Policy Priority Inference for Sustainable Development

Online Appendix

Omar A. Guerrero[1,2] and Gonzalo Castaeda[3]

[1]The Alan Turing Institute

[2]University College London

[3]Tecnológico de Monterrey Campus Puebla

A Data pre-processing

For clarity, let us introduce some notation. Let V denote a matrix where the rows are the units of observation (the development indicators) and the columns correspond to periods (years). Entry $V_{i,t}$ denotes the i^{th} element in period t. Then, if we perform an operation on one of the indices, while holding a specific value for the other, we replace the operated index by the dot symbol $\cdot$. For example, if we want the maximum value across time for the i^{th} value of V, then we write $\max(V_{i,\cdot})$. Similarly, if we want the lowest indicator in a given period t, then we write $\min(V_{\cdot,t})$. Finally, if we omit the second index it means we have a vector.

A.1 Normalization

We normalize the indicators in the range [0,1]. The purpose of normalizing is to make the indicators comparable. Data expressed in percentages, may not need this normalization. However, if a large sample across countries can be collected, then a normalization would be preferred as it would provide more realistic bounds of what is achievable (e.g. a 100% coverage of forest to total land ratio is impossible). This is so because the levels of other countries act as benchmarks for how low and how high can indicators be.

In order to normalize the indicators we employ the formula

$$\mathcal{I}_{i,t} = \frac{\mathscr{I}_{i,t} - \min(\mathscr{I}_{i,\cdot})}{\max(\mathscr{I}_{i,\cdot}) - \min(\mathscr{I}_{i,\cdot})}, \tag{1}$$

where $\mathscr{I}$ denotes the raw indicator and $\mathcal{I}$ the normalized one. The min and max operators are applied to the entire time series of indicator i across all available countries in the sample. In the case of Mexico, the data have been normalized across a larger sample covering 298 countries and territories for 27 years.

A.2 Imputation

PPI requires the initial and the final values of each indicator. However, should the user want to estimate the spillover network through quantitative methods, then it is desirable to also have observations in-between. While the data collected for this study has comprehensive time-series coverage in the sampling period, there are still some missing observations. To remedy this problem, we generate linear interpolations.

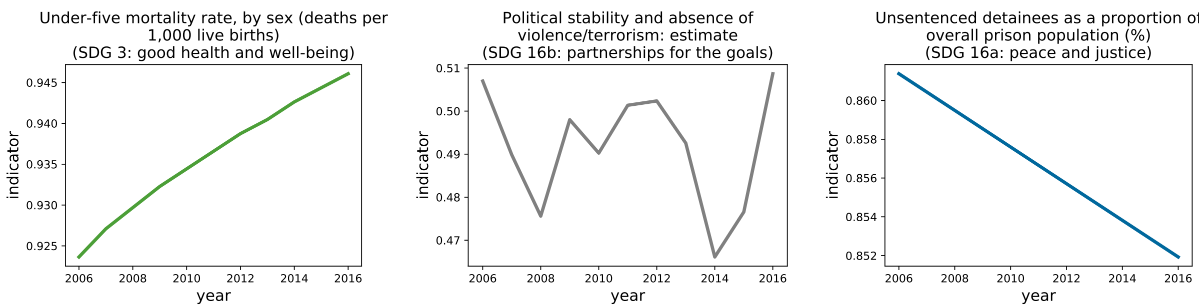
A.3 Reversing

For the purpose of an easier interpretation, it is desirable that the higher values of an indicator denote better outcomes. Since we normalized the indicators in the range [0,1], we can reverse them by using the complement $1 - \mathcal{I}_{i,t}$.

A.4 Target adjustment

The model underlying PPI guarantees convergence to a vector of targets T. It does not matter if those targets are above or bellow the initial values of the indicators. Nevertheless, there is a problem with targets that are lower than their initial values. Assuming that the indicators have been pre-processed as suggested above, and that higher values imply better outcomes, convergence to lower values would be inconsistent with the model's logic. This is so because negative dynamics would imply that the government's systematic investment drives the indicators to worse outcomes. Moreover, the spillover network should already account for the negative externalities. Hence, the target of an indicator should always be greater than its initial value.

Figure 1: Development indicators exhibit diverse dynamics



The indicators have been normalized in the interval [0,1] and have been reversed if necessary. Thus, higher values indicate better outcomes.

Figure 1 shows how different development indicators have various dynamics. PPI simplifies the challenge of modeling such diverse patterns through its stochastic growth process. However, this does not fix the problem of having indicators with final values lower than the initial ones. To remedy this issue for retrospective estimations, we propose an adjustment of the retrospective goals using the formula

$$T_i = I_{i,m} + |\min(I_{\cdot,m} - I_{\cdot,1})| + \epsilon, \tag{2}$$

where m is the final period in the sample and $\epsilon > 0$ is a small term close to zero. This calculation needs to be performed for all indicators, even if only one of them exhibits $I_{i,m} < I_{i,1}$

Equation 2 shifts all the final values upwards, guaranteeing $T_i > I_{i,1}$ for every i. Effectively, it assigns the smallest historical gap (the difference between final and initial values) to the worst-performing indicator, and the largest one to the best-performing one. Thus, the historical gaps capture how much progress was achieved in each indicator during the sampling period.

Besides the argument of model consistency, a second motivation for this adjustment is linked to the growth factors α. Assume there are no network effects, and that the inefficiencies and allocations are the same across all nodes. Then, the only parameter that could explain the variation between historical gaps is α_i. Since all the empirical indicators arrived to their final values at the same time, it must be the case that the worst-performing indicator has the smallest growth factor and the best one has the largest α_i. What we have done here is mapping the performance of the indicators into the growth factors. This is why α_i can be interpreted as everything else that explains the indicator dynamics but that is not explicitly considered in the model. Furthermore, we interpret this additional information captured in α as long-term structural factors.

B Model variables

Table 1 presents all the variables. We have arranged them according to their sources. Clearly most variables 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. Regarding the exogenous variables, all of them can be obtained from publicly available datasets for most countries.[1] 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

[1] For example, the World Bank's Worldwide Governance Indicators provide a rich source of information to obtain φ and τ.

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 is assumed to be exogenous.

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.

C Data

Here, we provide the complete list of development indicators.

Table 2: Development indicators

Description	Source	ODS	Instrumental	Reversed
Poverty gap at 5.50 dollars a day (2011 ppp) (%)	World Bank	1	yes	yes
Population in moderate poverty	CONEVAL	1	yes	yes
Population in extreme poverty	CONEVAL	1	yes	yes
Population that is vulnerable due to poor social capital	CONEVAL	1	yes	yes
Population that is vulnerable due to poor income	CONEVAL	1	yes	yes

Table 2: Development indicators

Description	Source	ODS	Instrumental	Reversed
Lack of health services	CONEVAL	1	yes	yes
Lack of social security	CONEVAL	1	yes	yes
Lack of quality and space in the dwelling	CONEVAL	1	yes	yes
Lack of basic house services	CONEVAL	1	yes	yes
Plant breeds for which sufficient genetic resources are stored (number)	UN	2	yes	no
Proportion of local breeds classified as being at unknown level of risk of extinction (%)	UN	2	yes	yes
Cereal yield (kg per hectare)	World Bank	2	no	no
Food production index (net, per capita)	FAO	2	yes	no
Prevalence of anemia among women of reproductive age (% of women ages 15-49)	World Bank	2	yes	yes
Under-five mortality rate, by sex (deaths per 1,000 live births)	UN	3	yes	yes
Number of new hiv infections per 1,000 uninfected population, by sex and age (per 1,000 uninfected population)	UN	3	no	yes
Tuberculosis incidence (per 100,000 population)	UN	3	yes	yes
Malaria incidence per 1,000 population at risk (per 1,000 population)	UN	3	yes	yes
Mortality rate attributed to cardiovascular disease, cancer, diabetes or chronic respiratory disease (probability)	UN	3	no	yes
Suicide mortality rate, by sex (deaths per 100,000 population)	UN	3	no	yes
Alcohol consumption per capita (aged 15 years and older) within a calendar year (litres of pure alcohol)	UN	3	no	yes
Proportion of the target population with access to 3 doses of diphtheria-tetanus-pertussis (dtp3) (%)	UN	3	yes	no
Proportion of the target population with access to measles-containing-vaccine second-dose (mcv2) (%)	UN	3	yes	no
Participation rate in organized learning (one year before the official primary entry age), by sex (%)	UN	4	yes	no
Internet access in schools, 1-7 (best)	World Economic Forum	4	yes	no
Quality of the education system, 1-7 (best)	World Economic Forum	4	yes	no
Quality of primary education, 1-7 (best)	World Economic Forum	4	yes	no
Quality of math and science education, 1-7 (best)	World Economic Forum	4	yes	no
Quality of management schools, 1-7 (best)	World Economic Forum	4	yes	no
Extent of staff training, 1-7 (best)	World Economic Forum	4	no	no
School enrollment, secondary (gross), gender parity index (gpi)	World Bank	4	yes	no
Proportion of seats held by women in national parliaments (% of total number of seats)	UN	5	yes	no
Proportion of women in managerial positions (%)	UN	5	no	no
Water body extent (permanent and maybe permanent) (% of total land area)	UN	6	yes	no
Proportion of population with access to electricity, by urban/rural (%)	UN	7	yes	no
Proportion of population with primary reliance on clean fuels and technology (%)	UN	7	yes	no
Access to clean fuels and technologies for cooking (% of population)	World Bank	7	yes	no
Annual growth rate of real GDP per capita (%)	UN	8	no	no
Number of commercial bank branches per 100,000 adults	UN	8	no	no
Unemployment rate, by sex and age (%)	UN	8	no	yes
Foreign direct investment, net inflows (% of GDP)	World Bank	8	yes	no

Table 2: Development indicators

Description	Source	ODS	Instrumental	Reversed
Index of economic complexity	Observatory of Economic Complexity	8	no	no
Efficiency of government spending	World Economic Forum	8	yes	no
Burden of government regulation, 1-7 (best)	World Economic Forum	8	yes	no
Burden of customs procedures, 1-7 (best)	World Economic Forum	8	yes	no
Regulation of securities exchanges, 1-7 (best)	World Economic Forum	8	yes	no
Business impact of rules on fdi, 1-7 (best)	World Economic Forum	8	yes	no
Strength of auditing and reporting standards, 1-7 (best)	World Economic Forum	8	yes	no
Protection of minority shareholders' interests, 1-7 (best)	World Economic Forum	8	no	no
Intensity of local competition, 1-7 (best)	World Economic Forum	8	yes	no
Effectiveness of anti-monopoly policy, 1-7 (best)	World Economic Forum	8	yes	no
Extent of market dominance, 1-7 (best)	World Economic Forum	8	yes	no
Efficacy of corporate boards, 1-7 (best)	World Economic Forum	8	no	no
Cooperation in labor-employer relations, 1-7 (best)	World Economic Forum	8	yes	no
Flexibility of wage determination, 1-7 (best)	World Economic Forum	8	yes	no
Pay and productivity, 1-7 (best)	World Economic Forum	8	no	no
Tax revenue (% of GDP)	World Bank	8	yes	no
New business density (new registrations per 1,000 people ages 15-64)	WDI	8	yes	no
Imports as a percentage of GDP	World Economic Forum	8	no	no
Strength of investor protection, 0-10 (best)	World Economic Forum	8	yes	no
Patent applications, residents	World Bank	8	no	no
Contribution of labor quality to GDP growth	The Conference Board	8	no	no
Exports of goods and services (% of GDP)	World Bank	8	no	no
Gdp, ppp (constant 2011 international dollars)	World Bank	8	no	no
Wage and salaried workers, total (% of total employment) (modeled ilo estimate)	World Bank	8	no	no
No. days to start a business	World Economic Forum	8	yes	yes
No. procedures to start a business	World Economic Forum	8	yes	yes
Rate of informal employment	INEGI	8	no	yes
Growth of total factor productivity	The Conference Board	8	no	no
Number of fixed internet broadband subscriptions, by speed (number)	UN	9	no	no
Internet users per 100 inhabitants	UN	9	no	no
Manufacturing value added per capita (constant 2010 united states dollars)	UN	9	no	no
Available airline seat km/week, millions	World Economic Forum	9	no	no
Quality of overall infrastructure, 1-7 (best)	World Economic Forum	9	yes	no
Quality of roads, 1-7 (best)	World Economic Forum	9	yes	no
Quality of air transport infrastructure, 1-7 (best)	World Economic Forum	9	yes	no
Quality of electricity supply, 1-7 (best)	World Economic Forum	9	yes	no
Availability of latest technologies, 1-7 (best)	World Economic Forum	9	yes	no
Firm-level technology absorption, 1-7 (best)	World Economic Forum	9	no	no
Fdi and technology transfer, 1-7 (best)	World Economic Forum	9	yes	no
Quality of scientific research institutions, 1-7 (best)	World Economic Forum	9	yes	no
Government procurement of advanced tech products, 1-7 (best)	World Economic Forum	9	yes	no
Soundness of banks, 1-7 (best)	World Economic Forum	9	yes	no
Venture capital availability, 1-7 (best)	World Economic Forum	9	no	no
Financing through local equity market, 1-7 (best)	World Economic Forum	9	yes	no

Table 2: Development indicators

Description	Source	ODS	Instrumental	Reversed
Availability of research and training services, 1-7 (best)	World Economic Forum	9	yes	no
Company spending on r&d, 1-7 (best)	World Economic Forum	9	no	no
Capacity for innovation, 1-7 (best)	World Economic Forum	9	yes	no
Availability of scientists and engineers, 1-7 (best)	World Economic Forum	9	yes	no
Quality of port infrastructure, 1-7 (best)	World Economic Forum	9	yes	no
Fixed telephone lines/100 pop.	World Economic Forum	9	yes	no
Investment in energy with private participation (current us dollars)	World Bank	9	yes	no
Investment in transport with private participation (current us dollars)	World Bank	9	yes	no
Mobile telephone subscriptions/100 pop.	World Economic Forum	9	no	no
Labour share of GDP, comprising wages and social protection transfers (%)	UN	10	no	no
Ease of access to loans, 1-7 (best)	World Economic Forum	10	yes	no
Income share held by lowest 10%	World Bank	10	no	no
Gini index (world bank estimate)	World Bank	10	no	yes
Pm2.5 air pollution, population exposed to levels exceeding who guideline value (% of total)	World Bank	11	yes	yes
Material footprint per capita, by type of raw material (tonnes)	UN	12	no	yes
Domestic material consumption per capita, by type of raw material (tonnes)	UN	12	no	no
Degree of customer orientation, 1-7 (best)	World Economic Forum	12	no	no
Ethical behavior of firms, 1-7 (best)	World Economic Forum	12	no	no
Adjusted net savings, excluding particulate emission damage (% of gni)	World Bank	12	yes	no
Coal rents (% of GDP)	World Bank	12	no	yes
Forest rents (% of GDP)	World Bank	12	no	yes
Mineral rents (% of GDP)	World Bank	12	no	yes
Natural gas rents (% of GDP)	World Bank	12	no	yes
Oil rents (% of GDP)	World Bank	12	no	yes
Total natural resources rents (% of GDP)	World Bank	12	no	yes
Intensity of emissions, meat and cattle	FAO	13	yes	yes
Temperature variation	FAO	13	no	yes
Average proportion of marine key biodiversity areas (kbas) covered by protected areas (%)	UN	14	yes	no
Average proportion of terrestrial key biodiversity areas (kbas) covered by protected areas (%)	UN	15	yes	no
Average proportion of mountain key biodiversity areas (kbas) covered by protected areas (%)	UN	15	yes	no
Red list index	UN	15	yes	no
Unsentenced detainees as a proportion of overall prison population (%)	UN	16a	yes	yes
Business costs of terrorism, 1-7 (best)	World Economic Forum	16a	no	no
Business costs of crime and violence, 1-7 (best)	World Economic Forum	16a	yes	no
Organized crime, 1-7 (best)	World Economic Forum	16a	yes	no
Reliability of police services, 1-7 (best)	World Economic Forum	16a	yes	no
Intentional homicides (per 100,000 people)	World Bank	16a	yes	yes
Public trust in politicians, 1-7 (best)	World Economic Forum	16b	no	no
Favoritism in decisions of government officials, 1-7 (best)	World Economic Forum	16b	yes	no
Transparency of government policymaking, 1-7 (best)	World Economic Forum	16b	yes	no
Property rights, 1-7 (best)	World Economic Forum	16b	yes	no

Table 2: Development indicators

Description	Source	ODS	Instrumental	Reversed
Intellectual property protection, 1-7 (best)	World Economic Forum	16b	yes	no
Judicial independence, 1-7 (best)	World Economic Forum	16b	yes	no
Government effectiveness: estimate	World Bank	16b	yes	no
Overall level of statistical capacity (scale 0 - 100)	World Bank	16b	yes	no
Legal rights index, 0-10 (best)	World Economic Forum	16b	yes	no
Political stability and absence of violence/terrorism: estimate	World Bank	16b	yes	no
Regulatory quality: estimate	World Bank	16b	yes	no
Corruption perception index	Transparency International	16b	no	no
Voice and accountability: estimate	World Bank	16b	yes	no
Debt service as a proportion of exports of goods and services (%)	UN	17	yes	yes
Prevalence of foreign ownership, 1-7 (best)	World Economic Forum	17	no	no
Prevalence of trade barriers, 1-7 (best)	World Economic Forum	17	yes	no
Gross national savings, % GDP	World Economic Forum	17	no	no
Inflation, annual % change	World Economic Forum	17	no	yes
Travel and tourism direct contribution to GDP percentage share of total GDP	World Travel & Tourism Council	17	yes	no

Table 3: Indicators with missing observations

Indicator	SDG	Missing years
Poverty gap at 5.50 dollars a day	1	2007, 2009, 2011, 2013, 2015
Population in moderate poverty	1	2007, 2009, 2011, 2013, 2015
Population in extreme poverty	1	2007, 2009, 2011, 2013, 2015
Population that is vulnerable due to poor social capital	1	2007, 2009, 2011, 2013, 2015
Population that is vulnerable due to poor income	1	2007, 2009, 2011, 2013, 2015
Lack of health services	1	2007, 2009, 2011, 2013, 2015
Lack of social security	1	2007, 2009, 2011, 2013, 2015
Lack of quality and space in the dwelling	1	2007, 2009, 2011, 2013, 2015
Lack of basic house services	1	2007, 2009, 2011, 2013, 2015
Plant breeds for which sufficient genetic resources are stored	2	2006, 2007, 2008, 2009, 2011, 2013, 2015
Malaria incidence per 1,000 population at risk	3	2006, 2007, 2008, 2009, 2011, 2012, 2013, 2014
Mortality rate attributed to cardiovascular disease, cancer, diabetes or chronic respiratory disease	3	2006, 2007, 2008, 2009, 2011, 2012, 2013, 2014
Suicide mortality rate, by sex	3	2006, 2007, 2008, 2009, 2011, 2012, 2013, 2014
Alcohol consumption per capita	3	2006, 2007, 2008, 2009, 2011, 2012, 2013, 2014
Proportion of women in managerial positions	5	2006, 2007, 2008, 2009, 2010, 2011, 2012
Proportion of population with primary reliance on clean fuels and technology	7	2006, 2007, 2008, 2009, 2011, 2012, 2013, 2014
Annual growth rate of real GDP per capita	8	2008, 2009, 2013
Unemployment rate, by sex and age	8	2006
Tax revenue	8	2006, 2007

Table 3: Indicators with missing observations

Indicator	SDG	Missing years
Investment in energy with private participation	9	2009
Income share held by lowest 10%	10	2007, 2009, 2011, 2013, 2015
Gini index	10	2007, 2009, 2011, 2013, 2015
Pm2.5 air pollution, population exposed to levels exceeding who guideline value	11	2006, 2007, 2008, 2009
Unsentenced detainees as a proportion of overall prison population	16a	2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015

D Model estimation and calibration

This section provides all the details on how to calibrate the model's free parameters and how to perform Monte Carlo simulations to generate inferences.

D.1 Estimation of growth factors

The model considers a vector $\alpha_1, \dots, \alpha_N$ of growth factors as part of the indicators' dynamics. The purpose of estimating each individual growth factor is to homogenize convergence times across indicators. That is, since all empirical indicators reach their final values in the same number of periods, we seek to choose a vector of αs that preserves this property in the synthetic indicators.

Finding the vector of growth factors can prove challenging because of the interdependencies between indicators. For for instance, increasing α_i may affect the convergence time of other indicators through the network because i's 'steps' become larger and so do the spillovers. Thus, simultaneously estimating all αs is not a trivial problem, and we have found that many non-linear optimization methods fail. For this reason, we have devised a heuristic to solve this problem.

Our estimation method computes the marginal effect of each growth factor independently until an error term is minimized. In order to think about the error, let us assume that we want all indicators to converge simultaneously after $\mathcal{T}$ periods. Then, the objective is to minimize the average deviation from $\mathcal{T}$ across all indicators and simulations.

First, let us determine an arbitrary vector of growth factors. Using these factors, we perform one simulation run until all indicators converge; then, we obtain a vector with the number of periods that it took each indicator to converge. By repeating this step m times, we obtain m convergence time vectors, which allows computing the average convergence time V_i for each indicator. Then, we compute the convergence error

$$r_c = \frac{1}{N} \sum_{i}^{N} |\mathcal{T} - V_i|. \tag{3}$$

Next, we want to identify those indicators whose individual convergence error $|\mathcal{T} - V_i|$ is greater than a tolerance threshold e_v. For one of these indicators, say i, we vary α_i marginally. Then, we perform m simulations and compute $|\mathcal{T} - V_i|$. We repeat these two steps for i, covering the range $(0, 1)$ for α_i. Then, we choose the level of α_i that minimizes the difference between convergence error and e_v. This greedy search is performed for each indicator with a convergence error $|\mathcal{T} - V_i| > e_v$, until we obtain a new vector of convergence factors. With this new vector, we re-estimate r_c and repeat all the previous steps. The procedure stops when $r_c < e_v$.

While our heuristic assumes a *ceteribus paribus* condition in every greedy search, it is effective in finding the growth factors. Since V_i consists of average convergence times, the error is sensitive to the size of m. That is, larger ms decrease the variance of convergence times. Consequently, the mapping from α_i to V_i during the greedy search becomes more accurate with more simulations. This of course, comes with a computational burden. Therefore, model estimation greatly benefits from parallel processing. Algorithm 1 shows the pseudocode of the estimation procedure.

Algorithm 1: Estimation pseudocode

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

while $r_c > e_v$ **do**

  foreach i *such that* $|\mathcal{T} - V_i| > e_v$ **do**

    set $\alpha_i = \text{argmin}|\mathcal{T} - V_i(\alpha_i)|$;

  update convergence error r_c;

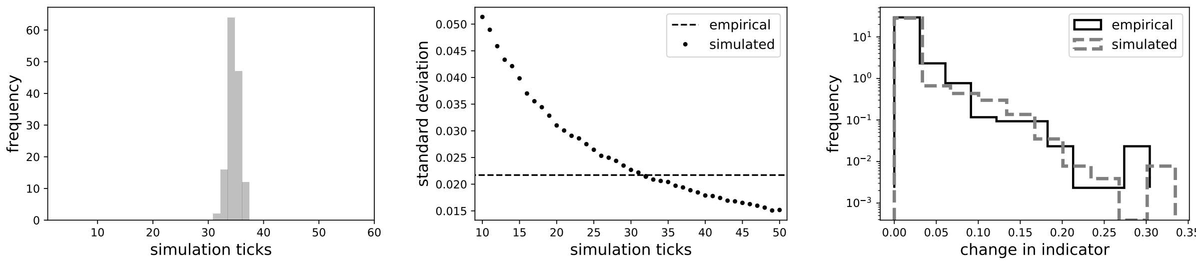
D.2 Calibration of simulation periods

Our estimation procedure assumes a number of periods $\mathcal{T}$ under which the model should converge. In order to calibrate $\mathcal{T}$, we aim at matching the total volatility of the indicators.

First, it is necessary to adjust the empirical data so that its volatility is comparable to the synthetic one. This is so because, while the empirical data may exhibit upward and downward dynamics, PPI's model only generates growth dynamics. Therefore, the adjustment consists of computing one-period changes in all the empirical indicators and, then, turning any negative change into zero. Now, we can calculate the standard deviation of the adjusted data. To calibrate $\mathcal{T}$, we need to find a number of periods under which the estimated growth factors yield indicator dynamics with similar volatility to the empirical one. This means that the entire estimation procedure needs to be performed every time a different $\mathcal{T}$ is chosen.

Figure 2 shows the results of the estimation and calibration procedures. The left panel presents a histogram of average convergence times across indicators once the model has been estimated and calibrated. Clearly, the estimated growth factors for $\mathcal{T} = 32$ generate a small divergence from the target number of periods. Here, the average error r_c is less than one. The middle panel shows the volatility of the simulated indicators obtained for different levels of $\mathcal{T}$ (each one with its estimated growth factors). For this study, $\mathcal{T} = 32$ yields the best match between the empirical and the simulated volatility. In the right panel we can see the histogram of the changes in the indicators (one for the empirical data and one for the simulated). Once estimated and calibrated, the model generates a similar distribution to the empirical one.

Figure 2: Model estimation and calibration



Model estimation for a calibration of $\mathcal{T} = 32$. Left: histogram of average convergence times across indicators. Middle: indicator volatility as a function of $\mathcal{T}$. Right: empirical and fitted distributions of the changes in the indicators.

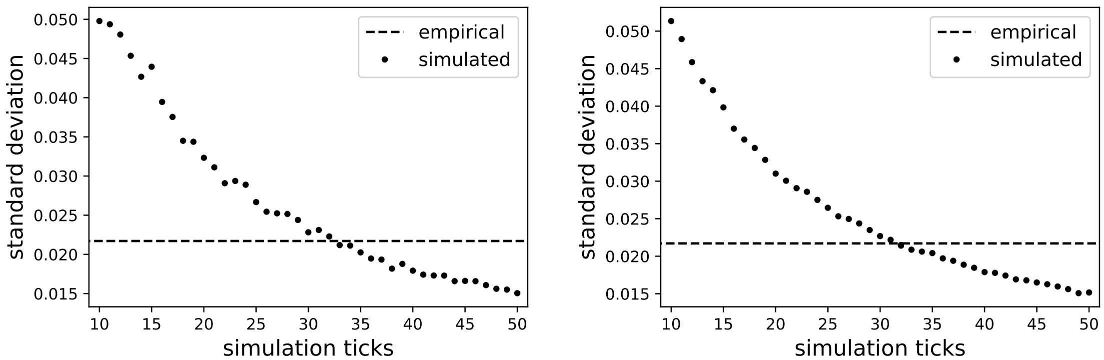
D.3 Computational efficiency

Combined, the estimation and calibration procedures can be computationally expensive. As we have mentioned earlier, one way to reduce the computational burden is to run these processes in parallel. However, through our understanding about the model, we can provide further advice on how to manage the computational burden of estimating the growth factors.

We have found that the volatility of the simulated indicators is not too sensitive to the precision with which the growth factors are estimated, but rather to the assumed number of convergence periods $\mathcal{T}$. In other words, as an initial step to find an optimal $\mathcal{T}$, one may relax the convergence error threshold in order to produce a mapping like the one in the middle panel of figure 2. By relaxing the error threshold, we do not need to run numerous simulations during the greedy search of algorithm 1, significantly reducing the computational burden. Once the mapping between $\mathcal{T}$ and the indicators' volatility has been produced, we can find in the optimal $\mathcal{T}^*$. Then, we can re-estimate the growth factors with more simulations and a more conservative error. As a verification step, one may repeat this last re-estimation with $\mathcal{T}^* - 1$ and $\mathcal{T}^* + 1$ to check that the best volatility is still given by $\mathcal{T}^*$. We have found this to be a very effective strategy to increase the computational efficiency of our estimation method.

Figure 3 shows the result of the calibration procedure under different computational burdens. Clearly, while there is some sensitivity to the number of simulations ran in the greedy search of the estimation method, the overall mapping of $\mathcal{T}$ into volatility is robust, yielding $\mathcal{T}^* = 32$ for the implementation with fewer simulations.

Figure 3: Reduction in computational burden



Left: calibration procedure running 10 simulations in the greedy search. Right: calibration procedure running 100 simulations in the greedy search.

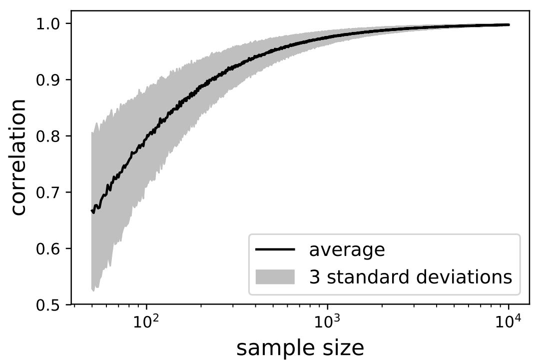
D.4 Monte Carlo simulation

Once the model has been estimated and calibrated, PPI can be used to produce a number of inferences via Monte Carlo simulation. It is important to run independent realizations of the model because the uncertain environment under which the agents learn may lead to decision paths that are specific to a particular simulation. The idea behind the Monte Carlo approach is to generate many realizations of the world, and to compute the expected values of the variables of interest. Besides the model parameters, it is also necessary to initialize the endogenous variables in a random fashion (e.g., P, H, X, etc.). Thus, in order to account for model uncertainty, one could construct confidence intervals from these distributions. The more simulations performed, the narrower those intervals become. In other words, inferences become more robust with a large number of simulations.

To demonstrate this point, let us concentrate on the main endogenous variable: the allocation profile P.

In order to assess the robustness, we measure the similarity between two expected allocation profiles: one obtained from with M simulations and another calculated from $M+1$. That is, for two samples of sizes M and $M+1$, we compute multiple pairs of expected allocation profiles and calculate their Spearman correlation. If sample size improves the estimation, then the variation of the Spearman correlation should decrease as we increase M. Figure 4 confirms this. After performing 1000 simulations, the estimated policy priorities are robust.

Figure 4: Robustness of allocation profiles across different sample sizes



D.5 Robustness under alternative government specifications

Recall that the government's adaptive heuristic uses two sources of information to allocate resources to indicator i: (1) the historical gap G_i and (2) the historical inefficiencies H_i. Then, the propensity to allocate resources to policy issue i is given by

$$q_{i,t} = {G_{i,t}}^{1+H_{i,t}}.$$

In the main text, we have justified why the historical gaps should be more important than the historical inefficiencies. Nevertheless, given that this function is key to determine the shape of P, it is natural to question whether alternative functional forms would dramatically change the resulting allocation profile. Here, show that this is not the case.

Of course, the alternative specifications should preserve our assumption of historical gaps being more important than historical inefficiencies. Otherwise, one is dealing with a different underlying theory of how the government behaves, and significantly different allocations are to be expected. Then, given the previous requirement, let us define three alternative specifications for equation 10 from the main text: a quotient form ($q_{i,t} = \frac{G_{i,t}}{1+H_{i,t}}$), a multiplicative form ($q_{i,t} = (G_{i,t})(1 + H_{i,t})$) and an exponential form ($q_{i,t} = {G_{i,t}}^{2-H_{i,t}}$).

We ran PPI for each of these specifications and compare all the resulting allocation profiles. Table 4 reports the Spearman correlation between each pair or allocation profiles. The upper numbers correspond to the correlation petween allocation profiles. Clearly, the results suggest robustness. The low numbers in parenthesis report a second test in which, for a given simulation, we divide each allocation of the prospective priorities by the each one of the retrospective ones. In other words, we obtain a vector of ratios between prospective and retrospective inferences, and then evaluate if they are robust across different specifications. Clearly, the results are also quite robust.

Table 4: Robustness to alternative specifications of the government's adaptive heuristic

Specification	$q_{i,t} = {G_{i,t}}^{1+H_{i,t}}$	$q_{i,t} = \frac{G_{i,t}}{1+H_{i,t}}$	$q_{i,t} = (G_{i,t})(1 + H_{i,t})$	$q_{i,t} = {G_{i,t}}^{2-H_{i,t}}$
$q_{i,t} = {G_{i,t}}^{1+H_{i,t}}$	1.00 (1.00)	0.974 (0.982)	0.976 (0.982)	0.971 (0.981)
$q_{i,t} = \frac{G_{i,t}}{1+H_{i,t}}$	- -	1.00 (1.00)	0.974 (0.988)	0.971 (0.987)
$q_{i,t} = (G_{i,t})(1 + H_{i,t})$	- -	- -	1.00 1.00	0.981 (0.987)
$q_{i,t} = {G_{i,t}}^{2-H_{i,t}}$	- -	- -	- -	1.00 (1.00)

E Network statistics

Table 5 provides the summary statistics of the spillover network estimated for this study.

Table 5: Summary statistics of SDG network

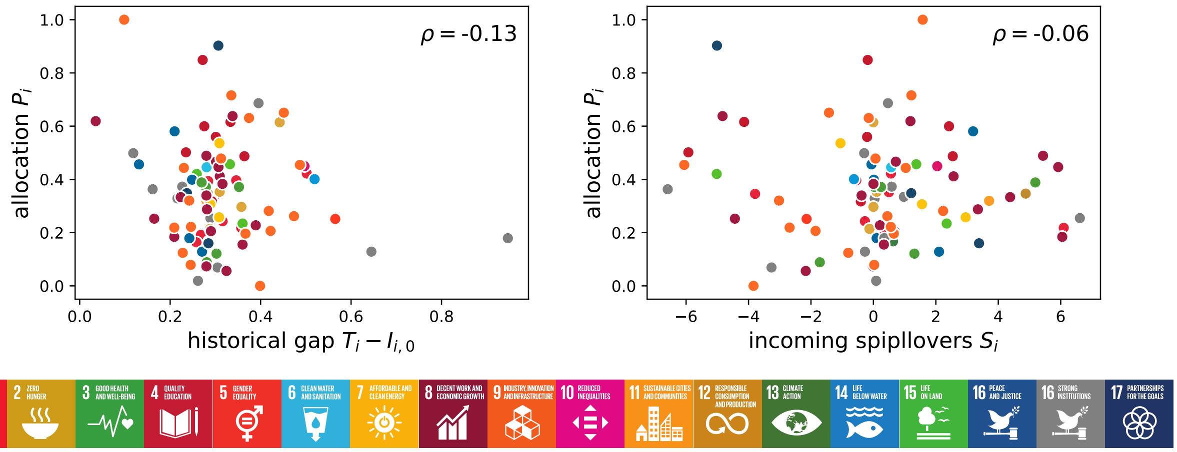
SDG or Pillar	In(Out)-Degree Synergies	In(Out)-Degree Trade-Offs	In(Out)-Strength Synergies	In(Out)-Strength Trade-Offs
1	2 (0)	3 (1)	1.46 (0)	1.94 (0.52)
2	14 (10)	17 (14)	11.26 (7.92)	13.93 (11.17)
3	26 (10)	23 (15)	19.17 (7.91)	17.68 (10.78)
4	19 (26)	18 (12)	14.93 (18.76)	14.03 (8.47)
5	9 (2)	8 (3)	6.83 (1.64)	5.74 (2.32)
6	5 (20)	5 (17)	3.76 (16.27)	3.86 (14.28)
7	11 (10)	8 (3)	7.74 (6.75)	5.98 (2.15)
8	61 (47)	31 (25)	47.0 (35.86)	21.39 (18.51)
9	63 (72)	36 (29)	48.77 (55.94)	26.01 (21.62)
10	12 (6)	7 (13)	9.55 (4.57)	4.77 (9.67)
11	3 (0)	2 (0)	2.55 (0)	1.26 (0)
12	8 (17)	8 (18)	5.8 (12.34)	5.42 (12.74)
13	1 (0)	0 (2)	0.73 (0)	0 (1.22)
14	3 (1)	0 (0)	1.68 (0.87)	0 (0)
15	3 (10)	6 (9)	2.22 (7.07)	4.6 (6.95)
16	6 (8)	6 (9)	4.31 (6.12)	4.63 (6.68)
17	3 (10)	2 (8)	2.33 (7.48)	1.24 (5.09)
18	22 (22)	11 (13)	16.5 (17.08)	8.77 (9.09)
social	40 (18)	37 (31)	31.64 (14.13)	27.64 (23.68)
environmental	23 (41)	19 (31)	16.12 (30.96)	14.45 (24.61)
economic	135 (146)	77 (80)	103.9 (111.62)	54.06 (57.95)
human capital	45 (36)	41 (27)	34.1 (26.66)	31.71 (19.25)
institutional	28 (30)	17 (22)	20.81 (23.2)	13.41 (15.77)

The statistics have been separated into synergies and trade-offs. 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.

F Non-trivial inferences

A natural question regarding the inference of policy priorities is whether they could be obtained from simple back-of-the-envelope calculations. Figure 5 shows that this is not the case. Each panel compares the estimated policy priorities against simple data manipulations: the historical gaps, and the sum of the weights of incoming edges. PPI's underlying model conveys non-trivial information because the inferred vector P does not correlate with either of these simple calculations. Therefore, the inferences are not trivial.

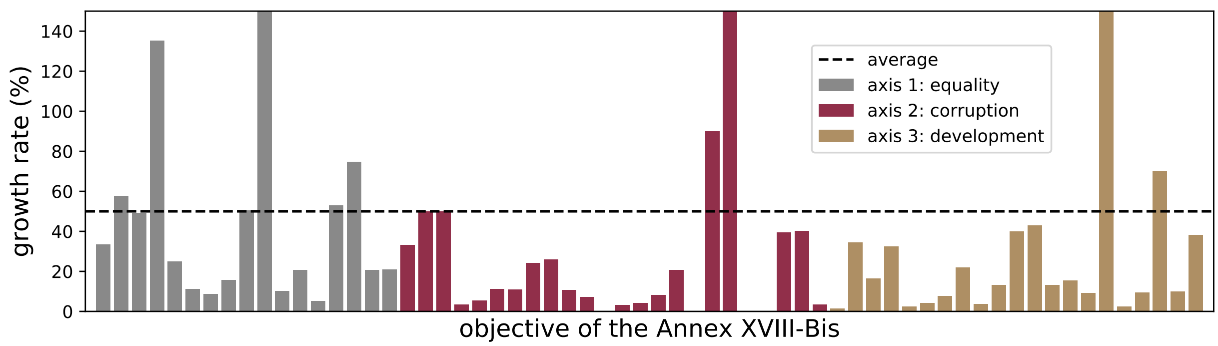
Figure 5: Non-trivial policy priorities



G Constructing development goals from official documents

In the Annex XVIII-Bis, Mexico's National Development Plan (NDP) identifies 234 specific policy issues that the government wants to improve in six years (from 2019 to 2024); let us call these issues objectives. Ideally, the specification of a development goal for an objective and the evaluation of the progress towards its achievement should be based on concrete measurements such as indicators. Unfortunately, the quantification of such a broad policy space is still challenging (even for the most advanced nations) and a work in progress. Thus, from all the 234 objectives, the NDP identifies a subset of 67 that can be associated to specific indicators. By establishing a baseline year and a goal for each of these indicators, the NDP provides an a picture of Mexico's development goals or aspirations. Figure 6 shows the the distribution of the different development goals in terms of growth rates. That is, each bar bar represents the growth that the government intends to achieve in six years for each indicator of the NDP. The bars have been colored in three tones that match the three broad 'development axis' established in the NDP. In some indicators, the growth rates can extremely high, so the figure has capped their actual values. For example, the tallest bar in the *equality* axis corresponds to an indicator of spatial closeness to cultural infrastructure. In the baseline year, this indicator measures an average distance of 50km to cultural infrastructure. The government aims to reduce such distance to 5km, so a growth rate of 900% in the indicator is in order. On average, the growth proposed growth rate for the NDP's indicators is approximately 50%.

Figure 6: Development goals from the National Development Plan



Not all the indicators presented in the NDP are suitable for usage in PPI. First, several indicators have been recently constructed, so their time series do not have enough observations to match those indicators built for the retrospective analysis. Second, some of these data are highly specific to Mexico and cannot be normalized in rates or percentages. Third, some PND indicators are rather the result of some political agreement to demonstrate that work is being done towards a goal, but not really to measure performance in such indicator. An example of this can be found in indicator 1.6.1: *Number of projects in benefit of national development, achieved through political agreements.* ***

H The role of public governance

Here, we provide a nuanced analysis on the role of public governance in the model underlying PPI. PPI accounts for public governance through two mechanisms: the monitoring of inefficiencies (φ) and the quality of the rule of law (τ). Here, we show the relevance of these mechanisms through their influence in the agent's efficiency choices. Recall that the contribution of public servant i is denoted by C_i. This is the effective amount of resources that this agent puts towards the public policy, out of the P_i resources allocated by the central authority. Then, efficiency is measured by the rate C_i/P_i.

The first exercise consists of analyzing the evolution of agent-level efficiencies under different configurations of φ and τ. This analysis serves a double purpose: (1) to show the effect of different institutional settings and (2) demonstrate that the learning model of the public officials works. For this, we present six parameterization cases of φ and τ in Figure 7.

Let us begin by looking at the two extreme cases in the upper panels: one with perfect monitoring and full effectiveness of the rule of law (left panel), and another where these mechanisms are absent (right panel). Clearly, when public governance is strong, agents learn that it does not pay to be inefficient, as their efficiency tends to 1. In contrast, in the absence of public governance, agents learn to become inefficient, decreasing their contributions towards zero. Note that, in both cases, agents exhibit different learning curves and occasional explorations. This is the kind of adaptive behavior that real agents exhibit in the presence of uncertainty and different forms of complexity in the environment. Thus, our learning model is well suited to study technical inefficiencies in the process of development.

Next, let us concentrate on the middle panels of Figure 7. Here, we present a case with poor monitoring with a strong rule of law (left panel) and another with good monitoring and a poor rule of law (right panel). When monitoring is weak, agents can spend several periods without being spotted. This allows them to explore being more inefficient and learn that it pays off. However, when they are caught, a strict enforcement of the law inflicts high penalties, so agents react strongly by increasing their efficiency to almost 1. This is shown in the left panel, where agents tend to stay with high contributions, but infrequent supervision allows them to decrease them and reach low levels until they are caught; reverting to high contributions. On the right panel we have a different type of dynamics, one of baring the costs of being inefficient. Here, strong monitoring efforts become a nuance to the agents because the penalties are so low that they are willing to bare with them, *i.e.* they are the price to pay for being inefficient. In this scenario, contributions tend to be low and they exhibit upward spikes when penalized.

Finally, the bottom panels show the scenarios combining poor and mediocre qualities for monitoring and rule of law. They provide a mixture of dynamics where agents can explore the full spectrum of relative contributions. The important point to take from this exercise is that, depending on the institutional setting described by φ and τ, PPI can model a society with a law-abiding culture, one where inefficiencies are tolerated and penalties are the price to pay, or one undergoing a transition between the previous two.

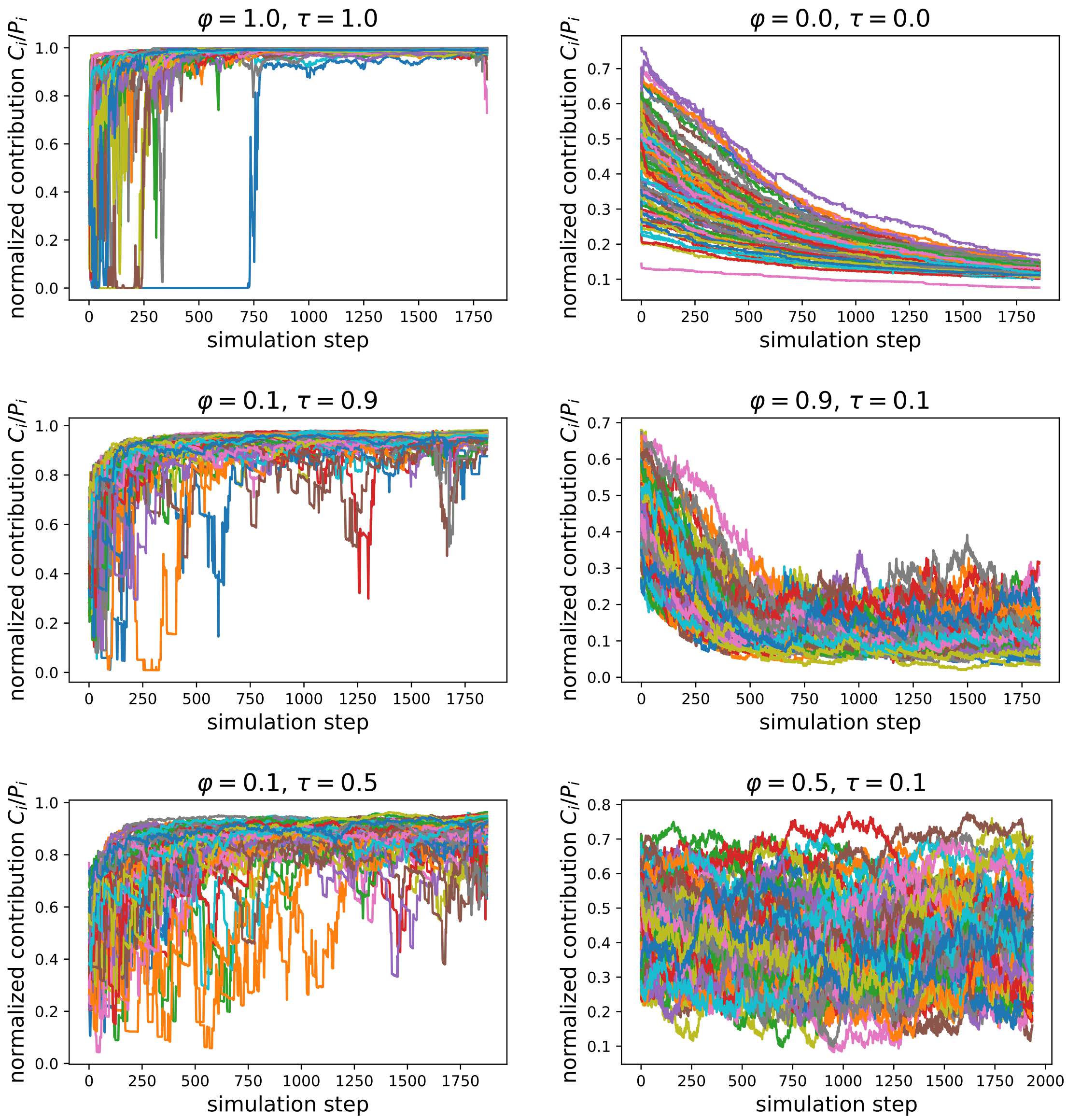
The second exercise illustrates the aggregate consequences of these micro-level dynamics. In particular, we show how different configurations of φ and τ can generate counter-intuitive aggregate relations between the level of inefficiency and the quality of the rule of law. When analyzing these results in detail, these apparent contradictions are explained by the emergence of social norms in the model.[2]

Figure 8 shows the relationship between the aggregate level of inefficiency and the quality of governance. The two vertical lines denote the empirical values of Mexico's indicators on the strength of the monitoring efforts (φ) and the quality of the rule of law (τ). Let us first focus on the solid line. This relationship was produced by setting $\varphi = \tau$ and running PPI to obtain the total level of inefficiency for all values of the parameters in [0,1]. This exercise means that both aspects of public governance are marginally improved in the same amounts, and that the relationship between the quality of governance and inefficiencies is negative; as predicted by most theories. There is nothing surprising from this result since clearly improving monitoring and the rule of law decreases the agent's incentives to be inefficient.

Next, let us focus on the dashed-dotted line, which also shows a negative relationship. Here, we fixed the quality of the monitoring efforts in Mexico's empirical level, and varied τ

[2] As explained in the main text, social norms are one of the factors that explain why many developing countries have failed in curving corruption through improvements to the role of law that have been isolated from other policy issues.

Figure 7: Inefficiencies and public governance



from 0 to 1. Clearly, more effective penalties decrease aggregate inefficiency. However, when the strength of the rule of law surpasses the quality of the monitoring efforts, the impact on inefficiencies is more effective than when improving both parameters in unison. This is an intriguing result because, according to the principal-agent perspective, agents should respond to both a shrinkage in the space of opportunities to be inefficient and a raise in the penalties. This result, on the other hand, suggests that it is more effective to leave some space of opportunity for inefficiency while focusing mainly on the rule of law. Our third experiment shows why this happens.

Now, note that the dashed line presents a U-shaped relationship between the quality of monitoring efforts and aggregate inefficiency. In this exercise, we fix the strength of the rule of law to its empirical level and manipulated φ. Why do we obtain an increase in total inefficiency when the quality of monitoring surpasses that of the rule of law? The answer lies in the micro-level dynamics presented in Figure 7; in particular, in the middle-right panel. A society with frequent monitoring but non-credible punishments learns that that those penalties are the price to pay for being inefficient. The more frequent is the monitoring, the quicker the agents learn about the poor rule of law, so society gets locked into a higher inefficiency social norm. This is precisely the case of countries in which high corruption prevails, while the government frequently prosecutes corrupt officials. Eventually the cases of such prosecutions are dropped or lost because the government was never serious about enforcing effective punishments (usually after the corruption scandal stops receiving media attention). Here, a complicit central authority simulates that it is fighting corruption, bus society has already learned that high corruption is tolerable.

Figure 8: Inefficiencies and public governance