# Narratives in Economic Modelling: A new kid on the block?

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Looking at the policy domain of growth and poverty reduction in developing countries there is agreement that public policy is a key determinant. Investment policies like CAADP, have time-delayed and/or indirect effects on the wanted targets. Therefore making a choice in this domain is highly complex problem and political practitioners faced with this challenge form simple mental models that allow them to form a decision, a narrative.

We are interested in the transformation of a policy choice, an allocation of budget to different policy instruments, into policy outcomes like poverty reduction. We separate this transformation into two parts: a policy - growth link and a growth - outcome link. The latter is derived by applying a meta-modeling approach to a CGE. The former is estimated applying the policy impact function approach. Using this approach we can extract the assumed underlying technology into a quantitative model.

Applying this framework we are able to estimate actor or group specific technologies and can quantify the implicit narratives actors have when making policy decisions. This also allows to measure the inefficiency of policy choices. In a second step it also allows to disentangle the inefficiency into two parts. Is the inefficiency due to missing knowledge or due to wrong incentives? Another interesting application is the comparison of the "scientific world" of economic modelers with the "practitioners world"? Are they fundamentally different?

Beyond the theoretical derivation of the framework, it is applied empirically to the case of CAADP in Senegal.



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# 1 Introduction

There is a broad agreement in the development literature that sustainable economic growth is the only successful strategy to lead developing countries out of poverty and even beyond into middle income status [Saith, 1981, Gaiha, 1989, Sen, 1997, Fan et al., 2000, Diao et al., 2012]. Furthermore, scholars agree that public policy is a key determinant of growth and poverty reduction [Fan et al., 2000, **?**]. This agreement in the theoretical literature is also echoed in political practice. For example, at the recent annual ReSAKSS Meeting in 2015 in Addis Abbaba Ousmane Badiane, IFPRI Director for Africa, highlights the key 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 key role in achieving sustainable growth putting this policy into an effective operation is a complex task. In this context considerable research efforts have been undertaken in the recent decades to untangle the determinants of growth and poverty, including the role of public policy (see for example [Durlauf et al., 2005] for a comprehensive review of this literature). In particular, reviewing the literature on the determinants of growth two strands can be identified. A first strand focus on proximity factors of growth, e.g. initial income, investment and macroeconomic policies, while more recently a second strand of the literature focus on fundamental factors of growth, e.g. geography, institutions, religion, and ethnic fractionalization. Governmental policy plays a key role in both strands, i.e regarding the first government has to implement appropriate policies promoting proximity growth factors, e.g policies promoting t.p., trade openness, investments in physical and human capital, etc..., while for the second strand government has to set appropriate institutions promoting economic growth.

However, the majority of empirical growth analyses focuses on macroeconomic policies, i.e. monetary, fiscal and trade policies, or regulatory policies, while the impact of public spending for social and sectoral policies, e.g. public investments in agriculture, infrastructure or research & development or provision of public goods like education, health care or social security, on economic growth have only rarely been studied in the econometric growth literature.

In contrast, public spending on sectoral policy programs has become the focus of practical politics in many development countries more recently. For example, more than a decade ago, many African countries committed to continent-wide goals of the Comprehensive African Agriculture Development Programme (CAADP) of the Africa Union and New Partnership for Africa's Development (NEPAD) following the 2003 Maputo Declaration on Agriculture and Food Security in Africa. The goals drew attention towards a shared commitment of allocating at least 10 percent of their national budgets to agriculture in order to achieve a 6 percent annual sector growth rate and improvements in food and nutrition security. A decade later, in the 2014 Malabo Declaration the principles and values of the CAADP process were reasserted and recommitted to by African Heads of State and the African Union (AU) in Malabo, Equatorial Guinea. As a result, policy makers continue to be called on to allocate resources and design strategies according to the CAADP framework and process. Hence, in political practice, it is well understood that beyond the fundamental factors and beyond macroeconomic and regulatory policies the allocation of scarce state budget resources across alternative social and economic policy programs, e.g. public investments in infrastructure, education as well as research & development and extension services, can have a significant impact on TFP growth and poverty reduction. A challenge, however, that continues to face African policy makers is how should a country optimally allocate its budget across the different policy programs, and which instruments are most appropriate? In particular, designing effective and efficient Pro-Poor Growth (PPG) policies requires an understanding of growth-poverty linkages and policy-growth linkages. The former corresponds to the fact that poor households benefit to a different degree from sectoral growth depending on their specific economic linkages to these sectors. The latter corresponds to the fact that economic growth does not fall from heaven, but rather has to be generated using scarce public budget resources, where amount of budget resources required to increase growth in a specific sector often varies significantly across sectors. Moreover, economic growth can be promoted via different channels, i.e. increasing factor input, promoting technical progress or international trade or reducing transaction costs, where different policies, e.g. public investments in research & development or in infrastructure, are differently effective promoting growth in different sectors.

In this regard governments often lack the knowledge and access to a sufficient national capacity for policy analysis and impact evaluation in order to generate the evidence needed on how certain investment and policy strategies can more effectively impact on development goals. Unfortunately, the general growth literature can not provide many valuable insights to this particular question as it is focused on macroeconomic and regulatory policies [1]. In the development economic literature, however, exists some interesting work studying the role of public spending as a determinant of economic growth and poverty reduction (see Fan et al. [2000], Fan and Rosegrant [2008] for a literature review). Reviewing this literature delivers heterogenous and sometimes even conflicting results Fan and Rosegrant [2008]. A prominent debate in this literature is the relative importance of agriculture versus non-agricultural sectors in promoting pro-poor growth.

This debate is supported by an extensive empirical literature that uses various methods to compare the growth linkages and poverty-growth elasticities of agriculture with those of nonagriculture (see, for example, Diao et al. [2012], Christiaensen et al. [2011], Diao et al. [2010a], De Janvry [2010], Loayza and Raddatz [2010], Thirtle et al. [2003]). Although most of these studies usually find that agricultural growth has larger economy-wide multiplier effects and stronger linkages to poverty reduction than nonagricultural

[1]Moreover, despite the vast amount of empirical research generated by new growth theories, there is remarkably little consensus on which mechanisms are most salient in explaining cross-country differences in empirically observed growth [Durlauf et al., 2007, Rodrik et al., 2002, ?].

growth Bezemer and Headey [2008], Bravo-Ortega and Lederman [2005], others, e.g. Loayza and Raddatz [2010], Hasan and Quibria [2004] find a significant relationship between growth and poverty for labor-intensive nonagricultural sectors. Analogously, **?** conclude from their CGE simulations undertaken for 5 African countries that growth-poverty linkages for manufacturing, trade, and transport services are often close to and sometimes exceed those of agriculture. Accordingly, the latter conclude that heterogeneous outcomes at the subsectoral level confirm the need for more detailed analysis of nonagriculture and its linkages to poverty.

A drawback of existing approaches is that they focus on growth-poverty linkages and neglect policy-growth linkages, i.e. from the viewpoint of a government economic growth does not fall from heaven, but rather has to be generated using scarce budget resources. Accordingly, a second strand of this literature explicitly investigates policy-growth linkages (e.g. [Fan et al., 2000, Fan and Zhang, 2004, Fan et al., 2009]. At methodological level, this literature typically applies econometric estimation techniques using cross-regional data regressing a GDP measure on a set of potential determinants selected in the light of modern growth theory [Fan et al., 2000, Saith, 1981, Gaiha, 1989]. For example, Fan and Rosegrant [2008], Fan et al. [2000, 2002], Fan and Zhang [2004] estimate a structural equation model including both policy-growth and growth-policy linkages within an simultaneous equation approach including multiple policies that impact on poverty reduction via different channels, i.e. productivity, production, commodity prices, wages, non farm employment, income growth. A similar approach has been applied by Fan et al. [2009] as well as Diao et al. [2010b]. This body of econometric work has significantly contributed to the understanding of the role of public spending as a determinant of growth and poverty reduction. Nevertheless, this work still suffers from serious econometric and data problems as well as from theoretical shortcomings. In particular, econometric analyses are based on reduced-form models and hence underlying structural mechanisms are typically not explicitly analyzed [Löfgren and Robinson, 2008]. Moreover, applied econometric approaches require a large set of statistical data that is normally not available in developing countries. Moreover, in contrast to the econometric growth literature cross-country data cannot be applied, because for public spending policy-growth and growth-poverty linkages are country-specific. In addition to the data problems that hamper most lines of analysis, econometric estimations are plagued by serious estimation problems, e.g. endogeneity or spurious correlation (see Fan and Rosegrant [2008] for a detailed discussion), which often can not adequately be addressed given the poor data available.



To overcome theoretical shortcomings of reduced form econometric approaches on the one hand and to incorporate simultaneously policy-growth and growth-poverty linkages on the other hand Löfgren and Robinson [2008] suggest a combined approach. In particular, they link an econometric approach estimating policy-growth linkages with a recursive dynamic general equilibrium model analyzing growth-poverty linkages. However, even the combined approach of Löfgren and Robinson [2008] still suffers from various shortcomings. First, modeling of policy-growth linkages Löfgren and Robinson [2008] rely on the reduced form econometric approach suggested by Fan and Zhang [2004]. Accordingly, they themselves admit that the criticism of this approach also applies to their combined approach. Secondly, while the general equilibrium model has the advantages in terms of internal consistency and allowing for clearer identification of causality than is possible with reduced form econometric estimations, the application of a CGE model requires simplifying assumptions that are open to challenge. Moreover, empirical results derived from CGE-model application are very sensitive to specific model specifications, that are often only weakly empirically justified, e.g. assumed closure rules and assumed elasticity parameters. Thus, growth-poverty linkages derived from a CGE model are plagued by model uncertainty implying a limited potential to generate robust policy-relevant messages.

Addressing these shortcomings this paper suggest an alternative approach. First, assessing policy-growth linkages empirically a nested two-stage policy impact function is suggested, where at a lower stage budget allocations across different policy programs are integrated to an effective budget input following a CES-function. At an upper stage effective budget input is transformed into TFP growth. Separate policy impact functions are defined for different economic sectors and subsectors. Following Löfgren and Robinson [2008] the policy impact function approach is linked with a recursive dynamic CGE model to an integrated approach, where public spending is transformed into sector specific TFP growth based on the set of policy impact functions and the DCGE translates the sectoral growth into income growth and poverty reduction.

To deal with model uncertainty inherent in the CGE-model application we derive a set of meta models via CGE-simulations conducted under different model parameter-settings. The latter correspond to different stylized macroeconomic adaption behavior of the economy to exogenous economic shocks. We apply a Bayesian estimation approach that combines existing statistical data with a priori information of political experts [Durlauf et al., 2005, Eicher et al., 2015] to estimate corresponding PIF-parameters conditional on each specific meta model. Based on these estimations we use Bayesian model selection methods [Durlauf et al., 2005, Eicher et al., 2015] to derive High Posterior Density estimation of PIF-parameters taking model uncertainty explicitly into account. Moreover, we are able to derive the a posteriori probability for each meta model that this model is the true model. Hence, in contrast to existing approaches we are able to draw statistical inferences on competing models of growth-poverty linkages that allow us to generate relative robust policy-relevant messages even in the presence of model uncertainty. In particular, based on our approach we derive indicators to identify key sectors and key policies of an efficient PPG-strategy.

Finally, the Bayesian estimation approach using available statistical data and apriori information collected from political experts significantly reduce data and estimation problems inherent in existing econometric approaches estimating PIFs.

The approach is empirically applied to Senegal analyzing the allocation of public spending on agriculture under CAADP.

The rest of the paper is organized as follows: The next section 2 introduces the theoretical framework of this paper and presents the methodological framework that relies on the integrated PIF-CGE approach. In section 3 we present the estimation strategy and the econometric models and the application of our approach to the CAADP-reform 2015 in Senegal. Section 4 shows some exemplary results, that are possible when applying this framework. It is followed by the conclusion and outlook on future research in section 5.

# 2 Theoretical Framework

## 2.1 Assessing growth goal linkages

Fan et al. [2000], Fan and Rosegrant [2008] nicely elaborate that public policies impact on poverty reduction and income growth of specific social groups via different channels. For example, policies have direct effects on productivity (TFP) or human and physical capital. Furthermore, indirect policy impact occur via spillover effects operating via induced changes in factor prices (labor wages or land rents) or via changed commodity prices. Theoretically, these direct and indirect policy impacts on poverty or income can be best captured in a general equilibrium modeling framework. Reviewing the literature, however, many different general equilibrium model approaches exists.

In particular, recursive-dynamic CGE models are efficient tools to generate theoretically founded hypotheses on how economic growth impacts on poverty reduction under specific structural and macroeconomic framework conditions characterizing a specific country. Applied recursive-dynamic CGE models can also incorporate many features highlighted in the endogenous growth theory, e.g. endogenous determinants of productivity growth. Given the fact that there is little empirical evidence that private agent act on the basis of perfect foresight a dynamic CGE-formulations is certainly plausible for a simulation analysis Löfgren and Robinson [2008].

Next, we derive a simple meta model corresponding to the complex DCGE-model regrading the description of direct relations between relevant model outputs and inputs. In particular, we consider average annual growth of relevant policy goals, $w = [W_j]$, as relevant outputs, while we take the annual average growth rates of factors ($f = [f_k]$ as relevant inputs:

The meta model is defined by:

$$\begin{aligned} \Delta w &= \xi \Delta f \\ w &= \xi^0 + \xi^f \Delta f \end{aligned} \tag{1}$$

$\xi^0$ is the vector of base run growth rates realized for policy goals assuming no change in factors. $\xi = \xi_{jk}^{CGE}$ is a matrix of impact elasticity defined as the change in an average annual growth rate of policy goal j induced by a change in the factors k. Impact elasticities are derived from the original DCGE-model via simulations.

## 2.2 Assessing policy-growth linkages

Following the literature [Fan and Rosegrant, 2008] policy-growth relations can be best captured applying the concept of policy impact functions, $PIF(\gamma)$.

However, empirical specification of policy impact functions is difficult for at least three reasons. First, to capture complex policy-growth relations a complex functional form has to be assumed for corresponding PIFs. Second, policy-growth linkages depend on very specific economic framework conditions, which are characteristic for each sector and for each country. Thirdly, estimating PIFs empirically is extremely data demanding including detailed data on production (input and output quantities and prices) as well as on public budget spending on different policy programs. Hence, standard econometric estimation of PIF approaches have been rather rarely applied, yet. An interesting exemption is Fan et al. [2000] who used a state-level panel data for 14 states of India to estimate a structural equation model including a PIF approach. Fan et al. [2000] significantly improved methodology to analyze and measure policy-growth linkages. For example, based on their approach they could derive marginal impact of different policies, such as expenditures on rural roads, R&D or eduction, on agricultural productivity and poverty reduction, respectively. However, although the approach contributes certainly a lot to analyzing policy-growth-poverty linkages is still has some shortcomings. A major problem of the approach of Fan et al. [2000] is certainly it's high demand of detailed data which makes it difficult to apply it to other countries. Especially, an application to African countries is often limited due to lack of adequate data [2]. Moreover, Fan and Rosegrant [2008] conclude that their structural equation model is a reduced from approach and that a more in-depth general equilibrium analysis is needed to analyze how government expenditure affect t.p. in agriculture and non-agriculture and how the latter impact on poverty reduction. In particular, Fan et al. [2000], Fan and Rosegrant [2008] considered the impact of policies on t.p. for total agriculture as an aggregate, while an analysis of policy-growth linkages at subsector level, e.g. crops versus livestock or food versus export crops, has not been provided.

### 2.2.1 A nested two-stage policy impact function

Consider the following two-stage policy impact function capturing the impact of different policy programs $i \in I$ on the technical progress realized in a sector s. At the upper-stage effective budget, $Be_s$, is transformed into technical progress (tp) realized in the sector s, $tp_s$, following a sigmoid function:

$$tp_s = tp_s^{max} \frac{exp[a_s Be_s + b_s]}{exp[a_s Be_s + b_s] + 1} \tag{2}$$

In Figure 1 the sigmoid form relating technical progress to effective budget is plotted.

To capture the impact of different policy programs on sectoral t.p. investment in different policy programs $[\gamma]$ is transformed into effective budget at a lower stage following

[2] Fan and Rosegrant [2008], however, applied their approach to analyze policy-growth-poverty relations in Uganda using district-level panel data. Nevertheless also Fan and Rosegrant [2008] conclude that most African countries do not provide the quality of data needed to estimated their structural equation model.

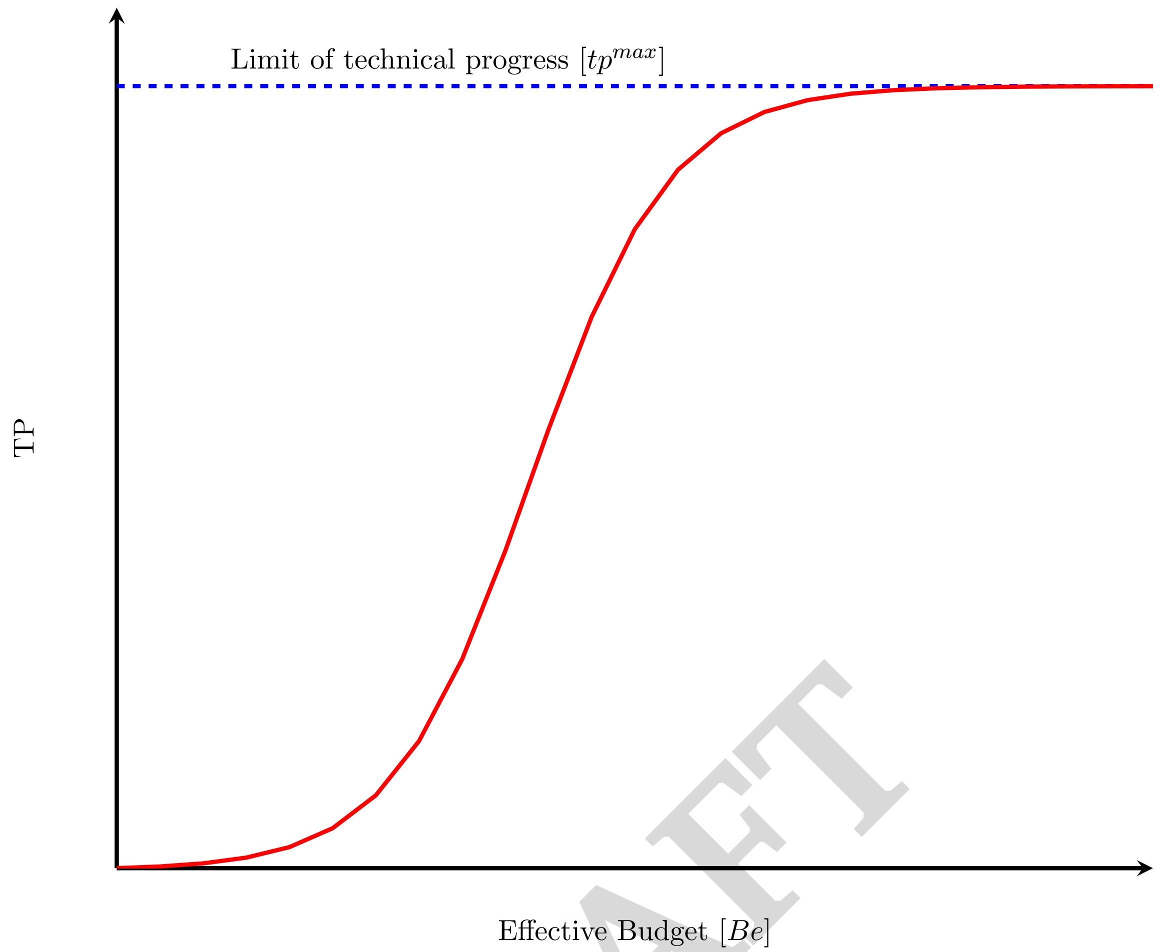


Figure 1: Sigmoid function relating effective budget to sectoral technical progress

a CES-function:

$$\begin{aligned} &Be_s = CES^s(\gamma) = \eta_s \left[ \sum_{i \in I} \mu_{is} \alpha_i^{-\rho} \right]^{-\frac{1}{\rho}} \\ &with: \quad \sum_i \mu_{si} = 1 \end{aligned} \tag{3}$$

, where $\alpha_i$ denotes the budget share of the policy program $i$, while $\gamma_i$ denotes the total budget spent on the program $i$ as already defined above.

In contrast to the constant elasticity Cobb-Douglas form suggested by Fan and Rosegrant [2008] the sigmoid function allows for flexible impact elasticities. As can be seen from the illustration in Figure 1 the sigmoid functional form assumes that for each sector technical progress can not be infinitely increased with public money, but marginal impact of public spending is initially increasing up to a threshold value and if effective budget lies above this threshold marginal impact is increasingly diminishing and there exist a maximal rate of technical progress that can be achieved with public policy programs in a specific sector $s$.

Moreover, our PIF approach incorporates not only different sector policies, e.g. agricultural versus non-agricultural policy programs, but also different agriculture policy programs focusing on improved natural resource management, i.e. land and water management, human resource management, i.e. agricultural extension and research, or focusing ion improving general farm management, i.e. the use of modern inputs like fertilizer or pesticides. Given the CES-specification the impacts of specific subprograms are mutually interdependent. Formally, interdependencies between policies are captured in the CES-parameters $\mu_{si}$ and $\rho$, respectively. In particular, the higher $\mu_{si}$ the higher is c.p. the impact of a specific policy program $i$ on the t.p. in sector $s$, where the impact of a program generally varies across different sectors, e.g. improving natural resource management might induce a significant increase in t.p. realized in the food crop sector, while it might have only moderate impact on t.p. in the livestock sector. Some $\mu_{si}$ can also be zero, e.g. spending on land or water management might have no impact on t.p. in non-agricultural sectors [3]

Finally, the scaling parameter $\eta_s$ incorporates the implementation efficiency of policy programs. Statistics on public expenditures provide information on the allocation of money across different policy programs like land and water management or infrastructure or research or extension. However, beyond the amount of money spent under a different program it is crucially important for the final impact on t.p. how programs are implemented. For example, under CAADP a large part of public expenditure allocated to different programs is essentially implemented via subsidy payments, where the effectiveness of subsidy payments is highly debated. Analogously, money allocated to agricultural extension services can be used to employ new well trained advisors or to buy new cars for already employed unskilled farm inspectors. Under the first implementation mechanism the same amount of public spending has a much higher effectiveness when compared to the second implementation. Formally, implementation efficiency is captured by the CES-scaling parameter $\eta_s$, where a higher $\eta_s$ implies c.p. a higher implementation efficiency. Please note further, that the focus of policy programs on specific sectors or subsectors can also be captured via $\eta_s$. For example, assume rural infrastructure program especially focused on infrastructure required by specific agricultural subsectors, say export crops, while investment in infrastructure required by other subsectors, say food crops and livestock, is comparatively low under this program. This implies a comparatively high $\eta$-parameter for export crops when compared to other agricultural subsectors, i.e. food crops and livestock, respectively.

[3]Please note that the PIF only captures policy-growths relations, while within our integrate approach growth-income and growth-poverty relations are captured in the dynamic CGE model. Accordingly, improving natural resource management might have an indirect impact on industrial growth, i.e. induced agricultural growth has general equilibrium effects on wages, prices and demand of both agricultural and non-agricultural industries. Nevertheless, these indirect effects have to be distinguished from direct impacts of policies on sectoral t.p., where for the case of natural resource management it can be expected that policies improving natural resource management have no direct impact on t.p. realized in the non-agricultural sector, e.g. chemistry industry.

## 3 Empirical Estimation

### 3.1 Data

The CGE-model for Senegal was calibrated using 2011 Social Accounting Matrix (SAM) constructed by XXX Sene (2014). Its formulation incorporates insights from the literature on the potential channels through which different kinds of government spending influence productivity and economic performance. In particular, it incorporates causal links between total factor productivity (TFP) and different types of government spending. Moreover, it includes an explicit treatment of transaction costs for commodities that enter the market sphere. In detail the constructed agricultural SAM is based on the 2011 Supply-Use table and trade data provided by the National Agency of Statistics. The breakdown of the agricultural sector is done using information from the most recent household poverty monitoring survey (ESPS) and agricultural surveys conducted by the DAPSA and the Senegalese Institute for Agricultural Research (ISRA). Furthermore, additional data from the balance of payments which records the transactions among the residents and the rest of the world and the Table of Government Financial Operation (TOFE) from DPEE providing data on tax and non-tax revenue of the government, as well as public transfers. Based on statistical data the SAM has been built in a perspective to construct and calibrate a dynamic CGE model of the IFPRI-type 2 defined by Löfgren et al. [2002]. The model features 43 production sectors, which are further subdivided in 14 agricultural, 6 agribusiness and 23 non-agricultural sectors. Agriculture is disaggregated into 11 crop, a livestock, a fishing and a forestry sector, respectively. 23 non-agricultural sectors are subdivided into 11 industrial, 8 market service and 5 public service sectors (see annex table 1). Furthermore, agricultural crop sectors are disaggregated into 14 regions to cover regional heterogeneity in the crop patterns and resource endowments.

In order to analyze the impact of economic growth on poverty reduction, the CGE-model was linked to a household level model that incorporates 5,953 individual households based on household survey data (ESPSII, 2011). The households are distinguished by 8 household-types defined around three categories: 1) "poor versus rich", 2) "farm versus non-farm", and 3) "rural versus urban". The poverty indicators are computed on the basis of a representative household (RH) approach in a separate poverty module. In this module, the within-group household distribution is specified by a log-normal frequency function. The 2015 poverty lines in rural and urban areas are calibrated to exogenous poverty rates; we use a log standard error of 0.35 for all RHs (representative households in the model). In the computation of poverty indicators for each simulation, the CGE model feeds the poverty module with simulated data for mean consumption and CPI for each RH.

Following Fan and Rosegrant [2008] we defined a TFP-index as aggregate output index minus aggregate input index. In detail we used a Thornquist-Theil-index to calculate aggregated output and input indices:

$$lnTFP_{st} = \frac{ln(Y_{st})}{ln(Y_{st-1})} - \sum_{v} 0.5(WC_{vst} + WC_{vst-1})\frac{ln(X_{vst})}{ln(X_{vst-1})} \tag{4}$$

$lnTFP_{st}$ is the log of the total factor productivity index of sector s in time t. $Y_{st}$ denotes the output index of sector s, while $X_{vst}$ denotes the amount of input v used for production in sector s. $W_{vst}$ is the share of input v in total production costs of output s. In detail we disaggregated four inputs (labor, land, capital and purchased inputs). Sector input of labor and capital as well as sectoral output data are taken from the National Agency of Statistics (ANSD), while land data was taken from FAO statistics and from the DAPSA. These data generally cover the period 1980-2009.

Furthermore, expert surveys were undertaken with relevant governmental and non-governmental organizations. Interviewed organizations were considered as experts in development and agricultural policy in Senegal. 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. Interviewers 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 to the list were added on the list when they are nominated more than three times. In total, we have 15 governmental organizations and 31 non-governmental organizations. These non-governmental organizations includes 7 donors, 10 research organizations, 4 civil society groups and 8 socioeconomic interest groups (2 farmer and 6 agribusiness interest groups) (see Henning et al. 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 10 years. Further, we asks interviewees to indicate the preferred policy positions ($\gamma$) from the view point of the 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 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 distinguish seven policy goals farm income ($Z_1$), Poverty reduction, ($Z_2$), Provision of public services ($Z_3$), profit of agricultural export sector ($Z_4$), urban consumer income ($Z_5$), profit of the industrial sector ($Z_6$) and protection of the environment ($Z_7$). 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, where the status level as well as the corresponding levels of the end points were specified. Hence, based on the interview data we could calculate the average annual linear growth rate experts desire to achieve, i.e. $W_{gj} = 0.1\frac{Z_{gj}-Z_{gj}^0}{Z_{gj}^0}$

Furthermore, we considered the following different policy programs formulated under

CAADP : water ($\gamma_1$) and land ($\gamma_2$) management, farm management policies for food crops ($\gamma_3$), export crops ($\gamma_4$) and for livestock ($\gamma_5$), investment in road ($\gamma_6$) and storage related infrastructure ($\gamma_7$), agricultural research and development ($\gamma_8$) and extension services ($\gamma_9$). Finally, we also distinguish investment in the non-agricultural sector ($\gamma_{10}$) as an additional policy instruments.

Data on state budget expenditures are from the Statistics of Public Expenditure for Economic Development (SPEED) compiled by IFPRI. For Senegal the budget data used in the estimations cover the period 1980-2009. The speed data base provides annual data on budget expenditures for ten sectors: agriculture, communication, education, defense, health, mining, social protection, transport, and transport and communication, and total expenditures. Moreover, we used national statistics and documents to derive data on public spending for specific agricultural programs, i.e. research and extension, infrastructure or water and land management. Based on available budget data we were able to derive data for annual spending on agricultural and non-agricultural policy programs from 1980 to 2013, where $PAE_t$ denotes the agricultural expenditure and $PNE_t$ the spending on non-agricultural policy programs in the year $t$. However, for detailed spending on specific agricultural programs we only got data for a few selected years.

### 3.2 A meta modeling approach for deriving GGF

A shortcoming of applied CGE-analyses corresponds to the fact that adoption to exogenous shocks of an economy depends on specific structural framework conditions, which are often country specific. In this context **?** identified five categories of market-supporting institutions, where the institutional framework depends on historical evolution of social institutions, which is country specific. Furthermore, structural conditions include economic structures which are also country specific, e.g. the factor endowment as well as the size and productivity of different economic sectors and the economic interlinkages among sectors as well as among sectors and households. Finally, governmental behavior, i.e. selected macroeconomic policies, is an essential part of the structural framework conditions determining the growth-poverty linkages, where the latter is also specific for a country. Country specific framework conditions are often not perfectly observed due to a lack of adequate data, but rather have to be calibrated based on available expert information and weak data.

In particular, macro closure and also elasticity parameters of CGE models are both a contentious topic with a large literature. For summaries, see for example Robinson [1991], Robinson et al. [1999], Rattsø [1982], Taylor [1990]. Closure rules and elasticity parameters reflect real-world trade-offs that are associated with alternative macroeconomic adjustment patterns. The latter depend on specific structural framework conditions of an economy, which are basically unknown or only known with uncertainty by the researcher. On the other hand, simulation results may differ substantially depending on the specific closure rule or elasticity parameter settings. Formally, any setting of closure rules and elasticities defines a specific model specification of the DCGE, where empirical predictions vary across model specifications. These parameters and settings, however, can hardly be estimated econometrically due to a lack of appropriate data, hence a standard procedure in applied CGE-modeling is to specify these based on best guesses of the researcher. Therefore, the specifications of a DCGE model are uncertain implying that empirical implications derived from CGE-simulations are plagued by model uncertainty.

In this context, it is a standard procedure in applied CGE-simulation analyses to undertake sensitivity analyses, e.g. to test if or how central simulation result would change if different parameter values or different macro closure rules, respectively, are assumed [Löfgren and Robinson, 2008]. Only if undertaken sensitivity analyses deliver stable simulation results, the CGE analyses provide robust policy relevant messages. Otherwise, the CGE-application produce policy-messages that are conditional on specific model assumptions. Since the latter are uncertain, standard CGE-applications are plagued by model uncertainty. High model uncertainty implies that ceteris paribus policy-messages derived from the DCGE-simulations are also highly uncertain.

We derive a set of meta models representing relevant growth poverty linkages via simulation of a recursive dynamic CGE model specified for Senegal. The model is solved annually for a period 2015-2025, where each model solution generates an extensive, economywide set of results covering sectoral, household and macro data in each solution period. In the analysis presented here we summarize this information in a set of indicators, including data on the evolution of different policy goals, i.e. disaggregated household income (welfare) and poverty as well as the evolution of the total governmental expenditures for public good services and firm profits. In particular, we denote $Z_{jt}$ the level of a policy goal $j \in J$ realized in time period t, while $W_j$ denotes the corresponding average annual growth rate realized for policy goal $j$ in the simulation time period 2015-2025.

Finally, the model specific assumptions about how macro adjustments operate have to be made. In detail, the three standard macroeconomic balances government balance, savings-investment balance, and balance of payments are considered. Technically, Sen [1963] showed that general equilibrium models are overdetermined without the assumption of additional macroclosure rules. Based on Sen [1963] CGE-modelers defined four different classes of closure rules 4 major subsets of closure rules: a neoclassical, Johannsen, Kaldorian and Keynsian closure. Formally, each of the rule drops a specific assumption of the original general equilibrium model. As regards content different closure rules correpsond to a different macroeconomic adaption of the economy to exogenous economic shocks. Accordingly, simulation results can significantly vary depending on the assumed specific combination of closure rules.The choice of a specific macroclosure rules. Hence, the choice of a particular macro closure depends crucially on how the CGE modeler views the functioning of the economy at hand Decaluwé et al. [1987].

In detail, for the IFPRI-type 2 recursive dynamic CGE model 5 different closure rules for the government balance, and 5 for the Savings-Investment closure have been formulated. Any of the 5 GOV-closure rules can be combined with any of the 5 SI-closures, i.e. overall 25 closure scenarios result. Detailed rules are described in Löfgren et al. [2002], thus we do not explain these in detail here.

Since particular macroeconomic adaption behavior of a specific economy in the real world is generally not known by the modeler closure rules are uncertain. Therefore, CGE modelers often suggest to explore simulation results under alternative macroclosure rules.

In addition we generated a set of 27 elasticity scenarios, where we shift import, export and production elasticities with a factor of $\{0.5, 1.0, 1.5\}$.

In particular, we simulate for each of the 25 macroclosure scenarios times the 27 elasticity scenarios (675 scenarios) the impact of an exogenous growth rate of $tp_s$, in percent TFP, separately assumed for each economic sector on the development of individual policy goals, $j \in J$. This results in about 30.000 simulation runs. In detail, we assumed an exogenous base growth rate for each sector in the base run, $tp_s^0$. The latter corresponds to historically observed sectoral $tp$, while in each simulation run we assumed a constant annual growth rate of TFP, $tp_s$, for a period of T years. For each simulation run we calculated the following growth-goal elasticity:

$$\begin{aligned} \xi_{mjs}^{tp} &= \frac{1}{T}\frac{\left[Z_{jT}^{m} - Z_{jT}^{0}\right]}{Z_{jt_0}^{0}}\frac{1}{\Delta tp} \\ \xi_{mj}^{0} &= \frac{\left[Z_{jT}^{0} - Z_{jt_0}^{0}\right]}{Z_{jt_0}^{0}} \\ \Delta tp_s &= tp_s - tp_s^0 \end{aligned} \tag{5}$$

Thus, for each macroscenario and each elasticity scenario we derive a meta model $\xi^m$ corresponding to a specific relation of sectoral growth and induced growth rates of relevant policy goals.

## 3.3 Empirical estimation of the PIF

To estimate the two-stage PIF-function one would need detailed panel data on technical progress realized in the different sectors $s = 1, ..n$. Since technical progress is not directly observable one would need indicator variables to measure it. One approach would be using annual data on relevant outputs and inputs to derive an aggregated index of total factor productivity, where a Tornquist-Theil index can be applied to aggregate outputs and inputs (see for example [Fan et al., 2000]).

Additionally, detailed data on public spending including the annual expenditure for each relevant policy program $j = 1, ..., m$ is required to estimate the parameters of the PIF as specified above. Please note that specification of the two-stage PIF would require many observations, i.e. assuming n sectors and m policies implies overall $m(n-1)\mu$-parameters and n $\eta$-parameters have to be specified at the lower stage, while 3n parameters ($tp_s^{max}, a_s$ and $b_s$) have to be specified at the upper stage. Taking 20 sectors and 10 policies this implies already 200 parameters, while, for example, Fan et al. [2000] used only 150 observations in their state-level panel estimation.

Finally, even assuming required data would be available an econometric estimation applying standard estimation techniques would be plagued by several estimation problems, e.g. endogeneity problems or spurious correlation (see Fan et al. [2000] and Fan and Rosegrant [2008] for a detailed discussion).

Accordingly, it is not surprising that in the present literature hardly any study can be found that provides an empirical estimation of a set of sector specific policy impact functions.

In this context we suggest an alternative Bayesian approach combining statistical data with expert information collected from a sample of political experts operating in the policy domain of poverty reduction in a specific country to estimate the parameters of our PIF-approach.

In detail, the Bayesian estimation approach proceeds as follows.

To estimate the relevant PIF-approach we identify a set of political expert, $G$, where $g \in G$ denotes the index of a specific expert $g = 1, ..., n_g$. Political experts are relevant stakeholder and governmental organizations operating in the policy domain of poverty reduction and development in a specific country under consideration.

In undertaken expert surveys political experts are asked to assess optimal future developments of relevant policy goals, , i.e. experts estimates the average linear growth, $\hat{w}_g = \hat{W}_{gj}$, for each relevant policy goal $j \in J$, which their organization desires to achieve realistically within the next T years. Moreover, political experts are asked to rank the relative importance of policy goals, where $X_{gj}$ 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 instrument, $i \in I$, to most efficiently achieve their desired policy goals, $\hat{w}_g$. In particular, $\hat{\gamma}_g = [\hat{\gamma}_{gi}]$ denotes the budget allocation preferred by expert $g$.

Furthermore, we assume that each expert evaluate future development of policy goals based on the following intertemporal CD-function $S_g(w)$:

$$S_g(w) = \sum_{t}^{T} \prod_{j} \delta^t \left(1 + w_{j,t}\right)^{X_{g,j}} dt \tag{6}$$

Let t=0 denote the base period and assume policy shocks $\gamma$ induce a constant linear growth rate for each policy outcome, i.e. it holds:

$$W_{j,t} = W_j^0(\gamma) + (\bar{W}_j + \Delta W_j(\gamma))t \tag{7}$$

, where $W_j^0(\gamma)$ denotes the percentage change of a policy goal $j$ induced in the period $t$ by a policy shock $\gamma$ that occurred in the period t, while $W_j(\gamma)$ is the change in the average linear annual growth rate of a policy goal $j$ induced by a policy shock that occurred in period $t-1$. $\bar{W}_j$ is the constant linear annual growth rate of a policy goal $j$ assuming no policy shock, i.e. $\gamma = 0$.

Approximatively, the intertemporal evaluation function can be represented as follows:

$$S_g(w) = S_g(w^0) + T\delta^{\lambda T} \prod_{j} \left(1 + W_j^0 + (\bar{W}_j + \Delta W_j)\lambda T\right)^{X_{gj}}, \quad for \quad 0 \leq \lambda \leq 1 \tag{8}$$

Given our approach policy impact on linear growth rates of policy goals operate via induced changes in technical progress:

Rearrangements results:

$$\begin{array}{l} \bar{W}_j = \xi_j^o \\ \Delta W_j = \sum_s \xi_{js}^{CGE} \Delta tp_s(\gamma) \\ \Delta tp_s(\gamma) = PIF(\gamma) \end{array} \tag{9}$$

Moreover, public spending in economic policy programs promoting tp has opportunity costs, e.g. assuming a constant state budget, these opportunity costs correspond to a reduction of state expenditures for public services. Provision of public services is an important policy goal, i.e. let $j_{ps}$ be the index denoting the policy goal 'provision of public services', then the following direct policy impact result:

$$W_j^0 = -\Delta_{jps} \frac{\sum_j \gamma_j}{B_0} \quad \Delta_{jps} = 0 \; j \neq j_{ps} \; \Delta_{jps} = 1 \; for \; j = j_{(ps}$$

Assuming political experts know the policy-growth (PIFs) and growth-outcome ($\xi$) 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 $S_g$ :

$$\begin{array}{l} \hat{\gamma}_g = arg \max_{\gamma} S_g(w^0) + T\delta^{\lambda T} \prod_j \left(1 + W_j^0 + (\bar{W}_j + \Delta W_j)\lambda T\right)^{X_{gj}} \\ s.t. \\ \Delta W_j = \sum_s \xi_{js}^{CGE} \Delta tp_s(\gamma) \\ \bar{W}_j = \xi_j^0, \quad \forall j \in J \quad W_j^0 = -\Delta_{jps} \frac{\sum_j \gamma_j}{B_0} \qquad \Delta_{jps} = 0 \; j \neq j_{ps} \; \Delta_{jps} = 1 \; for \; j = j_{(ps} \end{array} \tag{10}$$

$$\begin{array}{l} \Delta tp_s(\gamma) = tp_s^{max} \frac{exp[a_s Be_s(\gamma) + b_s]}{exp[a_s Be_s(\gamma) + b_s] + 1} \\ Be_s(\gamma) = \eta_s \left[\sum_i \mu_{is} \gamma_i^{-\rho}\right]^{-\frac{1}{\rho}} \end{array}$$

In particular, optimal policy intervention,$[\gamma_g]$ fulfill the following first order conditions in eq. (11):

$$-\frac{\partial S_g(w^0)}{\partial W_{j_{ps}}^0} \frac{1}{B_0} + T\delta^{\lambda T} \sum_j \frac{\partial S_g(w)}{\partial W_j} \left(\sum_s \xi_{js}^{CGE} \frac{\partial tp_s}{\partial \gamma_i} + \frac{\partial w_j^0}{\partial \gamma_i}\right) = 0 \tag{11}$$

Defining social shadow prices, $\Gamma$, for future growth outcomes by:

$$\Gamma_{jg} = \frac{T\delta^{\lambda T} \sum_j \frac{\partial S_g(w)}{\partial W_j}}{\frac{\partial S_g(w^0)}{\partial W_{j_{ps}}^0}} \tag{12}$$

and defining $\Phi_{ji} = \sum_s \xi_{js}^{CGE} \frac{\partial \Delta tp_s}{\partial \gamma_i}$ as the marginal budget impact of a policy $i$ on the policy outcome $j$, results in the following FOCs:

$$\sum_j \Gamma_{jg} \left( B_0 \Phi_{ji} - \Delta_{j_{ps}} \right) - 1 = 0 \tag{13}$$

Assuming we have data, $y$, on individual goal achievements $[\hat{w}_g]$ and optimal policy positions $[\hat{\gamma}_g]$ desired by political experts $g = 1, ..n_g$. This data is informative regarding the underlying parameters of the PIF and the meta CGE-model. For notational convenience let $\theta$ denote the vector of the unknown parameters of the PIF-function and the meta CGE-model, while y denotes the matrix of observed expert data. Then, $[\theta, y]$ has to fulfill the FOCs in eq. (13), i.e.:

$$FOC(y, \theta) \equiv 0 \tag{14}$$

As long as the number of expert is not extremely large the eq.system FOC(y,$\theta$) has a large number of solutions, ie. there exist many parameter vectors $\theta$ , for which the FOC hold given the data y. The expert data,y, however is informative in the sense that the data serves to narrow down the feasible space of solutions for the unknown PIF-parameters. In this regard additional prior information held by the analyst can be used to obtain a solution to the FOCs given the data y. If $Pr_k(\theta_k)$ represents a prior distribution for the $k^{th}$ component of $\theta$ and if the prior distributions are considered to be independent then a Bayesian estimation of the PIF-parameters can be obtain from the solution of the following maximization problem:

$$\begin{aligned} &\theta^* = arg \max_\theta p(\theta) = \prod_k P_k(\theta_k) \\ &s.t. \\ &FOC(y, \theta) \equiv 0 \end{aligned} \tag{15}$$

Formally, the Bayesian approach to parameter estimation treats the PIF-parameters,$\theta$, as stochastic variables. In particular, the Bayesian approach distinguished in this context between the prior density, $pr(\theta)$, summarizing prior information on parameters, the Likelihood function, $L(\theta \mid y)$, representing the information obtained from the data in conjunction with the assumed model, and the posterior density, $pr(\theta \mid y)$, where the latter is the result of combining prior and data information based on Bayes' theorem (see [Heckelei and Mittelhammer, 2008]). The relationship between these three elements can be expressed as (e.g. Zellner [1971]):

$$pr(\theta \mid y) \propto pr(\theta) L(\theta \mid y), \tag{16}$$

where the posterior density is proportional to the prior density multiplied by the Likelihood function. The posterior density allows drawing statistical inference about $\theta$ using probability statements or by deriving point estimates that are optimal with respect to some loss criteria.

The Likelihood function in this case can be interpreted as an indicator function $I_{FOC}$

that assigns weights of 1 to admissible values of $\theta$ and 0 otherwise. Hence, the posterior is then in the form: $pr(\theta \mid y) \propto pr(\theta) I_{FOC}(\theta)$.

Consequently, the argument, $\theta^*$, that maximized the prior probability $p(\theta)$ subject to the constraint $FOC(\theta, y)$ will provide a Bayesian highest posterior density (HPD) solution to the equation system FOC. In general, these results have been nicely derived by Heckelei and Mittelhammer [2008]. Moreover, Heckelei and Mittelhammer [2008] nicely demonstrate that under specific assumptions regarding the prior distribution, the HPD estimator corresponds to the Generalized Maximum Entropy (GME) or Generalized Cross Entropy (GCE) estimator techniques.

In particular, the Bayesian framework allows the use of any prior distribution. Thus, assuming the prior density function would be a normal distribution $\theta \sim N(\bar{\theta}, \Sigma)$, where the covariance matrix is set equal to the diagonal matrix $(\theta^2)$ implies that the HPD estimator results from the following maximization problem (see [Heckelei and Mittelhammer, 2008], p.17):

$$\begin{aligned} &\theta^* = arg \max_{\theta} \, [\theta - \bar{\theta}] \; \Omega^{-1} \; [\theta - \bar{\theta}] \\ &s.t. \\ &FOC(y, \theta) \equiv 0 \end{aligned} \tag{17}$$

As can be seen from eq.(17), the choice of a normal prior distribution results in a weighted least square approach implying numerically desirable properties for large scale problems. Therefore, we follow this approach in our empirical application below.

Finally, we can add noise to the FOCs. In particular, let $\epsilon_r$ denote a white noise variable, i.e. $\epsilon_r$ is iid N(0,1), where r denotes the $r^{th}$ equation of the FOCs. Then adding withe noise errors to the FOC's implies:

$$FOC(y, \theta) + \epsilon \equiv 0, \tag{18}$$

where $\epsilon = [\epsilon_{rg}]$ is the vector of errors. If we consider $\epsilon$ yet as further parameters to determine, and introduce the prior information that errors were drawn from $p_\epsilon = \prod_r N(0, 1)$, the HPD estimator for $\theta$ is found by solving the problem:

$$\begin{aligned} &\theta^* = arg \max_{\theta} \, [\theta - \bar{\theta}] \; \Omega^{-1} \; [\theta - \bar{\theta}] + \epsilon^{'} \epsilon \\ &s.t. \\ &FOC(y, \theta) + \epsilon \equiv 0 \end{aligned} \tag{19}$$

However, before we apply our method we consider another source of empirical data which is informative regarding the PIF parameters. In particular, following Fan et al. [2000] we use available production and public budget expenditure data to estimate PIF-parameters.

In particular, following our approach above defining $TFP_{st}$ as a TFP index for the sector s in the year t and defining $\alpha_{jt}$ the share of total public expenditure allocated to a policy program i in year t implies:

$$
\begin{aligned}
&TFP_{st} = tp_{st}^0 + \Delta tp_{st} \\
&\Delta tp_{st} = tp_s^{max} \frac{exp[a_s Be_{st} + b_s]}{exp[a_s Be_{st} + b_s] + 1} \\
&Be_{st} = \eta_s \left[ \sum_i \mu_{is} \gamma_{it}^{-\rho} \right]^{-\frac{1}{\rho}} \\
&with: \quad \sum_i \mu_{si} = 1
\end{aligned} \tag{20}
$$

$tp_{st}^0$ denotes the technical progress realized in sector s in the year t without any policy impact. In general, assuming sufficient observations for $tp_{st}$ 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 et al., 2000, Fan and Rosegrant, 2008] in the literature for most countries adequate data is not available. In particular, panel data on detailed budget allocation across specific policy programs is hardly available. In this context we suggest again a Bayesian estimation approach combining data and prior information. Analogously to our exposition above assuming prior information on parameters is encapsulated in normal prior distribution, $pr(\theta)$, while the data information follows from the equation system (20). 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 is missing, while data is only available on total agricultural budget (PAE) and total non-agricultural data (PNE). In the Bayesian framework missing data is simply considered as additional further parameters, which can be estimated assuming corresponding prior distributions.

Moreover, additional prior information might exists in form of additional restrictions on parameter values or values of unobserved variables, e.g. 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, i.e. the panel data on TFP and on budget expenditure, and let $EMP(y1, \theta)$ denote the eq.-system(20), while $RES(y1, \theta)$ denotes the additional restrictions on parameters and unobserved variables, the Bayesian estimation approach corresponds to the following maximization problem:

$$
\begin{aligned}
&\theta^* = arg \max_\theta \, [\theta - \bar{\theta}] \, \Omega^{-1} \, [\theta - \bar{\theta}] + \nu^{'} \nu \\
&s.t. \\
&TFP_{st} = tp_{st}^0 + \Delta tp_{st} + \nu_{st} \\
&\Delta tp_{st} = tp_s^{max} \frac{exp[a_s Be_{st} + b_s]}{exp[a_s Be_{st} + b_s] + 1} \\
&Be_{st} = \eta_s \left[ \sum_j \mu_{js} \alpha_{jt}^{-\rho} \right]^{-\frac{1}{\rho}} \quad with: \quad \sum_j \mu_{sj} = 1 \\
&\alpha_{jt} = \frac{\gamma_{jt}}{\sum_k \gamma_{kt}} \\
&RES(y1, \theta) \equiv 0
\end{aligned} \tag{21}
$$

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 $tp^0_{st}$ is included in the parameter vector $\theta$.

Finally, assuming there expert judgements on political goal achievements and preferred policy strategy of political experts are related to the same time 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 to one joint estimation approach.

If expert judgement, however, relate 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 implementation efficiency of policy programs differs between past and future time periods. Moreover, maximal achievable t.p. can change over time, e.g. assume in the past huge yield gaps exists, which have been addressed by increased public investment in extension services. To the extend these policies have been successful yield gaps have been reduced implying lower potential to promote t.p. in the future [4]

Thus, in general future and past policy-growth relations differ and therefore two estimation approaches can not be directly combined to one joint estimation approach, if expert judgements 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 ar least to a certain degree as long as future and past time periods are close to each other. Hence, in the following we use the estimation results based on empirical data to get better priors for the PIF-parameters which then will be used in the Bayesian estimation approach using expert data described above.

## 4 Results

In the following we will show some exemplary results, highlighting different challenges / problems.

## 5 Conclusion

Despite there being being borad agreement that government policy plays a crucial role in achieving sustainable growth, deciding on the policy choices is a complex task. In order to design effective and efficient policies for Pro-Poor Growth evidence and model based policy analysis is required. This paper provides a theoretical and methodological framework to derive indicators for key sectors and key policies.

There exists broad literature focusing on the analysis of growth - poverty linkages, but especially for the case of investment policies, like CAADP, the studies are missing a

[4]Please note that in the framework of sectoral production functions, TFP incorporates increase in technical efficiency, while the latter is by definition excluded analyzing micro level data of individual firms.

crucial point. From the viewpoint of a policy maker economic growth does not fall from heaven, but has to be generated by policies. This policy - growth linkage is neglected. The approach of [Fan and Rosegrant, 2008] integrates policy - growth linkages, but is plagued by estimation problems, lack of adequate data or it being a reduced form approach. We provide an alternative, integrated approach:

Based on a cge simulation study we derive meta models capturing the growth - poverty linkages. Using these we apply a Bayesian estimation strategy to estimate sector specific policy impact functions, combining statistical data and expert information in a novel way. This circumvents the problems the earlier studies had regarding data availability and estimation problems. In combination we provide policy - growth - poverty linkages, that take the investment policies explicitly into account.

Applying a CGE model there exists uncertainty in regard to closure rules and import, export and trade elasticities. In order to handle this we simulated a large set of combinations and applied Bayesian model selection to select the best fit model. The best fit model is only a point estimate and therefore the policy messages derived from it are still uncertain. In a next step we applied a Metropolis Hastings sampling procedure to check the stability of the results.

We applied our approach to the case of the 2015 CAADP reform in Senegal. Our results show that it is important, which concept is used to identify key sectors.



## References

Dirk J. Bezemer and Derek Headey. Agriculture, development, and urban bias. *World Development*, 36(8):1342–1364, 2008.

Claudio Bravo-Ortega and Daniel Lederman. Agriculture and national welfare around the world: causality and international heterogeneity since 1960. Policy Research Working Paper Series 3499, The World Bank, February 2005. URL `https://ideas.repec.org/p/wbk/wbrwps/3499.html`.

Luc Christiaensen, Lionel Demery, and Jesper Kuhl. The (evolving) role of agriculture in poverty reduction—an empirical perspective. *Journal of Development Economics*, 96(2):239–254, nov 2011. doi: 10.1016/j.jdeveco.2010.10.006.

Alain De Janvry. Agriculture for development: new paradigm and options for success. *Agricultural Economics*, 41:17–36, nov 2010. doi: 10.1111/j.1574-0862.2010.00485.x.

Bernard Decaluwé, André Martens, and Marcel Monette. Macroclosures in open economy cge models: A numerical reappraisal. pages 1–23, 1987.

Xinishen Diao, James Thurlow, Samuel Benin, and Shenggen Fan, editors. *Strategies and Priorities for African Agriculture - Economywide Perspectives from Country Studies.* International Food Policy Research Institute, Washington DC, 2012. URL `https://www.ifpri.org/event/strategies-and-priorities-african-agriculture`.

Xinshen Diao, Peter Hazell, and James Thurlow. The role of agriculture in african development. *World Development*, 38(10):1375–1383, oct 2010a. doi: 10.1016/j.worlddev.2009.06.011.

Xinshen Diao, Manson Nwafor, Vida Alpuerto, Kamiljon Akramov, and Sheu Salau. Agricultural growth and investment options for poverty reduction in Nigeria. Discussion Paper 00954, Governance and Development Strategy (DSG) Division, International Food Policy Research Institute (IFPRI), February 2010b. URL `https://core.ac.uk/download/files/153/6250129.pdf`.

Steven N. Durlauf, Andros Kourtellos, and Chih Ming Tan. Empirics of Growth and Development. Discussion Papers Series, Department of Economics, Tufts University 0520, Department of Economics, Tufts University, 2005. URL `https://ideas.repec.org/p/tuf/tuftec/0520.html`.

Steven N Durlauf, Andros Kourtellos, and Chih Ming Tan. Are any growth theories robust? pages 1–30, 2007.

Theo S Eicher, Cecilia García-Peñalosa, and David J Kuenzel. Constitutional rules as determinants of social infrastructure. 2015.

Shenggen Fan and Mark W. Rosegrant. Investing in agriculture to overcome the world food crisis and reduce poverty and hunger. IFPRI Policy Briefs 3, International Food Policy Research Institute (IFPRI), 2008.

Shenggen Fan and Xiaobo Zhang. Investment, reforms and poverty in rural China. *Economic Development and Cultural Change*, 52(2):395–422, 2004.

Shenggen Fan, Peter Hazell, and Sukhadeo Thorat. Government spending, growth and poverty in rural India. *American Journal of Agricultural Economics*, 82(4):1038–1051, 2000.

Shenggen Fan, Linxiu Zhang, and Xiaobo Zhang. Growth, inequality, and poverty in rural China: The role of public investments. IFPRI Research Report 125, International Food Policy Research Institute (IFPRI), 2002.

Shenggen Fan, Tewodaj Mogues, and Samuel Benin. Setting priorities for public spending for agricultural and rural development in africa. Policy briefs 12, International Food Policy Research Institute (IFPRI), 2009. URL `https://EconPapers.repec.org/RePEc:fpr:polbrf:12`.

Raghav Gaiha. Are the chronically poor also the poorest in rural india? *Development and Change*, 20(2):295–322, apr 1989. doi: 10.1111/j.1467-7660.1989.tb00349.x.

Rana Hasan and M. G. Quibria. Industry matters for poverty: A critique of agricultural fundamentalism. *Kyklos*, 57(2):253–264, may 2004. doi: 10.1111/j.0023-5962.2004.00253.x.

Thomas Heckelei and Ron Mittelhammer. A bayesian alternative to generalized cross entropy solutions for underdetermined econometric models. Discussion Paper 2, Institute for Food and Resource Economics University of Bonn, 2008.

Norman V. Loayza and Claudio Raddatz. The composition of growth matters for poverty alleviation. *Journal of Development Economics*, 93(1):137–151, sep 2010. doi: 10.1016/j.jdeveco.2009.03.008.

Hans Löfgren and Sherman Robinson. Public spending, growth, and poverty alleviation in sub-saharan africa: A dynamic general equilibrium analysis. *Public expenditures, growth, and poverty: lessons from developing countries*, 2008.

Hans Löfgren, Rebecca Lee Harris, and Sherman Robinson. A standard Computable General Equilibrium (CGE) model in GAMS. Microcomputers in Policy Research 5, International Food Policy Research Institute (IFPRI), 2002.

Jørn Rattsø. Different macroclosures of the original johansen model and their impact on policy evaluation. *Journal of Policy Modeling*, 4(1):85–97, mar 1982. doi: 10.1016/0161-8938(82)90006-0.

Sherman Robinson. Macroeconomics, financial variables, and computable general equilibrium models. *World Development*, 19(11):1509–1525, nov 1991. doi: 10.1016/0305-750x(91)90003-z.

Sherman Robinson, Antonio Yúnez-Naude, Raúl Hinojosa-Ojeda, Jeffrey D Lewis, and Shantayanan Devarajan. From stylized to applied models: Building multisector cge models for policy analysis. *The North American Journal of Economics and Finance*, 10(1):5–38, jan 1999. doi: 10.1016/s1062-9408(99)00014-5.

Dani Rodrik, Arvind Subramanian, and Francesco Trebbi. Institutions rule: The primacy of institutions over geography and integration in economic development. Technical report, nov 2002.

Ashwani Saith. Production, prices and poverty in rural india. *The Journal of Development Studies*, 17(2):196–213, jan 1981. doi: 10.1080/00220388108421788.

Amartya K. Sen. NEO-CLASSICAL AND NEO-KEYNESIAN THEORIES OF DISTRIBUTION. *Economic Record*, 39(85):53–64, mar 1963. doi: 10.1111/j.1475-4932.1963.tb01459.x.

Amartya K. Sen. From income inequality to economic inequality. *Southern Economic Journal*, 64(2):383, oct 1997. doi: 10.2307/1060857.

Lance Taylor. *Socially Relevant Policy Analysis: Structuralist Computable General Equilibrium Models for the Developing World.* The MIT Press, 1990. ISBN 9780262200752.

Colin Thirtle, Lin Lin, and Jenifer Piesse. The impact of research-led agricultural productivity growth on poverty reduction in africa, asia and latin america. *World Development*, 31(12):1959–1975, dec 2003. doi: 10.1016/j.worlddev.2003.07.001.

Arnold Zellner. *An Introduction to Bayesian Inference in Econometrics.* Wiley, New York, 1971.