Simulating Policy Priority Inference

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Abstract

Policy leaders have often need to make complex decisions on short timelines with incomplete information. Determining causal effects and spillovers across policies can be challenging. In this proposal, we plan to study the Policy Priority Inference (PPI), a research program started by two scholars, Omar Guerreo and Gonzalo Castañeda. It is a policy research program that is designed to model the causal relationship between government expenditure and policy outcomes, while considering the multidimensional and complex nature of systems of governance.

This study implements a streamlined network-based model that captures how interdependent policy domains evolve under budget constraints. Unlike the PPI that embeds numerous variables, our formulation isolates the core computational structure. By representing spillovers through a directed weighted graph, we model how policies affect each other as a network which makes it easier to update plans and decide where to allocate budget resources. The approach looks at current needs and how changes spread, checks that results are stable and efficient, and keeps the system simple, scalable, and clear about what causes outcomes.

Introduction and Description of the system

The PPI is an agent-based model that simulates the impact of budget shifts on the United Nations Sustainable Development Goals (SDGs), which are a set of 17 interconnected goals that form the foundation and direction of the UN's 2030 ambition and plan (United Nations, 2015). The PPI simulates government spending against the SDGs, looking at the potential impact of different spending decisions and its impact on policy outcomes and interdependent development indicators (Guerrero, 2023). The model allows government leaders to understand the feasibility of goals and provides insights on how to optimize spending to reach those goals (Guerrero & Castañeda, 2020; 2024).

The PPI aims to achieve several objectives. For one, it assesses how public expenditure affects the development outcomes of each country. Second, it supports evidence-based policymaking under conditions of budget constraints, competing policy priorities, multidimensional goals, imperfect governance, and context-specific interdependencies. Most importantly, the PPI uses agent-based modeling (ABM) that simulates the behavior and decision-making of socioeconomic actors. By using ABM, the approach allows transparency and interpretability compared to traditional black-box AI models.

Against the backdrop of the PPI, in this proposal, there are two-folded procedures. First and foremost, we intend to model government budget allocations across competing Sustainable Development Goal (SDG) targets, assessing trade-offs and synergies between policy areas under fiscal constraints. Secondly, it examines how a number of factors, including governance quality, corruption, and institutional context, shape policy coherence, thus highlighting how political economy dynamics shape development trajectories.

Literature review

Models like PPI are increasingly being used by public sector organizations and beyond (Gordon, 2019). These tools allow researchers to integrate multiple variables (interventions) to better understand the connection between policies and broader outcome objectives (Simangunsong and Sihotang, 2023) and can provide insights on how different interventions interact over time (Vasconcelos et al, 2021). Three types of models are introduced below – microsimulations, agent-based models (ABMs), and multidimensional models.

Microsimulations

Microsimulations model individual or household data to map the impact of policies. For example, a microsimulation model might explore the effect of tax reforms, public health interventions, or social welfare efforts and how those policies move poverty up (or down). One example is the World Bank's Commitment to Equity (CEQ) model, which looks at the impact of fiscal policies on income levels (World Bank, 2020). By simulating the impact of different interventions, leaders are better positioned to make informed decisions that lead to improved outcomes. Thus, these models can be a critical tool for evaluating public policies (Cogneau, Grimm, & Robilliard, 2003) and more specifically can unlock a sharper understanding of the potential impacts on different population groups and aid in crafting more effective poverty reduction measures (Zucchelli, Jones, & Rice, 2010).

Agent-Based Models

ABMs differ from microsimulations in that they consider interactions between so-called "agents," which could be individuals, households, organizations, etc. The models factor in responses from agents to policy interventions (Hammond, 2015). On the surface, this allows for a similar exploration of the impact of policy interventions on outcomes. But given the agent responses, they can also explore how social connections and community interactions affect results. For example, an ABM that models the effects of a microfinance program on poverty can factor in things such as social networks, information access, and the ability of recipients to pay back loans (Ghorbani, 2013).

This approach can provide insights into the changing behaviors of individuals (or organizations) which are not as easily observable in traditional econometric models (Ahmadi Achachlouei & Hilty, 2015). For example, a model in Mexico City simulated discrimination and income support, showing how "agents" responded to anti-discrimination policies and targeted support. The study shows how these types of models can identify differential effects, and in turn be used by leaders to shape more equitable and impactful policies (Aguilera et al, 2020).

Multidimensional Models

These models are considered microsimulations but can integrate multiple policy levers and interventions and simulate potential effects. The Commitment to Equity (CEQ) model is an example, as it can simulate the effect of multiple policies on poverty reduction across different target populations (World Bank, 2020; Mitton, Sutherland, & Weeks, 2000). The benefit of these types of models is that they can help leaders understand how different policies can work together to yield greater outcomes (Cogneau, Grimm, & Robilliard, 2003).

Two types of multidimension models include integrated modeling and dynamic systems modeling (DSM). The former brings together micro-level agent actions with macro-level policy outcomes (Malbon & Parkhurst, 2023). DSMs simulate feedback loops within systems, thus showing how one intervention might affect another area – for example, the impact of public transportation on housing. The PPI model leverages DSM to show how public spending can be optimized across different budget areas (Guerrero, 2023; PolicyPriority.org, 2024).

Conceptual Model of the System

Building on prior PPI research that combines agent-based, microsimulation, and dynamic system approaches to model policy interactions, this study develops a simplified variant centered on network analysis. The existing PPI framework integrates numerous behavioral, institutional, and multidimensional variables to capture decision-making complexity. While this is realistic, it can obscure computational mechanisms. Our model narrows the scope to structural spillovers among SDG indicators, representing policy domains as interconnected nodes linked by directed weights.

Motivation. Policy systems are highly interconnected. Progress in one domain can create synergies or trade-offs in others, so policies must be analyzed within a structural context. Capturing these cross-effects requires a representation of interdependencies, not simple correlations. Recent work shows that spillover networks effectively model these links, where each edge represents the direction and strength of influence between indicators or policy areas (Castañeda et al., 2018; Ospina-Forero et al., 2022).

From a computational view, network analysis reformulates the policy environment as a graph, allowing algorithmic study of how local actions propagate through the system. It supports iterative simulation, sensitivity analysis, and optimization under budget limits. Embedding such structures into the PPI framework enables evaluation of both individual policy outcomes and the systemic effects arising from their interaction.

Network Representation. We model the policy system as a discrete-time dynamical process on a directed weighted graph $G = (V, E, A)$, where each node $i \in V$ represents a policy domain or SDG indicator, and each edge $(j, i) \in E$ carries a spillover weight $a_{ji} \in \mathbb{R}$. Positive a_{ji} denote synergies, negative values denote trade-offs, and $a_{ii} = 0$. The adjacency matrix $A = [a_{ji}]_{N \times N}$ defines the structural backbone for all updates.

Edges represent channels through which improvements in one domain affect others. The network is assumed sparse, reflecting modular clusters observed in empirical SDG networks (Ospina-Forero et al., 2022). Sparsity reduces computational complexity from $O(N^2)$ to near-linear in active edges.

Each node carries degree-based attributes: out-degree K_i^{out} measures potential influence, in-degree K_i^{in} captures exposure to external effects. When weighted measures are preferred, out-strength $S_i^{out} = \sum_{k \neq i} \mid a_{ki} \mid$ and in-strength $S_i^{in} = \sum_{j \neq i} \mid a_{ij} \mid$ summarize cumulative connections.

State Dynamics. Let $I_{i,t} \in [0,1]$ denote the normalized performance of node i at time t, and T_i its target level. At each iteration, states evolve according to a propagation rule that combines self-adjustment and network diffusion:

$$I_{i,t+1} = I_{i,t} + \gamma(T_i - I_{i,t})(P_{i,t} + \sum_{j \neq i} a_{ji} P_{j,t}),$$

where $\gamma \in (0,1]$ controls adjustment speed, $P_{i,t}$ is the allocated budget share, and A encodes structural dependencies. The first term enforces diminishing updates near targets; the summation aggregates spillovers from connected nodes (Castañeda et al., 2018).

Allocation Rule. Allocations are computed endogenously through a priority-scoring heuristic that links performance gaps with structural influence:

$$q_{i,t} = (T_i - I_{i,t})(K_i^{out} + 1), P_{i,t} = B \cdot \frac{q_{i,t}}{\sum_k q_{k,t}},$$

where B is the total available budget. This rule directs resources to domains that are both lagging and influential, approximating a graph-based greedy allocation.

The dynamic system alternates between allocation and state updates. At each step, priority scores $q_{i,t}$ are computed from current states and network topology. Scores are normalized to obtain allocations $P_{i,t}$ under the budget constraint $\sum_i P_{i,t} = B$. Node states are then updated through the propagation rule. This process repeats until

$$\max_i \mid I_{i,t+1} - I_{i,t} \mid < \varepsilon,$$

ensuring numerical stability. The steady state represents a network-coherent allocation, where each domain's progress reflects both self-effort and relational feedback (Ospina-Forero et al., 2022). Through this iterative mechanism, the model functions as an active computational engine that reveals how network structure shapes convergence speed, budget efficiency, and systemic balance.

Evaluation Metrics. Model performance is assessed through two complementary measures: overall accuracy and allocation efficiency. All metrics are computed from simulation outputs and updated iteratively during runtime.

Accuracy reflects how closely simulated indicators match their targets. We measure it using the root mean squared error (RMSE):

$$RMSE = \sqrt{\frac{1}{NT}\sum_{i,t}(I_{i,t} - T_i)^2}\,, RMSE_{\text{steady}} = \sqrt{\frac{1}{N}\sum_{i}(I_i - T_i)^2},$$

where smaller values indicate stronger alignment. In parallel, the mean performance gap

$$g\bar{a}p_t = \frac{1}{N}\sum_{i}(T_i - I_{i,t})$$

is tracked over time and compared with a baseline scenario ($A = 0$) to quantify the added effect of spillovers.

Allocation efficiency measures the productivity of resource use. With total budget B and state gains $\Delta I_{i,t} = I_{i,t+1} - I_{i,t}$,

$$E_t = \frac{\sum_i \Delta I_{i,t}}{B},$$

where higher values indicate that resources are directed to nodes with stronger propagation effects, improving systemic returns (Castañeda et al., 2018).

Summary. This study develops a simplified network-based PPI model that captures how policy areas interact and evolve under budget constraints. Unlike earlier studies that incorporate numerous behavioral or governance factors, our approach isolates the core computational structure. We represent spillovers through a directed graph, translating policy interactions into a form suitable for iterative updates and rule-based allocation. The mechanism accounts for target gaps, structural influence, and resource flows, while evaluation metrics assess explanatory performance and allocation efficiency. This design balances interpretability and scalability, allowing us to link outcomes directly to network features.

Platforms & Modalities of Development

Given that the proposed model represents SDG domains as an interconnected network, and more specifically in the context of network analysis, we will be using graph algorithms since they form the backbone for exploring spillover effects, influence propagation, and optimal resource allocation. At this stage, we are exploring several algorithms although they will be changed based on the class lectures. For example, we can use Breadth-First Search (BFS) to explore the immediate and extended neighborhood of a policy domain to identify which SDG targets are mostly affected by an intervention. Similarly, we can also use Depth-First Search (DFS) to uncover the long chains of dependencies or feedback loops in the policy network. Since the focus is on network analysis, we also plan to measure the degree, betweenness, and centrality to compute the importance of the policy nodes. For instance, we plan to see how a node with the high betweenness centrality may represent an SDG policy domain that acts as a bridge between disconnected clusters.

To implement our simulation for the network model, we will be using C programming. Given that our network may represent 17 SDG domains with multiple weighted connections, C offers the flexibility to design custom data structures that fit the requirements of the network analysis task, while ensuring that the implemented algorithms can run with optimal performance.

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