  $\gamma$  and  $x$  to econometrically specify the parameters  $\beta$  of  $\phi$ .

Econometric model approaches have been increasingly used over the past decade to estimate the causal effects of policies. A causal linkage can be specified as a simple binary relationship between program participation and a relevant performance variable, for example, the impact of participation in a training program on farm-profits or employment. The most straightforward way to measure the policy impact in this context would be to compare the performance of a program participant with the counterfactual performance of the participant without participation. A significant challenge of this approach is to observe both performances, with and without participation simultaneously. The different methods applied in this area are designed to distinguish accidental association from causation. They provide empirical strategies to identify the causal impact of different reforms on any policy outcomes. The best approach to identifying program impact on a given performance variable is to conduct field experiments. A random selection of the units of interest into participating (treatment) and non-participating (control) groups in a policy program is made. Based on a comparison of the average performance of the randomly selected treatment and control groups, the impact of the policy program can be statistically evaluated. While experimental approaches can be applied for ex-post and ex-ante policy evaluation, a considerable drawback of this

approach is that it is costly. For many policies, it is impossible to design sophisticated field experiments allowing a quantitative evaluation. In this case, other econometric procedures based on observational data are available that allow one to identify the true impact of a policy program assuming a non-random selection of treatment and non-treatment groups. These econometric approaches can be subdivided into non-parametric and parametric approaches. An increasingly popular non-parametric approach to policy evaluation is matching on observable factors, especially propensity score matching (PSM) (Caliendo and Kopeinig, 2008). Matching and other econometric methods that build on the idea of controlling for observable factors have clear limitations. The policy impact is very often determined by factors that are unobserved by the researcher. This problem of unobservables implies that PSM delivers biased results or that policy impact is heterogeneous across participants. In order to get around these problems, alternative methods have been developed. They are used to emulate experimental settings using observational data. Examples are ‘natural’ experiments, such as the instrumental-variable approach and the regression-discontinuity approach, or panel-data-based methods that aim to account for endogeneity.

A general cutback of all econometric models, however, is the fact that they are limited to causal inferences, i.e., empirical testing on the question of whether a given policy program achieved its intended outcome or not. In general, they are not alone suitable to explain why or how a policy program works. Thus, econometric models are so-called reduced form approaches that do not allow understanding an elaborate intervention logic. Accordingly, these approaches are unable to explain how policy impact changes if specific framework conditions change or to simulate impacts of policies that have not yet been applied in the past as the specification of the policy result function is based on data observed in the past. A very interesting nonparametric approach applies PSM techniques, originally developed as an advanced ex-post evaluation technique, to simulate ex-ante policy effects at the micro-level (Todd and Wolpin, 2006a,b). An advantage of a nonparametric estimation strategy, when compared to parametric approaches, follows from the fact that the former are less demanding regarding data requirements and do not require any specific functional form assumptions (Todd and Wolpin, 2006b). However,

in many cases, nonparametric approaches are not applicable to ex-ante policy evaluation, but stronger modeling assumptions have to be made, like assuming a specific functional form.

### 2.1.2 Economic Equilibrium Models

As an alternative to econometric approaches, a common approach in economics to specify an intervention logic is to apply a theoretical economic equilibrium model. This means that  $T(\gamma, Z)$  corresponds to a system of non-linear equations. Different approaches are available for equilibrium model-based policy modeling, ranging from simple incidence analysis, over more advanced micro and macro behavioral models to complex micro-macro linkages models. These approaches differ regarding the set of agents and actions they consider, as well as the assumed coordination mechanism of individual actions and equilibrium concepts. The complexity increases with the number of agents and the level of behavioral response that models explicitly take into account. Technically, these differences are covered by  $\beta^m$  in the policy result functions in eq. (2.2).

The core of a standard economic equilibrium modeling application corresponds to the simulation of shocks, where shocks are defined as exogenous shifts in policies or economic framework conditions. In order to simulate policies within an economic modeling approach, the policies must be implemented into the model. Some policies (for example, direct and indirect taxes or tariffs) can be easily and directly implemented into standard economic models. However, for example, structural adjustment policies, policy programs aiming to increase technical progress in economic sectors or policies aiming to improve market access for enterprises (reducing transaction costs) or technology adoption and learning, must be translated into economic model parameters. For example, to model sustainable development policies, dynamic Computable General Equilibrium (CGE) models explicitly incorporate parameters representing sector-specific technical progress, as well as sector-specific transaction costs, subsidy payments, and tariffs (see Löfgren (2001); Löfgren, Harris, and Robinson (2002)). While modeling the impact of technical progress in different economic sectors on the growth of the average per-capita income, on income distribution and poverty is straightforward, the translation of different policy instruments into sector-specific technical progress or transaction costs is by no

means straightforward within a CGE approach. In this context, some scholars (see for example Henning, Badiane, and Krampe (2018); Zhang and Fan (2004)) suggest the implementation of a PIF. This function is defined as a transformation of policy instruments into relevant CGE parameters that correspond to sector-specific technical progress or transaction costs. Specifically, let  $\beta^p$  denote the vector of relevant CGE parameters corresponding to technical progress or transaction costs. We then define a policy impact function as the mapping of a policy  $\gamma$  into relevant CGE parameters:  $\beta^p = PIF(\gamma)$ . The suggested policy impact function basically follows the work of Zhang and Fan (2004). However, in contrast to the original approach, the approach suggested by Henning, Badiane, and Krampe (2018) is more general and implies a non-linear relationship between governmental spending and induced sectoral growth. Moreover, this approach explicitly considers the composition of budget spending for different policy programs. Further, a similar approach was also suggested by Bourguignon, Diaz-Bonilla, and Lofgren (2008); Bourguignon, Bussolo, and da Silva (2008) in their Maquette for MDG Simulations (MAMS) model, which models the impact of different policy instruments on MDGs.

Analogously linking a CGE model with an ecological model (e.g. the Impact model (Robinson et al., 2015)), that translates exogenous shifts in climate conditions (global warming, rainfall) into relevant CGE parameters, is possible. This allows modeling the impact of climate shocks on economic development as well as on the policy impact on development (see Wiebelt et al. (2015)). Formally, let  $\beta^u$  denote the CGE parameters that are changed by exogenous environmental shocks,  $ES$ , then it follows  $\beta^u = ECO(ES)$ . Finally, the CGE can be further linked with other ecological or economic micro-modules, for example, the poverty module used by IFPRI or a regional farm-model translating farm output into impacts on the local environment, like biodiversity or change in land fertility.

Based on the interlinked ecological-economic model framework, it is possible to model policy impact on the development of relevant policy outcomes  $Z$  under different environmental framework conditions. The policy result function  $\phi$

results as:

$$\begin{aligned} Z &= \phi(\gamma, \beta^p(\gamma), \beta^u(ES), \beta^o) \\ &= \phi(\gamma, PIF(\gamma), ECO(ES), \beta^o) \end{aligned} \quad (2.3)$$

Other relevant CGE parameters, for example Armington or production elasticities, are denoted by  $\beta^o$ .

A general problem of model-based policy evaluation is that models are often quite complex, and an empirical specification of the model is often impossible due to limited data. Central causal relationships assumed by a model cannot easily be verified or tested empirically. A significant challenge is, therefore, to develop methods that can provide empirical evidence suitable for guiding policy. This is not an easy task, because it refers to causal inferences that require special research methods that are not always easy to communicate due to their technical complexity.

### 2.1.3 Combining Econometric and Economic Equilibrium Models

Therefore, the best approach to policy evaluation is to combine model-based and econometric methods as complementary approaches. Econometric techniques are applied to identify causal relations between specific policy programs and central economic factors, and model-based techniques to analyze the impact of a change in these economic factors on central outcome indicators. The transformation function is separated into two parts:

1. a policy impact function (PIF) describing the relationship between policy interventions and the economic factors
2. a growth goal function (GGF), policy outcome function, describing the linkages between changes in economic factors and policy outcomes  $Z$ .

Econometric methods are more suitable for tackling the policy impact function, whereas economic models do a better job of tracking the policy outcome function.

A general problem facing classical policy analysis is model uncertainty. All actors, those involved in the policy choice as well as those in the policy analysis,

are fundamentally uncertain which of the different models  $m \in M$  corresponds to the true generative mechanism that represents the natural, economic or social phenomena on which policy analysis is focused (Marinacci, 2015; Wald, 1949; Fisher, 1957; Neyman, 1957; Haavelmo, 1944). At this point we abstract from any finer distinction of uncertainty, which includes for example uncertainty in the data, the structure (model assumptions, theories, like Keynesian versus New Classical specifications (Marinacci, 2015)) and the estimated parameters<sup>1</sup>. Intuitively, agents deal with uncertainty by forming beliefs. This corresponds to subjective prior probabilities that a specific model is the true generative mechanism. Individual beliefs are based on private information. Accordingly, fundamental uncertainty and private knowledge (or private information) are considered as twin notions (see (Marinacci, 2015)). As Manski (2018); Marinacci (2015) points out, model uncertainty is widely ignored by standard policy analysis and the employed classical statistical approaches. Both Manski (2018) and Marinacci (2015) demonstrate that the incorporation of model uncertainty has significant implications for policy analysis and in turn, for policy choice.

## 2.2 Political Economy Models of Policy Analysis

Thus far, we have looked at policy choice as a complex but purely technical task. In reality, the policy choice is more than this. Individual society members evaluate outcomes differently and need to agree on a common policy. Therefore, the policy choice is a collective choice, where heterogeneous policy preferences of individual society members are aggregated to a joint political decision based on specific constitutional decision-making rules.

Comprehensive policy analysis includes both the analysis of the technical transformation of policies into relevant outcomes, as well as the political process in which an actual policy is collectively selected. In representative democracies, preference aggregation is subdivided into two steps. First, heterogeneous voter preferences are transformed into the corresponding preferences of a subset of political representatives via democratic elections. A central prop-

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<sup>1</sup>For a finer distinction see for example Draper et al. (1987); Draper (1995), as well as section 3.3.2 and chapter 6



erty of democratic elections is their representativeness, the correspondence between the distribution of preferences among elected representatives with the distribution of preferences among the voting population. Second, the heterogeneous preferences of political representatives are aggregated into a final political decision via legislative voting procedures.

Differences between observed and ideal policy choices result from two different sources. First, a biased aggregation of society preferences, political weights of groups are different between real policy processes and the ideal democratic process. At a theoretical level, existing political economy models highlight this bias as a primary cause of persisting inefficient policies. Biased political weights correspond to biased incentives of elected politicians, and result from asymmetric lobbying activities (Grossman and Helpman, 1994) or biased voter behavior (Bardhan and Mookherjee, 2002). More recently, Persson and Tabellini (2000) highlight the role of formal constitutional rules as determinants of politicians' incentives to misrepresent society's interests and choose inefficient policies. Beyond biases resulting from the aggregation of society preferences, a second source of biased policy is that relevant political actors do not fully know the true political technology. Understanding the complicated relationship between policy instruments and induced policy outcomes is difficult. As a result, political actors use simple mental models to understand how policies translate into outcomes. We call these simple mental models policy beliefs. Technically, policy beliefs (as introduced by Henning, Badiane, and Krampe (2018)) correspond to model uncertainty as discussed above, i.e., policy beliefs correspond to agents' subjective prior probabilities for different models of policy impact. Hence, policy beliefs correspond to partial knowledge regarding the probabilities that the different models  $m$  are the true generative mechanism determining the policy impact. In general partial knowledge implies that agents focus only on a small subset of models,  $M^g \subset M$ . However,  $M^g$  might be based on expert advice, and its nonsingleton nature might reflect different advice.

Based on their policy beliefs, political actors derive their individual preferences for policies. Similarly, some authors have recently highlighted the role of biased voter beliefs as the primary determinant of inefficient policy choices (Beilhartz and Gersbach, 2004; Bischoff and Siemers, 2011; Caplan, 2007). In

particular, the work by Caplan (2007) has been highly recognized in public choice literature, as he has collected an impressive amount of evidence showing persistently biased voter beliefs. Based on his empirical findings, Caplan (2007) draws the rather pessimistic conclusion that democratic mechanisms of preference aggregation naturally lead to the choice of inefficient policies. In this context, two critical underlying premises that define the framework of evaluating policy processes are adopted here. The first premise is that biased voter beliefs imply biased voter behavior and hence, a biased aggregation of preferences. The second premise is that politicians and other stakeholders do not fully understand the complex relationship between political instruments and desired policy outcomes. Therefore, beyond biased incentives, a lack of political knowledge becomes another essential cause of policy failure.

Formally, political economy approaches taking these aspects into account can be formulated as follows (see, for example, Henning and Hedtrich (2017)). Legislative bargaining is modeled, a set of political agents  $g \in G$  select a policy  $\gamma$  according to given constitutional rules  $\xi$ . Each legislator has a spatial policy preference,  $U_g(\gamma, \hat{\gamma}_g)$ , where  $\hat{\gamma}$  denotes legislators' ideal point, the policy she prefers to all other policies. A legislative bargaining model  $\Xi$  transforms given policy preferences of legislators,  $U^G$ , and given constitutional rules  $\xi$ , into a legislative decision  $\gamma^*$ :

$$\gamma^* = \Xi(u^G, \xi). \quad (2.4)$$

Policy preferences of legislators are derived from political support maximization:

$$\begin{aligned} U_g(\gamma) &= \arg \max_{\gamma} S(Z, \gamma) \\ s.t. & \\ Z &= \tilde{\phi}^g(\gamma). \end{aligned} \quad (2.5)$$

$\tilde{\phi}^g(\gamma)$  denotes the subjective believed policy result function of a legislator  $g$ .

Finally, in democratic systems, political agents' policy support functions  $S(Z, \gamma)$  result from electoral competition. Following relevant literature (e.g. Grossman and Helpman (1996) or Henning, Badiane, and Krampe (2018)) it follows that political support functions can be derived as the following weighted

social welfare function:

$$S_g(z, \gamma) = \sum_v \Omega_v^g (\delta_v^g U_v(\gamma, \hat{\gamma}_v) + (1 - \delta_v^g) S_v(z)) + (1 - \sum_v \Omega_v^g) \sum_i \Omega_i^g U_i(\gamma, \tilde{\gamma}_i) \quad (2.6)$$

$v$  is an index denoting different social voter groups, and  $i$  is an index denoting different lobbying groups.  $\Omega_v^g, \delta_v^g$  are weighting parameters determined by the voting behavior, while  $\Omega_i^g$  is the relative political weight of a lobbying group  $i$  depending on the relative access to political agents  $g$ . In this regard Henning and Hedtrich (2017); Christiansen et al. (2018) suggest a modified Baron-Ferejohn legislative bargaining game and proof that in the equilibrium of this game the final policy choice  $\gamma^*$  follows from the following mean voter theorem:

$$\gamma^* = \sum_g C_g \tilde{\gamma}_g \quad (2.7)$$

$c = [C_g]$  denotes the vector of political control of legislators and is determined in the equilibrium of the game as a function of legislators' preferences and the constitutional decision-making rules  $c = c(U_g, \xi)$ . For large legislative systems comprising of many legislators, like the political system of the European Union with 28 member states, computation of the equilibrium becomes difficult or almost impossible at least with standard solution algorithms (see Christiansen et al. (2018)).

In the framework of a political economy model, comprehensive policy analysis can be conducted, including both the classical analysis of policy impact, as well as the evaluation of the policy process determining policy choice.

The evaluation of policy processes can be based on the comparison between actual, implemented policy choice  $\gamma^*$  and the ideal policy choice  $\gamma^{opt}$  resulting as the equilibrium of the political economy model. The latter assumes that the political preferences of all political agents are derived from the maximization of the social welfare function  $S(Z)$  and policy beliefs of all agents correspond to the true policy result functions  $\phi^{true}$ . Accordingly, total political performance gaps result as the welfare loss realized under the actual policy compared to the optimal policy. Furthermore, total performance gaps can be disentangled in incentive-induced and knowledge-based gaps (see section 4.9).



## Chapter 3

# Computational Techniques and Tools for Advanced Policy Analysis

### 3.1 Model Uncertainty as a Key Challenge for Policy Analysis

“A prevalent practice has been to report policy analysis with incredible certitude. That is, exact predictions of policy outcomes are routine, while expressions of uncertainty are rare” (Manski, 2018). As Manski (2018); Marinacci (2015) pointed out, model uncertainty has mainly been neglected in policy analysis. However, Marinacci (2015) correctly argues further that this practice is in strong contradiction with the fact that predictions and estimates often are fragile, resting on unsupported assumptions and limited data. Neglecting uncertainty has negative consequences for policy choices made in political practice, as this will lead to inefficient policy choices. Manski (2018) presented a list of specific political practices that, by ignoring the uncertainty imply inefficient policy choices. For example, conventional certitude, that is, politicians based their policy choices on model predictions taken as true although they are not true. Another example is dueling certitude, where alternative assumptions lead to contradictory predictions.

To better understand the role of model uncertainty in policy analysis, we

follow Marinacci (2015) to formally define model uncertainty. Formally the policy choice problem, defined as in section 2.1, is to choose a policy  $\gamma \in \Gamma$  that maximizes an objective function  $S(Z)$ , with  $Z$  being the vector of relevant policy outcomes. Policy outcomes are determined by policies, where a set of intervention logics or generative mechanisms  $M$  exists. Each generative mechanism corresponds to a model  $\phi^m$ , where  $m \in M$  denotes a specific mechanism. The decision-maker knows that the true mechanism generating the policy outcomes implied by a policy choice belongs to the set  $M$ . However, the decision-maker is fundamentally uncertain about which model is the true model. An individual decision-maker  $g$  has only partial information (knowledge), which model is the true generative mechanism. Technically, to deal with this fundamental uncertainty, agents form subjective beliefs,  $\mu_g(m)$ , about the relative likelihood that a model  $\phi^m$  is the true generative mechanism.  $\mu_g(m)$  can be interpreted as the probability that  $m$  is the true generative mechanism. Accordingly, beliefs correspond to the subjective probabilities of an individual decision-maker that any model  $m \in M$  is the true generative mechanism  $\phi^{true}$ .

In a Bayesian framework,  $\mu_g(m)$  can be interpreted as subjective prior probabilities. Therefore the policy choice  $\gamma_g^*$  can be derived from a subjective expected utility maximization:

$$\gamma_g^* = \arg \max_{\gamma} \sum_{m \in M} \mu_g(m) S(\phi^m(\gamma)) \quad (3.1)$$

The subjective priors  $\mu_g$  reflects some personal information on models that an agent  $g$  might have. This information can result from past subjective experiences, or it can be based on the advice of a set of experts.

Therefore, at the decision-theoretic level, ignoring model uncertainty implies that agents preselect one model  $m \in M$ . This preselection might be based on subjective priors or might be random. Following Manski (2018), we define policy analysis as a scientific evaluation of the impact of past public policies and the predictions of outcomes of potential future policies. Ignoring model uncertainty corresponds to the fact that scientists advising political decision-makers suggest only one model, with a probability of 1, as the correct model, although they have different private information allocating nonzero probability to more than one model. In both ways, the derived policy choice will lead to a loss of expected utility and thus is inefficient.

Moreover, in a dynamic and social environment, belief up-dating (learning) occurs. Generally, two learning mechanisms can be distinguished, observational and communication learning Acemoglu and Ozdaglar (2010). In a dynamic environment, observational learning occurs as belief-updating based on observed outcomes implied by implemented policies. In a social environment comprising of a set of political agents and experts, communication learning occurs as belief-updating based on communicated policy beliefs (see Acemoglu and Ozdaglar (2010)). At the decision-theoretic level, efficient learning occurs via Bayesian belief-up-dating.

However, in real political systems, belief formation and updating do not necessarily follow strict Bayesian procedures, but real-life political agents often apply simple heuristics and rule of thumbs corresponding to naive non-Bayesian updating rules Henning, Badiane, and Krampe (2018); Henning (2019). The latter is especially conceivable since Bayesian updating in real-world political decision-making situations can be rather complicated, and real-world agents do not have the capabilities to undertake these complex updates Acemoglu and Ozdaglar (2010). Therefore, analyzing the political decision-making of political agents in real-world political systems needs to include model uncertainty. That implies that agents based their decisions partly on rather biased policy beliefs and policy learning is also often rather inefficient.

In this regard, an advanced policy analysis includes an understanding, i.e., modeling, how real-world agents form and update their beliefs via observational and communication learning. Moreover, this includes the analysis of how model uncertainty can be better integrated into policy analysis, into scientific modeling as well as better communicated from science to society. Moreover, an advanced policy analysis includes the question if or how model uncertainty can be reduced, that is how partial knowledge of the science sector can be increased. A fascinating approach in this regard corresponds to transdisciplinary research, meaning the generation of scientific knowledge via an interaction (communication) between science and society, for example, represented by stakeholders Daniell, Morton, and Insua (2015).

Finally, please note that model uncertainty corresponds in essence to limited data. In the last several years, we have witnessed an explosion of data, which was not imaginable in years past. Beyond this, the technology used for

storing, computing, and modeling data has also evolved. Especially, the application of computational algorithms to solve statistical estimation problems resulting from limited data within a Bayesian framework as well as adequate dealing with model uncertainty or the development and empirical specification of large interdisciplinary model frameworks, integrating models of different science disciplines, demand for specific techniques, like metamodeling.

Computing power mostly grew as predicted by Moore's Law (Moore et al., 1965). Computational economics developed in line with the commoditization of computing power. The increase in available computing power and sparked by a problem in economics allowed the development of algorithms to solve, for example, linear programming, quadratic programming, and non-linear problems (Nagurney, 1996). These advances made it possible to develop and solve general equilibrium models that model multiple countries and a very diversified production structure, like, for example, the GTAP model (Corong et al., 2017). Another important strain in computational economics is Agent-based Computational Economics (ACE). Here the focus is more on economic processes and individual behavior and less on equilibria (Tsfatsion, 2006). It allows the application of models that can not be solved in closed form but can only be simulated. This is especially true when solving Bayesian estimation problems, where the integration problem usually cannot be solved analytically (Geweke, 1996). A solution to this problem is the application of Markov Chain Monte Carlo (MCMC) methods, where the Metropolis-Hastings algorithm is an often applied algorithm (Metropolis et al., 1953; Hastings, 1970).

In this thesis, new computational modeling approaches and analytical tools are developed and implemented. How these can be integrated with classical models of policy analysis to derive an empirically applicable CGPE approach, an interdisciplinary and transdisciplinary model framework that solves the above challenges of applied policy analysis, is demonstrated.

## **3.2 The Computable General Political Economy Equilibrium Model**

The challenge of analyzing participatory and evidence-based policy processes empirically is to develop an applicable model framework that allows for quan-



titative modeling of political decision making and policy-learning processes, including the endogenous formation of a legislator's political preferences and policy beliefs.

Overall, comprehensive policy analysis is plagued/confronted with the following challenges:

1. Integrating policy instruments into scientific models
2. Integrating models of different scientific disciplines into a consistent model framework
3. Empirical specification of models  $T(z, \gamma)$
4. Including model uncertainty into the policy analysis
5. Incorporating a positive model of real-life political decision-making
6. Specifying individual political beliefs of relevant political agents and stakeholders
7. Modeling policy learning that is belief updating

Finally, a comprehensive evaluation of policy processes should provide the possibility of developing a political therapy, the derivation of a strategy to reduce identified performance gaps. The latter, in particular, calls for model-based evaluation methodologies.

In this regard we suggest the CGPE model as well as the evolutionary CGPE model (Henning and Hedtrich, 2017) which allows the assessment and identification of different institutional reform strategies, including the reform of formal constitutional rules, as well as the design of informal policy network structures determining political participation of different stakeholders (see chapter 8 and Henning, Badiane, and Krampe (2018); Henning (2019)).

As can be seen from fig. 3.1, the CGPE approach follows the structure of a political equilibrium model outlined in section 2.2.

In detail, the CGPE model includes four modeling components:

- (i) the derivation of politicians' incentives from electoral competition and lobbying, i.e., modeling voter behavior and interest group activities

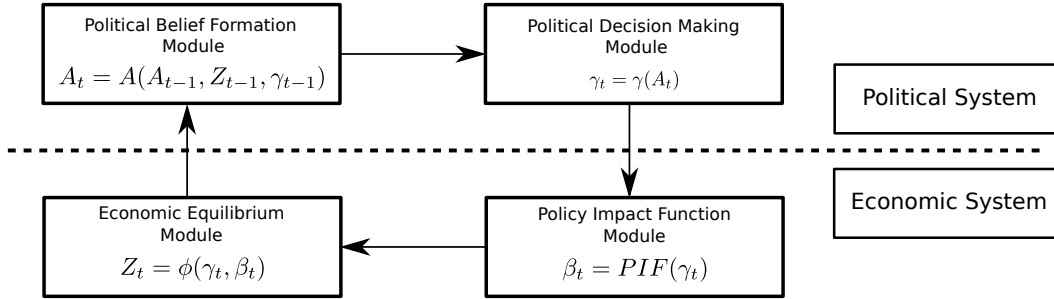


Figure 3.1: CGPE-model

- (ii) modeling legislative bargaining, i.e., the derivation of a collective policy decision by a set of heterogeneous legislators based on constitutional rules
- (iii) economic modeling of policy impacts, i.e., the transformation of policies into outcomes
- (iv) modeling of policy learning, i.e., the formation and updating of policy beliefs via observational and communication learning.

The CGPE is an extension of existing classical approaches in policy analysis found in the literature which focused only on the third component. The other three components represent aspects of the policy process that play a crucial role in explaining why some nations succeed while others fail in adopting efficient and effective policies.

Implementation of the CGPE approach requires the specification of the ecological-economic model as well as of the political decision-making model. Given limited available data classical econometric approaches are unable to estimate all relevant model parameters. Therefore, we apply a Bayesian estimation framework, that allows an adequate treatment of model uncertainty via Bayesian model selection averaging or model averaging. Moreover, we apply a Bayesian estimation technique to estimate relevant components of the political decision-making framework, individual policy beliefs, as well as the political influence of stakeholders. Metamodeling techniques are required to facilitate the Bayesian estimation of the policy impact function as well as the individual policy beliefs. In order to apply metamodeling, a large number of simulation runs of the economic-ecological model are required, which would be rather time-consuming using standard, sequential approaches. Therefore a specific computational simulation tool, Distributed Simulation Tool (DST),

has been developed that allows us to run a large number of model simulations within a reasonable time.

Accordingly, we will describe the three fundamental computational techniques in the following sections:

- A. Bayesian estimation techniques (see section 3.3)
- B. Metamodeling (see section 3.4)
- C. Computational simulation tool DST (see section 3.5)

### 3.3 Bayesian Estimation Techniques

In contrast to the classical view, in a Bayesian analysis, the observed data is considered fixed, and the model parameters as random quantities (Lynch, 2007). In this section, the focus will be on the maximum a posterior (MAP) technique. The building blocks are shared with other Bayesian estimation techniques. The fundamental building block is the Bayes' theorem (Bayes, 1763; LaPlace, 1820). It states that for events  $A$  and  $B$ , given that  $P(B) \neq 0$ :

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad (3.2)$$

In Bayesian estimation, the subject of interest is usually not discrete events, but probability distributions. The theorem is also valid for this case and defined as follows:

$$f(\theta|data) = \frac{f(data|\theta)f(\theta)}{f(data)} \quad (3.3)$$

The posterior distribution is  $f(\theta|data)$ ,  $f(data|\theta)$  the sampling density for the data,  $f(\theta)$  the prior distribution for the parameter  $\theta$  and  $f(data)$  is the marginal probability of the data.  $f(data)$  is calculated as follows for a continuous sample space (Lynch, 2007):

$$f(data) = \int f(data|\theta)f(\theta)d\theta \quad (3.4)$$

The normalizing part  $f(data)$  is often not needed in the Bayesian estimation context, and therefore the Bayes' theorem is often stated in the proportional variant:

$$f(\theta|data) \propto \mathcal{L}(data|\theta)f(\theta) \quad (3.5)$$

The prior  $f(\theta)$  represents the knowledge about the parameter  $\theta$  that is available beforehand. It is represented as a probability distribution. It can represent different restrictions like, for example, bounds or non-negativity. A low variance can be used if one is reasonably sure about a parameter, and a high variance if not. The likelihood  $\mathcal{L}(data|\theta)$  is proportional to the sampling density  $f(data|\theta)$ . The likelihood measures the probability of the data given some parameters. The posterior  $f(\theta|data)$ , the probability of the parameters given data. It is the combination of the prior knowledge with the observed data through the likelihood function.

In a MAP estimation the to be optimized function is  $\mathcal{L}(data|\theta)f(\theta)$ . The MAP estimate returns the mode of the distribution, that is the highest posterior density (HPD). We can retrieve the maximum likelihood (ML) estimation approach as a special case of the MAP by assuming a uniform prior distribution. Therefore the prior term becomes a constant in the optimization, and the only remaining term is the likelihood.

**Example** Suppose we have a series of observed technical progress data for a sector over time  $tfp_t$ , with  $t \in T = 1, \dots, 20$ . The observed values include some errors  $\epsilon_t$ , and we assume those are independent and identically distributed (iid). Assuming the data is generated by the following linear relationship  $tfp_t = A \cdot t + B$ , we want to estimate the parameters  $A, B$ . In the classical (frequentist) approach, this corresponds to linear regression. In the Bayesian way, the problem to solve is very similar. We need to specify our prior knowledge, due to previous studies, experiments, ..., as prior distributions for  $A$  and  $B$ . We also need to define a likelihood function: The observed data does not follow a perfect linear relationship, but it has some error. The assumed distribution for these errors gives us the likelihood.

For illustrative purposes, we assume that  $A$  is normally distributed with  $\mu_A$  and  $\sigma_a$ , and  $B$  as well with  $\mu_B, \sigma_B$ . The errors are iid and normally distributed

with  $\mu_\epsilon = 0$  and  $\sigma_\epsilon$ .

So the parameter vector  $\theta$  we are interested in, is  $\theta = \{A, B\}$ . Given that  $A$  and  $B$  are normally distributed, we have as a prior distribution for  $A$ :

$$p_A \sim N(\mu_A, \sigma_A^2) \quad (3.6)$$

$$p_A \sim \frac{1}{\sqrt{2\pi\sigma_A^2}} \exp^{-\frac{1}{2}\left(\frac{A-\mu_A}{\sigma_A}\right)^2} \quad (3.7)$$

and analogously for  $B$ :

$$p_B \sim N(\mu_B, \sigma_B^2) \quad (3.8)$$

$$p_B \sim \frac{1}{\sqrt{2\pi\sigma_B^2}} \exp^{-\frac{1}{2}\left(\frac{B-\mu_B}{\sigma_B}\right)^2} \quad (3.9)$$

The prior distribution  $p_\theta$  results as  $p_\theta = p_A p_B$ .

In a similar fashion, we can define the likelihood for a single period  $t$ . The likelihood measures the deviation of the observed  $\text{tfp}_t$  data from the estimated  $\widehat{\text{tfp}}_t = A \cdot t + B$  values, with  $\epsilon_t = \text{tfp}_t - \widehat{\text{tfp}}_t$ . Since we assumed a normal distribution the likelihood function  $\mathcal{L}(\theta|\epsilon_t) = p_\theta(\epsilon_t)$  is defined by:

$$p_\theta(\epsilon_t) \sim N(0, \sigma_\epsilon^2) \quad (3.10)$$

$$p_\theta(\epsilon_t) \sim \frac{1}{\sqrt{2\pi\sigma_\epsilon^2}} \exp^{-\frac{1}{2}\left(\frac{\epsilon_t-0}{\sigma_\epsilon}\right)^2} \quad (3.11)$$

Since the  $\epsilon_t$  are iid, the full likelihood for all observations results as the product of the individual terms:

$$\mathcal{L}(\theta|\epsilon) = \prod_{t \in T} \mathcal{L}(\theta|\epsilon_t) \quad (3.12)$$

Applying the Bayes rule we can now derive the posterior distribution  $p(\theta|\text{tfp})$ .

$$p(\theta|\text{tfp}) = \frac{p_\theta(\text{tfp})p(\theta)}{p(\text{tfp})} \quad (3.13)$$

$$\propto p_\theta(\text{tfp})p(\theta) = \mathcal{L}(\theta|\epsilon)p(\theta) \quad (3.14)$$

In the case of a maximum a posteriori (MAP) estimation we can drop the normalizing term  $p(\text{tfp})$  and use a proportional posterior (eq. (3.14)). This results in the following optimization problem:

$$\text{MAP}_\theta = \underset{\theta}{\text{argmax}} \mathcal{L}(\theta|\epsilon)p(\theta) \quad (3.15)$$

$$\text{s.t.} \quad (3.16)$$

$$\text{tfp}_t = A \cdot t + B + \epsilon_t \quad (3.17)$$

To improve numerical feasibility, we can transform the optimization problem by taking the log of the target function and dropping constants. This will change the value of the target function, but it will stay proportional to the posterior distribution. The solution to the optimization problem will remain the same.

For the likelihood we can derive:

$$\mathcal{L}(\theta|\epsilon) \propto \log \mathcal{L}(\theta|\epsilon) \quad (3.18)$$

$$= \log \prod_{t \in T} \mathcal{L}(\theta|\epsilon_t) \quad (3.19)$$

$$= \sum_{t \in T} \log \mathcal{L}(\theta|\epsilon_t) \quad (3.20)$$

$$= \sum_{t \in T} \log \left( \frac{1}{\sqrt{2\pi\sigma_\epsilon^2}} \exp^{-\frac{1}{2}\left(\frac{\epsilon_t - 0}{\sigma_\epsilon}\right)^2} \right) \quad (3.21)$$

$$\propto \sum_{t \in T} -\frac{1}{2} \left( \frac{\epsilon_t}{\sigma_\epsilon} \right)^2 \quad (3.22)$$

$$\propto - \sum_{t \in T} \left( \frac{\epsilon_t}{\sigma_\epsilon} \right)^2 \quad (3.23)$$

we can follow the same steps to derive the log priors for the prior distributions  $p_A$  and  $p_B$ . This means that  $p_A \propto -\left(\frac{A-\mu_A}{\sigma_A}\right)^2$  and  $p_B \propto -\left(\frac{B-\mu_B}{\sigma_B}\right)^2$ . Combining the log-likelihood with the log priors and dropping the negative sign, we end up with the following minimization problem instead:

$$\text{MAP}_\theta = \underset{\theta}{\text{argmin}} \sum_{t \in T} \left( \frac{\epsilon_t}{\sigma_\epsilon} \right)^2 + \left( \frac{A - \mu_A}{\sigma_A} \right)^2 + \left( \frac{B - \mu_B}{\sigma_B} \right)^2 \quad (3.24)$$

$$\mathbf{s.t.} \quad (3.25)$$

$$\text{tfp}_t = A \cdot t + B + \epsilon_t \quad (3.26)$$

The maximum likelihood estimation (MLE) can be derived as a special case of the MAP. This is done by assuming a uniform prior distribution for the parameters, in this case,  $A$  and  $B$ . This means  $p_A \sim U(l_A, u_A)$  and  $p_B \sim U(l_B, u_B)$  with lower bounds  $l_A, l_B$  and upper bounds  $u_A, u_B$ . Then  $p_A \propto \text{constant}$  and  $p_B \propto \text{constant}$ . So instead of the quadratic terms for  $A$  and  $B$  in eq. (3.24), there are only constants, and we can drop those. Then the only remaining part is the (log-) likelihood  $\mathcal{L}(\theta|\epsilon)$ , and this is precisely the MLE problem.

Even though an analytical solution could be derived for this simple example, the focus will be on the computational implementation. An analytical solution can not be retrieved for more complicated problems, and therefore, the computational one is needed. The computational one follows the same basic steps, regardless of how complicated the problem is.

**Code** After the theoretical derivation of the estimation problem, the next step is to implement it. This can be done in any language that supports solving non-linear optimization problems, for example, R Core Team (2018); GAMS Development Corporation (2013). Since the later chapters will mostly use General Algebraic Modeling System (GAMS), it will be used here exemplary as well.

For this example, the observed data will be generated by first choosing a “true”  $A$  and  $B$ . Then  $\text{tfp}$  data is generated according to the linear relationship and an error  $\epsilon_t \sim N(0, 1)$  is added. This can be done as follows:

Listing 3.1: data-generation.gms

```

1 * fix random number generator start point
2 execseed = 1;
3
4 sets
5   T /1*20/
```

```

6 ;
7
8 parameters
9   tfp(T) "observed_technical_progress"
10 ;
11
12 scalar
13   true_a /0.2/
14   true_b /2/
15 ;
16
17 tfp(T) = true_a * ord(T) + true_b + normal(0, 1);

```

To make the setup more easily reproducible, we fix the starting point of the random number generator, so it generates the same sequence of numbers on every invocation. Next, we need to define our estimation model. The values for  $\sigma_\epsilon$ ,  $\sigma_A$ , and  $\sigma_B$  have been set to 1, and therefore, they can be “left out”, and the code is simplified accordingly.

Listing 3.2: model.gms

```

1 scalars
2   prior_a
3   prior_b
4 ;
5
6 variables
7   A "estimated_a"
8   B "estimated_b"
9   ESTIMATED(T) "estimated_tfp"
10  OBJECTIVE
11 ;
12
13 variables
14   ERR(T) "epsilon"
15 ;
16
17 equations
18   def_map_dev(T)
19   def_map_obj
20 ;
21
22 def_map_dev(T)..
23   ESTIMATED(T) + ERR(T) =E= tfp(T);
24
25 def_map_obj..
26   OBJECTIVE =E= sum(T, sqr(ERR(T))) + sqr(A - prior_a) + sqr(b - prior_b);

```



```

27
28 model map /
29   def_estimated
30   def_map_dev
31   def_map_obj
32 /;

```

Finally, we need to supply start values for the model variables, and then the model can be solved. This can be done as follows:

Listing 3.3: solve.gms

```

1 prior_a = true_a;
2 prior_b = true_b;
3 A.l = prior_a;
4 B.l = prior_b;
5 ESTIMATED.l(T) = A.l * ord(T) + B.l;
6 ERR.l(T) = tfp(T) - ESTIMATED.l(T);
7 OBJECTIVE.l = sum(T, sqr(A.l - prior_a) + sqr(B.l - prior_b)
8               + sqr(ERR.l(T)));
9
10 solve map using nlp minimizing objective;
11
12 display A.l, B.l;

```

Implementing the MLE problem in GAMS is then straightforward. We simply need to change the objective function, but can reuse the rest of the model:

Listing 3.4: mle.gms

```

1 equations
2   def_mle_obj
3   ;
4
5 def_mle_obj..
6   OBJECTIVE =E= sum(T, sqr(ERR(T)));
7
8 model mle /
9   def_estimated
10  def_map_dev
11  def_mle_obj
12 /;

```

### 3.3.1 Metropolis-Hastings

The Metropolis-Hastings algorithm solves the problem of generating a representative sample from an arbitrary distribution. It belongs to the family of Markov Chain Monte Carlo (MCMC) methods. It was initially developed by Metropolis et al. (1953) and extended to the more general form by Hastings (1970). Generating a sample for the distribution  $p(x)$  only requires the distribution to be known up to a normalizing constant,  $p(x) = c \cdot \tilde{p}(x)$ ,  $\tilde{p}(x) \propto p(x)$ . Even if the distribution is fully known and available in analytical form, it might still be hard to generate samples from it. Following the algorithm creates a markov process that has as its stationary distribution  $\pi(x) = p(x)$  (Lynch, 2007; Chib and Greenberg, 1995).

To implement the algorithm mainly two things are needed: A function  $\tilde{p}(x) \propto p(x)$  and a proposal distribution  $q(x)$ . In the case of the original Metropolis algorithm, the proposal distribution is independent of the current state of the chain. In the more general Metropolis-Hastings variant, it is conditional on the current state. Therefore the proposal distribution is then  $q(x|x^{i-1})$ .

A start point  $x^0$  is chosen. Usually, the first part, the burn-in period, of the chain is dropped from further analysis to remove the dependency on the start point.

In the following a new candidate is proposed  $x^c \sim q(x^i|x^{i-1})$ . The candidate is accepted according to the acceptance ratio  $\alpha = \frac{\tilde{p}(x^c) \cdot q(x^{i-1}|x^c)}{\tilde{p}(x^{i-1}) \cdot q(x^c|x^{i-1})}$ . The acceptance ratio consists of the product of two ratios: The ratio of the target densities  $\frac{\tilde{p}(x^c)}{\tilde{p}(x^{i-1})}$  and the ratio of the proposal densities  $\frac{q(x^{i-1}|x^c)}{q(x^c|x^{i-1})}$ . The proposal is more likely to be accepted if the candidate is in a higher density region. This ratio is then multiplied by the proposal ratio. In the final step  $u \sim U(0, 1)$  is drawn and if  $u < \min(1, \alpha)$  the candidate is accepted as the new state of the chain. Otherwise, the previous state also becomes the new state.

The distribution  $\tilde{p}(x)$  is often calculated in log terms with all constant terms dropped, for example, to improve numerical stability. Therefore the acceptance

---

**Algorithm 1** Metropolis-Hastings
 

---

```

choose start point  $x^0$ 
for  $i \in \{1, 2, \dots\}$  do
  propose candidate:  $x^c \sim q(x^i|x^{i-1})$ 
   $\alpha = \frac{\tilde{p}(x^c) \cdot q(x^{i-1}|x^c)}{\tilde{p}(x^{i-1}) \cdot q(x^c|x^{i-1})}$ 
  draw  $u \sim U(0, 1)$ 
  if  $u < \min(1, \alpha)$  then
    accept:  $x^i \leftarrow x^c$ 
  else
    reject:  $x^i \leftarrow x^{i-1}$ 
  end if
end for

```

---

ratio is then:

$$\alpha = \frac{\exp(\log \tilde{p}(x^c))}{\exp(\log \tilde{p}(x^{i-1}))} \frac{q(x^{i-1}|x^c)}{q(x^c|x^{i-1})} = \exp((\log \tilde{p}(x^c)) - \log \tilde{p}(x^{i-1})) \frac{q(x^{i-1}|x^c)}{q(x^c|x^{i-1})} \quad (3.27)$$

In the case of a symmetric proposal distribution, this further simplifies to:

$$\alpha = \exp((\log \tilde{p}(x^c)) - \log \tilde{p}(x^{i-1})) \quad (3.28)$$

**Example** Continuing the example from above, we can solve the derivation of the  $A$  and  $B$  values with an application of the Metropolis-Hastings algorithm. Most of the required functions are already defined in the MAP example, that is: the prior distributions for  $A$  and  $B$ , the likelihood  $\mathcal{L}(\theta|\epsilon)$  and in combination the posterior distribution  $p(\theta|tfp)$ . Therefore only the proposal distributions  $q_A(x|y)$ ,  $q_B(x|y)$  for  $A$ ,  $B$  are needed. To keep the example simple, we will use normal distributions:

$$q_A(x|y) \sim N(y, \sigma_{q_A}) \quad (3.29)$$

$$q_B(x|y) \sim N(y, \sigma_{q_B}) \quad (3.30)$$

$$(3.31)$$

Given that we already know the “true”  $A$  and  $B$ , but also the results from the MAP, that returned the highest posterior density, we will assume rather small variances:  $\sigma_{q_A} = 0.05$ ,  $\sigma_{q_B} = 0.2$ . In a further simplification, we assume that the co-variances are zero; this will result in a worse acceptance rate. This is not a problem, given that the problem is so small, and generating additional samples is quick.

**Code** Now that we have all the needed parts defined, we can implement the algorithm. This is done again in GAMS. We need some additional parameters to store the sample points ( $\text{mh\_a}(\text{mh\_i})$ ,  $\text{mh\_b}(\text{mh\_i})$ ), for the candidate ( $\text{mh\_cand\_*}$ ) and some helpers ( $\text{mh\_estimated}(T)$ ,  $\text{mh\_err}(T)$ ,  $\text{mh\_alpha}$ ). The sample point’s log posterior is also stored ( $\text{mh\_log\_posterior}(\text{mh\_i})$ ), and for debugging purposes  $\text{mh\_accepted}(\text{mh\_i})$  stores if the iteration’s candidate was accepted or not. Lines 18 to 24 generate the initial candidate, and in lines 26 to 45 the samples are generated.

Listing 3.5: mh.gms

```

1  sets
2  mh_i /1*30000/
3  ;
4
5  parameters
6  mh_a(mh_i)
7  mh_b(mh_i)
8  mh_estimated(T)
9  mh_err(T)
10 mh_log_posterior(mh_i)
11 mh_cand_a
12 mh_cand_b
13 mh_cand_log_posterior
14 mh_alpha
15 mh_accepted(mh_i)
16 ;
17
18 mh_a("1") = true_a;
19 mh_b("1") = true_b;
20 mh_estimated(T) = true_a * ord(T) + true_b;
21 mh_err(T) = mh_estimated(T) - tfp(T);
22 mh_log_posterior("1") = sum(T, sqr(mh_err(T))) + sqr(true_a - prior_a)
23                       + sqr(true_b - prior_b);
24 mh_accepted("1") = 1;
25

```

```

26 loop(mh_i$(ord(mh_i) > 1),
27   mh_cand_a = mh_a(mh_i - 1) + normal(0, 0.05);
28   mh_cand_b = mh_b(mh_i - 1) + normal(0, 0.2);
29   mh_estimated(T) = mh_cand_a * ord(T) + mh_cand_b;
30   mh_err(T) = mh_estimated(T) - tfp(T);
31   mh_cand_log_posterior = sum(T, sqr(mh_err(T))) + sqr(mh_cand_a - prior_a)
32     + sqr(mh_cand_b - prior_b);
33   mh_alpha = exp(mh_log_posterior(mh_i - 1) - mh_cand_log_posterior);
34
35   if(uniform(0,1) < min(mh_alpha, 1),
36     mh_a(mh_i) = mh_cand_a;
37     mh_b(mh_i) = mh_cand_b;
38     mh_log_posterior(mh_i) = mh_cand_log_posterior;
39     mh_accepted(mh_i) = 1;
40   else
41     mh_a(mh_i) = mh_a(mh_i - 1);
42     mh_b(mh_i) = mh_b(mh_i - 1);
43     mh_log_posterior(mh_i) = mh_log_posterior(mh_i - 1);
44   );
45 );

```

Given the examples for MAP and Metropolis-Hastings, we can compare their results to the ones for MLE and a “classic” linear regression. In fig. 3.2 the estimates for  $A$ ,  $B$  are shown, with *lin-reg* denoting the results from a linear regression, *map* the maximum a posterior estimation, *mle* the maximum likelihood estimation and *mh* the sample average of the Metropolis-Hastings application. As can be seen, the estimates are very similar, except for the linear regression, which has a lower value for  $A$  and a higher constant  $B$  as its result. In fig. 3.3 the estimated linear Total Factor Productivity (TFP) relation is shown. The dots show the observed TFP values, and the lines the TFP calculated based on the estimates from the different estimation procedures. Again only the linear regression is somewhat different from the other three estimation approaches, but this is expected, as the values for  $A$ ,  $B$  were already quite similar.

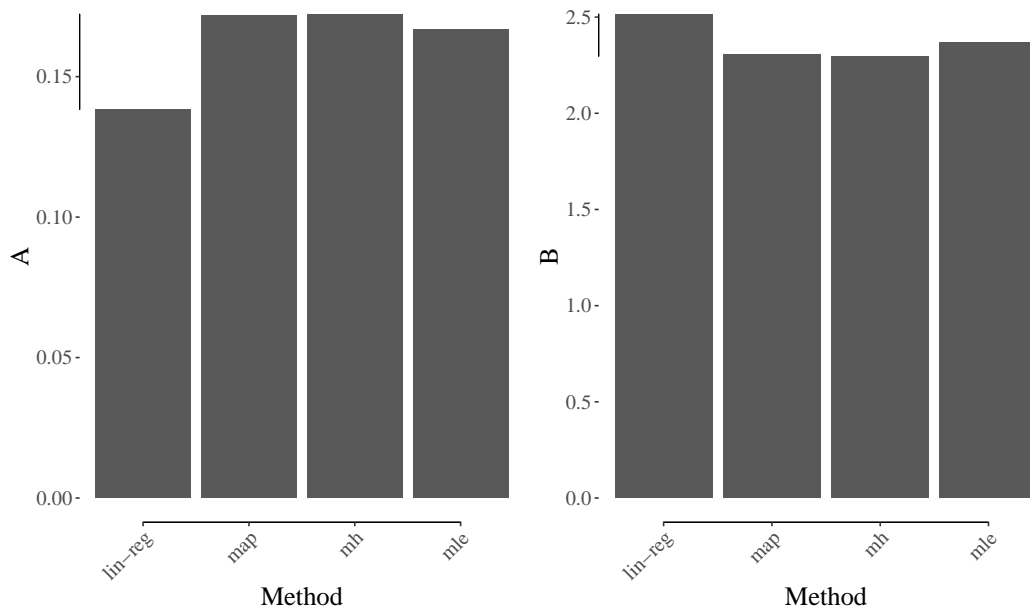
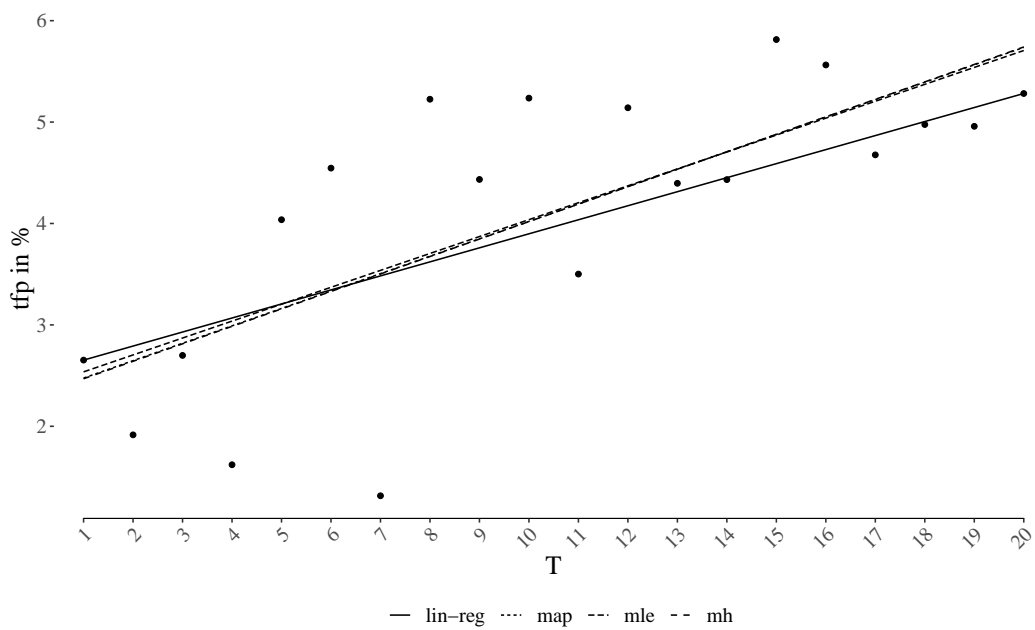
Figure 3.2: Estimates for  $A$ ,  $B$ 

Figure 3.3: Estimated TFP

### 3.3.2 Model Uncertainty

As motivated in chapter 2, model uncertainty is an essential factor of economic modeling in general, and model-based policy analysis in particular (Steel, 2019; Marinacci, 2015). According to Chatfield (1995), there are three primary sources of uncertainty. There is uncertainty in the structure of the model, the parameter estimates of the model, and the observed data. The two main strategies applied to handle model uncertainty are model selection and model averaging. For a more in-depth overview of model uncertainty, see Draper (1995); Chatfield (1995) and for model averaging see Steel (2019).

In a Bayesian framework, we can use the posterior odds to pairwise compare models (George and Clyde, 2004):

$$\frac{P(M_{m1}|y)}{P(M_{m2}|y)} = \frac{P(y|M_{m1}) P(M_{m1})}{P(y|M_{m2}) P(M_{m2})} \quad (3.32)$$

The prior ratio of model probabilities  $\frac{P(M_{m1})}{P(M_{m2})}$  is updated by the data through  $\frac{P(y|M_{m1})}{P(y|M_{m2})}$  to yield the posterior odds  $\frac{P(M_{m1}|y)}{P(M_{m2}|y)}$ . The posterior odds can be used in model selection by using the one with the largest  $P(y|M_{mk})$ . In model averaging, they are applied as well by using them as weights (George and Clyde, 2004). The posterior distribution of a quantity of interest, denoted by  $q$ , is the weighted average of the model-specific posterior distributions (Steel, 2019).

$$p_{q|y} = \sum_m p_{q|y, M_m} P(M_m|y) \quad (3.33)$$

## 3.4 Metamodeling

A metamodel is an explicit simplification of a more complex process, usually given in an analytical form. It is often a model of a model, a surrogate, or approximation. There are many applications of metamodeling, for example, but not limited to, in engineering or natural sciences (Srivastava et al., 2004; Noordeggraaf, Nielen, and Kleijnen, 2003; Kleijnen and Standridge, 1988).

The observed process might be a real-world experiment like, for example, a crop trial in agriculture or a simulation model. In the case of representing a simulation model, the original model can be stochastic or deterministic. The

chosen analytical form depends on the approximated process. It might, for example, be in simple linear form without interaction effects, or a quadratic form with interaction terms, or Kriging form, but it could also be a neural network (Cressie, 1993). It treats the observed process as a black box and, therefore, only depends on the input parameters and output of the process. Given input parameters  $\theta$  and output  $y$ , the metamodel is  $y = f(\theta)$ .  $f(\theta)$  denotes the mathematical function representing the metamodel (Kleijnen, 2005, 2018).

Metamodeling is motivated by the desire to better understand relationships in complex models, like, for example, general equilibrium models. The much simpler and explicit analytical form eases interpretation and quantification of main effects. Depending on the type of the original process, it might not be feasible to run it for all interesting inputs, which is especially true if it is a real-world experiment. Another factor is that a metamodel can be better included in further analysis (Kleijnen and Sargent, 2000; Kleijnen, 2008).

In order to derive a metamodel that provides a good fit and predictive capabilities, a good sample, a good experimental design is required. The experimental design, also known as Design of Experiments (DOE), is used to generate a sample from the design space (Eriksson et al., 2000). The design space gets so large quickly that it is not any more computable or practically feasible to handle all possible points. Therefore many different experimental designs have been developed, of which the Central Composite Design and Latin Hypercube sampling are examples that reduce the required number of sample points (Giunta et al., 2003; McKay, Beckman, and Conover, 1979; Stocki, 2005). Based on the derived sample, the metamodel can be estimated. Before the metamodel can be applied in other contexts, it needs to be validated. Dos Santos and Nova (1999) contains an extensive overview of different validation measures.

See Jin, Hedtrich, and Henning (2018) for a more detailed introduction into metamodeling and its possible applications in policy analysis.



## 3.5 Distributed Simulation Tool

### 3.5.1 Introduction

The task of handling model uncertainty in the PIF estimation, see chapter 6, requires running a large number of simulations using the CGE model. This was the initial spark that led to the development of the DST. This large number of simulations is a somewhat particular case: For every single simulation, ten solves of the CGE model have to be computed, where each depends on the previous one. One single simulation is the smallest unit of work. Even though there is probably still room for improving the solve time of the CGE model, a single simulation already only takes about 20 to 30 seconds. The used solvers and the modeling environment GAMS are mostly single-threaded.

The GAMS grid computing facility provides the ability to solve multiple model instances in parallel. Its primary focus is solving instances that are not dependent on each other. This is not the case for the CGE model, where a lot of the year-to-year updating code would have to be rewritten, and parallelizing using the grid computing facility would force a specific structure which is very complex and not very understandable for the typical user of such models.

Therefore the goal is to develop a tool, which provides the ability to split the units of work and calculate them in multiple processes in parallel. The tool also should be able to run at the same time on multiple machines. The tool, therefore, needs to take care of distributing the work across machines and aggregating the results back together. A clear and simple structure for running the simulations in a distributed fashion, requiring only minimal changes to the original code, is to be developed as well.

The major requirements influencing the development of the tool, and the chosen language and architecture are:

- simple to use
- simple to deploy
- works on Windows/platform independent

The last requirement is mainly driven by the fact that a larger number of machines running Windows are readily available in the department, while

also being able to run on most Linux variants eases the usage of computing resources available in the computing center of the university.

Even though other architectures are undoubtedly possible, a client-server architecture was chosen. An overview of the architecture and how the tool works is given in the following. Afterward, the two main components: the server and client, are described in more technical detail. For an overview of the API, see section 3.5.3. The chapter is concluded by a short example showing the required GAMS code and the steps necessary to run a model using the tool.

### 3.5.2 Overview

The primary motivation behind the tool was the desire a large number of CGE simulations, each of which is independent of each other, and solving a single instance does not take long. In this case, it is not suitable to parallelize the individual solves, but instead, parallelize units of work. A unit of work is, for example, 25 different simulation paths for the CGE model. The flow of the serial calculation can be seen in fig. 3.4. The calculation starts with the blue block, where the model definitions are loaded, and the simulations are set up. It is then followed by calculating the simulations, the green blocks, one after another. It is then concluded by calculating the second blue block, for example, calculating final indicators.



Figure 3.4: Serial Calculation of Simulations

The parallel computation also starts with the same code, the blue block. It is followed by an additional orange block, which takes care of creating the different units of work. These units of work are then calculated in parallel on multiple machines. The results of those are aggregated by another additional block, the second orange one. After the aggregation, the second blue block can run as before.

So this abstract overview already gives an idea that the required modifications to the code are not that big. Some additional steps are required nevertheless:

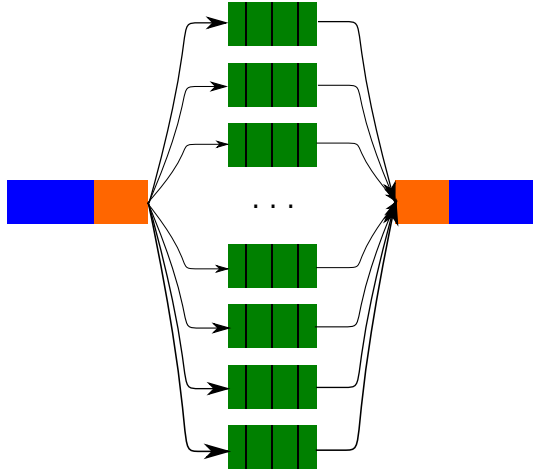


Figure 3.5: Parallel Calculation of Simulations

In the first step, the code has to be adapted to allow the parallel computation of multiple units of work. This involves deciding the size, i.e., the required computation time of a unit of work. The code to create the units of work has to be written. In the case of the simulations of the CGE, this only means that out of the full sample of simulations, a sub-set is selected and saved in a restart point. The computation code of the units of work has to be adapted so that it only calculates the selected sub-set. This can often be achieved by adding a simple \$-condition to the simulation-loop. The last part is to write the aggregation code for the results of the units of work.

The second step is to create the job on the server, which includes uploading the code and defining the commands for splitting the work, computing the work, and aggregating the work. This will be shown in more detail in section 3.5.5.

After the job is started, the clients will pick up different tasks and execute them. They will automatically download the code from the server, run the appropriate command, and upload the result back to the server.

During the computation of the job, the user can inspect some basic information like run-time of a task and also download individual results in the web-interface. After the completion of the job, the aggregated result can be retrieved. The clients communicate with the server using a JSON-based API.

### 3.5.3 Server

The server application has two main components: It provides the endpoint for the client application and also a web-interface for the user to check the status of the jobs. It also provides a rudimentary administration interface. The server application is written in Ruby (Matsumoto, 2017) using the Ruby on Rails framework (Hansson, 2017). The application follows the conventions for developing web applications of Ruby on Rails. These conventions include structuring the code following the Model-View-Controller (MVC) pattern.

The server has a model component, which contains the classes to store the required information. It also contains two controller-components, one for the API and one for the web-interface. The API controllers and the web-controllers both use views, which are either JSON or HTML based.

The model component includes a `User` model, which is used for authentication in the web-interface. It could also be used for the API interface with little modifications, but that does currently not use authentication. It also includes a `Download` model. The `Download` model allows the provision of updated versions of the client without having to redeploy the site.

The jobs are stored in the `Job` model and are named using the *name* column. They are grouped using the `Group` model. In this model, the commands for the split, computation, and aggregate steps are stored in the respective *\*\_command* fields. The *compute\_file* is the name of the file, which is created iteratively by the split task and used as the starting point of the compute tasks. The *result\_file* is the file name of the result of the compute task, and the *aggregate\_file*, respectively, the file name of the result of the aggregate task. The *split\_into* attribute specifies into how many units of work the computation should be split, meaning how many compute tasks.

Jobs have one `SplitTask` and one `AggregateTask`. The `SplitTask`, when executed by the client, creates multiple `ComputeTasks`. The `ComputeTask` represents the unit of work. After the completion of all of the `ComputeTasks` the `AggregateTask` is executed. All three task classes have status fields for:

**accepted\_at** when was the task accepted by a client

**computation\_time** how long did the computation take in seconds

**finished\_at** when was the task finished by the client

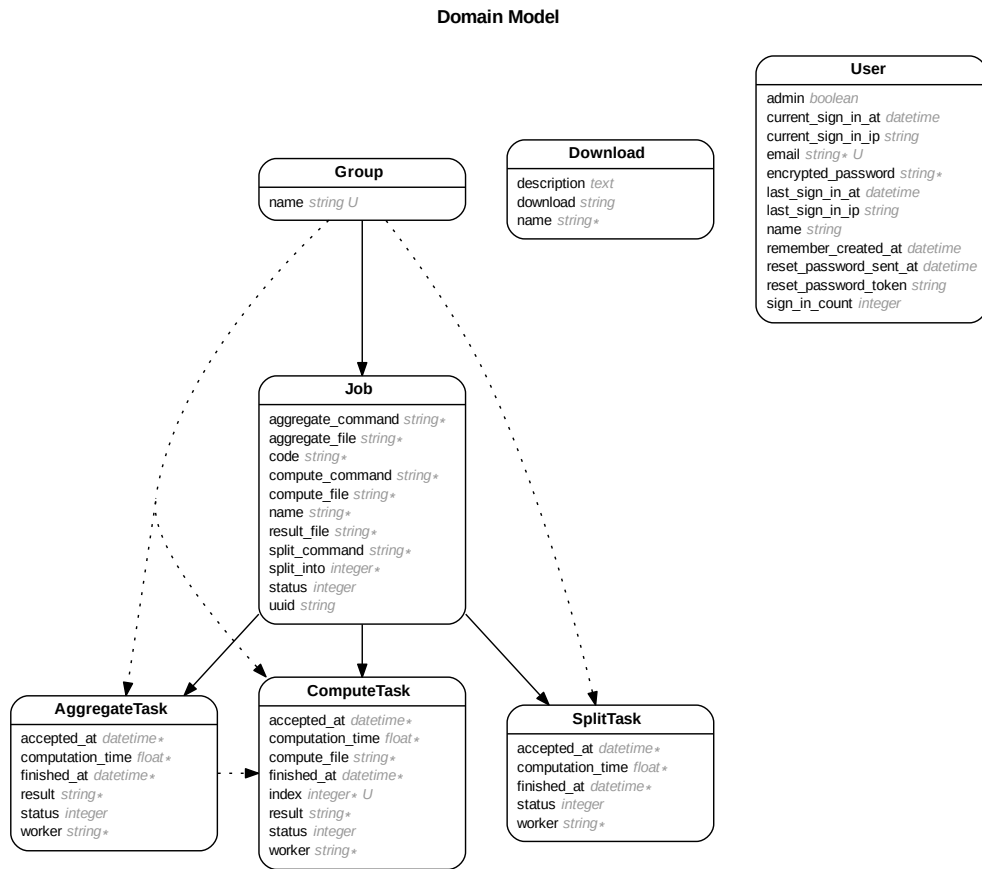


Figure 3.6: Models

**status** enumeration field, which stores the current execution status of the task, it can be one of *created*, *computing*, *completed*, *failed*

**worker** identification of the computer executing the task

The compute tasks are numbered from one to the total number of compute tasks, as specified in the *split\_into* field of the Job model. This is stored in the *index* field. The compute tasks and aggregate tasks both store the result of the computation. The results are stored in the file system, and a reference to the location is stored in the database.

The controllers can be grouped into the API controllers and the controllers for the web-interface. The API controllers are all in the `Api::V1` namespace. The web-interface controllers can again be grouped into two groups, one for providing administrative access to the models, and one for the user

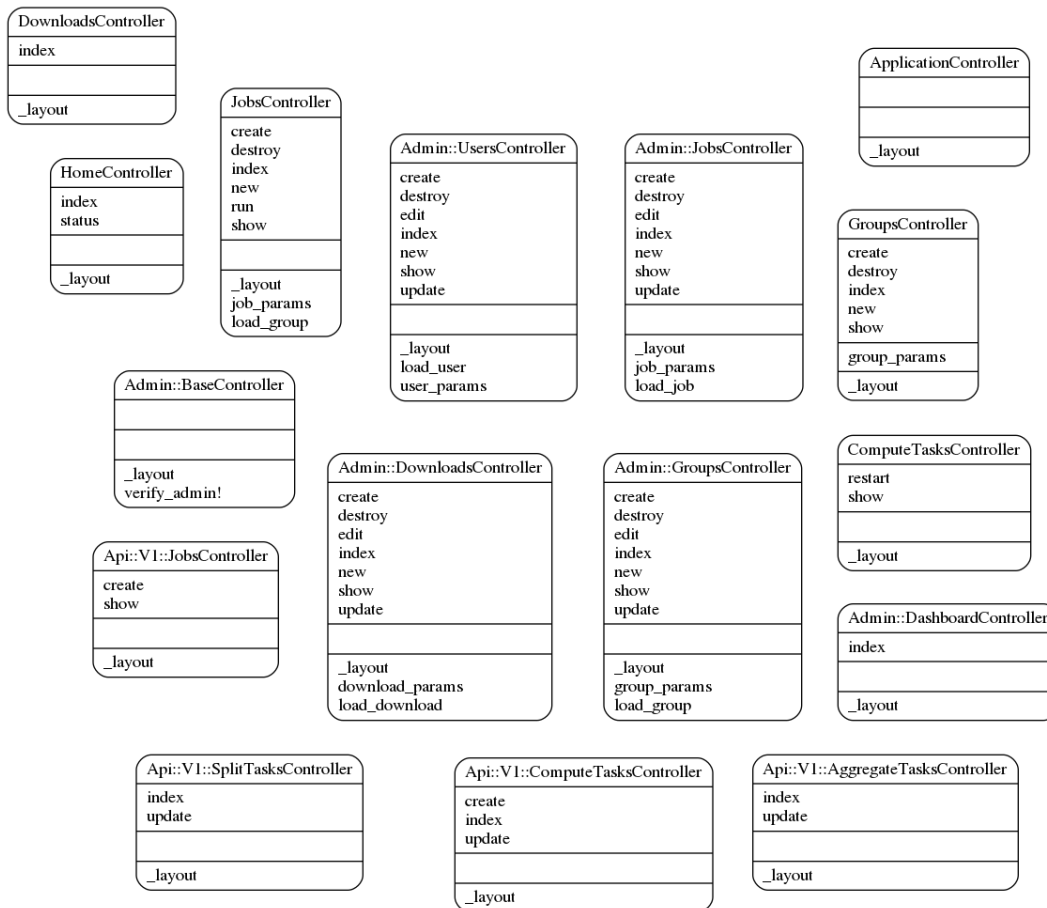


Figure 3.7: Controllers

managing the jobs. The administrative controllers are all in the `Admin` namespace. The administrative controllers provide basic create-read-update-delete (CRUD) functionality.

## API

The API controllers provide the endpoints for the client, which are needed to compute a job. Four controllers are used: `JobsController`, `SplitTasksController`, `ComputeTasksController` and `AggregateTasksController`. As the names suggest, they map closely to the models and are each responsible for handling the respective model. For a detailed description of the required parameters and responses, access the `DEPLOY_URL/apipie` URL. All responses are in JSON format.

The `JobsController` provides the following methods:

**GET** /api/v1/jobs/:id Get the details for a job

**POST** /api/v1/jobs Create a new job

The `SplitTasksController` provides the following methods:

**GET** /api/v1/split\_tasks List available split tasks

**PATCH** /api/v1/split\_tasks/:id Handles the status updates of a task. It allows accepting, completing, and failing a task.

The `ComputeTasksController` provides the following methods:

**GET** /api/v1/compute\_tasks List available compute tasks

**PATCH** /api/v1/compute\_tasks/:id Handles the status updates of a task. It allows accepting, completing, and failing a task.

**POST** /api/v1/compute\_tasks Create a new compute task

The `AggregateTasksController` provides the following methods:

**GET** /api/v1/aggregate\_tasks List available aggregate tasks

**PATCH** /api/v1/aggregate\_tasks/:id Handles the status updates of a task. It allows accepting, completing, and failing a task.

### 3.5.4 Client

The client is also written using the Ruby programming language (Matsumoto, 2017). It uses the previously described API methods to handle the actual computation of a job. Each instance of the client handles exactly one job at the time. There was no focus put into handling errors like network outages since its primary application was in the university, where the network is very stable. It was also developed under the assumption of completely trusting the code to be executed not to be malicious. It does not sandbox or limit the executed code in any way. This is a limitation that is acceptable in the current use case. The ruby code itself works across all major platforms like Windows, Linux, and Os X. The computers in the department usually do not have Ruby

installed, but they come with Java pre-installed. The code is also compatible with JRuby and can be bundled into a JAR file using the *warble* GEM. The generated JAR file can then easily be executed on the department's computers.

To further simplify the execution on multiple computers, a set of PowerShell scripts has been developed. They open remote desktop sessions to the computers, manage the retrieval of the current client executable, and start a set number of clients on each machine. They also take care of stopping them at an appropriate time and cleaning up afterward.

Exceptions occurring during the execution are logged using the *Airbrake* GEM. The reporting target for the exception logging can be configured. It can either be the *Airbrake* provided one, or the compatible, self-hosted, *errbit*<sup>1</sup>.

An overview of the classes in the client can be seen in fig. 3.8.

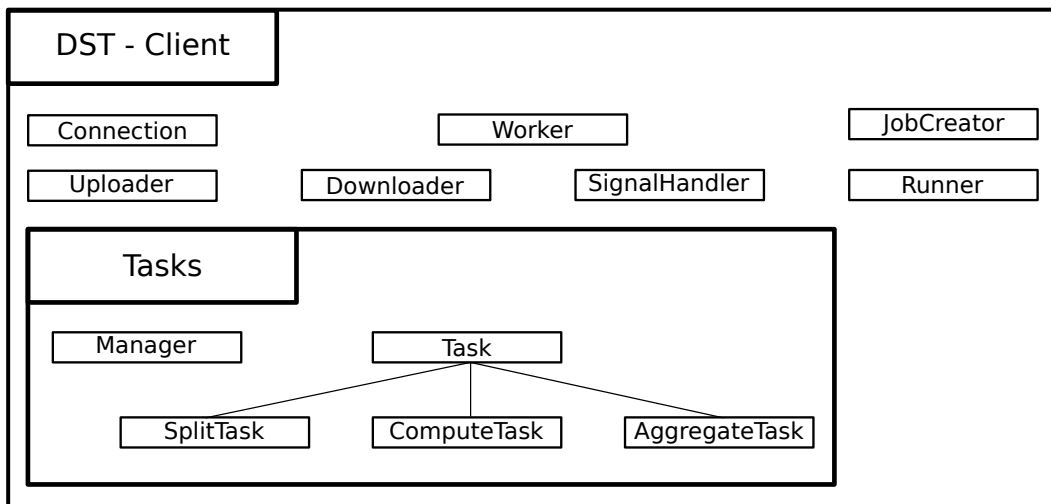


Figure 3.8: Client Class Overview

The client has two operation modes:

- It can create jobs from a YAML-file, which has been generated by another helper program and contains the attributes for the different jobs.
- It can execute the tasks it retrieves from the server.

The first one is relatively straightforward. When the client is started, a *Worker* instance is created, which then creates an instance of the *JobCreator* class and calls *create!* method on that instance. It then loads the attributes

<sup>1</sup><https://github.com/errbit/errbit>



from the YAML-file and sends a POST request to `/api/v1/jobs` using the `Uploader` class for each set of job attributes in the file. The `Uploader` class uses the `Connection` class for the technical handling of the request.

The client was initially created for the second use-case. When the client is started, a `Worker` instance is created, and an instance of the `Task::Manager` class is also created. The `start` method of that instance is then called, which in turn calls the `run` method. The `run` basically does three steps:

1. sleep for a certain amount of time
2. Ask task manager to look for work
3. call itself, forming an endless loop

The endless loop can be canceled by sending a `INT` or `TERM` signal to the process; this can, for example, be done by pressing CTRL+C in the process window. The `Task::Manager` instance then tries to retrieve a task from the server. It first queries for compute tasks, by sending a GET request to `/api/v1/compute_tasks`. If the server returns at least one task, the manager then tries to accept it. Since this happens on multiple computers at the same time, two different clients may try to accept the same task. The server captures this, and the client then restarts the loop. If there are no compute tasks available, the same process happens next for aggregate tasks and at last for split tasks. This is something that undoubtedly can be improved, but works good enough at the moment. It would be a possibility to have a dedicated task endpoint in the server, which returns one available task and assigns that to the requesting client.

When a task is accepted, the manager retrieves the attributes of the associated job. If the code has not been retrieved so far, it will be downloaded. Then the code will be extracted, and the required data for the task will be retrieved, for example, the compute file (the restart point) for the compute task and also put into the extracted directory. In the next step, the task will be executed; this is done using the appropriate `command` from the `Job` instance. The command is passed to a new instance of the `Runner` class. It takes care of launching the computation process and checking for the successful execution status. It would also be possible to capture the output of the computation process and store that, but this is not done currently. if the task was a split task,

it will create *split\_into* number of `ComputeTasks` by sending POST requests to `/api/v1/compute_tasks` with the appropriate data. The task will update the status by sending a PATCH request to `/api/v1/*_task`. The compute tasks, and the aggregate task will also upload the appropriate result file. After the task has been entirely handled, the next iteration of the endless loop is started.

### 3.5.5 Example

To further illustrate the usage of the previously described tool, the steps required to execute the code on multiple computers are shown. The differences in the required GAMS code are shown, and also the required steps in the web-interface.

#### Serial Execution

The serial execution code is shown in listing 3.6. It is a simple and contrived example, but it serves the illustration purposes. Lines one to nine represent the setup block. The first blue block in fig. 3.4. Lines eleven to thirteen the execution blocks, the green blocks. Lines fifteen to nineteen represent the second blue block, where, for example, derived results from the simulations are calculated.

Listing 3.6: serial\_execution.gms

```

1  sets
2    SIM /1*100/
3    ACTIVE(SIM)
4  ;
5
6  parameters
7    age(SIM)
8  ;
9  ACTIVE(SIM) = YES;
10
11 loop(ACTIVE,
12   age(ACTIVE) = uniformint(0,99);
13 );
14
15 parameters
16   average_age
17 ;
18 average_age = SUM(ACTIVE, age(ACTIVE)) / card(ACTIVE);

```

```
19 execute_unload "result.gdx" average_age;
```

### Parallel Execution

The parallel execution requires some more steps. The code has to be split into multiple files, namely *1setup.gms*, *2split.gms*, *3compute.gms*, *4aggregate.gms* and *5derive.gms*. In the second step, a job has to be created in the web-interface, and the clients have to be started.

**Code** The first split off file is the *1setup.gms* file, which can be seen in listing 3.7. It is the same as the first eight lines from the serial execution. This file will be executed prior to creating the job and the state of the program be stored in a GAMS save point, which will be used as the restart point for the *2split.gms*, *4aggregate.gms* and *5derive.gms* files. *1setup.gms* represents the first blue block in fig. 3.5, *2split.gms* the first orange block, *3compute.gms* the green blocks, *4aggregate.gms* the second orange block and *5derive.gms* the second blue block.

Listing 3.7: 1setup.gms

```
1 sets
2   SIM /1*100/
3   ACTIVE(SIM)
4 ;
5
6 parameters
7   age(SIM)
8 ;
```

The code in *2split.gms*, listing 3.8, is the first additional code required. It splits the big set of simulations into smaller chunks. The file is called *split\_into* number of times by the client. It receives the current iteration index *%current%* and the *%total%* number of iterations, being the *split\_into* number, as command line arguments. The result of each iteration is again stored in a save point, which will be the restart point for the *3compute.gms* file. The client will upload the save points to the server while creating the compute tasks.

Listing 3.8: 2split.gms

```
1 scalar lower, upper;
```

```

2 lower = floor(((%current% -1) * card(SIM)) / %total%) + 1;
3 upper = floor((%current% * card(SIM)) / %total%);
4
5 ACTIVE(SIM)$ (lower <= ord(SIM) and ord(SIM) <= upper) = YES;

```

The client will retrieve the previously created save points and then execute the code in listing 3.9, the *3compute.gms* file. The code starts the same as lines eleven to thirteen in the serial execution, but the *ACTIVE* set is this time not the full *SIM* set, but only a small sub-set of it. The result of the computation is stored in the *result.gdx* file, which will be uploaded by the client to the server.

Listing 3.9: 3compute.gms

```

1 loop(active,
2   age(active) = uniformint(0,99);
3 );
4
5 execute_unload "result.gdx" age;

```

In the aggregation step the *4aggregate.gms* file is used, listing 3.10. Before execution, the client will download all results from the compute tasks. This file is then again called iteratively similarly to the *2split.gms* file. The second orange block represents it in fig. 3.5.

Listing 3.10: 4aggregate.gms

```

1 parameters
2   age1(SIM)
3 ;
4
5 $INCLUDE 2split.gms
6
7 if(lower > 1,
8   execute_load "merged_result.gdx" age;
9 );
10 execute_load "results/%current%/result.gdx" age1=age;
11
12 age(ACTIVE) = age1(ACTIVE);
13
14 execute_unload "merged_result.gdx" age;

```

The final step is to retrieve the merged result and execute the *5derive.gms* file, shown in listing 3.11. It first loads the *age* parameter from the GDX file, and the rest of the code is the same as lines fifteen to nineteen in the serial execution.

Listing 3.11: 5derive.gms

```

1 execute_load "merged_result.gdx" age;
2
3 parameters
4   average_age
5 ;
6 average_age = SUM(ACTIVE, age(ACTIVE)) / card(ACTIVE);
7 execute_unload "result.gdx" average_age;

```

**Running it** In order to execute on multiple computers, the following steps have to be done:

1. Execute `gams 1setup.gms s=setup`
2. Create Zip-File of the code including the `setup.g00` restart point.
3. Create a job in the web-interface:

The screenshot shows the 'Create Job' web interface. At the top, there is a navigation bar with 'Gams Job Distributor', 'Downloads', 'Admin Area', 'Sign Out', and 'Johannes'. The main content area is titled 'Create Job' and contains several form fields:

- Name:** A text input field containing 'Dissertation Example'.
- Split into:** A text input field containing '10'.
- Split command:** A text input field containing 'gams 2split.gms -r setup -s run --current={current} --total={total}'.
- Compute file:** A text input field containing 'run.g00'.
- Compute command:** A text input field containing 'gams compute.gms -r run'.
- Result file:** A text input field containing 'result.gdx'.
- Aggregate command:** A text input field containing 'gams 4aggregate.gms -r setup --current={current} --total={total}'.
- Aggregate file:** A text input field containing 'merged\_result.gdx'.
- Code:** A section with a 'Datei auswählen' button and the text 'test.zip'.

At the bottom of the form, there is a 'Create Job' button.

Figure 3.9: Job Creation in Web-Interface

4. Start clients
5. Wait for completion

6. Download merged result from web-interface

7. Execute `gams 5derive.gms r=setup`

For this contrived example, which completes in a split second in serial execution, this is much work. In the case of running thousands of CGE simulations, the additional required code is mostly the same as shown here, but the setup and simulation code is thousands of lines. The computation of the simulations would take multiple days to weeks on a single computer. Using the approach described here, this can be done in a matter of hours.

### 3.5.6 Conclusion

The chosen architecture and language proved to be a good fit for the problem of creating a tool that allows the distribution of long computations across multiple machines. After the initial adaptation of the code to the structure shown in the previous section, it requires little manual attention to run the computation. This improves reproducibility and allows for more experimentation, as running a large simulation sample is no longer a week-long endeavor. It has been successfully applied in the empirical application, which is described in the later chapters of this thesis. Even though the primary motivation to develop the tool was running simulations using GAMS, it is not limited to it, and the general underlying idea and approach can be applied with any programming language.

Part II

Empirical Application





## Chapter 4

# Study Framework and Background

After having introduced the theoretical and methodological framework in the first part of the thesis, we will now show how to apply this framework to the case of CAADP in three African countries, namely Ghana, Senegal, and Uganda.

Imagine being a political practitioner: A politician who has to choose a policy that best achieves her goals or an interest group that wants to lobby for a policy that best fulfills their clientele interests. If one does not want to make a random guess, it is necessary to understand what impact a policy has on goals. A goal might be poverty reduction or income of smallholder farmers. In this section, a theoretical framework is derived that shows the impact mechanism and allows a quantitative analysis of the choice problem.

In the first step, the intervention logic is shown. The intervention logic describes the transformation of a policy choice, allocation of budget, into goal achievements. Based on the intervention logic the policy impact function (PIF) and growth goal function (GGF) are introduced. Indicators for the popular problem of key sectors and key policies can then be derived. The PIF and GGF can then also be used to estimate optimal policies. As a last essential step, it is then also possible to measure the impact of technological beliefs and incentives to check if it is an incentive bias (as is often assumed, see, for example, Persson and Tabellini (2000)) or a knowledge bias.

## 4.1 PEBAP

The empirical framework for this thesis is the Promoting Participatory and Evidence-Based Agricultural Policy Processes in Africa (PEBAP) project<sup>1</sup>. The German Federal Ministry for Economic Cooperation and Development (BMZ) funded the project. The project was jointly implemented by International Food Policy Research Institute (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.

Research on African policy processes was conducted in close collaboration with local stakeholders and policymakers in support of the CAADP. The goal of the project was to support political performance in order to achieve more effective policies and strategies. The research included both qualitative and quantitative methods. It includes studies from an individual level to the national level. At the individual level, voting decisions were analyzed, accompanied by research on the influence and integration of different organizations into the policy process and is complemented by studies on the impact of national investment plans. The project was implemented between 2012 and 2015.

## 4.2 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 percent of the national budget to agriculture in order to achieve a 6 percent 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; Os-

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<sup>1</sup><https://pebap.agrarpol.uni-kiel.de/>

termann, 2017). Inside the CAADP process, the countries develop national agriculture investment plans.

The national agriculture investment plans share a similar implementation, at least for the three countries, Ghana, Senegal, and Uganda. The investment plans focus on different policy instruments, which can be categorized into four pillars: Natural Resource Management (NR), Farm Management (FM), Market Access (MA) and Human Resource Management (HR). Inside the NR pillar, two instruments can be distinguished. The first being water management, and the second being land management. The FM pillar consists of programs focusing on food crops and livestock. A dedicated instrument accompanies them for export crops in Senegal and Ghana Policy instruments focusing on road and storage infrastructure and market support services belong to the MA pillar. The fourth pillar, HR, consists of programs focusing on extension services and research and development.

### 4.3 CGE

Following the definition of Dixon and Parmenter (1996) the model developed by Johansen (1960) is the first CGE model. In the following period, the theoretical underpinnings were refined, before gaining more considerable popularity in the 1970s (Dixon and Parmenter, 1996). Nowadays, it is an often applied tool in policy analysis, see, for example, Bourguignon and Pereira da Silva (2003); Löfgren, Harris, and Robinson (2002); Fan (2008).

A CGE model fulfills three specifications (Dixon and Parmenter, 1996):

**computable** A numerical solution can be found. Using a database, usually, including flows of commodities and factors between different accounts, the equations based on coefficients and parameters are solved.

**general** They model multiple different economic actors and are not limited to, for example, just producers. They usually include actors representing firms, households, and the government.

**equilibrium** The found solution is based on the assumption of market equilibrium. The prices are adjusted so that there is no excess demand.

The CGE model captures the effects of external shocks on all relevant actors. This is not limited not only to direct effects, but it also includes indirect effects. A technical progress shock in a sector might lead to lower prices for the produced goods of that sector, meaning in turn that households spent less of their budget good and have a higher demand for other goods, potentially increasing their prices. Various assumptions determine the equilibrium solution and quantity effects. The behavior is, for example, determined by elasticities for production or trade. The solution is also determined by the assumed closure rules, for example, if the state budget is fixed or not.

For a more complete introduction into CGE modelling, see for example Dixon and Parmenter (1996); Löfgren, Harris, and Robinson (2002).

The applied CGE models in this thesis are single country models. They are IFPRI Type II standard CGE models Löfgren, Harris, and Robinson (2002). For all three countries, the CGE model has been linked to a micro-level poverty module based on household surveys.

For Ghana, the model consists of 72 main activities and 72 commodities. The agricultural sector is regionalized across four regions, namely *coast*, *forest*, *south*, and *north*. The fifth region, *accra*, has no agricultural activities. There are four types of labor, and the land is also regionalized across the four regions with agricultural activity. There is only one type of capital. Households are separated into urban and rural in those four regions, with an extra household for the fifth region, *accra*. Therefore there are nine different household types in the Ghanaian CGE model. The social accounting matrix (SAM) is from 2007.

The Senegal model has 43 main activities and 36 commodities. The primary agricultural sectors are disaggregated across 14 regions, as is the production factor land. There are four types of labor and two types of capital. The model has four different rural and four different urban households. The base year of the SAM is 2011.

The Ugandan CGE model is not regionally disaggregated. It has 50 main activities and five different households. The factors are comprised of three types of labor, land, and two types of capital, capital, and cattle stock. The used SAM is from 2007.

## 4.4 Intervention Logic

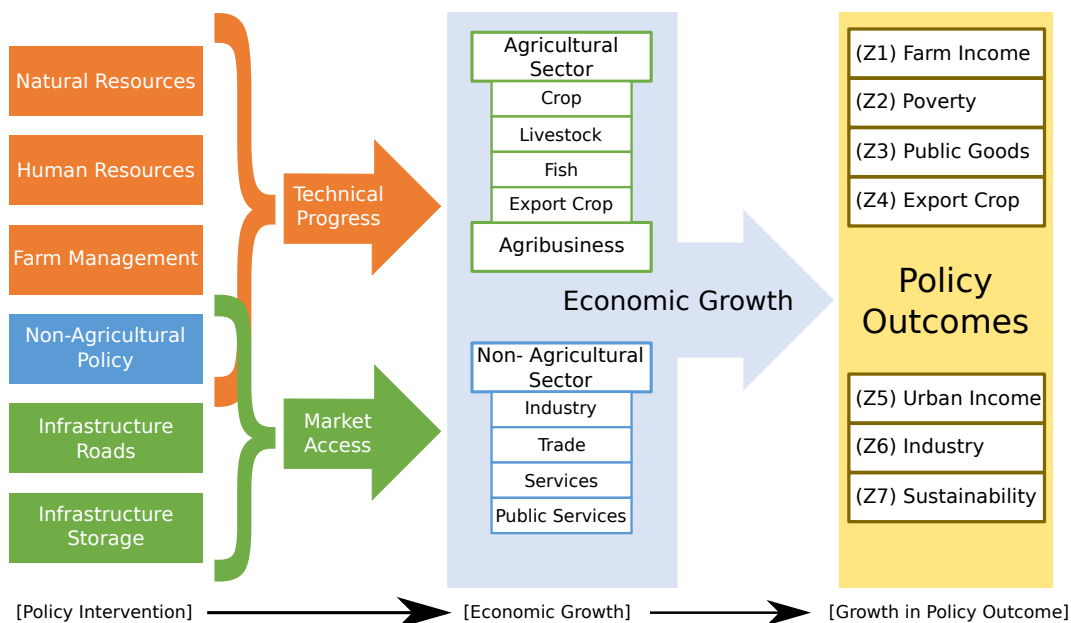


Figure 4.1: CAADP Intervention Logic

In the first step, a model capturing the relation between a chosen policy and policy outcomes is derived. We focus on modeling investment policies since these are crucial in solving the poverty goal, and here especially on CAADP. Looking at fig. 4.1, we see that we can split the impact mechanism into two parts. In order to understand how money spent on different programs leads to different goal achievements, one has first to understand how money transforms into economic growth in the different sectors. In the second step, one has to understand how economic growth in different sectors transforms into different goal achievements.

The modeled policy outcomes  $Z$  capture different aspects. The first ( $Z_1$ ) and fifth goal  $Z_5$ , farm income and urban income, are used as indicators for the income growth of the households. The second goal ( $Z_2$ ), poverty, models the vital aspect of poverty reduction. The third goal ( $Z_3$ ) captures the provision of public goods, i. e. schools, health care, military, . . . . About 70% of the total state budget is allocated to the provision of public goods. The fourth ( $Z_4$ ) and sixth goal ( $Z_6$ ) capture the impact on special producers' profits, namely of the export sector and the industry sector. The last goal, sustainability, is not actively modeled in this thesis. The framework can easily be extended to

include it, as it would be possible to include other goals.

We can measure achievement levels  $Z_{z,t}$  for a policy goal  $z \in \{1, \dots, 6\}$  in time period  $t$ . In general, we are interested in the average linear growth rate achieved over time  $T = t_1 - t_0$ . Given achievement levels  $Z_{z,t_0}$ ,  $Z_{z,t_1}$ , we can calculate the growth rate as follows:

$$w_j = \frac{Z_{z,t_1} - Z_{z,t_0}}{TZ_{z,t_0}} \quad (4.1)$$

A policy does not directly generate changes in the achievement levels of the policy goals. The level of goal achievement depends upon the economic growth achieved in the different sectors. The economic growth is measured in a change of factors  $f$ . This could, for example, be technical progress in a sector  $s$ , with  $s \in S$ . Growth in the agricultural sector might be more beneficial for poverty reduction than growth in the industry sector. Different sectors will also most likely have different effects on various goals. In order to analyze this relationship a growth goal function (GGF) ( $w = GGF(f)$ ) will be used to model this relationship. The following section will describe it in more detail.

Understanding how economic growth leads to goal achievement is not enough. Economic growth does not fall from heaven, but it has to be generated. Investment policies generate it, with the policies being an allocation of budget to the different policy instruments  $i \in I$  shown in fig. 4.1. The vector of budget allocation is  $\gamma$ . Similarly to how different sectors have different impacts on policy goals, different policies generate different levels of economic growth across the various sectors. A policy focused on market access might be best for generating growth in the export sector, but a policy focusing on farm-management might be best for the crop sector. The relationship between policy and economic growth is modeled with a policy impact function ( $f = PIF(\gamma)$ ). It will be introduced in more detail in section 4.6.

Given we have a GGF and PIF, we can define a function  $F(\gamma) = GGF(PIF(\gamma))$  that relates a policy  $\gamma$  to growth rates of goal achievements  $w$ . Based on the GGF and PIF we can derive indicators for the popular problem of (Diao et al., 2006; Christiaensen, Demery, and Kuhl, 2006; Dorosh and Thurlow, 2018):

**Key Sectors?** Which sectors should one promote growth in to improve a specific goal?

**Key Policies?** Which policies should one invest in to improve a specific goal?

The indicators will be introduced in more detail in section 4.7. Based on the intervention logic just described, it is possible to compare this approach to previous ones, that focused only on growth - goal - linkages. Applying the functions also allows the derivation of optimal policies and the comparison of technological beliefs and incentives. This will be described in section 4.8 and section 4.9.

## 4.5 Specification of GGF

The growth goal function (GGF), as introduced in section 4.4, captures the relationship between economic growth and policy goals. This relationship is modeled in the CGE model. The applied target measure for the growth will be the growth rates  $w$  of the policy goals. Since the CGE model is a rather complex model that can not easily be included in further estimations, we will derive the GGF as a metamodel of the CGE. In particular, we will derive a linear metamodel, that captures the main effects. The derived linear metamodel implicitly includes the equilibrium effects modeled in the CGE. In order to derive the metamodel, a simulation study will be done. This is described in more detail in section 5.1.

The linear metamodel will have the following form:

$$w = w^{base} + \xi^{GGF} \Delta f \quad (4.2)$$

The constant term  $w^{base}$  is derived using a base scenario, where no policy shock is implemented. The GGF - Elasticity  $\xi^{GGF}$  is defined and calculated to assess the impact of different shocks in economic sectors on the policy concerns,  $Z_z, z \in \{1, \dots, 6\}$ . This elasticity is the linear growth rate for the six policy concerns induced by a shock  $\Delta f$  per year. This is, for example, total factor productivity growth in the different economic sectors, but could also be, for example, subsidies paid to the different sectors. In the case of changes to total factor productivity, the vector of changes  $\Delta f$  results as  $\Delta f = \Delta tp_s =$

$tp_s^{\text{SIM}} - tp_s^{\text{base}}$ . The GGF - Elasticity can then be calculated as follows:

$$\xi_{z,s}^{\text{GGF}} = \left( \frac{Z_{z,t_1}^s - Z_{z,t_0}^{\text{base}}}{Z_{z,0}^{\text{base}}} \right) \frac{1}{(t_1 - t_0)\Delta f} \quad (4.3)$$

## 4.6 Specification of PIF

A policy impact function (PIF) transforms a budget allocation (vector of  $\gamma_i$ ) into a vector of economic growth outcomes. In this thesis, the budget allocation focuses on the CAADP implementation, combined with spending on non-agricultural policy programs and the spending on public goods. The economic growth outcome used is sector-specific technical progress.

In this thesis, a two-stage function is used for the PIF. At first (in the lower stage) the budget  $\sum_{i \in I} \gamma_i = B$  is transformed into effective budget for each sector  $Be_s$ . The effective budget is transformed into technical progress in the second step (in the upper stage).

$$\text{PIF}(\gamma) = tp_s(Be_s) \quad (4.4)$$

$$tp_s(Be_s) = tp_s^{\text{max}} \frac{1}{1 + e^{-(a_s Be_s + b_s)}} \quad (4.5)$$

$$Be_s(\gamma) = \eta_s \left( \sum_{i \in I} \mu_{s,i} \gamma_i^{-\rho} \right)^{\frac{-1}{\rho}} \quad (4.6)$$

The transformation of budget spent into the sector-specific effective budget is done using a CES-function. As described in sections 4.2 and 4.4 the focus is not only on agricultural versus non-agricultural policies, but on specific policy programs under CAADP. The interdependencies between the different policies are captured in the lower stage parameter  $\mu_{s,i}$ . The higher  $\mu_{s,i}$  is compared to  $\mu_{s,i'}$ , the higher the impact of policy program  $i$  compared to  $i'$  is on technical progress in sector  $s$ . 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  $\eta_s$  could be used to incorporate the implementation efficiency of policy programs. Given the lack of data for this, we choose  $\eta_s$ , so that the upper limit of  $Be_s$



equals  $B$ :

$$\eta_s = \left( \sum_i \mu_{s,i}^{\frac{1}{1+\rho}} \right)^{\frac{1+\rho}{\rho}} \quad (4.7)$$

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

$$\frac{\alpha_{s,i}}{\alpha_{s,j}} = \left( \frac{\mu_i}{\mu_j} \right)^{\frac{1}{1+\rho}} \quad (4.8)$$

$$1 = \sum_i \alpha_{s,i} \quad (4.9)$$

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

On the upper level, a logistic function is used to transform an effective budget into technical progress. This allows for flexible impact elasticities, in contrast to the Cobb-Douglas form suggested by Fan and Rosegrant (2008). In fig. 4.2 the sigmoid form, as defined in eq. (4.5), relating technical progress to effective budget is plotted. This functional form maps nicely to what one would intuitively expect for the effect of money on the promotion of technical progress for a sector. If one only spends very little money, one will not get much of an effect. One needs to spend a certain amount of money for it to become effective, then spending more has a significant effect. After a certain amount of money has been spent, money gets less and less effective. There exists a maximal rate of technical progress ( $tp^{max}$ ) that can be achieved with public policy programs in a specific sector  $s$ .

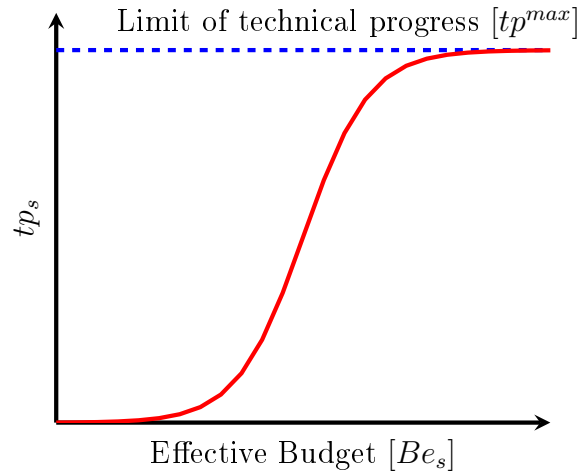


Figure 4.2: Sigmoid function relating effective budget to sectoral technical progress

## 4.7 Key Sectors and Key Policies

The derivation of indicators for key sectors and key policies is an often looked at problem. For key sectors, we are looking for an indicator, that assigns a higher value for a sector  $s$  compared to another sector  $s'$ , if it is more “productive” in achieving a policy goal  $j$ . Similarly, for key policies, we are looking for an indicator, that assigns a higher value to policy  $i$  compared to  $i'$ , if it is more *productive* than the other. Let  $\gamma$  be a vector of a policy realization, that is, allocation of budget to the different policy instruments  $i$ . The target measures are the additional achieved annual growth rates  $w_z$  for the different policy goals  $z \in Z$ . Based on the intervention logic defined in section 4.4 we will derive the indicators for key sectors and key policies on an abstract level and then show how they are derived based on the specifications given for the GGF and PIF in sections 4.5 and 4.6.

In the following, we will focus on the second goal, as defined in section 4.4, poverty reduction. The same structure applies to the other policy goals, as well.

Given the function

$$F(\gamma) = w : \mathbb{R}^{|I|} \rightarrow \mathbb{R}^{|Z|}, \quad (4.10)$$

as introduced before and the two partial functions PIF and GGF

$$PIF(\gamma) = f : \mathbb{R}^{|I|} \rightarrow \mathbb{R}^{|K|} \quad (4.11)$$

$$GGF(f) = w : \mathbb{R}^{|K|} \rightarrow \mathbb{R}^{|Z|}. \quad (4.12)$$

$K$  denotes the dimensions of changed factors  $f$ , in our case this is sector specific technical progress. Therefore  $|K| = |S|$ . The PIF transforms a policy realization  $\gamma$  into economic growth  $f$ . Sector-specific total factor productivity is such a factor of economic growth. That, in turn, is transformed using the GGF into policy growth rates  $w$ . Based on these functions, we can define growth - goal elasticities and policy - growth elasticities.

Growth - goal elasticities measure the marginal impact of factor change  $f_s$  on growth rates  $w$ :

$$\xi_s^{GGF} = \frac{\partial w}{\partial f_s} = \frac{\partial GGF(f)}{\partial f_s} \quad (4.13)$$

As described in section 4.5, we will focus on technical progress as the main factor of growth. The way we constructed the GGF,  $\xi^{GGF}$  results directly from it. The  $\xi^{GGF}$  capture the second part of the relation between a policy intervention and the growth in policy outcomes, as described in section 4.4.

Policy - growth elasticities measure the marginal impact of total budget  $B$  on factor changes  $f$ , with  $B = \sum_{i \in I} \gamma_i$ :

$$\xi_s^{PIF} = \frac{\partial f_s}{\partial B} = \frac{\partial PIF(\gamma)}{\partial B}. \quad (4.14)$$

Given the derived two-stage form in eq. (4.4), the derivative can be calculated as follows:

$$\xi_s^{PIF} = \frac{\partial t p_s(B e_s)}{\partial B e_s} \frac{\partial B e_s(\gamma)}{\partial B}. \quad (4.15)$$

The  $\xi^{PIF}$  complement the  $\xi^{GGF}$  and capture the first part of the relation described in section 4.4.

Based on the growth goal elasticities and policy growth elasticities it is now possible to define policy goal elasticities  $\xi^{PGE}$ :

$$\xi^{PGE} = \xi^{GGF} \xi^{PIF}. \quad (4.16)$$

Equation (4.16) is the key sector indicator. It is defined in the same way for every other policy goal. In the later chapters, we will mainly focus on key sectors of a Pro-Poor-Growth (PPG)-strategy and name the indicator for poverty reduction ( $\xi_2^{PGE}$ ) PPG elasticity.

Based on the partial elasticities, it is also possible to define policy instrument  $i$  specific elasticities:

$$\xi_i^{PIE} = \frac{\partial f}{\partial \gamma_i} \xi^{PIF}. \quad (4.17)$$

Equation (4.17) denotes the key policies indicator. Similar to the key sectors indicator, we will focus on poverty reduction as the primary goal, and therefore mainly look at  $\xi_{2,i}^{PIE}$ .

## 4.8 Optimal Policies

Beyond the key sector and key policy indicators, which are just marginal point indicators, it is of interest to also be able to find optimal policies. In order to do this, a function  $S(Z)$  is needed. This function, like a utility function, orders the different states of the world consistently. The state of the world includes the previously defined policy goals  $Z$ . The achievement levels of those goals are determined by the policy  $\gamma$ . The policy  $\gamma$  is a chosen budget allocation and therefore is equivalent to the costs associated with reaching that level of  $Z$ .

Then it is possible to define an optimization problem that results in an optimal policy  $\gamma^*$ .

$$\begin{aligned} \max_{\gamma} \quad & S(Z) \\ \text{s.t} \quad & \\ & Z = GGF(PIF(\gamma)) \end{aligned} \quad (4.18)$$

The function  $S$  usually only allows ordering of different states of the world but does not allow a comparison like this state is 50% better than another state. A possible measure for how much better/worse a given policy is would be the amount of money that could be saved by an optimal distribution across

the different policy instruments  $\gamma_i$ , while reaching an as preferable as state of the world as before. This results in the definition of a loss function  $L(\gamma^0)$

$$L = |\gamma'_{|S(Z') \geq S(Z^0)} - \gamma^0| \quad (4.19)$$

In order to derive  $\gamma'$  we can define a similar optimization problem to the one for optimal policies:

$$\begin{aligned} \min_{\gamma} \quad & |\gamma| \\ \text{s.t} \quad & \\ & Z = GGF(PIF(\gamma)) \\ & Z^0 = GGF(PIF(\gamma^0)) \\ & S(Z) \geq S(Z^0) \end{aligned} \quad (4.20)$$

In the next section, this loss function will be applied to measure the impact of *wrong* technological beliefs and incentives.

## 4.9 Incentives and Beliefs

As shown in chapter 2, the uncertainty inherent to the political process leads to actors forming beliefs of how a policy is transformed into outcomes. These outcomes are evaluated from the viewpoint of the actor, which does not necessarily correspond with an evaluation the society would perform. Political actors choose specific policies because of actor specific incentives and technological beliefs. One actor might have the reduction of poverty as his main incentive for choosing a specific policy, while another might base his decision on the improvement of urban consumer income. The technological beliefs are another essential part, that is, the actor specific mental model of how policies influence the different policy goals. This leads to inefficient policies being chosen. This process of policy choice is depicted in fig. 4.3.

This ignores an important aspect, though, policy choice in a democracy is a collective choice. Therefore, as described in section 2.2, the decision process is another source of inefficiency that needs to be considered. The final policy choice is not only determined by political incentives and knowledge, but also political power.

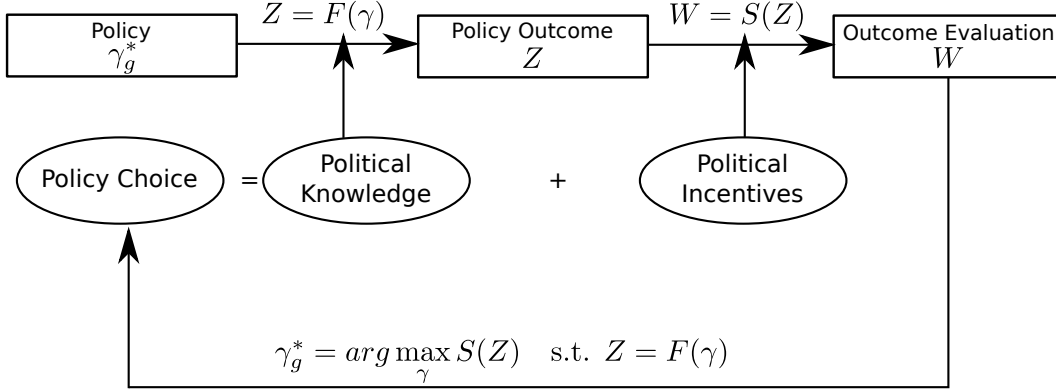


Figure 4.3: Individual Policy Choice

In the following, we will derive a way to measure the political performance gaps quantitatively. This is done exemplary for individuals, but the same steps can be used to measure a collective choice. The previously introduced framework allows us to measure the impact of incentives and beliefs on goal achievement and also disentangle both factors. This allows checking if sub-optimal policies are chosen because of biased incentives or wrong technological beliefs. In this context, biased incentives mean incentives that do not represent society's interests in different goals.

Different incentives result in different specifications of the measuring function  $S(Z, \gamma)$ . The technological beliefs are captured by the parameters defining the  $PIF(\gamma)$  function.

Assuming we know the true technology, that is the true specification of the PIF parameters, and we have a social welfare function capturing the society's interests  $SWF(Z, \gamma)$  we can derive the impact of biased incentives and wrong beliefs in the following way:

In a first step we derive an optimal policy based on actor  $j$  specific incentives  $X_j$  and technological beliefs  $\tilde{T}_j$ , that is we solve the optimization problem from eq. (4.18) with  $S_j(Z, \gamma)$  and  $PIF_j(\gamma)$ . This results in a vector  $\gamma_j^{real}$ .

In the next step, the true technology  $T$  and social interests  $X_{SF}$  are used to evaluate  $\gamma_j^{real}$ . We then apply the loss function eq. (4.19) using eq. (4.20). As a result, we get the total performance gap  $G_j$ , measured as the budget that could have been saved to achieve an as desirable state of the world.

This performance gap  $G$  consists of two parts, the knowledge gap  $G^T$  and the incentive gap  $G^X$ , i.e.  $G = G^T + G^X$ . Be aware that  $G^T$  and  $G^X$  do not

Table 4.1: Gaps Summary

Policy Interests		Policy Beliefs	
		True	Biased
		$[T]$	$[\tilde{T}]$
Social	$[X_{SF}]$	0	$G^T$
Biased	$[X_g]$	$G^X$	$G$

necessarily have the same sign, given the biased incentives the wrong technological beliefs might push the chosen policy in the right direction or vice versa.

The same procedure can be applied to measure the knowledge gap  $G^{know}$  and the incentive gap  $G^{bias}$ . For the knowledge gap, we use the actor specific beliefs, but use the  $SWF$  as the evaluation function. For the incentive gap, we use the actor specific incentives, which is the actor specific evaluation function  $S_j$  but combined with the true technology.

Table 4.1 shows a summary of the different gaps. Assuming an actor would have both the true technological beliefs  $T$  and society's interests  $X_{SF}$ , the resulting performance gap would be by definition zero.

After applying these steps, we have not only a measure for the total performance gap but also a quantitative measure for the influence of biased incentives and wrong technological beliefs. In order to compare the different beliefs, one could apply a factor analysis of the parameter space. Another avenue might be to look at the different levels of changed factors and in turn, the different levels of goal achievement that are achieved under the actor specific beliefs. This methodology not only allows an evaluation of individuals but in the same way also of groups of individuals, for example, donors or civil society organizations.





# Chapter 5

## Empirical Estimation of PIF

In this chapter, the derivation of the GGF and the empirical estimation of the PIF is shown. This approach follows the general estimation strategy, as described in Henning et al. (2017). The employed estimation models and their derivation are shown. The required data will also be described and how it has been derived. The application will be exemplarily shown for Senegal, but the same steps have been applied for Ghana and Uganda. The shown results in the following chapters are based on applying the steps described here. In a first step the GGF will be derived based on CGE simulations. The next step then is to calibrate the PIF with historical data. In the final step, these results are used to estimate a PIF with a future perspective incorporating expert knowledge. After these steps we have a GGF and a PIF, which then allows us to derive/calculate the indicators described in the theoretical framework (see chapters 3 and 4).

### 5.1 Derivation of GGF

The GGF we will derive focuses on the impact of technical progress. A good model for measuring this impact is a CGE model.

We apply an IFPRI-Type-2 standard CGE model (Löfgren, Harris, and Robinson, 2002), that has been linked with a micro-based poverty module (see for example Sene (2015b)). This allows the definition of measures that capture the policy concerns defined in section 4.4. The last goal, sustainability, will not be 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.

The used measures are:

Z1 Small-Scale Farm Income

Z2 Poverty Reduction

Z3 Public Goods Provision

Z4 Welfare of Agricultural Export Sector

Z5 Welfare of Urban Consumers

Z6 Welfare of Industrial Sector

We are looking for a model that has the average linear growth rates  $w_j$  as the output. The CGE model output can be used to calculate these. We want to use the model in the estimation of the PIF. Therefore we need an analytical form. We can apply the metamodeling concept here. So instead of  $CGE(\Delta f) \rightarrow w_j$ , we have  $M^{CGE}(\Delta f) = w_j$ . In the empirical application, we will focus on the prominent effect of technical progress. So the vector of changed factors  $f$  is  $[tp_s]$ , with  $s \in S$ . We will derive a simple linear metamodel.

$$\begin{aligned} w &= \xi^{\text{base}} + \Delta w \\ \Delta w &= \xi^{GGF} \cdot \Delta f \end{aligned} \quad (5.1)$$

We can derive the values for  $\xi^{\text{base}}$  and  $\xi^{GGF}$  via a simulation study. To derive  $\xi^{\text{base}}$ , we simulate a baseline run with all parameters set to default values. To derive  $\xi^{GGF}$ , we run the following simulations: For each sector  $s$  a run is generated and calculated, where  $\Delta f = tp^0 + \Delta tp$ , with  $\Delta tp_s = 4$ , and  $\Delta tp_{k|k \neq s} = 0$ . In each run, the baseline run  $tp$  is increased for this sector  $s$  by 4. After the simulations we can compute  $\xi^{\text{base}}$  and  $\xi^{GGF}$  as follows:

$$\begin{aligned} \xi_j^{\text{base}} &= \frac{Z_{j,t_1}^{\text{base}} - Z_{j,t_0}^{\text{base}}}{Z_{j,t_0}^{\text{base}.T}} \\ w_j &= \frac{Z_{j,t_1}^s - Z_{j,t_0}^{\text{base}}}{Z_{j,t_0}^{\text{base}.T}} \\ \Delta w_j &= w_j - \xi_j^{\text{base}} \\ \xi_{s,j} &= \frac{\Delta w_j}{\Delta tp_s} \\ \xi_j &= [\xi_{s,j}] \end{aligned} \quad (5.2)$$

$t_0, t_1$  denote the starting and end period of the simulation, with  $T = t_1 - t_0 = 10$ .  $Z_j^{base}$  denotes the achievement levels reached in the baseline scenario. We have  $|S|$  scenarios, where  $tp$  is shifted for each sector  $s \in S$  separately.  $Z_j^s$  denotes the achievement levels reached in such a scenario.

With this we can define  $M^{CGE}(\Delta tp) = w^{base} + \xi^{GGF} \cdot \Delta tp$ . This is a linear approximation, a metamodel, of the full CGE model. It only captures the relationship between  $\Delta tp$  and  $w$ , but it includes the general equilibrium effects that led to the derived coefficients. This metamodel can now be applied in the derivation of the PIF.

### 5.1.1 Implementation

The applied CGE model is implemented in GAMS, therefore also the derivation of the GGF is implemented in GAMS. GAMS provides no language support for something like modules or classes. The original code was split into two main parts: The first part defines the algebraical structure of the CGE and calibrates it. The second part is a basic simulation module that solves different scenarios over time and takes care of the year to year updating. This also includes the poverty module that runs after the CGE has been completely solved. The parameters for the scenarios were defined using Excel files. We are following this basic structure, though we are only using the Excel files for the *base* scenario and define the simulation scenarios programmatically. This reduces possibilities for errors and allows for more quickly experiments with different simulation scenarios.

This means that deriving the GGF involves three steps. First, define and calibrate the CGE model, second run the simulations, and last derive the metamodel based on the simulation results.

## 5.2 Derivation of policy impact function

To complete our theoretically derived model, we also need to estimate the PIF. As described before, this is done in two steps. The first step uses historically observed data to find a first good fit for the parameters. The model is calibrated to replicate the past observations; it learns the past relationship. This is what we call the empirical PIF. The goal is not to replicate the past but

to predict the future. In order 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.

As described in section 4.6 we want to derive sector specific PIFs. Given the chosen nested two-stage form, this leads to a large number of required parameters. We need  $|S| \times 3$  parameters for the upper stage, this being the  $tp_s^{max}, a_s, b_s$  parameters.

As described in section 4.4, we consider different policy programs under CAADP, namely: water and land management, farm management policies for food crops, export crops, and livestock, investment in road and storage-related infrastructure, agricultural research and development and extension services. Finally, we also distinguish investment in the non-agricultural sector as an additional policy instrument. The set of policy instruments  $I$  is  $\{water, land, fm - crop, fm - export, fm - live, fm - road, fm - storage, hr - research, hr - extension, non - agr\}$ . The vector of budget allocation  $\gamma$  then is  $[\gamma_i]$  with  $i \in I$ . For the lower stage we need  $|I| \times |S|$  parameters,  $\mu_{i,s}$ .

So in total we have  $(|I| + 3) \times |S| \approx 600$  parameters. Estimating these with a classical estimation approach is hardly possible because of limited data availability and inherent estimation problems. To be able to estimate these parameters, we propose a Bayesian estimation procedure. In this approach, prior information gained from a literature review and previous studies is combined with statistical/historical data or expert information. This approach is based on the work of Heckelei and Mittelhammer (2008) and closely follows Henning et al. (2017).

### 5.2.1 Empirical PIF

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

In particular, following Fan, Hazell, and Thorat (2000); Fan (2008); Sene (2015a) we use available production and public budget expenditure data to estimate PIF-parameters. Defining  $TFP_{s,t}$  as a TFP index for the sector  $s$  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:

$$\begin{aligned}
TFP_{s,t} &= tp_{s,t}^0 + \Delta tp_{s,t} \\
\Delta tp_{s,t} &= tp_s^{max} \frac{1}{1+e^{-(a_s B e_s + b_s)}} \\
B e_{s,t} &= \eta_s \left[ \sum_i \mu_{i,s} \gamma_{i,t}^{-\rho} \right]^{-\frac{1}{\rho}} \\
\eta_s &= \left( \sum_i \mu_{s,i}^{\frac{1}{1+\rho}} \right)^{\frac{1+\rho}{\rho}} \\
with : & \sum_i \mu_{i,s} = 1
\end{aligned} \tag{5.3}$$

$tp_{st}^0$  denotes the technical progress realized in sector  $s$  in the year  $t$  without any policy impact. In general, assuming sufficient observations for  $TFP_{s,t}$  and  $\gamma_t$  PIF parameters could be estimated applying standard econometric estimation methods. However, as has been pointed out by many other authors (e.g., (Fan, Hazell, and Thorat, 2000; Fan and 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. In this context, we suggest a Bayesian estimation approach combining data and prior information.

Assuming prior information on parameters is encapsulated in normal prior distribution,  $pr(\theta)$ , while the data information follows from the equation system (eq. (5.3)). Moreover, in the Bayesian framework, it is straightforward to deal with missing data problems, e.g., assuming some (or all) data on detailed budget allocations across policy programs are missing, while data are only available on the total agricultural budget ( $PAE$ ) and total non-agricultural data ( $PNE$ ). In the Bayesian framework, missing data is considered as additional further parameters, which can be estimated assuming corresponding prior distributions.

Moreover, additional prior information might exist in the form of additional restrictions on parameter values or values of unobserved variables. For example, the analyst might have prior information on lower or upper bounds for specific parameters or unobserved variables derived from theory, expert knowledge, or other empirical information.

Denoting by  $y1$  the matrix of available empirical panel data, that is the panel data on TFP and on budget expenditure, and let  $RES(y1, \theta)$  denote additional restrictions on parameters and unobserved variables, the Bayesian

estimation approach corresponds to the following minimization problem:

$$\begin{aligned}
\theta^* &= \arg \min_{\theta} [\theta - \bar{\theta}] \Omega^{-1} [\theta - \bar{\theta}] + \nu' \nu \\
\text{s.t.} & \\
TFP_{s,t} &= tp_s^0 + \Delta tp_{s,t} + \nu_{s,t} \\
\Delta tp_{s,t} &= tp_s^{max} \frac{1}{1+e^{-(a_s B e_s + b_s)}} \\
B e_{s,t} &= \eta_s \left[ \sum_i \mu_{i,s} \gamma_{i,t}^{-\rho} \right]^{-\frac{1}{\rho}} \\
\eta_s &= \left( \sum_i \mu_{i,s}^{\frac{1}{1+\rho}} \right)^{\frac{1+\rho}{\rho}} \\
\sum_i \mu_{i,s} &= 1 \\
RES(y1, \theta) &\equiv 0
\end{aligned} \tag{5.4}$$

Please note that we assumed that the TFP index can only be measured with some error,  $\nu$ , 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  $\theta$ . Additionally, since we are mainly interested in the general underlying trend in the TFP index, we applied the Hodrick - Prescott filter.

## Implementation

The optimization problem, as defined in eq. (5.4), has been implemented as a nonlinear programming problem in GAMS. Given the lack of support for modules in GAMS, a poor man's version of namespacing has been applied. Namely, all parameters, variables, and equations belonging to the estimation problem have been prefixed by `pif_emp`. This structuring helps in separating the code and preventing accidental side-effects into other parts of the program. The estimation results of the TFP index and the budget data have been collected into Excel files. These are converted to GAMS's file format in order to be loaded into the program. The complete model definition is shown in listing A.1. The model definition is accompanied by code that initializes the variables with start values and computes based on that a mostly feasible start point in order to help the solver in finding a solution. A good start point is often required so that the solver does not get stuck in corner solutions.

### 5.2.2 Expert PIF

Given the calibrated parameters from the empirical PIF, we want to adapt those in a way that they 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 non-governmental organizations. Interviewed organizations were considered as experts in development and agricultural policy. Interviewed organizations were carefully selected using a list of potentially relevant organizations compiled based on desk research and expert interviews. Based on this initial list and by using a snowball sampling method, personal interviews were conducted with the representatives of the preselected organizations. Interviewees were asked to identify all the influential organizations on the provided list or suggest the new ones. The suggested organizations that were not initially included in the list were added to the list when they are nominated more than three times. In Senegal, for example, we have 15 governmental organizations and 31 non-governmental organizations in total. These non-governmental organizations include seven donors, ten research organizations, four civil society groups, and eight socio-economic interest groups (two farmer and six agribusiness interest groups) (see (Henning et al., 2019) for detailed survey data description).

During the interview, we asked experts to amount the desired achievement levels for seven different policy goals ( $Z$ ) within the next ten years. Further, we asked them to indicate the preferred policy positions ( $\gamma$ ) from the viewpoint of their organization. Policy positions correspond to preferred budget allocations for public good services vis-a-vis state budget resources spend on policy programs as well as budget shares spend on CAADP and non-agricultural policy programs, respectively. Finally, interviewed organizations were asked to subdivide the CAADP budget across four pillars and 9 CAADP programs. Moreover, from the elite survey data, we derive the relative interests ( $X$ ) of interviewed governmental and non-governmental organizations in the achievement of different policy goals. In detail, in the interview, we distinguished the seven policy goals previously described in section 4.4. For each goal, interviewees were asked to indicate on a 7 point rating scale the level their organization desires realistically to achieve within the next ten years. The status quo level,

as well as the corresponding levels of the endpoints, were specified for the scales. Based on the interview data we could calculate the average annual linear growth rate experts desire to achieve, i.e.  $\hat{w}_{g,j} = \frac{1}{10} \frac{Z_{g,j} - Z_{g,j}^0}{Z_{g,j}^0}$ . Political experts are also asked to rank the relative importance of policy goals, where  $X_{g,j}$  denotes the relative importance of the goal  $j$  from the viewpoint of expert  $g$ . Finally, experts are asked to indicate how they allocate the budget across policy instruments,  $i \in I$ , to most efficiently achieve their desired policy goals,  $\hat{w}_g$ . In particular,  $\hat{\gamma}_g = [\hat{\gamma}_{g,i}]$  denotes the budget allocation preferred by expert  $g$ .

We have time periods  $t \in \{0, \dots, T\}$ . Assuming that each expert evaluates future development of policy goals based on the following inter-temporal Cobb-Douglas-function  $S_g(\psi)$ :

$$S_g(\psi) = \sum_t \prod_j \delta^t (1 + \psi_{j,t})^{X_{g,j}} \quad (5.5)$$

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

$$\psi_{j,t} = \psi_j^0(\gamma) + \psi_j(\gamma) \cdot t \quad (5.6)$$

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

Given our intervention logic, policies impact on policy goals via induced changes in technical progress. Inserting the derived GGF, rearrangements results:

$$\begin{aligned} \psi_j(\gamma) &= \xi_j^{\text{base}} + \xi_j \cdot \Delta tp(\gamma) \\ \Delta tp(\gamma) &= PIF(\gamma) \end{aligned} \quad (5.7)$$

Public spending in economic policy programs promoting  $tp$  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. Let  $j_{ps}$  be the index denoting the policy goal ‘provision of public services’. The level of the state budget not spent on investment policies measures the achievement level for  $j_{ps}$ . This means without a policy we achieve  $Z_{ps}^{\text{no-policy}} = B_0$ , with  $B_0$  being the



total state budget in the base period. If we 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 for the base period we have:

$$Z_{j_{ps},0} = B_0 - \sum_j \gamma \quad (5.8)$$

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

$$Z_{j_{ps},1} = B_0 - \sum_j \gamma + B_0 \cdot \psi_{j_{ps}}(\gamma) \cdot 1 = B_0 \cdot \left( 1 + \psi_{j_{ps}}(\gamma) - \frac{\sum_j \gamma}{B_0} \right) \quad (5.9)$$

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

$$Z_{j_{ps},t} = B_0 - \sum_j \gamma + B_0 \cdot \psi_{j_{ps}}(\gamma) \cdot t = B_0 \cdot \left( 1 + \psi_{j_{ps}}(\gamma) \cdot t - \frac{\sum_j \gamma}{B_0} \right) \quad (5.10)$$

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

$$\begin{aligned} \psi_j^0 &= -\Delta_j^{\text{ps}} \frac{\sum_i \gamma_i}{B_0} \\ \Delta_j^{\text{ps}} &= \begin{cases} 0 & j \neq j_{ps} \\ 1 - \alpha_{\text{donor}} & j = j_{ps} \end{cases} \end{aligned} \quad (5.11)$$

Assuming political experts know the policy-growth (PIF) and growth-outcome (GGF) relations, they can derive their optimal policy interventions,  $\hat{\gamma}_g$ , and desired future policy goal achievements  $\hat{w}_g$  from maximizing their evaluation

function  $S_g$  :

$$\begin{aligned}
\hat{\gamma}_g &= \arg \max_{\gamma} \sum_t \prod_j \delta^t (1 + \psi_{j,t})^{X_{g,j}} \\
\mathbf{s.t.} \\
\psi_{j,t} &= \psi_j^0(\gamma) + \psi_j(\gamma) \cdot t \\
\psi_j^0(\gamma) &= -\Delta_j^{ps} \frac{\sum \gamma_j}{B_0} \\
\psi_j(\gamma) &= \xi_j^{\text{base}} + \xi_j \cdot \Delta tp(\gamma) \\
\Delta tp_s(\gamma) &= tp_s^{\text{max}} \frac{1}{1+e^{-(a_s B e_s + b_s)}} \\
B e_s(\gamma) &= \eta_s \left[ \sum_i \mu_{i,s} \gamma_i^{-\rho} \right]^{-\frac{1}{\rho}}
\end{aligned} \tag{5.12}$$

The agents choose their policy by maximizing the following support function  $S_g(\psi) = \sum_t \prod_j \delta^t (1 + \psi_{j,t}(\gamma))^{X_{g,j}}$ . Therefore given an optimal allocation  $\hat{\gamma}$ , it has to fulfill the first-order conditions. We want to derive  $\frac{\partial S_g(\psi)}{\partial \gamma_k}$ . For the derivation let  $f_j(\gamma, t) = 1 + \psi_j^0(\gamma) + \psi_j(\gamma) \cdot t$  and  $F_j(\gamma, t) = f_j(\gamma, t)^{X_{g,j}}$ .

In a first step, we derive the partial derivatives for  $f_j$  and  $F_j$ .

$$\frac{\partial f_j(\gamma, t)}{\partial \gamma_k} = \frac{\partial \psi_j^0(\gamma)}{\partial \gamma_k} + \frac{\partial \psi_j(\gamma)}{\partial \gamma_k} \cdot t \tag{5.13}$$

$$= \frac{-\Delta_j^{ps}}{B_0} + t \cdot \xi_j \frac{\partial \Delta tp}{\partial B e} \frac{\partial B e}{\partial \gamma_k} \tag{5.14}$$

The derivative for  $\frac{\partial \Delta tp}{\partial B e}$  is:

$$\frac{\partial \Delta tp_s}{\partial B e} = \Delta tp_s \cdot \left(1 - \frac{\Delta tp}{tp_s^{\text{max}}}\right) \cdot a_s \tag{5.15}$$

The derivative for  $\frac{\partial B e}{\partial \gamma_k}$  is derived as follows:

$$\begin{aligned}
\frac{\partial B e_s}{\partial \gamma_k} &= \frac{\partial \left( \eta_s \left[ \sum_i \mu_{i,s} \gamma_i^{-\rho} \right]^{-\frac{1}{\rho}} \right)}{\partial \gamma_k} = \eta_s \left[ \sum_i \mu_{i,s} \gamma_i^{-\rho} \right]^{-\frac{1}{\rho}-1} \frac{-1}{\rho} (\mu_{k,s} \gamma_k^{-\rho-1} (-\rho)) \\
&= \eta_s^{-\rho} \eta_s^{1+\rho} \left[ \sum_i \mu_{i,s} \gamma_i^{-\rho} \right]^{-\frac{1}{\rho} \cdot (1+\rho)} (\mu_{k,s} \gamma_k^{-(1+\rho)}) \\
&= \eta_s^{-\rho} \left[ \eta_s \left[ \sum_i \mu_{i,s} \gamma_i^{-\rho} \right]^{-\frac{1}{\rho}} \right]^{(1+\rho)} (\mu_{k,s} \gamma_k^{-(1+\rho)}) \\
&= \eta_s^{-\rho} \mu_{k,s} \left( \frac{B e_s}{\gamma_k} \right)^{1+\rho}
\end{aligned} \tag{5.16}$$

In the next step we build the derivative for  $F_j$ :

$$\begin{aligned}
\frac{\partial F_j(\gamma, t)}{\partial \gamma_k} &= X_{g,j} \cdot f_j(\gamma, t)^{X_{g,j}-1} \cdot \frac{\partial f_j(\gamma, t)}{\partial \gamma_k} \\
&= F_j(\gamma, t) \cdot \frac{X_{g,j}}{f_j(\gamma, t)} \frac{\partial f_j(\gamma, t)}{\partial \gamma_k} \\
&= F_j(\gamma, t) \cdot \frac{X_{g,j}}{f_j(\gamma, t)} \cdot \left( \frac{-\Delta_j^{ps}}{B_0} + t \cdot \xi_j \frac{\partial \Delta t_p}{\partial B_e} \frac{\partial B_e}{\partial \gamma_k} \right) \\
&= F_j(\gamma, t) \cdot \frac{X_{g,j}}{f_j(\gamma, t)} \cdot \left( \frac{-\Delta_j^{ps}}{B_0} + t \cdot \sum_s \xi_{j,s} \frac{\partial \Delta t_{p_s}}{\partial B_{e_s}} \frac{\partial B_{e_s}}{\partial \gamma_k} \right)
\end{aligned} \tag{5.17}$$

Using the result from eq. (5.17), we find the derivative for  $\frac{\partial \left( \prod_j F_j(\gamma, t) \right)}{\partial \gamma_k}$ :

$$\begin{aligned}
\frac{\partial \left( \prod_j F_j(\gamma, t) \right)}{\partial \gamma_k} &= \prod_j F_j(\gamma, t) \cdot \left( \sum_j \frac{\frac{\partial F_j(\gamma, t)}{\partial \gamma_k}}{F_j(\gamma, t)} \right) \\
&= \prod_j F_j(\gamma, t) \cdot \left( \sum_j \frac{F_j(\gamma, t) \cdot \frac{X_{g,j}}{f_j(\gamma, t)} \cdot \left( \frac{-\Delta_j^{ps}}{B_0} + t \cdot \sum_s \xi_{j,s} \frac{\partial \Delta t_{p_s}}{\partial B_{e_s}} \frac{\partial B_{e_s}}{\partial \gamma_k} \right)}{F_j(\gamma, t)} \right) \\
&= \prod_j F_j(\gamma, t) \cdot \left( \sum_j \frac{X_{g,j}}{f_j(\gamma, t)} \cdot \left( \frac{-\Delta_j^{ps}}{B_0} + t \cdot \sum_s \xi_{j,s} \frac{\partial \Delta t_{p_s}}{\partial B_{e_s}} \frac{\partial B_{e_s}}{\partial \gamma_k} \right) \right)
\end{aligned} \tag{5.18}$$

This allows us in the final step to find the derivative for  $\frac{\partial S_g(\psi)}{\partial \gamma_k}$ , which are the first order conditions:

$$\begin{aligned}
\frac{\partial S_g(\psi)}{\partial \gamma_k} &= \frac{\partial \left( \sum_{t=0}^T \delta^t \prod_j F_j(\gamma, t) \right)}{\partial \gamma_k} = \sum_{t=0}^T \delta^t \frac{\partial \left( \prod_j F_j(\gamma, t) \right)}{\partial \gamma_k} \\
&= \sum_{t=0}^T \delta^t \left( \prod_j F_j(\gamma, t) \cdot \left( \sum_j \frac{X_{g,j}}{f_j(\gamma, t)} \cdot \left( \frac{-\Delta_j^{ps}}{B_0} + t \cdot \sum_s \xi_{j,s} \frac{\partial \Delta t_{p_s}}{\partial B_{e_s}} \frac{\partial B_{e_s}}{\partial \gamma_k} \right) \right) \right)
\end{aligned} \tag{5.19}$$

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 set for Senegal is rather small, with only 46 organizations. 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  $\chi$  denote the parameters of the PIF. We can then denote the derived first order conditions (see eq. (5.19)) of the support maximization problem

as  $FOC(\chi)$ , with  $RES(\chi)$  denoting additional restrictions on the parameters. The prior values  $\bar{\chi}$  are taken from the results of the empirical PIF,  $\theta^*$ . The covariance matrix  $\Omega$  for the PIF parameters can be derived from the hessian of the empirical PIF estimation<sup>1</sup>. Following Heckeles and Mittelhammer (2008) we can derive  $\chi^*$  solving the optimization problem in eq. (5.20).

$$\begin{aligned} \chi^* &= \arg \min_{\chi} [\chi - \bar{\chi}] \Omega^{-1} [\chi - \bar{\chi}] + \epsilon' \epsilon \\ \text{s.t.} & \\ FOC(\chi) + \epsilon &= 0 \\ RES(\chi) &= 0 \end{aligned} \tag{5.20}$$

## Implementation

Similar to the implementation of the empirical PIF, the expert PIF has also been implemented as a nonlinear programming problem in GAMS. The definitions are again prefixed with a common prefix, namely `pif_exps`. Again an accompanying file has been written that initializes the variables with start values and computes a feasible start point. Given the highly nonlinear target function and the many interdependencies, this is especially important for the solver to find a solution consistently. The complete model implementation in GAMS, based on the specified model from eq. (5.20), can be found in listing A.2.

## 5.3 Results

### 5.3.1 Empirical PIF

Exemplary results of the filtering and the estimated TFP from the Bayesian estimation of the empirical PIF are shown in fig. 5.1. We can see the different stages of the estimation. In the first step, the *original* data was estimated, as described above. The next step then applied the Hodrick - Prescott filter to retrieve the general underlying trend of the data, shown as the *smoothed* line. This data was then used in the Bayesian estimation, and the results are shown

---

<sup>1</sup>Please note, that we set the covariance matrix to the diagonal matrix with the elements  $\Omega = [(\bar{\chi})^2]$

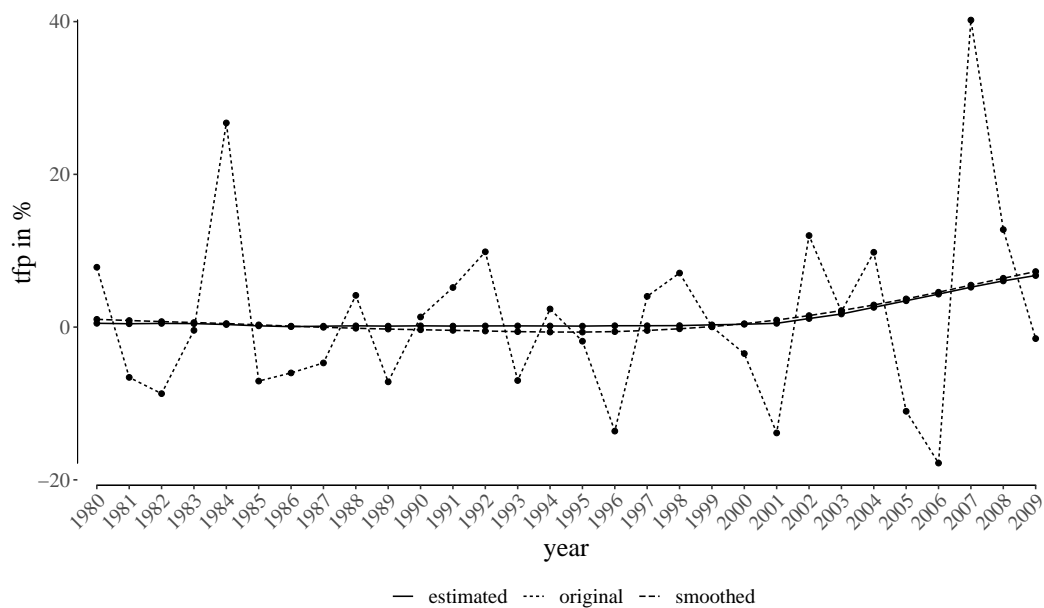


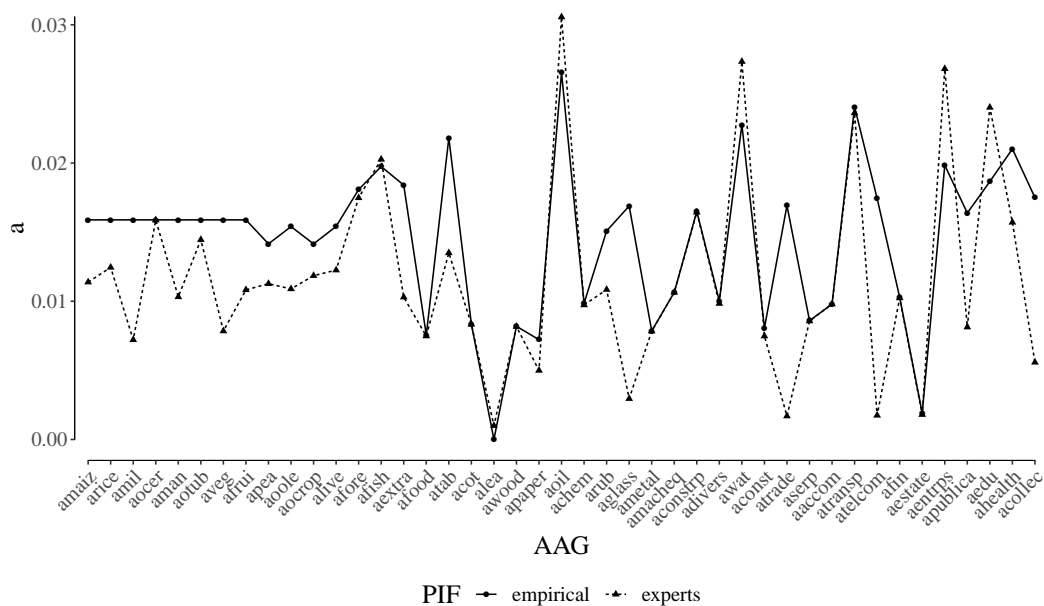
Figure 5.1: Replication of TFP for Maize Sector

in the *estimated* line. As can be seen, the estimation closely reproduces the filtered data, showing that our calibration approach works.

### 5.3.2 Comparison

Given the estimation results from the two different PIFs, empirical, and expert, we can now look at their differences. That is, which impact did the experts' opinion have on the parameters of the two stages of the PIF. On the upper stage of the PIF, transforming effective budget into additionally realized technical progress, we see that the experts appear to be a bit more conservative regarding the efficiency of budget (see figs. 5.2 to 5.4). As can be seen from fig. 5.3 experts think that a little bit more money is needed before it has an effect on technical progress. Figure 5.2, with mostly slightly lower values for the expert PIF, indicates that experts think that slightly more money to achieve a comparable level of technical progress is needed, compared to the empirical PIF. They are also slightly less optimistic about the maximum level of technical progress, that can be achieved (see fig. 5.4).

On the lower stage, transforming the budget into an effective budget, we do not see a big difference in the driving parameter  $\mu$ . The general picture is the same, as can be seen in figs. 5.5 and 5.6. The agricultural sector appears to be

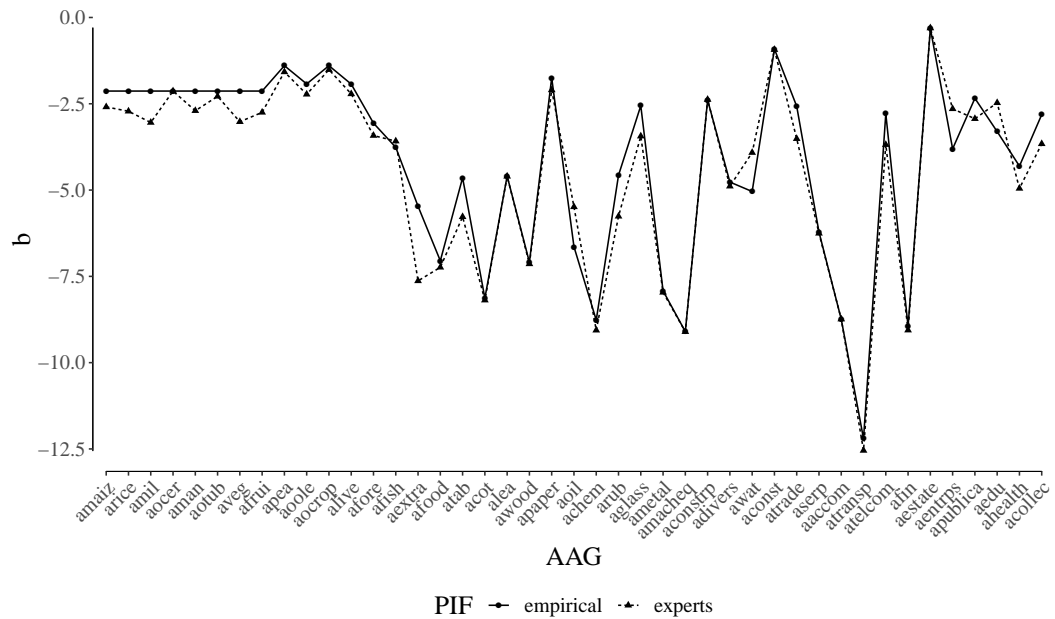
Figure 5.2:  $a$ 

a little bit more diversified in what instruments are important for the different sectors.

Applying the two different PIFs, we can calculate the expected, achieved levels of technical progress, given the status quo allocation of budget. As shown in fig. 5.7, we mostly only see a difference in the agricultural sector. This similarity is expected since the parameters for the other sectors do not differ much between the two PIFs. Given the captured technology beliefs of the experts, they would expect a lot less technical progress for the agricultural sector.

Finally, assuming that expert judgments on political goal achievements and preferred policy strategy of political experts are related to the same period, which is also covered by the empirical observations, both approaches estimate the same PIF parameters. In this case, the two approaches could be directly combined into one joint estimation approach.

If expert judgment, however, relates to future developments, estimated PIF-parameter might differ between the two approaches, since future policy-growth relations might change when compared to past/historic policy-growth relations. In particular, it appears conceivable that the implementation efficiency of policy programs differs between past and future periods. Moreover, max-

Figure 5.3: *b*

imal achievable TFP can change over time; for example, assume in the past substantial yield gaps existed, which have been addressed by increased public investment in extension services. To the extent, these policies have been successful yield gaps have been reduced, implying lower potential to promote TFP in the future<sup>2</sup>.

Thus, in general, future and past policy-growth relations differ, and therefore the two estimation approaches can not be directly combined to one joint estimation approach, if expert judgments are on future policy-growth-relations, while statistical data describes past policy-growth relations. The two sets of PIF-parameters still correspond to each other, at least to a certain degree, as long as the future and past periods are close to each other.

<sup>2</sup>Please note that in the framework of sectoral production functions, TFP incorporates an increase in technical efficiency, while the latter is by definition excluded analyzing micro-level data of individual firms.

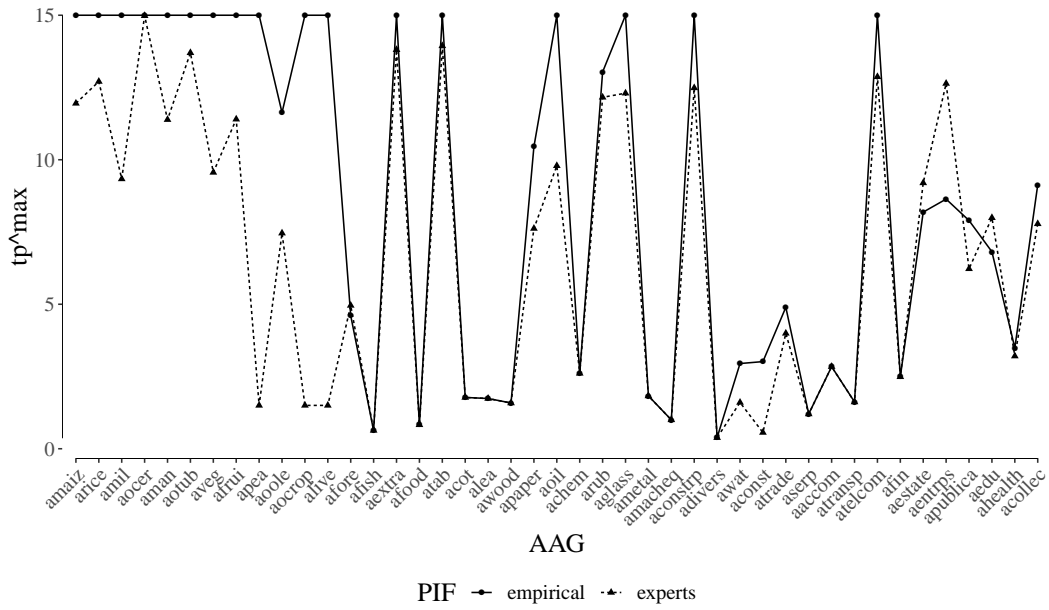


Figure 5.4:  $tp^{max}$

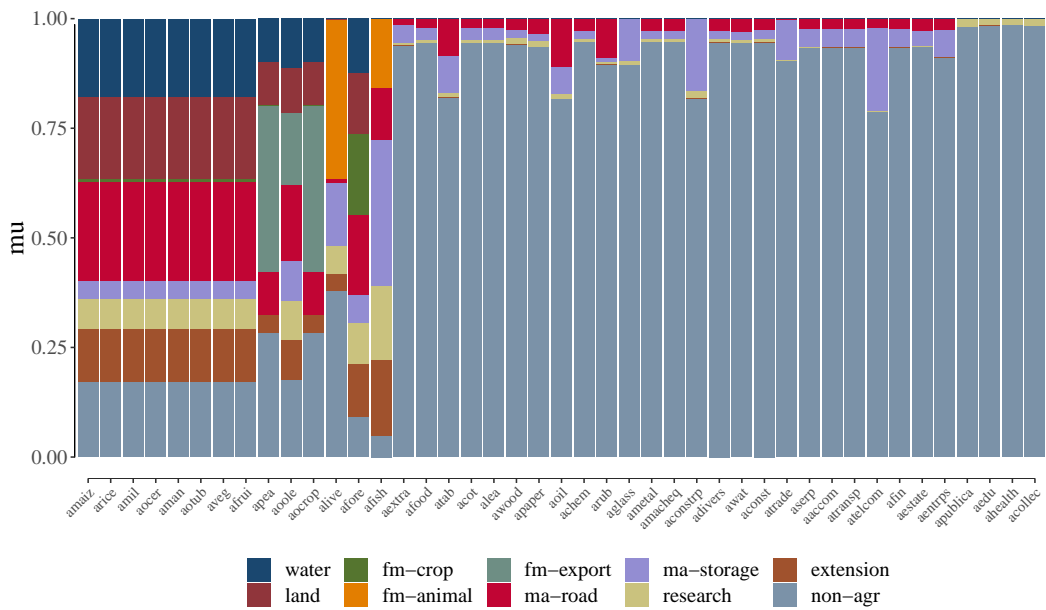


Figure 5.5: Empirical PIF  $\mu$



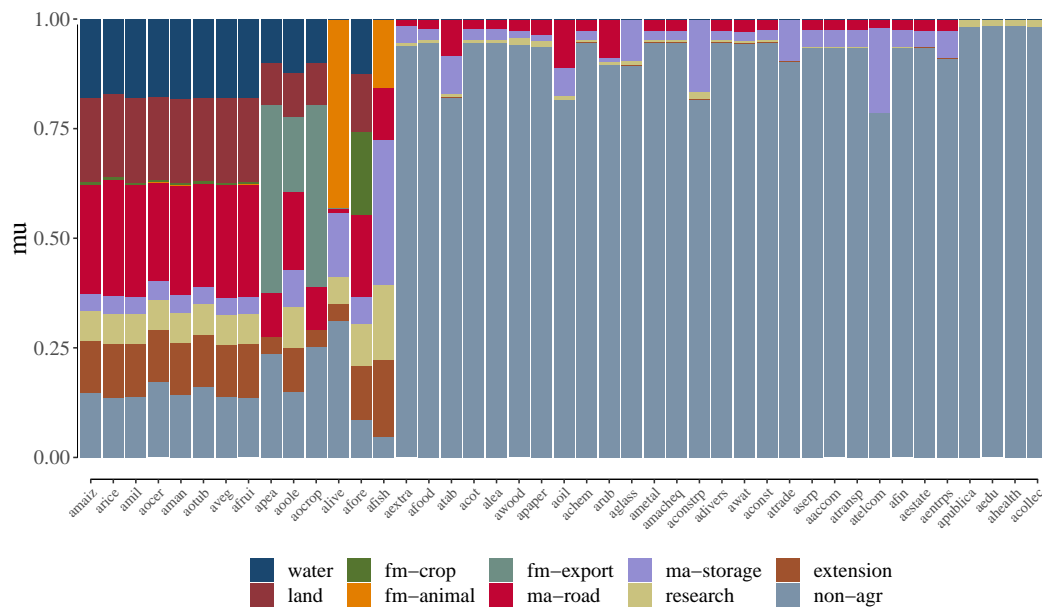


Figure 5.6: Expert PIF  $\mu$

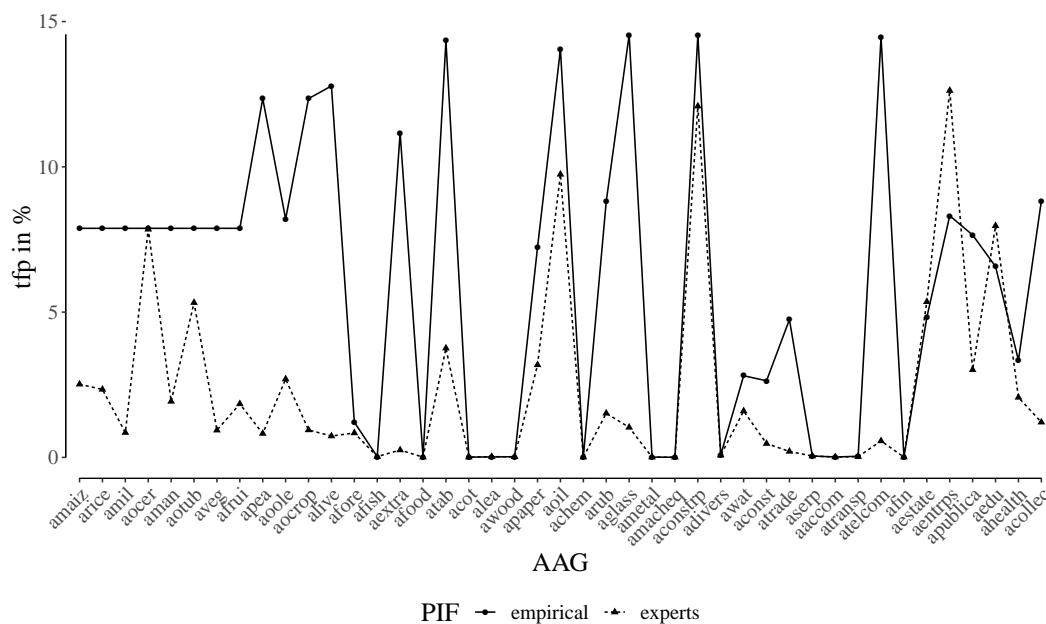


Figure 5.7:  $\Delta tp$  under status quo budget allocation



# Chapter 6

## Model Uncertainty

As has been introduced in section 3.1 and section 3.3.2 model uncertainty is an important aspect of economic modeling. In this chapter, we will derive steps that give a view of the uncertainty inherent in our models. These steps are derived based on our goal of estimating the transformation of policies into outcomes, but the general underlying approach can be applied to different problems as well.

The looked-at system is very complex and plagued by uncertainty. The system is approximated by a combination of models that depend on assumptions. Therefore it is interesting to see how specific model assumptions influence the estimation results. It is also not enough to only give the best estimate. However, it would be better also to give credible intervals and be able to quantify the uncertainty associated with the result. In using the results to advise political experts on future decisions, this is especially true.

The derived estimation framework provides a good solution to the complex problem of estimating sector-specific PIFs. It consists of two main parts, the GGF and the PIF. In both parts, we have sources of uncertainty. In the derivation of the GGF, the results depend on the model assumptions for the used CGE model. These assumptions include the choice of closure rules, the value of elasticities for production or trade. Therefore we will estimate PIFs, that 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.

The estimation approach used for the PIF results in a mode of the poste-

rior distribution, the 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. As has been described in section 3.3.1, the Metropolis / Metropolis-Hastings (Metropolis et al., 1953; Hastings, 1970) algorithms provide a solution for this problem. There are many variants available nowadays that build upon the basic variant<sup>1</sup>. We will use the Differential Evolution Markov Chain (DE-MC) algorithm by Braak (2006); ter Braak and Vrugt (2008). The chosen solution will be described in more detail in section 6.3. The sample generation is potentially very time-consuming. As a first step, we will only apply it to the most probable model.

From the viewpoint of the model, we can think of the first part as structural uncertainty and the second part 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:

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**Algorithm 2** Model Uncertainty Steps

---

```

for  $c \in \{\text{Ghana, Senegal, Uganda}\}$  do
  estimate empirical  $PIF_c$  (see section 5.2.1)
  Start Structural Uncertainty
    for  $e \in$  elasticity scenarios do
      for  $l \in$  closure scenarios do
        calibrate CGE model
        derive  $GGF_c^{e,l}$  based on CGE simulations (see section 5.1)
        estimate expert  $PIF_c^{e,l}$  (see section 5.2.2)
      end for
    end for
  End
  Start Parameter Uncertainty
    select most probable model specification  $PIF_c^*$ 
    generate representative sample for  $PIF_c^*$ 
  End
end for

```

---

For each country, we estimate an empirical  $PIF_c$ , derive the different meta-

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<sup>1</sup>see [https://m-clark.github.io/docs/ld\\_mcmc/](https://m-clark.github.io/docs/ld_mcmc/) for an overview of different algorithms

models  $GGF_c^{e,l}$  based on the different structural assumptions, and use that to estimate the expert pif  $PIF_c^{e,l}$  conditional on those assumptions. These steps are performed to handle the structural uncertainty and are described in section 6.1. Sections 6.2 and 6.3 describe the final describes the final step, which is to handle the parameter uncertainty by applying Bayesian model selection and generating a representative sample. In all three sections, some initial results highlighting the uncertainty are shown. The chapter is concluded by a summary in section 6.5.

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 be applied to many other problems as well.

## 6.1 Structural Uncertainty

The structural uncertainty relates to the assumptions used for the CGE model in the derivation of the GGF. The applied CGE model is a standard IPFRI-Type-II CGE model (Löfgren, Harris, and Robinson, 2002). To see the impact of the assumptions, not only a single metamodel has been derived, but conditional on each set of assumptions a specific metamodel has been derived, which is then used in the estimation of the expert PIF. We consider two main assumptions in our analysis: closure rules and elasticities. The closure rules are a combination of a Savings/Investment rule and a Government Savings rule. Tables 6.1 and 6.2 show the possibilities along with the explanation taken from the original model implementation.

Table 6.1: 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 6.2: 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

For the elasticities, we looked at trade, import and export, and production elasticities. As a very first, brute force step to capture the uncertainty around elasticities, they have been shifted 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. These are combined with the 25 closure scenarios. So we end up with  $27 * 25 = 675$  scenarios, for which a conditional metamodel, the GGF, is derived and in turn a conditional PIF is estimated.

As shown in section 5.1, we need to run a simulation path for each sector. Therefore we end up with  $|S| * 27 * 25$  simulations; for Senegal, there are about 34000 simulations that have to be calculated. For Ghana and Uganda, a similar number of different paths have to be calculated, since the number of sectors is very similar.

### 6.1.1 Implementation

This large number of simulations is not feasible to solve serially on just one computer. Assuming one simulation takes about 10s to compute, we would need roughly 4 days of non-stop computing to compute all scenarios for one country. Each simulation path is independent of each other, and therefore, this provides an opportunity to solve them in parallel. This requires a process that allows splitting the work into smaller units, distribute it to potentially multiple computers, collect computation results, and aggregate them back together.

The DST handles this process, which is described in detail in section 3.5.

In order to improve the reproducibility of the simulations, a small Ruby (Matsumoto, 2017) script has been written, that generates everything required for the computation to be run using the DST. As a first step, the script checks out a specific revision of the model code from the Subversion<sup>2</sup> repository. In the next step, it creates the base calibration point of the CGE model, which is dependent on the shifted elasticities. The files are then cleaned to only include the required files for the simulation and then compressed into a single ZIP-file. The script also creates a descriptive file; the DST client can use that to create the jobs automatically. The only manual step required is then to start the jobs and run the DST clients. In order to use the computers available in the department's computer lab, Powershell<sup>3</sup> scripts have been developed. The lab is in use during weekdays; therefore, the clients have to be stopped before that. For the complete process of launching clients on the many machines and stopping them, scripts have been developed. They launch remote desktop sessions, start the clients, and take care of stopping the clients and cleaning up generated files.

After the simulations have been computed, we can derive the GGF and in turn, estimate the PIF, not once, but 675 times. The PIF estimation process also takes multiple hours. Different from the CGE simulations, though, we now have multiple, independent estimation problems that we want to solve. Therefore it has been parallelized using the GAMS Grid and Multi-Threading Solve Facility<sup>4</sup>. The grid computing facility provides different ways to implement parallel solves. We have adopted the approach of using multiple threads on one machine. This involves creating something similar to a thread pool and managing it on a highly abstract level, by submitting only as many jobs, meaning model instances to be solved, as threads are available, storing the solve results when one has finished and then submit a new job. Given the cheaply available many-core machines in cloud offerings like Amazon Web Services (AWS) or Google Cloud Platform (GCP), the estimation process has been adapted to make use of that. This allows the estimation of all PIFs to be completed in about an hour. We are using the AWS offering for now. For the

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<sup>2</sup><https://subversion.apache.org/>

<sup>3</sup><https://docs.microsoft.com/de-de/powershell/>

<sup>4</sup>[https://www.gams.com/latest/docs/UG\\_GridComputing.html](https://www.gams.com/latest/docs/UG_GridComputing.html)

estimation process, a custom Amazon Machine Image (AMI) has been created that contains the required environment for the PIF estimation. The estimation process has been automated using Ansible<sup>5</sup>. The automation script requests a new spot instance for each country and then loads the estimation script onto the launched machine. This estimation script, in turn, downloads the results of the simulation sample and then runs the PIF estimation. The estimation results are stored in a private S3 bucket, from where they are downloaded for further analysis onto the local machine.

## 6.2 Model Selection

After having derived steps to determine the impact of model assumptions on the resulting PIFs, it is interesting to look at the odds ratios of the different PIFs, to select the most probable one. It is also of interest to see if certain assumptions are clearly preferred over others. In this regard, we use expert opinions as filters. The model specifications can be ranked by how well they replicate the expert opinions, and therefore, the experts implicitly select the model specification, that is in line with their not directly observable mental model.

Let  $y$  denote the data used in the PIF expert estimation. The posterior density  $h(\chi|y)$  is proportional to  $L(\chi|y)p(\chi)$ .  $p(\chi)$  denotes the prior density and  $L(\chi|y)$  the likelihood function. The objective function (see eq. (5.20)) 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.

Let  $M_m$  with  $m \in \{1, \dots, 675\}$  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  $P(M_m) = \frac{1}{675}$ . If we are only interested in selecting the model that best replicated the data, we could select the one with the minimum objective value  $t(M_m)$ .

Given the derivation and assumptions of the objective function and the

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<sup>5</sup><https://www.ansible.com/>



$P(M_m)$  we can calculate the posterior odds ratios for models  $M_{m1}, M_{m2}$  as follows:

$$\frac{P(M_{m1}|y)}{P(M_{m2}|y)} = \frac{e^{-0.5t(M_{m1})} P(M_{m1})}{e^{-0.5t(M_{m2})} P(M_{m2})} \quad (6.1)$$

Since  $P(M_{mi}) = P(M_{mk}) \forall i, k \in \{1, \dots, 675\}$  the ratio further simplifies to:

$$\frac{P(M_{m1}|y)}{P(M_{m2}|y)} = e^{0.5(t(M_{m2})-t(M_{m1}))} \quad (6.2)$$

Having the estimation results based on the model implementation, as described in the previous section, model selection is straight forward to implement: Find the minimal target function value out of the solved value.

### 6.3 Parameter Uncertainty

The next step is to look at the parameter uncertainty. Based on the best fit model selected in section 6.2, we will derive a representative sample of the estimated PIF parameters. This section will also briefly discuss the technical implementation of the sampling procedure.

In a first naive approach, the classical Metropolis-Hastings algorithm was implemented. That led to meager acceptance rates of below 1%, which made the sampling practically infeasible. In the next step, a block-wise variant was tried, but it still was plagued by low acceptance rates. This finally led to the DE-MC algorithm developed initially by Braak (2006). In order to derive the sample, we will apply the  $DE - MC_Z$  algorithm, a derivation of the original algorithm that requires fewer chains and therefore making it applicable to our problem (ter Braak and Vrugt, 2008). It belongs to the family of the MCMC algorithms. It builds upon the same principles as the Metropolis-Hastings algorithm, which has been introduced in section 3.3.1. The applied variant “is an adaptive Metropolis sampler” (ter Braak and Vrugt, 2008). It allows efficient sampling of the relatively large parameter space of the PIF parameters.

Let  $\chi$  denote the parameters of the PIF with dimensionality  $d$ . The evaluation function of the posterior is denoted by  $\pi(\chi)$ . The algorithm proceeds as follows:

1. Generate an initial sample  $Z$  of size  $M_0 \times d$ , with  $M_0 > \max(d, N)$ .  $N$  denotes the number of chains, which is at least three, but usually between five and ten. The sample can, for example, be generated using the prior distributions for the parameters.
2. The first  $N$  rows of the matrix  $Z$  are assigned to  $X$ , the initial population and  $M$  is set to  $M_0$ .
3. The population  $X$  is updated  $K$  times by the following procedure:
  - (a) For each chain  $i$ , with current state  $X_i$ , two rows  $z_{r1}$ ,  $z_{r2}$  of  $Z$  are selected without replacement
  - (b) A new proposal  $x^*$  is calculated:

$$x^* = X_i + \gamma \cdot (z_{r1} - z_{r2}) + e. \quad (6.3)$$

The current state is updated into the direction of the difference between the past states  $z_{r1}$ ,  $z_{r2}$ . The value of  $\gamma$  is proposed to be  $\frac{2.38}{\sqrt{2d}}$ . And finally a random jitter  $e \sim N(0, b)^d$  is added, with  $b$  small.

- (c) Using this proposal the Metropolis ratio  $r$  is calculated by  $\frac{\pi(x^*)}{\pi(X_i)}$  and the proposal is accepted with probability  $\min(1, r)$ . This means  $X_i$  becomes  $x^*$  in the acceptance case and is left unchanged otherwise.
4. After the  $K$  updates, append  $X$  to  $Z$ , and the new number of total samples becomes  $M = M + N$ .
5. This is repeated by starting again at step 3 until the desired sample size has been reached or the chains have converged.

This way, the algorithm only stores a thinned part of the entire past, as only each  $K$ th iteration is added to the sample, which helps with storage requirements. The extended version of this algorithm that also includes a snooker update, as described in ter Braak and Vrugt (2008), will not be applied.

### 6.3.1 Implementation

The complete sampling procedure has been implemented in Julia<sup>6</sup>. Julia is a relatively new language, build with the goal of high performance. A relevant

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<sup>6</sup><https://julialang.org/>

target of the language is scientific computing. It is open-source and freely available. The sampling procedure was implemented with the help of many packages, but the most important one being *DEMC.jl*<sup>7</sup>.

The parameters of the PIF have certain restrictions on them that prohibit efficient direct sampling. Therefore the parameters have been transformed so that they can be sampled without restrictions from  $\mathbb{R}$ . The  $a, b$  and  $tp^{max}$  parameters are bounded in an interval  $l < x < u$ , with  $l, r \in \mathbb{R}$  and  $x$  being a value of those three parameters. To get the unbounded value  $y$ , we apply the following transformation:

$$y = -\log\left(\frac{u-l}{x-l} - 1\right) \quad (6.4)$$

To transform the unbounded value  $y$  back into the bounded value  $x$ , we apply the reverse:

$$x = l + \frac{1}{1 + e^{-y}} \cdot (u - l) \quad (6.5)$$

This can be easily implemented in Julia, as can be seen in listing 6.1.

Listing 6.1: pack.jl

```

1 function boundsPack(x::Float64, l::Float64, u::Float64)::Float64
2   -log((u - l) / (x - l) - 1)
3 end
4 function boundsUnpack(y::Float64, l::Float64, u::Float64)
5   l + (1 / (1 + exp(-y))) * (u - l)
6 end

```

The  $\mu$  parameters are a little bit more complex, since they are not only bounded between zero and one, but in addition  $\sum_{i \in I} \mu_{s,i} = 1 \forall s \in S$ . This makes the transformation a little bit more complicated, but it is still straightforward. For all sectors the *non-agr* policy instrument is active, that means  $\mu_{s,\text{non-agr}} > 0$ . This allows us to use it as the normalizing instrument in the following transformation into the unbounded value:

$$\begin{aligned} \eta_s &= \frac{1}{\mu_{s,\text{non-agr}}} \\ y_{s,i} &= \log(\eta_s * \mu_{s,i}) \quad \forall s \in S, i \in I \setminus \{\text{non-agr}\} \end{aligned} \quad (6.6)$$

<sup>7</sup><https://github.com/chrished/DEMC.jl>

To transform it back into the bounded space, the following transformation is applied:

$$\begin{aligned}\eta_s &= 1 + \sum_{i \in I \setminus \{\text{non-agr}\}} e^{y_{s,i}} \\ \mu_{s,i} &= \frac{e^{y_{s,i}}}{\eta_s} \\ \mu_{s,\text{non-agr}} &= \frac{1}{\eta_s}\end{aligned}\tag{6.7}$$

This transformation is only applied to  $\mu_{s,i}$  that are active, meaning they are not fixed to zero.

Given those transformations, the DE-MC algorithm runs in the unbounded space, and for the posterior calculation, which is needed in the acceptance ratio, the parameters are transformed back into the model parameter space. The posterior calculation has been optimized so that it computes quickly. The starting point was a naive transformation of the GAMS code using nested dictionaries, which is structurally similar to the GAMS code. This version requires between 60 and 80 milliseconds to compute the posterior value. This has been verified to calculate the same values as the GAMS code. In a second step, it has been used to verify that the optimized version also computes the same values. The optimized version precomputes some static values and uses vector and array math instead of loops where possible. Also, repeated memory allocations have been reduced. It employs, for example, the fact, that currently the CES function exponent is always 0.5, and therefore the various exponents often simplify to 0.5 or  $-0.5$ . The code has been optimized using the *BenchmarkTools.jl*<sup>8</sup> package and the `@profile` command of the Juno IDE<sup>9</sup>. They were used to find slow areas of the code and to verify changes actually resulted in improvements. The optimized version of the posterior calculation requires under one millisecond to compute the value. This means, roughly speaking, we can compute 100 times as many samples with the optimized as with the naive version, alternatively only a hundredth of the time is required to compute the same sample size. This optimization allows the generation of a sample with 200000 sample points in under an hour. The algorithm could be further sped up by employing parallel computing, which has not been done so far. The samples for the three countries are computed in parallel using

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<sup>8</sup><https://github.com/JuliaCI/BenchmarkTools.jl>

<sup>9</sup><http://junolab.org/>

independent processes, as a poor man's version of parallelism.

The starting sample  $Z$  that is required by the algorithm can be generated from the prior distributions of the parameters. Given that we already have the HPD estimate, we can help the algorithm and create the initial sample around the HPD estimate, an area where we expect a higher density of the posterior. The HPD estimate and the parameters of the PIF are transformed into a *RData* file using an R script, which in turn is then loaded into the Julia program. The sample is written to *CSV* files, as this provided the easiest and best-performing way to load them back into the GAMS framework for further analysis. Running further analysis based on the sample, we ran into some performance problems with GAMS. GAMS implements sparse data structures using linked lists. For each sample point  $sp_i \in \{1, \dots, 200000\}$  we want to calculate some derived value  $d_i$ . This results in GAMS in doing  $\frac{200000 \cdot (200000 - 1)}{2}$  lookups, as it iterates the list always from the beginning. This can be solved by splitting the iteration index into multiple dimensions like for example  $sp_i^{outer} \in \{1, \dots, 400\}$  and  $sp_i^{inner} \in \{1, \dots, 500\}$ . This then results in only  $\frac{(400+500) \cdot (400+500-1)}{2}$  searches.

## 6.4 Results

We derived an approach to handle structural and parameter uncertainty and also implemented it. In the following, some exemplary results showing the impact of model uncertainty are shown.

### 6.4.1 Structural Uncertainty: Impact on GGF

In the first step, we can look at what impact the different model specifications have on the estimations. Looking at the derived GGF elasticities for poverty reduction on the meso-sector level, shown in fig. 6.1, we can see that all three countries follow the same pattern. The crop sector has the largest values, followed by the export sector. The livestock and fish sectors have the lowest values of the agricultural sectors, except for Senegal, where the livestock sector achieves a similar level as the export sector. In all the agricultural sectors, the impact of the different model assumptions is small, and the elasticities are highly concentrated. The agribusiness sector has values between the export and crop sector. The non-agricultural sectors are not as clear cut. The industry

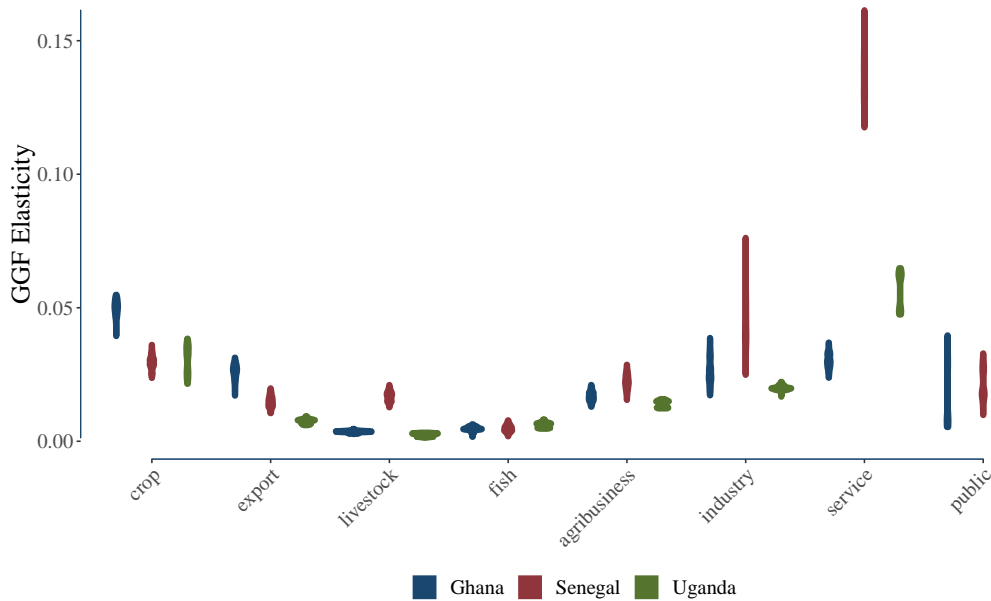


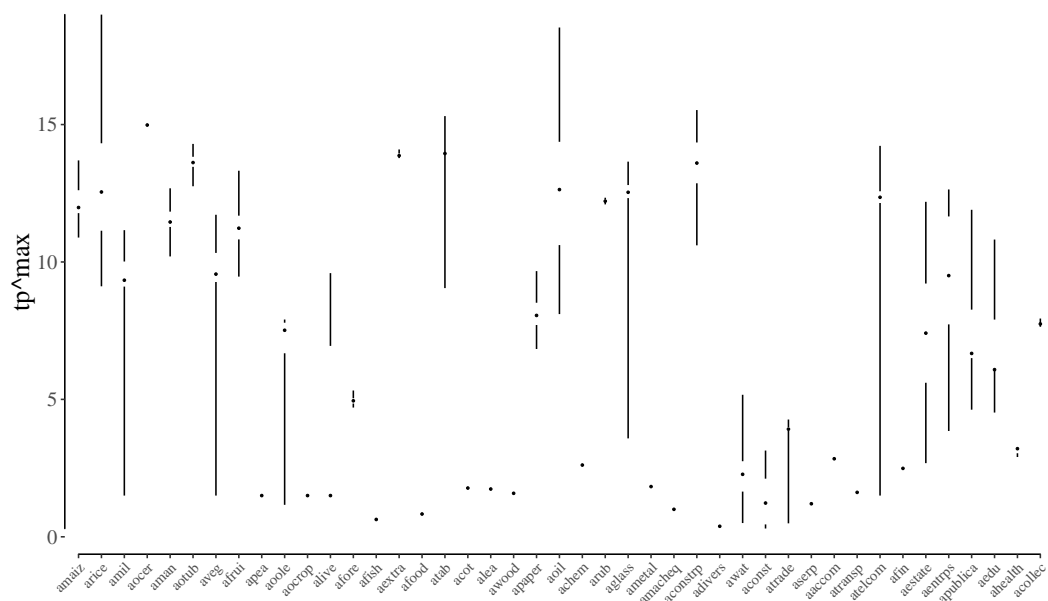
Figure 6.1: Meso Sector GGF Elasticities

sector elasticities for Uganda are not impacted much by the different model assumptions, but they are for Ghana, and to a much larger extent for Senegal. The public sector also has a larger variance in all three countries, but with similar values across the countries. The service sector has roughly the same values for Ghana, with a similar variance. In Senegal, the service sector has the highest elasticity, by a factor of two to three. The service sector in Uganda also has the highest elasticity, but only by a fraction.

In summary, there appears to be a larger uncertainty around the impact of growth on poverty reduction in the non-agricultural sectors than in the agricultural sectors. In the agricultural sectors, the three countries are also very similar in both the level and the variance of the elasticity.

#### 6.4.2 Structural Uncertainty: Impact on PIF

In the next step, we will look at the impact of the different model assumptions on the estimated PIFs. As an example, fig. 6.2 show the distribution of the  $tp^{max}$  parameter for Senegal on sector level. We can see that there are many sectors for which there is a broad range of values, for example, the vegetables and fruits sectors (*aveg* and *afrui*), but also in the industry and services sectors, for example, the telecommunications sector (*atelcom*) or the enterprise services

Figure 6.2: Senegal:  $tp^{max}$ 

sector (*anetrps*). Some sectors have only minimal variance; for example, the fisheries sector (*afish*) or the chemical industry sector (*achem*). For Ghana, a very similar picture can be observed, while the variances are, in general, smaller for Uganda.

As a first indicator of what this means, we can look at the predicted technical progress levels, given the status quo budget allocation. In fig. 6.3, we can see the different achieved levels for the three countries. 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.

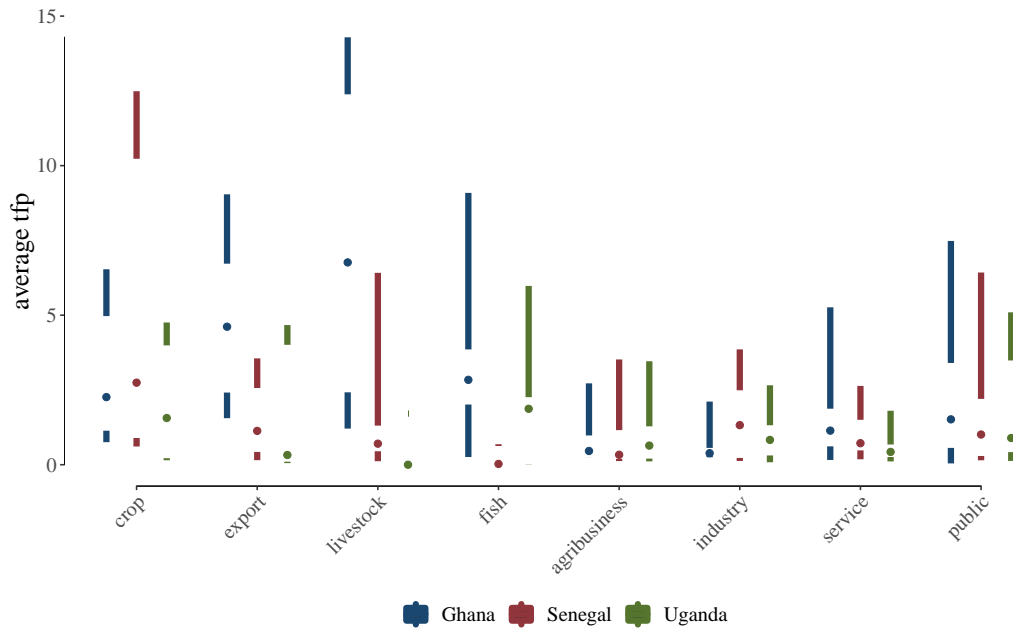


Figure 6.3: Meso Sector Average TFP

### 6.4.3 Model Selection

Figures 6.4 to 6.6 show the distribution of the posterior odds ratios relative to the best fit model. The best fit model has a value of 1.00, with a value of 0.25 meaning, that the best fit model is four times as likely as the comparison to be the correct model.

For Ghana, we can see that there is one specification clearly preferred over the others: The specification with closure scenario 3 – 2 and elasticity scenario 0.5 – 1.5 – 1.5. This means that the model with government savings closure rule 3 (see table 6.2) and savings/investments closure rule 2 (see table 6.1) best fit the expert data. The import elasticity parameters for the CGE have been multiplied by 0.5, export elasticity parameters by 1.5, and production elasticities also by 1.5. Elasticity scenario 0.5 – 1.5 – 1 also has relatively high odds ratios. These higher odds ratios indicate that lower import and higher export elasticities are preferred. Most of the simulated specifications have low odds ratios, as shown by the abundant light gray area in fig. 6.4.

For Senegal, the picture is not as clear cut. The preferred model has higher values for the import, export, and as well for production elasticities. The closure scenario is 3 – 4, meaning government savings closure rule 3, and saving/investments closure rule 4. There is no clear preference for a specific



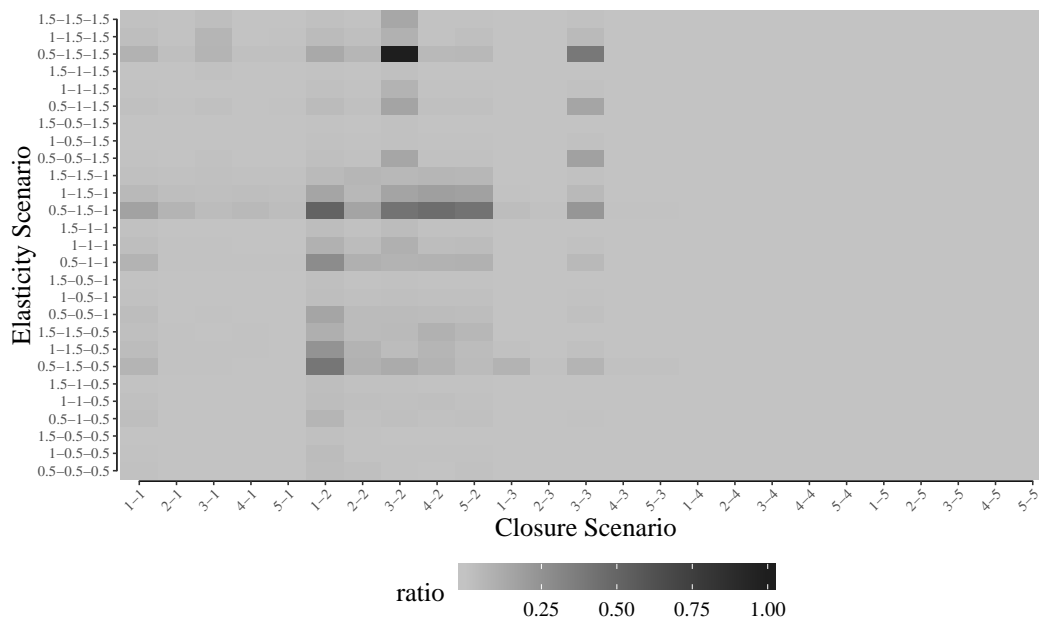


Figure 6.4: Ghana: Odds Ratios

elasticity scenario, with higher import and export elasticities being slightly preferred. Government savings closure rule 3 is preferred over the alternatives. For the savings/investments closure rule, rule 1 has the lowest odds ratios, followed by rule 5. Rule 4 has the highest odds ratios, with the other rules falling in the middle.

In Uganda, we see a clear dominance of the closure scenarios 3–1 and 3–2. Again the government savings rule 3 is preferred. The preferred model has shifters of 0.5 for import and export elasticities and 1 for production elasticities. Six more model specifications have an odds ratio higher than 0.9. They all are under the same closure scenario, but varying elasticity scenarios. This is similar to Senegal, where no clear separation between the elasticity scenarios can be found. In all countries, though the government savings rule 3 is preferred, a model specification where government savings are fixed, and a scaled direct tax rate for selected institutions is implemented.

Figure 6.7 provides a different look at the same data. We sorted the models according to their odds ratios with the most probable model from highest to lowest and then normalized the sum of all odds ratios to one. This means the most probable model is the first, and the least probable one the last. The figure shows the running sum of the normalized odds ratios. Here we can see

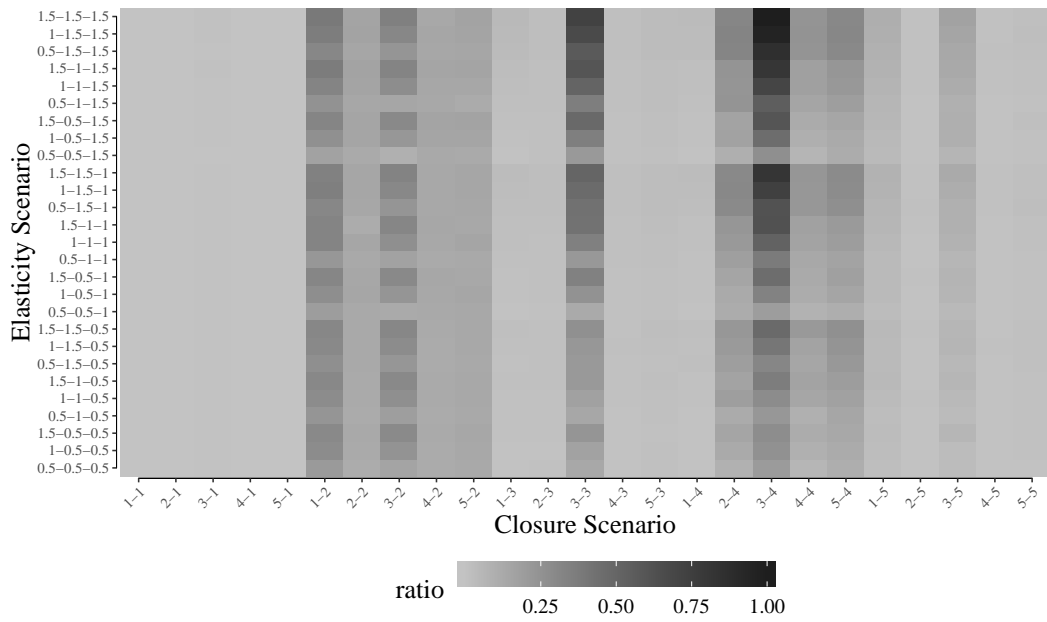


Figure 6.5: Senegal: Odds Ratios

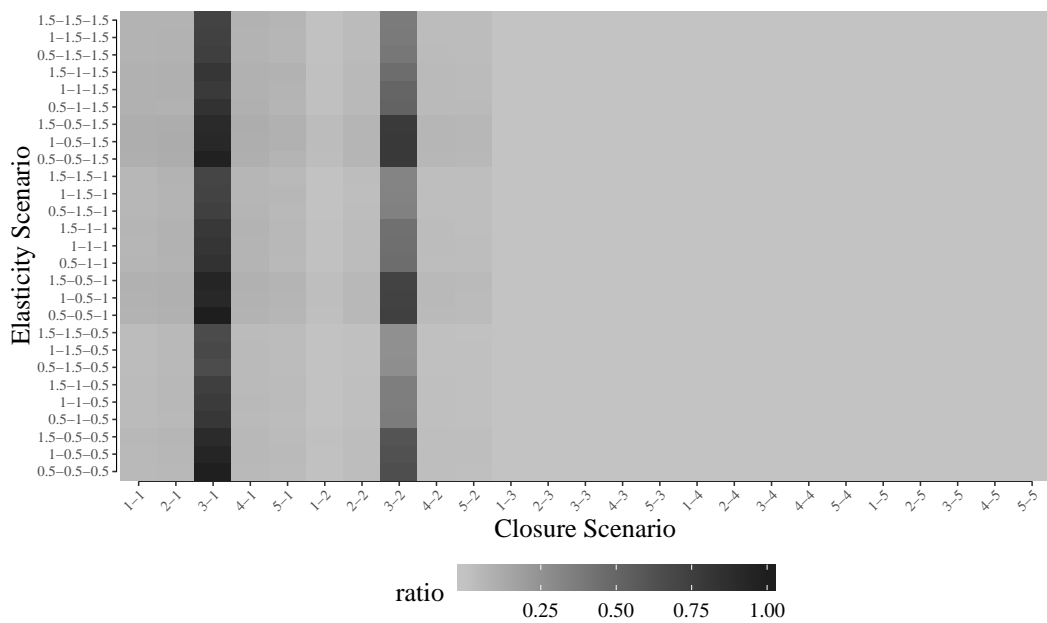


Figure 6.6: Uganda: Odds Ratios

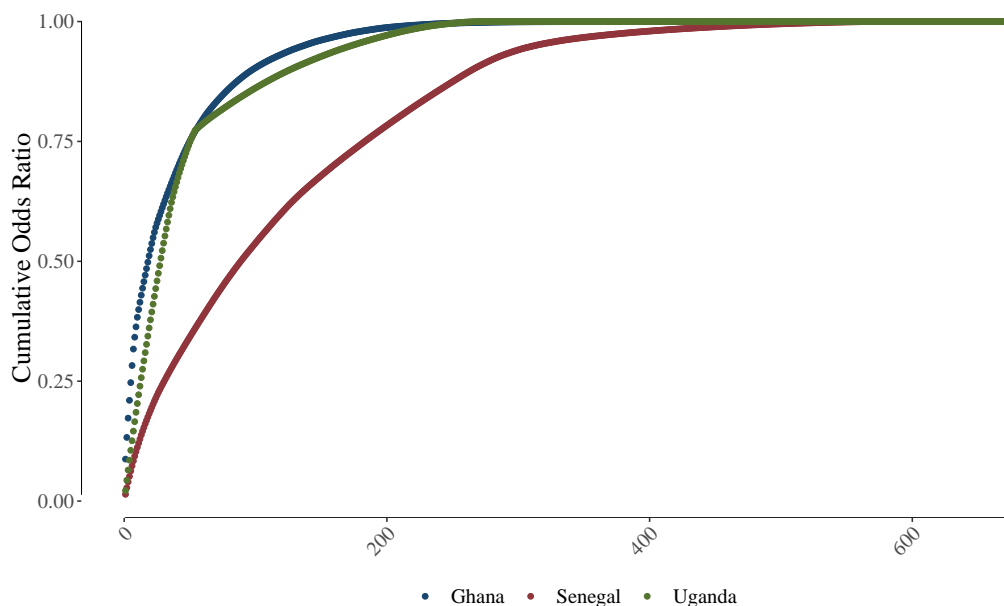


Figure 6.7: Cumulative Odds Ratios

that for Ghana and Uganda, compared to Senegal, a much smaller number of models is required to reach 70% of the mass. A more clear preference for specific models can be observed for Ghana and Uganda, as shown by those results. In combination with the previous figures, we can conclude that there is a preference for specific model structures.

#### 6.4.4 Parameter Uncertainty

The generated sample is based on eight chains, with 25000 iterations per chain. Therefore the total sample size is 200000. The sample computes in about an hour, including the burn-in period. The full set of PIF parameters has been changed in the sample.

Figure 6.8 shows the posterior values of the accepted draws for Uganda. As can be seen, each chain moves through different areas. Even though the posterior values of the accepted draws are quite distant to the posterior value of the HPD estimate, the posterior value of the mean and median is quite close to the HPD estimate.

For illustrative purposes fig. 6.9 shows the sample distribution for the  $tp_s^{max}$  parameter in Senegal. We can see that for most sectors, a vast range of values got accepted. The interquartile range is, compared to the first and third quar-

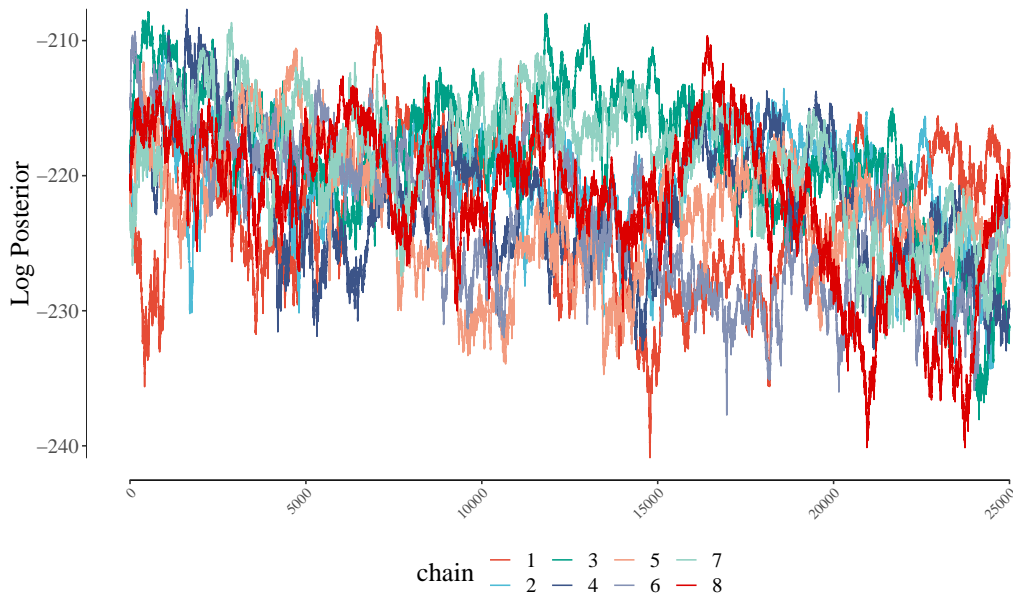


Figure 6.8: Uganda: Log Posterior

tiles for most sectors rather small. The mean (thick dot) and median (small dot) values are also usually close to each other.

In the next step, we can look again at the average TFP per meso-sector predicted under the status quo budget allocation. We can see in fig. 6.10 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 non-agricultural 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.

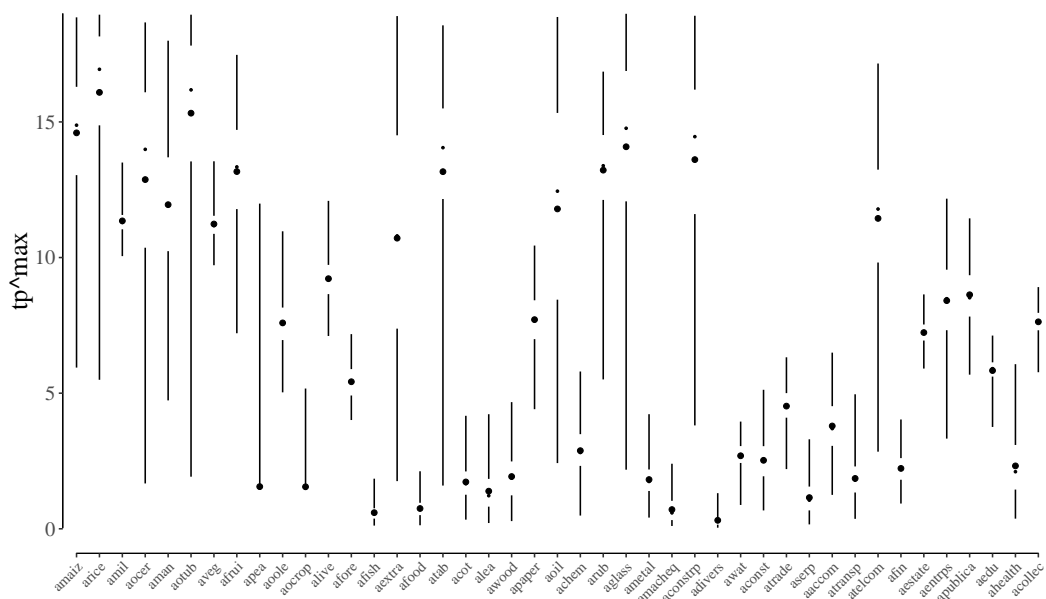


Figure 6.9: Senegal:  $tp^{max}$

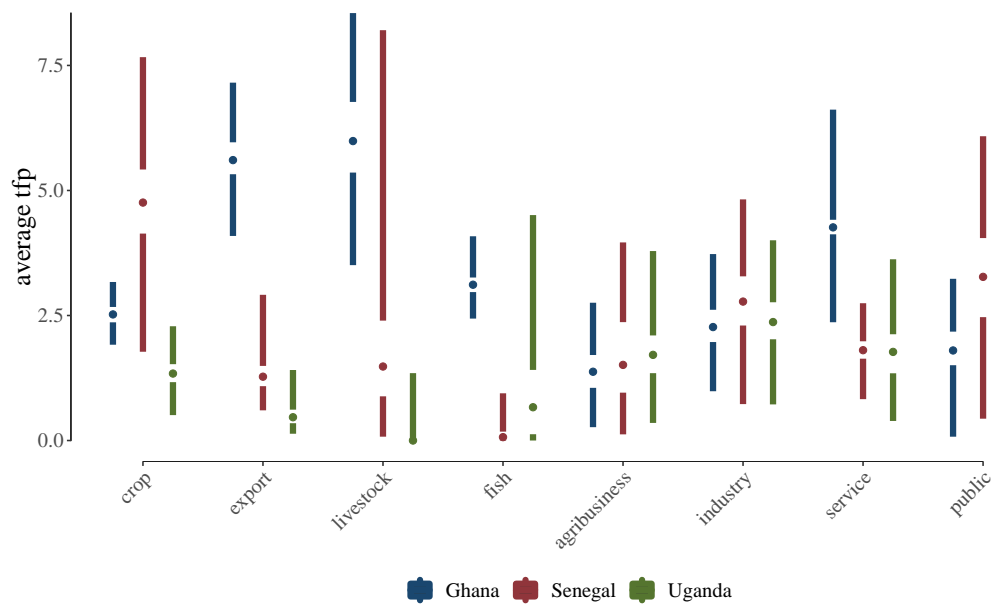


Figure 6.10: Meso Sector Average TFP

## 6.5 Conclusion

Handling model uncertainty is an important but complex task. The required computational resources increase by a significant factor. For each country, instead of about 45 simulations, 35000 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. The large simulation samples required for the structural uncertainty led to the development of the previously described DST (see section 3.5). This tool made it possible to compute the simulation sample and approach the handling of structural uncertainty. A representative sample of the posterior distribution could be generated by applying the DE-MC algorithm, as well as of the associated parameter distributions. This involved transforming the evaluation of the posterior from GAMS to Julia. The transformation is right now still a manual process since it also involves rewriting the code to optimize the performance. There appear to be some first attempts at conversion tools (see, for example, <https://github.com/jac0320/toJuMP.jl>), improving and applying these tools is interesting for future work.

Regarding the model results, we see that both structural and parameter uncertainty are present. The ranges of possible values are broad in both cases. In Ghana, a clear preference for one model specification has been determined, while in Uganda, at least a specific closure rule combination is preferred. The picture is much more diffuse in Senegal.

Even though the estimation and model uncertainty steps have been implemented with a specific case in mind, the underlying approach is much more general.

# Chapter 7

## Key Sectors - Key Policies

After having developed the estimation framework in chapter 5 for PIFs and a framework for handling uncertainty in chapter 6 around it, we now want to apply it to the first empirical application: The problem of finding key sectors and key policies for poverty reduction. We are trying to find sectors and policies, if invested in, have a substantial effect on poverty reduction. Beyond the indicators for key sectors and key policies, it is interesting to derive optimal policies from the point of view of society. Only first-best policies are derived; that is, they do not take political feasibility into account.

In this chapter, we will first compare the derived indicators with previously used measures that were derived based solely on a CGE. The next step is then to look for similarities and differences between the three countries. The final step is then to look at the impact of model uncertainty on our results and if we can find stable results that are applicable in political advisement. Here we will focus mainly on poverty reduction, though the same steps can be applied to the other policy goals (see section 4.4) as well. This problem is a first step in policy advice in the context of pro-poor-growth.

### 7.1 Methodological Implementation

#### 7.1.1 Indicators

The applied indicators have already been derived in an abstract form in section 4.7.

The indicator for key sectors is an extension of previously used measures. It is a combination of growth - goal elasticities with policy - growth elasticities. Let  $z \in Z$  denote a policy goal, as introduced in section 4.4.

The growth - goal elasticities  $\xi_{s,z}^{GGF}$  are based on the derived GGF (see section 5.1) and measure the impact of TFP changes  $\Delta tp$  on goal achievement levels. Studies based solely on a CGE analysis derive the same indicator under the name CGE elasticity.

$$\xi_{s,z}^{CGE} = \xi_{s,z}^{GGF} = \frac{\partial GGF(\Delta tp)}{\partial \Delta tp} \quad (7.1)$$

Policy - growth elasticities  $\xi_s^{PIF}$ , measuring the marginal impact of total budget  $B$  on  $\Delta tp$  changed levels, are defined as follows:

$$\begin{aligned} \xi_s^{PIF} &= \frac{\partial \Delta tp_s}{\partial B} = \frac{\partial PIF(\gamma)}{\partial B} \\ &= \frac{\partial \Delta tp_s(Be_s)}{\partial Be_s} \frac{\partial Be_s(\gamma)}{\partial B}. \end{aligned} \quad (7.2)$$

Using these two measures, we can now define policy - goal elasticities:

$$\xi_{s,z}^{PGE} = \xi_{s,z}^{GGF} \xi_{s,z}^{PIF}. \quad (7.3)$$

Looking at the second goal  $Z2$ , poverty reduction, we will call the policy - growth elasticity PPG - elasticity, denoted by  $\xi_{s,z}^{PPG}$ .

### 7.1.2 Optimal Policies

As a first step, we define an optimization problem that returns the optimal policies given one specific model. As described in section 4.8 we can use the estimated GGF and PIF to define an optimization problem, that is very similar to the one from eq. (5.12). The only difference is that the interest factors  $X_{g,z}$ , which were actor specific, are now replaced by  $\alpha_z$ , capturing society's interest in the goal  $z$ . A more detailed explanation of the derivation of these weights



is given in section 9.1. Therefore the following optimization problem results:

$$\begin{aligned}
\hat{\gamma} &= \arg \max_{\gamma} \sum_t \prod_z \delta^t (1 + \psi_{z,t})^{\alpha_z} \\
\mathbf{s.t.} \\
\psi_{z,t} &= \psi_z^0(\gamma) + \psi_z(\gamma) \cdot t \\
\psi_z^0(\gamma) &= -\Delta_z^{\text{ps}} \frac{\sum_i \gamma_i}{B_0} \\
\psi_z(\gamma) &= \xi_z^{\text{base}} + \xi_z \cdot \Delta t p(\gamma) \\
\Delta t p_s(\gamma) &= t p_s^{\text{max}} \frac{1}{1 + e^{-(a_s B e_s + b_s)}} \\
B e_s(\gamma) &= \eta_s \left[ \sum_i \mu_{i,s} \gamma_i^{-\rho} \right]^{-\frac{1}{\rho}}
\end{aligned} \tag{7.4}$$

The function  $\sum_t \prod_z \delta^t (1 + \psi_{z,t})^{\alpha_z}$  is the evaluation function for the goal achievements derived from investing into the policy  $\gamma$ . Since the derived PIF is a local approximation lower ( $B^{\text{low}}$ ) and upper bounds ( $B^{\text{up}}$ ) on the total spent budget are added:

$$\begin{aligned}
B^{\text{low}} &\leq \sum_i \gamma_i \\
B^{\text{up}} &\geq \sum_i \gamma_i.
\end{aligned} \tag{7.5}$$

In a similar fashion also a fixed budget restriction can be added:

$$B^{\text{fix}} = \sum_i \gamma_i. \tag{7.6}$$

The combination of eq. (7.4) and eq. (7.5) is the employed model to find optimal policies for a specific model.

In the previous chapters chapters 6 and 7, we looked at the results under model uncertainty and have given ranges of possible values. Now we are trying to find optimal policies, meaning we need to optimize conditional on the different model specifications. As a first approximation, we might solve each model independently with the just described optimization problem, and use the weighted average of the obtained results. This approach might lead to wrong results, however. Therefore we will adapt the optimization problem and solve them all at once (Rockafellar, 2001; Steel, 2019). We will introduce a new target function, that weighs the individual model results, as defined in the individual optimizations target function, according to the odds ratios derived

in section 6.2.  $w_{M_j}$  denotes these weights, and they are normalized so that their sum equals one, with  $M_j$  denoting the different model specifications.

$$\sum_{M_j} w_{M_j} = 1 \quad (7.7)$$

The constraints become model specific, but we search for a single  $\gamma$  vector. Therefore the complete optimization problem then is:

$$\begin{aligned} \hat{\gamma} &= \underset{\gamma}{arg \max} \sum_{M_j} w_{M_j} R_{M_j} \\ \text{s.t.} & \\ R_{M_j} &= \sum_t \prod_z \delta^t (1 + \psi_{M_j,z,t})^{\alpha_z} \\ \psi_{M_j,z,t} &= \psi_{M_j,z}^0(\gamma) + \psi_{M_j,z}(\gamma) \cdot t \\ \psi_{M_j,z}^0(\gamma) &= -\Delta_z^{\text{ps}} \frac{\sum_i \gamma_i}{B_0} \\ \psi_{M_j,z}(\gamma) &= \xi_{M_j,z}^{\text{base}} + \xi_{M_j,z} \cdot \Delta t p_{M_j}(\gamma) \\ \Delta t p_{M_j,s}(\gamma) &= t p_{M_j,s}^{\text{max}} \frac{1}{1+e^{-(a_{M_j,s} B e_{M_j,s} + b_{M_j,s})}} \\ B e_{M_j,s}(\gamma) &= \eta_{M_j,s} \left[ \sum_i \mu_{M_j,i,s} \gamma_i^{-\rho} \right]^{-\frac{1}{\rho}} \\ B^{\text{low}} &\leq \sum_i \gamma_i \\ B^{\text{up}} &\geq \sum_i \gamma_i \end{aligned} \quad (7.8)$$

Following Varian (1994), our target function  $\sum_{M_j} w_{M_j} R_{M_j}$  fulfills the expected utility form, with  $R_{M_j}$  being the utility derived from the policy choice  $\gamma$  under model  $M_j$ .

## 7.2 Results

### 7.2.1 Key Sectors

As described in the original derivation of the key sectors indicator (see section 4.7), the PPG elasticity, looking only at growth-outcome relations might not be enough. Standard CGE-concepts, i.e. CGE-elasticities and -multipliers, as derived for example by (Diao et al., 2006; Christiaensen, Demery, and Kuhl, 2006; Dorosh and Thurlow, 2018), capture only this part, but neglect the

policy-growth linkages. Figure 7.1 shows an exemplary comparison of the different indicators for Senegal. All indicators are given relative to the maize sector (*amaiz*).

As can be seen from fig. 7.1 identified key sectors crucially depend on the applied concept. In particular, standard CGE-concepts imply that especially growth in non-agricultural 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 for economic growth in agriculture, especially the food sector.

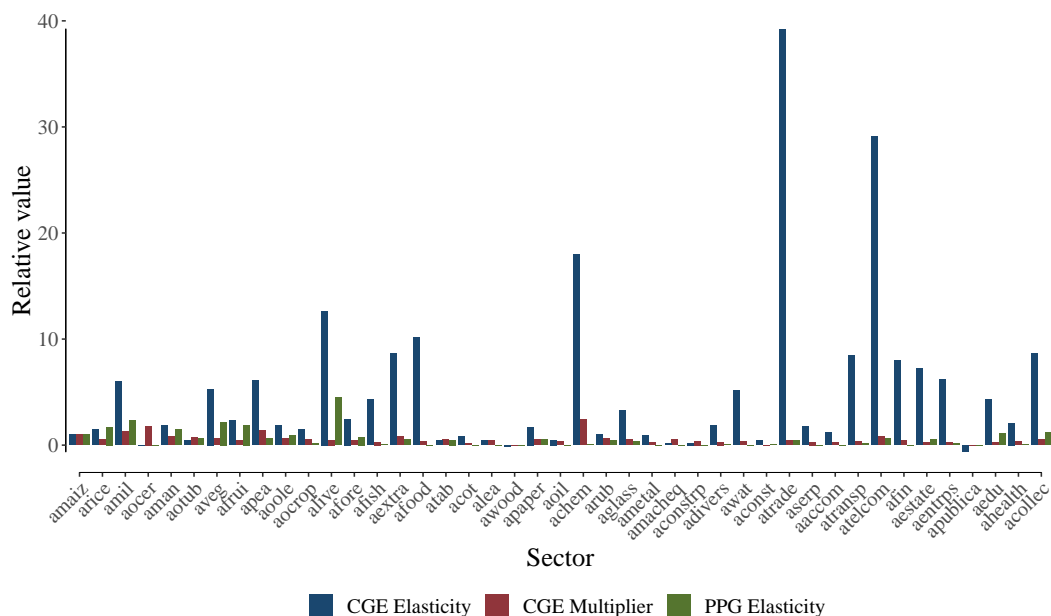


Figure 7.1: Senegal: Key Sectors

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

### Country Comparison

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)? We will answer this question by using the indicators derived from the best fit model (see section 6.2).

To ease the comparison, we have aggregated the sector-specific PPG elasticities to meso-sector PPG elasticities. Figure 7.2 shows the derived elasticities, for all three countries, relative to the crop meso-sector. We can see that for all three countries, the crop meso-sector has the highest relative PPG elasticity, but beyond that, we can not see a clear picture. Ghana has the lowest relative PPG elasticities for the other meso-sectors, especially for the non-agricultural sectors. Uganda has relatively high elasticities for the non-agricultural meso-sectors, entirely different from the other countries.

### Trade offs between policy goals

Given our framework, we are not only able to compute the elasticities for poverty reduction ( $Z_2$ ), the PPG elasticities, but also for the other policy goals: Farm Income ( $Z_1$ ), Public Goods ( $Z_3 = Z_{ps}$ ), Agr. Export Income ( $Z_4$ ), Urban Consumer Income ( $Z_5$ ), and Industry income ( $Z_6$ ). Figure 7.3 shows the correlation of the elasticities for poverty reduction with the ones for the other goals. In addition, we can again see the comparison between all three countries, and  $Z_2$  has been kept as a comparison, even though its value is by definition 1.

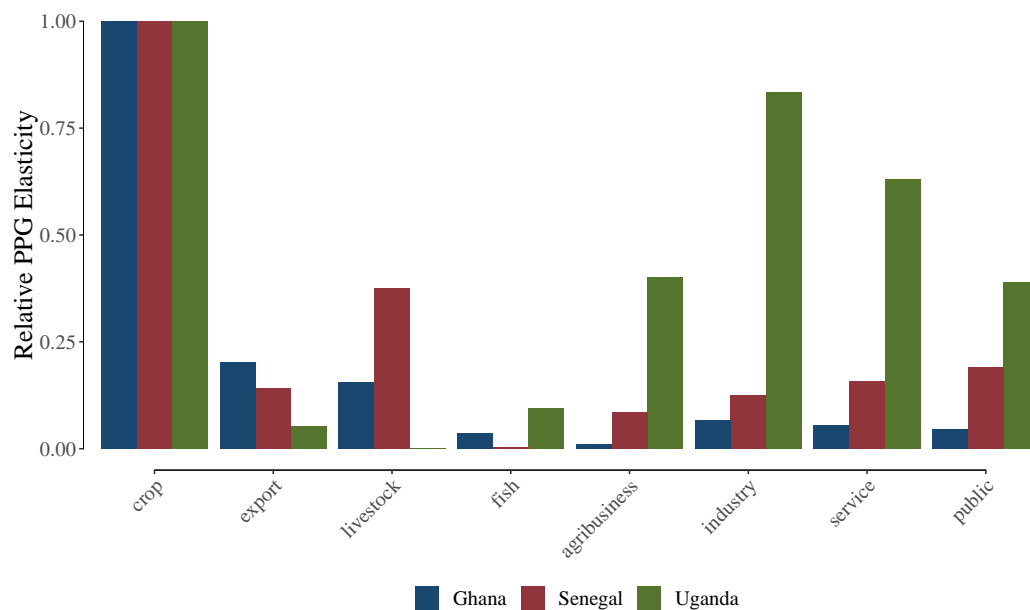


Figure 7.2: PPG Key Sectors

We can see that for all three countries  $Z_1$ ,  $Z_{ps}$  and  $Z_5$  are positively correlated with  $Z_2$  but to a very different degree. Ghana generally has the highest correlations between the goals, while in comparison, Senegal and Uganda have lower values. For  $Z_4$ , the countries are different. Ghana and Uganda have a negative correlation, while for Senegal, a positive correlation can be observed. Industry income is only positively correlated in Uganda, while it is strongly negatively correlated in Ghana. This means that policy not focusing on poverty reduction as its goal, will often also lead to poverty reduction, but to a usually much lesser degree. The importance of the different goals for a policy decision, the incentives, will be more closely looked at in chapter 9.

### Model Uncertainty

So far, we have only looked at the results from the best fit model, but as seen in chapter 6, the results might change with model assumptions and when taking the estimation uncertainty into account. Therefore we will now check the previous results while taking the model uncertainty into account.

**Structural Uncertainty** The first step is taking the uncertainty from the model assumptions into account, as described in section 6.1. Figure 7.4 shows

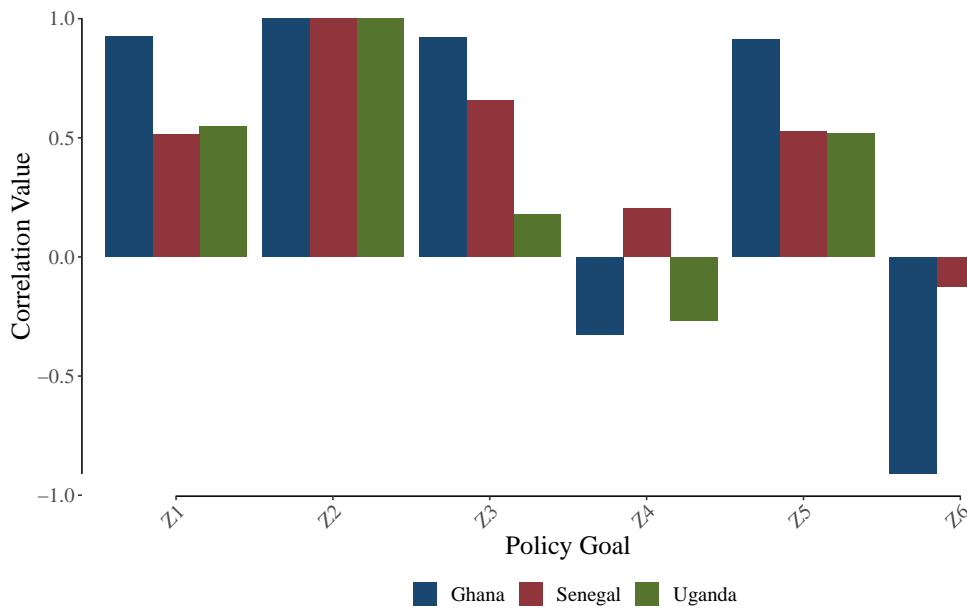


Figure 7.3: Tradeoffs

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 also shown. If we take the full model variance, the clear cut dominance of crop is not replicated 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.

**Parameter Uncertainty** Now we want to look at the impact of the uncertainty of the parameter estimates. As described in section 6.3 a MCMC sample has been generated. The indicators for key sectors and key policies have been calculated for each sample point.

Given the large range of acceptable values for  $tp_s^{max}$ , as shown in fig. 6.9, it does not surprise that the messages for the PPG elasticity indicator are not as

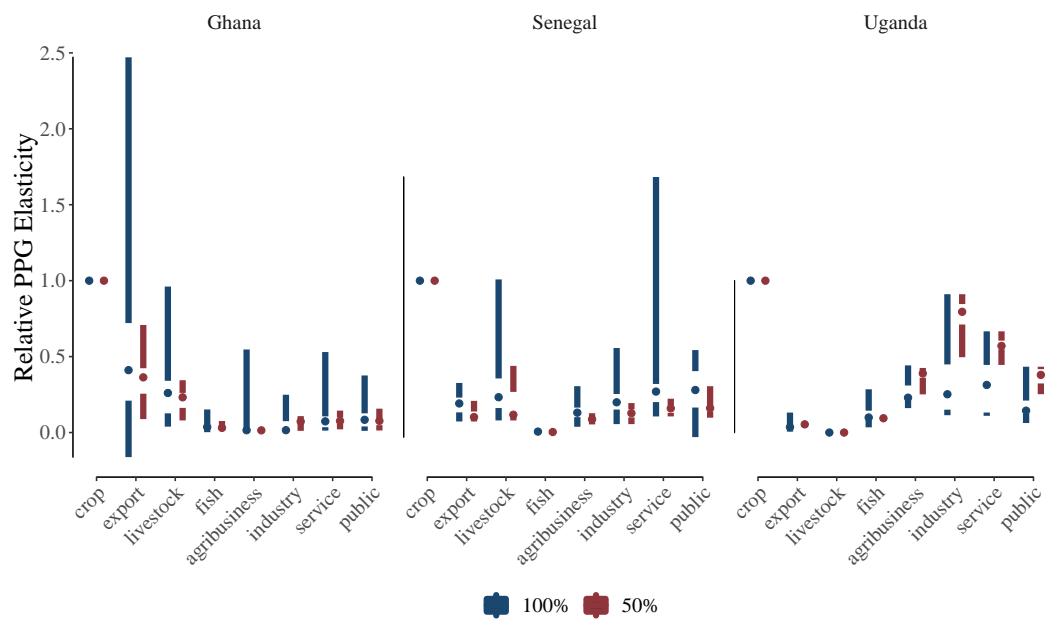


Figure 7.4: PPG Key Sectors

clear cut as before. Figure 7.5 again 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 (for example, livestock) and small ones for the others. 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). Looking at the general picture, it is similar to the one for the best fit model, as shown in fig. 7.2.

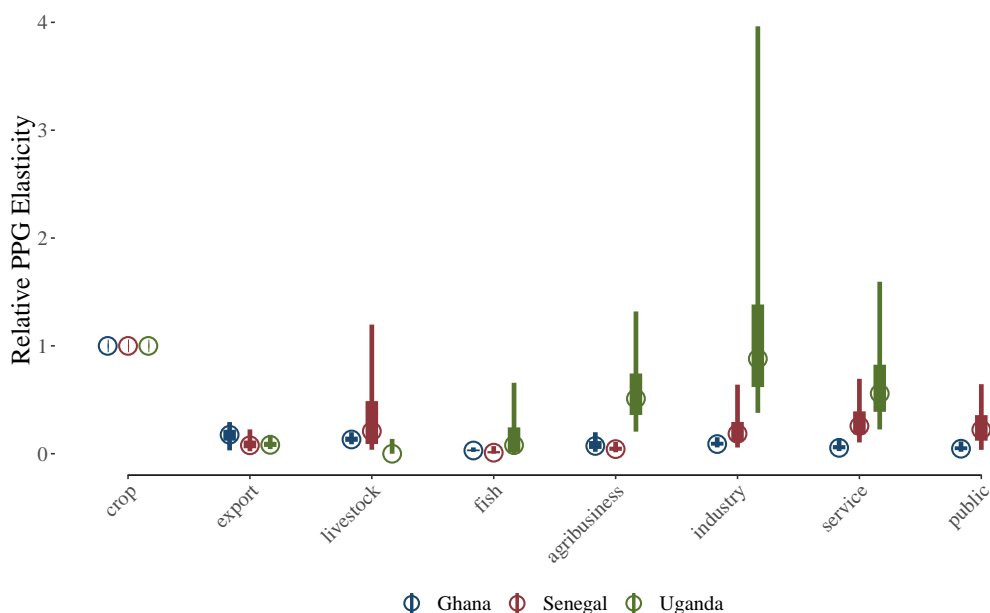


Figure 7.5: MCMC Sample: PPG Key Sectors

## 7.2.2 Key Policies

The on-going political debate on designing optimal CAADP-policy strategies highlights the problem of identifying key policies. In the presented framework, key policies correspond to policy programs and investment strategies that achieve a maximal TFP for PPG key sectors. In fig. 7.6, we present the relative marginal impact of different agricultural policy programs on poverty reduction calculated relative to the marginal impact of non-agricultural investments. Calculations are based on CAADP implementation in 2015. We are comparing the key policy indicator for the two different stages of the PIF estimation, the empirical stage, which is based on historical data and the expert stage, which combines the empirical PIF with expert views on future outcomes. We can see that under both PIFs, the agricultural policies have a much higher marginal impact on poverty reduction than the non-agriculture policy. The expert PIF mostly strengthens this view, with generally higher elasticities, except for *fm-export*. Therefore experts have a slightly different view on the future than looking back.

We can see that investment in agriculture, especially investments in rural infrastructure (MA) and human resources (HR), are significantly more productive in reducing poverty when compared to non-agricultural programs.



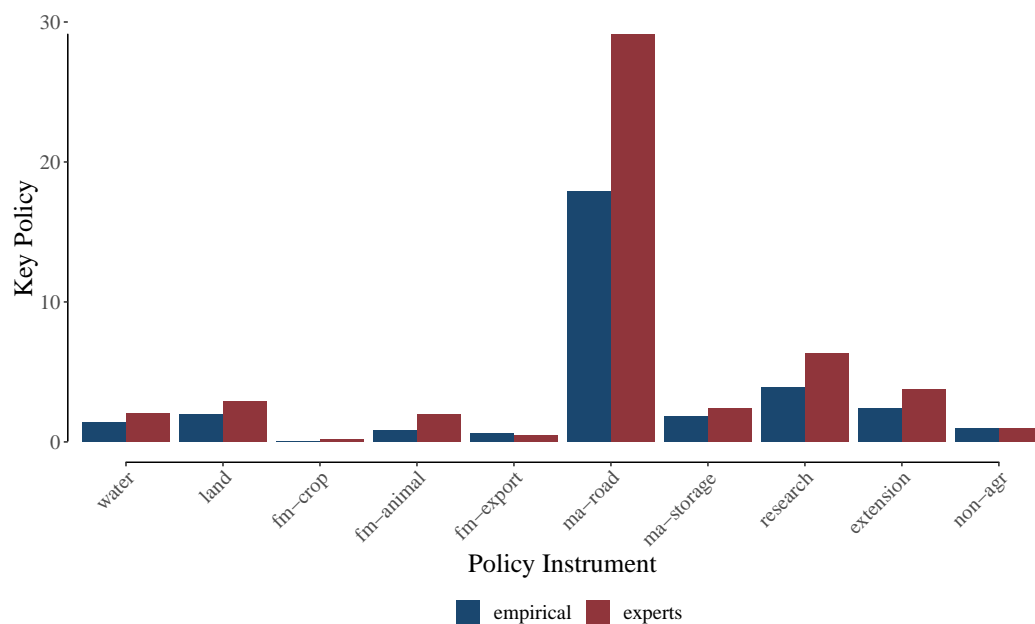


Figure 7.6: Senegal: Key Policies

However, investments in the FM pillar have a comparatively low relative marginal impact on poverty. This low impact is remarkable since significant resources are allocated to the FM pillar. However, the marginal productivity of public expenditures under different policy programs is a local indicator that crucially depends on the distribution of public expenditure across policy programs. Thus, these can be interpreted as indicators in which direction public money needs to be reallocated to maximize poverty reduction.

### Country Comparison

Similar to the key policies indicator, we can again compare them across the three countries. Figure 7.7 shows the key policy indicator aggregated to pillar level, normalized to the non-agriculture (NA) pillar. Compared to the other two countries, we see relatively low values for Uganda, indicating the budget is already allocated in a good way. In Senegal, especially the MA pillar has a sizeable marginal impact, followed by the HR pillar. The HR pillar shows the largest potential in Ghana. We can not observe a clear ranking of policy pillars across the countries.

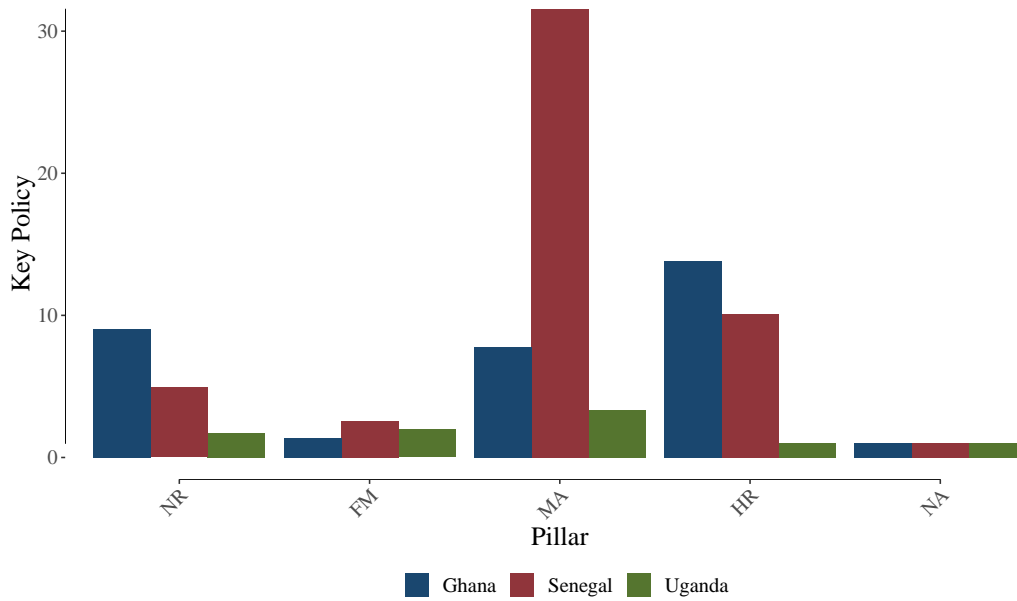


Figure 7.7: Pillar Key Policies

### Structural Uncertainty

If we now look at the second indicator, the key policies, we see in fig. 7.8 the intervals of the full model variance again mostly overlap and are quite large. Therefore no clear ranking of the different pillars can be observed. The results of the 50% scenario, defined as before, show that the variance is strongly reduced. The intervals mostly do not overlap anymore, and therefore, a clear ranking of pillars can be made. These results replicate the ordering obtained under the best fit model.

### Parameter Uncertainty

For the key policy indicator, shown in fig. 7.9, we observe a little different picture regarding the variances. This time Ghana and Uganda have the smallest variances, and Senegal has the largest ones. The 50% and 90% credible intervals mostly do not overlap, providing strong evidence for stable results regarding key policies under model uncertainty. The ranking of the different pillars is stable.

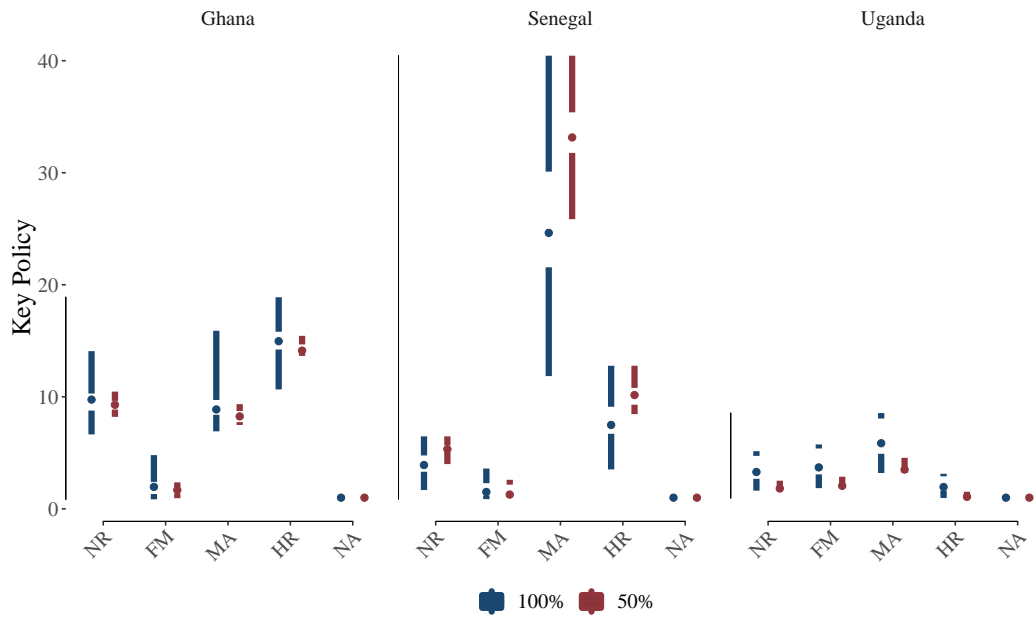


Figure 7.8: Pillar Key Policies

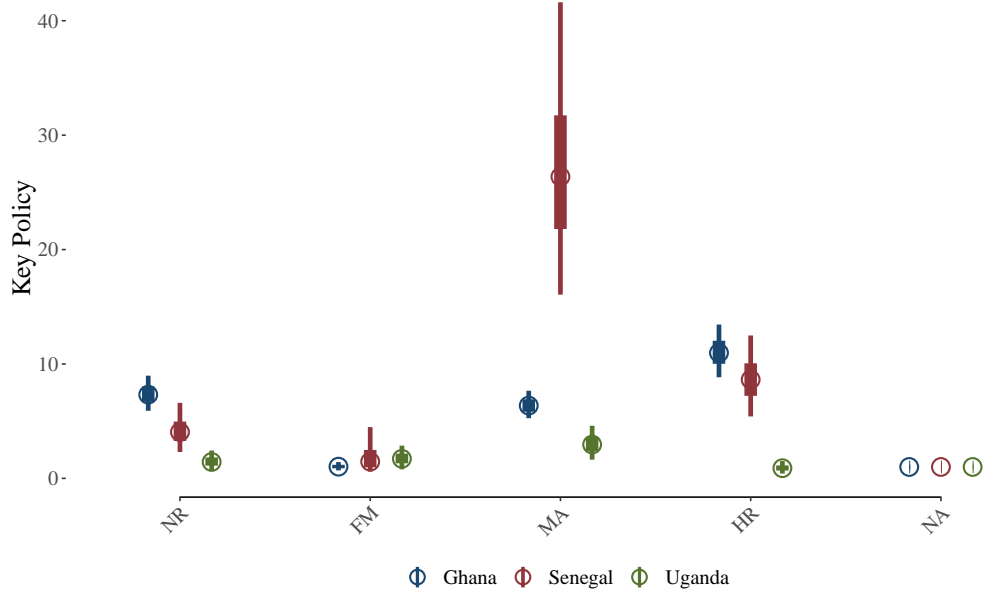


Figure 7.9: MCMC Sample: Pillar Key Policies

## 7.2.3 Optimal Policies

### Model Selection

First, we are going to look at the results for the best fit model, which provides a comparison for the results of the model averaging approach in the following section. We applied the optimization model from eq. (7.4), combined with eq. (7.5) to derive the optimal budget allocation  $\gamma$  for the investment policies.

In line with the results from the analysis of key sectors and key policies in chapter 7, we can not find similar patterns between countries. In fig. 7.10, we see very different optimal budget allocations, denoted as the share of the total state budget, for the different countries. Ghana has slightly higher budget shares for agricultural investment policies (AG), compared to non-agricultural investment policies (NA), with a total of about 30%. Senegal is very different, and given our results, only very little investment should be made into agricultural policies, while about 13% of the total budget should be spent on non-agricultural policies. Uganda is again very different, with a very high agricultural investment share compared to the non-agricultural investment share.

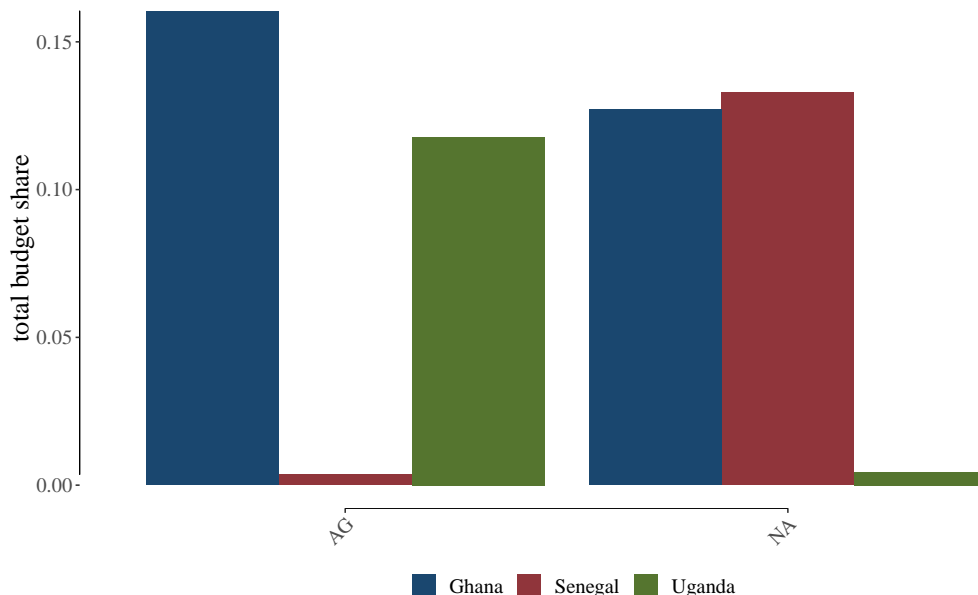


Figure 7.10: Policy Direction Budget Shares

In fig. 7.11 the relative shares of the four different CAADP shares are shown. Ghana and Uganda appear to be similar to some extent. Senegal is different,

with much higher shares for market access policies (MA) and also the largest share for farm management policies (FM). The share of human resources policies (HR) is much lower compared to the other two countries.

Therefore both the total amount of state budget allocated is different between the countries and also the distribution of money inside the agricultural investment policies.

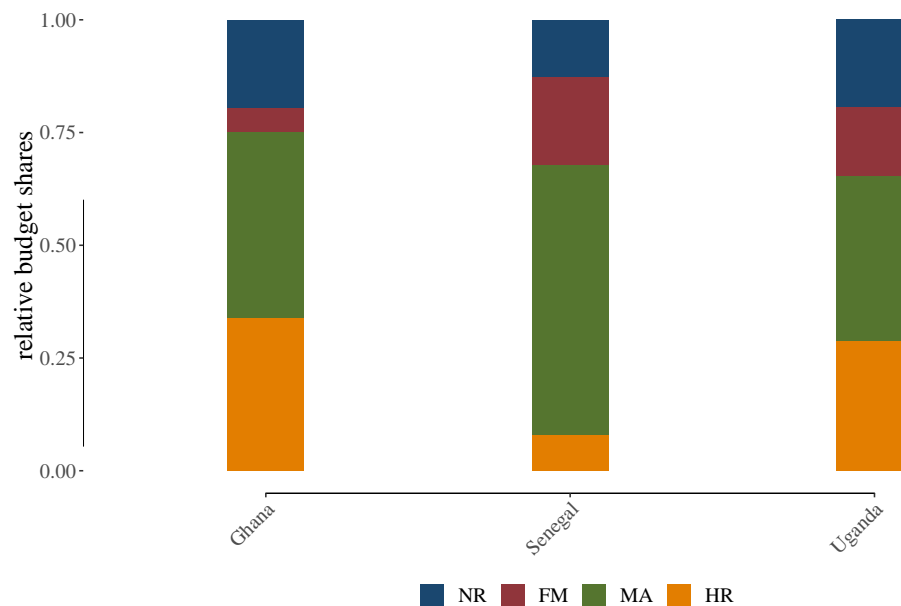


Figure 7.11: CAADP Pillar Shares

### Model Averaging

In the previous section, we looked at the results of the best-fit model, and therefore taking model uncertainty in a limited way into account. This is a limited picture, though, since, for example, in Senegal, the odds ratios for the best fit model compared to the next best ones are not that high. Therefore, predictions made relying only on the best-fit model will lead to biased results (Steel, 2019).

For the results in this section, we solved the extended optimization problem from eq. (7.8).

In fig. 7.12, we again see the optimal budget shares for the two policy directions across the three countries. As introduced, this is now not based on

optimizing a single model, but instead on the optimization that uses all model specifications, weighted according to their odds ratios (see section 6.2).

For Ghana and Uganda, similar results to the ones based on the best fit model are obtained. For Senegal, on the other hand, a very different picture results. Instead of very little investment into agriculture, about 10% of the total budget is now allocated to it. The inverse is true for non-agricultural investment, instead of the main investment share, it now only has a tiny share.

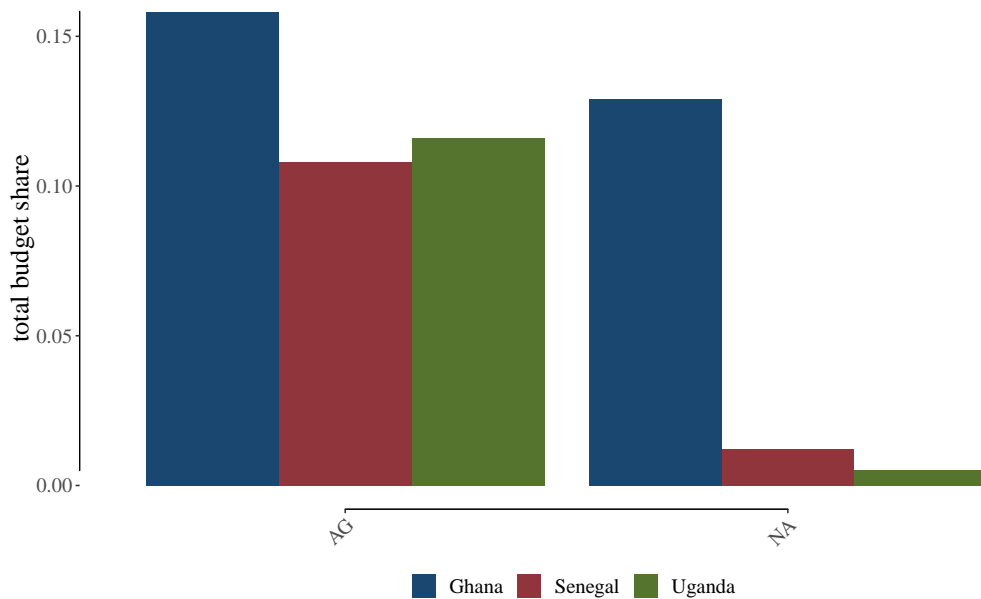


Figure 7.12: Policy Direction Budget Shares

Looking at the CAADP pillar shares, that is the distribution of budget inside the agricultural investment policies, in fig. 7.13, again very similar picture for Ghana and Uganda can be observed. This is not true for Senegal. The natural resources pillar (NR), together with the market access pillar (MA), have now the largest shares. The farm management pillar (FM) receives very little investment, and also the human resources pillar (HR) has a smaller share than before.

For Ghana, the results can be explained by having a single model with a relatively large share of the weight (see fig. 6.4). In Uganda the majority of the weight is on models with similar model assumptions (see fig. 6.6). Senegal, on the other hand, has neither a particular model dominating the other ones nor a specific model assumption being strongly preferred (see fig. 6.5).

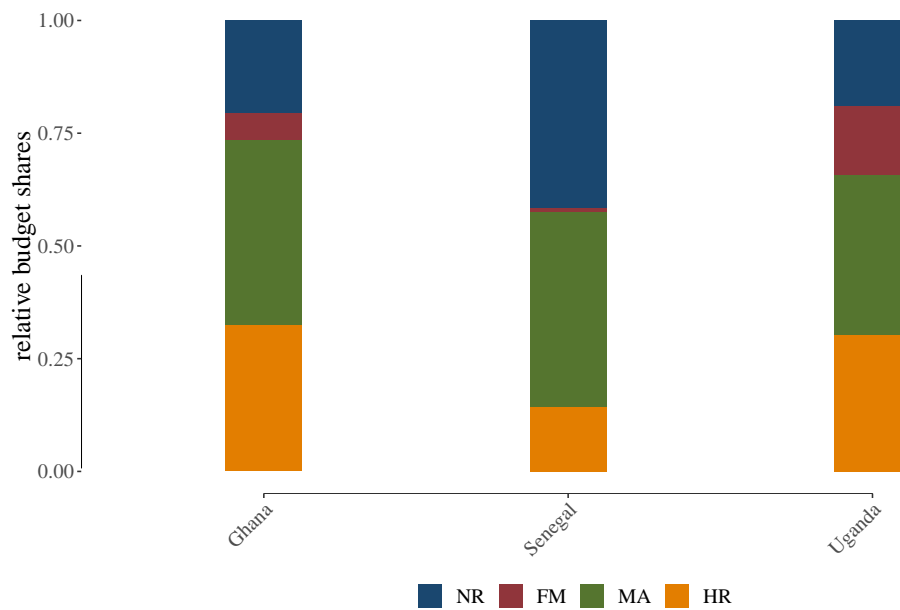


Figure 7.13: CAADP Pillar Shares

### 7.3 Summary

The identification of key sectors crucially depends on the applied concept. The results dramatically shift between the partial indicators like CGE elasticity and our concept of the PPG elasticity, and therefore the partial indicators might be misleading. The shown results are in support of the derivation made in section 4.7. There are no clear blueprints across the countries discernible from the results. For the key sectors indicator, the only commonality is the dominance of the crop meso-sector, with Senegal and Ghana being at least somewhat similar. For the key policies indicator, there is also no clear ranking across all countries, that would allow a blueprint for policy changes. The shown correlation values between the different policy goals show some indication that incentives might be an important factor, and these will be looked at in more detail in chapter 9. The derived results are stable under model uncertainty, both from the viewpoint of model assumptions and parameter estimation. There is also no clear pattern of uncertainty across countries. Uganda, for example, has the highest variances for the PPG elasticity under the MCMC sample, but the smallest for the key policies indicator.

The results of this chapter show that handling model uncertainty is an essential aspect of policy advice. They also give an indicator that more straight-

forward to apply model selection might not be enough, and we need to apply model averaging techniques. The derived optimal policies are only first-best policies, meaning they are a technically optimal solution, but they do not take political feasibility into account. Under this perspective, the low investment shares for non-agricultural investment policies in Senegal and Uganda appear questionable. The same is true for the FM pillar that in practice mainly consists of subsidies paid to the farmers, having such a low share. Additionally, we also do not find a blueprint that is true for all countries, neither on the allocation of budget to agricultural versus non-agricultural investment policies nor in the distribution of budget to the different CAADP pillars within agricultural policies. Thus, strengthening our similar results from the analysis of the key sector and key policy indicators.



# Chapter 8

## Modeling and Evaluation of Participatory Policy Processes

This chapter was published in “Social Networks”, 58, Christian Henning, Christian Aßmann, Johannes Hedtrich, Julian Ehrenfels and Eva Krampe, “What Drives Participatory Policy Processes: Grassroot Activities, Scientific Knowledge or Donor Money? - A Comparative Policy Network Approach -”, 78 – 104, Copyright Elsevier (2019) (Henning et al., 2019).<sup>1</sup>

### 8.1 Introduction

Academic studies and policy statements lauding the benefits of participatory policy processes have made participation one of the most widely used concepts in development politics (Reed, 2008; Young, 1980; Pretty, 1995). The beneficial claims include normative claims, such as the claim that participation promotes the realization of democratic values like empowering the poor or other marginalized groups (Greenwood, Whyte, and Harkavy, 1993; Okali et al., 1994; Macnaughten and Jacobs, 1997; Wallerstein, 1999). Moreover, stakeholder participation may increase public trust in decisions and civil society when participatory processes are perceived as more transparent and fair (Richards, Blackstock, and Carter, 2004), thus implying less conflict (Martin and Sherington, 1997). Beyond normative claims, pragmatic claims focus on higher quality and sustainability of political decisions arising from participa-

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<sup>1</sup>DOI: <https://doi.org/10.1016/j.socnet.2019.03.001>

tory policy processes (Webler, 1999; Beierle, 2002; Brody, 2003; Blackstock, Kelly, and Horsey, 2007).

However, there is little quantitative evidence for the claimed benefits of participatory policy processes (Beierle, 2002; Reed, 2008) and on the relative influence that different stakeholders have on policy decisions. Disillusionment has grown among practitioners and stakeholders who feel let down when these claims may not be realized (Reed, 2008). Accordingly, many scholars are increasingly taking a critical look at participation as a mere label or metaphor and warn against misuses of participation (Eberlei, 2007; Colletta, 1976; Gow and VanSant, 1983; Kelly and Van Vlaenderen, 1996; Lineberry, 1989; Rahnema, 1992; White, 1996). One critique is that stakeholder participation has not been meaningfully implemented by governments (Siebold, 2007), with marginalized groups still being excluded from political decision-making or their involvement being limited to pure consultation (Burton, 2004; Cosgrove and Rijsberman, 2000; Duane, 1999; Handley et al., 1998). The failure of participatory policy processes is explained by the fact that participating stakeholders lack the capacity and technical knowledge to make good political decisions (Hage, Leroy, and Petersen, 2010). Although participatory policy processes are still at the center of the development discourse in political practice, there is neither a comprehensive theory of participatory policy processes nor an empirical analysis of stakeholder systems.<sup>2</sup> Current studies basically claim many benefits of stakeholder participation and relate these claims vaguely to abstract theories, such as the theory of communicative action of Habermass (1987) or the theory of polycentric governance of Ostrom (2010). What is still lacking is a comprehensive theory relating interaction structures among stakeholders with political performance at the system level, which can be applied empirically (Dowding, 1995). A prerequisite for applying this kind of theory is a methodology allowing an empirical measurement of interaction structures.

As a contribution to fill this gap, this paper suggests a policy network approach to empirically analyze participatory policy processes in terms of the

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<sup>2</sup>For example, stakeholder participation is one of the cornerstones of the Poverty Reduction Strategy approach (PRS) launched in 1999 by the IMF and the World Bank; see <http://www.imf.org/external/np/exr/facts/prsp.htm>.

influence that different stakeholders have in policy processes in the context of the implementation of the Comprehensive Africa Agriculture Development Programme (CAADP) in three countries: Senegal, Ghana, and Uganda. The CAADP policy processes are especially suited for this kind of analysis as promoting greater participatory and evidence-based policy processes is one of the key principles during the design and implementation of the CAADP agenda at the country level. Following previous network approaches (Friedkin and Johnsen, 1990; Pappi and Henning, 1998), measures of lobbying and informational influence with regard to relevant stakeholder organizations are provided and empirically assessed. These measures depend on two different policy networks: an information exchange network and a political support network. To account for the uncertainty of observed networks and to identify the determinants of network structure, the empirical analysis is based on the estimation of exponential random graph models (ERGM).<sup>3</sup> Given the estimation results on the network generating process, we provide statistical inferences about the political influence of specific non-governmental organizations, such as donor organizations versus research and grassroots organizations. In particular, we assess whether different organizations apply different influence mechanisms, such as whether research organizations specialize in providing expert information, while interest groups or grassroots organizations specialize in providing political support to the government. Furthermore, we empirically test the extent to which political influence in development politics is dominated by international donor organizations dictating governmental policies via strategically granted development funds, as well as how this may differ across the three countries. Moreover, we shortly discuss options for designing participatory policy networks.

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<sup>3</sup>Analyzing determinants of the formation of policy network ties and applying econometric models is not new in the literature (e.g., (Carpenter, Esterling, and Lazer, 2004; Adam and Kriesi, 2007; Weible, Pattison, and Sabatier, 2010)). Although these countries differ with regard to macro-political and macro-economic conditions, we focus on all three countries in the same policy domain; i.e., the implementation of CAADP, including the same types of governmental and non-governmental organizations. In particular, the exponential random graph models (ERGM)-model has already been used to analyze determinants of political communication and participation in industrialized countries (Henry, Lubell, and McCoy, 2011; Leifeld and Schneider, 2012; Lee, Lee, and Feiock, 2012). Furthermore, Prell, Hubacek, and Reed (2009) applies social network analysis to stakeholder systems.

Overall, we can conclude from our analyses that many of the criticisms of participatory policy processes in developing countries also apply to stakeholder participation induced under CAADP. In particular, participation is dominated by donors in Ghana and Senegal and by non-farm interests and public agencies in Uganda, while in all countries, marginalized groups are still not strongly involved in political decision-making processes. However, at least in Senegal and Ghana, we found clear and positive empirical support for the promotion of evidence-based policy processes under CAADP in that research organizations exert high informational lobbying influence. In contrast, in Uganda, the old patronage networks that have been characteristic of many autocratic African states of the old days (Gibbon, Bangura, and Ofstad, 1992) are still prevailing. For example, the government is controlled by particular economic non-farm interests and is mainly advised by subordinated state agencies.

The rest of the paper is organized as follows. In section 8.2, we describe the conceptual background of policy network studies and corresponding measures of political influence. In section 8.3, we present the empirical approach and explain the collected policy network data, while section 8.4 discusses the main results. Section 8.5 concludes the paper.

## 8.2 Theoretical framework

### 8.2.1 Policy networks and political influence in participatory policy processes

The theoretical background relates to interest group theory, which nowadays comes in two versions. The first is classical lobbying theory, where politicians seeking reelection grant political favors to particular interest groups in exchange for political support. Typically, these classical lobbying approaches are described as models of vote buying, where interest groups trade resources such as campaign contributions for favorable votes (Grossman and Helpman, 1994, 1996).<sup>4</sup> However, vote-buying models do not explain interest-group behaviors

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<sup>4</sup>Classical models correspond to a market organization of political exchange (Coleman, 1966; Wilson, 1969), whereas other approaches assume a non-market organization of political exchange (Koford, 1982) or (Weingast and Marshall, 1988). The most prominent current

to the full extent. For example, lobbying expenditures greatly exceed campaign contributions for most interest groups, and lobbying expenditures are generally not direct transfers to politicians. Furthermore, lobbying firms exert more efforts to hire policy experts, conduct policy research, and make substantive claims to politicians than would be expected from a pure vote-buying perspective. Thus, these models should be supplemented with explanations for how lobbyists substantively advocate for policy alternatives. Accordingly, informational lobbying has been suggested as a second mechanism for interest group influence (Austen-Smith, 1993; Ball, 1995). Politicians have only limited information about the impact of policies on voters' welfare and implied electoral responses. For example, interest groups have policy information that legislators crave and gain influence by strategically revealing that information to sway legislators toward their preferred policy.

However, both the vote-buying model and informational lobbying theory neglect the fact that lobbyists need access to politicians to be successful, regardless of the mechanism. Vote-buying and informational lobbying are plagued by the problem of opportunistic behavior. Hence, vote-buying models have motivated efforts to explain how contributions influence policy despite the incentives of politicians to renege on agreements after contributions are made, or vice-versa in terms of how an interest group can commit to their promises to honor policy favors after policy decisions have been made by legislators. Analogously, more recent studies on informational lobbying highlight the importance of the limited access that lobbyists have to politicians (Schnakenberg, 2016). In this context, the organization of actions in social networks is studied as a decentralized form of self-governance that controls for opportunistic behavior by applying a reputation-based punishment mechanism (Buskens, 2003; Raub and Weesie, 1990). Gaining access to politicians is not trivial since establishing social relations is costly and often requires an existing level of social embeddedness. At an empirical level, applied policy network studies are perfectly aware of this fact (Laumann and Knoke, 1987; Knoke et al., 1996; Pappi, König, and Knoke, 1995). At a theoretical level, Pappi and Henning (1998)

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approach to classical lobbying is the Grossman and Helpman (1994) model, which conceptualizes political exchange among welfare-seeking interest groups and politicians seeking reelection as a menu auction.

suggest an organization of political exchange in social networks, and Friedkin and Johnsen (1990) suggest a model of how actors update their beliefs based on information exchange organized in a social network. These models hence provide the theoretical basis for the measures of political influence used in this paper linking network structure and political decisions.

To illustrate, we model a collective policy decision,  $\gamma \in \mathcal{R}^L$ , which is consequential for a set of policy outcomes  $z = (Z_1, \dots, Z_K)$  among a set of stakeholders  $E = \{i = 1, \dots, N\}$ . We define a stakeholder as an organization that is involved and interested in the formulation of policies in a certain policy domain. Organizations can be formally involved based on constitutional rules or informally based on lobbying. Accordingly, we further subdivide stakeholders into a subset of political agents  $G \subset E$ , with generic elements of  $G$  denoted as  $g \in G$ , and a subset of interest groups. Political agents include the government; that is, ministries, the prime minister, members of the cabinet, the president, and legislative groups. Many different organizations form the subset of interest groups, such as farmer associations, civil society, or grassroots organizations. In contrast to political agents, these organizations are only informally involved in political decision-making. Collective policy choices are made by political agents based on constitutional rules. To model the outcome of legislative decision-making, we apply the following mean voter decision rule<sup>5</sup>

$$\gamma^M = \sum_g C_g P_g = C' P, \quad (8.1)$$

where  $C_g$  denotes the political control of agent  $g$  determined by constitutional

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<sup>5</sup>Note that the mean voter decision rule can be interpreted as a “legislative norm” that can be derived from non-cooperative legislative bargaining models under specific assumptions (Grossman and Helpman, 1996; Schofield, 2007; Weingast, 1979). We do not model the political decision-making process in detail. However, following existing approaches, such as (Baron and Ferejohn, 1989; Grossman and Helpman, 1996), we assume that the outcome of legislative bargaining corresponds to a lottery of the ideal points of political agents (legislators), where the probability that a political agent will be successful in implementing her ideal point depends on constitutional rules. Let  $C_g$  denote this probability for a political agent  $g$ . Furthermore, assuming that political agents are risk averse implies ex ante that every agent prefers a common policy proposal that corresponds to the weighted mean,  $\gamma^M = \sum_{g \in G} C_g P_g$ , compared to the lottery over proposals. Hence, following Weingast (1979), we interpret the mean voter decision rule as a self-enforcing legislative norm.

rules, while  $P_g$  denotes the policy positions of an agent and  $C = (C_1, \dots, C_N)'$  and  $P = (P_1, \dots, P_N)'$  are corresponding vectors.<sup>6</sup> Political exchange implies that agents trade some of their political control against political support provided by other stakeholders, resulting in a political control vector  $C^T = (C_1^T, \dots, C_N^T)'$ , where  $C_i^T \geq 0$  for all  $i = 1, \dots, N$ . Accordingly, including political exchange policy choices result by the mean voter decision rule

$$\gamma^M = C^T P. \quad (8.2)$$

Policies are translated into outcomes that are related to the political support that a stakeholder organization receives from society members. Stakeholders maximize their political support. We assume that stakeholders perceive the former by the political impact function,  $F(\gamma, a_i)$ , while the latter is captured by the political support function  $V(\phi_i)$ . Thus, individual policy positions depend on the relative interest  $\phi_i$  that a stakeholder has in the different policy outcomes, as well as the personal beliefs  $a_i$  on how policies transform into outcomes  $z$ , i.e.,  $P = P(\phi, A)$  and  $P_i = P_i(\phi_i, a_i)$ . We denote the set of relative interests of stakeholders as  $\phi = (\phi_1, \dots, \phi_N)'$ , where  $\phi_i = (\Phi_{i1}, \dots, \Phi_{iK})$  with  $\sum_{k=1}^K \Phi_{ik} = 1$ , whereas  $A = (a_1, \dots, a_n)'$  denotes the set of individual beliefs on the transformation of policies into outcomes and  $a_i = (a_{i1}, \dots, a_{iJ})$  denotes the individual beliefs of stakeholder  $i$ .<sup>7</sup>

Different lobbying models then describe how values of  $C^T$  and  $P(A, \phi)$  are determined. We follow the approach of (Pappi and Henning, 1999) in assuming that political exchange is organized in networks and defines a Walras equilibrium that incorporates actor-specific transaction costs of political exchange. Thus, the political control held by different organizations in the exchange equilibrium arises from a network of actor-specific support transfers,  $T = [t_{i,j}]$ , and the interest of political agent  $g$  in a political support resource is denoted by  $\omega_g$ . As many lobby groups have no direct access to powerful political agents, they search for indirect access via other lobby groups. Providing indirect access to political agents is not free, but lobby groups take a part of support resources provided by other lobby groups as a brokerage commission. Summarizing the

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<sup>6</sup>Note that this implies  $C_i = 0$  for all  $i \notin G$ .

<sup>7</sup> $J$  denotes the number of parameters describing stakeholders' belief how policies translate in outcomes.

individual broker shares  $\mu_i$  of a stakeholder  $i$  by a diagonal matrix  $\mu$ , and following Henning (2009), the political control is given as

$$C^T = M^E(I - \Omega)C \quad \text{with} \quad M^E = [I - \mu[I - (I - \mu)T]^{-1}T\Omega]^{-1}, \quad (8.3)$$

where  $\Omega$  is the diagonal matrix with diagonal elements  $\omega_i$  with  $\omega_i = 0$  for all  $i \notin G$ , and  $I$  denotes an identity matrix of corresponding size. Accordingly,  $C^T$  is the vector of total political control of different governmental and non-governmental organizations in the political equilibrium. Hence, the policy choice of a political agent  $i$  results in the weighted mean of ideal positions of all actors in the policy network where the individual actor's weight in the ideal position of an agent equals the network multiplier; i.e., the corresponding elements of the matrix  $M^E$ .

With regard to policy positions, lobbying and network structure determine how beliefs regarding the transformation of policies into outcomes are updated. We focus on communication learning (Acemoglu and Ozdaglar, 2010). Individual agents are only imperfectly informed about the true political technology. However, in the aggregate, the total set of agents is generally well informed if the number of agents is sufficiently large. Therefore, agents are interested in a collective communication process through which they communicate their received signals and avoid strategic behavior by limiting their communication to only people they trust.<sup>8</sup> To analyze communication structures, we define a network relation  $b_{i,j}$ , where  $b_{i,j} > 0$  indicates that agent  $i$  and agent  $j$  have an established communication tie. We define  $B_{i,j} = \frac{b_{i,j}}{\sum_{j'} b_{i,j'}}$  with  $\sum_j B_{i,j} = 1$ . Accordingly,  $B = [B_{i,j}]$  denotes the normalized communication network, where  $B_{i,j} > 0$  indicates that actor  $i$  pays attention to actor  $j$ . Within one period, a political communication process occurs, where stakeholders repeatedly update

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<sup>8</sup>Note that an optimal communication process would correspond to a super-agent who aggregates the privately received signals of all agents and communicates the aggregated signals back to all individual agents. However, in reality, actors' ability to communicate their experience may be limited, as actors have heterogeneous preferences. Thus, they also have incentives to strategically communicate biased signals to induce other agents to form biased beliefs. Rational social learning is generally possible even in this setting (Acemoglu and Ozdaglar, 2010). However, the mental capabilities of real-life political actors are often too limited to justify the assumption of perfect rational learning. Alternatively, scholars assume that actors apply a naive non-Bayesian learning mechanism such that beliefs are formed by taking the average of all beliefs communicated by other agents (Golub and Jackson, 2010).



their political opinion by taking weighted averages of their neighbors' opinions with  $B_{i,j}$  being the weight or trust that actor  $i$  places on the current belief of agent  $j$  in forming his or her belief for the next period. Summarizing all initial beliefs of individual actors with regard to the political technology parameters in the matrix  $\tilde{A} = (\tilde{a}_1, \dots, \tilde{a}_n)'$ , the process of belief formation has a stationary point since  $B$  is a stochastic matrix. Following Friedkin and Johnsen (1997) as well as Jackson (2008), the stationary beliefs on political technology parameters summarized as  $\hat{A} = (\hat{a}_1, \dots, \hat{a}_n)'$  are given as

$$\hat{A} = M^B \tilde{A}, \quad \text{where} \quad M^B = [I - (I - \Lambda)B]^{-1}\Lambda, \quad (8.4)$$

where  $\Lambda$  denotes a diagonal matrix with elements  $\lambda_i$  corresponding to the individual weights that stakeholders put in their own initial belief. Since individual weights are larger than zero, the assumed communication process converges to an equilibrium, where stakeholders hold heterogeneous final beliefs.<sup>9</sup> The limit belief of each stakeholder,  $\hat{a}_i$ , results in a weighted average of the initial beliefs ( $\tilde{A}$ ), where the weights of stakeholders' initial beliefs ( $\tilde{A}$ ) for stakeholder  $i$ 's final belief are given as the  $i$ th row of the multiplier matrix  $M^B = (M_1^B, \dots, M_N^B)'$ .<sup>10</sup>

To relate the network multipliers,  $M^B$ , with informational lobbying power, stakeholders' policy positions,  $P(\phi, A)$ , are determined by their beliefs. For the sake of simplicity, assume that policy positions can be expressed as linear functions of policy beliefs and political interests, i.e.

$$P^i(\phi_i, \hat{a}_i) = \gamma_i^0(\phi_i) + \hat{a}_i D_a, \quad (8.5)$$

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<sup>9</sup>Friedkin and Johnsen (1990) assume that all actors attribute the same weight to their own initial belief. In our more general model, the relative weight that actors put on their own beliefs and that of other actors might significantly differ across actors. Different levels of self-control might reflect an actor's individual information level. For example, highly uncertain actors might put more weight on the communicated positions of other actors when compared to actors that are more certain regarding their knowledge of the impact of policies on outcome. Thus, our model includes the deGroot model (DeGroot, 1974) and the Friedkin model (Friedkin and Johnsen, 1990) as special cases.

<sup>10</sup> $M^B$  is the matrix of network multipliers  $m_{i,j}^B$  given as the elements of  $M_i^B$ , which are similar to the Hubbell index (Hubbell, 1965). The multiplier also defines the field strength of stakeholder  $j$ 's initial beliefs operating on another stakeholder  $i$ 's final belief.

where the matrix  $D_a$  is the same for all  $i$ .<sup>11</sup> Substituting eq. (8.5) into the mean voter decision rule given by eq. (8.1) and noting that  $\hat{a}_i = M_i^B \tilde{A}$  implies that the final policy choice results in

$$\gamma^M = \sum_i C_i^T \gamma_i^0(\phi_i) + \sum_i C_i^T M_i^B \tilde{A} D_a. \quad (8.6)$$

Based on eq. (8.6), we define  $C^B = (C_1^B, \dots, C_n^B)'$  as the vector resulting from  $C^T M^B$ .  $C_i^B$  can be interpreted as the weight of the initial beliefs of an individual stakeholder in determining the final political decision. Accordingly, we interpret  $C_i^B$  as the informational lobbying influence of a stakeholder  $i$ . Analogously, the vote-buying influence  $C_i^T$  can be interpreted as the relative impact of the political interests in policy outcomes of an individual stakeholder on the final political decision. Hence, while classical lobbying theories like Grossman and Helpman (1994) focus on vote-buying lobbying assuming perfect knowledge and theories of informational lobbying focus on beliefs only ignoring vote-buying, our theory combines both approaches and simultaneously incorporates both vote-buying and informational lobbying.<sup>12</sup>

To operationalize our approach, we need empirical observations of relevant input variables; that is, the political support ( $T$ ) and communication network ( $B$ ), the broker shares  $\mu$ , the relative interest of stakeholder in political support  $\Omega$ , and the importance of one's own initial beliefs  $\Lambda$ . Finally, we also need a measurement of the constitutional voting power,  $C$ . We follow Pappi and Henning (1999) to survey relevant data and specify all relevant input variables empirically. Details are provided in the empirical section.

Overall, this framework allows us to analyze political power structures in participatory policy processes empirically based on underlying policy network structures. Beyond a descriptive analysis of political power structures, our framework would also allow us to evaluate observed political power structures by comparing policy choices derived from empirically observed power structures with specific benchmark policies, such as policies that are considered as desirable from a social welfare perspective. It would also be interesting

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<sup>11</sup>For example, a first-order Taylor approximation of  $P^i(\phi_i, \hat{a}_i)$  could be used to obtain a corresponding linear function.

<sup>12</sup>Technically, this follows as we disentangle stakeholders' preferences over policies into stakeholder's preferences over policy outcomes ( $\phi_i$ ) and stakeholders' initial beliefs how policies translate into outcomes ( $\tilde{a}_i$ ).

to analyze how individual multipliers and political power structures can be changed by influencing the underlying support and communication network structures. Particularly, understanding the network-generating process and the impact of network structures on policy choices enables the design of effective lobbying structures (i.e., policy network structures that imply desirable policy outcomes). However, empirical information on policy choice functions  $P(\phi, \hat{A})$  would be needed. This especially includes information on how decisions transform into observable outcomes (i.e., the policy impact function) and initial policy beliefs,  $(\tilde{a})$ , which are rather difficult to derive empirically. Therefore, we restrict our empirical analyses to the empirical estimation of the two lobbying influence measures,  $C^T$  and  $C^B$ , and the empirical estimation of the network-generating process regarding the two policy networks  $B$  and  $T$ , respectively. We leave the evaluation of policy choices and optimal design of underlying policy network structures for future research.<sup>13</sup>

Given the theoretical measures of political influence, we consider hypothesis

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<sup>13</sup> However, to further motivate the potential of our theoretical network approach as a useful framework for future evaluation and design of optimal participatory policy processes, intuitively, we define a benchmark policy  $\gamma^* = \gamma_i^0(\phi^*) + aD_a$ . Then, the policy bias becomes:  $[\gamma^M - \gamma^*]^2 = \left[ \sum_i C_i^T (\gamma_i^0(\phi_i) - \gamma^*(\phi^*)) + \sum_i C_i^T M_i^B [\tilde{A} - A] D_a \right]^2$ . Note that in eq. (8.6), the term  $\tilde{A} D_a$  is a vector with the components  $\tilde{a}_i D_a$ . Assuming that initial individual beliefs follow from individual information signals Golub and Jackson (2010), where for each stakeholder, information signals are drawn independently from a symmetric distribution around the true political technology, parameter  $a$  implies that individual components of  $\tilde{A} - AD_a$  (i.e.,  $(\tilde{a}_i - a)D_a$ ) are stochastic variables, which are statistically independent of each other and all have an expectation value of zero. Obviously, the variance of an individual component corresponds to the level of uncertainty of a stakeholder. Let  $\sigma_i^2$  denote this variance. Accordingly, the policy bias becomes a stochastic variable, where the variance of this variable results in a linear function of the variances  $\sigma_i^2$  and the constant  $\sum_j \sum_i C_j^T C_i^T [\gamma_j^0(\phi_j) - \gamma^*(\phi^*)][\gamma_i^0(\phi_i) - \gamma^*(\phi^*)]$ . The weight of each individual variance,  $\sigma_i^2$ , is just equal to the square of the informational lobbying power of a stakeholder,  $[C_i^B]^2$ . Therefore, minimizing the expected policy bias implies that the relative informational power is just the inverse relation of the individual variances; i.e., the less uncertain an individual stakeholder is in assessing policy impacts, the higher her relative informational power would be in an optimal stakeholder communication. Moreover, note that the constant corresponds to the policy bias induced by biased representation of society's interests through stakeholder participation via vote-buying lobbying. Accordingly, total policy bias resulting from stakeholder participation can be subdivided into incentive and knowledge bias.

on the structure of policy networks.

## 8.2.2 Hypothesis on emergence and determinants of policy network structures

In order to draw valid conclusions on political influence from observed network data, empirical policy network analysis requires statistical assessment of the robustness of derived influence measures. Estimating the network-generating process in terms of tie formation enables one to draw statistical inferences about empirically derived network measures.<sup>14</sup> Regarding the understanding of network generating processes, scholars point out that the formation of network structures is determined by actors' preferences and the structure of the meeting process among the set of relevant actors (Moody, 2001; Currarini, Jackson, and Pin, 2009; Carpenter, Esterling, and Lazer, 2004). We follow these scholars and consider preferences and meeting opportunities as the two main categories of determinants of political communication.

Given the purpose of lobbying as an interest-mediation mechanism, lobbying organizations try to contact highly influential governmental organizations. Analogously, stakeholders like research organizations try to communicate their (scientific) knowledge to powerful politicians. However, because access to powerful governmental organizations is rather restricted, organizations might also apply an indirect influence strategy (i.e., contacting other non-governmental organizations that have access to powerful politicians). Therefore, we expect that the higher the perceived influence of an organization is, the more likely it will be that other stakeholder organizations will want to establish an information exchange or a political support tie with this organization. We consider perceived political influence to reflect both informal and formal legislative power for two other reasons. The first directly considers brokerage relationships. The second is in line with Weingast (1979) and Shepsle and Weingast (1987), who argue that beyond formal constitutional rules, real legislative decision-making processes are determined by specific informal legislative norms. Informal legislative norms appear especially relevant in developing countries with young

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<sup>14</sup>Further, the formation of policy network ties might be of particular interest because as it is a prerequisite for designing desirable policy network structures, e.g. structures which imply a more efficient political decision-making process in development politics.

democracies, in which the rule of law is often only weakly developed (Bratton, 2007). For example, political power tends to be intensely concentrated around the president. As a result, the government often dominates legislative decision-making (van de Walle, 2003). Furthermore, analyzing policy network tie formation from the viewpoint of politicians, it is interesting to form political support ties with interest groups that have a high capacity to influence the electoral choices of the voter. The number of members or the budget of a stakeholder organization might be good indicators of the capacity to influence voter decisions. Moreover, organizations are interested in obtaining technical information on policy impacts from other organizations that have reputations of being knowledgeable. As discussed by Sabatier (1987), scientific organizations are perceived as sources of high-quality information that can be used to strengthen one's own policy proposals. Other actors try to receive expert information from scientific organizations or other organizations with a high reputation of political knowledge, such as donors.

However, access to powerful governmental organizations or knowledgeable non-governmental organizations is restricted by meeting opportunities. Accordingly, many empirical network studies stress the importance of institutional and structural context factors (Lubell, Henry, and McCoy, 2010; Leifeld and Schneider, 2012). Membership in umbrella organizations or common membership in political committees indicates meeting opportunities, which increases the probability of a pair of actors forming a policy network tie. We further argue that established network ties provide meeting opportunities. Established political support relations induce the establishment of information exchange ties, and vice versa: *ceteris paribus*, established information exchange ties facilitate the formation of political support ties. Analogously, within the same network relation, an established tie from actor  $i$  to  $j$  provides an opportunity to establish a reciprocal tie from  $j$  to  $i$ .

Furthermore, beyond actors' utility derived from an established network tie and beyond cost to establish and maintain a tie, transaction costs of political interactions determine the formation of policy network relations (Moody, 2001). As explained above, both exchange processes (exchanging political support as well as information) are plagued by the problem of opportunistic behavior. Accordingly, organizations seek to form ties with actors that they can

trust. Formally, trust corresponds to the probability that exchange partners will not behave opportunistically. Hence, the risk of opportunistic behavior implies transaction cost for actors interacting with these partners. As demonstrated in the literature, potential opportunistic behavior of exchange partners is fundamentally determined by interaction structures among partners (Raub and Weesie, 1990; Henning, Henningsen, and Henningsen, 2012). In particular, we distinguish two sets of factors that determine transaction costs. The first are factors that determine actors' potential to punish opportunistic behavior, and the second are factors determining actors' incentive to behave opportunistic.

Regarding the first set, there is well-established literature on social exchange and networks (Cook and Emerson, 1978; Raub and Weesie, 1990; Buskens, 2003), as well as on relation-based self-governance (Dixit, 2003; Greif, 1994). A common implication of these studies is that, c.p., the potential to punish divergent exchange partners is promoted if binary exchange relations are socially embedded; i.e., exchange partners share a large set of joint other exchange partners (Raub and Weesie, 1990; Buskens, 2003; Dixit, 2003; Henning, Henningsen, and Henningsen, 2012). If *ego* has many shared neighbors with *alter*, then *alter* is more likely to trust *ego* as a sender of high-quality information (Carpenter, Esterling, and Lazer, 2004; Berardo and Scholz, 2010). A policy network tie formation is scrutinized by common neighbors, resulting in a situation of social control (Leifeld and Schneider, 2012). It is also easier for *alter* to contact other actors if there are many common neighbors. This strengthens clustered regions in the network (Henry, Lubell, and McCoy, 2011; Sabatier, 2007). We expect patterns of transitivity to be at work in policy networks. That is, an organization will seek information exchange or support relations from another organization if a third party links them both (Holland and Leinhardt, 1971; Berardo and Scholz, 2010). Analogously, reciprocity of network relations provides the potential to punish divergent behavior of exchange partners.

A second line of argumentation relates to actors' incentives to behave opportunistic. In this regard, political homophily might be an important determinant for both network relations. A similarity of policy preferences is expected to reduce commitment problems inherent in information exchange.

Receiving information from sources with similar policy preferences decreases the likelihood of receiving information that does not match one's own interests (see (Festinger, 1954; Austen-Smith, 1993)). Moreover, approaching organizations with similar political interests is rational because it reduces the financial, emotional, and processing costs of political communication.<sup>15</sup> Analogously, political homophily is also important in explaining the establishment of support relations because it reduces political transaction costs in as much as politicians can expect that a support relation with ideologically different organizations, such as a socialistic party with a business organization, will be punished by negative electoral responses of their voters.

Overall, it is of interest to compare the importance of different determinants regarding the tie formation in political support and expert information exchange networks. Are policy network ties mainly determined by expected benefits resulting from an established tie, or are they mainly determined by the costs to establish and maintain a tie? Are they mainly determined by transaction cost due to the risk of opportunistic behavior? Are these transaction costs mainly driven by structural relations that increase stakeholders' potential to punish divergent exchange partners, or are they mainly driven by homophily reducing agent's incentive to behave opportunistically? Moreover, it is interesting to analyze the extent to which the importance of specific determinants differs for political support when compared to political information networks. Especially, regarding the design of participatory policy networks it will be instructive to identify the relative impact of variables on policy network formation that can be easily controlled, such as meeting opportunities, when compared to different structural and preference variables, which hardly can be controlled exogenously.

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<sup>15</sup>For experimental evidence on political preference similarity as a driver of tie choice, see Ahn et al. (2013).

## 8.3 Empirical study

### 8.3.1 Study background and empirical hypotheses

Our analyses is embedded within a project analyzing participatory policy processes in development politics (PEBAP) through the Comprehensive Africa Agriculture Development Programme (CAADP) as a major development strategy in African countries. African leaders of over 23 countries endorsed in 2003 in Maputo and again 2014 a decade later in Malabo CAADP as an action plan for putting agriculture back on Africa's development agenda. A challenge that continues to face African policy makers in moving beyond their commitments is ensuring that the final selected policies and investment strategies are effective in producing their intended goals. In this regard, one of the key principles of the CAADP reform process is promoting greater participatory and evidence-based policy processes during the design and implementation of the CAADP agenda at the country level. CAADP follows a central strategy that is promoted by most important international donor organizations, such as the World Bank and IMF, which emphasize broad-based participation of stakeholders inside and outside the governments, including parliaments, civil society organizations (CSOs), private-sector representatives, and other stakeholders at the national and local levels as one of the core principles of their poverty-reduction strategy. However, the implementation of participatory policy processes including CAADP is still criticized as being a mere label or metaphor. Accordingly, even nowadays, it is debated to what extent the CAADP process has succeeded in becoming an effective participatory policy process. In this regard, very little substantial empirical evidence has been provided so far.

To undertake our analysis, we use data collected within an international comparative analysis of CAADP policy processes in Ghana, Senegal, and Uganda.<sup>16</sup> One essential part of the study is a policy network survey that was conducted in all three countries on political interactions, policy goals, and

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<sup>16</sup>The PEBAP project was jointly implemented by the International Food Policy Research Institute (IFPRI) and the Universities of Kiel and Hohenheim in collaboration with local research institutions: 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 (AFRISA).



preferred policy positions of key policy makers and stakeholders regarding the most appropriate state budget allocations to different policy programs under the CAADP agenda. The three countries were selected because they vary systematically in both their economic and political development. Thus, comparing policy network structures within the same CAADP policy domain might reveal interesting insights on how participatory policy processes vary with the level of economic and political development. According to the GDP per capita and the poverty index, Ghana is the most economically developed country, followed by Senegal, while Uganda is less developed. Analogously, according to the Freedom House indices of Civil Liberty (Freedom House, 2014) and Political Rights, as well as the polity IV score of democratization (Marshall, Jaggers, and Gurr, 2012), Ghana is the most advanced democracy, followed by Senegal and Uganda.

Given the general considerations from above, we provide in the context of our empirical analysis of participatory structures under CAADP the following hypotheses. Are marginalized groups such as the poor meaningfully involved in the CAADP process; i.e., do grassroot organizations and CSOs as well as parliamentary groups that represent them exert significant political influence, or is the CAADP process dominated by international donor organizations? Furthermore, do grassroot organizations and CSOs have their own political expertise, or are they swayed by information provided by donor organizations? To what extent do these organizations exert informational lobbying power beyond vote-buying lobbying power? Moreover, since the CAADP agenda also promotes evidenced-based policy processes, it is interesting to test whether research organizations exert high informational influence. We can analyze these central hypotheses of participatory and evidenced policy processes under the CAADP agenda by applying our quantitative policy network-based influence measures, vote-buying ( $C^T$ ) and informational lobbying power ( $C^B$ ).

### 8.3.2 Statistical model

To assess the derived measures in terms of inference and gauging potential differences between groups of stakeholders, we need to characterize the uncertainty of network measurements in terms of the network generating process. A well-established model class for social networks is the ERGM framework

developed by Wasserman and Pattison (1996) and modified by Snijders et al. (2006). Lusher, Koskinen, and Robins (2013) illustrate a wide range of ERGM applications and give a detailed introduction to the ERGM framework. This model class can represent the structure and the driving factors of a network by using an *a priori* defined set of sufficient network statistics. These network statistics are sub-graphs that represent particular patterns of social behavior like reciprocity or triangulation, which allows for the modeling of the endogenous self-organization of a network. The model can also represent the influence of exogenous covariates on network tie formation.

To illustrate the ERGM framework, consider an  $N \times N$  directed adjacency matrix  $y$  on a set of  $N$  nodes. If actor  $i$  sends a directed tie to actor  $j$ , then,  $y_{i,j} = 1$ ; otherwise,  $y_{i,j} = 0$ . As self-ties are not of interest, the diagonal of  $y$  is always empty. Furthermore, let  $X$  denote the exogenous covariates including dyadic and nodal specific attributes, and let  $s(y, X) = (s_1(y, X), \dots, s_Q(y, X))'$  denote a known vector of  $Q$  sufficient network statistics that contains endogenous configurations of network self-organization and the exogenous covariates.<sup>17</sup> The probability density function of an ERGM can be formulated as

$$\Pr(y|X) = \frac{\exp\{\theta s(y, X)\}}{\sum_{\tilde{y} \in \mathcal{Y}} \exp\{\theta s(\tilde{y}, X)\}}, \quad (8.7)$$

where  $\theta = (\theta_1, \dots, \theta_Q)$ . The normalizing constant  $\sum_{\tilde{y} \in \mathcal{Y}} \exp\{\theta s(\tilde{y}, X)\}$  summing over all possible network configurations denoted as  $\mathcal{Y}$  ensures that eq. (8.7) is a probability distribution. The choice with regard to  $s(y, X)$  depends on the research question and the underlying hypotheses about the network tie formation.

Due to the enormous number of possible realizations in  $\mathcal{Y}$ , the normalizing constant is intractable even for networks of moderate size. This makes parameter estimation challenging within the ERGM framework. Maximum Likelihood and Bayesian estimation, which both use Markov Chain Monte Carlo (MCMC) techniques, are prominent approaches in the literature (see Snijders (2002); Hunter and Handcock (2006)). In this paper, we refer to a

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<sup>17</sup>The endogenous sufficient statistics are network counts for directed sub-graph configurations like multiple triangles, two-paths, or star configurations; see Robins et al. (2007) for a detailed introduction. The exogenous covariates enter the model as statistics of the form  $\sum_j (\sum_i y_{ij}) X_j$ ,  $\sum_j (\sum_i y_{ji}) X_j$ , or  $\sum_i \sum_j y_{ij} X_{ij}$ .

Bayesian estimation approach applying the R package `Bergm` (see Caimo and Friel (2014)).<sup>18</sup> The parameter estimates are then available as sample moments for a sample drawn from the posterior distribution. This approach can then be extended to provide inference on the derived measures of political influence. The ERGM specifications characterize the network generating process. Via simulating networks for each configuration of  $s(y, X)$  of interest and recalculation of the influence measures  $C^T$  and  $C^B$  for each parameter value of the posterior distribution sample, we have access to the corresponding posterior distributions.<sup>19</sup>

With regard to interpretation of the estimated parameters, we reformulate eq. (8.7) as a conditional logit (Goodreau, Kitts, and Morris, 2009; Cranmer and Desmarais, 2011) and obtain

$$\ln \left[ \frac{\Pr(y_{ij} = 1, Y_{ij}^C | X)}{\Pr(y_{ij} = 0, Y_{ij}^C | X)} \right] = \theta \delta(y_{ij}, Y_{ij}^C, X), \quad (8.8)$$

where  $Y_{ij}^C$  denotes all dyads other than  $y_{ij}$ , and  $\delta(y_{ij}, Y_{ij}^C, X)$  denotes the vector of changes in the sufficient statistics when  $y_{ij}$  is toggled from 0 to 1. Correspondingly, we have

$$\begin{aligned} \Pr(y_{ij} = 1 | Y_{ij}^C, X) &= \frac{\Pr(y_{ij}=1, Y_{ij}^C | X)}{\Pr(y_{ij}=0, Y_{ij}^C | X) + \Pr(y_{ij}=1, Y_{ij}^C | X)} \\ &= \frac{\exp\{\theta \delta(y_{ij}, Y_{ij}^C, X)\}}{1 + \exp\{\theta \delta(y_{ij}, Y_{ij}^C, X)\}}. \end{aligned} \quad (8.9)$$

To interpret the relative importance of different network statistics, the effects on the probability given in eq. (8.9) resulting from changes in  $\delta(y_{ij}, Y_{ij}^C, X)$  need to be considered. Given that these effects might differ for each observation in the sample, estimates are based on conditional average effects in terms of marginal effects or log-odds.<sup>20</sup> As we are also interested in effects on the

<sup>18</sup>Bayesian and maximum likelihood estimations deliver similar results. However, for more complex models, convergence is easier to achieve with the Bayesian approach because the corresponding MCMC algorithm is less prone to local maxima than the maximum likelihood approach.

<sup>19</sup>Specifically, using the estimated ERGM specifications, we draw a sample of 10,000 networks, and for each network, we calculated the political influence measures ( $C^T, C^B$ ) for each individual organization. We interpret the mean influence calculated for the drawn network sample as our empirically estimated influence measures and calculated 95% confidence intervals to draw statistical inferences about these measures.

<sup>20</sup>Note that a total of  $N^2 - N$  sample observations are available. To facilitate inter-

probability given in eq. (8.9) resulting from exogenous variables and to ease analysis slightly by making use of the directly available vectors of changes in the sufficient statistics, we refer to marginal effects of the network statistics, which can be expressed as

$$\frac{\partial \Pr(y_{ij} = 1 | Y_{ij}^C, X)}{\partial \delta(y_{ij}, Y_{ij}^C, X)} = \Pr(y_{ij} = 1 | Y_{ij}^C, X) (1 - \Pr(y_{ij} = 1 | Y_{ij}^C, X)) \theta. \quad (8.10)$$

Individual marginal effects are locally defined and thus depend on all network statistics, as they are derived as partial derivatives at a specific point.

### 8.3.3 Survey design and network data

Within the PEPAB project, network data has been collected via questionnaires answered in personal interviews with all relevant governmental and non-governmental organizations in 2012-2013. The unit of observation in the surveys is the organization that is interpreted as a corporative actor (Coleman, 1990). For each specific policy domain, the respondents are considered to be experts for the organizations representing that domain. Targeted organizations were carefully identified. As a starting point, country-specific lists of potentially relevant organizations were compiled based on desk research and expert interviews. For Ghana, Senegal, and Uganda, the lists included 89, 90, and 91 non-governmental organizations and 40, 45, and 39 governmental organizations, respectively. Based on the lists, personal interviews were conducted with representatives of the listed organizations. The interviews began with targeting governmental organizations, especially the Ministry of Agriculture and Ministry of Finance, subordinate agencies, and later, the most important interest groups (such as farm organizations).

Within the interviews, a reputation question was asked first, and the interviewees were instructed to identify all influential organizations based on the interpretation of the effects from the estimated ERGM specifications, we report the mean of the  $N^2 - N$  values as an estimate for the effects of specific network statistics. The corresponding estimates can then be calculated as  $\frac{1}{S} \sum_{s=1}^S \frac{1}{N^2 - N} \sum_{i \neq j} \theta^{(s)} \delta(y_{ij}, Y_{ij}^C, X)$  or  $\frac{1}{S} \sum_{s=1}^S \frac{1}{N^2 - N} \sum_{i \neq j} \Pr(y_{ij} = 1 | Y_{ij}^C, X) (1 - \Pr(y_{ij} = 1 | Y_{ij}^C, X)) \theta^{(s)}$ , where  $\{\theta^{(s)}\}_{s=1}^S$  denotes a MCMC sample from the posterior distribution of  $\theta$ . In this sense, we mimic conditional average treatment effects as discussed in Heckman, Lopes, and Piatek (2013) and Jacobi, Wagner, and Frühwirth-Schnatter (2016) from a Bayesian perspective and use the MCMC sample to approximate the involved integral.

provided list or suggest new ones. Based on the responses, suggested organizations that received more than three nominations were also interviewed.<sup>21</sup> Overall, the final tally involved interviews of 46 organizations in Senegal (7 governmental and 39 non-governmental organizations), 43 in Uganda (7 governmental and 36 non-governmental organizations), and 46 in Ghana (6 governmental and 40 non-governmental organizations). Non-governmental organizations included international donors, national research organizations, civil society groups, and socioeconomic interest groups, such as farmers, agribusiness, and non-agricultural interest groups (for the complete lists of organizations, see tables B.1 to B.3). Overall, this procedure guarantees the identification of the most influential organizations operating in a policy domain and provides policy network boundaries.

The data collected during the interview included two parts: a) policy networks and b) policy preferences (i.e., information concerning interest and position with respect to relevant CAADP policy issues). In part a) of the questionnaire, we collected data on reputation, political support, expert information, social relation, and organizational membership networks. To collect reliable networks, we designed our network questions using an established format from previous network studies (Pappi and Henning, 1999; Henning, 2009). Interviewees were asked to check the organizations on the list with which they maintain a specific relation. To facilitate orientation, the list of organizations was organized according to the type of organization or the branch of interest represented by the respective organizations (see table B.4). Based on our theoretical framework, political support and expert information networks are especially relevant.

The expert information network (*B*) is the centerpiece of our belief formation model for characterizing the policy process. We consider expert information to be any kind of information about policy impacts that an actor can communicate to another actor (e.g., knowledge about the impact of farm input subsidies on central policy outcomes, such as the welfare of different social groups). To collect data on the information flow in the elite network, the interviewees were asked to check the organizations on the list of organizations

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<sup>21</sup>By extending the list of relevant organizations based on the nominations of the respondents, possible initial selection effects are mitigated.

with which they share information about the consequences of agricultural policies. Specifically, expert information transfers were collected from a supplier perspective (i.e., an organization delivers information to another organization) and a demander perspective (i.e., an organization receives information from another organization). Therefore, we could construct a confirmed expert knowledge network, which is more reliable from a network theoretical point of view (Pappi, König, and Knoke, 1995). A particular knowledge transfer is considered as *confirmed* if the supplier and demander of knowledge independently report the transfer. The weight that an actor places on her own initial belief ( $\Lambda$ ) is another key input in our model. To identify an actor's own level of control, interviewees were asked to ascertain the extent to which they use externally provided expert information as opposed to their own expertise when formulating policy strategies.

The other network question we consider is political support ( $T$ ). As described in the theory section, politicians seeking reelection engage in political exchange relations and grant political favors to interest groups to receive political support from their constituency. To collect data on specific political support relations, we followed Pappi and Henning (1999) and considered interest groups as suppliers and politicians as demanders of political support. Hence, we could again construct a *confirmed* political support network, see Appendix B.1 for the detailed network questions. Moreover, empirical policy network studies reveal a large proportion of indirect exchange relations, such as support relations among interest groups (Pappi and Henning, 1999; Austen-Smith, 1993). Therefore, we also included indirect political exchange relations via brokerage, as indicated in our theoretical model of political exchange. To determine brokerage shares ( $\mu$ ) empirically, we followed Henning (2009) who showed that individual brokerage shares could be derived from observed political support networks. In detail, assuming that the average number of competitors on export markets reached by an agent in relation to the number of stakeholders using an agent as a broker determine the bargaining power, the approach of Henning (2009) calculates the individual broker shares

$\mu_i$  approximately based on the observed transfer network  $T$  via

$$\begin{aligned}\mu_i &= 1 - \frac{1}{TOT_i}, \text{ where} \\ TOT_i &= \exp\left(\frac{1}{\sum_j \mathcal{T}_{i,j}} \sum_{\mathcal{T}_{i,j}=1} \frac{\sum_k \mathcal{T}_{k,i}}{\sum_l \mathcal{T}_{l,j}}\right) \\ \mathcal{T}_{i,j} &= \begin{cases} 1 & \text{for } t_{i,j} > 0, \\ 0 & \text{else.} \end{cases}\end{aligned}\tag{8.11}$$

Moreover, we directly asked politicians during the interviews to assess their relative interest in political support supplied by interest groups in regard to political control ( $\Omega$ ).

In part b) of the questionnaire, we collected data on the policy preferences of organizations. We asked about the relative interest and the preferred position of an organization with respect to relevant CAADP policy issues. Specifically, we assumed a nested structure of policy preferences. At the top level, we asked about the relative interest and preferred position regarding relevant policy concerns. These policy concerns are relevant policy outcomes determined by CAADP, including the welfare of small scale-farmers, poverty reduction, state budget expenditures, and the welfare of urban consumers.<sup>22</sup>

At the second level, we considered interest and positions in specific policy programs formulated in CAADP investment plans: PINA in Senegal, METASIP in Ghana, and DISIP in Uganda. Specifically, all national plans include specific pillars, where each pillar comprises different national subprograms.<sup>23</sup> For each pillar and subprogram, we collected policy positions preferred by an organization, where a policy position corresponds to the amount of budget expenditures allocated to a specific subprogram or pillar. The actors' relative interests in different policy concerns were measured by asking interviewees to subdivide 100 points across concerns. Analogously, we measured the relative interest of organizations in pillars and subprograms. Since

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<sup>22</sup>Overall, we considered seven policy concerns:  $Z_1$  = Welfare of small-scale farmers,  $Z_2$  = Poverty reduction,  $Z_3$  = Provision of public goods,  $Z_4$  = Profits in agricultural export sectors,  $Z_5$  = Welfare of urban consumer households,  $Z_6$  = Profits of non-agricultural sectors,  $Z_7$  = Environmental protection.

<sup>23</sup>Pillar I is "Food security and risk management;" pillar II is "Agribusiness and market development;" pillar III is "Sustainable land and water management;" and pillar IV is "Technology generation and dissemination/Institutional strengthening and capacity building".

we mainly deal with influence and less with final policy decisions in this paper, we do not further describe CAADP policies here. However, more details on CAADP policies are provided in Henning, Badiane, and Krampe (2018).

Based on collected network data, we are able to calculate our theoretically derived influence measures  $C^T$  and  $C^B$ . However, beyond network data, the calculation of these influence indices requires information on constitutional decision-making power ( $C$ ). To assess decision-power empirically, we applied the concept of the Banzhaf power index to transform constitutional rules into decision-making power (Banzhaf, 1966; Ben-Dov and Shilony, 1982; Pappi and Henning, 1998; Napel, 2006; Henning, Badiane, and Krampe, 2018).<sup>24</sup> In particular, we assumed six different constitutional scenarios for the CAADP-reform decision.<sup>25</sup> Applying the modified legislative bargaining model (Henning, 2008) it is possible to predict the outcome of legislative decision-making for each constitutional scenario as long as political preferences of legislators are known. Since we observed the CAADP-budget allocation which have been implemented in all three countries in 2015, we were able to select the constitutional scenario which gave the best prediction for empirically observed CAADP allocations. This was the scenario assuming that the government dominates political decision-making vis-a-vis the parliament and within the government the Ministry of Agriculture and the President have agenda setting power vis-a-vis the cabinet. However, we simulated lobbying power for all six constitutional scenarios regarding  $C$ . Interestingly, the relative lobbying influence of non-governmental organizations did not differ significantly across constitutional scenarios (except the power of parliamentary groups which sig-

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<sup>24</sup>We are aware that the application of classical voting power indices like the Banzhaf index as a positive model of legislative decision-making is critically discussed in the literature Tsebelis and Garrett (1996). However, there are also interesting extensions of classical voting power that demonstrate the potential to assess decision-making power in real-life political systems (Ben-Dov and Shilony, 1982; Henning, Badiane, and Krampe, 2018). For example, Henning, Badiane, and Krampe (2018) identify specific conditions under which the Banzhaf index corresponds to the voting power derived from a modified non-cooperative legislative bargaining game of a Baron-Ferejohn type.

<sup>25</sup>A first set of 3 scenarios assumes CAADP investment plans are decided by the government alone, while the parliament is not engaged in this decision. For a second set of constitutional scenarios, CAADP investment plans are considered as a legislative decision made by the parliament alone.



nificantly increased assuming political decisions are made by the parliament). In the following we present simulated influence measures derived for the best-fit constitutional scenario defined above.<sup>26</sup>

### 8.3.4 Network statistics used in the ERGM estimation

The ERGM framework can test our hypotheses on the determinants of political support relations and expert information exchange among governmental and non-governmental organizations in Ghana, Senegal, and Uganda. Accordingly, we used confirmed expert information exchange ( $B$ ) and political support ( $T$ ) network ties as dependent variables. Furthermore, we used endogenous network effects as well as specific exogenous nodal and dyadic attributes as explanatory variables. In detail, we calculated various network statistics corresponding to the hypothesized mechanisms of endogenous tie formation. Table B.5 gives an overview of the network statistics used as model terms. This explains the internal self-organizing structure of the dependent network variable.

The total number of edges ( $EDGES$ ) can be used to model the general propensity of tie formation and corresponds to the unconditional probability of tie formation.<sup>27</sup> The number of reciprocal edges ( $MUTUAL$ ) represents the tendency to answer received ties. This term adds one network statistic to the model and is equal to the number of pairs of actors  $i$  and  $j$  for which both ties exist ( $y_{ij} = y_{ji} = 1$ ). The effects of triadic transitivity are modeled using the geometrically weighted edgewise shared partner statistic ( $GWESP$ ) and the geometrically weighted dyad wise shared partner statistic ( $GWDSP$ ).  $GWESP$  measures a specific mechanism to count the number of triangles in the network while taking into account the number of links that are involved in multiple triangles (multimodality) (for details, see Hunter et al. (2008)). It thereby captures how frequently two nodes are connected by a direct link as well as by an indirect connection of length 2 (i.e., two-path) through another node (e.g., Hunter (2007)). If a positive coefficient is found for this statistic, there is a tendency towards triadic closure in the network.  $GWDSP$  is an

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<sup>26</sup>Results for all constitutional scenarios are available upon request from the authors.

<sup>27</sup>Technically, the term  $EDGES$  adds one network statistic that is equal to the number of edges in the network.

advanced version of the alternating  $k$ -two-path statistic put forward by Snijders, Steglich, and Schweinberger (2006). It measures the extent to which a network shows a tendency of nodes being directly linked or not directly linked to each other while being at least indirectly linked. In other words, *GWDS*P captures multi-connectivity for nodes. This approach has been shown to work well in practice in overcoming model degeneracy and producing models that fit a wide range of data well (Hunter, Goodreau, and Handcock, 2008; Goodreau, 2007).<sup>28</sup> If one includes both *GWESP* and *GWDS*P, then *GWDS*P is the base effect, which now isolates the effect for those not tied only, while *GWESP* occurs on top of this base and isolates the effect for those who are tied. For *GWESP*, a strong positive and significant effect is often observed, while for *GWDS*P, an insignificant and weak effect has often been found (Goodreau, 2007). Alternatively, Lee, Lee, and Feiock (2012) found a positive *GWESP* and a negative *GWDS*P parameter, which they interpreted as a propensity to avoid structural holes like four-cycles. Analogously, Leifeld and Schneider (2012) also found a significantly positive parameter for *GWESP* and a significantly negative parameter for *GWDS*P, which they interpreted as structural

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<sup>28</sup>The two shared partner statistics, *GWESP* and *GWDS*P, use a geometrical series to weight the importance of additional common neighbors; i.e.,

$$GWESP = e^{\alpha_v} \sum_{h=1}^{n-2} \left(1 - (1 - e^{-\alpha_v})^h\right) EP(h), \quad \text{and} \quad GWDS\!P = e^{\alpha_w} \sum_{h=1}^{n-2} \left(1 - (1 - e^{-\alpha_w})^h\right) DP(h),$$

where  $EP(h)$  is the number of directed edges that are the basis for  $h$  transitive triads, and  $DP(h)$  is the count of pairs of nodes  $i, j$  that are connected by  $h$  two paths. Unlike  $EP(h)$ ,  $i, j$  do not have to be connected directly. Therefore,  $EP(h)$  is nested in  $DP(h)$ .  $\alpha_v$  and  $\alpha_w$  are tuning parameters that have to be exogenously fixed prior to estimation. For our analysis, both parameters have been fixed at relatively low baseline values of  $\alpha_v = \alpha_w = 0.1$ . For further discussion of the parameterization of these multiple network statistics, see Snijders et al. (2006); Hunter and Handcock (2006); Hunter (2007); Robins, Lewis, and Wang (2012). Interpreting *GWESP* and *GWDS*P in terms of underlying social behavior, scholars studying friendship or collaboration networks generally refer to the classical process of triad closure first suggested by Rapoport (1957). This process explains that triads containing two ties will tend to form a third, thus creating a triangle (a set of three people who are all tied). This may be due to propinquity (two people encounter each other through their shared time with a third) or cognitive processes that causes two people to value each other because of their agreement about a third (cf. structural balance theory: Cartwright and Harary (1956); Heider (1958)).

determinants of transaction costs.

Following our theoretical considerations, three different categories of determinants of policy network ties exist: factors determining actors' benefits derived from an established tie; the cost of establishing and maintaining a tie; and transaction costs of political interaction. Accordingly, in our specific context, we follow Lee, Lee, and Feiock (2012); Leifeld and Schneider (2012) and consider the endogenous network statistics as determinants of dyadic specific transaction costs involved with political support or expert information exchange. Furthermore, the statistics *EDGES* and *MUTUAL* can also be interpreted as indicators of the costs of establishing and maintaining network ties. Additionally, while established network ties can also be used to engage in new political interactions, we include the support and the expert networks as explanatory variables for each other. The expert structural model includes the support network as an explanatory edge attribute (*SUPPORT*), and vice versa. The support structural model includes the expert information network as an explanatory edge attribute (*EXPERT*).<sup>29</sup>

Beyond network statistics, we include the following exogenous covariates as nodal and edge-specific attribute effects into the estimate. To assess the costs of establishing and maintaining network ties, we use the number of overlapping memberships in umbrella organizations or political committees with other organizations as an indicator of meeting opportunities (Leifeld and Schneider, 2012; Lubell, Henry, and McCoy, 2010; Ansell and Gash, 2008; König and Bräuninger, 1998). The corresponding edge-specific network statistic (*MEMBER*) is equal to the sum of overlapping memberships for all edges in the network. Furthermore, as discussed in the theoretical section, we include perceived power and political knowledge of ALTER as indicators for the benefit EGO expects from a tie with ALTER. It is not straightforward to measure political decision-making power, and we use the collected reputation network data to identify an organization's perceived political power. We calculated the normalized indegrees of the reputation network as an informal power measure

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<sup>29</sup>Technically, the term *EXPERT* (*SUPPORT*) adds a single network statistic to the ERGM specification of the support network (the ERGM model of the expert information network), which is equal to the sum of confirmed expert information ties (the sum of confirmed political support ties) that exist for all edges in the support network (the expert information network).

of an organization. Accordingly, we added a nodal specific network statistic (*POWER*) to the ERGM, which is equal to the sum of reputation power of all organizations that receive a tie in the network. Furthermore, we included a nodal attribute effect (*EXEC*) representing ties where the target is a governmental organization to check whether tie formation is driven by formal political power. The latter term counts the number of edges in the network for which a governmental organization is the receiver of a tie.

As explained in the theory section, the benefit from received information is driven by the political knowledge of the sender. The benefit of received political support ties is that, c.p., more of it results in a larger capacity to mobilize voters of an organization. It is impossible to observe political knowledge or the capacity to mobilize voters directly, so we use organizational dummy variables as proxies for these variables. Hence, we include two additional nodal attribute effects (*RESEARCH*) and (*DONOR*), which represent ties where the sending node is a research organization or a donor organization. Again, the corresponding network statistics are equal to the sum of edges in the network for which the sending node is a research or a donor organization. In particular, we expect organizations to demand expert information primarily from scientific organizations because they are technically knowledgeable. We further expect politicians to demand political support from donors because these organizations often control international development funds granted to national governments. For example, in selected African states, 40% of total CAADP expenditures comprises donor funds (Gibbon, Bangura, and Ofstad, 1992; Mogues and Benin, 2012).

Finally, we include different measures of political homophily (i.e., similarity of policy preference) as indicators of dyadic specific transaction costs. Policy preferences include the actors' political interests and positions in various policy issues nested in three levels. For the first homophily measure, we use top-level preferences regarding policy concerns. In particular, we constructed a dissimilarity matrix by calculating for each pair of organizations  $i$  and  $j$  the political distance index

$$DI_{ij} = \sqrt{\sum_{k=1}^K (d_{ik} - d_{jk})^2},$$

where  $d_{ik}$  denotes the interest of individual  $i$  in policy concern  $k$ . The dis-

similarity measure was converted into a dyad specific similarity index (*PREFSIM*) via  $(\max_{i,j}\{DI_{ij}\} - DI_{ij})$ . We calculated an analogous homophily index (*POLSIM*) for collected policy positions regarding organizations' preferred budget allocations across CAADP sub-programs. Thus, the index *POLSIM* measures the similarity of organizations' preferred positions regarding detailed CAADP-implementations, while the index *PREFSIM* measures the similarity of the organizations' fundamental ideological positions.

Young democracies are often characterized by weakly developed interest mediation structures. That is, governmental organizations grant only slight access to interest groups representing the political interest of the society. Thus, we introduced a dyad-specific binary variable (*IG*) to check whether governance structures are especially focused on coalition building among interest groups. This variable could be interpreted as empirical evidence that political conflicts between society and the governing elite are still more important than political conflict lines running between different social groups, such as labor versus capital. The corresponding advocacy coalitions comprise both opposing social groups and their political leaders. The term *IG* adds one network statistic that counts the edges in the networks where both vertices are socio-economic interest groups.

Overall, we estimated three model specifications for each dependent variable: an endogenous model containing only endogenous network effects and two structural models containing the same endogenous effects plus specific exogenous nodal and dyadic attributes as a control. In particular, we estimated a model specification including endogenous network effects and additional covariates, where *POWER* and *EXEC* are used for receiver effects, while *RESEARCH* and *DONOR* are used for sender effects, and *IG* is used as a pure homophily effect, as explained above. However, to identify our expected sender, receiver, and homophily effects correctly, it is important to control for all possible effects of corresponding nodal and dyadic attributes. Therefore, for both endogenous network variables, we estimated a third model including the full set of sender and receiver terms (see tables B.6 to B.8).<sup>30</sup>

As data are surveyed via personal interviews, missing information inevitably occurs in some variables. Therefore, inferences on the importance of covariates

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<sup>30</sup>We thank an anonymous referee for pointing out this enriched specification.

or structural parameters can be biased due to missing information (Cranmer and Desmarais, 2011; Snijders et al., 2006). Appendix B.5 provides details on how missing information has been addressed via robustness checks within the empirical analysis.

## 8.4 Results

### 8.4.1 ERGM parameter estimates

Tables B.6 to B.8 show the estimation results with respect to the specified ERGM models for all countries and specifications. Models 1-3 take the confirmed information expert exchange network as the dependent variable, while models 4-6 take the confirmed political support networks as the dependent variable. Models 1 and 4 include only the endogenous structural network variables as explanatory variables, while models 2-3 and 5-6 consider additional covariates. However, controlling for exogenous covariates does not alter the level of significance and the parameter signs of the endogenous statistics.<sup>31</sup> The model that best fit our data was determined by using likelihood-based measures: log-likelihood, Akaike information, and Bayesian information criteria, which are reported in tables B.6 to B.8. The results reveal that for all three countries, the full model specifications with exogenous variables fit best: specifications 2 and 5 or 3 and 6. We will report results on specifications 3 and 6 and indicate differences to the other specifications when necessary. However, these criteria may reveal only a little about the specific features of the data captured or not captured by the model specifications. Therefore, additional goodness-of-fit approaches have been developed (for example, see Hunter et al. (2008); Goodreau, Kitts, and Morris (2009)). In appendix B.4, we discuss details about these goodness-of-fit criteria indicating sufficient match of the model specifications to observed data and the potential limitations of the ERGM approach.

As shown in tables B.6 to B.8, all three countries have political interactions that are significantly embedded in endogenous network structures; i.e.,

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<sup>31</sup>Only models 5 and 6 in Ghana show an insignificant parameter for the GWESP statistic, indicating that clustering is explained by exogenous covariates.

all relational attribute effects are significant in all models for all countries. Hence, interpreting *MUTUAL*, *GWESP*, *GWDSP*, *EXPERT*, and *SUPPORT* as indicators of social embeddedness that allow actors to punish deviating political exchange partners implies that ERGM estimates clearly reveal the important effect of transaction costs on tie formation in policy networks in all three countries. When organizations choose potential interaction partners, they consider not only the potential benefit they derive from an established political exchange, but also the risk that exchange partners will break their trade promises. In particular, *MUTUAL* is significant and positive for all models in all three countries. In all three countries, the *GWESP* statistic is positive, and the *GWDSP* statistic is negative for both networks. Moreover, both statistics are significant for all model specifications in Senegal and Uganda and for most specifications in Ghana, where *GWDSP* is insignificant for model 3 and *GWESP* is insignificant for models 5 and 6. This empirical result corresponds to the literature in that political organizations rely on others to reduce transaction costs when finding trustworthy sources of information or political support (Baumgartner and Leech, 1996; Pappi and Henning, 1998; Carpenter, Esterling, and Lazer, 2004; Henry, Lubell, and McCoy, 2011; Henning, Henningsen, and Henningsen, 2012; Leifeld and Schneider, 2012).

Moreover, social embeddedness via multiplexity appears to be important for political exchange interactions; if two organizations already engage in one of the two political interactions captured by *EXPERT* and *SUPPORT*, they are also significantly more likely to engage in the other interactions. However, reciprocity as well as multiplexity might also be interpreted as relational opportunity structures; i.e., they potentially reduce the cost of establishing and maintaining ties. Nevertheless, beyond endogenous self-governance, our estimation also included institutional opportunity structures via overlapping committee memberships captured by *MEMBER*. Since this has a significant impact on only the establishment of ties for the information network in Ghana, we conclude that reciprocity and multiplexity mainly work as structural factors that reduce transaction costs related to opportunistic behavior and less as relational opportunity structures that decrease the costs of establishing and maintaining network ties, at least in regard to the emergence of policy networks analyzed in this study.

When testing for preference homophily effects, both edge-specific covariates *PREFSIM* and *POLSIM* were found to be insignificant in all models for all countries. Accordingly, we conclude that policy preferences are not important drivers of policy network tie formation in development politics, at least for our selected African states. This contrasts with the result of many policy network studies that examine developed democracies, such as (Carpenter, Esterling, and Lazer, 2004; Henry, Lubell, and McCoy, 2011; Weible, 2005; Zafonte and Sabatier, 1998; Stokman and Berveling, 1998; Stokman and Zeggelink, 1996). This implies that the transaction costs of lobbying seem to be less driven by stakeholders' incentive to behave opportunistic. Moreover, these results provide empirical evidence against the counteractive lobbying hypothesis formulated by Austen-Smith (1993).

Interest group homophily *IG* is significant and positive for models 5 and 6 in Uganda, model 2 and 3 in Senegal as well as models 3 and 6 in Ghana. Hence, for all three states we found some empirical evidence that socio-economic interest groups tend to form coalitions among themselves to counterbalance the transgressions of the ruling governmental elite. For Senegal we found IG-homophily only for informational lobbying and for Uganda only for vote-buying lobbying, while for Ghana we found this for both lobbying mechanisms, but only in models 3 and 6.

Following our hypothesis, perceived power is an important covariate that determines political interaction among stakeholders. In particular, perceived power of the receiver node (*POWER (indegree)*) is positive and significant in determining political support relations for both models 5 and 6 in all three countries, while for information exchange, perceived power of the sender (*POWER (outdegree)*) is positive and significant for all countries. Interestingly, (*POWER (outdegree)*) is only significant and positive for the support network in Uganda, while (*POWER (indegree)*) is positively significant in determining information exchange for models 2 and 3 in Senegal as well as for model 2 in Uganda, but not in Ghana.

Further, we applied our statistical model to test whether donor organizations are prominent suppliers of political support, and whether research organizations are especially important providers of expert information. Tables B.6 to B.8 show the corresponding nodal attribute effect for research and donor or-



ganizations. For *RESEARCH (outdegree)*, this value is always significant and positive in both models 2 and 3, which implies strong evidence that research organizations are consulted more frequently than others during expert information exchange in all three countries. In contrast, for models 5 and 6, the effect of *RESEARCH (outdegree)* is never positive and significant, which implies that research organizations are not important suppliers of political support. These results confirm our hypothesis for expert information exchange and indicate that the CAADP process has been successful in regard to the promotion of evidence-based policy, at least in these countries.

Regarding donor organizations, we found less empirical evidence for our theoretical hypothesis that political support is driven by donor money. In detail, *DONOR (outdegree)* only has a positive and significant impact on support relations in Ghana, while it is not significant in Senegal and even negative and significant in Uganda. Being a donor organization also seems not to increase the probability of supplying expert information to other organizations, as indicated by the insignificant or even significantly negative ERGM parameters for *DONOR (outdegree)* found for models 2 and 3. Interestingly, we found statistically significant receiver effects for donors; i.e., *DONOR (indegree)* is significant for political support in all three countries (model 6), as well as for information exchange in Senegal (model 3). In Senegal and Uganda significant positive receiver effects for political support are observed. Hence, donor organizations appear to be structurally equivalent to powerful governmental agents being targeted by vote-buying activities of other stakeholders. However, we found a negative receiver effect in Ghana. Analogously, the receiver effect for information exchange is also significantly negative in Senegal. Thus, overall, we obtained mixed results indicating that the role of donors in participatory policy processes might be more complex and heterogeneous across countries than assumed in our theoretical considerations. However, one should not jump to general conclusions too quickly in regard to the overall role or influence of specific organizations. First of all, the reported parameters correspond to partial effects of specific network statistics, but the probability that a specific organization will form a tie depends on all network statistics. For example, donors received above-average reputation indegrees as they are generally perceived as highly influential organizations. Accordingly, the probability that

organizations form information or support relations with donor organizations can still be high, despite the insignificant or even negative parameter estimates for the nodal specific statistics related to the organizational type *donor*. Therefore, in the next subsection, we analyze the political influence derived from our model estimations in more detail.

Before we come to this, it is interesting to analyze the importance of identified effects in quantitative terms as well. In this regard, we apply the conditional average marginal effects, see eq. (8.10) and footnote (20). Table B.9 provides the corresponding results.<sup>32</sup> As shown in table B.9, in quantitative terms, the ERGM estimation results clearly reveal a high importance of relational factors for the tie formation in policy networks in all three countries. In particular, reciprocity is the most dominant effect given the highest marginal effects for *MUTUAL* for all model specifications (see table B.9).<sup>33</sup> In absolute terms, average marginal effects amount to roughly 0.3 for all countries and models. This implies the probability that expert information or political support flows from EGO to ALTER will increase by roughly 30 percentage points if the change in this network statistic marginally increases (see table B.9). Beyond reciprocity, multiplexity is another important relational factor for all three countries. In quantitative terms, the probability that an organization will engage in expert information exchange with another organization increases marginally by 8.1 up to 14.1 percentage points if these organizations already have an established political support relation, and vice versa: the probability of political support increases marginally by 9.3 up to 13.2 percentage points if organizations already have an established information exchange relation. This social embeddedness effect is relatively homogenous across all countries. For *GWESP* and *GWDSP*, the estimated average marginal effects are lower when compared to *MUTUAL*. There were significant average marginal effects ranging from 4.8 to 14.2 percentage points for *GWESP* and from  $-0.6$  to  $-1.2$  percentage points for *GWDSP*.

In contrast to relational factors, average marginal impacts of covariates were found to be lower or insignificant. The only exemptions are found for

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<sup>32</sup>Conditional average marginal effects have been calculated for the best-fit model specifications 3 and 6, as described above.

<sup>33</sup>An exception results from model 5 in Uganda, where a higher marginal effect occurs for the nodal attribute *POWER* (*outdegree*)

the covariates *POWER* and *RESEARCH*. Especially high marginal effects of *POWER* (*indegree*) are found for the political support network, with values amounting to 26.8 percentage points in Ghana, 19.7 percentage points in Uganda, and 9.1 percentage points in Senegal. In contrast, average marginal effects of *POWER* (*indegree*) are negative and insignificant for the information networks except for Senegal where a positive and significant average marginal effect of 16.2 percentage points was found. Moreover, we also found high average marginal effects of *POWER* (*outdegree*) with regard to the information network, amounting to 20.7 percentage points in Ghana, 13.7 percentage points in Senegal, and as much as 44.9 percentage points in Uganda. Thus, perceived power of the sender significantly increases the probability of information supply in all three countries. Analogously, estimated ERGM parameters imply relatively strong average marginal effects of *RESEARCH* (*outdegree*) for political information supply, which range from 12.1 percentage points in Ghana to over 20 percentage points in Senegal and Uganda. Furthermore, research organizations are less likely to be receivers of expert information given average marginal effects of *RESEARCH* (*indegree*) for political information demand, amounting to  $-11.1$  percentage points in Ghana,  $-10.0$  percentage points in Senegal, and as much as  $-29.4$  percentage points in Uganda.

In contrast, estimated average marginal effects of (*DONOR*) as well as private interest groups (*IG*) are rather low and negative and often not significant for all network relations and for all countries. Only for the support network in Ghana, the average marginal effect of the nodal attribute (*DONOR*(*outdegree*)) is positive and significant, amounting to 9.6 percentage points. However, we found significant marginal impacts of interest group homophily in all three countries, which range from 3.7 to 7.2 percentage points in Ghana for the expert and support networks, respectively. In Senegal, significant interest group homophily was only found for expert networks with an average marginal effect amounting to 6.3 percentage points, as well as in Uganda for the support network with an average marginal impact of 7.3 percentage points.

Overall, the results of ERGM estimates can be summarized as follows. First, tie formation in participatory policy networks within the CAADP setup is strongly determined by transaction costs resulting from the risk of opportunis-

tic behavior. The latter is mainly driven by structure-based potentials to punish deviating stakeholders, while stakeholders' incentives to deviate from established commitments seem to be less important determinants of transaction costs. In contrast, costs to establish or maintain network ties appear to have only a minor impact on tie formation. We consider this to be a remarkable result for the following reason. In contrast to relational factors, institutional opportunity structures can be systematically controlled. For example, within the CAADP process committee, the membership of specific farm and CSOs has been promoted. Hence, at least technically, these would be promising access points for a successful strategy to design more effective participatory structures.

Beyond transaction costs, our ERGM estimation results also emphasize the importance of expected benefits from lobbying activities as driving forces of policy network formation. Stakeholders direct their lobbying activities towards other stakeholders that they perceive as political powerful. This applies to vote-buying lobbying in all three countries but also to informational lobbying activities, which were given highly significant positive receiver effects in two of the three countries analyzed. As expected, lobbying interactions seem to be less determined by constitutional power structures, as legislative decision-making is driven by informal legislative norms, especially in young democracies, where the rule of law is often only weakly developed. Moreover, this result also emphasizes that stakeholders take vote-buying lobbying into account when assessing the political power of other stakeholders. Our ERGM estimation results imply the following results in regard to the impact of specific organizational characteristics on the emergence of policy network ties. The technical knowledge of organizations turns out to be an important determinant of information exchange ties, with significant and positive sender effects arising for research organizations for the information networks in all three countries. In contrast, ERGM estimation delivers only mixed results in regard to the importance of donor money as a driver of vote-buying lobbying.

Accordingly, to obtain a more global picture, we next explicitly analyze individual vote-buying and the informational lobbying power of stakeholders.

### 8.4.2 Assessing political influence measures

Using the posterior sample of ERGM parameters, we simulated a sample of 10,000 networks for each country using model specifications 3 and 6.<sup>34</sup> The exogenous variables are thereby sampled from the observed distributions. We calculated the individual influence measures for each simulated network. Accordingly, for each of the three countries, we generated a sample of 10,000 influence vectors, which includes our theoretically derived influence measures  $C^T$  and  $C^B$  for all individual organizations of the identified political elite networks. In particular, we calculated lobbying power  $C^B$ , including vote-buying lobbying; i.e.,  $C^T$  is equal to the vector derived from eq. (8.3). Given our sampling procedure, the corresponding sample means can be interpreted as the estimated empirical influence of individual organizations derived from the observed network and corresponding uncertainty measures; for example, the highest density intervals and variances can be calculated.

To better identify the overall influence patterns in the selected countries, we calculated aggregated political influence measures for specific types of organizations: government (*EXEC*), public agencies (*PUBAG*), international donors (*DONOR*), research (*RESEARCH*), and society organizations. The latter is further subdivided into CSOs (*CSO*) as well as farm (*IG:FARM*) and non-farm industrial business associations (*IG:IND*).<sup>35</sup> In fig. B.1, the aggregated political influence of these different types of organizations and their corresponding 95% highest density intervals are presented for the simulated political support exchange networks and the expert information exchange networks.

In analyzing empirical power, structures we undertake separate analyses for the two lobbying mechanisms (vote-buying ( $C^T$ ) and informational lobbying ( $C^B$ )). Furthermore, for each mechanism, we focus on two aspects of the distribution of the  $C^T$  and  $C^B$  across stakeholders. The first is total power outflow from governmental organizations that collectively exert total constitutional power. The second is the relative distribution of power outflows across stakeholder groups. Given the central empirical questions in regard to partici-

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<sup>34</sup>Again, the sampler of Hunter et al. (2008) is used as described above.

<sup>35</sup>Originally, we also included two additional organizational categories: political parties and international NGOs. However, to facilitate the interpretation, we excluded political parties and international NGOs in fig. B.1, which have negligible influence in all countries.

patory structures in development politics, we are particularly interested in the extent to which power outflows are dominated by donors or public agencies or whether they are mainly directed towards society organizations representing the poor; i.e., small-scale farm organization and CSOs or the urban rich (urban non-farm interests). Moreover, we test whether power structures reflect evidence-based policy processes in terms of the extent to which research organizations exert informational lobbying power.

As shown in fig. B.1, total aggregated power outflows resulting from vote-buying lobbying range from 38% in Senegal to 54% in Uganda, whereas the lobbying influence of stakeholders takes the middle ground in Ghana at 45%. Compared to vote-buying power, outflows resulting from informational lobbying are higher, with outflows around 70% for Uganda, 58% for Ghana, and 52% for Senegal. These overall power outflows are basically comparable to participation structures observed in developed democratic countries. For example, based on a policy network, analyses of the European Common Agricultural Policy (EU CAP) Pappi and Henning (1999) found an aggregate political power outflow from governmental to non-governmental organizations amounting to 52% via vote-buying lobbying and 58% via informational lobbying.<sup>36</sup> However, informational power outflows are higher in Uganda, indicating rather low political knowledge capacities of the Ugandan government.

Regarding the distribution of power outflows across different types of organizations, we identify the following similar patterns for both lobby mechanisms and across all three countries. In all three countries, non-governmental organizations can be subdivided into three blocks. The first block represents highly influential organizations comprising donor and research organizations. The second is a low-influence block comprising CSO and farmer organizations, while public agencies and industrial interest groups take the middle ground between these blocks. These patterns partly contrast with non-governmental influence in the European CAP.

First, the high political influence of international donor organizations is specific for African development politics. The aggregated vote-buying lobbying

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<sup>36</sup>Note that Pappi and Henning (1999) did not calculate combined power outflows resulting from both lobbying mechanisms; power outflows were calculated separately for each lobbying mechanism.

power ( $C^T$ ) of donors ranges from 13.1% in Ghana to only 8.7% in Uganda. In Ghana and Uganda, we found the highest aggregated informational lobbying power for donors with over 15.1% and 11.2%, respectively, while in Senegal, donors are only ranked second to research organizations in terms of informational lobbying power, amounting to 10.9% of total informational lobbying power (see fig. B.1). Hence, our results provide empirical support for the criticism of donor dominance in development politics, especially in Ghana and Senegal. In particular, donor organizations exert strong lobbying influence on the government via vote-buying in that the granting of international funds is often conditional to a specific domestic policy output (Mogues and Benin, 2012; Dreher, Fuchs, and Nunnenkamp, 2013). Moreover, donors often invest financial resources to establish domestic stakeholder organizations and hence exert indirect vote-buying lobbying influence by determining the agenda of domestic stakeholders (Ohanyan, 2009). Furthermore, donor organizations also exert high informational lobbying power in development politics since they are often prominent members of advisor committees to the government. Furthermore, non-governmental stakeholders can depend on the advice of donors due to a lack of their own knowledge capacities.

Second, research organizations exert significant informational lobbying power in the three African countries (see fig. B.1). In contrast, research organizations are barely identified as influential in informational lobbying in developed democracies (Henning, 2009). We interpret this as an indicator that African states have successfully implemented evidenced-based politics within the CAADP framework. The aggregated informational lobbying influence of research organizations was over 17% in Senegal, almost 12% in Ghana, and only 6.7% in Uganda. Interestingly, we also found high aggregated vote-buying lobbying power for research organizations amounting to roughly 9% in both Ghana and Senegal, but only about 6% in Uganda (see fig. B.1, upper panel).

Thirdly, society organizations such as CSOs and farmers organizations representing marginalized groups, especially the rural poor, exert rather little lobbying power in all three countries. This applies to both lobbying mechanisms. As shown in fig. B.1, aggregated vote-buying lobbying power for CSOs and farm interest groups is below 10% in all three countries. The same results occurred for informational lobbying in Ghana and Senegal, while in Uganda,

farm interest groups exert some informational lobbying power with 11%. Comparing these rather low levels of lobbying influence found at the aggregate level for both farm organizations and CSOs to the corresponding population shares of poor and farm households clearly contradict the CAADP manifesto. Interestingly, in all three countries, the aggregated lobbying power of private interest groups is dominated by non-farm industrial business associations. This basically applies to both vote-buying and informational lobbying. In quantitative terms, the lobbying influence of non-farm interest groups is more than double that of farm interests (see fig. B.1). This dominance of non-farm interest over farm interest sharply contrasts with the absolute dominance of farm interests in the agricultural policy domain of industrialized countries.<sup>37</sup>

Beyond donors and research, public agencies are also important lobbyists outside society organizations. Especially in Uganda, public agencies exert significant informational lobbying power at over 14% of the total power. In Ghana and Senegal as well, public agencies hold 6.5% and 5.4% of the total informational lobbying power (see fig. B.1 (lower panel)). Furthermore, public agencies are also strong vote-buying lobbyists in Uganda, where they hold 6.5% of total vote-buying lobbying power. As the calculated 95% highest density intervals in fig. B.1 do not overlap for most of the power indices, strong evidence for differences across the different organizational categories is implied. We consider the possibility to drawing statistical inferences about derived power structures as an advantage of our suggested approach.<sup>38</sup>

Beyond aggregate influence patterns, it is also interesting to analyze the political influence of individual non-governmental organizations. In fig. B.2, we report the relative political influence measures of individual non-governmental organizations, which were calculated as the relation of the estimated individ-

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<sup>37</sup>Note that the farm lobby exerts over 40% of total political power in the EU CAP (Pappi and Henning, 1999). However, these contrasting patterns between African developing countries and developed EU countries can be well explained by standard lobbying theory, particularly the development paradox (Anderson and Hayami, 1986; Krueger, 1992). The negligible lobbying influence of CSOs, however, is a pattern that is analogously observed in many developed countries (Henning, 2009).

<sup>38</sup>However, given the fact that we have only one observation for each policy network in each country and only three countries, we are aware of the fact that conducting our analyses based on dynamic network data for many countries would certainly further increase the robustness of derived results.



ual influence indices of an organization and the corresponding mean influence across all identified non-governmental organizations in a country. Accordingly, values above one indicate influence above the average influence of all non-governmental stakeholders in the network, and lower values indicate below-average influence. As shown in fig. B.2, compared to aggregate influence, a higher variance of political influence can be observed at the individual organizational level. In particular, while we found clear differences in the mean influence between individual organizations, we also observed large and overlapping 95% density intervals in all three countries. We tested whether the 95% highest density interval of estimated relative influence measures includes the value of one, where we interpret an interval excluding this value as strong evidence for high or low relative influence. Thus, as shown in fig. B.2, applying this test reveals that only very few individual organizations can be considered as highly influential or non-influential in the three countries. Namely, the outstanding vote-buying lobbyists are the World Bank and FAO in Ghana, while we find no evidence for outstanding vote-buying influence for any other individual organization in any of the countries. Interestingly, we also find only very few individual organizations that we can strongly conclude to have no vote-buying lobbying influence. Specifically, the calculated 95% high density intervals lie completely below one only for the parliamentary groups.

Analogously, for informational lobbying, we find also only a few organizations being outstanding influential or non-influential. In particular, the main national research organizations ISRA as well as ITA in Senegal and ISSER in Ghana can be considered as outstanding influential political experts, given that their 95% high density intervals are completely above one. Moreover, according to this criterion, the international donor and research organizations USAID and IFPRI, respectively, have been found to be a highly influential group of political experts in both countries, along with the World Bank in Senegal and with FAO in Ghana. As for vote-buying lobbying influence we also find only very few individual organizations that we can strongly conclude to have no informational lobbying influence in Ghana as well as in Senegal. Again, for the parliamentary groups the calculated 95% high density intervals lie completely below one. In contrast to Ghana and Senegal, neither individual donor nor research organizations are found to exert outstanding high informa-

tional lobbying influence in Uganda. Only the public agency NARO, as well as the fish processing industry UFPEA and manufacture industry UMA, and interestingly, the farmer interest groups NOGAMU and UCA are found to exert outstanding high influence in Uganda. These results imply that based on empirical network data, we still can draw only very limited conclusions in regard to the political influence of individual organizations. In contrast, at least at the aggregate level, it is possible to draw significant conclusions in regard to the political influence of specific types of stakeholders. However, it is still fair to conclude that empirical network analyses of participatory policy processes are in their infancy.

Overall, we can conclude from our analyses that many of the criticisms of participatory policy processes in developing countries also apply to stakeholder participation induced under CAADP. In particular, participation is dominated by donors in Ghana and Senegal and by non-farm interests and public agencies in Uganda, while in all countries, marginalized groups are still not strongly involved in the political decision-making processes. However, at least in Senegal and Ghana, we found clear and positive empirical support for the promotion of evidence-based policy processes under CAADP in that research organizations exert high informational lobbying influence. In contrast, in Uganda, old patronage networks that have been characteristic for many autocratic African states of the old days (Gibbon, Bangura, and Ofstad, 1992) are still prevailing. For example, the government is captured by particular economic non-farm interests and is mainly advised by subordinated state agencies.

Furthermore, it is fair to conclude that we cannot yet explain all identified structural differences in detail, especially in regard to the influence of individual organizations. Nevertheless, we are confident that the robust differences we identified are not just artefacts due to limitations of the data, the ERGM estimation, or both. This confidence results from the fact that advanced goodness-of-fit statistics clearly reveal that the estimated ERG model can reproduce observed policy network relations. Accordingly, the described influence patterns are rather robust, at least at the aggregate level, given the calculated 95% density intervals (see fig. B.1). A very interesting endeavor for further research would be explaining the identified structural differences among countries, especially the reason for specific organizations exerting high

political influence in some but not in all countries. We consider our approach as a promising starting point in this regard.

Moreover, we have to admit that presented influence measures are crucially based on both our theoretical framework and our empirical strategy to measure constitutional power. While we provide robustness checks regarding our empirical network data we did not provide any test or robustness checks for our theoretical assumptions and measurement of constitutional power. However, first we argue that any empirical measurement of political influence depends on an explicit theory/model of political decision-making. Accordingly, the only robust test of derived influence measures would be the relative prediction power of competing models regarding observable political decisions. But, this endeavor is by far not trivial, especially since alternative models can lead to observationally equivalent results. Accordingly, the best test would be conducting an experimental study, e.g. shifting exogenously the political positions of individual stakeholder organizations and comparing theoretically predicted and empirically observed implied changes in final policy choices. However, conducting such an experiment for real political systems is rather difficult. Accordingly, we argue that derivation of theoretically based influence measures based on empirical network data is a promising approach to empirically assess political influence of stakeholders given the state of art in the literature. Secondly, please note that our main results, i.e. the identified relative influence structures of non-governmental stakeholder organization categories are rather robust across all constitutional scenarios. Only the relative influence of parliamentary groups significantly increased assuming constitutional decision-making follows a truly parliamentary system, that is political decision are made by majority voting in the parliament.<sup>39</sup>

Finally, the question remains in regard to what extent the observed participatory structures impact the overall political performance. For example, it is unclear whether the dominance of donor and research organizations induce efficient policy choices that match society's needs or whether these patterns imply policy biases at the expense of society's welfare. As explained above, although evaluating participatory structures is generally possible based on our theoretical framework (for example, see (Henning, Badiane, and Krampe, 2018)), this

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<sup>39</sup>Results for all constitutional scenarios are available from the authors.

is beyond the scope of this paper.<sup>40</sup>

Based on the evaluation of empirically observed participatory structures, it would be interesting to identify potential strategies to design future policy network structures that imply a higher political performance (i.e., reduce identified policy biases). In this regard, the undertaken ERGM-estimation can be used as a starting point. In particular, based on estimated marginal effects, we conclude that an active design of an optimal policy network structure is rather difficult in political practice. This follows since most identified important determinants of policy network tie formation are difficult to control exogenously. In particular, relational factors especially depend on organizations' social networking capacity. Hence, these factors are difficult to control exogenously because the process of social networking has not been fully understood yet. For example, the roles of the number and qualification of organizational staff or the organizational budget have not yet been sufficiently analyzed in this context. Furthermore, perceived political power is an important covariate that is also difficult to control exogenously; i.e., changing organizations' perceptions of political power or the perceived potential to generate political support is extremely limited. An interesting analysis of the emergence of political influence perceptions is given by (Heaney, 2014), who highlights "the roles organization play in multiple networks" as determinants of influence reputation. However, a question arises about the extent to which and how these multiple network roles can be actively controlled by an exogenous designer. In contrast to relational factors, institutional opportunity structures can be

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<sup>40</sup>However, a first intuitive assessment is given in the following. Following our expositions in the theoretical section in footnote 13, optimal influence structures imply that the relative political influence of organizations is just equal to their relative political knowledge. Under these assumptions, the relative political-knowledge advantages of donors in comparison to average private interest groups would correspond to a factor ranging between 1.7 and 4.5 for donors, while the corresponding factor for research organizations would range between 1.0 and 4.7. To the extent that real relative political knowledge advantages of donors and researchers do not match the identified relative informational influence, one has to conclude that the identified dominance of donor and research influence is suboptimal. Although we did not measure the knowledge capacities of individual stakeholders in detail, the calculated knowledge advantages appear rather high. In particular, there is convincing qualitative evidence suggesting that the relevance of donors' technical expertise in the CAADP process is rather questionable Mockshell and Birner (2015).

systematically controlled. For example, within the CAADP process, committee membership of specific farm organizations and CSOs has been promoted. However, our ERGM estimation results imply that institutional opportunity structures are hardly significant determinants of policy network tie formation.

Overall, we conclude that both the empirical evaluation of participation structures and the active design of optimal participatory policy processes are interesting and important topics for future research. However, more detailed theoretical and empirical analyses are needed. In particular, this includes a more detailed analysis of the extent that different organizational properties impact tie formation. Particularly, to manage social networking, the impact of political capacities, (such as political knowledge or representation of important society interests) have to be disentangled from organizational capacities (such as financial and personal resources). Moreover, understanding the formation of policy networks as the outcome of strategic behavior of a set of stakeholder organizations is essential for an effective design of policy networks. In this regard, dynamic models of network formation are very interesting methodological approaches (as suggested by Snijders, van de Bunt, and Steglich (2010) for example). However, beyond statistical models, game-theoretic models of network formation might also be important for better understanding of the social process of network formation (Jackson, 2008).

## 8.5 Conclusion

Although stakeholder participation is increasingly promoted in development politics, it is commonly observed that there is hardly any study that provides a quantitative measure of political influence. Starting with this observation, this study applied a comprehensive policy network approach to measure empirically the political influence of stakeholder organizations within the CAADP reform process in Ghana, Senegal, and Uganda. Based on comprehensive theoretical considerations, we calculated influence measures related to two different influence mechanisms: vote-buying and informational lobbying. For each mechanism, separate measures were defined and calculated empirically based on surveyed policy network data. ERGM specifications were estimated to assess the network generating process. Based on simulated networks, we

provided mean values and the highest density intervals for individual influence measures for all identified organizations.

Our central results are as follows. First, we found significant stakeholder participation in all three countries given aggregated power outflows ranging between 40 and 70%. Political participation of non-governmental organizations is dominated by international donors, followed by research organizations and industrial interest groups, as well as public agencies. Farmer interest groups and CSOs have only minor political influence. These findings support existing critiques about the CAADP process of excluding marginalized social groups, such as small-scale farmers and the poor (Randall, 2011). Interestingly, donor money not only seems to dominate classical vote-buying lobbying relations, but donors are also influential political experts next to research organizations. The high informational influence of research organizations appears to be in line with the concept of evidence-based policy processes promoted within the CAADP framework. Surprisingly, we found that research organizations are also strong vote-buying lobbyists, at least in Senegal and Ghana.

Second, in contrast to aggregated influence by types of organizations, individual influence measures are far less robust. Hence, although we found high differences in mean political influence between individual organizations, the corresponding 95% highest density intervals are large and overlapping for most organizations. Accordingly, based on our simulated network sample, we found only very few individual organizations that can be considered as significantly more or less influential than the average of all non-governmental organizations.

Further, our analyses imply that an active design of an optimal policy network structure is rather difficult in political practice. This follows directly from our ERGM estimate, which implies an important impact of transaction costs on tie formation in policy networks. The latter is mainly determined by relational factors, which especially depend on organizations' social networking capacity. Relational factors are difficult to control exogenously because the process of social networking has not been fully understood yet. In contrast to relational factors, institutional opportunity structures can be systematically controlled. For example, within the CAADP process committee, the membership of specific farm and CSOs has been promoted. However, ERGM estimation reveals

that institutional opportunity structures are hardly significant determinants of policy network tie formation. Moreover, the perceived political power and specific organizational categories (i.e., donor and research organizations) are important nodal and edge-specific attributes that determine tie formation for policy networks. These attributes, however, are also difficult to control exogenously in that changing organizations' policy goals, perceptions of political power, or the perceived potential to generate political support is extremely limited. Overall, we conclude that both the empirical evaluation of participation structures and the active design of optimal participatory policy processes are interesting and important topics for future research. We consider our provided policy network approach as a promising methodological starting point to contribute to these research topics.

Finally, despite the strength of the results of our analyses, it is also essential to recognize the limitations of the present study. The social processes behind the formation of policy networks may be more complex than reflected in the estimated models. In particular, there might be other relevant covariates, such as organizational resources including staff, budgets, or the age of an organization, that determine policy network relations among stakeholder organizations. Moreover, there might be more complex dynamic processes, such as sequential interaction between nodal and dyadic attributes and endogenous network statistics. For example, specific perceived organizational power might not only determine tie formation, but existing policy network ties might also impact perceived power estimates (Heaney, 2014). These dynamic processes could be captured in the estimation of a dynamic network model based on longitudinal data (Snijders, van de Bunt, and Steglich, 2010; Fowler et al., 2011). Compared to ERGM specifications that are estimated using cross-sectional data, these dynamic models will certainly give further insights into the understanding of formation and design of policy networks. However, in this study, our main aim was to theoretically derive consistent network indices that measure the political influence of individual stakeholders and to contrast the identified influence patterns consistently with typical ideal participatory structures politically proclaimed under CAADP. Furthermore, given the critique of empirical network studies, we wanted to apply a methodological approach that enables us to take care of the potential uncertainty of network influence measures de-

rived from empirical network data. In this respect, we consider the estimated ERGM specifications using cross-sectional data as an appropriate approach that allows us to draw statistical inferences on the robustness of our results.



## Chapter 9

# What Drives Policy Failure: Biased Incentives or Beliefs?

Until now, we have taken a more general view of both the economic system and the political system separately. Those systems are not separated in real policy systems. Therefore we now want to combine them. Political practitioners make the policy choices, so it is interesting to understand better their underlying beliefs and incentives that drive their decision making. This understanding is crucial since participatory and evidence-based policy processes are promoted in development policies and also in CAADP. Despite this promotion, sub-optimal policy decisions persist. Is it because of biased incentives, and would constitutional reforms help, as, Persson and Tabellini (2000) assume? Most political economy literature assumes perfect knowledge of the underlying transformation, what we capture with the combination of the PIF and GGF. This assumption does not hold, and therefore, it would be interesting to also capture the effect of wrong technological beliefs on the policy choice. The political actors make the decisions; therefore, they must have at least a partial, simplified mental model of how the policy choice transforms into outcomes.

In section 9.1, the stated policy space, as gathered from the surveys, of the different political actors and organizational groups are shortly described. In the following section 9.2, we will derive a framework allowing the estimation of individual policy beliefs and their impact on political performance through a collective political decision. Section 9.3 looks at the question of knowledge

versus incentive gaps and evaluates different strategies for improvement. A short conclusion is given at the end of this chapter.

## 9.1 Policy Space

The political incentives for the different policy goals, as introduced in section 4.4, are derived from the relative interest in that concern. These were collected in personal interviews with relevant political agents.

Figure 9.1 gives an overview of the distribution of the weights for the different concerns across the three countries. In general, the incentives are quite diverse for different organizations and concerns. For Senegal and Uganda, the range of values for  $Z2$  (poverty reduction) and  $Z3$  (provision of public goods) are much larger than for the other concerns. This is not the case for Ghana. For all countries, we observe mostly small interquartile ranges, denoted by the gap in the lines, when compared to the lower and upper quartiles. The median values, denoted by the single dot, are very similar for Senegal and Uganda. Poverty reduction ( $Z2$ ) and provision of public goods ( $Z3$ ) are the most important goals for Senegal and Uganda. In Ghana,  $Z4$  (export crop sector income) has the highest median weight, but  $Z1$ ,  $Z2$ , and  $Z3$  have very similar values. This might be an indicator for more specialized lobby groups, with Ghana being the most developed country in terms of democracy, according to the Polity IV index (Marshall, Jaggers, and Gurr, 2012).

Using the collected stakeholder interests, we derive weights  $\alpha$  for a social welfare function. We set the weights for the special sector interests ( $Z4$  and  $Z6$ ) to zero. We then take the average of the stated interests by the political actors as follows:  $\alpha_z = \frac{\sum_g X_{g,z}}{|G|}$ . Then we normalize the averages, so that the sum of the weights for the other goals except  $Z3$  ( $Z_{ps}$ ) equals  $1 - \alpha_{Z_{ps}}$ .

This is motivated by the way the interests in the policy goals were asked in the survey. They were asked in a nested fashion, with the top-level being the importance of public good provision ( $Z_{ps}$ ) versus the other goals, which then were in turn further subdivided. Table 9.1 shows the derived weights for the social welfare function.

In fig. 9.2, the distribution of the desired budget allocation to agricultural and non-agricultural investment policies of the interviewed organizations is

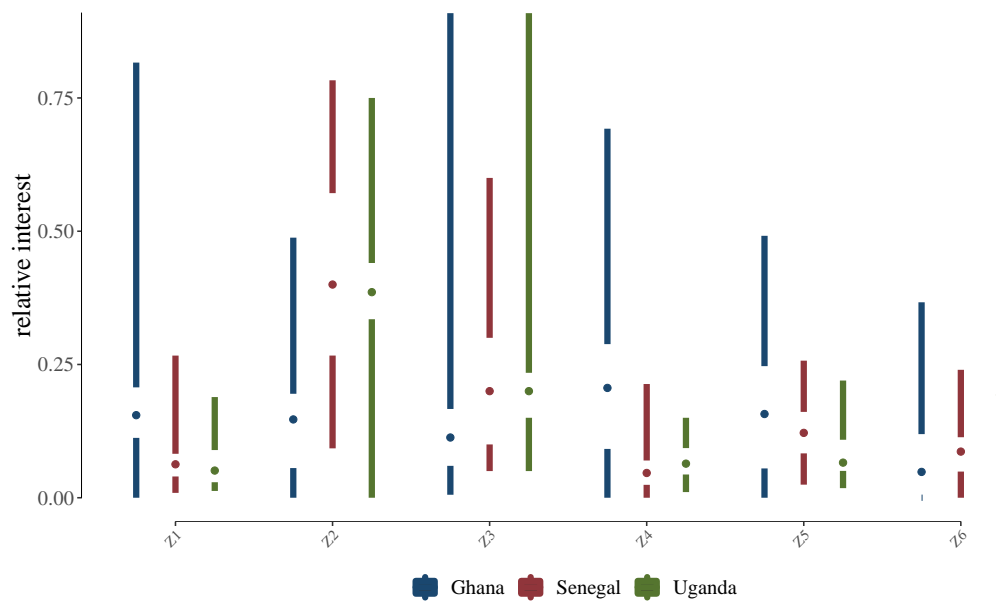


Figure 9.1: Political Incentives

Table 9.1: Social Welfare Weights

Country	Z1	Z2	Z3	Z4	Z5	Z6
Ghana	0.293	0.229	0.228	0	0.250	0
Senegal	0.084	0.519	0.238	0	0.158	0
Uganda	0.100	0.569	0.212	0	0.119	0

shown. The graph depicts the desired share of the total state budget. We observe a large share for non-agricultural policies (NA) in Ghana and Senegal. Looking at the median value for Uganda, a higher share for agricultural investment policies can be seen. In Senegal, the highest share for non - agricultural policies of the three countries can be observed, with the agricultural shares being mostly similar. Ghana has slightly lower desired shares for agriculture.

Figure 9.3 shows the stated policy positions in more detail, disaggregated to pillar level. Here we observe a similar variance across all pillars in all countries. The natural resources pillar (NR) in Uganda is the only exception.

The next step is to estimate actor specific PIFs using this data.

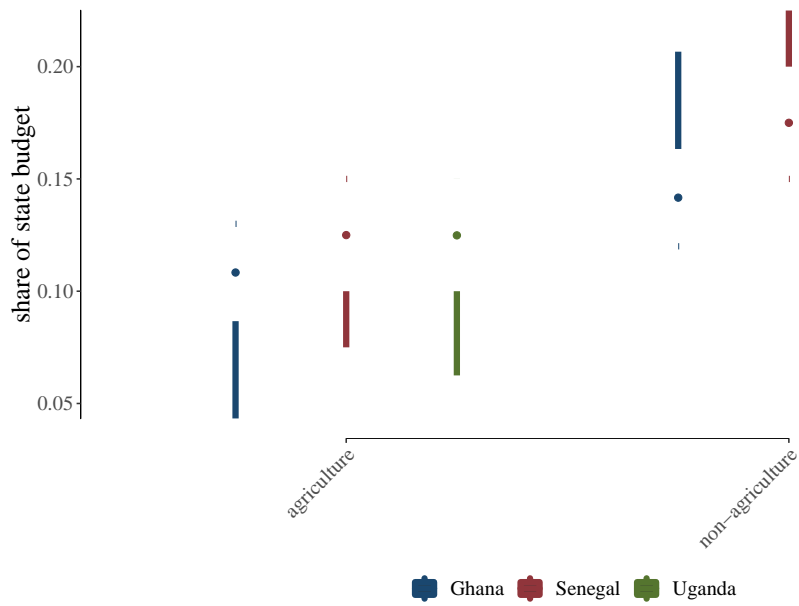


Figure 9.2: Stated Policy

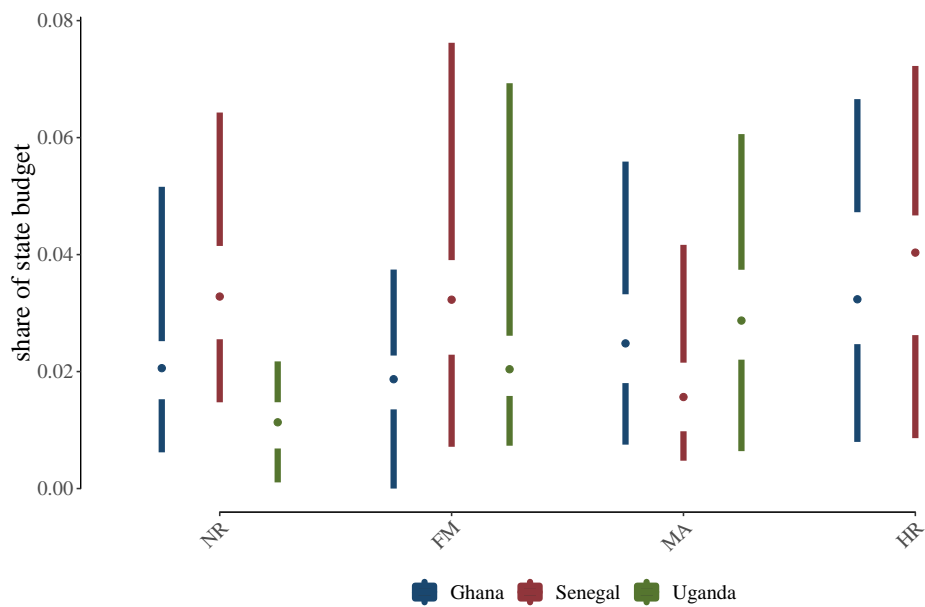


Figure 9.3: Stated Policy by Pillar

## 9.2 Estimating Individual Policy Beliefs

Thus far, we have looked at how to specify the economic system, the technical evaluation of policies in the economic system, and how to evaluate the political decision-making process. Now we want to combine this and fully use the developed CGPE framework.

In order to capture the implicit technological beliefs of the political actors, we will estimate individual PIFs. The estimation follows the same general procedure as described in section 5.2.2. In particular, instead of using the data of all actors at the same time, the estimation problem is reduced to only using the data of one specific actor at a time. This approach allows the extraction of the assumed technology into model parameters, based on the stated policy positions ( $\hat{\gamma}_g$ ), desired goal achievements ( $\hat{Z}_g$ ) and policy interests ( $\hat{\alpha}_g$ ) of actor  $g$ . The set of first-order conditions in eq. (5.20) are reduced to only include those for the actor under consideration. The results of the estimated empirical PIF are used as priors for the individual PIF estimation as well. The required GGF for the estimation is based on the selected model from section 6.2. We will ignore model uncertainty in this part, but it would mainly be a computational exercise, albeit significant, to include it as well.

Using the derived individual policy beliefs and individual interests, we can apply the optimization problem from eq. (7.4) to derive the individual policy preferences  $U_g(\gamma)$ .

As shown in section 2.2 a legislative bargaining model is needed, that combines the individual policy preferences  $u^G$  under given constitutional rules  $\xi$  into a collective policy choice  $\gamma^* = \Xi(u^G, \xi)$ . Using a modified Baron/Ferejohn legislative bargaining game, that combines the original model of Baron and Ferejohn (1989) with a Grossman/Helpman model (Grossman and Helpman, 1996), Henning and Hedtrich (2017); Christiansen et al. (2018) proofed that in the equilibrium of this game the final policy choice  $\gamma^*$  follows from the following mean voter theorem:

$$\gamma^* = \sum_g c_g \gamma_g \tag{9.1}$$

The weights  $c_g$  in eq. (9.1) can be derived from the modified game, but as shown in chapter 8 we can approximatively derive them from empirically

observed networks. This policy choice is then transformed into policy outcomes in the economic system. We apply the derived GGF and estimated PIF from chapter 5 for this.

Finally, we can evaluate the derived outcome as described in section 4.9. This framework is shown in fig. 9.4.

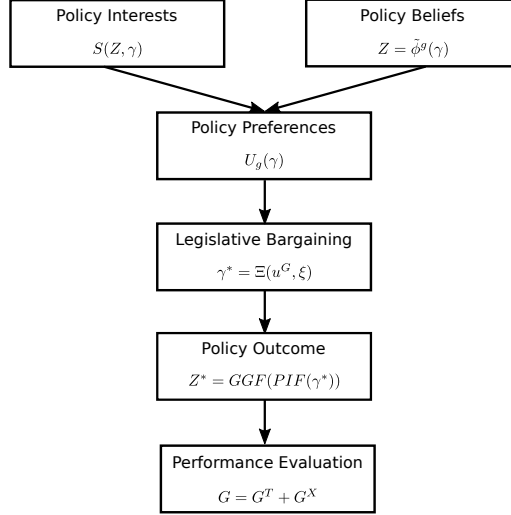


Figure 9.4: Framework: Individual Policy Beliefs

We can quantify the total performance gap and disentangle it into knowledge and incentive gaps. This is done by applying the loss function (eq. (4.20)) as defined in section 4.8 to compute the total, knowledge and incentive gaps (see section 4.9). In this framework, this is done by changing the individual policy interests or policy beliefs and replacing them with the “true” versions. Using this, we can evaluate different strategies for political therapy. We can simulate the effect of different constitutional reforms. We can measure the impact of participation of stakeholders in the policy process by using the derived influence measure from chapter 8.

In order to analyze the individual beliefs further, it is interesting to find groups of organizations that share similar technological beliefs. Finding the groups directly based on the estimated parameters  $\chi_g^*$  is hard since the parameter vector includes about 500 parameters. Therefore, based on the estimated parameters, we calculate  $[\frac{\partial Z}{\partial \gamma}]$ , which is a linear approximation of the political technology. In the countries we have nine or ten policy instruments, therefore the resulting matrix has a size of either  $6 \cdot 9 = 54$  or  $6 \cdot 10 = 60$  entries for each actor  $g$ . We interpret this approximation as the policy belief of a political ac-

tor. In order to be able to visualize and explore the belief space, we conducted a factor analysis. As we are right now not interested in using the factors to explain the underlying technology further, we fixed the number of factors to two, even though the different tests for the number of factors suggest to use a higher number of factors. Using the computed factor scores, we conducted a cluster analysis to find groups with similar technological beliefs. Here we preferred a four cluster solution.

Beyond the descriptive differences, it is interesting what these different beliefs and incentives mean in terms of political performance. We use the individual beliefs and incentives of actor  $g$  as the “truth” and then compute for each actor  $i$  the performance gaps as well.

This framework builds upon the previous work and applies the previously derived optimization models in GAMS: The factor and cluster analysis is done in R and loads the estimated parameters using the *gdxrrw* package from a gdx file. The results are also stored in a gdx file for further analysis done in GAMS. The complete exchange and analysis in R are automated, where only the appropriate script file has to be called with no further manual intervention.

### 9.3 Knowledge or Incentive Gaps

Applying the derived framework in section 9.2, we are now able to measure political performance. We use the derived social welfare weights from section 9.1 and as the “true” technology the selected model from section 6.2. This selection is to our understanding the closest we can get to the actual real technology.

The results are shown in fig. 9.5. The performance gaps are shown as the share of the status quo budget that could have been saved with an optimal allocation to achieve the same welfare level as with the decision derived from the mean voter rule. In all three countries, notable performance gaps exist, with Senegal having the largest. In Uganda, the interaction effect of biased incentives and wrong technological beliefs can be observed, as the total performance gap is smaller than the knowledge gap. The knowledge gaps are significant in all three countries, and they are also larger than the incentive gaps.

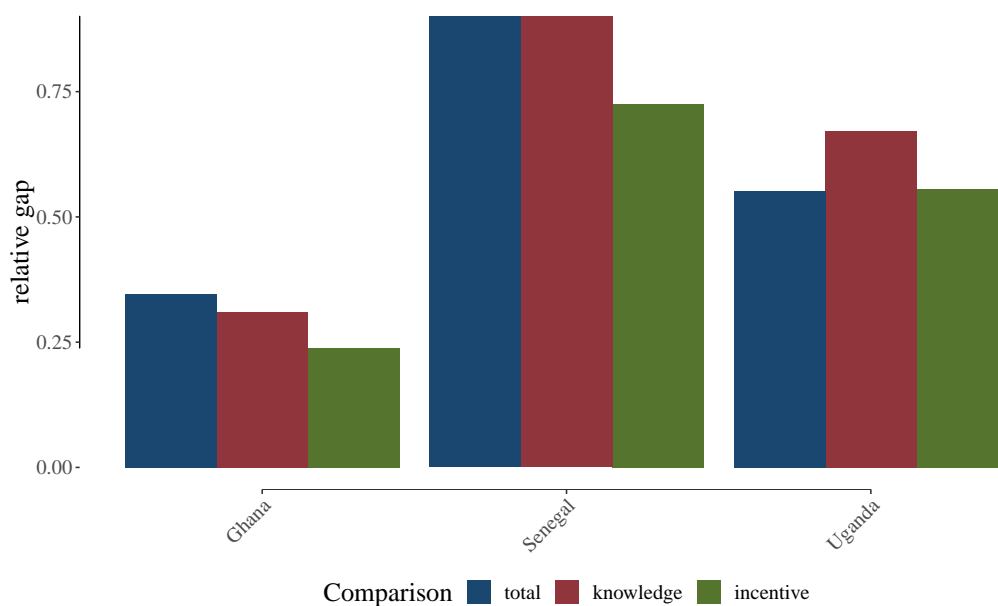


Figure 9.5: Political Performance Gaps

### 9.3.1 Participation a Successful Political Therapy?

Having seen that we have significant performance gaps in all three countries, it would be interesting to see if constitutional reforms or increased participation of stakeholders help in solving the problem.

We defined different constitutional reform scenarios: *PRES*, *DUO*, *DUOL*, *MOFA*, *MOFAPARL* and *PRESPARL*. In the constitutional scenarios, different actors of the legislative and executive groups have different levels of power, determined by assumed agenda-setting power and relative influence (see footnote 25). The weights  $c_g$  are derived from formal decision-making rules using Banzhaf indices (Banzhaf, 1965; Coleman, 1971). The constitutional scenarios are used for a technical, what-if analysis.

Table 9.2 shows the aggregated power on the organizational category level, that is used in the mean voter decision rule. The *EQUAL* and *EXPERT.LOBBY* columns denote two different participation scenarios. In the *EQUAL* scenario, all actors have the same weight  $c_g$ , while we use the empirically derived weights in the *EXPERT.LOBBY* scenario.

Figure 9.5 shows the performance gaps as the share of the status quo budget that could have been saved with an optimal allocation to achieve the same welfare level as with the decision derived from the mean voter rule. In all



Country	type	PRES	DUO	DUOL	MOFA	MOFA PARL	PRES PARL	EQUAL	EXPERT .LOBBY
Ghana	EXEC	1.00	1.00	0.81	1.00	0.74	0.74	0.13	0.42
	LEG	0.00	0.00	0.19	0.00	0.26	0.26	0.04	0.02
	PUBAG	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.07
	DONOR	0.00	0.00	0.00	0.00	0.00	0.00	0.15	0.15
	RESEARCH	0.00	0.00	0.00	0.00	0.00	0.00	0.15	0.12
	IG:FARM	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.04
	IG:IND	0.00	0.00	0.00	0.00	0.00	0.00	0.15	0.08
	CSO	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.03
iNGO	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.08	
Senegal	EXEC	1.00	1.00	0.79	1.00	0.79	0.79	0.15	0.47
	LEG	0.00	0.00	0.21	0.00	0.21	0.21	0.02	0.01
	PUBAG	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.05
	DONOR	0.00	0.00	0.00	0.00	0.00	0.00	0.15	0.11
	RESEARCH	0.00	0.00	0.00	0.00	0.00	0.00	0.22	0.17
	IG:FARM	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.03
	IG:IND	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.05
	CSO	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.05
iNGO	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.02	
Uganda	SUPRA	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.04
	EXEC	1.00	1.00	0.79	1.00	0.79	0.79	0.16	0.29
	LEG	0.00	0.00	0.21	0.00	0.21	0.21	0.05	0.02
	PUBAG	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.14
	DONOR	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.11
	RESEARCH	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.07
	IG:FARM	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.11
	IG:IND	0.00	0.00	0.00	0.00	0.00	0.00	0.23	0.19
CSO	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.02	
iNGO	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.05	

Table 9.2: Aggregated Decision Power

three countries, notable performance gaps exist. Across the three countries, Ghana still has the smallest gaps, while Senegal has the largest gaps. Across all scenarios, the total performance gap in Uganda is smaller than the knowledge gap, and about the same as the incentive gap. Therefore in Uganda, it appears that the biased incentives improve the political performance, given the wrong technological beliefs. For Senegal, we can see the same level of total and knowledge performance gaps across all scenarios; this is because the PIF is only a local approximation.

The constitutional scenarios, denoted by *PRES* to *PRES**PARL*, have little influence on the political performance in Ghana, Senegal, and Uganda. The only exception being the *MOFAPARL* scenario in Uganda, where at least the incentive gap can be reduced. Beyond the formal constitutional scenarios, the

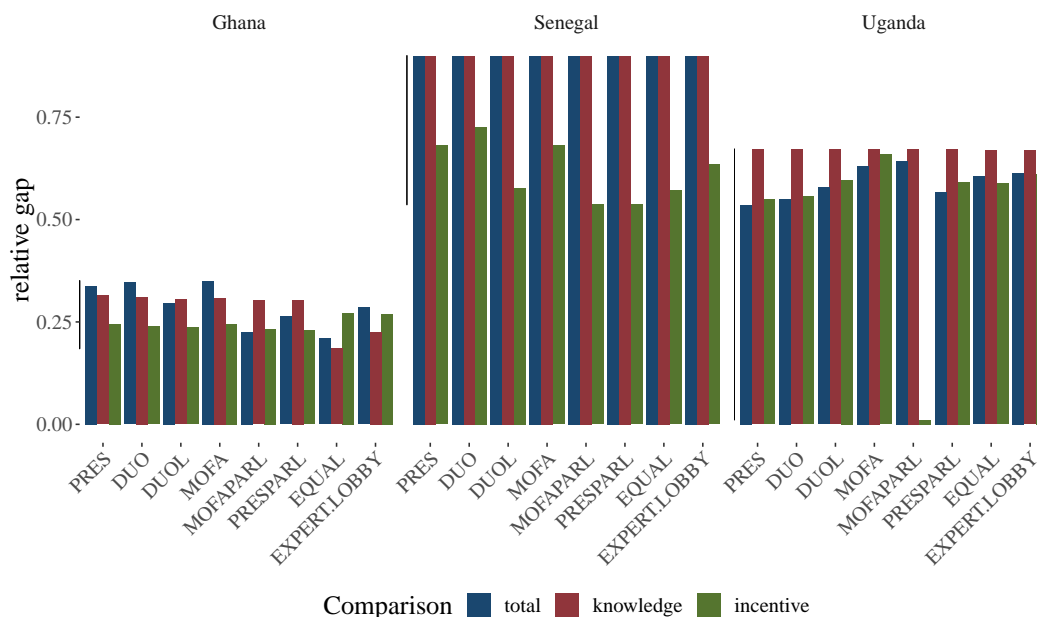


Figure 9.6: Therapy: Political Performance Gaps

*EQUAL* scenario shows the resulting performance if all organizations had the same influence. In Senegal and Uganda, no real difference to the other scenarios can be observed. The total performance and knowledge gap are a bit smaller in Ghana, while the incentive gap is larger than in the other countries. There does not appear to be a substantial difference when comparing these results with the ones for the empirically observed influence measure, denoted by *EXPERT.LOBBY*. Looking at table 9.2, we see that in the empirical case, all organizational types have at least some influence in the political decision process. The *EXPERT.LOBBY* and the *EQUAL* scenario show that simply increasing stakeholder participation does not improve political performance. Therefore beyond the result from chapter 8 that the design of efficient participation structures is hard, participation also does not seem to help.

### Model Uncertainty in Political Modeling

The empirically observed influence measure, denoted by *EXPERT.LOBBY*, comes with its own source of uncertainty, as has been shown in section 8.3. We used the sample of 10000 influence vectors from the previous chapter and calculated the performance gaps for each of them. Figure 9.7 shows the resulting performance gaps, again measured as the share of status quo budget

that could be saved. The results show some variance in the performance gaps, but the general ordering is the same as before. The results again show the limitation of the estimated PIF, with no variance, for example, for the total performance gap in Senegal.

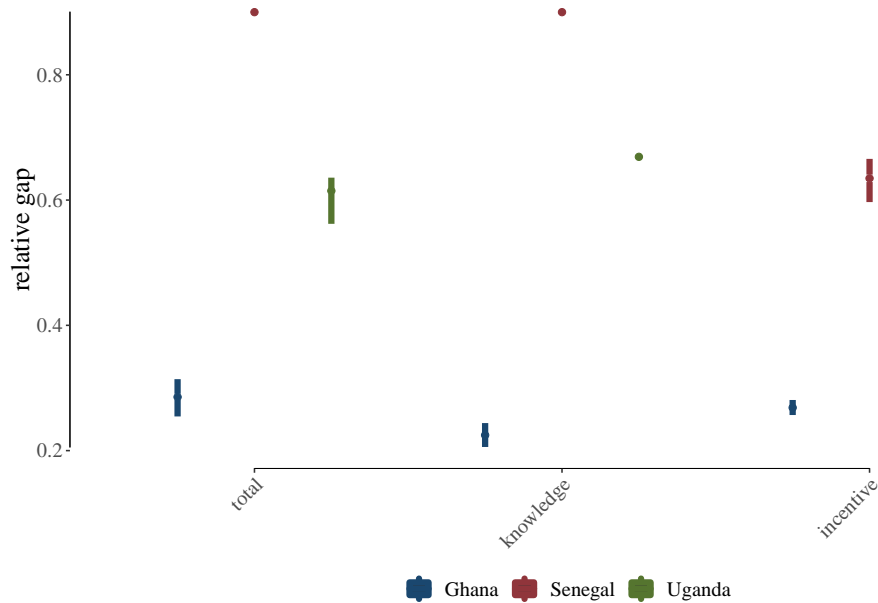


Figure 9.7: Political Performance Gaps

### 9.3.2 Individual Beliefs

After having seen that knowledge gaps are a significant factor in the total performance gaps, it is interesting to understand the underlying beliefs a little bit better.

As described in the framework (section 9.2), individual PIFs have been estimated for all three countries, but for the sake of brevity, only exemplary results for Senegal are shown.

For example, in Malawi, the actors had a somewhat unrealistic belief that they can achieve tremendous technical progress values, over 20% in some cases (Henning et al., 2017). Figure 9.8 shows the predicted  $\Delta tp$  levels for Senegal under the status quo policy, with the bars denoting the different values of the stakeholders and the light gray line showing the predicted value under the estimated and selected expert PIF, the best approximation of the true technology. There are substantial differences for many sectors, though, the

variance is small for some. This shows that different actors have different technological beliefs in mind. For most sectors, the individuals expect a larger value, often significantly larger, even though the beliefs are not as extreme as in Malawi. There are some extreme examples, like the telecommunications sector (*atelcom*) or the glass manufacturing sector (*aglass*).

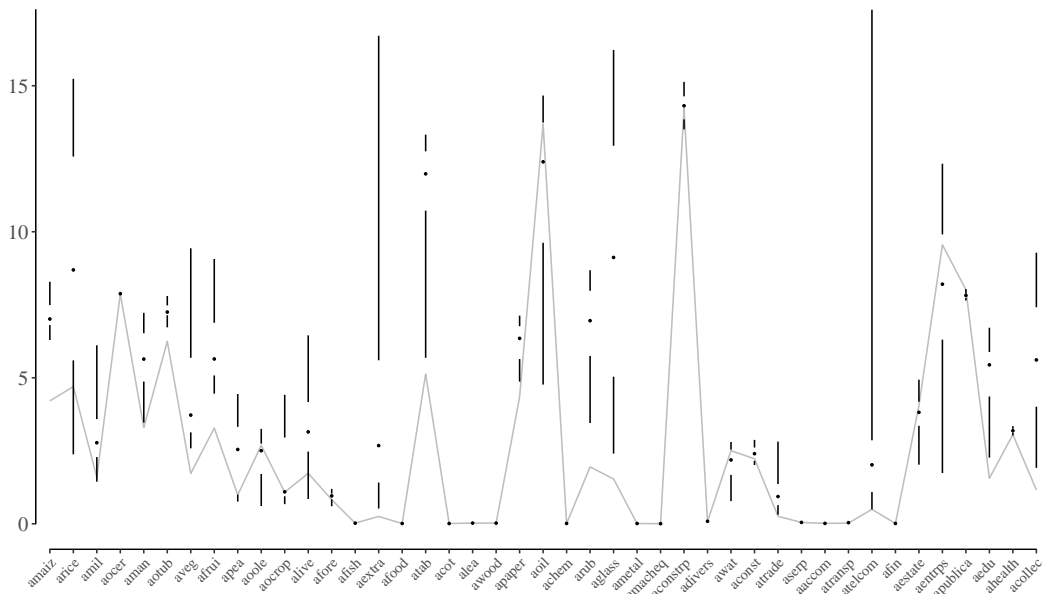


Figure 9.8: Political Technology: Achieved  $\Delta tp$  under status quo Policy - Senegal

### Belief Analysis

The next interesting step is to check if we can find groups with similar technological beliefs. This is done using a cluster and factor analysis, as described in section 9.2. Figures 9.9 to 9.10 show the results of the factor and cluster analysis. Tables B.1 to B.3 contain the complete lists of organizations along with their organizational type. In all three countries, there is no clear separation between different organizational types. Actors of the research and executive organizational groups tend to be in the same cluster. We find a clear separation between the clusters, however.

Figure 9.12 shows the desired budget allocation to the different pillars relative to the status quo allocation. In all three countries, we can find pillars, where both in a cluster itself and between clusters, there is only a little vari-

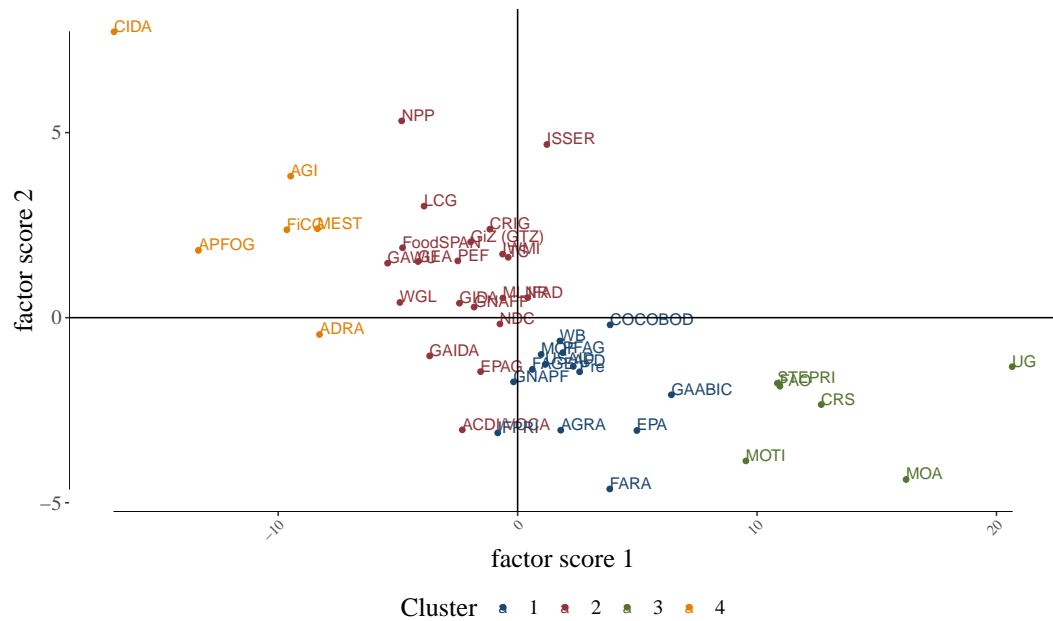


Figure 9.9: Factor Scores: Ghana

ance in the desired budget shares: For example, the FM pillar in Ghana or the non-agricultural pillar in Senegal. Of the three countries, Uganda has the smallest variances across the different pillars, while Ghana has the largest, and Senegal is in the middle. For most pillars, there is little variance between the different clusters with the HR pillar in Ghana being an exception. The non-agricultural pillar in Uganda is another example, to a lesser extent.

### Individual Performance

So far, we have assumed that our estimated expert PIF is the truth, but on a technical level, it is interesting to see what happens with the gaps if we use the individual actors PIFs as the “true” one.

In figs. 9.13 to 9.15 the resulting gaps are shown, derived using the individual actors beliefs and incentives as the “truth”. The bars denote the average gap for the comparison group under the truth group. The gap is shown as the share of the allocated budget in the status quo. We observe notable differences across the countries both in the scale of the gaps and if biased knowledge or incentives mainly drive the gap.

In all three countries, we observe much smaller knowledge gaps compared to the results from section 9.3.1. In Senegal, the smallest gaps are observed with



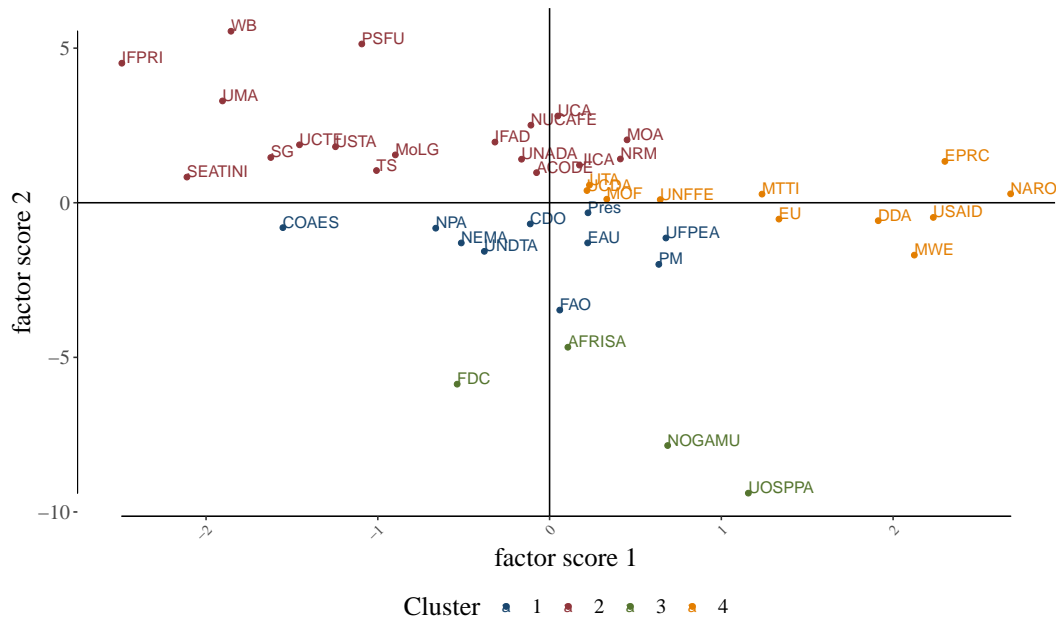


Figure 9.11: Factor Scores: Uganda

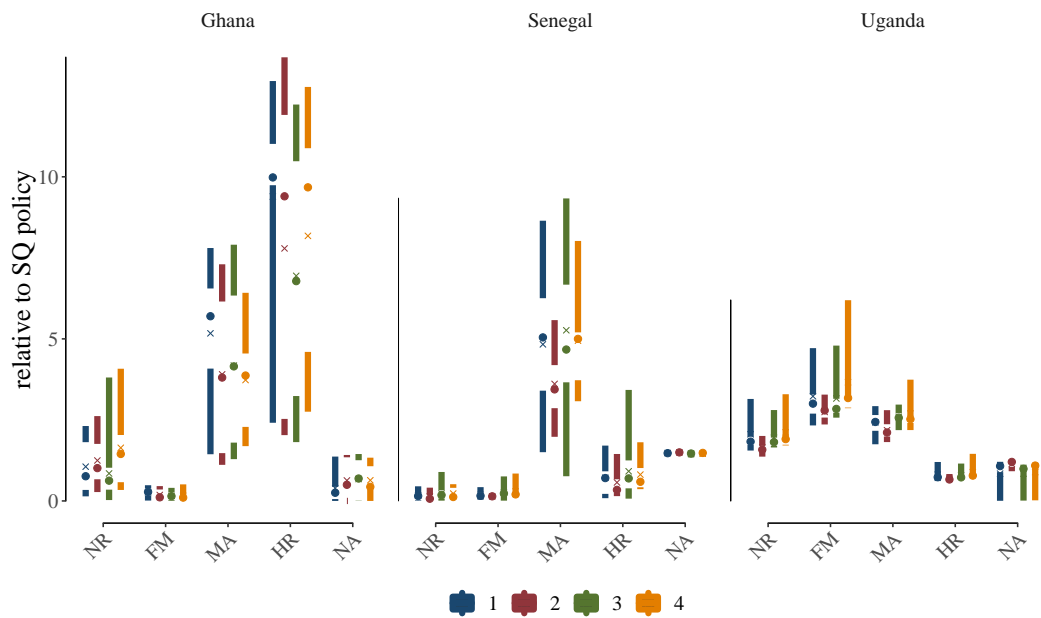


Figure 9.12: Policy Choice: Pillar Budget per Cluster

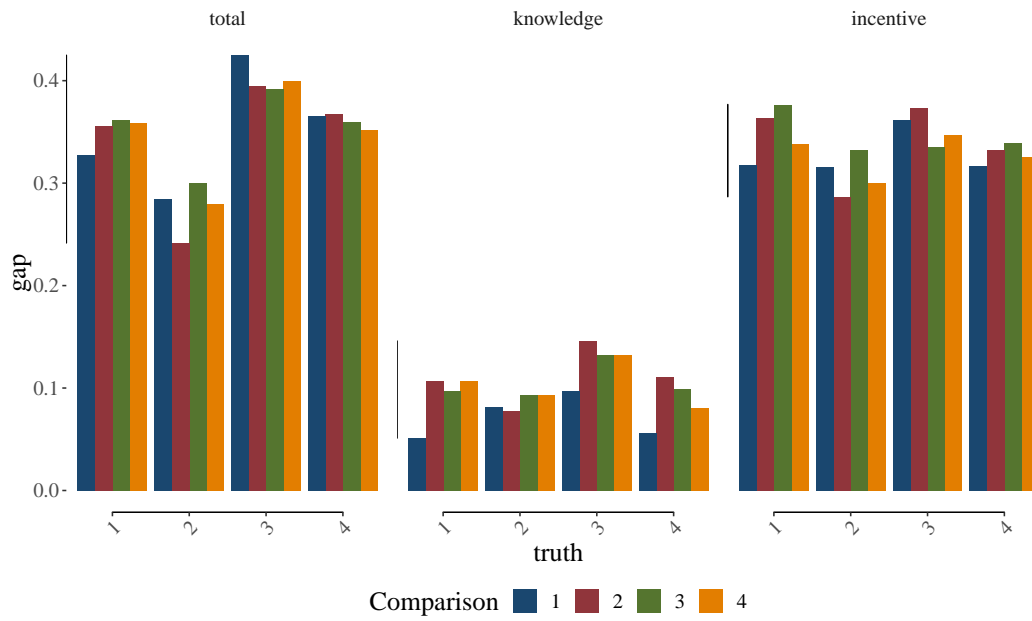


Figure 9.13: Cluster Gaps: Ghana

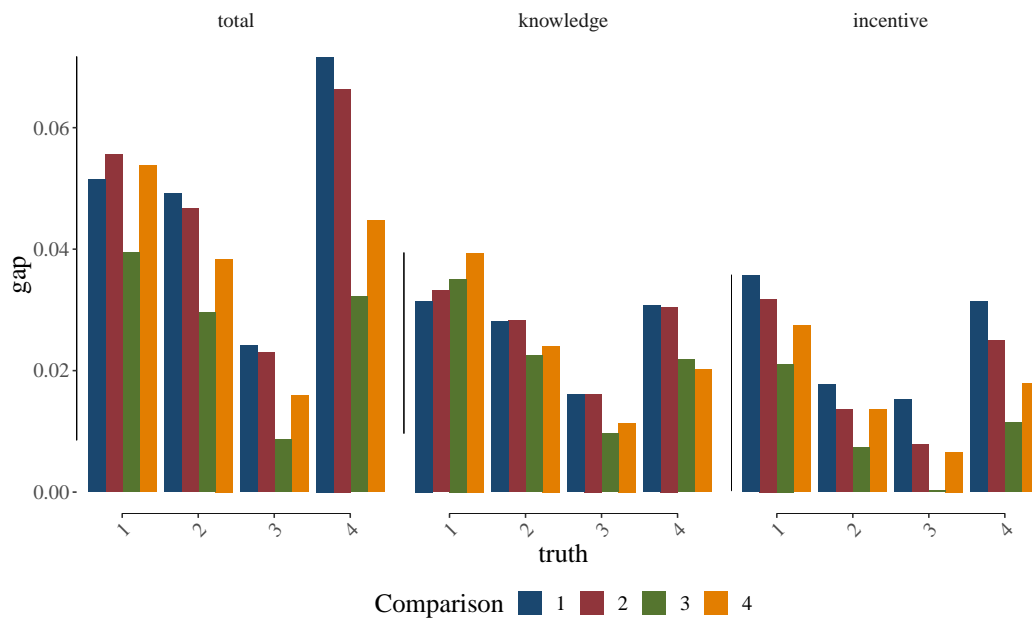


Figure 9.14: Cluster Gaps: Senegal



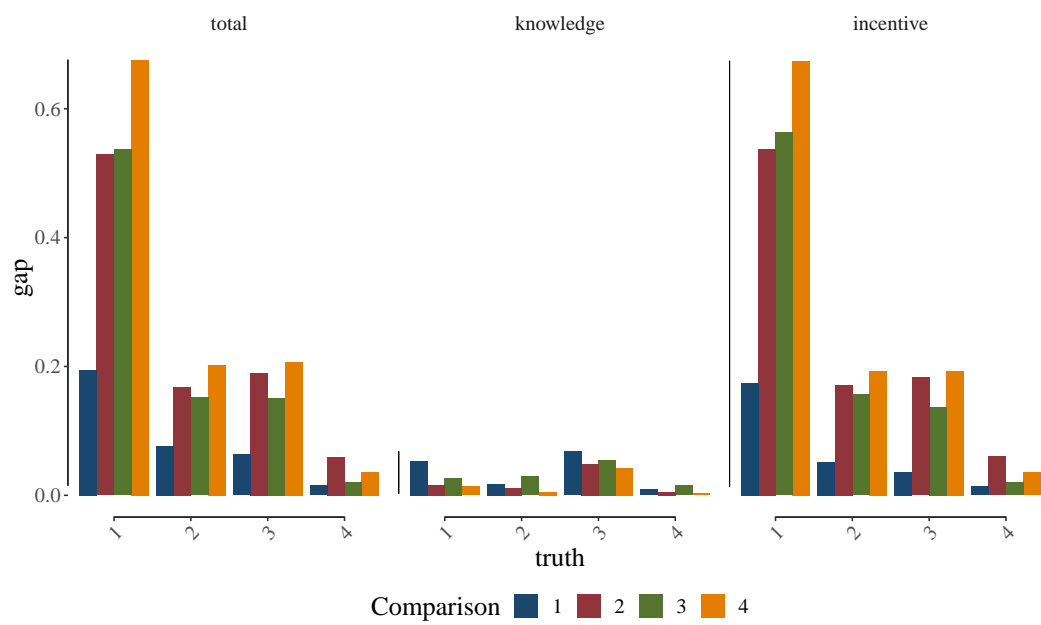


Figure 9.15: Cluster Gaps: Uganda

## 9.4 When Science meets Society: Potentials of Transdisciplinary Research

So where does this lead to when neither constitutional reforms nor increased participation help in reducing the political performance gap, as the results indicate. Figure 9.16 might contain a clue for this problem. Here we can see the policy positions derived in different scenarios, the original position of the stakeholders denoted by *stated*, the optimal position derived when the empirical PIF is the “true” technology, denoted by *science*, and the optimal position derived when the expert PIF is the “true” one, denoted by *combined*. The shown positions are based on a factor analysis of the individual  $\gamma$  vectors. We can see that in all three countries, there is a clear separation between the *stated* and the *science* scenario. The *science* scenario can be thought of as the modeling world, while the *stated* scenario represents the practitioners’ world. There is a clear cleavage between the two worlds, and we can confirm the common assumption that scientific policy analysts and political practitioners are separated in reality (see, for example, Geurts and Joldersma (2001)).

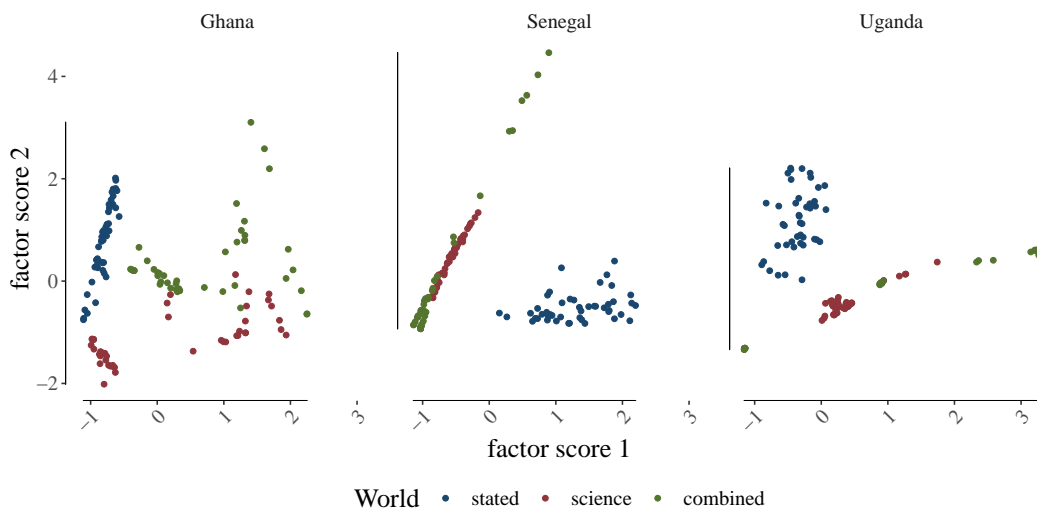


Figure 9.16: Political Worlds

Getting out of this dilemma is not easy. As changing constitutional rules, or increasing participation can only shift the position inside one world, but not get into another world. Combining the knowledge of the two different worlds using a transdisciplinary approach might prove fruitful. This combination

would then result in a third world, denoted by *combined*.

## 9.5 Conclusion

In this chapter we have shown that we can use the developed modeling and estimation framework, as described in chapters 4 and 5, not only for understanding the technological transformation process better, which was more the focus of the two previous chapters but also for understanding the political decision better. Applying the framework, we can disentangle the drivers behind persisting policy failure in the context of CAADP.

This application allows us to transform implicit mental models of actors into a quantitative model representing those beliefs. Our analysis shows that, contrary to what the political economy literature (Persson and Tabellini, 2000) often assumes, both biased incentives and wrong technological beliefs have a significant effect on political performance. However, improving political performance, as both increasing participation and constitutional reforms do not truly help, is a challenge. In this regard, a transdisciplinary approach should be applied, that connects the science world with the society's world.



# Chapter 10

## Summary and Outlook

Policy analysis is defined as the scientific evaluation of policy impact. It is, however, important to analyze not only the technical transformation but also the political decision process that determines the final policy choice. Therefore, a political economy equilibrium framework is required for comprehensive policy analysis, as presented in chapter 2.

Limited data is a significant challenge for all policy analysis. This challenge includes not only limited observational data but also limited information on political transformation and decision processes. This difficulty results in model uncertainty, which is mostly ignored in policy analysis so far (Marinacci, 2015; Manski, 2018). There are two main aspects to model uncertainty. The first aspect, from a decision-theoretic point of view, is ignoring model uncertainty leading to inefficient policies by selecting a single model. The derived policy choice leads to a loss of expected utility. Model averaging using the expected utility framework would lead to a higher utility. The second aspect is that political decision-makers are also faced with model uncertainty in political practice. They deal with this by forming simple mental models of how policies translate into outcomes, policy beliefs. Model uncertainty and private knowledge (beliefs) are considered as twin notions (Marinacci, 2015). As shown in chapter 2, these beliefs can be biased, and therefore, they are a second source for inefficient policy choices, which has so far been mainly neglected in policy analysis. The more prominent source in classical policy analysis are biased incentives of decision-makers (see, for example, (Persson and Tabellini, 2000)). Therefore we need to disentangle the influence of biased beliefs and incentives

on political performance gaps.

This leads to the following challenges when implementing such a political equilibrium model with model uncertainty. Including model uncertainty into the technical modeling process is technically complex and requires large amounts of computational resources to compute large samples. Beyond this technical handling of model uncertainty, we also need to include policy beliefs into the modeling framework explicitly. In order to be able to measure the impact of biased incentives and beliefs on political performance, we need a quantitative model that allows just that. In addition, the developed framework needs to be able to evaluate different strategies for political therapy, like constitutional reforms or increased participation of stakeholders.

In this thesis, we do this by deriving computational tools and implementing them into the CGPE framework. The CGPE consists of four main modules covering both the economic and the political system: Policy Impact Function Module, Economic Equilibrium Module, Political Belief Formation Module, and Political Decision Making Module (see chapter 3).

We have developed a distributed simulation tool, DST, that allows the computation of large simulation samples. The computational work is split into smaller units and distributed across multiple machines and computed in parallel (section 3.5). These large simulation samples are, for example, required to measure the impact of different model assumptions, like production or trade elasticities in a CGE. This tool enables the application of the metamodeling approach, for which a more complex model like a CGE is approximated by an explicit analytical form (section 3.4). We developed a framework for estimating sector-specific PIFs, functions that transform a given policy choice into changed factors of economic growth. This derivation is done in a Bayesian estimation framework, combining observational with expert data in a novel transdisciplinary research approach. This approach allows the estimation of about 500 parameters of the PIF using only limited data. Some background on Bayesian estimation techniques is given in section 3.3. Finally, the developed framework allows the estimation of individual policy beliefs and to quantitatively disentangle political performance gaps caused by biased incentives and beliefs.

In the second part of this thesis, the developed computational tools, and

CGPE approach are applied empirically to the case of CAADP in three African countries, namely Ghana, Senegal, and Uganda.

Chapter 4 gives a short introduction to the study background. The empirical applications were undertaken as part of the PEBAP project. In the CAADP, most African countries committed to allocating about 10% of the national budget to agriculture in order to achieve a 6% annual sector growth rate. This is motivated by the fact that the rural population is still mostly poor and dependent on agriculture. The chapter then introduces the empirical specification of the GGF, capturing economic growth to outcome relations, and PIF, capturing the transformation of policies into economic growth. The following chapter, chapter 5, demonstrates how the GGF can be derived and the PIF be empirically estimated. The GGF is derived as a metamodel of a CGE. The PIF is estimated using a Bayesian estimation framework by combining observational, historical data with expert data. In chapter 6, a framework to handle model uncertainty in the technical modeling part is introduced. This includes both structural uncertainty, uncertainty about assumptions of the model, and parameter uncertainty, uncertainty in the estimated values of the models. Structural uncertainty is handled by a combination of an extensive simulation study with metamodeling. An MCMC sample of the estimated parameters derived by applying the  $DE - MC_Z$  algorithm is used to take estimation uncertainty into consideration.

This framework is used in three empirical applications.

The first application is about the technical transformation of policies into outcomes (chapter 7). It tries to answer the question in which sectors should investment happen to reduce poverty; that is, what is a key sector? It looks at the detailed policy choice in a similar way, that is, which policies should be chosen. What is a key policy? The final step in this application is then the derivation of optimal policies from a technical point of view. In all these steps, model uncertainty is explicitly incorporated.

The second application focuses on the political system. In particular, we derived a theoretical framework that allows the measurement and evaluation of participatory policy structures. Using observed networks, we derived separate measures for lobbying and informational influence. As the observed networks are only a single observation at a specific point in time, we estimated the

network generating process by applying an ERGM. Based on the estimated process, we applied MCMC simulations to show the influence of uncertainty on the influence measures.

The third application combines the previous applications and asks the question, “What Drives Policy Failure: Biased Incentives or Beliefs?” In order to do this, we have estimated individual policy beliefs and, based on a modified Baron-Ferejohn legislative bargaining game, explicitly incorporated them into the political decision process. This not only allows the quantification of political performance gaps (see section 4.9) but also the evaluation of different political therapy strategies.

Summarizing central results of these applications, we show that:

Identifying key sectors based on partial concepts like CGE elasticities might be misleading, as they do not take the necessary generation of economic growth by policies into account (section 7.2.1). Under model uncertainty, a broad range of values for the key sector and key policy indicator is observed. No clear dominance of a sector can be observed within a country and across the countries. This missing dominance is especially true for optimal policies, as the results can dramatically change when applying model averaging. In Senegal, for example, model selection leads to a policy dominated by non-agricultural investments. Applying model averaging, that is maximizing the expected utility, the primary budget share of investment policies shifts to agricultural policies.

The results from chapter 8 show that individual influence is highly uncertain, but some patterns among organizational types can be found. Donor and research organizations dominate the participatory research process, while farm interests and civil society organizations have only a negligible influence. On a theoretical level, we derived a framework that allows the evaluation of formal, as determined by constitutional scenarios, and informal influence. Using this, we show that the design of stakeholder systems is challenging since relational factors mainly determine the underlying network structures.

In the last application, we show that actors have different policy beliefs (chapter 9). These varying beliefs lead to clear and significant knowledge gaps, showing that they are a factor why inefficient policies are being chosen. Biased incentives are also important, and as shown, biased incentives and knowledge are not necessarily additive, there are interaction effects between them. The



developed framework allows the evaluation of proposed strategies to alleviate the observed performance gaps. We have simulated different constitutional scenarios and shown that the performance gaps do not change significantly. A second strategy is the increased participation of stakeholders, and we can show that this does not help either. This means that the design of optimal participation structures is not only complicated (see chapter 8), but also that it does not really help. Transdisciplinary research, an interaction between science and society, can be thought of as a way out. As a step in this direction, we developed a Bayesian estimation framework that connects implicit stakeholder knowledge with statistical data.

The complete project of implementing all the necessary parts resulted in a small to a medium-sized software project. During the implementation, different tools and languages have been used and combined into a more elaborate tool. The project is structured around the core steps that are mostly implemented in GAMS. R has been used for the network estimation (see chapter 8), smaller analysis parts like the factor analysis and the visualization of the results. The MCMC sample generation is implemented in Julia. Julia provided both the required performance, language constructs, and structures that made it easy to implement. For the vast number of simulations required due to the inclusion of model uncertainty, a custom simulation tool, DST, has been developed. The DST sits between lower-level language support of concurrent programming and more sophisticated tools like, for example, BOINC<sup>1</sup>. All these different tools are connected by little scripts in those languages, as well as in Ruby, PowerShell, or Ansible. These scripts automate the execution and setup of the required steps. Therefore, allowing one to focus more on the actual development of the model and not having to worry about managing everything manually. As shown by Open Science Collaboration (2015), reproducibility is an integral part of research. Therefore this structuring was made with this goal in mind. In order to improve reproducibility, all code is stored in a version control system. Additionally, the code has been refactored, so that common parts between countries are extracted and shared between them. The code is now in a state where it only requires little effort to include new data or to do the same analysis for a different country (the more significant effort being in conducting

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<sup>1</sup><https://boinc.berkeley.edu/>

the required surveys and collecting the data).

As pointed out in chapter 2 and shown by the empirical analysis, we need approaches that go beyond classical approaches. This means we need approaches that model the complete system combined out of the political and economic system. These approaches also need to handle model uncertainty on a technical level, but also on a conceptual level, as the resulting policy beliefs of actors drive the policy decision. They can be summarized under the term “Policy Analytics” (Daniell, Morton, and Insua, 2015; De Marchi, Lucertini, and Tsoukiàs, 2016; Tsoukias et al., 2013). They connect different scientific disciplines like computer science, economics, and policy analysis, but also society and science in transdisciplinary research approaches.

Recapitulating that the primary source of model uncertainty is limited data, that is encapsulated in highly uncertain and decentralized knowledge. An obvious avenue for improvement is using more data that is becoming available due to new technological advances. This data is often highly unstructured and of large volume, which classical approaches can not handle. This can be summarized under the term “big data” and requires applying and developing new computational methods. Only using more data will not be enough, as the studied processes are highly dynamic and complex, and therefore, we need theory-based models to understand them better and be able to develop well-founded intervention strategies.

As knowledge is highly decentralized, we need processes that capture the knowledge aggregation. So far, we applied the Friedkin and Johnsen (1990) model for belief updating/learning in networks. In the future, it would be interesting to apply more advanced models or model belief updating in an agent-based setting. This would allow modeling actors more realistically, as for example rule of thumbs can be easily integrated.

As shown in the last empirical application, knowledge aggregation is only a partial solution, as we need a way to generate new knowledge in an interactive exchange between science and society. Political practitioners need to be informed about the uncertainty around the results derived based on the CGPE. Therefore the results should not be communicated or used as the absolute truth, but instead as advice of moving into that direction and thereby allowing step-wise policy learning. In return, the models can learn from new

observations and adapt to new framework conditions. Work has been started on an interactive toolkit that facilitates this exchange, where the goal is to include the learning of stakeholders from the model, of models from stakeholders, and interactive learning between those two (see Hedtrich et al. (2018); Hedtrich (2018)).



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# Appendix A

## Code Samples

### A.1 Empirical PIF

Listing A.1: models/empirical.gms

```
1  sets
2    PIF_EMP_ENTROPY_PARTS /1*8/
3  ;
4
5  parameters
6    pif_emp_p_tp(AAG, YEAR)
7    pif_emp_p_bud_mu(AAG, POL_INST)
8    pif_emp_p_budshare(POL_INST, YEAR)
9    pif_emp_p_pae(YEAR)
10   pif_emp_p_bud_rho
11   pif_emp_p_gamma_non_agr(YEAR)
12   pif_emp_p_tp_exp_logistic_a(AAG)
13   pif_emp_p_tp_exp_logistic_b(AAG)
14   pif_emp_p_elast_max_logistic(AAG)
15   pif_emp_p_budshare_up(POL_INST, YEAR)
16   pif_emp_p_budshare_lo(POL_INST, YEAR)
17   pif_emp_entropy_weights(PIF_EMP_ENTROPY_PARTS)
18   pif_emp_delta(PIF_EMP_ENTROPY_PARTS)
19  ;
20
21  variables
22    PIF_EMP_V_ENTROPY
23  ;
24
25  positive variables
26    PIF_EMP_V_BUDSHARE(POL_INST, YEAR)
27    PIF_EMP_V_GAMMA_NON_AGR(YEAR)
28    PIF_EMP_V_TP_EXP_LOGISTIC_A(AAG)
29    PIF_EMP_V_ELAST_MAX_LOGISTIC(AAG)
30    PIF_EMP_V_BUD_MU(AAG, POL_INST)
31  ;
32
33  negative variables
34    PIF_EMP_V_TP_EXP_LOGISTIC_B(AAG)
35  ;
36
37  equations
38    pif_emp_def_entropy
```

```

39   pif_emp_def_tp(AAG, YEAR)
40 ;
41
42 * intermediary equations and variables
43 variables
44   PIF_EMP_V_LOGISTIC(AAG, YEAR)
45   PIF_EMP_V_EPSILON(AAG, YEAR)
46   PIF_EMP_V_TFP_CONST0(AAG)
47   PIF_EMP_V_TFP(AAG, YEAR)
48   PIF_EMP_V_BUD(AAG, YEAR)
49   PIF_EMP_V_BUD_NORM(AAG)
50   PIF_EMP_V_ENTROPY_I(PIF_EMP_ENTROPY_PARTS)
51 ;
52
53 equations
54   pif_emp_def_v_bud(AAG, YEAR)
55   pif_emp_def_v_tfp(AAG, YEAR)
56   pif_emp_def_entropy_i1
57   pif_emp_def_entropy_i2
58   pif_emp_def_entropy_i3
59   pif_emp_def_entropy_i4
60   pif_emp_def_entropy_i5
61   pif_emp_def_entropy_i6
62   pif_emp_def_entropy_i7
63   pif_emp_def_entropy_i8
64   pif_emp_def_res1(POL_INST, YEAR)
65   pif_emp_def_res2(POL_INST, YEAR)
66   pif_emp_def_res3(YEAR)
67   pif_emp_def_bud_norm(AAG)
68   pif_emp_def_mu_norm(AAG)
69   pif_emp_logistic(AAG, YEAR)
70   pif_emp_def_logistic_res(AAG)
71   pif_emp_def_logistic_res2(AAG)
72 ;
73
74 pif_emp_def_v_bud(AAG, YEAR)..
75   PIF_EMP_V_BUD(AAG, YEAR) =E= PIF_EMP_V_BUD_NORM(AAG) * (
76     sum(CAADP$pif_emp_p_bud_mu(AAG, CAADP), PIF_EMP_V_BUD_MU(AAG, CAADP) *
77       (PIF_EMP_V_BUDSHARE(CAADP, YEAR) * pif_emp_p_pae(YEAR))**(-pif_emp_p_bud_rho)
78       + PIF_EMP_V_BUD_MU(AAG, "non-agr") * PIF_EMP_V_GAMMA_NON_AGR(YEAR)**(-
79         pif_emp_p_bud_rho)
80       )**(-1/pif_emp_p_bud_rho);
81
82 pif_emp_def_bud_norm(AAG)..
83   PIF_EMP_V_BUD_NORM(AAG) =E= sum(POL_INST, PIF_EMP_V_BUD_MU(AAG, POL_INST))*1 / (1+
84     pif_emp_p_bud_rho)**((1+pif_emp_p_bud_rho)/pif_emp_p_bud_rho);
85
86 pif_emp_def_mu_norm(AAG)..
87   sum(POL_INST, PIF_EMP_V_BUD_MU(AAG, POL_INST)) =E= 1;
88
89 pif_emp_logistic(AAG, YEAR)..
90   PIF_EMP_V_LOGISTIC(AAG, YEAR) =E= 1 / ( 1+exp(-1 * (PIF_EMP_V_BUD(AAG, YEAR)*
91     PIF_EMP_V_TP_EXP_LOGISTIC_A(AAG)+PIF_EMP_V_TP_EXP_LOGISTIC_B(AAG) ) ) );
92
93 pif_emp_def_v_tfp(AAG, YEAR)..
94   PIF_EMP_V_TFP(AAG, YEAR) =E= PIF_EMP_V_ELAST_MAX_LOGISTIC(AAG) * PIF_EMP_V_LOGISTIC
95     (AAG, YEAR);
96
97 pif_emp_def_tp(AAG, YEAR)..
98   PIF_EMP_V_TFP(AAG, YEAR) + PIF_EMP_V_TFP_CONST0(AAG) + PIF_EMP_V_EPSILON(AAG, YEAR)
99     =E= pif_emp_p_tp(AAG, YEAR);
100
101 pif_emp_def_logistic_res(AAG)..
102   PIF_EMP_V_TP_EXP_LOGISTIC_A(AAG) =L= (log(0.99 / (1 - 0.99)) -
103     PIF_EMP_V_TP_EXP_LOGISTIC_B(AAG)) / sum(POL_INST, p_gamma("sq", POL_INST));
104
105 pif_emp_def_logistic_res2(AAG)..

```

```

100   PIF_EMP_V_TP_EXP_LOGISTIC_A(AAG)=G= (log(0.01 / (1 - 0.01)) -
      PIF_EMP_V_TP_EXP_LOGISTIC_B(AAG)) / sum(POL_INST, p_gamma("sq", POL_INST));
101
102   pif_emp_def_res1(CAADP, YEAR)..
103   PIF_EMP_V_BUDSHARE(CAADP, YEAR) =L= pif_emp_p_budshare_up(CAADP, YEAR);
104   pif_emp_def_res2(CAADP, YEAR)..
105   PIF_EMP_V_BUDSHARE(CAADP, YEAR) =G= pif_emp_p_budshare_lo(CAADP, YEAR);
106
107   pif_emp_def_res3(YEAR)..
108   sum(CAADP, PIF_EMP_V_BUDSHARE(CAADP, YEAR)) =E= 1;
109
110   pif_emp_def_entropy_i1..
111   PIF_EMP_V_ENTROPY_I("1") =E= sum((AAG, YEAR), sqrt(PIF_EMP_V_EPSILON(AAG, YEAR)));
112
113   pif_emp_def_entropy_i2..
114   PIF_EMP_V_ENTROPY_I("2") =E= sum((POL_INST, YEAR), sqrt(pif_emp_p_budshare(POL_INST, YEAR) -
      PIF_EMP_V_BUDSHARE(POL_INST, YEAR) ) / sqrt( pif_emp_p_budshare(POL_INST, YEAR)+
      pif_emp_delta("2")$(pif_emp_p_budshare(POL_INST, YEAR)=0)));
115
116   pif_emp_def_entropy_i3..
117   PIF_EMP_V_ENTROPY_I("3") =E= sum(YEAR, sqrt(pif_emp_p_gamma_non_agr(YEAR) -
      PIF_EMP_V_GAMMA_NON_AGR(YEAR) ) / sqrt(pif_emp_p_gamma_non_agr(YEAR)+pif_emp_delta("3
      ")$(pif_emp_p_gamma_non_agr(YEAR)=0)));
118
119   pif_emp_def_entropy_i4..
120   PIF_EMP_V_ENTROPY_I("4") =E= sum(AAG, sqrt(pif_emp_p_elast_max_logistic(AAG) -
      PIF_EMP_V_ELAST_MAX_LOGISTIC(AAG) ) / sqrt( pif_emp_p_elast_max_logistic(AAG)+pif_emp_delta
      ("4")$(pif_emp_p_elast_max_logistic(AAG)=0)));
121
122   pif_emp_def_entropy_i5..
123   PIF_EMP_V_ENTROPY_I("5") =E= sum((AAG, POL_INST), sqrt(pif_emp_p_bud_mu(AAG, POL_INST) -
      PIF_EMP_V_BUD_MU(AAG, POL_INST) ) / sqrt( pif_emp_p_bud_mu(AAG, POL_INST) +pif_emp_delta
      ("5")$(pif_emp_p_bud_mu(AAG, POL_INST) =0)));
124
125   pif_emp_def_entropy_i6..
126   PIF_EMP_V_ENTROPY_I("6") =E= sum(AAG, sqrt(pif_emp_p_tp_exp_logistic_a(AAG) -
      PIF_EMP_V_TP_EXP_LOGISTIC_A(AAG) ) / sqrt( pif_emp_p_tp_exp_logistic_a(AAG) +pif_emp_delta(
      "6")$(pif_emp_p_tp_exp_logistic_a(AAG) =0)));
127
128   pif_emp_def_entropy_i7..
129   PIF_EMP_V_ENTROPY_I("7") =E= sum(AAG, sqrt(pif_emp_p_tp_exp_logistic_b(AAG) -
      PIF_EMP_V_TP_EXP_LOGISTIC_B(AAG) ) / sqrt( pif_emp_p_tp_exp_logistic_b(AAG) + pif_emp_delta
      ("7")$(pif_emp_p_tp_exp_logistic_b(AAG)=0)));
130
131   pif_emp_def_entropy_i8..
132   PIF_EMP_V_ENTROPY_I("8") =E= sum(AAG, sqrt(PIF_EMP_V_TFP_CONST0(AAG)));
133
134   pif_emp_def_entropy..
135   PIF_EMP_V_ENTROPY =E= sum(PIF_EMP_ENTROPY_PARTS, pif_emp_entropy_weights(
      PIF_EMP_ENTROPY_PARTS) * PIF_EMP_V_ENTROPY_I(PIF_EMP_ENTROPY_PARTS));
136
137   model pif_empirical /
138   pif_emp_def_tp
139   pif_emp_logistic
140   pif_emp_def_logistic_res
141   pif_emp_def_logistic_res2
142   pif_emp_def_v_tfp
143   pif_emp_def_v_bud
144   pif_emp_def_bud_norm
145   pif_emp_def_mu_norm
146   pif_emp_def_res1
147   pif_emp_def_res2
148   pif_emp_def_res3
149   pif_emp_def_entropy_i1
150   pif_emp_def_entropy_i2
151   pif_emp_def_entropy_i3
152   pif_emp_def_entropy_i4
153   pif_emp_def_entropy_i5
154   pif_emp_def_entropy_i6

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155   pif_emp_def_entropy_i7
156   pif_emp_def_entropy_i8
157   pif_emp_def_entropy
158   /;

```

## A.2 Expert PIF

Listing A.2: models/experts.gms

```

1  sets
2    PIF_EXPS_ENTROPY_PARTS /1*6/
3    PIF_EXPS_TS /1*10/
4  ;
5
6  alias(AAG, AAG2);
7
8  parameters
9    pif_exps_entropy_weights(PIF_EXPS_ENTROPY_PARTS)
10   pif_exps_p_gamma(POL_AGG, POL_INST)
11   pif_exps_p_bud_rho
12   pif_exps_p_tp_exp_logistic_a(AAG)
13   pif_exps_p_tp_exp_logistic_b(AAG)
14   pif_exps_p_elast_max_logistic(AAG)
15   pif_exps_p_cge_const(HZ)
16   pif_exps_p_cge_mult(AAG, HZ)
17   pif_exps_p_x(POL_AGG, HZ)
18   pif_exps_p_bud_mu(AAG, POL_INST)
19   pif_exps_p_pol_z3_base "B_0"
20   pif_exps_delta(PIF_EXPS_ENTROPY_PARTS)
21   pif_exps_discount
22   pif_exps_donor_share
23   pif_exps_delta_ips(HZ) "=_(1_-_pif_exps_donor_share)_for_Z3"
24   pif_exps_t(PIF_EXPS_TS) "ord(PIF_EXPS_TS)_-_1"
25   pif_exps_ideo_variance(POL_INST)
26   pif_exps_epsilon_variance(HZ)
27 ;
28
29 variables
30   PIF_EXPS_V_Z(POL_AGG, HZ, PIF_EXPS_TS) growth rate of policy concern Z
31   PIF_EXPS_V_ENTROPY
32 ;
33
34 positive variables
35   PIF_EXPS_V_TP_EXP_LOGISTIC_A(AAG)
36   PIF_EXPS_V_ELAST_MAX_LOGISTIC(AAG)
37   PIF_EXPS_V_BUD_MU(AAG, POL_INST)
38 ;
39
40 negative variables
41   PIF_EXPS_V_TP_EXP_LOGISTIC_B(AAG)
42 ;
43
44 equations
45   pif_exps_def_v_tfp(POL_AGG, AAG)
46   pif_exps_def_foc(POL_AGG, POL_INST)
47   pif_exps_def_bud_norm(AAG)
48   pif_exps_def_wz(POL_AGG, HZ, PIF_EXPS_TS)
49   pif_exps_def_entropy
50 ;
51
52 * intermediary equations and variables
53 variables
54   PIF_EXPS_V_EPSILON(POL_AGG, HZ)

```

```

55 PIF_EXPS_V_IDEO(POL_AGG, POL_INST)
56 PIF_EXPS_V_DTFP(POL_AGG, AAG)
57 PIF_EXPS_V_DBE(POL_AGG, POL_INST, AAG)
58 PIF_EXPS_V_BUD_NORM(AAG)
59 PIF_EXPS_V_BUD_I1(POL_AGG, AAG)
60 PIF_EXPS_V_DP1F(POL_AGG, HZ, POL_INST)
61 PIF_EXPS_V_WZ_I1(POL_AGG, HZ)
62 PIF_EXPS_V_WZ_I2(POL_AGG, HZ)
63 PIF_EXPS_V_FOC_I1(POL_AGG, POL_INST, PIF_EXPS_TS)
64 PIF_EXPS_V_FOC_I2(POL_AGG, PIF_EXPS_TS)
65 PIF_EXPS_V_LOGISTIC(POL_AGG, AAG)
66 ;
67
68 positive variables
69 PIF_EXPS_V_TFP(POL_AGG, AAG) sectoral PIF function
70 PIF_EXPS_V_BUD(POL_AGG, AAG)
71 PIF_EXPS_V_ENTROPY_I(PIF_EXPS_ENTROPY_PARTS)
72 ;
73
74 equations
75 pif_exps_def_vbud_i1(POL_AGG, AAG)
76 pif_exps_logistic_restriction(POL_AGG, AAG)
77 pif_exps_logistic(POL_AGG, AAG)
78 pif_exps_def_wz_i1(POL_AGG, HZ)
79 pif_exps_def_wz_i2(POL_AGG, HZ)
80 pif_exps_def_v_dtfp(POL_AGG, AAG)
81 pif_exps_def_v_dbe(POL_AGG, POL_INST, AAG)
82 pif_exps_def_dp1f(POL_AGG, HZ, POL_INST)
83 pif_exps_def_foc_i1(POL_AGG, POL_INST, PIF_EXPS_TS)
84 pif_exps_def_foc_i2(POL_AGG, PIF_EXPS_TS)
85 pif_exps_def_v_bud(POL_AGG, AAG)
86 pif_exps_def_mu_norm(AAG)
87 pif_exps_def_entropy_i1
88 pif_exps_def_entropy_i2
89 pif_exps_def_entropy_i3
90 pif_exps_def_entropy_i4
91 pif_exps_def_entropy_i5
92 pif_exps_def_entropy_i6
93 ;
94
95
96 pif_exps_def_mu_norm(AAG)..
97 sum(POL_INST, PIF_EXPS_V_BUD_MU(AAG, POL_INST)) =e= 1;
98
99 pif_exps_def_bud_norm(AAG)..
100 PIF_EXPS_V_BUD_NORM(AAG) =e= sum(POL_INST, PIF_EXPS_V_BUD_MU(AAG, POL_INST))*(1 / (1+
    pif_exps_p_bud_rho))*(1+pif_exps_p_bud_rho)/pif_exps_p_bud_rho);
101
102 pif_exps_def_vbud_i1(POL_AG_EST, AAG)..
103 PIF_EXPS_V_BUD_I1(POL_AG_EST, AAG) =E= sum(POL_INST, PIF_EXPS_V_BUD_MU(AAG, POL_INST
    ) *
104
105
106
107
108
109
110
111
112
113
114
115
    pif_exps_p_gamma(POL_AG_EST, POL_INST)**(-
        pif_exps_p_bud_rho));
106 pif_exps_def_v_bud(POL_AG_EST, AAG)..
107 PIF_EXPS_V_BUD(POL_AG_EST, AAG) =e= PIF_EXPS_V_BUD_NORM(AAG) * PIF_EXPS_V_BUD_I1(
    POL_AG_EST, AAG)**(-1/pif_exps_p_bud_rho);
108
109
110 *numerical bound!
111 pif_exps_logistic_restriction(POL_AG_EST, AAG)..
112 PIF_EXPS_V_BUD(POL_AG_EST, AAG)*PIF_EXPS_V_TP_EXP_LOGISTIC_A(AAG)+
    PIF_EXPS_V_TP_EXP_LOGISTIC_B(AAG) =G= -100;
113
114 pif_exps_logistic(POL_AG_EST, AAG)..
115 PIF_EXPS_V_LOGISTIC(POL_AG_EST, AAG) =E= 1 / (1 + exp(- (PIF_EXPS_V_BUD(POL_AG_EST, AAG
    )*PIF_EXPS_V_TP_EXP_LOGISTIC_A(AAG)+PIF_EXPS_V_TP_EXP_LOGISTIC_B(AAG) ) ) );

```

```

116
117 pif_exps_def_v_tfp(POL_AG_EST, AAG)..
118 PIF_EXPS_V_TFP(POL_AG_EST, AAG) =E= PIF_EXPS_V_ELAST_MAX_LOGISTIC(AAG) *
    PIF_EXPS_V_LOGISTIC(POL_AG_EST, AAG);
119
120 pif_exps_def_v_dtfp(POL_AG_EST, AAG)..
121 PIF_EXPS_V_DTFP(POL_AG_EST, AAG) =e= PIF_EXPS_V_TFP(POL_AG_EST, AAG) *
    PIF_EXPS_V_TP_EXP_LOGISTIC_A(AAG) * (1 - PIF_EXPS_V_LOGISTIC(POL_AG_EST, AAG));
122
123 pif_exps_def_v_dbe(POL_AG_EST, POL_INST, AAG)$pif_exps_p_gamma(POL_AG_EST, POL_INST)..
124 PIF_EXPS_V_DBE(POL_AG_EST, POL_INST, AAG) =e= PIF_EXPS_V_BUD(POL_AG_EST, AAG) * ((
    PIF_EXPS_V_BUD_MU(AAG, POL_INST) * pif_exps_p_gamma(POL_AG_EST, POL_INST)**(-
    pif_exps_p_bud_rho - 1)) / PIF_EXPS_V_BUD_I1(POL_AG_EST, AAG));
125
126 * wv_z_i1 is exogoneously fixed except for Z3, where epsilon is fixed at zero.
127 pif_exps_def_wz_i1(POL_AG_EST, HZ)..
128 PIF_EXPS_V_WZ_I1(POL_AG_EST, HZ) =e= pif_exps_p_cge_const(HZ) + sum(AAG, PIF_EXPS_V_TFP(
    POL_AG_EST, AAG)/100 * pif_exps_p_cge_mult(AAG, HZ)) + PIF_EXPS_V_EPSILON(POL_AG_EST,
    HZ);
129
130 pif_exps_def_wz_i2(POL_AG_EST, HZ)..
131 PIF_EXPS_V_WZ_I2(POL_AG_EST, HZ) =e= pif_exps_delta_ips(HZ) / pif_exps_p_pol_z3_base * sum(
    POL_INST, pif_exps_p_gamma(POL_AG_EST, POL_INST));
132
133 pif_exps_def_wz(POL_AG_EST, HZ, PIF_EXPS_TS)..
134 PIF_EXPS_V_Z(POL_AG_EST, HZ, PIF_EXPS_TS) =e= 1 + pif_exps_t(PIF_EXPS_TS) *
    PIF_EXPS_V_WZ_I1(POL_AG_EST, HZ) - PIF_EXPS_V_WZ_I2(POL_AG_EST, HZ);
135
136 pif_exps_def_dpif(POL_AG_EST, HZ, POL_INST)$pif_exps_p_gamma(POL_AG_EST, POL_INST)..
137 PIF_EXPS_V_DPIF(POL_AG_EST, HZ, POL_INST) =e= sum(AAG, pif_exps_p_cge_mult(AAG, HZ) *
    PIF_EXPS_V_DBE(POL_AG_EST, POL_INST, AAG) * PIF_EXPS_V_DTFP(POL_AG_EST, AAG) /
    100);
138
139 pif_exps_def_foc_i1(POL_AG_EST, POL_INST, PIF_EXPS_TS)$pif_exps_p_gamma(POL_AG_EST, POL_INST)
    ..
140 PIF_EXPS_V_FOC_I1(POL_AG_EST, POL_INST, PIF_EXPS_TS) =e= sum(HZ$(pif_exps_p_x(
    POL_AG_EST, HZ) > 0), (pif_exps_p_x(POL_AG_EST, HZ) / PIF_EXPS_V_Z(POL_AG_EST, HZ,
    PIF_EXPS_TS)) * ((-pif_exps_delta_ips(HZ) / pif_exps_p_pol_z3_base) + pif_exps_t(PIF_EXPS_TS) *
    PIF_EXPS_V_DPIF(POL_AG_EST, HZ, POL_INST)));
141
142 pif_exps_def_foc_i2(POL_AG_EST, PIF_EXPS_TS)..
143 PIF_EXPS_V_FOC_I2(POL_AG_EST, PIF_EXPS_TS) =E= prod(HZ$(pif_exps_p_x(POL_AG_EST, HZ) > 0),
    PIF_EXPS_V_Z(POL_AG_EST, HZ, PIF_EXPS_TS)**(pif_exps_p_x(POL_AG_EST, HZ)));
144
145 pif_exps_def_foc(POL_AG_EST, POL_INST)$pif_exps_p_gamma(POL_AG_EST, POL_INST) > 0.0001..
146 PIF_EXPS_V_IDEO(POL_AG_EST, POL_INST) =e= sum(PIF_EXPS_TS, pif_exps_discount**(pif_exps_t(
    PIF_EXPS_TS)) * PIF_EXPS_V_FOC_I2(POL_AG_EST, PIF_EXPS_TS) * PIF_EXPS_V_FOC_I1(
    POL_AG_EST, POL_INST, PIF_EXPS_TS));
147
148 pif_exps_def_entropy_i1..
149 PIF_EXPS_V_ENTROPY_I("1") =e= sum((POL_AG_EST, POL_INST), sqrt(PIF_EXPS_V_IDEO(
    POL_AG_EST, POL_INST)) / pif_exps_ideo_variance(POL_INST));
150
151 pif_exps_def_entropy_i2..
152 PIF_EXPS_V_ENTROPY_I("2") =e= sum((POL_AG_EST, HZ), sqrt(PIF_EXPS_V_EPSILON(POL_AG_EST,
    HZ)) / pif_exps_epsilon_variance(HZ));
153
154 pif_exps_def_entropy_i3..
155 PIF_EXPS_V_ENTROPY_I("3") =e= sum(AAG, sqrt(pif_exps_p_elast_max_logistic(AAG) -
    PIF_EXPS_V_ELAST_MAX_LOGISTIC(AAG)) / sqrt(pif_exps_p_elast_max_logistic(AAG)+
    pif_exps_delta("3")$(pif_exps_p_elast_max_logistic(AAG) = 0)));
156
157 pif_exps_def_entropy_i4..
158 PIF_EXPS_V_ENTROPY_I("4") =e= sum((AAG, POL_INST), sqrt(pif_exps_p_bud_mu(AAG, POL_INST) -
    PIF_EXPS_V_BUD_MU(AAG, POL_INST)) / sqrt(pif_exps_p_bud_mu(AAG, POL_INST) +
    pif_exps_delta("4")$(pif_exps_p_bud_mu(AAG, POL_INST) = 0)));
159
160 pif_exps_def_entropy_i5..
161 PIF_EXPS_V_ENTROPY_I("5") =e= sum(AAG, sqrt(pif_exps_p_tp_exp_logistic_a(AAG) -
    PIF_EXPS_V_TP_EXP_LOGISTIC_A(AAG)) / sqrt(pif_exps_p_tp_exp_logistic_a(AAG) + pif_exps_delta
    ("5")$(pif_exps_p_tp_exp_logistic_a(AAG) = 0)));
162

```

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163 pif_exps_def_entropy_i6..
164 PIF_EXPS_V_ENTROPY_I("6") =e= sum(AAG, sqrt(pif_exps_p_tp_exp_logistic_b(AAG) -
PIF_EXPS_V_TP_EXP_LOGISTIC_B(AAG)) /sqrt(pif_exps_p_tp_exp_logistic_b(AAG) +
pif_exps_delta("6"))$(pif_exps_p_tp_exp_logistic_b(AAG) = 0));

165
166
167 pif_exps_def_entropy..
168 PIF_EXPS_V_ENTROPY =e= sum(PIF_EXPS_ENTROPY_PARTS, pif_exps_entropy_weights(
PIF_EXPS_ENTROPY_PARTS) * PIF_EXPS_V_ENTROPY_I(PIF_EXPS_ENTROPY_PARTS));

169
170 * model for estimation with expert data
171 model pif_experts /
172 pif_exps_def_v_tfp
173 pif_exps_def_foc
174 pif_exps_def_bud_norm
175 pif_exps_def_wz
176 pif_exps_def_entropy
177 pif_exps_def_vbud_i1
178 pif_exps_logistic_restriction
179 pif_exps_logistic
180 pif_exps_def_wz_i1
181 pif_exps_def_wz_i2
182 pif_exps_def_v_dtfp
183 pif_exps_def_v_dbe
184 pif_exps_def_dpif
185 pif_exps_def_foc_i1
186 pif_exps_def_foc_i2
187 pif_exps_def_v_bud
188 pif_exps_def_mu_norm
189 pif_exps_def_entropy_i1
190 pif_exps_def_entropy_i2
191 pif_exps_def_entropy_i3
192 pif_exps_def_entropy_i4
193 pif_exps_def_entropy_i5
194 pif_exps_def_entropy_i6
195 /;

```





# Appendix B

## Social networks

### B.1 Survey questions

#### B.1.1 Expert information

*“Stakeholder organizations, research institutes or political actors can frequently provide expert information to other organizations, especially when consequences of complex policies have to be evaluated. Such kind of expert information comprises the knowledge of the effects of different policy instruments on the welfare of different social groups. Therefore expert information is very interesting for political organizations as well as for other interest groups when designing and influencing agricultural policy programmes.”*

***Sending information:***

*“Using the list of organizations again, please check all organizations to which your organization provides expert information on agricultural policies.”*

***Receiving information:***

*“Using the list of organizations again, please check all organizations from which your organization receives expert information on agricultural policies.”*

#### B.1.2 Political support

*“In democracies stakeholder organizations are representatives of their members and their interests. Therefore the policy position of such a group is highly connected with the resulting welfare for their members. Thus, a major role of stakeholder organizations in democracies is intermediating their clientele’s in-*

terest to politicians, i.e. trying to influence policy or politicians to generate as much welfare as possible for their members. Obviously, politicians won't support a stakeholder organization's position without any reward. On their part they expect in return the political support of members of the stakeholder organization. However, political agents also represent their electorate in parliament. Therefore, political agents are interested to find political solutions supported by a majority of their electorate."

**Governmental actor:**

"Please check those organizations which are important for you regarding the intermediation of political positions supported by voters."

**Non-governmental actor:**

"Taking now the above described kind of support relation between organizations and political agents into account, please check those political institutions on the list with which your organization has such a relationship."

### B.1.3 Social relation

"The formulation and development of FASDEP II is already dating back several years. A lot of organizations which are nowadays active in the agricultural policy domain have been already active in the formulation process of previous agricultural programmes. Thus, it frequently occurred that the same people of different organizations have been communicating and working together for a very long time period. Therefore, some organizations have established social relations which go beyond their pure professional contacts facilitating the cooperation among these organizations at the same time."

"Please tell me with which organization on this list does your organization have such a relationship?"

## B.2 Tables

Table B.1: List of Organizations: Ghana

acronym	full name	type
Pre	President	EXEC
MOA	Ministry of Food & Agriculture	EXEC
MOF	Ministry of Finance and Economic Planning	EXEC
MLNR	Ministry of Lands and Natural Resources	EXEC
MEST	Ministry of Environment, Science & Technology	EXEC
MOTI	Ministry of Trade and Industry	EXEC
NDC	New Democratic Congress	LEG
NPP	New Patriotic Party	LEG
EPA	Environmental Protection Agency	PUBAG
COCOBOD	Ghana Cocoa Board	PUBAG
GIDA	Ghana Irrigation Development Authority	PUBAG
LCG	Lands Commission Ghana	PUBAG
FCG	Fisheries Commission Ghana	PUBAG
GIZ (GTZ)	Deutsche Gesellschaft für internationale Zusammenarbeit GmbH	DONOR
CIDA	Canadian International Development Agency	DONOR
AFD	Agence Française de Développement	DONOR
USAID	U. S. Agency for International Development	DONOR
WB	The World Bank	DONOR
FAO	Food and Agriculture Organization of the United Nations	DONOR
IFAD	International Fund for Agricultural Development	DONOR
CRIG	Cocoa Research Institute of Ghana	RESEARCH
ISSER	Institute of Statistical, Social and Economic Research, University of Ghana	RESEARCH
STEPRI	Science and Technology Policy Research Institute	RESEARCH
UG	College of Agriculture and Consumer Science University Ghana	RESEARCH
FARA	Forum for Agricultural Research in Africa	RESEARCH
IWMI	International Water Management Institute	RESEARCH
IFPRI	International Food Policy Research Institute	RESEARCH
GAIDA	Ghana Agriculture Input Dealers Association	IG:IND
GAABIC	Ghana Agricultural Associations Business Information Centre	IG:IND
WGL	Wienco Ghana Limited	IG:IND
FAGE	Federation of Association of Ghanaian Exporters	IG:IND
AGI	The Association of Ghana Industries	IG:IND
PEF	The Private Enterprise Foundation	IG:IND
GEA	Ghana Employers' Association	IG:IND
GNAFF	Ghana National Association of Farmers and Fishermen	IG:FARM
GNAPF	Ghana National Association of Poultry Farmers	IG:FARM
PFAG	Peasant Farmers Association of Ghana	IG:FARM
APFOG	Apex Farmers Organization of Ghana	IG:FARM
FoodSPAN	Food Security Policy Advocacy Network	CSO
EPAG	Environmental Protection Association of Ghana	CSO
GAWU	General Agricultural Workers' Union	CSO
AGRA	Alliance for a Green Revolution in Africa	iNGO
ACDI/VOCA	ACDI/VOCA	iNGO
TS	TechnoServe	iNGO
ADRA	The Adventist Development and Relief Agency	iNGO
CRS	Catholic Relief Services	iNGO

Table B.2: List of Organizations: Senegal

acronym	full name	type
Pres	Président de la République	EXEC
PM	Premier Ministre	EXEC
MOA	Ministère de l'agriculture et de l'équipement rural	EXEC
MOF	Ministère de l'économie et des finances	EXEC
MINEL	Ministère de l'élevage	EXEC
MPEM	Ministère de la pêche et des affaires maritimes	EXEC
MTA	Ministère du commerce, de l'industrie et du secteur informel	EXEC
Assemblée Nationale	Commission du développement et de l'aménagement du territoire	LEG
CEDEAO	Communauté économique des états de l'Afrique de l'ouest	SUPRA
UEMOA	Union économique et monétaire ouest africaine	SUPRA
ANCAR	Agence nationale de conseil agricole et rural	PUBAG
ASEPEX	Agence sénégalaise de promotion des exportations	PUBAG
CSA	Commissariat à la sécurité alimentaire	PUBAG
FNRAA	Fonds national de recherches agricoles et agroalimentaires	PUBAG
SAED	Société d'aménagement et d'exploitation des terres du delta, de la moyenne vallée et de la falémé	PUBAG
CIDA	Agence canadienne pour le développement international	DONOR
AFD	Agence Française de développement	DONOR
BAD	Banque africaine de développement	DONOR
WB	Banque Mondiale	DONOR
IFAD	Fonds international pour le développement agricole	DONOR
EU	Union européenne	DONOR
USAID	United States agency for international development	DONOR
CRES	Consortium pour la recherche économique et sociale	RESEARCH
ENSA	Ecole nationale supérieure d'agronomie	RESEARCH
IPAR	Initiative prospective agriculture rurale	RESEARCH
ITA	Institut de technologie alimentaire	RESEARCH
INP	Institut national de pédologie	RESEARCH
ISRA	Institut Sénégalais de Recherches Agricoles	RESEARCH
UCAD	Université Cheikh Anta Diop de Dakar	RESEARCH
UGB	Université Gaston Berger	RESEARCH
CORAF	Conseil ouest et centre africain pour la recherche et le développement agricoles	RESEARCH
IFPRI	International food policy research institute	RESEARCH
CNIA	Comité national interprofessionnel pour l'arachide	IG:IND
FENAFILS	Fédération nationale des acteurs de la filière lait local du Sénégal	IG:IND
ONAPES-SEPAS	Organisation nationale des producteurs exportateurs de fruits et légumes du Sénégal	IG:IND
UNIS	Union nationale interprofessionnelle des semences	IG:IND
GDS	Grands domaines du Sénégal	IG:IND
SODEFITEX	Société de développement et des fibres textiles	IG:IND
CNCR	Conseil national de concertation et de coopération des ruraux	IG:FARM
RESOPP	Réseau des organisations paysannes et pastorales du Sénégal	IG:FARM
CONGAD	Conseil des organisations non gouvernementales d'appui au développement	CSO
FONGS	Fédération des organisations non gouvernementales du Sénégal	CSO
UNCS	Union nationale des consommateurs du Sénégal	CSO
CNTS/SNTPA	Confédération nationale des travailleurs du Sénégal	CSO
ENDA Diapol	Enda tiers monde	iNGO
OXFAM GB	Oxfam	iNGO

Table B.3: List of Organizations: Uganda

acronym	full name	type
Pres	Office of the President	EXEC
PM	Office of the Prime Minister	EXEC
MOA	Ministry of Agriculture Animal Industry and Fisheries	EXEC
MOF	Ministry of Finance Planning and Economic Development	EXEC
MoLG	Ministry of Local Government	EXEC
MTTI	Ministry of Trade and Tourism Industry	EXEC
MWE	Ministry of Water and Environment	EXEC
FDC	Forum for Democratic Change	LEG
NRM	National Resistance Movement	LEG
CDO	Cotton Development Organisation	PUBAG
DDA	Dairy Development Authority	PUBAG
NARO	National Agricultural Research Organisation / System	PUBAG
NEMA	National Environment Management Authority	PUBAG
NPA	National Planning Authority	PUBAG
UCDA	Uganda Coffee Development Authority	PUBAG
EU	European Union	DONOR
FAO	Food and Agricultural Organization	DONOR
IFAD	International Fund for Agriculture	DONOR
JICA	Japanese International Cooperation Agency	DONOR
USAID	United States Agency for International Development	DONOR
WB	World Bank	DONOR
ACODE	Advocates Coalition for Development and Environment	RESEARCH
AFRISA	African Institute for Strategic Animal Resources Development	RESEARCH
COAES	College of Agriculture and Environmental Sciences, Makerere University	RESEARCH
EPRC	Economic Policy Research Center	RESEARCH
IFPRI	International Food Policy Research Institute	RESEARCH
NUCAFE	National Union of Coffee Agribusinesses and Farm Enterprises	IG:IND
UCTF	Uganda Coffee Trade Federation	IG:IND
UFPEA	Uganda Fish processors and Exporters Association	IG:IND
UNADA	Uganda National Agro-Input Dealers Association	IG:IND
UNDTA	Uganda National Dairy Traders Association	IG:IND
UOSPPA	Uganda Oil Seed Producers and Processors Association	IG:IND
USTA	Uganda Seed Traders' Association	IG:IND
UTA	Uganda Tea Association	IG:IND
PSFU	Private Sector Foundation Uganda	IG:IND
UMA	Uganda Manufacturers Association	IG:IND
NOGAMU	National Organic Agricultural Movement of Uganda	IG:FARM
UCA	Uganda Cooperative Alliance	IG:FARM
UNFFE	Uganda National Farmers' Federation	IG:FARM
EAU	Environmental Alert Uganda	CSO
SG	Sasakawa Global 2000	iNGO
SEATINI	Strengthening Africa in World Trade	iNGO
TS	Techno Serve	iNGO

Table B.4: Classification of actors with absolute and relative frequency (in parentheses)

Category	Group	Ghana	Senegal	Uganda
Political Agents	Executive (EXEC)	6 (0.13)	7 (0.15)	7 (0.16)
	Public Sector Agencies (PUBAG)	5 (0.11)	5 (0.11)	6 (0.14)
	Legislative (LEG)	2 (0.04)	1 (0.02)	2 (0.05)
	Supra National Government (SUPRA)	0 (0.00)	2 (0.04)	0 (0.00)
Interest Groups	Donor (DONOR)	7 (0.15)	7 (0.15)	6 (0.14)
	(RESEARCH)	7 (0.15)	10 (0.22)	5 (0.12)
	Industrial Interest Groups (IG:IND)	7 (0.15)	6 (0.13)	10 (0.23)
	Farm Interest Groups (IG:FARM)	4 (0.09)	2 (0.04)	3 (0.07)
	Civil Society Organizations (CSO)	8 (0.17)	6 (0.13)	4 (0.09)
$\Sigma$		<b>46</b>	<b>46</b>	<b>43</b>

Table B.5: Model Terms

	Ghana		Senegal		Uganda	
	Expert	Support	Expert	Support	Expert	Support
<i>EDGES</i>						
network density <sup>a</sup>	0.2261	0.2145	0.2812	0.1585	0.2542	0.2259
<i>POLSIM</i>						
mean simil. <sup>e</sup>	0.4232 (0.1313)		0.3405 (0.1210)		0.5980 (0.1687)	
<i>PREFSIM</i>						
mean simil. <sup>e</sup>	0.2311 (0.1190)		0.2441 (0.1152)		0.2734 (0.1672)	
<i>MEMBER</i>						
network density <sup>a</sup>	0.0203		0.1623		0.0587	
mean member <sup>e</sup>	1.0118 (0.1081)		1.6310 (1.2293)		1.0189 (0.1367)	
<i>MUTUAL</i>						
reciprocity <sup>b</sup>	0.3868	0.3604	0.3591	0.3171	0.3399	0.3137
<i>GWESP &amp; GWDSP</i>						
transitivity <sup>d</sup>	0.3907	0.3597	0.4541	0.3437	0.4287	0.3947
<i>EXPERT &amp; SUPPORT</i>						
mean degree <sup>c</sup>	20.35 (11.79)	19.30 (12.02)	25.30 (13.40)	14.26 (9.95)	21.35 (11.74)	18.98 (12.24)
<i>POWER</i>						
mean reputation <sup>e</sup>	0.3391 (0.1157)		0.6899 (0.1444)		0.4668 (0.1291)	
mean i.degree <sup>e</sup>	19.50 (8.65)		31.38 (9.06)		22.78 (8.50)	
mean o.degree <sup>e</sup>	19.50 (8.65)		31.38 (9.06)		22.78 (8.50)	
<i>EXEC</i>						
mean i.degree <sup>g</sup>	17.33 (10.33)	16.33 (6.74)	13.00 (7.42)	7.71 (5.77)	13.57 (8.83)	11.00 (11.82)
mean o.degree <sup>g</sup>	16.50 (10.45)	15.17 (6.43)	16.57 (6.11)	9.43 (6.92)	13.71 (6.42)	9.57 (8.96)
<i>DONOR</i>						
mean i.degree <sup>f</sup>	12.29 (3.63)	15.00 (2.71)	10.86 (8.36)	10.57 (6.58)	9.00 (4.00)	11.00 (6.32)
mean o.degree <sup>f</sup>	13.29 (4.39)	17.71 (3.68)	11.43 (6.27)	9.14 (6.62)	12.50 (5.36)	7.33 (5.96)
<i>RESEARCH</i>						
mean i.degree <sup>f</sup>	12.86 (6.31)	8.86 (5.79)	21.70 (6.67)	7.40 (7.32)	15.60 (10.50)	8.40 (5.32)
mean o.degree <sup>f</sup>	8.14 (4.10)	8.86 (7.01)	13.60 (7.78)	6.60 (5.89)	2.80 (1.64)	6.60 (6.35)
<i>IG</i>						
share IG:IG <sup>h</sup>	0.2579	0.2033	0.1787	0.1754	0.2707	0.3277
mean i.degree <sup>f</sup>	6.86 (3.32)	4.86 (3.76)	8.83 (6.22)	5.58 (3.78)	9.93 (5.89)	10.43 (5.56)
mean o.degree <sup>f</sup>	7.29 (3.58)	5.71 (4.32)	11.33 (6.01)	5.58 (4.60)	10.86 (5.17)	12.14 (6.30)

Notes: <sup>a</sup> share of directed ties among all possible  $N^2 - N$  ties, <sup>b</sup> share of reciprocal ties, <sup>c</sup> mean degree (standard deviation), <sup>d</sup> clustering coefficient, see Wasserman and Faust (1994), <sup>e</sup> mean value (standard deviation), <sup>f</sup> mean outdegree (standard deviation), <sup>g</sup> mean indegree (standard deviation), <sup>h</sup> share of homophilic ties among all IG ties.

Table B.6: Bayesian estimation of ERGM specifications for Ghana

	Expert <i>B</i> network			Support <i>T</i> network		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
EDGES	-4.332*** (0.445)	-3.776 (4.722)	-4.271 (4.732)	-2.333*** (0.259)	-3.203 (4.645)	-3.59 (4.559)
MUTUAL	3.733*** (0.245)	3.54*** (0.258)	3.951*** (0.302)	3.263*** (0.231)	3.1*** (0.236)	3.171*** (0.255)
SUPPORT		1.167*** (0.172)	1.072*** (0.174)			
EXPERT					1.112*** (0.157)	1.06*** (0.161)
GWESP	1.554*** (0.377)	1.268*** (0.361)	1.155*** (0.364)	0.347** (0.164)	0.171 (0.157)	0.114 (0.161)
GWDSP	-0.061** (0.031)	-0.042* (0.029)	-0.021 (0.029)	-0.174*** (0.026)	-0.118*** (0.027)	-0.092*** (0.028)
MEMBER		1.007*** (0.247)	0.933*** (0.261)		0.158 (0.237)	0.146 (0.244)
POWER (indegree)		0.803 (0.807)	-0.738 (0.995)		2.792*** (0.826)	3.062*** (0.968)
POWER (outdegree)			2.753*** (0.991)			0.993 (0.883)
EXEC (indegree)		0.311* (0.239)	-0.278 (0.306)		0.532*** (0.223)	0.118 (0.261)
EXEC (outdegree)			0.764*** (0.317)			0.481** (0.274)
DONOR (indegree)			-0.191 (0.304)			-0.619** (0.28)
DONOR (outdegree)		-0.294 (0.265)	-0.164 (0.336)		0.879*** (0.215)	1.101*** (0.278)
RESEARCH (indegree)			-1.478*** (0.33)			-0.14 (0.257)
RESEARCH (outdegree)		0.802*** (0.222)	1.601*** (0.291)		0.115 (0.224)	0.341 (0.273)
POLSIM		-1.593 (7.037)	-1.42 (7.024)		-0.795 (6.904)	-0.511 (6.772)
PREFSIM		-1.467 (7.028)	-1.136 (7.021)		-1.234 (6.901)	-1.435 (6.788)
IG (indegree)			-0.611** (0.277)			-0.868*** (0.255)
IG (outdegree)			0.205 (0.298)			0.151 (0.247)
IG (homophily)		0.142 (0.262)	0.491* (0.364)		0.219 (0.273)	0.829** (0.356)
log Likelihood	-848.064	-736.081	-706.022	-871.407	-744.025	-735.617
Akaike Inf. Crit.	1704.128	1498.161	1450.044	1750.814	1514.051	1509.235
Bayes Inf. Crit.	1726.669	1571.42	1557.115	1773.355	1587.31	1616.306

Notes: Parameter estimates are based on mean value and standard deviation of MCMC sample. MCMC sample is based on multiple chains (number of parameters times four), where each chain has a length of 10000 and 50% of each chain is discarded for burn-in. \*, \*\*, and \*\*\* indicate that the corresponding 90%, 95%, and 99% one-sided highest posterior density intervals do not include zero.



Table B.7: Bayesian estimation of ERGM specifications for Senegal

	Expert <i>B</i> network			Support <i>T</i> network		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
EDGES	-3.749*** (0.671)	-4.632 (4.35)	-5.439 (4.316)	-3.196*** (0.27)	-3.801 (4.262)	-3.993 (4.174)
MUTUAL	2.951*** (0.209)	2.973*** (0.212)	3.399*** (0.266)	2.927*** (0.238)	2.687*** (0.244)	2.755*** (0.252)
SUPPORT		1.401*** (0.181)	1.395*** (0.186)			
EXPERT					1.488*** (0.154)	1.485*** (0.158)
GWESP	1.68*** (0.585)	1.373*** (0.528)	1.406*** (0.522)	0.856*** (0.156)	0.66*** (0.159)	0.607*** (0.161)
GWDSP	-0.211*** (0.037)	-0.113*** (0.038)	-0.089** (0.04)	-0.094*** (0.035)	-0.088*** (0.034)	-0.075*** (0.033)
MEMBER		0.063 (0.082)	0.059 (0.088)		-0.026 (0.095)	-0.07 (0.102)
POWER (indegree)		1.867*** (0.566)	1.611*** (0.613)		1.571*** (0.617)	1.146** (0.679)
POWER (outdegree)			1.365** (0.675)			0.541 (0.647)
EXEC (indegree)		0.603*** (0.208)	0.276 (0.261)		-0.371* (0.235)	-0.184 (0.291)
EXEC (outdegree)			-0.13 (0.287)			0.271 (0.27)
DONOR (indegree)			-0.596** (0.274)			0.616** (0.271)
DONOR (outdegree)		0.11 (0.216)	0.103 (0.282)		0.193 (0.205)	-0.014 (0.271)
RESEARCH (indegree)			-0.999*** (0.265)			0.358* (0.245)
RESEARCH (outdegree)		1.746*** (0.19)	2.026*** (0.248)		-0.488*** (0.199)	-0.53** (0.248)
POLSIM		-1.788 (7.189)	-1.471 (7.122)		-1.39 (7.1)	-1.51 (6.973)
PREFSIM		-1.954 (7.192)	-1.751 (7.109)		-0.863 (7.108)	-1.07 (6.985)
IG (indegree)			-0.058 (0.24)			0.023 (0.262)
IG (outdegree)			-0.192 (0.273)			-0.228 (0.266)
IG (homophily)		0.708*** (0.259)	0.627** (0.341)		-0.119 (0.305)	0.311 (0.374)
log Likelihood	-1020.097	-854.297	-834.505	-746.997	-661.261	-656.091
Akaike Inf. Crit.	2048.194	1734.594	1707.011	1501.993	1348.522	1350.181
Bayes Inf. Crit.	2070.735	1807.853	1814.081	1524.534	1421.781	1457.252

Notes: Parameter estimates are based on mean value and standard deviation of MCMC sample. MCMC sample is based on multiple chains (number of parameters times four), where each chain has a length of 10000 and 50% of each chain is discarded for burn-in. \*, \*\*, and \*\*\* indicate that the corresponding 90%, 95%, and 99% one-sided highest posterior density intervals do not include zero.

Table B.8: Bayesian estimation of ERGM specifications for Uganda

	Expert <i>B</i> network			Support <i>T</i> network		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
EDGES	-3.348*** (0.439)	-3.015 (5.776)	-3.897 (5.633)	-2.631*** (0.311)	-2.549 (5.659)	-3.463 (5.602)
MUTUAL	2.761*** (0.216)	2.73*** (0.226)	3.703*** (0.298)	2.483*** (0.21)	2.284*** (0.223)	2.357*** (0.235)
SUPPORT		1.254*** (0.164)	1.189*** (0.175)			
EXPERT					1.2*** (0.147)	1.188*** (0.156)
GWESP	1.326*** (0.362)	1.092*** (0.35)	0.791*** (0.338)	0.807*** (0.221)	0.577*** (0.223)	0.492*** (0.213)
GWDSP	-0.174*** (0.035)	-0.137*** (0.037)	-0.02 (0.037)	-0.165*** (0.03)	-0.132*** (0.031)	-0.109*** (0.032)
MEMBER		0.389* (0.263)	0.277 (0.276)		0.044 (0.268)	0.122 (0.271)
POWER (indegree)		1.2** (0.599)	-0.663 (0.776)		2.306*** (0.591)	1.785*** (0.68)
POWER (outdegree)			5.002*** (0.759)			2.107*** (0.681)
EXEC (indegree)		0.392** (0.198)	-0.18 (0.268)		0.203 (0.193)	0.511** (0.234)
EXEC (outdegree)			0.523** (0.296)			-0.384* (0.246)
DONOR (indegree)			0.197 (0.299)			0.448** (0.261)
DONOR (outdegree)		-0.12 (0.218)	-0.714** (0.332)		-0.515*** (0.215)	-0.928*** (0.27)
RESEARCH (indegree)			-3.262*** (0.439)			0.703*** (0.259)
RESEARCH (outdegree)		1.319*** (0.212)	2.351*** (0.29)		-0.415** (0.226)	-0.735*** (0.281)
POLSIM		-1.652 (6.627)	-2.344 (6.477)		-1.344 (6.48)	-1.275 (6.391)
PREFSIM		-1.184 (6.638)	-1.668 (6.477)		-1.876 (6.484)	-1.752 (6.402)
IG (indegree)			-0.538** (0.25)			0.053 (0.237)
IG (outdegree)			0.065 (0.27)			0.029 (0.215)
IG (homophily)		0.134 (0.228)	0.4 (0.329)		0.563*** (0.212)	0.657** (0.286)
log Likelihood	-864.493	-774.599	-679.051	-832.544	-738.143	-724.768
Akaike Inf. Crit.	1736.985	1575.199	1396.101	1673.088	1502.287	1487.537
Bayes Inf. Crit.	1758.981	1646.684	1500.58	1695.084	1573.772	1592.015

Notes: Parameter estimates are based on mean value and standard deviation of MCMC sample. MCMC sample is based on multiple chains (number of parameters times four), where each chain has a length of 10000 and 50% of each chain is discarded for burn-in. \*, \*\*, and \*\*\* indicate that the corresponding 90%, 95%, and 99% one-sided highest posterior density intervals do not include zero.

Table B.9: Average marginal effects for Expert  $B$  and Support  $T$  networks

	Ghana		Senegal		Uganda	
	Expert	Support	Expert	Support	Expert	Support
EDGES	-0.322 (0.363)	-0.309 (0.4)	-0.551 (0.438)	-0.317 (0.335)	-0.349 (0.504)	-0.381 (0.624)
MUTUAL	0.297*** (0.009)	0.277*** (0.01)	0.342*** (0.013)	0.219*** (0.012)	0.332*** (0.012)	0.260*** (0.017)
SUPPORT	0.081*** (0.014)		0.141*** (0.019)		0.107*** (0.016)	
EXPERT		0.093*** (0.015)		0.118*** (0.013)		0.132*** (0.017)
GWESP	0.087*** (0.029)	0.01 (0.014)	0.142*** (0.052)	0.048*** (0.013)	0.071*** (0.03)	0.055*** (0.024)
GWDSP	-0.002 (0.002)	-0.008*** (0.003)	-0.009** (0.004)	-0.006*** (0.003)	-0.002 (0.003)	-0.012*** (0.004)
MEMBER	0.071*** (0.02)	0.013 (0.022)	0.006 (0.009)	-0.006 (0.008)	0.025 (0.025)	0.013 (0.03)
POWER (indegree)	-0.055 (0.076)	0.268*** (0.084)	0.162*** (0.062)	0.091** (0.054)	-0.059 (0.069)	0.197*** (0.077)
POWER (outdegree)	0.207*** (0.074)	0.087 (0.078)	0.137** (0.069)	0.044 (0.051)	0.449*** (0.067)	0.232*** (0.075)
EXEC (indegree)	-0.021 (0.023)	0.011 (0.023)	0.028 (0.026)	-0.014 (0.023)	-0.016 (0.024)	0.057** (0.026)
EXEC (outdegree)	0.058*** (0.024)	0.042** (0.024)	-0.013 (0.029)	0.021 (0.021)	0.047** (0.026)	-0.043* (0.027)
DONOR (indegree)	-0.014 (0.023)	-0.054** (0.024)	-0.06** (0.028)	0.05*** (0.021)	0.018 (0.027)	0.05** (0.029)
DONOR (outdegree)	-0.012 (0.025)	0.096*** (0.024)	0.011 (0.028)	-0.001 (0.022)	-0.064** (0.03)	-0.103*** (0.029)
RESEARCH (indegree)	-0.111*** (0.024)	-0.012 (0.023)	-0.100*** (0.025)	0.029* (0.019)	-0.294*** (0.036)	0.078*** (0.028)
RESEARCH (outdegree)	0.121*** (0.021)	0.030 (0.024)	0.204*** (0.024)	-0.042** (0.020)	0.211*** (0.023)	-0.082*** (0.031)
POLSIM	-0.107 (0.537)	-0.053 (0.596)	-0.143 (0.724)	-0.122 (0.558)	-0.212 (0.579)	-0.144 (0.713)
PREFSIM	-0.086 (0.537)	-0.133 (0.598)	-0.172 (0.722)	-0.086 (0.56)	-0.15 (0.578)	-0.195 (0.714)
IG (indegree)	-0.046** (0.021)	-0.076*** (0.022)	-0.005 (0.024)	0.002 (0.021)	-0.049** (0.023)	0.006 (0.026)
IG (outdegree)	0.015 (0.022)	0.013 (0.022)	-0.019 (0.028)	-0.019 (0.021)	0.006 (0.024)	0.003 (0.024)
IG (homophily)	0.037* (0.027)	0.072** (0.031)	0.063** (0.035)	0.024 (0.03)	0.036 (0.03)	0.073** (0.032)

Notes: Estimates are based on mean value and standard deviation of MCMC sample for marginal effects. \*, \*\*, and \*\*\* indicate that the corresponding 90%, 95%, and 99% one-sided highest posterior density intervals do not include zero.

## B.3 Figures

Figure B.1: Aggregated Power Plots: Support  $T$  (upper panel) and Expert  $B$  (lower panel) networks

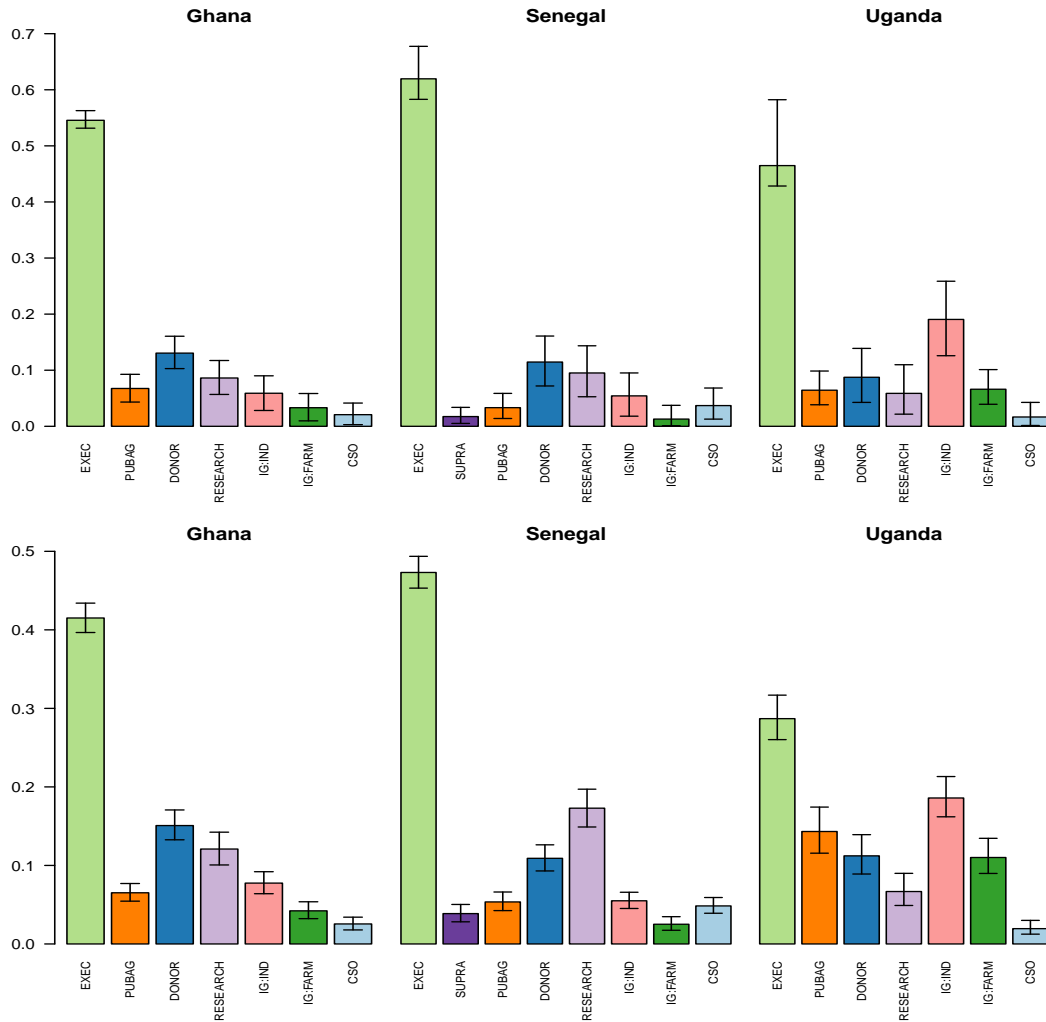
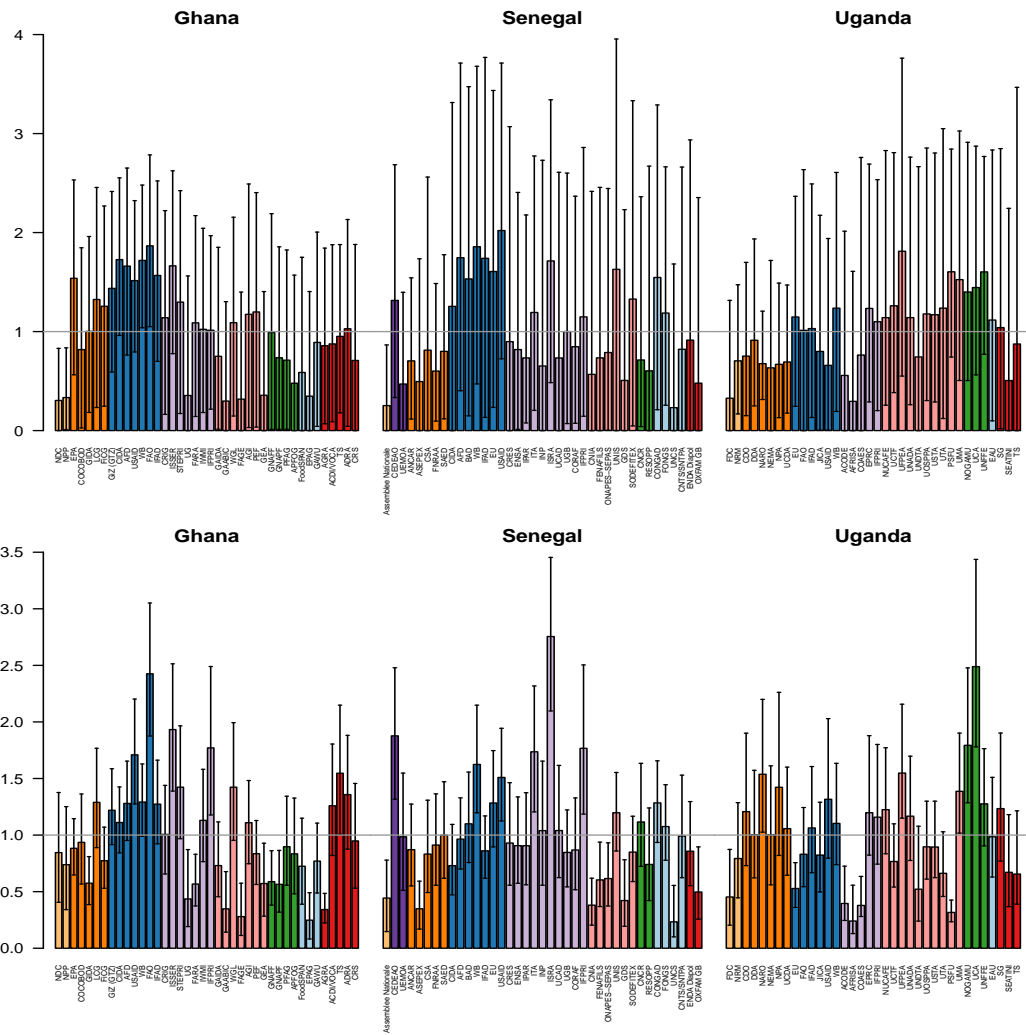


Figure B.2: Power Plots: Support  $T$  (upper panel) and Expert  $B$  (lower panel) networks



## B.4 Goodness of fit

Model fit can be assessed using traditional likelihood-based measures such as AIC, which we report in tables B.6 to B.8. According to AIC, BIC, and log likelihood, model specifications with exogenous variables are preferred across all countries against model specifications with only endogenous network statistics. However, these criteria may reveal only little about the specific features of the data captured or not captured by the model specifications. Therefore, additional goodness-of-fit approaches have been developed (see for example Hunter et al. (2008); Goodreau, Kitts, and Morris (2009)). In particular, the MCMC algorithm of described by Hunter et al. (2008) is used to generate a sample based on the estimated ERGM parameters, where each sample comprises of 10,000 networks for each model specification and each of the three countries.<sup>1</sup>

We gauge the model fitness via comparing the empirically observed frequency of edgewise network statistics, i.e. edgewise in-degrees, edgewise out-degrees, edge-wise shared partners, and the minimum geodesic distances, with expected distributions of edgewise network statistics as implied by the estimated parameter estimates characterizing the network generating process. Expected distributions are thereby assessed via simulating 10,000 networks using the estimated parameter configurations per model specification and country and calculation of the edgewise distributions of network characteristics of interest. In general, the distributions arising from model specifications 2 and 3 or 5 and 6 respectively are much more in line with the observed distributions compared to model specifications 1 and 4.

However, it possibly suffers (Cranmer and Desmarais, 2011; Goodreau, Kitts, and Morris, 2009) from degeneracy problems. Essentially, degeneracy results from a specification of a model that fits the data poorly.<sup>2</sup> However, as Cranmer and Desmarais (2011) nicely put it ‘degeneracy is, in some sense, a statement about the model fit’ and therefore they consider degeneracy not

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<sup>1</sup>Note that within the Bayesian context, each network is drawn conditional on a draw from the posterior distribution of parameters provided by the MCMC estimation output.

<sup>2</sup>If the model is not well specified, the MCMC process will move to an extreme graph of all or no edges, where it will stay, and the model is said to be degenerate, see Hunter, Goodreau, and Handcock (2008) for details

as a serious limitation of the ERGM approach, as all empirical models are supposed to fit observed data. Given the goodness of fit observed within the application, we are confident that the estimated ERGM specifications sufficiently match observed network data.

Figure B.3: GOF: Ghana Expert network Models 1 to 3 (first three rows) and Ghana Support network Models 3 to 6 (last three rows)

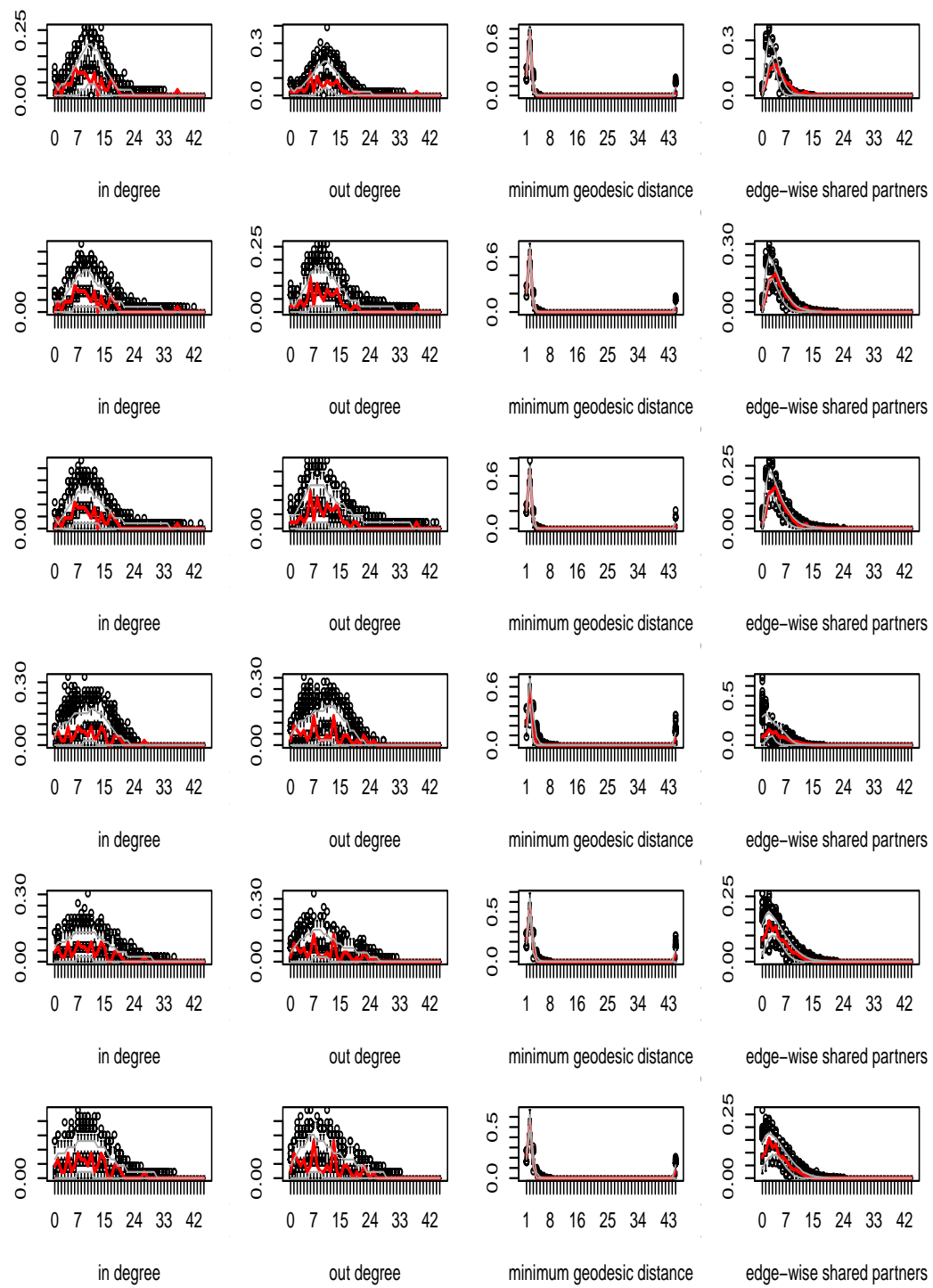




Figure B.4: GOF: Senegal Expert network Models 1 to 3 (first three rows) and Senegal Support network Models 3 to 6 (last three rows)

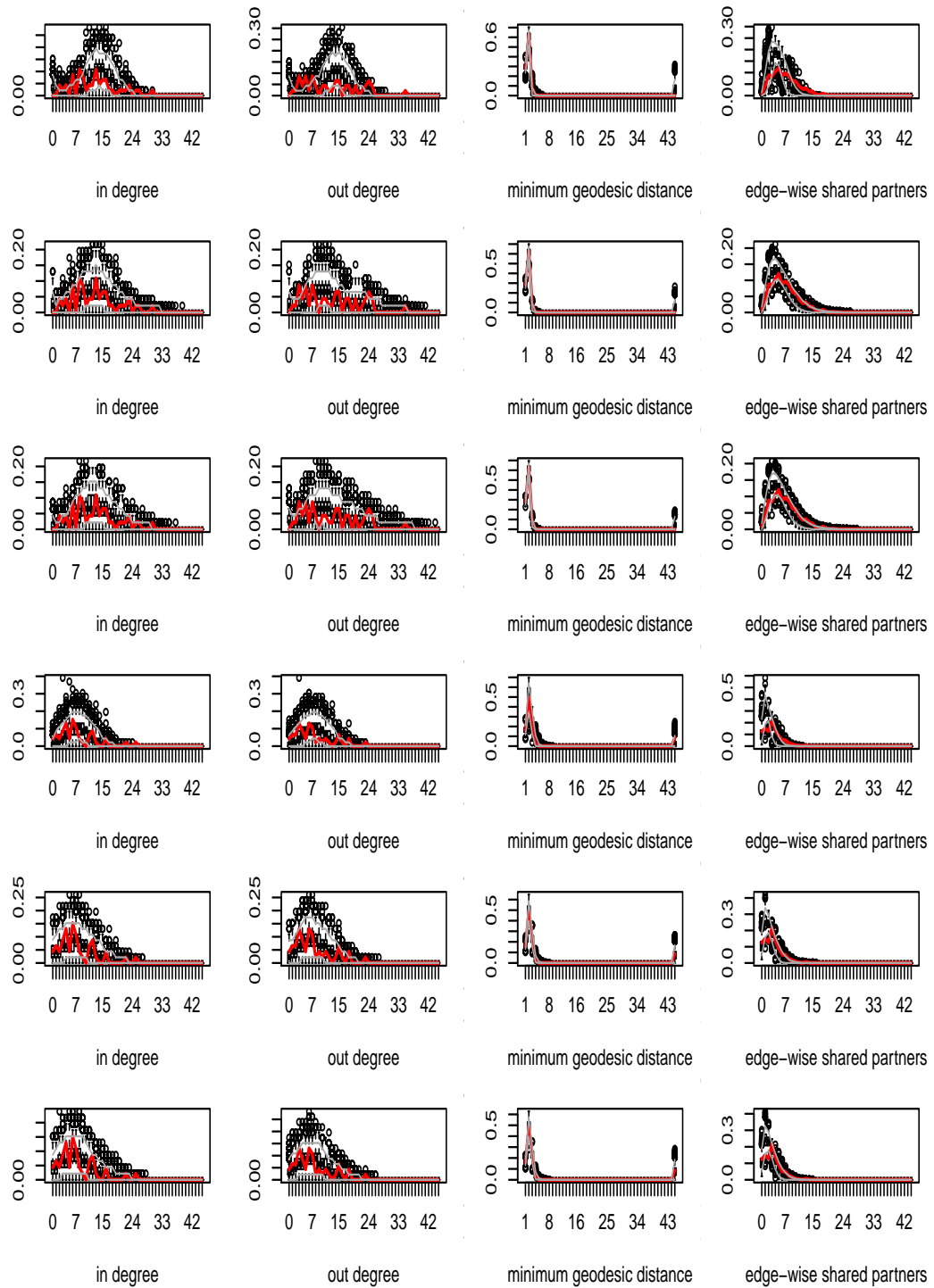
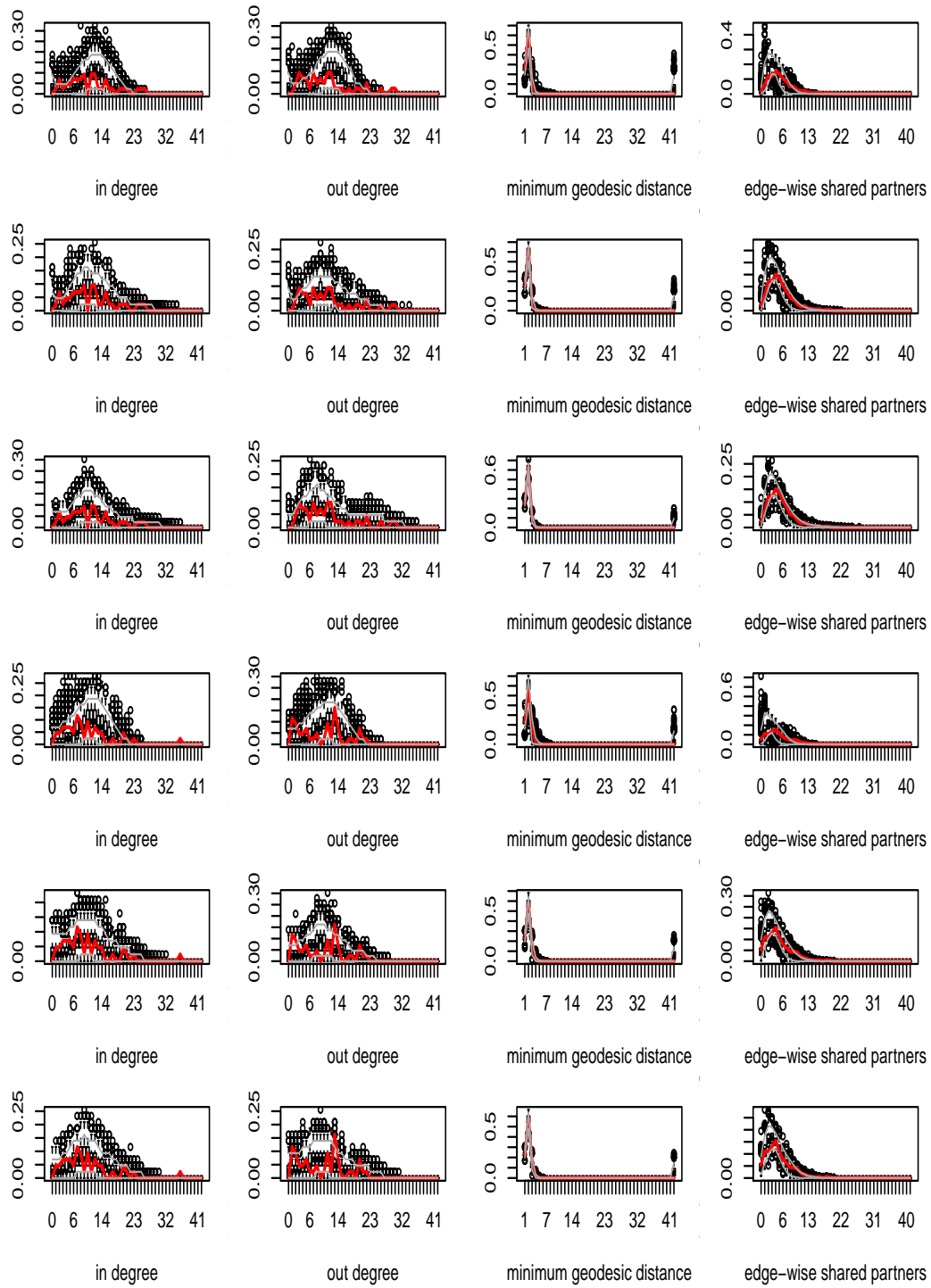


Figure B.5: GOF: Uganda Expert network Models 1 to 3 (first three rows) and Uganda Support network Models 3 to 6 (last three rows)



## B.5 Handling of missing information in surveyed data

Missing information within the surveyed data relates either to non-confirmed ties within the political support network or to personal, i.e. node, characteristics of organizations not provided within the survey interview due to time constraints. To deal with missing information, we proceed as follows. Missing information regarding confirmation of political support ties is substituted with information on links available from surveyed network on social relations. This substitution is necessary as governmental organizations have been asked to mark only organizations from whom they receive political support, while vice versa non governmental organizations by design only marked organizations or agents to whom they supply political support. This design was chosen to reduce the response burden but does provide complete network information only when brokerage is absent. However, to account for the likely possibility of brokerage within the exchange of political support, we used surveyed network information on social contacts to confirm political support ties between agents or organizations. Note that non confirmed political support ties are present in 25 cases in Ghana, in 19 cases in Senegal, and in 18 cases in Uganda. Information with regard to individual characteristics is only missing with regard to political preferences. Thereby, missing values are handled via hot deck imputations referring to a set of plausible candidate values delineated from the set of observed values using similar types of organizations and expert knowledge on political proximity of organizations. Model estimations using different draws from the candidate sets provided substantially the same results. Corresponding estimation results are available upon request.