Policy Priority Inference for Sustainable Development

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1 Introduction

In its 2030 Agenda Declaration (cite resolution A/RES/70/1***), the United Nations acknowledged the importance of understanding development not only as a multidimensional process, but as a complex one where these many dimensions interact with each other: "*The interlinkages and integrated nature of the SDGs are of crucial importance in ensuring that the purpose of the new Agenda is realized.*" (p.2) Since then, the question of *how should public policies be prioritized?* has shifted to the center of international forums and policy discussions[1].

The moment we step out of topical silos and walk into the realm of policy prioritization on a landscape with positive and negative interdependencies, the limitations of traditional analytic tools become self-evident. For example, ***citeRodrik argues that development indicators typically used to explain changes in GDP in growth regressions are not really exogenous variables but rather the result of intentional policies by governments. Thus, the common practice of determining policy priorities based on the magnitude and significance of regression coefficients is unfit for purpose. In previous works, we have assessed the adequacy of other popular tools such as Systems Dynamics and Network Analysis in the problem of policy prioritization ***cite. Overall, these methods are useful to address the type of questions they were designed to answer, for example, to study aggregate world dynamics or

[1]The experience from the Millennium Development Goals suggest that most countries focused on evaluation rather than planning cite***

to describe interdependencies between SDGs. However, they are not ideal to generate advice on policy prioritization, as they lack the crucial micro-economic foundations that give raise to the observed dynamics of development indicators. Here, we introduce a new framework that we term *Policy Priority Inference* (PPI). PPI builds on a model developed in cite*** (CCG form here on), consisting on a computational micro-economic model where a central authority allocates resources across a multidimensional and interconnected policy space. The CCG model was successfully deployed to study ***, but it only considered socioeconomic dimensions and positive interlinkages. Nevertheless, its potential to capture the complexity of the SDGs was evident. In this paper, we introduce PPI as a generative framework to model the interdependent (positive and negative) dynamics of development indicators, and to infer, among many things, policy priorities. Our benchmark application stems from a project sponsored by the United Nations Development Programme. It focuses at the case of Mexico, a leading country in the generation of SDG indicators at national and sub-national levels, as well as being a pioneer in SDG budgeting.

1.1 A bird's eye view of PPI

The underlying principle of PPI is that, when allocating resources across multiple policy issues, governments need face an environment with uncertainty, a complex network of interdependencies between policy issues, and inefficiencies by those in charge of implementing public policies. While there may be many other factors that shape the development process, these are the critical ones that we have identified necessary to produce a simple-enough analytically framework that is not too demanding in terms of data; something important for scalability and a generalized adoption across governments with various levels of statistical and expert capacity.

In PPI, the allocation of resources is conceived as an adaptive process where agents learn in response to a misalignment of incentives. More specifically, PPI consists of a political economy game between a central authority (or government) and policymaking agents. The government, on the one hand, allocates resources in order to reach specific development goals. The agents, on the other, use part of these resources to advance their development indicators through policy, but they also try to be inefficient due to the misalignment of incentives. This process becomes more complex when the performance of the policies *i.e.*, the progress of the indicators depends on spillovers (synergies and trade-offs) from other policy issues.

Although we propose a specific model of the policymaking process, it is natural to think that more detailed and context-relevant models could be built in the future. Thus, PPI should be thought of as a modeling philosophy rather than the specific model here presented. Perhaps the most distinctive feature of such philosophy is that, in order to understand policy prioritization, a production account of causation is necessary ***cite. in other words, it is not enough to study dependencies between aggregate variables, but to model the micro-level processes that gives raise to their dynamics. This is so because, ultimately, policy priorities materialize through micro-level policy interventions. For this reason, the pertinent analytic tools should allow vertical causation across different levels of aggregation. Here, we adopt one such tool: agent-computing, also known as agent-based modeling.

The rest of the paper is structured in the following way. Section **??** provides all the details of the model underlying PPI. In section 3, we present the data built for the project of Mexico and provide descriptive statistics. Section 4 present the analysis for the Mexican case at the national level. ***more Throughout the paper, we will elaborate on novel ways in which PPI can be used to address salient concepts of the 2030 Agenda. Three specific concepts stand out: *policy coherence for sustainable development* (PCSD), *accelerators*, and *SDG budgeting*. By demonstrating the usefulness of PPI in tackling these problems, we hope to make a strong case for why the PPI philosophy should become an integral part of any government's planning toolkit.

2 Model

PPI is a bottom-up approach of the policymaking process. Hence, we explain it in that fashion, firstly, elaborating on the behavior of policymaking agents, secondly, on the government's strategy and, thirdly, on the aggregate dynamics of the development indicators.

2.1 Micro-foundations 1: inefficiencies

2.1.1 Benefits

Let us assume that there are n agents, each in charge of a public policy that is specific to a single policy issue.[2] In order to implement the mandated policy in a given period t, agent i receives $P_{i,t}$ resources from the central authority. With these resources, the policymaker tries to leverage two potential benefits: (1) the reputation from being a proficient public servant and (2) the utility derived from being inefficient. Proficiency, on the one hand, is beneficial because it signals competence to the central authority and the political system. Therefore, proficient agents gain political status that may catapult their careers in the future. Inefficiency, on the other hand, is also beneficial because it appeals to the most basic utility of private gains. That is, by devoting time and resources to other activities such as shirking, diverting funds, or benefiting friends, an agent may substitute the benefits from proficiency with the private gains of becoming inefficient. Of course, there is no free lunch in becoming inefficient, as central authority may exert monitoring activities and take punitive measures with the purpose of increasing proficiency. The effectiveness of such mechanisms, however, is bound to the institutional setting of each nation, so we elaborate on that later.

We formalize the trade-off between proficiency and inefficiency through

$$F_{i,t+1} = \Delta I^{*}_{i,t}\frac{C_{i,t}}{P_{i,t}} + (1-\theta_{i,t}\tau)\frac{(P_{i,t}-C_{i,t})}{P_{i,t}}, \tag{1}$$

where $F_{i,t+1}$ represents the benefit or utility obtained in the next period.

[2] An agent may well represent a specific bureaucrat, a minister, or a government agency.

The first summand of equation 1 captures the benefit from being proficient. $\Delta I^*_{i,t}$ is the change in indicator i with respect to the previous period (its performance), relative to the changes of all other indicators. More specifically, the relative change in indicator i is computed as

$$\Delta I^*_{i,t} = \frac{I_{i,t} - I_{i,t-1}}{\sum_j |I_{j,t} - I_{j,t-1}|}, \tag{2}$$

an it captures the idea that the central authority evaluates the performance of each policy through development indicators.

Going back to the first summand of equation 1, we find that the relative change in the indicator is pondered by $\frac{C_{i,t}}{P_{i,t}}$. Here, $C_{i,t}$ is the fraction of the allocated resources $P_{i,t}$ that is effectively used towards the policy. We call it the contribution of agent i. As we will show ahead, $0 \leq C_{i,t} \leq P_{i,t}$, so the factor $\frac{C_{i,t}}{P_{i,t}}$ represents the efficiency with which resources are being used in policy issue i.

Next, let us focus on the second addend of equation 1, which corresponds to the utility derived from being inefficient. Here, $P_{i,t} - C_{i,t}$ is the benefit extracted from not devoting resources to the policy. Thus, when dividing by $P_{i,t}$, it represents the level of inefficiency. We previously mentioned that monitoring and penalties may hinder inefficiencies. This is captured by factor $(1 - \theta_{i,t}\tau)$. Variable $\theta_{i,t}$ is the binary outcome of monitoring inefficiencies. If $\theta_{i,t} = 1$, it means that the government has spotted agent i in inefficient behavior. In that case, i is penalized by a factor τ, such that the benefit from these private gains are reduced. In the literature of public governance, θ and τ represent two fundamental institutional factors: the quality of monitoring efforts and the rule of law. Appendix *** provides further details about the role of these factors.

In order to model the binary outcomes of monitoring efforts, we assume that, every period, an independent realization $\theta_{i,t}$ takes place for each indicator. This is nothing more than a Bernoulli process with a probability of success $\lambda_{i,t}$ determined by

$$\lambda_{i,t} = \varphi \frac{1}{1 + e^{-D_{i,t}}}. \tag{3}$$

Parameter φ in equation 3 corresponds to the quality of the monitoring efforts. Note that both $\varphi \in [0, 1]$ and $\tau \in [0, 1]$, and that they are time- and indicator-independent. This means that these parameters can be directly calibrated from empirical data such as development indicators of public governance.[3]

The second factor that determines whether inefficiencies are spotted in equation 3 is $D_{i,t}$. This represents the level of the private gain extracted by agent i, relative to the private gains of all other agents. Formally, this quantity is obtained from

$$D_{i,t} = \frac{(P_{i,t} - C_{i,t}) - \min(P_{\cdot,t} - C_{\cdot,t})}{\max(P_{\cdot,t} - C_{\cdot,t}) - \min(P_{\cdot,t} - C_{\cdot,t})} - \frac{1}{2}, \tag{4}$$

where the term -1/2 is necessary to specify a balanced logistic function in equation 3.

Our motivation to correlate the probability of being spotted with the relative level of inefficiency is rather intuitive. Large inefficiencies such as corruption scandals come into the spotlight when they stand out of the norm. Thus, in contrast with the traditional principal-agent view, PPI considers the collective-action problem of social norms that prevents the principal from aligning the agents' incentives. It should be noted that the lack of collective action has been identified as a major limitation of the principal agent theory, and an explanation of why the international governance agenda has failed to eradicate corruption in the developing world ***cite.

Now that we have established how the benefit function in equation 1 works, it is clear that the task of the agent is to determine the level of contribution $C_{i,t}$. Since agents face an environment with uncertainty and, as we will show ahead, there are interdependencies between the indicators, a rational approach to choosing $C_{i,t}$ is ill-suited. Thus, we adopt a robust and expensively validated learning model: *directed learning* ***cite.

[3] An alternative approach where both parameters are endogenous and time-dependent can be found in ***.

2.1.2 Learning

The principle behind directed learning is that actions can go in one of two directions: positive or negative; and outcomes reward or disencourage future actions in the same direction. For example, if an agent became more inefficient and, then, his/her benefits increased, then s/he would become even more inefficient the next period. If, in contrast, the government was able to penalize the agent so that his/her benefits decreased, s/he would become more proficient the next period. Formally, action $X_{i,t}$ of agent i can be modeled as

$$X_{i,t+1} = X_{i,t} + \text{sgn}((X_{i,t} - X_{i,t-1})(F_{i,t} - F_{i,t-1}))|F_{i,t} - F_{i,t-1}|, \tag{5}$$

where $\text{sgn}(\cdot)$ is the sign function.

In reality, $X_{i,t}$ is an abstraction of any type of action that an agent may take in order to be inefficient, so X may have any real value. In order to map action $X_{i,t}$ into the amount of effective resources, we define

$$C_{i,t} = \frac{P_{i,t}}{1 + e^{-X_{i,t}}}. \tag{6}$$

Equation 6 incorporates the directed learning model into the policymaking process, while making sure that $C_{i,t} \leq P_{i,t}$. This completes the micro-foundations that give place to technical inefficiencies, *e.g.* those arising from the policymaking process. This part of the model has no free parameters (since φ and τ can be obtained from data). Therefore, the learning model does not require any calibration procedure.

2.2 Micro-foundations 2: policy priorities

The policy priorities are represented by the allocation profile $P = P_i, \dots P_n$. At this point, it is important to introduce a distinction between indicators that can be *directly intervened* via public policies and those that cannot. Direct interventions to shift specific indicators may be unfeasible because these metrics are composite aggregations of various topics, for example, GDP per capita of financial development. Alternatively, it is possible that an indicator is not relevant to the government priorities, so there may not exist any policy to improve it. We differentiate between indicators that can and cannot not be directly influenced via public policy by classifying them into *instrumental* and *collateral*. Which indicators are instrumental and which ones are collateral may vary from country to country. So far, the model has only being concerned about n instrumental indicators, but we can say there are $N \geq n$ policy issues in total.

Governments determine their policy priorities over the n instrumental nodes, but they may well have aspirations to improve the N indicators, even without explicit policy instruments for the collateral ones. Such aspirations are captured a vector of targets or goals (we use there two terms interchangeably) $T_0, \dots, T_N$. Note that we have established a clear difference between goals and priorities, two concepts that are often confused in the literature of sustainable development. Goals, on the one hand, represent the aspirations of a government. They are the exogenous variables in PPI and consist of specific values what the central authority wants to reach for each indicator. Priorities, on the other hand, are not aspirations, but actions. In PPI, they are the resources put forward by the central authority to move each indicators. Because of the political economy of the policymaking process, priorities are endogenous variables.

The objective of the government is to close the gap between targets and indicators by solving the problem

$$\min \left[\sum_{i}^{N} (T_i - I_{i,t})^2 \right] \tag{7}$$

in every period through different allocations. The central authority achieves this through its allocation profile P. Note that this formulation implies that the government wants to achieve goals for topics in which it may not necessarily have policy instruments. This is why concepts such as *accelerators*[4] are so important in the 2030 Agenda; so we will formally treat

[4]Informally, accelerators are issues whose improvement also produce advancements in other topics via

this idea in section ***.

What determines the distribution of resources P? Different countries and their governments may have various motivations for allocating different resources across policy issues. For example, a welfare-state oriented nation may be more welcoming of pro-social policies such as unemployment benefits and social housing, while a technological oriented one may prioritize investments in research and development. In principle, PPI is flexible enough to allow any functional specification through which a government shapes its policy priorities, as well as a high degree of restrictions to the flow of resources from one topic to another. This, of course, requires certain priors and data from the user. In absence of such information, we try to remain agnostic about the specificity of each government and provide a simple yet non-trivial policy prioritization heuristic. First, governments use the rule of prioritizing laggard topics because there is a generalized belief that these issues are bottlenecks to development. In fact, this was the approach in the Millennium Development Goals (cite accelerators paper*** p. 1). Hence, the government measures the normalized gaps between targets and indicators

$$G_{i,t} = \frac{(T_i - I_{i,t}) - \min(T_{\cdot} - I_{\cdot,t})}{\max(T_{\cdot} - I_{\cdot,t}) - \min(T_{\cdot} - I_{\cdot,t})}. \tag{8}$$

Besides supporting poorly developed issues, we assume that governments do not like to systematically allocate resources to ineffective policies. Therefore, our government heuristic also takes into account the normalized history of spotted inefficiencies of each agent, represented by

$$H_{i,t} = \frac{\sum_l^t \theta_{i,l}(P_{i,l} - C_{i,l}) - \min\left[\sum_l^t \theta_{\cdot,l}(P_{\cdot,l} - C_{\cdot,l})\right]}{\max\left[\sum_l^t \theta_{\cdot,l}(P_{\cdot,l} - C_{\cdot,l})\right] - \min\left[\sum_l^t \theta_{\cdot,l}(P_{\cdot,l} - C_{\cdot,l})\right]}. \tag{9}$$

Together, the target-indicator gaps are encourage prioritization, while a reputation of inefficiency discourages it. However, the international experience suggests that the gaps

spillovers.

play a more central role than the inefficiencies (cite***). Thus, we look for a function where the allocation $P_{i,t}$ depends mainly on $G_{i,t}$ and, in a lesser measure, on $H_{i,t}$. Since we want to avoid introducing new free parameters, we adopt the functional form.

$$q_{i,t} = {G_{i,t}}^{1+H_{i,t}}, \tag{10}$$

which can be normalized to obtain the policy priorities

$$P_{i,t} = \frac{q_{i,t}}{\sum_j q_{j,t}}. \tag{11}$$

Equation 10 is rather intuitive. In term $G_{i,t}^{1+H_{i,t}}$, the base is always fractional, while the exponent is always greater than one. This means that policy issues with more visible inefficiencies will be penalized more. Appendix *** shows that the estimated allocation profiles are robust across different functional forms of equation 10.

2.3 Macro-dynamics: development indicators

Now that we have built the micro-foundations of the model, we connect them to the evolution of the development indicators. In doing so, we aim at generating indicator dynamics that resemble empirical data by fitting three attributes: (1) that each indicator starts at a specific value and reaches particular final value, (2) that all indicators arrive to their final values at the same time, and (3) that these data presents a certain level of variance. We address attribute (1) here, and leave (2) and (3) for the calibration procedure.

2.3.1 Indicator dynamics

From the micro foundations, we know that a fraction $C_{i,t}$ of an allocation $P_{i,t}$ is efficiently used in public policies. In conjunction with the incoming spillover effects $S_{i,t}$ (these could be positive and negative), public policies transform the associated indicator $I_{i,t}$. We model this transformation through a random growth process. Let α_i denote the amount of growth experienced in indicator i, conditional on a successful outcome. By successful outcome we mean that the event of growing at a rate α_i is a random variable where the success rate depends on incoming spillovers and public policies (if any). Therefore, the growth process is modeled as independent Bernoulli trials with probability of success

$$\gamma_{i,t} = \frac{\alpha_i + C_{i,t}/P_t^*}{\alpha_i + e^{-\frac{NS_{i,t}}{\sum_j (T_j - I_{j,t})/(T_j - I_{j,0})}}}, \tag{12}$$

where P_t^* is the maximum amount of allocated resources across all policy issues in period t. Note that $\frac{C_{i,t}}{P_t^*} = \frac{C_{i,t}}{P_{i,t}} \frac{P_{i,t}}{P_t^*}$, which means that the effect of the contribution is the combination of how efficiently are the resources being used $(C_{i,t}/P_{i,t})$ and how much resources policy issue i receives in relation to all other issues $(P_{i,t}/P_t^*)$. The sum dividing the spillover term is a correction that we explain ahead together with α_i.

Next, we define the growth equation of indicator i as

$$I_{i,t+1} = I_{i,t} + \alpha(T_i - I_{i,t})\xi(\gamma_{i,t}), \tag{13}$$

where $\xi(\cdot)$ is the binary outcome (0 or 1) of a growth trial. The growth factor α_i lives in $(0, 1)$, and is linked to both the probability of success and the amount of growth. We can think of α_i as all the other determinants responsible for an indicator's growth, but that are not explicitly specified in the model. Therefore, this factor can be calibrated in order to match the second attribute of the data: all indicators reach their final values at the same time, which we show in Appendix ***. Note that the gap $T_i - I_{i,t}$ shrinks as the indicator grows, and $I_{i,t} < T_i$ all the time because α_i. This means that the indicator is guaranteed to converge to T_i, which takes care of the first attribute of the data: reaching the indicator's specific final value. Because of these logistic-like convergence dynamics, the change in the indicator becomes, on average, smaller as it approaches T_i, so the amount of spillovers are reduced with time. In order to compensate for this artifact, equation 12 divides the spillover term in the exponent by the average normalized gap at time t.

2.3.2 SDG networks and spillovers

Let us define a network with N nodes, each one corresponding to an indicator. An arrow $i \rightarrow j$ represents a change on indicator j conditioned on a change by indicator i, not a causal link. That is, the existence of $i \rightarrow j$ means that if we observe a change in j it must be the case i also changed. However, a change in i may not always trigger a change in j. In terms of our spillover narrative, edge $i \rightarrow j$ indicates that spillovers from i to j are part of the change in j, but they are not always effective in moving j. This could be because the agent in charge of j may be highly inefficient, or because j may receive other spillovers in the opposite direction. A further discussion of why SDG networks –by themselves– cannot capture causal relations is provided in ***cite. In this paper, we just want to make it clear that causality comes from the socioeconomic mechanisms specified in the model, for example, the political economy game on the network. Finally, the weight of $i \rightarrow j$ indicates the intensity of the conditional dependency, while its sign tells us whether such relation is a synergy (a positive sign) or a trade-off (a negative one).

Let us be more precise regarding the spillovers. We say that a spillover from i to j takes place through the interaction of i's change $\Delta I_{i,t} = I_{i,t} - I_{i,t-1}$ and the intensity of the conditional dependency specified in the adjacency matrix $\mathbb{A}$. Therefore, the incoming spillovers from i to j in period t are

$$S_{i \rightarrow j,t} = \Delta I_{i,t-1} \mathbb{A}_{ij}, \tag{14}$$

which can be positive, negative or zero. We are particularly interested in the amount of incoming spillovers that each node receives. Thus, the relevant measure to consider is the net incoming spillovers

$$S_{j,t} = \sum_i \Delta I_{i,t-1} \mathbb{A}_{ij}, \tag{15}$$

which is one of the determinants of successful growth in equation 12.

Note that the direct incidence of the spillovers takes place only at the macro-level, while the indirect effects to the micro-level happen through the agents' behavioural model; specifically, through the benefit function 1. Such consistency acknowledges that the SDG network does not tell us anything about the causal channels and, instead, that causation takes place across different aggregation levels through the mechanisms specified in the model.

As a summary of the model, Table 1 presents all its variables. We have arranged the variables according to their sources. Clearly most of them are endogenous. The free parameters that need to be calibrated: the growth factors α_i (one for each indicator) and the number of ticks that the simulation should take to converge; we elaborate on this in section ***. Regarding the exogenous variables, all of them can be obtained from publicly available datasets for most countries. For example, the World Bank's Worldwide Governance Indicators provides a rich source of information to obtain φ and τ. Given a sample of development indicators for a given period, their initial values $I_{i,0}$ determine the initial conditions of the country, region or sector under study. The targets T, on the other hand, represent the aspirations that a government or society has, so they represent specific values to be reached by each indicator. From a retrospective point of view: $T_i = I_{i,-1}$, where $I_{i,-1}$ denotes the final value of indicator i. In other words, we assume that the final values of the data sample represent the real aspirations that the government had in the past. This provides a benchmark to calibrate the model. Finally, the adjacency matrix $\mathbb{A}$ may be estimated via different methods. Whichever is the chosen approach to infer the spillover network, it assumed to be exogenous.

To close the presentation of the model, we would like to make it clear that PPI takes three inputs: (1) initial conditions, (2) spillover network, and (3) targets or goals. The first one is usually collected by governments and international organizations. The second one can be estimated via quantitative ***cite or qualitative methods ***cite. The third is an exogenous variable that can be built from societal consensus, political platforms, public consultations, etc. Note that there are no requirements about the length of the indicator time series, which

Table 1: Variables of the model

Symbol	Variable	Source
α	growth factor	calibration
$\mathcal{T}$	retrospective convergence time	calibration
I	development indicators	data
$\mathbb{A}$	spillover network adjacency matrix	data
T	goals	data
φ	quality of monitoring	data
τ	quality of the rule of law	data
X	actions	endogenous
F	functionaries' benefits	endogenous
C	contributions	endogenous
D	relative private gains	endogenous
γ	probability of successful growth	endogenous
λ	probability of spotting inefficiencies	endogenous
θ	binary outcome of monitoring	endogenous
ξ	binary outcome of random growth process	endogenous
S	net incoming spillovers	endogenous
P	allocation profile	endogenous
G	target-indicator gaps	endogenous
H	history of inefficiencies	endogenous

Sub-indices have been omitted.

makes PPI easily scalable. Finally, algorithm 1 summarizes the model in a few lines.

Algorithm 1: PPI pseudocode

Input: $\alpha_1, \ldots, \alpha_N$, initial I, T, $\mathbb{A}$, φ, τ

while $T_i - I_i > \varepsilon$ *for every* i **do**

  foreach *public servant* i **do**

    determine contribution C_i;

  foreach *node* i **do**

    update indicator I_i;

  foreach *node* i **do**

    adapt allocation P_i;

3 Data

As we have previously mentioned, PPI takes three types of data as inputs: (1) initial conditions, (2) spillover network, and (2) goals. In most applications, these data may come from a sample of development indicators. The case of Mexico, however, is special because the federal government has also produced data on targets (the government's aspirations) and on the allocation of fiscal resources. Therefore, we present all these data sources, leaving further details about their pre-processing and normalization procedures for Appendix ***.

3.1 Development indicators

We compiled a dataset with 141 development indicators from Mexico, covering the period 2006-2016. Each one SDG has at least one indicator in the sample. Given the current social context of Mexico and the interest of the stakeholders of the project, special attention was given to collecting indicators from SDG 16. In fact, we have split SDG 16 into its two components: *peace and justice* (SDG 16a) and *strong institutions* (SDG 16b). This is separation is important in the Mexican context as the former covers sensitive violence issues while the latter touches on important anti-corruption policies. All indicators have been preprocessed so that their values are in the range [0,1], and larger magnitudes denote better outcomes.

A common limitation of the official UN SDG database ***cite is that many indicators lack comprehensive time coverage. For this reason, we have collected data the sources enlisted in Table 2. In addition, several indicators tend to be redundant for PPI because they are disaggregations of other indicators (*e.g.*, by geographical region, by gender, by age, etc.). For this reason, we manually curated them to remove 'redundancies'. Finally, we labeled each indicator as instrumental or collateral according to the inputs received in a workshop that we ran with the UNDP for government officials from Mexico.

We provide the complete list of indicators in Appendix B. The most salient feature in

Table 2 is the relative large number of missing observations coming from CONEVAL. This is because CONEVAL's (the national watchdog of social policy in Mexico) indicators are constructed on a bi-annual basis. Overall, whenever we encounter missing values, we impute them through a linear interpolation. Further details can be found in Appendix A.

There are a few important data manipulations that we did in order to include indicators that were of high interest to the stakeholders of the project. First, CONEVAL's indicators start in 2008 and are are collected on the previous year to their publication. In order to make these data compatible with our sample, we lagged them by two years, meaning that the observations for 2008 correspond to those from 2006 in our data. This decision was concerted with the stakeholders, who dimmed important to have multiple indicators on poverty. Second, the index of perception of corruption by transparency international had a methodological change in 2012. This change increased the level of the indicator by one order of magnitude. Thus, we divided all observations after 2011 by 10, something we have found to be a common practice ***cite.

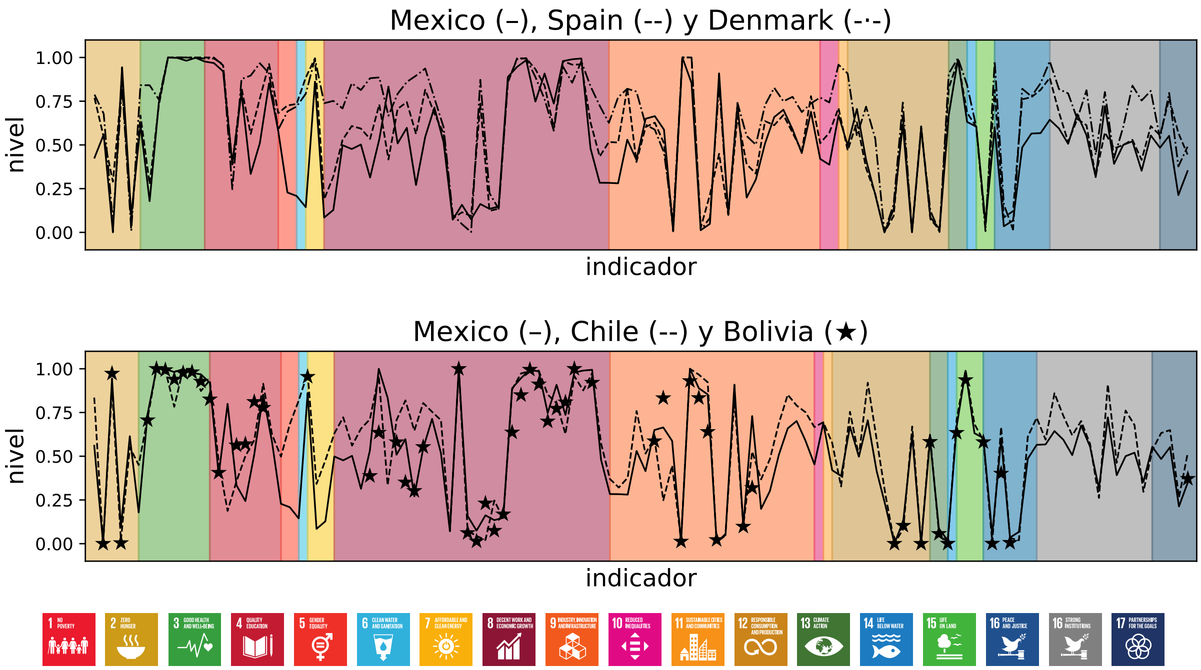
Table 2: Development-indicator data by source

Source	Indicators	SDGs	Observations	Missing	Mean	Min	Max
CONEVAL	8	1	88	40	0.75	0.35	0.95
FAO	3	2	33	0	0.51	0.14	0.92
INEGI	1	1	11	0	0.41	0.4	0.43
Observatory of Economic Complexity	1	1	11	0	0.71	0.67	0.73
The Conference Board	2	1	22	0	0.6	0.56	0.62
Transparency International	1	1	11	0	0.06	0.03	0.38
UN	32	14	352	68	0.58	0.0	1.0
WDI	1	1	11	0	0.0	0.0	0.0
World Bank	29	11	319	22	0.54	0.0	1.0
World Economic Forum	62	8	682	0	0.46	0.04	1.0
World Travel & Tourism Council	1	1	11	0	0.15	0.14	0.16

notes.

We also classify the indicators into the SDG 5 P's: 'People' (SDGs 1-6), 'Prosperity' (SDGs 7-12), 'Planet' (SDGs 13-15), 'Peace' (SDG 16) and 'Partnerships' (SDG 17).

Figure 1: Indicator levels in 2016

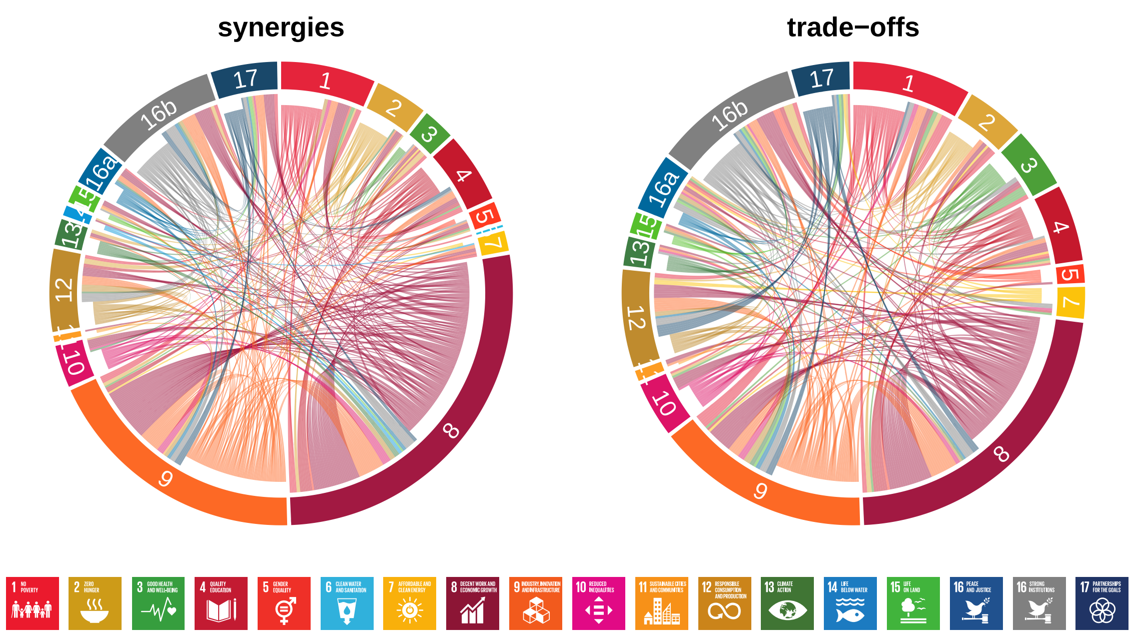


3.2 Network

A network of interdependencies between development indicators can be obtained through various methods, each one implying certain assumptions about the data and about its underlying generating mechanisms. ***cite provide a comprehensive survey on various methods that can be employed for the estimation of SDG networks. We must highlight that network estimation is a burgeoning research area, so there is no strongly preferred method or accepted gold standard, especially given that development-indicator time series tend to be quite short; with generally no more than 10 observations if one wants to capture a high-dimensional policy space. In this study, we employ the Bayesian approach of ***explicar mas.

Once the network has been estimated from the indicators' time series, we obtain a matrix where the weight of an edge indicates the strength of an interdependency between two variables. These edges are directed, meaning that an arrow $i \to j$ indicates that the movements of j are condition upon the movements of i; but not the other way around (unless $i \leftarrow j$ also exists). If the sign of the weight is positive(negative), we have a synergy(trade-off). Note that the network has no connotations of causality; even if the method employed for its estimation was designed for causal inference. This is so because because development indicators are mostly endogenous variables, so one could hardly argue that causal relations can be actually inferred at such aggregate level and high dimensionality. In other words, we argue that, for this level of aggregation and number of dimensions, it is impossible to disentangle all confounders and latent variables. This is not a problem for PPI because, as explained in section ***, causation is given by the model through the vertical mechanisms of the policymaking process. Therefore, the network should be interpreted as a stylized fact –a collection of conditional dependencies– that the model takes into account to explain the dynamics of the indicators. These conditional dependencies are important because they represent the co-movement of variables that the community of sustainable development often interpret as synergies and trade-offs. Table *** shows the descriptive statistics of the network obtained for this study.

Figure 2: SDG networks of synergies and trade-offs



Left: network of synergies. Right: network of trade-offs.

Table 3: Network statistics

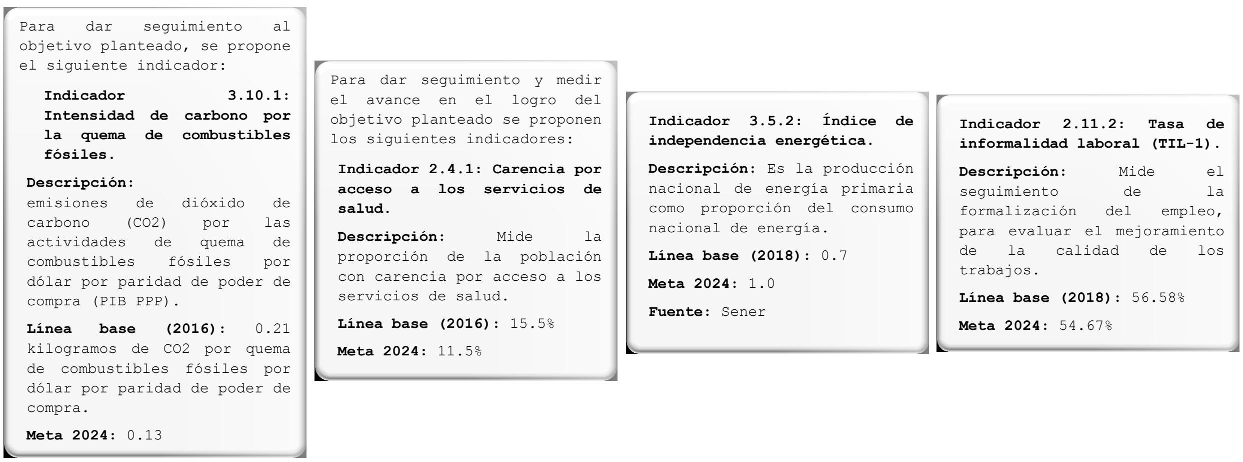
SDG/Pillar	In(Out) Degree Synergies	In(Out) Degree Trade-offs	In(Out) Strength Synergies	In(Out) Strength Trade-offs
1	24 (26)	22 (24)	317.54 (21.62)	13.97 (23.5)
2	12 (27)	11 (15)	178.92 (29.95)	2.68 (17.09)
3	21 (25)	22 (15)	24.09 (442.0)	452.94 (455.39)
4	19 (26)	14 (21)	11.46 (15.3)	11.91 (15.7)
5	10 (3)	1 (9)	373.0 (0.45)	0.29 (2.46)
6	1 (0)	3 (0)	0.01 (0)	0.01 (0)
7	9 (2)	7 (8)	3.5 (1.29)	0.33 (6.64)
8	91 (123)	60 (75)	149.06 (1399.23)	442.96 (485.64)
9	78 (70)	47 (46)	676.02 (50.11)	106.35 (11.07)
10	8 (13)	9 (13)	9.27 (4.85)	3.39 (4.73)
11	1 (2)	4 (1)	0.0 (335.6)	0.0 (61.71)
12	29 (14)	28 (11)	18.01 (4.24)	41.84 (42.3)
13	5 (11)	5 (7)	11.58 (14.51)	51.52 (6.09)
14	6 (4)	0 (2)	381.25 (0.13)	0 (0.8)
15	10 (3)	8 (4)	122.05 (2.11)	1.9 (0.76)
16a	12 (11)	21 (9)	6.97 (4.5)	31.11 (69.07)
16b	40 (26)	31 (24)	46.6 (8.01)	73.68 (4.81)
17	23 (13)	8 (17)	8.01 (3.48)	7.09 (34.19)
People	87 (107)	73 (84)	905.02 (509.31)	481.79 (514.14)
Prosperity	187 (210)	127 (143)	837.85 (1791.06)	553.03 (569.8)
Planet	50 (32)	41 (24)	532.89 (20.98)	95.26 (49.95)
Peace	52 (37)	52 (33)	53.58 (12.51)	104.78 (73.87)
Partnerships	23 (13)	8 (17)	8.01 (3.48)	7.09 (34.19)

The statistics have been separated into synergies and trade-offs. They have been normalized by dividing the node-specific statistic by the number of indicators in the relevant SDG or pillar. In(out)-degree is the number of incoming(outgoing) connections to(from) a node. The in(out)-strength is the sum of the weights of all incoming(outgoing) connections to(from) a node.

3.3 Targets

When calibrating the model to historical data, we assume that the government's aspirations or goals are the final values of the indicators. However, from a prospective point of view, aspirations can be any hypothetical combination of values for the indicators. An innovation developed by the Mexican government consists of linking specific development indicators to the national development plan. This is an document official document that, by law, every incoming government has to prepare in order to delineate the development goals and strategies that it will follow throughout its 6-year term. The elaboration of the Mexican national development plan has been refined through a few decades. In its latest edition (2019-2024, since each term lasts six years), the plan identified 234*** development objectives, and identified 60*** that could be linked to development indicators. Through such linkage, the Annex XVIII-Bis ***cite of the national plan of development has established concrete development-indicator values as the government's development goals. Thus, PPI is well suited to infer the policy priorities that would lead to such goals. Figure *** shows a extracts of the Annex XVIII-Bis and the government's development goals, which we use to construct the target vector T in our prospective analysis.

Figure 3: Example


Para dar seguimiento al objetivo planteado, se propone el siguiente indicador:

Indicador 3.10.1: Intensidad de carbono por la quema de combustibles fósiles.

Descripción: emisiones de dióxido de carbono (CO2) por las actividades de quema de combustibles fósiles por dólar por paridad de poder de compra (PIB PPP).

Línea base (2016): 0.21 kilogramos de CO2 por quema de combustibles fósiles por dólar por paridad de poder de compra.

Meta 2024: 0.13

Para dar seguimiento y medir el avance en el logro del objetivo planteado se proponen los siguientes indicadores:

Indicador 2.4.1: Carencia por acceso a los servicios de salud.

Descripción: Mide la proporción de la población con carencia por acceso a los servicios de salud.

Línea base (2016): 15.5%

Meta 2024: 11.5%

Indicador 3.5.2: Índice de independencia energética.

Descripción: Es la producción nacional de energía primaria como proporción del consumo nacional de energía.

Línea base (2018): 0.7

Meta 2024: 1.0

Fuente: Sener

Indicador 2.11.2: Tasa de informalidad laboral (TIL-1).

Descripción: Mide el seguimiento de la formalización del empleo, para evaluar el mejoramiento de la calidad de los trabajos.

Línea base (2018): 56.58%

Meta 2024: 54.67%

Extracts from the Annex XVIII-Bis of Mexico's National Development Plan. Each box describes an indicator that will be used to evaluate progress in a specific policy issue of the National Development Plan, as well as its baseline value (*Lnea base*) and its target/goal (*Meta*). From left to right, the indicators track the following policy issues: carbon emissions from burning fuels; poor access to health services; energetic independence; informal labor. In the same order, the extracts were obtained from pages 187, 103, 166 and 128.

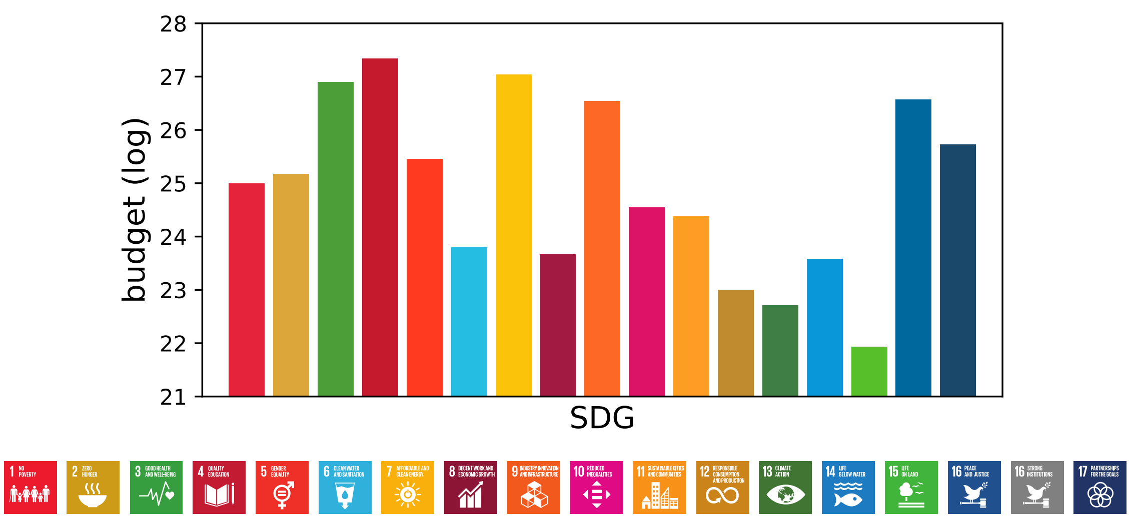
Linking development goals to indicators is still a work in progress, so not every objective has a corresponding. Furthermore, not every indicator identified by the national development plan is in our dataset. This is mainly because some of the indicators identified by the government are new, so we do not have time series to consider them in the analysis. Nevertheless, another innovation of the Annex XVIII-Bis is that it links each objective to one or more SDGs. We exploit this information to construct our target vector. For those indicators in our database that are not linked to the national development plan, we assign the average target from all those linked indicators in the same SDGs. Figure *** shows the result of this assignment.

3.4 SDG budgeting

The last data that we use in this study is fiscal. These are broad categories of public expenditure that the Mexican Treasury has mapped into the SDGs for the fiscal exercise of 2019. To provide some context, these data does not exist in most countries, so this is a pioneering study in this respect. In fact, Mexico was the first nation in publishing fiscal-SDG linked data, and is its Treasury leads the development of methodologies for such purpose. These and other similar data can be obtained from the public repository of the Global Initiative for Fiscal Transparency ***.

These data consists of more than 1,500 expenditure records, each one categorized into one SDG. We use these records to map the Mexican budget into the SDGs. Figure shows the distribution of resources allocated through the Mexican budget for 2019 across the 17 SDGs. The fiscal data that has been classified into SDGs do not represent the entire budget of the government because some types of expenditure do not fit any SDG, for example, national defense. Nevertheless, the fact that the Treasury has been able to map their budget into the SDGs provides an important source of information about policy priorities that we will exploit in section ***.

Figure 4: 2019 budget distribution across SDGs



The units in the vertical axis are current Mexican pesos.

4 Inferring Policy Priorities

We can use PPI to estimate the unobservable allocation profile P as well as other unobservable variables by simulating the observed dynamics of the empirical indicators which, in turn, are fueled by the political economy game specified in section 2. For this, it is necessary to determine the vector $\alpha_1, \ldots, \alpha_N$ of growth factors. Appendix *** shows the method that we have developed to estimate such vector. Overall, the idea is to find a configuration of growth factors such that the simulated indicators match three features of their empirical counterparts: (1) all the indicators converge to their empirical final values, (2) all indicators converge at the same time, and (3) the total volatility of the simulated indicators corresponds to that of the empirical ones. Feature 1 is given by construction; one only needs to define T as the final values from the empirical data in order to obtain convergence. Features 2 and 3 are a direct result of finding the correct configuration of growth factors; we provide a detailed explanation in appendix ***.

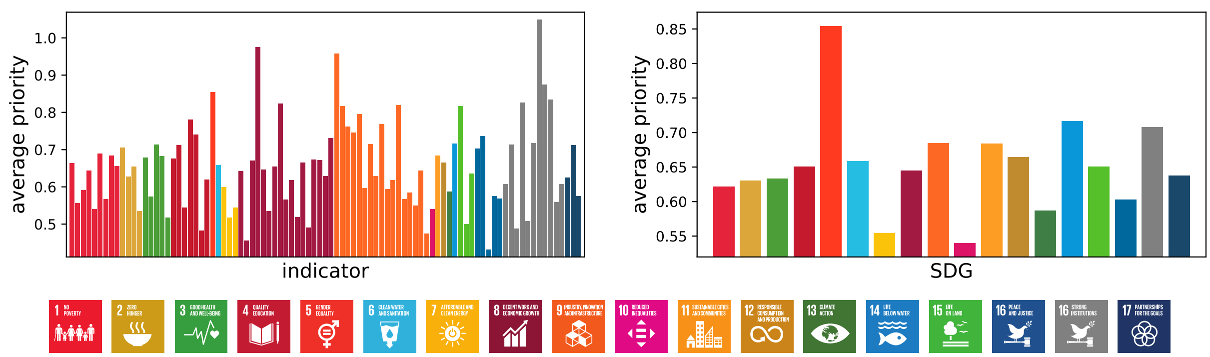
The calibrated vector $\alpha_1, \ldots, \alpha_N$, represents all the other factors that the model does not consider to explain why the empirical indicators behave in the observed way. There is a subtle but important implication in this calibration exercise, and in particular, in attaining feature 2. Effectively, the calibration is a retrospective estimation of what the government 'did' in the sampling period. Therefore, by finding the growth factors that make all indicators reach their final values in unison, this retrospective estimation acquires temporal value. That is, assuming that $\alpha_1, \ldots, \alpha_N$ remain fixed for some time in the future (because they convey structural information), prospective estimations (those with hypothetical goals) that use these growth factors can be interpreted in calendar time rather than in simulation ticks; an important improvement over earlier studies using PPI.

4.1 Retrospective policy priorities

An estimated allocation profile consist of the average distribution of resources across independent Monte Carlo simulations. For a single simulation, we obtain N indicator time series. Since allocations are defined only on instrumental indicators, we focus on n policy issues only. The inferred allocation profile is built by, first, computing the inter-temporal sum of allocations in each indicator and, then, calculating the average of this quantity across simulations for each indicator. More formally, the expected allocation to indicator i is given by

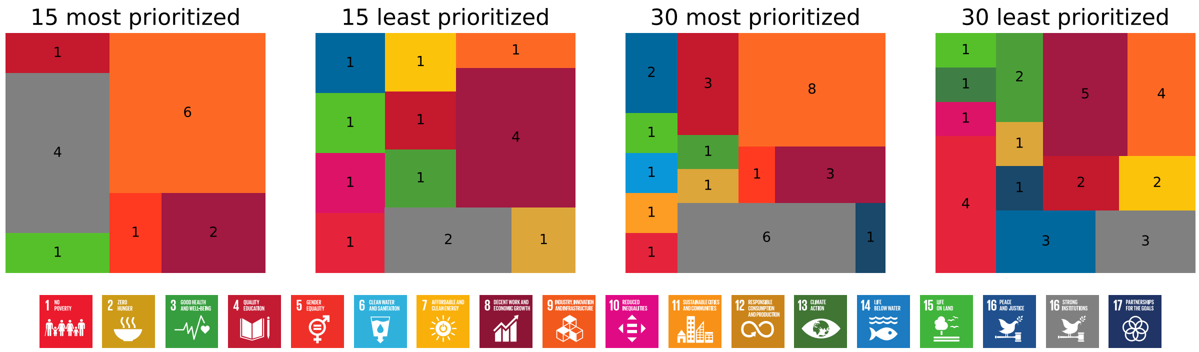
$$\mathscr{P}_i = \frac{1}{M} \sum_m \sum_t P_{i,t,m} \tag{16}$$

Figure 5: Retrospective allocation profile



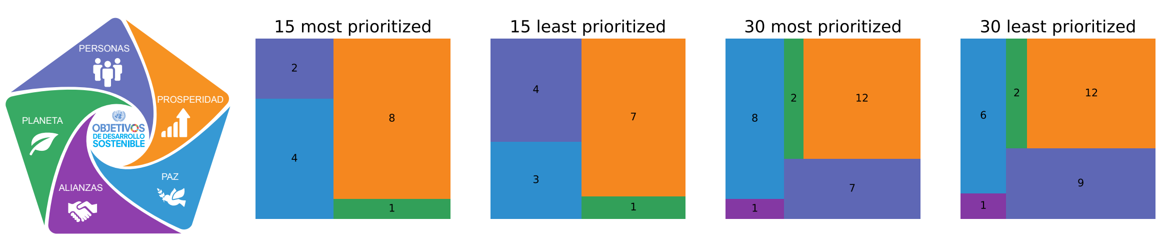
4.2 Prospective priorities

Figure 6: Distribution of the most and least prioritized indicators across SDGs



Notas.

Figure 7: Distribution of most and least prioritized indicators across development pillars



Notas.