Modeling Development Policies with Multiple Objectives

by

Will Martin, Maros Ivanic and Abdullah Mamun

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Abstract

In recent years, policymakers have become more insistent in seeking advice on policies targeting multiple objectives in addition to the traditional economists' concerns for economic efficiency and equity. Dealing with multiple goals in a serious manner is quite challenging given that it generally requires roughly as many instruments as goals, each instrument typically affects multiple goals, and the effects of instruments on goals are typically non-linear. Economists have adapted to the need to incorporate multiple goals using simple devices such as radar diagrams to highlight the local impacts of individual instruments on all goals. While useful in understanding these differential impacts, these approaches do not take us far in terms of designing policy packages needed to best achieve multiple goals. This paper proposes using programming approaches based on quantitative models to design policy packages for multiple goals. Two illustrative applications are provided—one to the setting of carbon tax rates for agricultural commodities and one to the allocation of R&D resources across agricultural activities in Ethiopia.

Keywords: Development policy; efficiency; equity; multiple goals; policy modeling; optimization models; quantitative economic policy.

JEL Codes: C54; C61; O21

Modeling Development Policies with Multiple Objectives

Policy makers are increasingly seeking to achieve multiple goals, but much economic analysis focuses primarily on the single goal of increasing economic efficiency. While some influential economists, such as Harberger (1971), have argued that policy evaluation should focus on the single goal of efficiency, economists and policy makers have generally been skeptical. Many approaches have been offered to incorporate distributional concerns (eg Boadway 1976; Loomis 2011), and even Harberger (1978) conceded the case for applying higher weights on benefits to the poor.

In recent years, policy makers have become much more insistent on incorporating multiple goals. The widely supported United Nations' Sustainable Development Goals (SDGs), for instance, seek to make improvements in many dimensions, including elimination of poverty, hunger, and progress towards gender equality and climate sustainability. Economists working on development policies have tended to accept the associated challenges and to provide results for multiple goals. This has required considerable extension of modeling tools to provide quantitative estimates of these impacts.

Despite this progress, we are concerned that acceptance of the move to multiple goals may not have been accompanied by enough consideration of the ability of economists' toolkits to handle such a fundamentally different set of challenges. When analysis focusses solely on efficiency, policy outcomes can be assessed using well-understood measures such as Equivalent Variation and simple policy benchmarks—such as zero tariffs for small open economies or for the world as a whole—apply. Many economists working with multiple goals have adopted simple heuristic devices such as radar diagrams that show the impacts of one policy change on multiple goals, or tables of results showing the impacts of different policy instruments on individual goals. While these tools are useful, they are very partial and leave users far from being able to identify the best policy packages or the best tradeoffs between goals.

When there are multiple policy goals, multiple policy instruments are needed to achieve these goals. As pointed out by Tinbergen (1952), when the model is linear, the number of instruments should exactly equal the number of goals. With multiple instruments and multiple goals, the number of potential policy combinations rises very rapidly, as does the number of parameters needed to identify the best policy settings. Finding the best policy package is like looking for a needle in a multi-dimensional haystack. And it is difficult to assess the loss in overall welfare if policy makers choose—as they inevitably do—a package slightly, or a lot, different from the proposals suggested by policy analysts and advisers.

The need to use multiple instruments complicates the analysis in several ways other than the increase in dimensionality of the problem. First is the possibility that each policy may have impacts not just on the outcome to which it is directed but (positive or negative) impacts on other objectives. A second is that policies may interact nonlinearly. An increase in investment in roads may, for instance, increase the returns on investments in irrigation facilities. A third is that policy changes may interact with existing distortions to make even the direction of impacts on the objective function unclear (Lipsey and Lancaster 1956).

Key elements in the literature on which this paper draws include the theory of quantitative economic policy (eg Tinbergen 1952; Theil 1964; Preston and Pagan 1982); the literature on policy modeling in general equilibrium (Dervis, de Melo and Robinson 1973; Dixon and Jorgenson 2014); and the literature on nonlinear mathematical programming (eg Fox 2021). Recent studies seeking to identify the best policy setting to achieve multiple development goals using multiple instruments (eg Laborde, Parent and Smaller 2020; Gautam et al 2022) provide a valuable point of comparison.

The broad approach suggested in this paper is first to specify an objective function that encompasses the goals being targeted. A policy model is then used to link the arguments of the objective function with the available policy instruments. Finally, a nonlinear programming approach is used both to choose the best policy instruments from the available set, and the optimal settings for those instruments. Most of the analysis uses tools routinely applied to analyze problems with multiple objectives. The one additional informational need is weights on the different goals. In some cases, these weights can be identified readily—as when emission reductions are to be assessed against changes in efficiency, and an agreed social cost of carbon is available. In other cases, these weights will inevitably be more conjectural and analysis will need to be accompanied by sensitivity analysis.

The proposed approach addresses many of the key problems associated with managing multiple instruments with multiple goals. It moves beyond simple rules of thumb like Tinbergen's (1952) famous rule that "achieving n targets requires n instruments" to allow choice of the most effective instruments. It identifies the settings for these instruments that maximize the objective function, while allowing comparison of this optimal policy package with alternatives. It incorporates interactions between instruments and between instruments and goals and allows tradeoffs between policies to be evaluated. When the problem involves constrained optimization, as with investment subject to budget constraints, it can provide shadow prices showing the benefits of incrementally relaxing those constraints.

The next section of the paper considers broad approaches to policy modeling with multiple policy instruments and goals, drawing relevant elements from the literature on quantitative economic policy. The third section develops the proposed approach to endogenous policy choice with multiple objectives. The fourth section discusses the two applications—one using unconstrained optimization and one using constrained optimization—used to illustrate the approach. The fifth section points to the possible relevance of the approach even in situations where there is only a single goal. The sixth section highlights the potential relevance of the approach when policy makers are seeking to address political economy goals as well as the economic goals that are the primary focus of the paper. The last section provides conclusions.

Approaches to Policy Modeling

An essential feature of a model for policy analysis is that it includes a vector of variables (***y***) determined endogenously within the model, and a set of policy instruments (***x***) that influence the endogenous variables, and particularly the policymakers' objectives. There may well be other exogenous variables (***z***) such as weather outcomes or prices determined outside the system under study. Such a system can be represented mathematically using *n* structural equations in the *n* endogenous variables under consideration.

$$
\begin{aligned}
(1)\qquad & f_1(y_1 \ldots y_n\,;\, x_1 \ldots\ldots x_m;\, z_1 \ldots\ldots z_k) = 0 \\
& f_2(y_1 \ldots y_n\,;\, x_1 \ldots\ldots x_m;\, z_1 \ldots\ldots z_k) = 0 \\
& \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\
& f_n(y_1 \ldots y_n\,;\, x_1 \ldots\ldots x_m;\, z_1 \ldots\ldots z_k) = 0
\end{aligned}
$$

While there are no guarantees that a nonlinear system of equations will have a unique solution for any given the policy settings (*x*) and exogenous variables (***z***), experience with practical economic policy models suggests that multiple equilibria are rarely a problem (Dervis, de Melo and Robinson 1982). Modeling techniques and the data on which they build have improved enormously in recent years, allowing analysis of systems with greater coverage and greater sophistication than in the 1980s. However, the primary techniques of policy analysis have not greatly changed since then. In most cases, changes in the policy variables, $\boldsymbol{x}$, are used to assess the impacts on the endogenous outcomes, $\boldsymbol{y}$**.**

Interestingly, modern modeling of development policy began with a different approach, under which policy makers specified an objective, such as income maximization, and solved the model subject to constraints on the availability of resources. Much of this work was focused on improved planning for mixed, or for socialist, economies (see Manne 1973). Computable General Equilibrium (CGE) models built on this earlier work and moved to specifications like equation (1) with optimization built into the specification of the individual behavioral equations—such as consumer demand systems based on utility maximization and representations of supply based on profit maximization—where the model is solved as a set of simultaneous equations without any need to specify an objective function.

Curiously, perhaps partly because of the popularity of the GAMS (2020) software for solving these models, many equilibrium models are solved using a maximization approach. Under this approach, an objective function is maximized or minimized subject to n constraints on n endogenous variables. Since, with a well-behaved model, there is only one solution to such a problem, the objective function used is unimportant and maximization is simply a way to solve the system of simultaneous equations for its unique solution.

Many key insights into the challenges of setting policies with multiple instruments can be obtained by creating a first-order approximation to equation (1) and then converting this structural form into a reduced form that expresses the endogenous variables ($\boldsymbol{y}$) as functions of the instruments ($\boldsymbol{x}$), with the $\boldsymbol{z}$ variables held constant. The effects of the instruments on the goals can then be identified from:

(2) $$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} \beta_{11} & \beta_{12} & \vdots & \beta_{1n} \\ \beta_{21} & \beta_{22} & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \beta_{n1} & \vdots & \vdots & \beta_{nn} \end{bmatrix} . \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

or, in matrix terminology:

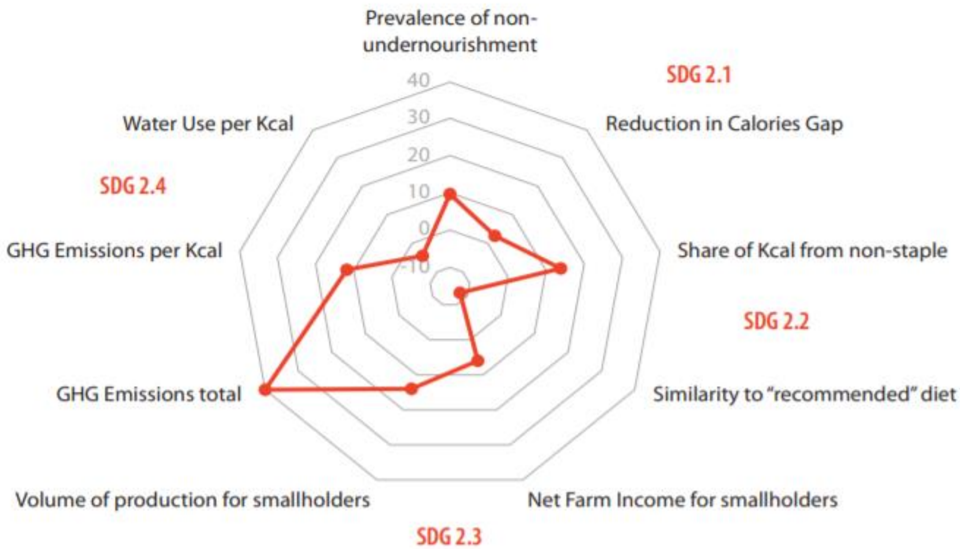
(3) $$\boldsymbol{y} = \boldsymbol{\beta}.\boldsymbol{x}$$

The $\boldsymbol{y}$ vector can include a wide range of outcome variables, such as prices, quantities of output and input, and also policy goals such as money measures of welfare (Equivalent Variation or

Compensating Variation), poverty rates, the cost of nutritious diets, the prevalence of undernourishment, or greenhouse gas emissions.

The elements of $\boldsymbol{\beta}$ appear in many forms in recent analyses of development policy impacts with multiple goals. Columns of $\boldsymbol{\beta}$ represent the effects of a single policy instrument on the full set of specified goals. These coefficients are frequently presented as radar diagrams such as Figure 1, or as panels of impacts on different variables, as in Gautam et al (2022). The rows of $\boldsymbol{\beta}$ represent another useful set of impacts—the effects of all the policy instruments on one policy goal. An example of coefficients of this type in agricultural development policy is the columns in Tables 6 to 8 of Thurlow, Randriamamonjy and Benson (2018), which show the impact of different policy instruments on the same goal.

Figure 1. Impacts of a Fertilizer Subsidy on SDG-2 Sub-Targets



Source: Laborde, Bizikova and Smaller (2020, p10)

Clearly, presenting information on the impacts of different policies is an important step towards allowing informed assessments of the impacts of different policies. The radar diagram is a useful way to present information on the impacts of an individual project to policy makers. The impacts of policy bundles can be presented as new radar diagrams that reflect the sum of these impacts. There is no need to use objective function weights to evaluate outcomes, and policymakers are free to pick the policy packages that best suit their preferences.

Unfortunately, however, the gap between presenting information in this way and identifying desirable policy packages is wide. One key problem is the curse of dimensionality. While the human brain is said to be able to evaluate individual outcomes in up to 11 dimensions[1], it seems unlikely that the human memory can satisfactorily remember and rank the enormous potential numbers of outcomes when there are multiple policy instruments with multiple possible policy settings. If, for example, there are four policy instruments, each with ten possible settings, 10,000 outcomes need to be evaluated and ranked. The problem is even more serious when the impacts of policies on outcomes are nonlinear and, hence, not captured in fixed coefficients of the type presented in a radar diagram.

The Theory of Quantitative Economic Policy

The theory of quantitative economic policy originated by Tinbergen (1952) allows some important insights to be derived by building from equations (2) and (3). If we have a set of fixed targets, $\boldsymbol{y}^*$, and linear relationships between the instruments and the targets, the policy settings needed to achieve these goals can be inferred as:

(4) $$\boldsymbol{x}^* = \boldsymbol{\beta}^{-1}\boldsymbol{y}^*$$

Equation (4) yields the important policy conclusion that policy makers need at least *n* instruments if they are to achieve *n* targets. It is also very illuminating about an important challenge in practical policy making. A change in a single target, such as y_i^*, requires changes not just in policy instrument x_i —an adjustment represented by the diagonal element $\beta_{ii}{}^{-1}$—but potentially in all elements of $\boldsymbol{x}$ for which there is a non-zero coefficient in column *i* of the matrix $\boldsymbol{\beta}^{-1}$. Similarly, a change in any one instrument sets off a need to adjust potentially all the other instruments if all targets are to be met.

While generating valuable insights, Tinbergen's fixed-target approach does not take us very far in development policy formulation for several reasons. First because we do not usually have fixed targets in development policy. The goal of policy is more likely to be to maximize a goal such as a combination of overall income growth and growth in income of the poor, subject to the available resource constraints, than to achieve a particular target. Second, the coefficients linking instruments and goals are unlikely to remain constant—with the marginal impact of many policy

[1] See https://www.sciencedaily.com/releases/2017/06/170612094100.htm Accessed 11 January 2022.

instruments tending to decline as the instruments are applied more intensively. Third, the need to adjust all policy instrument settings every time any one goal changes makes it challenging to identify and adjust policy packages.

Mundell (1962) offered a partial solution to the third problem by assigning each policy instrument to a particular goal. If each policy instrument is assigned to the policy goal that it affects most strongly, then the second-round adjustments required in response to changes in any goal are smaller than they would be with policies assigned in other ways. In the limit, if each instrument only affects one target, the $\boldsymbol{\beta}^{-1}$ matrix is diagonal and no second-round adjustments are needed when a target changes. While very useful in the simple macroeconomic modeling framework in which Mundell identified this solution, it is less useful with development policy problems involving more instruments and targets, and more complex interactions.

The flexible target model proposed by Theil (1964) builds on Tinbergen's static model. In most expositions of this model, fixed goals are still specified and the objective function is a quadratic function of deviations from desired policy outcomes (see, for example, Hughes-Hallett 1989, p203) so that, for instance, positive or negative deviations from a target rate of inflation are punished symmetrically at rates that increase quadratically with the size of the deviation. Simplifying from Preston and Pagan (1982, p31) the resulting problem might be written:

(4) $\quad \text{Min } (\boldsymbol{y} - \boldsymbol{y}^*)'\boldsymbol{W}(\boldsymbol{y} - \boldsymbol{y}^*) \text{ subject to } \mathbf{y} = \boldsymbol{\beta x}$

Where $\boldsymbol{y}^*$ is a vector of policy goals, $\boldsymbol{W}$ is a matrix of weights on deviations of the goals from their target levels and all other terms are as previously defined.

This flexible target approach potentially avoids situations where there is no solution to the fixed target problem. It also softens the "Tinbergen Rule" that the number of policy instruments must equal the number of goals. Optimization using equation (4) with fewer instruments than goals is feasible although it is likely to result in a lower value of the objective function than optimizing with as many instruments as targets. It also resolves the question of which instruments to use when there are more available instruments than targets. If some instruments are not needed, the solution excludes them while determining settings for those interventions that contribute to the optimal solution. Cicowiez, Decaluwé and Nabli (2017) use an approach in the spirit of Theil to choose policy settings that minimize deviations from a set of desired macroeconomic outcomes.

The emphasis on penalizing deviations from fixed goals in the Quantitative Economic Policy literature is probably a consequence of the focus of much of this literature on macroeconomic stabilization. In this context, there are usually well-defined targets for key variables such as the rate of inflation and the unemployment rate. While zero unemployment would be desirable, attempting to maintain an unemployment rate below the level consistent with price stability may result in accelerating inflation, so policy makers typically target a non-accelerating inflation rate of unemployment (NAIRU) (Modigliani and Papademos 1975). Similarly, a modest non-zero inflation target is generally seen as desirable because it allows real wage rates to decline if needed without requiring declines in nominal wages that may generate strong opposition (Bernanke and Mishkin 1997). In this situation, it makes sense to have more-or-less symmetric penalties for deviations above or below these targets. But in the context of development policy, such fixed targets are much less common. There is unlikely to be a case for penalizing a more-rapid-than-expected decline in poverty or hunger. However, the penalty function approach may be appropriate for some questions, such as consumption levels of nutrients—where both excessively low and excessively high levels of consumption have adverse nutritional consequences.

Endogenous Policy Choice with Multiple Objectives

The approach to modeling policy choice with multiple objectives proposed in this paper builds on Theil's (1964) approach and involves a programming approach involving:

(i) An objective function, and

(ii) Optimization subject to model constraints.

The Objective Function

Specifying the objective function is perhaps the most difficult challenge and one that has caused many to avoid attempting this approach. However, the task is greatly reduced by the increased availability of rigorous methods for assigning values to achievement of goals other than market based economic welfare.

The approach taken in this paper is to begin with money measures of economic welfare, like Equivalent Variation (EV), and then to add elements of more complete objective functions. Depending on the context, important augmentations needed to account for the multiple objectives of policy makers might include: (i) the external costs imposed by greenhouse gas emissions; (ii) the utility losses and/or economic losses (Ravallion 2012) associated with poverty and inequality, (iii) accounting for differences in the welfare benefits of income to different groups; and/or (iv) costs, such as losses of Disability Adjusted Life Years (DALYs), associated with unhealthy diets (Candari, Cylus and Nolte 2017). With these considerations incorporated, the objective function can become a money measure of social welfare, just as EV provides a money metric of utility from personal consumption (Mas-Colell, Whinston and Green 1995).

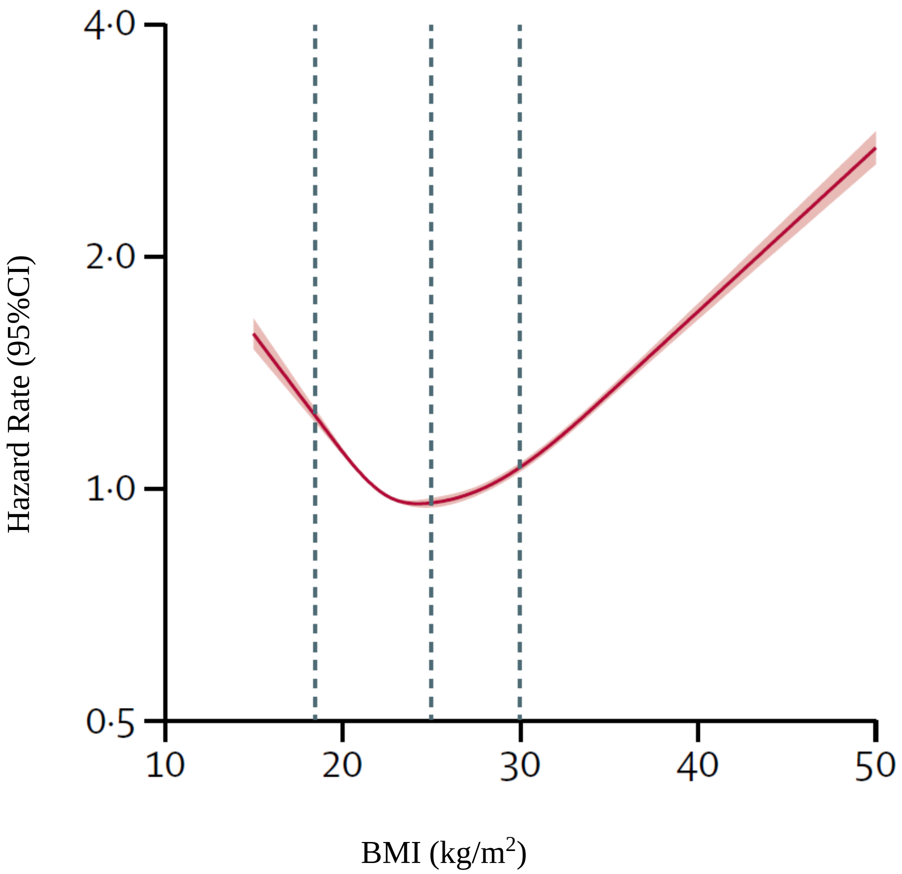
In many cases, available estimates allow conversion of a cost into money terms and hence construction of a welfare function that is EV plus or minus a linear term. For emissions, estimates of the social cost of Greenhouse gas (GHG) emissions are available, derived from Integrated Assessment Models whose scope is far wider than most models used for national economic development policies (see Newbold et al 2010). These models assess the economic impact of increases in GHG through their future impacts on the climate and hence on real incomes. Once information on the discounted costs of these emission outcomes is available, the social objective function becomes a linear combination of EV and the social cost of emissions.

Distributional concerns may be addressed in several ways. Hendren (2021) infers from tax schedules an implicit weight of 1.5 to 2 on income accruing to the poor relative to that accruing to the rich, allowing a social welfare function to reward improvements in the welfare of the poor more highly than improvements in overall economic welfare. Squire and van der Tak (1975) propose utilitarian weights based on initial household incomes. The Foster, Greer and Thorbecke (FGT) (1984) poverty headcount and poverty gap provide measures that fall as the situation for poor people improves—and provide a basis for allocating an economic gain when poverty rates decline. Because the FGT measures do not increase when the incomes of the poor rise above the poverty line, they make the poverty component of the welfare function a discontinuous function of household income, which creates serious challenges for programming approaches based on disaggregated household data (McCarl 2014). An alternative is a measure like the Theil-L index of inequality, used by Apell et al (2021), which rewards reductions in income inequality.

The U-shaped link between mortality rates and the Body Mass Index depicted in Figure 2 suggests that the relationships between diets and health are likely strongly nonlinear. As previously noted, applications addressing this question might well use an approach like that of

Theil (1964) with a target level of nutrient consumption and penalties associated with positive or negative deviations from the target.

Figure 2. The Relationship Between BMI and All-Cause Mortality, Never smokers



Source: Bhaskaran et al (2018). Cox regression model stratified by sex and adjusted for alcohol use, diabetes, economic deprivation and calendar period.

Programming Approaches

A nonlinear programming approach is used to identify both the policy set to be used and the optimal settings for those policies. The approach used strongly resembles those used in business applications such as profit maximization or cost minimization (see Simon and Blume 2019), but with the choice variables being policy instruments, rather than quantities chosen by producers. As in standard economic theory, some problems are best solved using unconstrained optimization, while others require optimization subject to constraints. The Karush-Kuhn-Tucker conditions allow some policy variables to enter at zero levels, thus choosing which—if any—of the available policy instruments are to remain unutilized. This ability to choose which policies to use is a potentially valuable feature of the approach, particularly when there are many potential policy instruments.

To provide an illustrative example of a simple, unconstrained maximization problem, consider a case where the objective function is to maximize real GDP less the social cost of carbon and the goal is to set carbon tax rates on emissions from production of two commodities. If the two carbon tax rates, t_1 and t_2, are set optimally, the value of the objective function will be maximized at the peak of the social welfare possibility surface in Figure 3. At this point, the marginal social costs associated with emissions from each product are equal to the marginal abatement costs. If one of the tax rates is set too low (high), social welfare will be below its maximum level because the marginal social cost of emissions from that product will be above (below) its marginal abatement cost. The optimal solution requires that both rates be set correctly since the level of the tax on each good influences the output of both goods.

Figure 3. Maximizing the Objective Function by Choosing Two Tax Rates

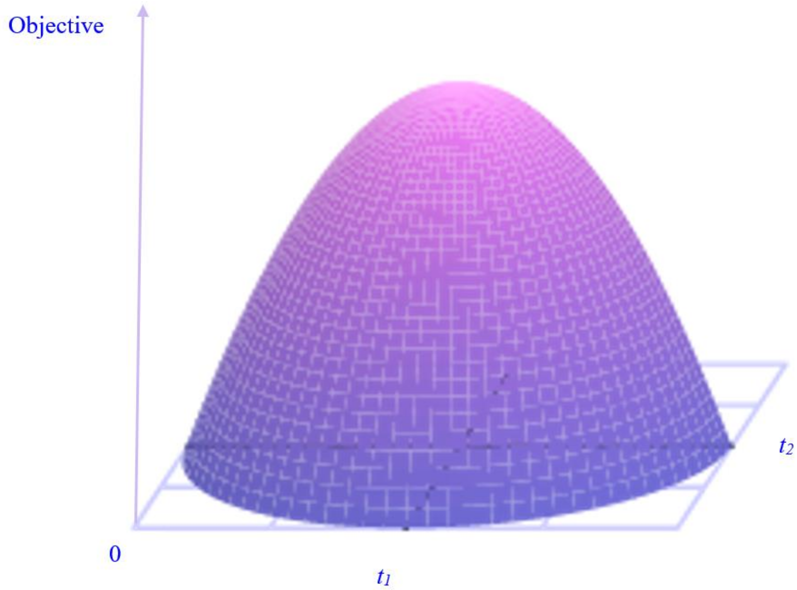


Figure 3 highlights a key problem with relying on local slopes of the policy response function. Projecting the benefit from moving either of the tax rates to its efficient level by multiplying the change in the tax rate by the slope of the objective function at an early point in the transition is clearly likely to substantially overstate the benefit of the move. The use of local inferences about the slope of responses to changes in individual policies is reminiscent of the parable of the blind men and the elephant—trying to infer the features of an elephant from a series of local observations.

If the problem involves constrained optimization, then the challenge is to find the highest value of the social welfare function consistent with the constraint. If, for instance, the problem is to allocate resources to research and development across commodities, with a social welfare function that depends on both the resulting increase in national income and the degree of poverty reduction, then the goal is to achieve the highest level of social welfare consistent with the available resources.

One approach to solving the optimization problem is to augment the model with inequalities for the policy variables, allowing them to enter the solution if that improves the outcome, or not to enter the solution if they are not needed. Maximization of the objective function subject to a combination of these constraints and the equations of the behavioral model can then be used to determine the values of all the endogenous variables of the model, now including the policy decision variables. This is a relatively straightforward extension of standard practice with a program like GAMS for which maximization subject to constraints is widely used as a solution procedure for the behavioral model. A key difficulty with this approach is that objective functions involving measures such as poverty rates or poverty gaps involve discontinuities that create challenges for the solution algorithms.

An alternative approach, adopted in this paper, is to use the behavioral model in the background to solve for values of the objective function as functions of the policy variables, and to use a nonlinear solver to evaluate the gradients of the response function and iterate towards the maximum of the objective function. To facilitate replication, we used the open-source NLopt nonlinear optimization program with the derivative free COBYLA optimization algorithm (Johnson 2021) invoked from the open-source R program (R Core Team 2013). For the CGE representation, we used the publicly available GTAP Version 8 solved with the publicly available version of GEMPACK (Horridge et al 2021). Impacts on household incomes, and hence on poverty, were assessed by applying price and wage changes from the model to household survey data. We utilized the standard long-run closure with capital and labor mobile, and land sluggishly mobile between agricultural activities.

Experiments and Results

To investigate the performance of the proposed approach, we conducted two simple experiments. The first incorporates a global externality created by greenhouse gas emissions into a global objective function and solves an unconstrained optimization problem to identify optimal tax rates for different agricultural products. The second, focusing on Ethiopia, involves allocating research resources to improving productivity for eight agricultural sectors in Ethiopia. In this analysis, the objective function is extended beyond the traditional EV measure to put weight on the extent to which the investments reduce poverty.

Incorporating Environmental Externalities

This experiment was conducted at global scale since the externalities associated with greenhouse gas emissions are global. The social welfare function was modified to include the social costs of emissions by subtracting these costs from the measure of welfare change at market prices (EV) in the model. The experiment performed was to use the model to identify the optimal carbon taxes on production of key agricultural commodities if these externalities are to be internalized. Because GHG emissions from agriculture are almost completely in ruminant meat, milk, rice, other cereals, pork and poultry emissions, the analysis focused on these commodities. While we know that there are considerable variations in emission intensities across regions (Mamun, Martin and Tokgoz 2021), the analysis assumed a constant emission intensity to allow the estimated optimal carbon taxes to be compared with the social external costs.

For this analysis, the database was aggregated into the ten commodities and nine regions described in

Table A.1 and A.2. GHG emissions by commodity were obtained from FAOSTAT and converted into social costs using the widely accepted social cost of carbon of \$50 per ton of CO_2 equivalent[2]. These social costs were converted into ad valorem equivalents at base prices by dividing by production values from FAOSTAT. The total social cost of carbon in each solution was then obtained by updating these values by changes in the volume of output of each commodity. A composite social welfare function was obtained by subtracting these social costs from the EV at market prices generated by the model.

Optimal global output taxes were estimated with the social cost of carbon included in the objective function. The marginal social cost of the carbon emissions at base prices is presented in the first column of Table 1 and the estimated social welfare maximizing ad valorem tax rates in the second column of Table 1.

Table 1: Results for the optimal carbon tax experiment, %

	Initial Marginal Social Costs	Carbon Tax Rate
Rice	10.5	10.0
Beef	39.2	33.2
Milk	13.0	11.1
Other Cereals	5.1	5.7
Other Meat	2.8	2.7

As expected, the optimal carbon tax rates are very similar to the marginal social costs. A key question is why they are not precisely the same? One explanation is second-best interactions

[2] See https://www.edf.org/true-cost-carbon-pollution

between the carbon tax instrument and other taxes and trade measures in the model. Another is changes in the world prices of commodities in response to introduction of the carbon tax—because the world price of beef rises in response to the tax, a smaller tax rate is required than would have been the case at initial prices.

Ethiopia agricultural investment experiment

In this experiment, we solve the problem of distributing resources for agricultural research and development resources with the goal of maximizing a composite objective of economic growth and poverty reduction in Ethiopia. This problem of identifying the interventions that maximize the policy objective is similar to the Thurlow et al (2018) problem of identifying priority value chains. It is very similar to the research resource allocation problem considered by Minot, Valera and Balié (2021), except that it uses an optimization approach rather than a grid search to identify the optimal combinations of interventions.

Because our focus is on Ethiopia alone, we aggregate the database to just three regions—Ethiopia, the Rest of Africa, and the Rest of the World. Eight major agricultural commodity groups that are important in both the GTAP database and the household surveys are used in the analysis. While the problem addressed in the emission externality case involved unconstrained optimization, this optimization problem involves a budget constraint.

We initially distribute a budget of 160 units that would allow 20 units of R&D investment to be allocated to each of eight agricultural sectors. If the marginal productivity of investment were constant, this would generate a 20 percent increase in TFP in each sector. But we follow Jones (1995, p765) and introduce diminishing marginal returns as more research effort is applied to increasing productivity in a particular commodity—perhaps because the first researchers to work on the problem work on the most prospective problems, and additional researchers either move to less prospective problems or undertake research that overlaps with the work of the original team. In this situation, each investment i_c into commodity c generates a proportional increase in TFP of $a_c = i_c^{0.9}$.

After applying shocks to the GTAP model, we captured the impacts on household incomes using the full sample of the Ethiopian household survey (CSA 2017) for 2013. Applying productivity shocks to the GTAP model generates changes in commodity prices and wages. The same productivity shocks were applied to the output of households, along with the price and wage changes to obtain a first order estimate of the impact of the productivity changes on the incomes of each household. The poverty line in the model was determined as the income level that resulted in the 19.54 percent poverty headcount estimated using the World Bank's Povcalnet for Ethiopia in 2019.

The main objective function that we maximize using the investments is a weighted average of real GDP and the reduction in the poverty rate. Because we are unsure about the weight that policy makers apply to average income and to poverty reduction, we consider different weights on GDP growth versus poverty reduction. We also consider different limits on total investment in R&D.

Formally, our optimization program can be described as:

Maximize: $w_G\hat{y} + w_P\hat{p}$, subject to: $\hat{a}_c = {i_c}^{0.9}$ and the R&D budget constraint $\sum_C i_c \leq N$. Relative to the baseline, $\hat{y}$ is the proportional increase in income and $\hat{p}$ is the proportional reduction in the poverty headcount. At each iteration of the model, resources are allocated in a way that maximizes the increase in the objective function, and the feasible increase in the objective function declines towards zero as the model approaches the solution

Table 2: Scenario assumptions and objectives obtained for the Ethiopia R&D Investment Plan

	Initial	Higher budget	Poverty focus	Poverty focus & higher budget	Growth focus
Parameters					
Budget	160	240	160	240	160
Growth weight	0.5	0.5	0.25	0.25	0.75
Poverty weight	0.5	0.5	0.75	0.75	0.25
Outcomes					
Objective	0.36	0.45	0.23	0.28	0.15
Real GDP change	0.10	0.15	0.10	0.13	0.12
Poverty change	-0.25	-0.31	-0.27	-0.33	-0.22
Resource Allocations					
Coarse Grains	80.8	109.1	102.2	145.1	61.7
Wheat & Rice	0.0	0.0	0.2	0	0.0
Vegetables & Fruit	32.5	31.3	27.1	52.9	44.2
Beef	0.0	0.1	0.2	0.1	0.3
Processed Food	44.3	82.2	30.2	41.3	20.7
Other Crops	1.2	15.2	0.1	0.4	33.0
Other Animal Products	1.1	2.1	0.0	0.1	0.0
Milk	0.0	0.0	0.0	0.1	0.0

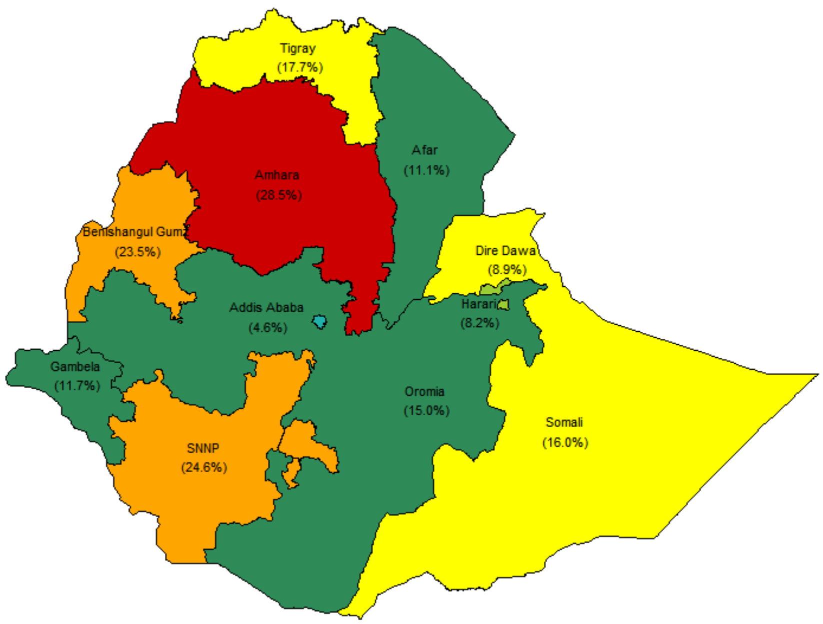
The results presented in Table 2 suggest that the approach has considerable potential for guiding the allocation of scarce research resources. Rather than spreading resources thinly, it tends to concentrate them in a few key sectors with large income and expenditure shares, such as Coarse grains and Vegetables and Fruits. This is an important illustration of the ability of the procedure to identify not just the desired settings for the instruments that enter the solution, but also to identify which instruments should enter the solution.

Increasing the weight on poverty reduction in column (3) increases the share of R&D applied to Coarse grains and reduces the share on Vegetables and Fruit. The impacts of increasing the focus on poverty reduction are substantial in terms of the poverty reduction achieved, with poverty reduction rising from 22 percent with a small weight (0.25 percent) on poverty reduction to 27 percent with a larger weight (75 percent) and the initial budget. Placing a higher weight on poverty reduction and increasing the budget by 50 percent increases poverty reduction to 33 percent.

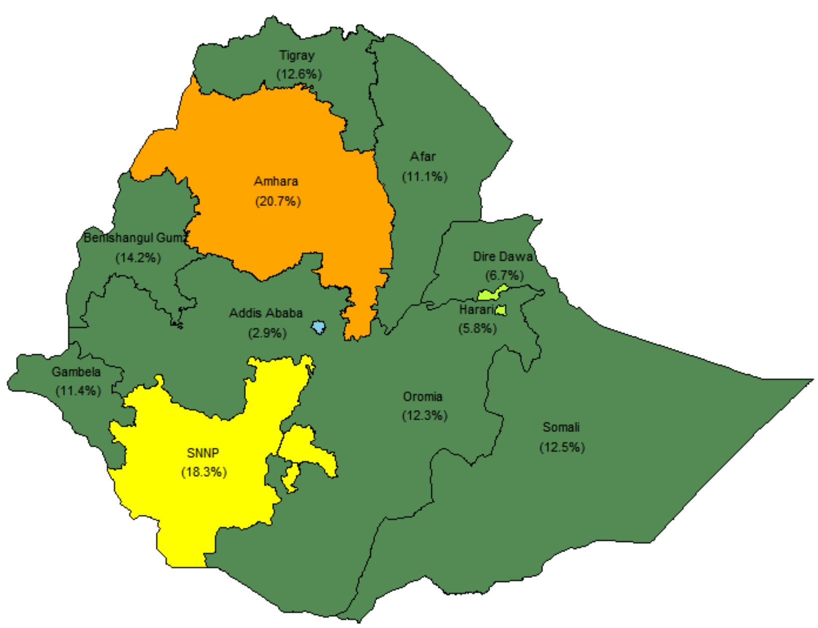
Because the poverty analysis is conducted using household models whose location is identified—albeit only by Region in this survey—it is possible to map the consequences for poverty rates by region. This provides a broad indication of whether the reform leaves large areas without substantial gain and whether some Regions continue to have high poverty rates. The results mapped for 11 regions of Ethiopia in Figure 4 highlight improvements in all regions except Afar, where agricultural activity is primarily pastoral. Importantly, the reductions in poverty rates were particularly large in the three regions with the highest initial poverty rates—Amhara, SNNP and Benishangul Gum. Information of this type can be enormously valuable for policymakers, perhaps as a basis for designing supplementary policy measures that deal with the challenges identified in regions not benefiting from the initial policy package.

Figure 4. Poverty rates before and after the initial policy package

Poverty Rates at baseline



Poverty rate after Initial Experiment



Potential Relevance with a Single Goal

The approach to optimization proposed in this paper was designed specifically to deal with problems with multiple objectives. However, it may also be useful even with a single objective when the outcome depends on a number of interactions between instruments, and/or a number of endogenous variables change in response to the interventions. In the research case considered above, the optimum could be determined using very simple rules if the problem were slightly simpler than the one considered here. If the goal were merely to maximize income growth without considering distribution, the optimal allocation of resources would be easy to determine if: (i) research productivity is constant, (ii) output and factor prices do not respond to the changes in productivity, and (iii) there are no interactions between the intervention and existing distortions. If all these conditions are satisfied, then the optimal allocation would be to employ all resources on the commodity with the largest initial value added.

But, when these conditions are not all satisfied, the research allocation question requires much more careful consideration. Non-constant research productivity requires at least use of a simple model of research productivity to track the slope of the productivity response function for each commodity. Once commodity and factor prices change, it becomes essential to use some form of model to track the consequences of these changes for a welfare metric like EV. If increases in productivity interact with existing distortions, an innovation that appears to raise national income may have much lower benefits than it at first appears or may even be welfare reducing (Alston and Martin 1995). Only a model that incorporates the interaction of the technical change and the distortions will reveal whether this is the case.

Incorporating Political Economy Considerations

To this point, the paper the objective function to be maximized has been specified in largely economic terms. The social costs of carbon were, for instance, specified on the basis of economic impacts estimated using integrated assessment models, rather than policymakers' subjective assessments of this parameter. An alternative approach might be to introduce a political economy objective function of the type proposed by Grossman and Helpman (1994) in which politicians place a different weight on some outcome. A pioneering contribution by Rausser and Freebairn

(1974) demonstrated an approach to estimating policy preference functions of this type, while Goldberg and Maggi (1999) estimated the parameters of the Grossman-Helpman model. Another example of this approach is the use of parameter values like Hendren's (2020) estimate of the political value of redistribution inferred from past decisions about the progressiveness of the tax schedule.

A purely political-economy approach might better represent the policy choices that policy makers are likely to choose than one based on economic weights. On one level, such an approach might seem redundant in because it would, if done correctly, choose the policies that policymakers would, select themselves. However, if the dimensionality of the problem is such that policy makers find it difficult to make decisions that satisfy the basic axioms of rational choice theory, and particularly the requirement for policy consistency imposed by the transitivity axiom, then it could be quite useful.

Another potentially important use of this approach might be to allow assessments of the economic costs associated with policy choices that are guided by political rather than purely economic considerations. If the function that was originally the "economic" objective function is retained as a measure of the benefits of the policy actually chosen, the reduction in economic "welfare" associated with choosing the more "political" policy settings can be measured. This approach could provide important insights, allowing policy makers and external observers to assess the economic costs of "political" policy choices.

Conclusions

This paper begins by noting the serious imbalance between the increasing demand for policies that target multiple goals and analysts' ability to provide guidance on the design of policy packages to meet these needs. While the ability to model economic policies has greatly improved, with improvements in data, hardware and software, the approaches to policy analysis have not greatly changed, with a strong focus on assessing the reduced-form impacts of changes in policy settings on outcomes. While the set of outcome variables now typically considered has expanded these reduced-form impacts are insufficient to assemble the multi-instrument policy packages needed to achieve multiple goals.

The theory of quantitative economic policy provides important insights into the formulation of policy packages to achieve multiple goals. It highlights, in particular, the need to combine multiple policies if multiple goals are to be satisfactorily achieved. Much work has been done to assess the impacts of a range of policies on achievement of a range of goals. While the results of these analyses provide valuable information for policy formulation, they remain insufficient for assembling policy packages that will most cost-effectively achieve those goals. Most importantly, they fail to account for the interactions between policies in achieving these goals and the changing impacts as policies are used more intensively, and the extraordinarily high dimensionality of many of the resulting policy choices.

The approach suggested in this paper involves forming objective functions—sometimes nonlinear, but often simply linear—that combine policy makers' goals, and then using nonlinear programming techniques to identify the approaches that can most effectively achieve those goals. The approach used to illustrate the method is based on a standard general equilibrium model that links policy instruments to objectives and imposes constraints on the nonlinear programming algorithm so that it can identify the best policy instruments and the settings of those instruments. The particular examples used rely entirely on software and data that are in the public domain.

Depending on the problem, the approach may involve unconstrained or constrained maximization of the objective function. An example of unconstrained maximization seeks to identify optimal carbon tax rates for key agricultural commodities, with the environmental externalities incorporated into the objective function. The application shows that this approach can deliver sensible estimates of optimal tax rates on emissions from agricultural activities. A second application seeks to identify optimal allocations of research resources to raise productivity within Ethiopian value chains. This example of constrained optimization allocates a defined budget across commodities to raise productivity and increase a social welfare function that combines income growth and poverty reduction. It incorporates the importance of each commodity in production and consumption; diminishing returns in R&D investments; impacts on commodity prices and wages; and impacts on household incomes, particularly the incomes of the poor.

We hope and expect that the approach proposed will be particularly useful when policy makers seek to achieve multiple goals. But we think that it may also turn out to be useful for assembling packages of development policies using multiple instruments even in cases with a single objective such as maximization of economic welfare. It may also provide an informative approach to assessing the economic costs of choosing policies based on non-economic objectives.

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Appendix

Table A.1: Regional aggregation—the optimal carbon tax experiment

Commodities	GTAP Sectors
Rice	Pdr
OthCereals	wht, gro
OthAgric	v_f, osd, c_b, pfb, ocr, wol, frs, fsh
Beef	Ctl
OthMeat	Oap
Milk	Rmk
Extraction	coa, oil, gas, omn, nmm
Manuf	cmt, omt, vol, mil, pcr, sgr, ofd, b_t, tex, wap, lea, lum, ppp, p_c, crp, i_s, nfm, fmp, mvh, otn, ele, ome, omf
OthServices	ely, gdt, wtr, cns, ofi, isr, obs, ros, osg, dwe
TransComm	trd, otp, wtp, atp, cmn

Table A.2: Regional aggregation—the optimal carbon tax experiment

Regions	GTAP Regions
Oceania	aus, nzl, xoc
EastAsia	chn, hkg, jpn, kor, mng, twn, xea
SEAsia	khm, idn, lao, mys, phl, sgp, tha, vnm, xse
SouthAsia	bgd, ind, npl, pak, lka, xsa
NAmerica	can, usa, mex, xna
LatinAmer	arg, bol, bra, chl, col, ecu, pry, per, ury, ven, xsm, cri, gtm, hnd, nic, pan, slv, xca, xcb
EU_25	aut, bel, cyp, cze, dnk, est, fin, fra, deu, grc, hun, irl, ita, lva, ltu, lux, mlt, nld, pol, prt, svk, svn, esp, swe, gbr
RestofWorld	che, nor, xef, alb, bgr, blr, hrv, rou, rus, ukr, xee, xer, kaz, kgz, xsu, arm, aze, geo, bhr, irn, isr, kwt, omn, qat, sau, tur, are, xtw
Africa	xws, egy, mar, tun, xnf, ben, bfa, cmr, civ, gha, gin, nga, sen, tgo, xwf, xcf, xac, eth, ken, mdg, mwi, mus, moz, rwa, tza, uga, zmb, zwe, xec, bwa, nam, zaf, xsc