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Supplementary appendix

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SUPPLEMENTARY METHODS ANNEX

Future of Global Health Financing

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Global Burden of Disease Health Financing Collaborator Network – full author list in final pages of appendix

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SECTION 1. INTRODUCTION

Information on future health spending is critical for planning and policymaking and ultimately for improving population health. Globally, tepid growth in development assistance for health, and locally, competing national priorities heighten the need and relevance of such forecast data to facilitate adequate planning to limit any losses in global health gains made in recent times.

The objective of this study is to provide data on future health spending patterns that can guide decision-makers. In order to achieve this objective, we conducted two types of analyses. First, we employed novel methods to generate expected health spending and potential health spending estimates. Second, we empirically assessed two avenues in government fiscal policy – increases in taxation and reprioritizing of the health sector in the government budget – through which potential government health spending could be adjusted to provide more resources to the health sector.

These analyses produced a comprehensive and comparable set of gross domestic product and all-sector government spending estimates which were used to examine prospective counterfactuals to illustrate expected and potential health spending in the years to come. Besides the baseline guidance that expected health spending estimates provide, the estimates on potential health spending provide alternative scenarios for decision-makers on what might be possible with policy adjustments.

The purpose of this appendix is to describe in detail the methodology used in our analyses. Subsequent sections contain information on all data sources, ensemble forecasting strategies, inclusion criteria, and uncertainty estimation used to generate our estimates as well as our guidelines on how our counterfactual analysis was conducted. Section 2 describes how the datasets used for the analyses were created. Section 3 details how the data were used in our analyses.

SECTION 2. DATA

We used data from seen sources for the analyses: (i) WHO's Global Health Observatory (WHO), ii) Institute for Health Metrics and Evaluation's Development Assistance for Health Database (IHME), iii) International Monetary Fund (IMF) database, iv) Penn World Tables (PWT), v) World Bank World Development Indicators database (WB), vi) Maddison Project, and vii) United Nations World Population Prospects (WPP). Specifically, we collected health expenditure information on all available sources defined in Table 1 that is comparable across countries and complete for most countries from WHO and IHME, and demographic data from the WPP, while the underlying data for producing gross domestic product (GDP) and general government expenditure (GGE) were extracted from the IMF, WB, and PWT. Table 1 below presents the definitions for the various health expenditure sources.

Data sources

Table 1. Definitions of health expenditure sources

Health expenditure type	Definition
Development assistance for health	Financial and in-kind contributions from global health channels that aim to improve or maintain health in low- or middle-income countries.
Government health expenditure as source	Government health expenditure as source only includes domestically financed government expenditure on health.
Out-of-pocket expenditure	Paid by individuals for health services; considered catastrophic if exceeding 40% of a household's annual income.
Prepaid private health expenditure	Private risk pooling against catastrophic health expenditure; includes private insurance and non-governmental organizations.

Institute for Health Metrics and Evaluation's Development Assistance for Health Database

Development assistance for health estimates were obtained from the Institute for Health Metrics and Evaluation's Development Assistance for Health Database.[1] To generate these estimates, IHME collected audited budgets, annual reports, and project records from the primary development agencies providing assistance for the health sector. These records are augmented by information acquired via correspondence, and are standardized and compiled to provide a comprehensive perspective on international financial flows for health. These estimates are tracked backward to the source of the funds and forward to the country recipient, and are available through 2016 and 2014, respectively.

World Health Organization's Global Health Observatory

WHO estimates health spending by source for 184 countries from 1995 to 2014. This database is updated annually and draws on publicly available documents from countries and international organizations such as National Health Accounts (NHAs), government ministry reports, and estimates from the World Bank and International Monetary Fund. NHAs are considered the gold standard and adhere to the guidelines set forth in *A System of Health Accounts*, 2011.

We adjusted these data by converting them from current local currency to fractions of GDP (both extracted from WHO), completed the series using multiple imputation, and converted them back into 2015 purchasing-power-parity (PPP$) terms. Multiple imputation is a common method used to impute missing data.[2]

UN World Population Prospects

The UN World Population Prospects (WPP) provides population forecasts by age, sex, country, and year from 1950 until 2100. Using a cohort-component approach, WPP utilizes life tables to generate forecast age-specific mortality rates. Their modeling strategy involves a hierarchical Bayesian model of female life expectancy that prioritizes country data if available, but otherwise draws on regional data. A separate step models the male-female difference in life expectancy. From this data source, we generate multiple indicators of demographic context, such as the proportion of the population under the age of 20, and the dependency ratio (the ratio of working-age population [20 to 65 year olds] to the non-working-age population). We use the dependency ratio to measure the effect of the demographic dividend, a term used to signify a period where country fertility rates decrease due to declines in child mortality rates.

WB, IMF, PWT, and Maddison

The World Bank World Development Indicators Database provides data on a wide range of development-related variables, including data on GDP and GDP per capita. Data series in this database begin in 1960. The IMF World Economic Outlook Database provides data on various macroeconomic indicators. Macroeconomic series data are available from 1980 to present. The Penn World Tables is a database that provides real national accounts data for 167 countries and territories. The data series starts in 1950. The Maddison Project database provides historical GDP, GDP per capita, and population data dating as far back as Roman times. We utilized GDP per capita as a primary covariate to produce forecasts. GDP per capita from 1950 through 2015 was constructed using the method described in James *et al.*[3] The method utilized extracted data from a number of sources (IMF, WB, PWT and Maddison), and used multiple random effects models to estimate a mean GDP per capita series to be used in our analysis. Similarly, we used the same methodology to produce a mean GGE per GDP series, from 1950 through 2015.

Imputation of missing variables

We used the Amelia 1.7 package to impute missing values.[4] This procedure improves on mean imputation and single imputation and is specifically designed for cross-sectional longitudinal data such as our own.[4] Amelia has the capability to identify a panel data structure, and therefore executes the imputation in country- and year-specific dimensions. We converted the fractions to be imputed in logit space in order to ensure that the reverse transformation is between 0 and 1, and included them in three degrees of lags and leads each. Additionally, we included the log of GDP per capita as one of the supporting variables in the imputation process.

A complete panel of data for this study, 184 countries for 1995–2014, makes up 3,680 country-years of data. The missingness ranges from 1.8% in government health expenditure to 14.8% in prepaid private expenditure. Taking the dataset, D, which has observed and missing country-years, Amelia assumes that the variables are jointly multivariate normally distributed and the missingness in the data is random.

That is:

$$P(D \mid \mu, \Sigma) \sim MVN\ (D \mid \mu, \Sigma)$$

with the following likelihood function:

$$L(\mu,\Sigma \mid D) \sim \sum_{i=1}^{N} MVN(d(i) \mid \mu,\Sigma)$$

where *d(i)* is observation *i* in the dataset, μ is the mean, and Σ is the variance.

Amelia uses an expectation-maximization algorithmic approach in order to estimate the unknown parameters, μ and Σ. The predicted value for missing country-years is the mean of the imputed values across 100 datasets. The uncertainty is represented by the variation across the multiple imputations for each missing value. We use the full set of WHO data, IHME's DAH, GDP per capita, and GGE per capita data, linear country-specific time trends, and a ridge prior to inform our imputations.

Descriptive statistics

Table 2 presents descriptive statistics for all the variables included in the analyses, while Table 3 has the Pearson's correlation values among the variables.

Table 2. Summary statistics of variables included in the analyses

Variable	Mean	Median	Standard deviation	Minimum	Maximum
GHES / GGE	0.129	0.121	0.063	0.001	0.405
OOP / GDP	0.020	0.018	0.012	0.001	0.094
PPP / GDP	0.004	0.002	0.008	0.001	0.117
DAH / GDP	0.007	0.001	0.015	0.001	0.362
GDP per capita	18,805.210	10,834.700	21,272.080	294.305	156,479.100
GGE / GDP	0.268	0.258	0.100	0.042	0.969
Pop	3.95 * 10^7	8.47 * 10^6	1.43 * 10^8	48,614.000	1.51 * 10^9
% Pop < 20	0.268	0.257	0.111	0.074	0.505
TFR	2.797	2.241	1.406	1.155	7.746

Table 3. Correlation matrix of variables included in the analyses

	GHES / GGE	OOP / GDP	PPP / GDP	DAH / GDP	GDP per capita	GGE / GDP	Pop	% Pop < 20	TFR
GHES / GGE	1								
OOP / GDP	-0.1509	1							
PPP / GDP	0.1932	0.0342	1						
DAH / GDP	-0.2127	0.0589	0.0381	1					
GDP per capita	0.3931	-0.2924	0.0736	-0.2468	1				
GGE / GDP	0.1817	-0.2595	-0.0776	-0.0092	0.1911	1			
Pop	-0.0531	0.0422	0.041	-0.0626	-0.0478	-0.1182	1		
% Pop < 20	-0.1088	0.0603	0.0166	-0.0488	-0.09	-0.1564	0.9655	1	
TFR	-0.4569	0.1296	-0.031	0.3332	-0.488	-0.309	-0.0832	-0.0179	1

SECTION 3. STATISTICAL MODEL

Ensemble modeling

We used an ensemble modeling technique to create our forecasts, similar to our previous publication.[5] The strength of ensemble modeling is that our forecasts draw on multiple predictions derived from different specifications in order to create a stronger overall prediction, eliminating the need for a researcher to select one preferred model.[6–9]

This study capitalizes on past trends and relationships in health financing to forecast health expenditure by source for 184 countries, from 2014 through 2040, utilizing an advanced ensemble modeling approach.[5] We assessed 10,800 model variants, out of which a total of 2,833 models passed our inclusion criteria to be included in the ensembles. To begin with, we forecast the gross domestic product (GDP) of 188 countries and the general government expenditure (GGE) of 187 countries from 2016 to 2040. After that, we forecast each of the components of total health expenditure (GHE, PPP, OOP, DAH) and then aggregated each country's forecasts to generate total health expenditure from 2015 to 2040 for 184 countries. Four countries (Taiwan, Palestine, North Korea, and Zimbabwe) had to be excluded from the analyses due to inadequate data.

Universe of model specifications and ensembles

After assembling the data, we developed a diverse set of plausible forecasting models. We assessed 10,800 model variants. These models included autoregressive terms, population, total fertility rate, other health financing variables, share of the population below 20, convergence terms, auto-correlated residuals and country-specific random intercepts. We converted all our data to use first differences in order to account for non-stationarity.

Dependent variables

We forecast a sequence of dependent variables in this paper in the following order: GDP per capita, GGE per GDP, DAH per GDP, GHES per GGE, OOP per GDP, and PPP per GDP. The last four components in the list were aggregated to produce total health expenditures.

Autoregressive terms

An autoregressive term is a lag of the dependent variable; for example, the i^{th} lag of an outcome Y_t is Y_{t-i}, and we explored models with zero to three lags.

Unique country trajectories

We allowed for unique country trajectories by including country-specific random intercepts.

Convergence term

We included the convergence term in our differenced models as the level of the dependent variable in the past time period, used to predict the forecast change in the dependent variable in the current time period. Convergence term was only used in forecasting GDP and GGE. Additionally, we had a prior belief on the coefficient of the convergence term (it must always be negative).

Up-weighting of recent years

For each unique model in our ensemble, we allowed four other combinations of the same model, with the condition that the recent-most years of the in-sample data should have higher weights than the further past. We used a simple decay function with four decay parameters, and each of those up-weighting decay functions are considered in the universe of ensembles. Weighting functions were not used for forecasting development assistance for health due to the very volatile and noisy nature of in-sample data.

Autoregressive residuals

We also allowed for autocorrelations in our models by allowing the residual terms to have autoregressive processes of their own. This allowed us to evaluate models that could do a better job at explaining the in-sample secular trend. We tested up to three orders of auto-correlated models, and have only included this option in the GDP forecasts.

Health financing dependencies

We also considered dependencies between the different types of health expenditures. It is well established that there is a relationship between GHES and DAH.[10] Moreover, it has been established that increased government health expenditure can reduce the amount of out-of-pocket expenditure.[11] We consider the lag of each other health spending source variable to affect each health spending source.

Summary of universe of model considered

Figure 1 summarizes all combinations of models tested for the health expenditure variables. Green indicates a variable that was considered. Red indicates that we did not test a covariate due to prior beliefs about the health financing timeline. Black indicates that a certain combination was not possible to test. In addition to these covariates combinations, we also considered estimating parameters as fixed across all countries, random country-specific slopes, and country-specific coefficients by interacting the covariate with country dummies. In total, we considered 10,800 models. We did not have any prior beliefs on the coefficients when forecasting GDP and GGE.

Additionally, Table 4 displays the results of unit root tests on the covariates forecast in terms of p-values, and we see that none of our covariates have any unit roots at a statistically significant level. We analyzed the unit roots using four sets of unit root tests: the covariate-augmented Dickey-Fuller test (CADF), the Levin-Lin-Chu test (LLC), the Im-Pesaran-Shin test (IPS) and the Hadri Lagrange Multiplier stationarity test (Hadri LM). All four tests satisfied the conclusion of stationarity.[12–17]

Figure 1. All combinations of covariates tested for health expenditure forecasting

Table 4. Unit root tests on the dependent variables

Unit root test	ln GDPpc	logit GGE/GDP	logit DAH / L2.GDP	logit DAH / Σ DAH	logit GHES / GDP	logit OOP / GDP	logit PPP / GDP
CADF	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.0024	< 0.0001
LLC	0.01373	< 0.0001	0.0017	< 0.0001	< 0.0001	< 0.0001	< 0.0001
IPS	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.0005	< 0.0001
Hadri LM	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001

Ensemble model selection

The steps we used in the selection of models for our ensemble forecasts are as follows:

1) We ran all possible combinations of model specifications using the in-sample data and produced forecast estimates at the mean level.

2) We applied a set of inclusion criteria to the estimated forecasts from the potential model, and recorded whether or not it passed all requirements. More information on these criteria are provided below.

3) Additionally, by leaving out the most recent years from our sample, we reran our models in order to assess their out-of-sample predictive validity (OOSPV). This allows us have a measure of which model had the best out-of-sample prediction for each country and out-of-sample year.

   The measure of OOSPV we used is country-year-model-specific root mean squared error (RMSE).

4) We reran the models that passed our inclusion criteria and applied four different types of uncertainty (outlined in section below) in order to generate approximately 10,000 draws of forecasts for each of our dependent variables.

5) For each year of in-sample data we left out in Step 3, we forecast the same number of years into the future:

   For example, when forecasting GDP series, we left out 10 years of in-sample data (2006 through 2015). When creating the forecasts for the year 2016, we assess the models that were run by leaving out the in-sample data for the year 2006. It should be noted that for all of the health expenditure variables, we use five years of in-sample data as opposed to 10 years for GDP and GGE. This is because our complete time series for the health expenditures go from 1995 through 2014, whereas GDP and GGE data exist for 1980 through 2015.

6) Following that, we forecast the draws for the year 2017 using the draws from the sub-models that were run by leaving out the in-sample data for the years 2006 and 2007, and so on. When forecasting the years 2025 through 2040, we assessed all of the models with out-of-sample predictive validity based on leaving out the years 2006 through 2015.

7) For each of the years in 2016 through 2024, we ranked each country's RMSE value (in ascending order) for that sub-model and year left out. The top 25% of the sub-models for each country were chosen to be included in the forecasts for a particular year. Therefore, for each country and year, we were able to collect 10,000 unique forecasts.

   From the years 2025 through 2040, we chose the same pool of sub-models in the ensemble, and so each of the countries had the same set of sub-models for those years.

8) Once we generated approximately 10,000 draws for each country and year, we needed a way to make sure that each draw across years for each country had some level of correlation, since our year-by-year forecasting method does not map sub-models to draws between the years forecast using single-year out-of-sample windows (i.e., 2016 through 2025 for GDP). We used the following strategy to achieve that:
    a. For each country, we recorded the Spearman's correlation coefficients for each draw across the years 2025 through 2040, and took the mean of all the correlations.

    b. We simulated a bivariate uniform distribution with the recorded mean correlation from step 8.a, using a Gaussian copula (which is imposed using Sklar's Theorem).[18,19]

    c. We recorded the ranks of the simulated distributions, and imposed them each year going backward from 2024 through 2016. Therefore, our complete time series data for all draws for each country and year will have the same rank correlation structure. The copula were simulated using R's VineCopula package.[20]

9) Finally, we computed the means and the 2.5th and 97.5th percentiles to generate our final ensemble forecasts.

Development assistance for health modeling strategy

We started from the belief that DAH is a supply-driven market. That is, DAH commitments are determined first by source countries on the "supply" side, not by recipient countries the "demand" side. With this in mind, we employed a unique three-step process for forecasting development assistance for health (DAH).

1. We extracted data and forecast the total amount of DAH provided between 2015 and 2040 using an ensemble model.

   Due to the anomalous level of growth in DAH disbursed in the decade of 2000–2010, we included a time dummy variable indicating whether the sample was part of that decade (and zero otherwise), with the prior belief of a positive coefficient on this indicator variable.

2. DAH received by each country, measured as a share of the total amount of DAH disbursed that year, was forecast using a second ensemble model and characteristics of the recipient. Potential covariates were the same as those described above.

3. We forecast transition of middle-income countries away from DAH as the transition to attaining high-income status. The transition was identified when the country's GDP per capita reached $18,108 per person. These countries were then excluded from that specific point onward for that model. We allow for uncertainty in graduation by performing this analysis over random GDP forecast draws. The amount $18,108 was determined by converting the World Bank's gross national income (GNI) of $12,736 into GDP. This conversion was made by regressing logged GDP per capita on logged GNI per capita for all countries in our dataset.

For the countries that did not transition to high-income status, the product of total DAH (predicted in the first step) and the share they would receive (predicted in the second step) provided an estimate of DAH received by a country for a given year, 2015 through 2040.

Let $DAH_{R,t}$ denote the DAH received before applying the graduation algorithm, and $DAH_{G,t}$ the DAH received after graduation. Therefore, for all recipient countries i, the new adjusted estimate of DAH received by a country for a given year between 2015 and 2040, inclusive, was given by:

$$DAH_{G,t} = \sum_{i} DAH_{R,i,t} \cdot \frac{DAH_{R,i,t}}{\sum_i DAH_{G,i,t}}$$

This three-part model helped us to ensure that *all* of the DAH supplied went to the countries demanding development assistance.

Baseline model specification

Our baseline model specification was as follows. Using the example of GDP per capita as our dependent variable, the regression specification was of the form:

$$\Delta\ \ln GDP_{c,t} = \alpha_i + \sum_{i=1}^{3} \Delta\ \ln GDP_{c,t-i} + \gamma\Delta\ \ln POP_{c,t} + \zeta\Delta\ \mathrm{logit}\left(\frac{Pop < 20}{Pop}\right)_{c,t} + \eta\Delta\ \ln TFR_{c,t}\ +\ \epsilon_{c,t} + \sum_{i=1}^{3} \epsilon_{c,t-i}$$

where the error term ϵ_t was decomposed into two terms:

$$\delta_{c,t} = \left(\epsilon_{c,t} - \overline{\epsilon_t}\right)$$
$$\tau_t = \overline{\epsilon_t}$$

Each of the decomposed error terms is simulated as uncertainty (fundamental uncertainty) in either of two methods:

1) As respective random walk processes (only for GDP sub-models):

$$\tau_t \sim N(\widetilde{\tau_t}, [MAD(\tau_t - \tau_{t-1})]^2))$$
$$\delta_{c,t} \sim N(\widetilde{\delta_{c,t}}, \left[MAD\left(\delta_{c,t} - \delta_{c,t-1}\right)\right]^2)$$

   where the mean and variances of the normal distributions are the median and the squared median absolute deviations of each of the components respectively.

2) As a static random sample from a normal distribution with the respective mean and standard errors being the median and the median absolute deviation (MAD) of the observed country-specific residuals, respectively.

3) Furthermore, the standard errors of the fundamental uncertainty were capped using the MAD of the MADs across all models.

The details of simulating this vector of residuals are detailed in the section on fundamental uncertainty.

Inclusion criteria

Our model selection consisted of three criteria:

1) Screening out models that estimated statistically insignificant relationships.
2) Screening out models that estimated relationships that contradict known relationships in health financing.

3) Screening out models that contradicted observed empirical norms in growth.

Statistically significant relationships

We required that all estimated model parameters be statistically significant at the 10% level, with the exception of country-specific random intercepts. This meant that all included covariates must be statistically significant in order to pass this inclusion criterion. Insignificant parameters reduced the accuracy of our forecasts and added unnecessary uncertainty.

Expected direction on parameter estimates

Table 5 details the relationships that we expect between different outcome variables and potential covariates. Models that did not produce the expected sign on the covariate were excluded from the ensemble model.

Table 5. Covariates considered and expected relationships

	Dependent variable						
Independent variable	ln GDPpc	logit GGE/GDP	logit GHES/GGE	logit OOP/GDP	logit PPP/GDP	logit DAH / GDP	logit DAH / Σ DAH
AR term (1-6)	No prior	No prior	No prior	No prior	No prior	No prior	No prior
Convergence term	-	-	-	-	-	-	-
ln GDPpc	Not possible	No prior	+	-	+	+	-
logit GGE/GDP	Not possible	No prior	No prior	No prior	No prior	No prior	No prior
ln TFR	No prior	No prior	No prior	No prior	No prior	No prior	No prior
ln Pop	No prior	No prior	No prior	No prior	No prior	No prior	+
logit ((pop < 20)/pop)	No prior	No prior	No prior	No prior	No prior	No prior	No prior
logit GHES/GGE	Not tested	Not tested	Not possible	No prior	Not tested	Not possible	Not possible
logit OOP/GDP	Not tested	Not tested	Not tested	Not possible	Not tested	Not possible	Not possible
logit PPP/GDP	Not tested	Not tested	Not tested	No prior	Not possible	Not possible	Not possible
logit DAH/GDP	Not tested	Not tested	-	Not tested	Not tested	Not possible	Not possible

Empirically derived norms for allowed growth

We excluded models that contradicted observed empirical norms in growth. To do this, we considered the observed percent growth in health expenditure (as a percent of GDP) in each year as a function of the level of health expenditure (as a percent of GDP) for all available data. The observed percent change of the fraction (health expenditure/GDP) is the right-hand side variable, and it is a function of how much a country is already allocating to health expenditure (the level of health expenditure/GDP).

The motivation behind this is demonstrated in Figures 2 through 7. Countries with low levels of health expenditure are more prone to large increases or decreases. As a country's health expenditure increases, the percent growth in the fraction attenuates as it becomes less likely that a country's health expenditure would change drastically year to year. This is observed in the pattern of the black dots in Figure 2.

Figure 2. Observed percent growth as a function of government health expenditure quantity

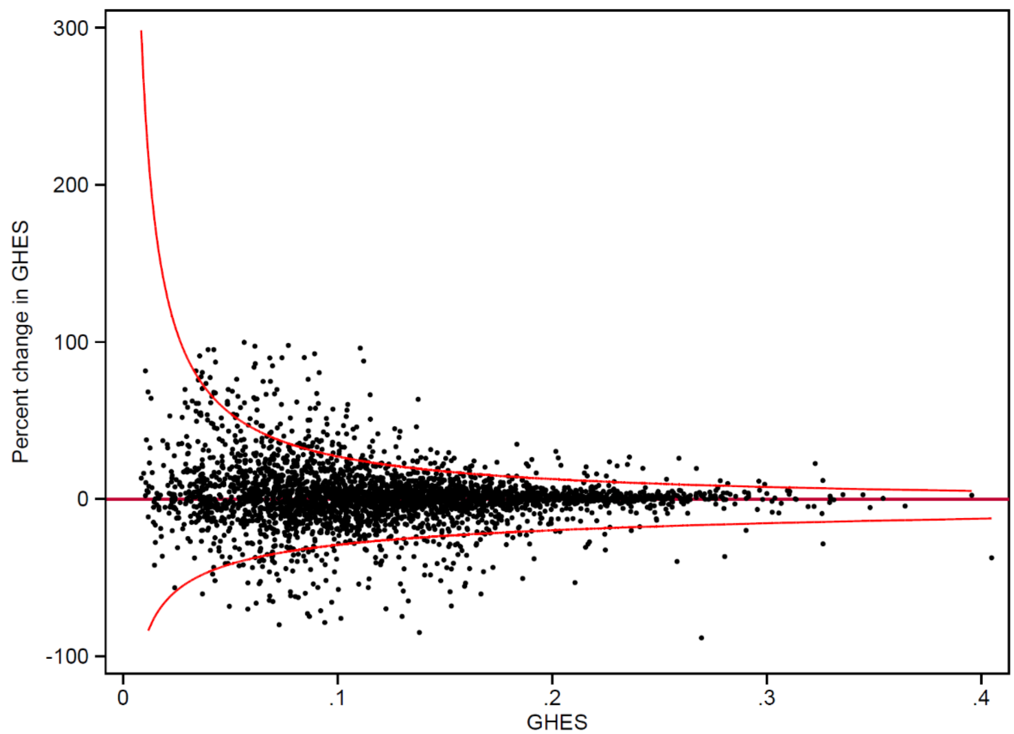


Figure 3. Observed percent growth as a function of out-of-pocket expenditure quantity

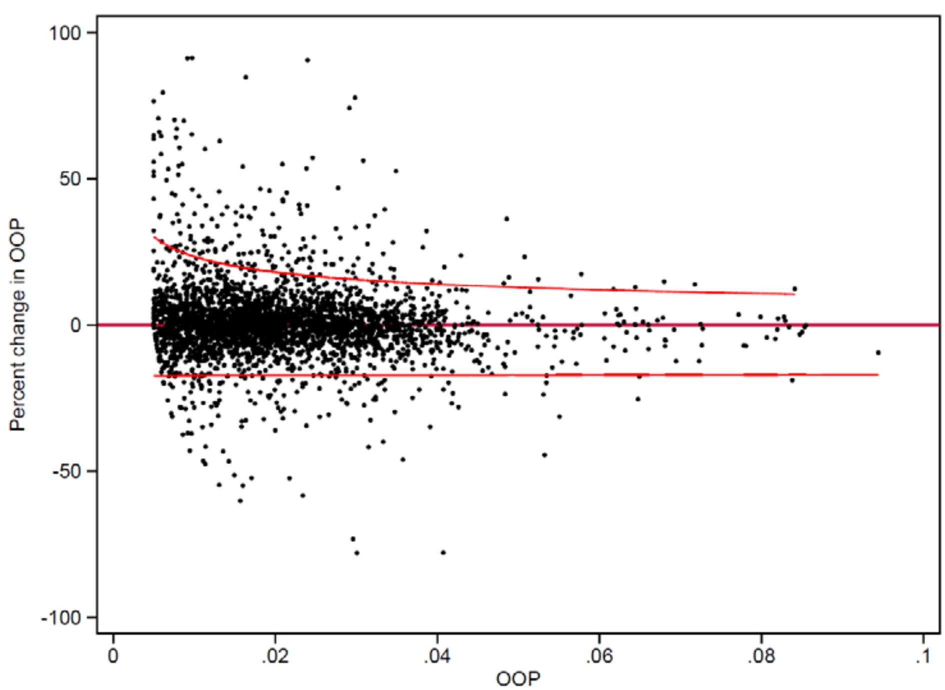


Figure 4. Observed percent growth as a function of prepaid private expenditure quantity

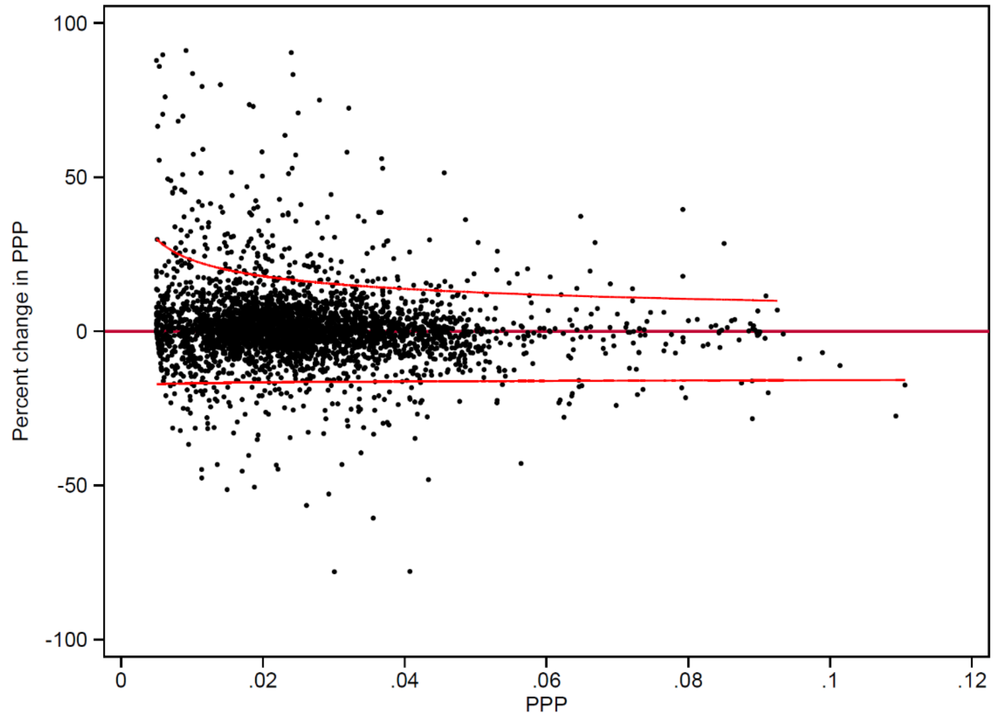


Figure 5. Observed percent growth as a function of DAH disbursed

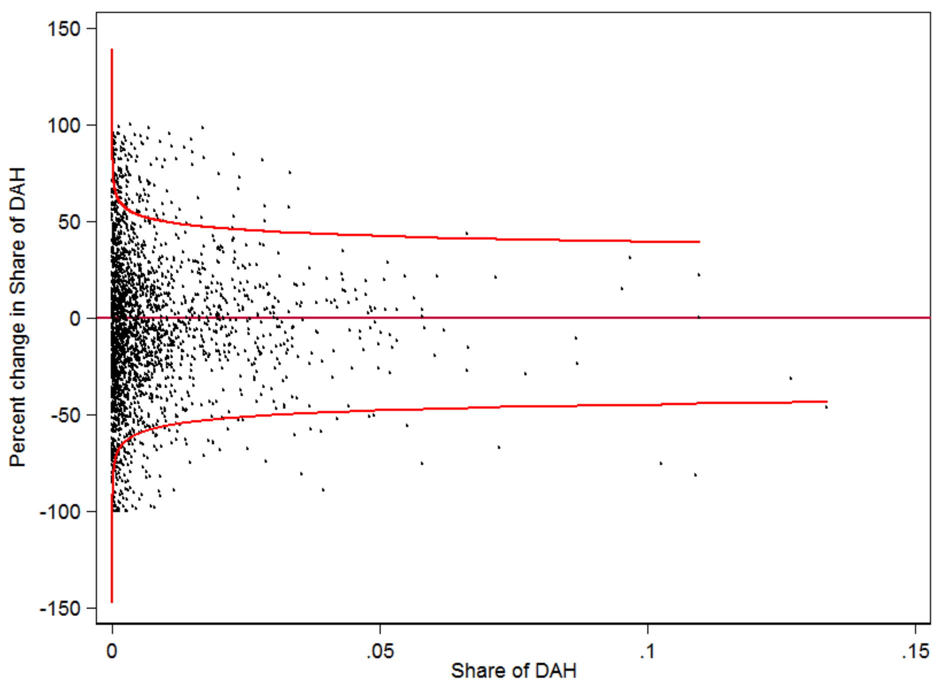


Figure 6. Observed percent growth as a function of DAH received

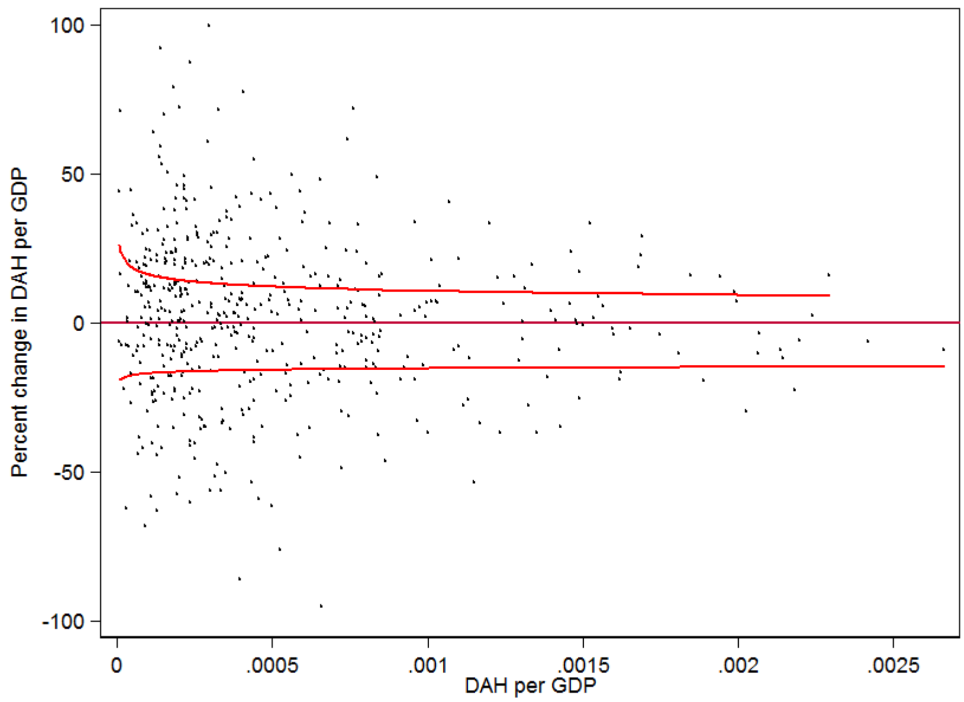
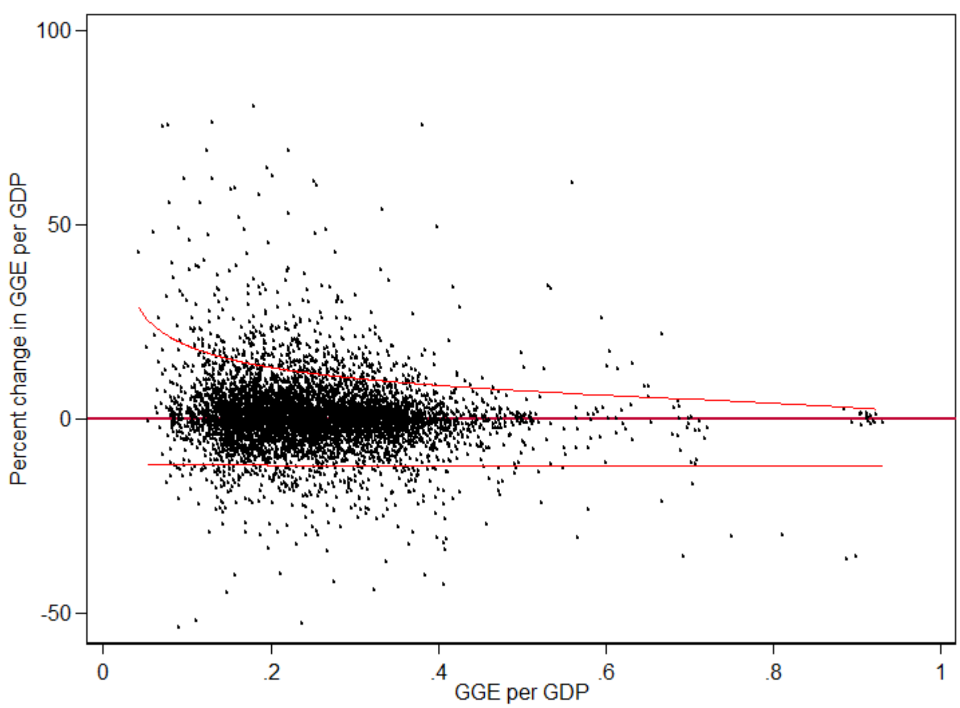


Figure 7. Observed percent growth as a function of GGE per GDP



We used stochastic frontier analysis (SFA) as a method to estimate a boundary around a series of scattered points. In order to estimate an upper and lower bound for allowed percent growth, we first divided the observations into two categories: positive and negative percent change. For each category, we estimated a frontier of maximum percent change based on estimation of one-sided residual. Specifically, we implemented SFA with a half-normally distributed error term. The generalized version of a stochastic frontier analysis involves the maximum likelihood estimation of the following half normal stochastic frontier model:[21]

$$y_{it} = \alpha + x_{it}'\beta + \epsilon_{it}$$

$$\epsilon_{it} = \nu_{it} - u_{it}$$

$$\nu_{it} \sim \mathcal{N}(0, \sigma_v^2)$$

$$u_i \sim \mathcal{N}^+(0, \sigma_u^2)$$

This gave us an upper bound that is the greatest value observed in the data, allowing for some noise and measurement error. The data showed us that countries with greater spending per GDP have smaller percent changes, so we get a convex, decreasing boundary. That means, intuitively, countries with very little spending per GDP may have more volatility, but for countries already spending a lot on health, potential growth is more constrained. Most important, this reflected the data.

Estimation and inclusion statistics

This analysis was executed on a high-performance 20,000-node computing cluster with a CentOS interface. All of the codes are written in Stata 13.1; R 3.3.2; and Linux bash scripts.[4,22–28] We assessed a total of 10,800 model variants. The number of models that pass our inclusion criteria for each variable are included in the table below, Table 6.

Table 6. Number of models included in forecasts

	Gross domestic product	General government expenditure	Government health spending	Out-of-pocket health spending	Private pre-paid health spending	Development assistance for health	
						Disbursed	Received
Number of models tested	1,664	128	1,720	3,838	2,814	381	255
Number of models that passed exclusion criteria and are included in the ensemble	767	46	588	953	445	20	14

Table 7 reports the mean parameter estimate for each covariate, calculated from the models that pass our inclusion criteria. All parameter estimates are statistically significant at the 10% level, by virtue of the inclusion criteria. Parameters with values of zero indicates that sub-models containing those covariates were not included to forecast the respective dependent variable.

Table 7. Mean parameter estimates of covariates included in the ensemble forecast by dependent variable

	GDP per cap	GGE per GDP	GHE-S	OOP	PPP	DAH disbursed	DAH received
GDP per capita	-	0.52864	0.00019	-0.23596	0.00776	1.62373	-0.3512
GGE per GDP	-	-	-0.14373	0.05175	0.02934	-0.55923	0.00000
TFR	0.15999	-0.08471	0.40304	-0.06131	0.12031	2.63185	-2.48478
% Pop < 20	-0.03578	0.10104	0.54790	0.04684	0.19031	-3.37962	0.34928
Pop	0.11532	-0.15885	0.00000	0.00000	0.00000	10.48206	0.14264
GHE-S	-	-	-	0.00634	-0.02993	-	-
OOP	-	-	0.05532	-	-0.05998	-	-
PPP	-	-	-0.02797	0.01245	-	-	-
DAH	-	-	-0.14277	0.00801	-0.02969	-	-

Uncertainty

Since the mean forecast estimate is a function of its underlying distribution of estimates, the estimation of uncertainty is of great importance. Uncertainty intervals should be plausible; it is unreasonable to expect an upper bound of 100% of GDP going to health expenditure, as it is unprecedented and the economy could not function with such an expenditure pattern. The uncertainty interval is also policy-relevant, as it demonstrates that the future is ambiguous and amenable to policy intervention.

Four types of uncertainty were incorporated in the forecasting methodology:

1) Uncertainty in model specification
2) Uncertainty in parameter estimates
3) Uncertainty in past and forecast data
4) Fundamental uncertainty

Uncertainty in model specification

Ensemble models provide a clear strategy to capture model specification uncertainty and reduce the need to find the perfect set of predictors. We described our ensemble modeling approach above. The final forecast is a result of many different models that pass empirically derived inclusion criteria.

Uncertainty in parameter estimates

Uncertainty in parameter estimates was included by drawing parameter estimates from a multivariate normal distribution of the estimated model parameters as the mean and the model's variance-covariance matrix used to inform variance. We calculated 10,000 forecasts based on this estimated multivariate normal distribution around the model parameter estimates.

Uncertainty in past and forecast data

We propagate uncertainty in GDP per capita forecasts by selecting a random draw to use in our forecasting calculation.

Fundamental uncertainty

Fundamental uncertainty, also called systematic variance, captures general uncertainty about our forecast. In order to calculate this uncertainty, we calculate residuals (error term) for each model. For the GDP sub-models, we decomposed this total residual into a time component and a country-specific component. We then simulated each of the decomposed residuals using a random walk process of autoregressive order 1 and a normal distribution. For the rest of the covariates, we took a random sample from a normal distribution using the specifications below.

In order to account for the skewness of the residuals, we used the medians and a capped squared median absolute deviations (MAD) for each of the residuals as the mean and variance of the normal distributions, respectively. The variance term was derived by analyzing all country-model-specific median absolute deviations of the model residuals, and then we took the MAD of all the MADs for each covariate to be forecast. Finally, we added these simulated residuals to each of the draws.

Putting all four types of uncertainty together

1. We determined the number of models included in the ensemble based on the universe of potential models and the inclusion criteria.
2. We calculated the model-country-specific normal distribution of residuals and decomposed the residuals into a time- and country-specific component.
3. We determined the number of draws from each model included so that the total amount of draws exceeds 10,000; number of draws per model = ceiling of (10,000/# of models)
4. For each draw:
    a. We randomly selected a forecast GDP and GGE series from the 10,000 GDP draws (data uncertainty).
    b. We randomly selected a forecast total DAH series from the 10,000 total DAH draws (data uncertainty).
    c. We randomly drew from the variance-covariance matrix of the model (parameter estimate uncertainty).
    d. We simulated and added residuals based on the model-specific, time- and country-specific distribution of residuals (fundamental uncertainty).

We aggregated across the draws to estimate the mean and uncertainty interval (2.5th and 97.5th percentiles; model uncertainty).

Additional tables

Table 8. Classifications of countries by World Bank income groups

High-income	Upper-middle	Lower-middle	Low-income
Andorra	Albania	Armenia	Afghanistan
Antigua and Barbuda	Algeria	Bhutan	Bangladesh
Australia	Angola	Bolivia	Benin
Austria	Argentina	Cameroon	Burkina Faso
Bahrain	Azerbaijan	Cape Verde	Burundi
Barbados	Belarus	Congo	Cambodia
Belgium	Belize	Cote d'Ivoire	Central African Republic
Brunei	Bosnia and Herzegovina	Djibouti	Chad
Canada	Botswana	Egypt	Comoros
Chile	Brazil	El Salvador	Democratic Republic of the Congo
Croatia	Bulgaria	Federated States of Micronesia	Eritrea
Cyprus	China	Georgia	Ethiopia
Czech Republic	Colombia	Ghana	Guinea
Denmark	Costa Rica	Guatemala	Guinea-Bissau
Equatorial Guinea	Cuba	Guyana	Haiti
Estonia	Dominica	Honduras	Kenya
Finland	Dominican Republic	India	Kyrgyzstan
France	Ecuador	Indonesia	Liberia
Germany	Fiji	Kiribati	Madagascar
Greece	Gabon	Laos	Malawi
Iceland	Grenada	Lesotho	Mali
Ireland	Hungary	Mauritania	Mozambique
Israel	Iran	Moldova	Myanmar
Italy	Iraq	Mongolia	Nepal
Japan	Jamaica	Morocco	Niger
Kuwait	Jordan	Nicaragua	Rwanda
Latvia	Kazakhstan	Nigeria	Sierra Leone
Lithuania	Lebanon	Pakistan	Somalia
Luxembourg	Libya	Papua New Guinea	South Sudan
Malta	Macedonia	Paraguay	Tajikistan
Netherlands	Malaysia	Philippines	Tanzania
New Zealand	Maldives	Samoa	The Gambia
Norway	Marshall Islands	Sao Tome and Principe	Togo
Oman	Mauritius	Senegal	Uganda
Poland	Mexico	Solomon Islands	
Portugal	Montenegro	Sri Lanka	
Qatar	Namibia	Sudan	
Russia	Panama	Swaziland	

High-income	Upper-middle	Lower-middle	Low-income
Saudi Arabia	Peru	Syria	
Singapore	Romania	Timor-Leste	
Slovakia	Saint Lucia	Ukraine	
Slovenia	Vincent and the Grenadines	Uzbekistan	
South Korea	Serbia	Vanuatu	
Spain	Seychelles	Vietnam	
Sweden	South Africa	Yemen	
Switzerland	Suriname	Zambia	
The Bahamas	Thailand		
Trinidad and Tobago	Tonga		
United Arab Emirates	Tunisia		
United Kingdom	Turkey		
United States	Turkmenistan		
Uruguay	Venezuela		

Table 9. Classifications of countries by Global Burden of Disease geographical regions

High-income	Central Europe, Eastern Europe, and Central Asia	Sub-Saharan Africa	North Africa and Middle East	South Asia	Southeast Asia, East Asia, and Oceania	Latin America and Caribbean
Andorra	Albania	Angola	Afghanistan	Bangla desh	Cambodia	Antigua and Barbuda
Argentina	Armenia	Benin	Algeria	Bhutan	China	Barbados
Australia	Azerbaijan	Botswana	Bahrain	India	Federated States of Micronesia	Belize
Austria	Belarus	Burkina Faso	Egypt	Nepal	Fiji	Bolivia
Belgium	Bosnia and Herzegovina	Burundi	Iran	Pakista n	Indonesia	Brazil
Brunei	Bulgaria	Cameroon	Iraq		Kiribati	Colombia
Canada	Croatia	Cape Verde	Jordan		Laos	Costa Rica
Chile	Czech Republic	Central African Republic	Kuwait		Malaysia	Cuba
Cyprus	Estonia	Chad	Lebanon		Maldives	Dominica
Denmark	Georgia	Comoros	Libya		Marshall Islands	Dominican Republic
Finland	Hungary	Congo	Morocco		Mauritius	Ecuador
France	Kazakhstan	Cote d'Ivoire	Oman		Myanmar	El Salvador
Germany	Kyrgyzstan	Democratic Republic of the Congo	Qatar		Papua New Guinea	Grenada
Greece	Latvia	Djibouti	Saudi Arabia		Philippines	Guatemala
Iceland	Lithuania	Equatorial Guinea	Sudan		Samoa	Guyana
Ireland	Macedonia	Eritrea	Syria		Seychelles	Haiti
Israel	Moldova	Ethiopia	Tunisia		Solomon Islands	Honduras
Italy	Mongolia	Gabon	Turkey		Sri Lanka	Jamaica
Japan	Montenegro	Ghana	United Arab Emirates		Thailand	Mexico
Luxembourg	Poland	Guinea	Yemen		Timor-Leste	Nicaragua
Malta	Romania	Guinea-Bissau			Tonga	Panama
Netherlands	Russia	Kenya			Vanuatu	Paraguay
New Zealand	Serbia	Lesotho			Vietnam	Peru
Norway	Slovakia	Liberia				Saint Lucia
Portugal	Slovenia	Madagascar				Saint Vincent and the Grenadines
Singapore	Tajikistan	Malawi				Suriname
South Korea	Turkmenistan	Mali				The Bahamas
Spain	Ukraine	Mauritania				Trinidad and Tobago
Sweden	Uzbekistan	Mozambique				Venezuela
Switzerland		Namibia				
United Kingdom		Niger				
United States		Nigeria				

High-income	Central Europe, Eastern Europe, and Central Asia	Sub-Saharan Africa	North Africa and Middle East	South Asia	Southeast Asia, East Asia, and Oceania	Latin America and Caribbean
Uruguay		Rwanda				
		Sao Tome and Principe				
		Senegal				
		Sierra Leone				
		Somalia				
		South Africa				
		South Sudan				
		Swaziland				
		Tanzania				
		The Gambia				
		Togo				
		Uganda				
		Zambia				

Table 10. Observed health spending in 2014 and expected health spending in 2030

	2014 total health spending		2030 expected health spending		2030 expected health spending by source			
	Per capita ($)	Per GDP (%)	Per capita ($)	Per GDP(%)	Government as a share of total (%)	Prepaid private as a share of total (%)	Out-of-pocket as a share of total (%)	Development assistance as a share of total (%)
Global	1279	8.3	1983 (1793, 2199)	8.2 (7.4, 9.1)	62.0 (57.9, 66.0)	15.1 (13.3, 17.2)	22.4 (19.7, 25.3)	0.5 (0.3, 0.7)
High-income	5221	11.7	7334 (6786, 7815)	12.5 (11.5, 13.3)	64.2 (61.1, 66.7)	22.7 (20.8, 25.2)	13.1 (12.0, 14.4)	0.0 (0.0, 0.0)
Upper-middle-income	914	5.9	2072 (1698, 2583)	6.4 (5.2, 7.9)	66.0 (58.4, 73.8)	7.2 (5.5, 9.2)	26.7 (20.1, 33.3)	0.1 (0.0, 0.2)
Lower-middle-income	267	4.3	525 (485, 582)	4.7 (4.3, 5.1)	41.3 (36.7, 46.9)	2.9 (2.5, 3.2)	54.1 (48.8, 58.4)	1.8 (1.0, 2.8)
Lower-income	120	7.3	154 (133, 181)	6.6 (5.8, 7.8)	25.6 (20.8, 30.6)	14.0 (11.4, 16.7)	30.5 (25.5, 35.4)	29.9 (20.3, 40.6)
Central Europe, Eastern Europe, and Central Asia	1364	6.7	1877 (1766, 2018)	6.9 (6.5, 7.4)	60.8 (56.8, 63.5)	3.1 (2.7, 3.6)	35.9 (33.2, 40.0)	0.2 (0.1, 0.4)
High-income	5460	12.3	7643 (7076, 8146)	13.1 (12.1, 14.0)	63.5 (60.3, 66.0)	23.4 (21.5, 26.0)	13.1 (11.9, 14.4)	0.0 (0.0, 0.0)
Latin America and Caribbean	1082	7.3	1534 (1350, 1745)	8.2 (7.2, 9.3)	56.0 (50.2, 61.6)	15.4 (13.0, 18.6)	28.2 (24.4, 32.5)	0.4 (0.1, 0.7)
North Africa and Middle East	870	5.2	1246 (1137, 1416)	5.8 (5.3, 6.6)	62.3 (58.4, 67.1)	4.1 (3.5, 4.7)	33.0 (28.7, 36.6)	0.7 (0.4, 1.1)
South Asia	223	4.2	529 (467, 619)	4.8 (4.2, 5.6)	38.5 (31.4, 47.8)	2.2 (1.9, 2.6)	58.5 (49.7, 65.3)	0.8 (0.4, 1.3)
Southeast Asia, East Asia, and Oceania	588	4.8	1867 (1436, 2471)	5.6 (4.3, 7.4)	68.5 (58.6, 78.0)	5.0 (3.5, 7.0)	26.3 (17.9, 35.5)	0.1 (0.1, 0.3)
Sub-Saharan Africa	218	5.9	259 (238, 286)	5.6 (5.2, 6.2)	36.9 (32.9, 41.0)	16.8 (14.9, 18.7)	31.0 (27.6, 34.4)	15.3 (9.5, 22.2)
Afghanistan	159	9.7	201 (161, 268)	10.2 (8.1, 13.6)	16.2 (9.5, 32.5)	0.5 (0.4, 0.7)	51.3 (37.6, 62.8)	32.0 (20.9, 47.9)
Albania	642	5.9	1202 (1022, 1424)	6.6 (5.6, 7.8)	56.7 (50.0, 64.6)	0.8 (0.6, 1.0)	41.8 (34.2, 48.4)	0.7 (0.0, 1.7)
Algeria	1004	7.2	1567 (1248, 2146)	9.1 (7.2, 12.4)	78.9 (72.7, 85.5)	0.6 (0.4, 0.9)	20.4 (14.0, 26.6)	0.0 (0.0, 0.1)
Andorra	5723	8.1	7230 (5789, 8606)	8.6 (6.9, 10.3)	78.7 (73.5, 82.8)	6.2 (4.9, 8.0)	15.1 (12.0, 18.9)	0.0 (0.0, 0.0)
Angola	228	3	256 (169, 321)	2.5 (1.7, 3.1)	64.1 (46.6, 73.4)	2.1 (1.5, 3.2)	30.7 (22.1, 46.3)	3.1 (1.5, 5.9)
Antigua and Barbuda	1213	5.5	2165 (1727, 2767)	7.4 (5.9, 9.4)	74.9 (68.3, 81.1)	7.0 (5.1, 9.1)	18.2 (13.4, 23.5)	0.0 (0.0, 0.0)

	2014 total health spending		2030 expected health spending		2030 expected health spending by source			
	Per capita ($)	Per GDP (%)	Per capita ($)	Per GDP(%)	Government as a share of total (%)	Prepaid private as a share of total (%)	Out-of-pocket as a share of total (%)	Development assistance as a share of total (%)
Argentina	1322	4.8	2177 (1769, 2985)	5.7 (4.6, 7.8)	62.3 (54.0, 73.5)	11.7 (8.1, 14.9)	26.0 (17.9, 33.1)	0.0 (0.0, 0.0)
Armenia	395	4.5	674 (549, 907)	4.9 (4.0, 6.7)	48.0 (38.3, 62.2)	3.2 (2.2, 4.4)	46.4 (33.5, 55.7)	2.4 (0.7, 5.4)
Australia	4032	9	5606 (5186, 6165)	9.7 (9.0, 10.7)	71.5 (68.1, 74.7)	9.8 (8.5, 11.5)	18.7 (16.1, 22.0)	0.0 (0.0, 0.0)
Austria	5471	11.2	7416 (6788, 8143)	11.6 (10.6, 12.7)	78.8 (76.3, 81.2)	5.7 (4.9, 7.2)	15.5 (13.5, 17.5)	0.0 (0.0, 0.0)
Azerbaijan	1030	5.9	1734 (1524, 1978)	6.3 (5.5, 7.2)	24.2 (18.6, 32.1)	4.0 (3.3, 5.1)	71.7 (64.0, 77.4)	0.0 (0.0, 0.5)
Bahrain	2258	4.8	3289 (2738, 4136)	5.3 (4.4, 6.7)	70.7 (64.6, 77.3)	10.1 (7.6, 13.1)	19.2 (14.6, 24.0)	0.0 (0.0, 0.0)
Bangladesh	92	2.9	173 (149, 198)	2.8 (2.4, 3.2)	26.9 (21.4, 34.3)	1.8 (1.4, 2.2)	65.3 (57.6, 71.5)	6.1 (2.6, 10.9)
Barbados	1116	7.5	1641 (1412, 1926)	8.7 (7.5, 10.2)	66.9 (60.8, 72.8)	6.3 (5.0, 8.0)	26.8 (21.6, 32.6)	0.0 (0.0, 0.0)
Belarus	1093	5.6	1825 (1432, 2308)	7.0 (5.5, 8.9)	67.5 (58.2, 76.4)	0.7 (0.5, 1.1)	31.7 (22.9, 40.9)	0.0 (0.0, 0.1)
Belgium	4751	10.6	6437 (5759, 7278)	11.2 (10.0, 12.7)	79.2 (76.5, 82.1)	4.2 (3.4, 5.0)	16.6 (14.2, 18.9)	0.0 (0.0, 0.0)
Belize	503	5.8	678 (593, 776)	6.3 (5.5, 7.2)	66.7 (61.6, 71.5)	9.7 (8.0, 11.9)	21.2 (17.8, 24.8)	2.5 (1.1, 4.4)
Benin	105	5.1	169 (134, 221)	6.2 (4.9, 8.1)	49.9 (38.6, 62.6)	1.3 (0.7, 1.9)	29.3 (21.6, 36.9)	19.4 (10.9, 30.0)
Bhutan	279	3.6	563 (397, 774)	3.5 (2.5, 4.8)	73.3 (62.4, 82.1)	1.5 (1.0, 2.2)	23.6 (15.5, 33.7)	1.6 (0.5, 3.2)
Bolivia	404	6.3	673 (565, 814)	7.3 (6.1, 8.8)	75.3 (70.1, 80.4)	2.9 (2.1, 4.2)	19.9 (15.6, 24.6)	1.8 (0.9, 3.1)
Bosnia and Herzegovina	992	9.5	1734 (1331, 2104)	10.4 (8.0, 12.6)	75.4 (67.9, 81.2)	0.5 (0.4, 0.6)	23.2 (17.6, 30.3)	0.9 (0.0, 2.3)
Botswana	903	5.5	1395 (1168, 1723)	6.3 (5.2, 7.7)	58.2 (49.4, 67.2)	34.9 (27.5, 42.2)	4.5 (3.4, 5.7)	2.3 (0.0, 10.0)
Brazil	1357	8.3	1994 (1657, 2402)	10.0 (8.3, 12.1)	51.7 (42.5, 60.4)	26.6 (21.3, 32.9)	21.6 (17.1, 27.2)	0.0 (0.0, 0.1)
Brunei	1811	2.6	2254 (1741, 3135)	3.5 (2.7, 4.8)	93.7 (90.8, 95.9)	1.5 (1.0, 2.0)	4.8 (2.9, 7.5)	0.0 (0.0, 0.0)
Bulgaria	1490	8.4	2659 (2116, 3624)	9.7 (7.7, 13.2)	58.3 (48.4, 70.3)	0.7 (0.5, 1.2)	41.0 (29.2, 50.8)	0.0 (0.0, 0.0)
Burkina Faso	83	5	108 (93, 127)	5.0 (4.3, 5.9)	39.9 (32.4, 46.8)	1.0 (0.8, 1.4)	38.3 (31.4, 45.3)	20.8 (12.4, 31.4)
Burundi	65	8.3	85 (62, 120)	9.6 (7.0, 13.6)	30.9 (19.3, 43.0)	0.8 (0.5, 1.2)	17.3 (11.4, 23.9)	51.0 (35.6, 66.9)
Cambodia	209	6.4	397 (352, 448)	6.0 (5.3, 6.7)	20.9 (14.5, 27.0)	0.9 (0.8, 1.2)	68.3 (60.9, 75.5)	9.9 (4.6, 16.8)
Cameroon	116	4	156 (135, 179)	4.1 (3.5, 4.7)	21.8 (16.2, 29.5)	3.4 (2.8, 4.3)	66.1 (58.4, 72.8)	8.6 (4.7, 14.0)
Canada	4576	10.3	5926 (5389, 6601)	10.7 (9.7, 11.9)	73.9 (70.9, 77.0)	13.2 (11.4, 15.0)	12.9 (11.0, 15.0)	0.0 (0.0, 0.0)

	2014 total health spending		2030 expected health spending		2030 expected health spending by source			
	Per capita ($)	Per GDP (%)	Per capita ($)	Per GDP(%)	Government as a share of total (%)	Prepaid private as a share of total (%)	Out-of-pocket as a share of total (%)	Development assistance as a share of total (%)
Cape Verde	318	4.8	529 (412, 686)	4.8 (3.8, 6.3)	65.2 (54.9, 74.4)	1.1 (0.8, 1.6)	22.3 (16.6, 28.7)	11.4 (5.3, 19.5)
Central African Republic	35	5.7	46 (29, 77)	9.4 (6.0, 15.8)	11.9 (5.4, 18.6)	0.6 (0.3, 0.9)	22.7 (12.4, 34.7)	64.8 (47.9, 80.6)
Chad	89	3.8	111 (74, 150)	3.9 (2.6, 5.3)	50.2 (29.8, 65.1)	1.5 (1.0, 2.3)	37.0 (25.4, 53.1)	11.3 (5.5, 20.3)
Chile	1780	7.8	3217 (2622, 3793)	8.8 (7.1, 10.3)	54.3 (44.4, 61.7)	17.0 (13.9, 21.0)	28.8 (23.7, 35.4)	0.0 (0.0, 0.0)
China	697	5.1	2493 (1851, 3402)	6.0 (4.5, 8.2)	70.4 (59.5, 80.3)	4.9 (3.3, 7.0)	24.7 (15.8, 34.8)	0.0 (0.0, 0.0)
Colombia	975	7.2	1620 (1168, 2206)	7.8 (5.7, 10.7)	75.6 (66.5, 82.9)	10.4 (7.2, 14.7)	13.0 (8.9, 18.2)	1.0 (0.0, 3.3)
Comoros	111	7.1	121 (101, 148)	8.6 (7.1, 10.5)	24.8 (17.4, 36.1)	18.2 (14.6, 22.1)	40.5 (31.7, 49.2)	16.5 (8.9, 27.4)
Congo	312	5.2	424 (336, 543)	6.1 (4.8, 7.8)	82.7 (77.5, 87.3)	0.8 (0.6, 1.1)	15.0 (11.0, 20.0)	1.4 (0.6, 2.5)
Costa Rica	1418	9.3	2142 (1628, 2636)	9.0 (6.8, 11.1)	72.5 (63.9, 78.5)	1.8 (1.4, 2.4)	25.7 (20.0, 33.7)	0.0 (0.0, 0.0)
Cote d'Ivoire	179	5.3	242 (214, 275)	5.4 (4.8, 6.1)	28.1 (22.5, 34.8)	8.3 (6.7, 10.1)	51.8 (45.5, 57.8)	11.7 (6.5, 18.8)
Croatia	1734	7.8	2263 (2064, 2445)	7.8 (7.1, 8.5)	81.4 (78.5, 83.7)	7.4 (6.4, 9.1)	11.1 (9.3, 13.6)	0.0 (0.0, 0.0)
Cuba	1706	11.1	2326 (1635, 3134)	11.3 (7.9, 15.2)	95.0 (92.8, 96.5)	0.5 (0.3, 0.6)	4.4 (3.1, 6.4)	0.1 (0.0, 0.3)
Cyprus	2019	7.2	2864 (2520, 3352)	8.0 (7.0, 9.4)	51.4 (45.3, 58.8)	4.4 (3.5, 5.6)	44.2 (37.3, 49.9)	0.0 (0.0, 0.0)
Czech Republic	2384	7.4	3146 (2753, 3657)	7.1 (6.3, 8.3)	84.6 (81.8, 87.2)	0.9 (0.7, 1.2)	14.5 (12.0, 17.3)	0.0 (0.0, 0.0)
Democratic Republic of the Congo	46	4.5	67 (52, 86)	5.1 (3.9, 6.6)	30.6 (20.8, 43.2)	1.0 (0.7, 1.5)	36.9 (26.2, 47.2)	31.5 (19.1, 46.4)
Denmark	5075	10.8	6251 (5488, 6890)	10.7 (9.4, 11.8)	84.4 (81.9, 86.5)	2.1 (1.8, 2.7)	13.4 (11.5, 15.8)	0.0 (0.0, 0.0)
Djibouti	357	10.9	613 (486, 838)	13.9 (11.0, 18.9)	65.2 (56.2, 75.9)	0.4 (0.3, 0.5)	29.2 (20.1, 37.2)	5.2 (2.6, 8.8)
Dominica	599	5.5	859 (740, 1012)	6.2 (5.3, 7.3)	71.5 (65.9, 76.8)	2.7 (2.1, 3.5)	25.7 (20.8, 31.2)	0.0 (0.0, 0.1)
Dominican Republic	601	4.4	1211 (930, 1567)	4.9 (3.7, 6.3)	72.5 (63.8, 79.8)	10.9 (7.9, 14.8)	16.3 (11.3, 22.3)	0.3 (0.0, 2.4)
Ecuador	1071	9.2	1491 (1261, 1758)	10.2 (8.6, 12.0)	50.3 (41.9, 58.5)	2.1 (1.6, 2.7)	47.3 (39.3, 55.4)	0.3 (0.2, 0.6)
Egypt	581	5.4	903 (820, 1016)	5.5 (4.9, 6.1)	39.0 (34.4, 45.6)	1.6 (1.3, 2.1)	59.3 (52.8, 63.8)	0.1 (0.1, 0.2)
El Salvador	567	6.8	1018 (826, 1354)	7.7 (6.3, 10.3)	70.8 (63.7, 79.1)	4.9 (3.2, 6.6)	23.3 (16.5, 29.9)	0.9 (0.3, 1.9)
Equatorial Guinea	1411	3.7	1435 (1163, 1792)	3.6 (2.9, 4.5)	77.2 (69.2, 83.0)	1.4 (1.1, 1.8)	21.3 (15.8, 29.4)	0.0 (0.0, 0.0)
Eritrea	59	5.1	68 (53, 88)	4.8 (3.7, 6.2)	21.9 (13.6, 30.4)	1.1 (0.8, 1.5)	37.4 (27.7, 47.2)	39.6 (25.9, 54.8)

	2014 total health spending		2030 expected health spending		2030 expected health spending by source			
	Per capita ($)	Per GDP (%)	Per capita ($)	Per GDP(%)	Government as a share of total (%)	Prepaid private as a share of total (%)	Out-of-pocket as a share of total (%)	Development assistance as a share of total (%)
Estonia	1830	6.4	3274 (2683, 4230)	7.9 (6.5, 10.2)	80.7 (75.1, 85.9)	0.6 (0.5, 0.8)	18.7 (13.6, 24.2)	0.0 (0.0, 0.0)
Ethiopia	85	5.5	149 (115, 197)	4.9 (3.8, 6.5)	33.6 (23.9, 43.3)	1.1 (0.8, 1.5)	30.5 (21.7, 39.5)	34.9 (19.6, 51.3)
Federated States of Micronesia	490	16.1	608 (359, 972)	17.2 (10.1, 27.5)	8.4 (3.7, 15.8)	0.3 (0.2, 0.5)	7.8 (4.4, 12.6)	83.5 (72.8, 91.1)
Fiji	399	4.5	558 (503, 614)	4.6 (4.1, 5.0)	64.1 (59.0, 68.5)	8.1 (6.8, 9.7)	22.9 (19.3, 27.8)	4.9 (2.4, 8.7)
Finland	3935	9.3	5061 (4654, 5562)	9.5 (8.8, 10.5)	78.4 (76.0, 80.9)	3.2 (2.7, 3.8)	18.4 (16.1, 20.7)	0.0 (0.0, 0.0)
France	4589	11.3	5963 (5487, 6689)	11.6 (10.6, 13.0)	79.5 (76.8, 82.2)	14.3 (12.2, 16.7)	6.2 (5.2, 7.3)	0.0 (0.0, 0.0)
Gabon	612	3.4	985 (799, 1248)	4.7 (3.9, 6.0)	77.5 (71.6, 83.0)	6.1 (4.5, 8.3)	15.7 (11.5, 20.5)	0.7 (0.0, 2.0)
Georgia	700	7.3	1236 (1026, 1427)	8.9 (7.4, 10.3)	20.9 (15.6, 29.0)	31.5 (21.9, 38.4)	45.9 (38.7, 54.6)	1.8 (0.6, 3.7)
Germany	5356	11.2	7612 (6630, 8575)	12.0 (10.5, 13.5)	78.8 (75.4, 81.6)	8.6 (7.3, 10.1)	12.6 (10.6, 14.9)	0.0 (0.0, 0.0)
Ghana	146	3.5	218 (177, 264)	3.7 (3.0, 4.4)	59.3 (49.9, 67.5)	3.0 (2.3, 4.1)	26.0 (20.5, 32.6)	11.8 (6.4, 18.7)
Greece	2170	8.1	2833 (2484, 3383)	8.3 (7.3, 9.9)	62.7 (57.5, 68.9)	3.8 (3.0, 5.0)	33.5 (27.9, 38.4)	0.0 (0.0, 0.0)
Grenada	737	6.1	1096 (967, 1259)	6.3 (5.6, 7.2)	49.2 (43.6, 56.4)	2.4 (2.0, 2.9)	48.3 (41.2, 53.8)	0.1 (0.0, 0.3)
Guatemala	466	6.2	594 (540, 648)	6.2 (5.6, 6.7)	37.1 (32.3, 41.8)	8.6 (7.5, 10.0)	51.7 (47.1, 56.3)	2.5 (1.3, 4.2)
Guinea	101	7.4	127 (100, 163)	7.9 (6.2, 10.1)	34.8 (24.1, 46.1)	1.0 (0.5, 1.5)	33.8 (25.6, 42.7)	30.4 (18.3, 45.2)
Guinea-Bissau	77	5.3	98 (75, 131)	5.7 (4.4, 7.6)	3.2 (1.8, 6.9)	0.9 (0.6, 1.2)	49.0 (35.6, 62.8)	46.9 (32.2, 61.3)
Guyana	438	5.4	685 (589, 812)	5.8 (5.0, 6.9)	56.6 (49.6, 64.1)	2.9 (2.3, 3.7)	35.6 (29.2, 42.2)	4.9 (2.3, 8.7)
Haiti	154	8.9	205 (164, 262)	9.4 (7.5, 12.0)	0.7 (0.4, 1.5)	33.9 (25.8, 42.1)	27.8 (21.0, 34.9)	37.5 (24.1, 51.4)
Honduras	420	8.8	568 (513, 654)	8.8 (8.0, 10.1)	49.5 (44.5, 56.4)	5.1 (3.9, 6.6)	41.9 (36.0, 46.7)	3.5 (1.4, 6.1)
Hungary	1855	7.2	2706 (2522, 3028)	7.3 (6.8, 8.2)	68.6 (64.9, 72.4)	4.1 (3.5, 4.8)	27.2 (23.8, 31.1)	0.0 (0.0, 0.0)
Iceland	3959	8.7	5491 (4824, 6314)	9.2 (8.1, 10.6)	82.6 (79.7, 85.4)	0.5 (0.4, 0.6)	16.9 (14.1, 19.7)	0.0 (0.0, 0.0)
India	253	4.5	629 (550, 747)	5.1 (4.4, 6.0)	38.7 (31.0, 48.7)	2.0 (1.7, 2.4)	59.0 (49.3, 66.5)	0.3 (0.1, 0.5)
Indonesia	265	2.5	509 (443, 588)	2.6 (2.3, 3.0)	45.5 (38.6, 53.1)	2.9 (2.3, 3.7)	51.2 (43.8, 57.9)	0.4 (0.0, 1.0)
Iran	1073	6.5	1558 (1263, 1874)	7.3 (5.9, 8.8)	44.9 (33.5, 54.2)	5.8 (4.5, 7.7)	49.2 (40.5, 60.1)	0.0 (0.0, 0.0)
Iraq	828	5.7	1018 (787, 1401)	5.9 (4.6, 8.2)	60.4 (49.6, 72.2)	3.3 (2.2, 4.4)	36.0 (25.1, 46.3)	0.3 (0.0, 0.6)

	2014 total health spending		2030 expected health spending		2030 expected health spending by source			
	Per capita ($)	Per GDP (%)	Per capita ($)	Per GDP(%)	Government as a share of total (%)	Prepaid private as a share of total (%)	Out-of-pocket as a share of total (%)	Development assistance as a share of total (%)
Ireland	4006	7.6	5989 (4758, 7222)	7.8 (6.2, 9.4)	66.6 (58.2, 73.0)	15.8 (12.5, 20.4)	17.6 (13.8, 22.5)	0.0 (0.0, 0.0)
Israel	2722	7.7	3747 (3312, 4249)	8.4 (7.4, 9.5)	61.5 (56.4, 66.6)	11.8 (10.0, 14.1)	26.7 (22.7, 30.8)	0.0 (0.0, 0.0)
Italy	3311	9	4154 (3805, 4502)	8.8 (8.1, 9.6)	77.1 (73.0, 80.6)	0.9 (0.8, 1.2)	22.0 (18.4, 26.1)	0.0 (0.0, 0.0)
Jamaica	477	5.4	773 (650, 955)	7.0 (5.9, 8.6)	59.9 (52.7, 68.0)	16.3 (12.7, 20.0)	22.2 (17.5, 26.8)	1.6 (0.7, 3.0)
Japan	3816	10.2	5729 (4452, 6820)	11.7 (9.1, 13.9)	85.2 (80.9, 88.2)	2.4 (1.9, 3.3)	12.4 (9.8, 16.1)	0.0 (0.0, 0.0)
Jordan	839	7.4	1097 (982, 1226)	7.4 (6.6, 8.3)	66.6 (61.6, 71.1)	9.0 (7.6, 10.9)	20.6 (16.9, 25.2)	3.7 (1.9, 6.3)
Kazakhstan	1143	4.3	1545 (1343, 1817)	4.2 (3.6, 4.9)	54.5 (48.3, 61.7)	1.2 (0.9, 1.4)	44.3 (37.3, 50.5)	0.0 (0.0, 0.0)
Kenya	197	6.4	237 (194, 302)	5.9 (4.9, 7.6)	36.8 (28.3, 50.0)	4.9 (3.7, 6.0)	25.7 (19.6, 31.9)	32.6 (20.6, 45.3)
Kiribati	168	9.6	184 (81, 281)	9.9 (4.4, 15.2)	71.9 (43.5, 86.7)	0.6 (0.3, 1.2)	3.0 (1.6, 6.1)	24.6 (10.7, 50.8)
Kuwait	2075	3	3208 (2309, 4950)	4.2 (3.0, 6.5)	88.9 (83.9, 93.4)	1.3 (0.8, 1.7)	9.8 (5.8, 14.6)	0.0 (0.0, 0.0)
Kyrgyzstan	236	6.9	315 (272, 369)	7.4 (6.4, 8.6)	51.2 (43.7, 58.8)	1.3 (1.0, 1.7)	35.6 (29.3, 42.0)	11.9 (6.6, 19.3)
Laos	113	2	186 (144, 234)	1.5 (1.2, 1.9)	32.3 (22.1, 43.9)	3.0 (2.1, 4.2)	41.3 (30.3, 52.6)	23.5 (12.3, 37.0)
Latvia	1427	5.9	2036 (1833, 2247)	5.8 (5.2, 6.4)	62.4 (57.0, 67.4)	1.9 (1.6, 2.8)	35.7 (30.7, 41.1)	0.0 (0.0, 0.0)
Lebanon	1060	6.4	1484 (1222, 1825)	6.3 (5.2, 7.8)	49.2 (39.7, 59.8)	16.0 (12.5, 20.1)	34.4 (25.8, 42.9)	0.3 (0.0, 1.5)
Lesotho	319	11.6	521 (371, 667)	12.3 (8.8, 15.8)	66.7 (53.0, 76.7)	0.4 (0.3, 0.7)	13.4 (9.7, 18.9)	19.5 (10.3, 31.7)
Liberia	345	39.3	287 (257, 333)	27.1 (24.3, 31.4)	0.7 (0.2, 2.0)	0.2 (0.2, 0.3)	11.2 (9.1, 13.4)	87.9 (85.4, 90.2)
Libya	751	5	781 (534, 1147)	6.8 (4.7, 10.0)	79.2 (66.3, 88.0)	0.8 (0.5, 1.1)	19.9 (11.4, 32.8)	0.1 (0.0, 0.2)
Lithuania	1830	6.5	2904 (2579, 3381)	6.6 (5.9, 7.7)	66.9 (62.1, 72.0)	0.8 (0.7, 1.1)	32.3 (27.2, 37.0)	0.0 (0.0, 0.0)
Luxembourg	7105	6.9	10593 (9569, 12306)	7.4 (6.7, 8.6)	84.6 (82.2, 87.1)	5.5 (4.5, 7.1)	9.9 (8.0, 11.6)	0.0 (0.0, 0.0)
Macedonia	887	6.5	1368 (1240, 1504)	6.8 (6.2, 7.5)	61.7 (56.7, 66.7)	0.7 (0.6, 0.9)	37.4 (32.4, 42.4)	0.1 (0.0, 0.4)
Madagascar	52	3.7	65 (54, 80)	4.2 (3.5, 5.2)	38.2 (30.2, 45.7)	1.3 (0.9, 1.7)	30.6 (23.9, 37.6)	29.9 (18.6, 43.2)
Malawi	148	12.9	184 (148, 233)	13.4 (10.8, 17.0)	43.1 (33.0, 52.8)	12.5 (9.3, 16.0)	8.9 (6.7, 11.5)	35.5 (23.1, 49.3)
Malaysia	1047	4.1	1783 (1576, 2102)	4.1 (3.6, 4.8)	55.3 (50.0, 62.7)	9.3 (7.5, 11.4)	35.4 (29.0, 40.4)	0.0 (0.0, 0.0)
Maldives	1980	13.5	3623 (2656, 5154)	13.1 (9.6, 18.6)	77.7 (69.8, 85.1)	2.2 (1.5, 3.2)	20.0 (13.3, 27.4)	0.0 (0.0, 0.0)

	2014 total health spending		2030 expected health spending		2030 expected health spending by source			
	Per capita ($)	Per GDP (%)	Per capita ($)	Per GDP(%)	Government as a share of total (%)	Prepaid private as a share of total (%)	Out-of-pocket as a share of total (%)	Development assistance as a share of total (%)
Mali	162	7.4	229 (193, 275)	7.3 (6.2, 8.8)	31.4 (23.3, 41.5)	9.9 (6.9, 13.8)	41.9 (34.0, 49.6)	16.8 (9.7, 26.4)
Malta	3058	9.7	5997 (5097, 7328)	12.1 (10.3, 14.8)	74.9 (69.8, 80.4)	1.8 (1.4, 2.3)	23.3 (18.1, 28.2)	0.0 (0.0, 0.0)
Marshall Islands	599	17.2	679 (495, 851)	15.7 (11.5, 19.7)	64.3 (50.3, 74.6)	2.4 (1.7, 3.4)	12.7 (9.6, 17.4)	20.7 (10.9, 34.2)
Mauritania	153	3.7	204 (171, 251)	4.0 (3.3, 4.9)	50.0 (41.6, 60.1)	1.5 (1.1, 1.9)	41.3 (32.6, 49.4)	7.1 (3.8, 11.8)
Mauritius	880	4.6	1942 (1454, 2542)	5.5 (4.1, 7.2)	60.1 (47.5, 70.8)	1.0 (0.7, 1.5)	38.9 (28.4, 51.3)	0.0 (0.0, 0.0)
Mexico	1088	6.3	1413 (1217, 1611)	6.7 (5.8, 7.7)	53.3 (45.8, 59.2)	4.6 (3.7, 5.8)	42.0 (36.5, 49.3)	0.0 (0.0, 0.1)
Moldova	527	10.3	711 (620, 822)	10.5 (9.1, 12.1)	46.5 (39.3, 53.6)	9.1 (7.4, 11.6)	39.8 (33.4, 46.8)	4.7 (1.0, 10.8)
Mongolia	575	4.7	1078 (837, 1406)	4.7 (3.7, 6.2)	55.2 (43.7, 67.3)	1.2 (0.8, 1.6)	42.6 (30.8, 53.9)	1.0 (0.0, 5.1)
Montenegro	1015	6.6	1613 (1373, 2074)	7.5 (6.4, 9.6)	59.4 (52.3, 68.9)	2.4 (1.7, 3.4)	38.1 (29.1, 44.9)	0.1 (0.0, 0.7)
Morocco	505	5.9	765 (700, 833)	5.6 (5.2, 6.1)	30.5 (26.3, 34.5)	8.5 (7.2, 10.1)	60.5 (56.2, 64.7)	0.6 (0.3, 1.1)
Mozambique	92	7.8	96 (62, 142)	5.3 (3.4, 7.8)	11.4 (4.9, 22.1)	1.0 (0.6, 1.5)	15.0 (9.5, 22.3)	72.6 (58.5, 83.4)
Myanmar	121	2.5	394 (273, 613)	3.3 (2.3, 5.1)	58.8 (43.1, 75.5)	1.7 (1.0, 2.6)	32.1 (18.7, 45.4)	7.4 (2.5, 14.9)
Namibia	936	9.3	1437 (1277, 1692)	9.8 (8.7, 11.5)	57.7 (52.2, 64.7)	29.7 (24.4, 34.2)	6.4 (5.2, 7.9)	6.2 (3.4, 10.2)
Nepal	138	5.8	226 (197, 259)	5.6 (4.9, 6.5)	35.0 (29.5, 41.8)	6.2 (4.8, 8.1)	47.5 (40.6, 53.5)	11.3 (4.3, 19.4)
Netherlands	5234	10.7	7799 (6370, 9036)	12.2 (10.0, 14.2)	89.3 (86.6, 91.2)	6.0 (4.8, 7.7)	4.7 (3.7, 6.2)	0.0 (0.0, 0.0)
New Zealand	4050	11	5496 (4595, 6193)	11.4 (9.5, 12.9)	82.5 (78.8, 85.1)	7.1 (5.9, 8.8)	10.4 (8.6, 12.8)	0.0 (0.0, 0.0)
Nicaragua	450	9.1	652 (518, 753)	9.3 (7.4, 10.7)	53.8 (42.5, 60.9)	3.9 (3.0, 5.3)	36.7 (30.5, 46.1)	5.6 (2.2, 9.6)
Niger	66	6.7	81 (66, 101)	6.8 (5.6, 8.5)	35.9 (26.3, 48.1)	0.8 (0.6, 1.1)	47.7 (37.3, 57.2)	15.6 (8.2, 27.2)
Nigeria	225	3.7	287 (245, 343)	3.8 (3.2, 4.5)	23.4 (15.1, 34.4)	1.4 (1.1, 1.8)	68.2 (58.1, 76.5)	6.9 (3.7, 11.5)
Norway	6537	10	9758 (8486, 11459)	11.6 (10.1, 13.6)	85.6 (83.1, 88.1)	3.2 (2.6, 4.1)	11.2 (9.2, 13.3)	0.0 (0.0, 0.0)
Oman	1467	3.5	2507 (1908, 4034)	4.5 (3.4, 7.2)	93.3 (90.7, 96.1)	1.9 (1.1, 2.7)	4.8 (2.7, 7.0)	0.0 (0.0, 0.0)
Pakistan	132	2.7	212 (184, 250)	2.9 (2.6, 3.5)	41.7 (34.7, 51.1)	5.6 (4.4, 7.1)	47.8 (39.6, 54.6)	4.9 (2.6, 8.1)
Panama	1743	8	3094 (2659, 3563)	8.0 (6.9, 9.2)	73.9 (69.1, 78.7)	5.2 (4.2, 6.5)	20.9 (16.6, 25.2)	0.0 (0.0, 0.0)
Papua New Guinea	108	4.4	168 (139, 206)	4.7 (3.9, 5.7)	71.2 (61.9, 79.1)	2.0 (1.5, 2.5)	10.1 (7.6, 13.1)	16.7 (9.3, 26.2)

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	Per capita ($)	Per GDP (%)	Per capita ($)	Per GDP(%)	Government as a share of total (%)	Prepaid private as a share of total (%)	Out-of-pocket as a share of total (%)	Development assistance as a share of total (%)
Paraguay	863	9.8	1374 (1146, 1760)	10.8 (9.0, 13.8)	51.4 (42.7, 62.5)	4.3 (3.2, 5.5)	43.9 (33.8, 52.1)	0.3 (0.2, 0.6)
Peru	626	5.2	942 (807, 1158)	5.3 (4.6, 6.5)	64.4 (58.2, 71.7)	6.2 (4.8, 8.1)	29.2 (22.9, 34.9)	0.3 (0.0, 0.5)
Philippines	330	4.7	559 (494, 624)	5.2 (4.6, 5.8)	39.7 (32.7, 45.9)	10.4 (8.8, 12.5)	48.7 (43.0, 55.0)	1.1 (0.6, 2.0)
Poland	1629	6.3	2836 (2528, 3134)	5.9 (5.3, 6.5)	71.5 (67.0, 75.9)	5.7 (4.6, 7.4)	22.9 (18.6, 26.9)	0.0 (0.0, 0.0)
Portugal	2697	9.3	3774 (3110, 4600)	9.8 (8.1, 12.0)	65.9 (58.1, 73.0)	6.9 (5.2, 9.0)	27.2 (21.1, 34.1)	0.0 (0.0, 0.0)
Qatar	2663	2.2	3785 (2922, 5426)	2.7 (2.1, 3.9)	88.4 (84.1, 92.4)	6.4 (4.1, 9.1)	5.2 (3.1, 8.2)	0.0 (0.0, 0.0)
Romania	1077	5.5	2258 (1703, 3063)	6.8 (5.1, 9.2)	84.2 (78.8, 89.1)	0.8 (0.6, 1.1)	15.0 (10.3, 20.2)	0.0 (0.0, 0.0)
Russia	1877	7.1	2287 (2100, 2623)	7.5 (6.9, 8.6)	52.9 (46.0, 57.4)	2.9 (2.3, 3.7)	44.3 (39.7, 51.4)	0.0 (0.0, 0.0)
Rwanda	158	9.4	217 (165, 289)	8.5 (6.4, 11.3)	1.0 (0.4, 2.3)	26.3 (18.7, 34.4)	26.1 (18.6, 34.3)	46.6 (31.8, 61.1)
Saint Lucia	755	6.7	1023 (897, 1212)	6.8 (6.0, 8.1)	54.9 (48.7, 62.4)	0.9 (0.7, 1.2)	40.5 (33.7, 46.4)	3.7 (1.3, 7.0)
Saint Vincent and the Grenadines	917	8.8	1203 (968, 1545)	8.7 (7.0, 11.2)	48.9 (38.6, 61.2)	1.7 (1.2, 2.9)	46.4 (34.9, 56.4)	2.9 (1.0, 5.6)
Samoa	365	7.2	433 (338, 643)	6.7 (5.2, 9.9)	84.4 (77.8, 90.6)	0.8 (0.5, 1.0)	6.4 (4.0, 8.5)	8.4 (4.0, 14.6)
Sao Tome and Principe	251	7.9	317 (241, 416)	8.1 (6.2, 10.6)	43.6 (31.0, 56.9)	6.1 (4.0, 9.2)	11.5 (7.9, 16.6)	38.8 (24.5, 54.1)
Saudi Arabia	2320	4.4	3355 (2554, 5027)	5.3 (4.0, 8.0)	80.9 (74.8, 88.0)	6.0 (3.7, 8.2)	13.1 (8.1, 18.1)	0.0 (0.0, 0.0)
Senegal	121	5.2	153 (130, 184)	5.3 (4.5, 6.4)	43.9 (35.7, 52.6)	1.0 (0.8, 1.4)	33.3 (26.7, 39.8)	21.8 (12.9, 32.9)
Serbia	1392	10.3	1864 (1714, 2037)	10.4 (9.6, 11.4)	61.3 (56.5, 65.2)	0.5 (0.4, 0.7)	38.1 (34.2, 42.9)	0.1 (0.0, 0.2)
Seychelles	853	3.3	1599 (1118, 2226)	4.0 (2.8, 5.5)	95.7 (93.2, 97.3)	2.6 (1.6, 4.7)	1.7 (1.0, 3.1)	0.0 (0.0, 0.0)
Sierra Leone	255	13.5	250 (214, 311)	15.7 (13.4, 19.5)	6.4 (4.3, 8.8)	8.7 (6.5, 10.8)	48.3 (38.3, 57.5)	36.6 (28.2, 48.8)
Singapore	3981	4.8	6990 (5335, 9135)	6.0 (4.6, 7.9)	50.7 (37.0, 62.9)	1.8 (1.3, 2.6)	47.5 (35.7, 60.7)	0.0 (0.0, 0.0)
Slovakia	2203	7.7	3798 (3306, 4375)	8.0 (7.0, 9.2)	76.5 (71.8, 81.3)	0.6 (0.5, 0.8)	22.8 (18.1, 27.5)	0.0 (0.0, 0.0)
Slovenia	2845	9.1	3970 (3482, 4776)	9.4 (8.2, 11.3)	72.9 (68.7, 77.7)	15.5 (12.5, 18.8)	11.7 (9.4, 13.7)	0.0 (0.0, 0.0)
Solomon Islands	107	5.8	111 (75, 157)	4.9 (3.3, 7.0)	52.4 (34.7, 69.4)	1.1 (0.7, 1.6)	4.8 (3.2, 7.2)	41.7 (24.7, 59.8)
Somalia	33	6.9	36 (27, 50)	6.9 (5.2, 9.5)	25.1 (16.4, 33.4)	1.1 (0.7, 1.7)	28.9 (20.2, 37.5)	44.9 (30.2, 61.1)
South Africa	1172	8.9	1499 (1346, 1684)	9.7 (8.7, 10.9)	51.4 (45.9, 56.9)	40.4 (35.7, 45.5)	5.6 (4.6, 6.8)	2.5 (1.2, 4.5)

	2014 total health spending		2030 expected health spending		2030 expected health spending by source			
	Per capita ($)	Per GDP (%)	Per capita ($)	Per GDP(%)	Government as a share of total (%)	Prepaid private as a share of total (%)	Out-of-pocket as a share of total (%)	Development assistance as a share of total (%)
South Korea	2507	7.1	4838 (4088, 5783)	9.0 (7.6, 10.8)	63.3 (56.4, 70.2)	6.2 (4.8, 8.2)	30.4 (24.5, 36.6)	0.0 (0.0, 0.0)
South Sudan	94	3.6	120 (84, 182)	5.1 (3.6, 7.7)	25.9 (13.1, 48.1)	1.0 (0.6, 1.5)	28.2 (17.7, 39.2)	44.9 (26.1, 63.5)
Spain	3096	9	4245 (3808, 4645)	9.0 (8.0, 9.8)	71.0 (66.1, 75.0)	4.6 (3.9, 6.1)	24.4 (20.4, 29.2)	0.0 (0.0, 0.0)
Sri Lanka	402	3.5	911 (716, 1180)	3.8 (3.0, 5.0)	59.1 (48.8, 69.3)	1.8 (1.2, 2.5)	38.8 (29.2, 48.7)	0.3 (0.0, 1.5)
Sudan	334	8.3	457 (380, 543)	8.0 (6.6, 9.5)	22.3 (15.8, 29.3)	1.0 (0.7, 1.3)	74.9 (67.7, 81.6)	1.8 (0.9, 3.1)
Suriname	731	4.3	940 (765, 1171)	4.2 (3.4, 5.2)	67.8 (60.0, 75.1)	16.3 (12.2, 21.1)	15.3 (11.3, 20.2)	0.5 (0.0, 2.3)
Swaziland	745	9.5	1132 (923, 1430)	11.5 (9.4, 14.5)	69.0 (60.0, 77.4)	6.8 (5.1, 8.8)	8.6 (6.4, 11.2)	15.6 (8.5, 24.6)
Sweden	5446	11.8	8048 (6984, 9231)	13.1 (11.4, 15.0)	86.2 (83.4, 88.6)	0.6 (0.5, 0.8)	13.1 (10.8, 15.9)	0.0 (0.0, 0.0)
Switzerland	7831	12.8	9702 (8612, 10687)	13.4 (11.9, 14.7)	65.3 (60.7, 69.0)	10.6 (9.3, 12.2)	24.0 (21.1, 27.9)	0.0 (0.0, 0.0)
Syria	562	3.4	736 (618, 908)	3.7 (3.1, 4.5)	49.2 (41.0, 59.4)	3.3 (2.4, 4.3)	47.0 (37.2, 55.0)	0.6 (0.2, 1.1)
Tajikistan	200	7.3	309 (266, 362)	8.9 (7.7, 10.5)	34.3 (26.9, 43.2)	5.3 (3.4, 9.5)	52.1 (44.2, 59.4)	8.3 (4.5, 13.6)
Tanzania	166	6.4	239 (194, 303)	6.2 (5.0, 7.8)	29.1 (20.8, 42.0)	22.7 (16.8, 28.6)	20.4 (15.3, 25.7)	27.8 (16.8, 41.0)
Thailand	633	4.1	1113 (861, 1390)	4.3 (3.4, 5.4)	80.7 (74.7, 85.4)	9.1 (6.8, 12.3)	10.3 (7.2, 13.9)	0.0 (0.0, 0.4)
The Bahamas	1996	7.7	2658 (2387, 3054)	8.6 (7.7, 9.8)	48.4 (42.7, 55.1)	23.8 (20.2, 27.6)	27.8 (23.4, 33.1)	0.0 (0.0, 0.0)
The Gambia	151	9.2	174 (138, 228)	10.2 (8.1, 13.4)	48.1 (35.7, 59.3)	0.5 (0.4, 0.7)	12.7 (9.1, 16.7)	38.7 (25.4, 54.0)
Timor-Leste	105	1.9	216 (139, 329)	3.0 (2.0, 4.6)	56.9 (34.8, 74.9)	1.7 (1.1, 2.6)	5.6 (3.1, 9.5)	35.8 (18.5, 58.3)
Togo	81	5.5	114 (99, 134)	6.1 (5.2, 7.1)	38.0 (30.6, 46.9)	7.2 (5.9, 8.8)	41.1 (34.3, 47.5)	13.6 (7.7, 21.4)
Tonga	253	5.3	399 (279, 594)	6.4 (4.5, 9.5)	72.9 (59.8, 84.2)	0.8 (0.5, 1.3)	9.5 (6.0, 13.5)	16.7 (7.7, 29.0)
Trinidad and Tobago	1823	5.8	2518 (2216, 2919)	6.3 (5.5, 7.3)	55.1 (48.5, 62.0)	7.0 (5.7, 8.7)	37.8 (31.6, 44.5)	0.0 (0.0, 0.0)
Tunisia	791	6.9	1099 (992, 1232)	7.2 (6.5, 8.1)	59.8 (55.0, 64.6)	4.5 (3.7, 5.5)	35.6 (31.1, 40.4)	0.1 (0.1, 0.2)
Turkey	1040	5.3	1748 (1556, 2032)	5.7 (5.1, 6.6)	79.1 (75.9, 82.5)	3.0 (2.5, 3.7)	17.9 (14.9, 20.8)	0.0 (0.0, 0.0)
Turkmenistan	396	2.3	925 (763, 1132)	2.7 (2.2, 3.3)	64.4 (56.6, 71.7)	6.7 (5.2, 8.5)	28.8 (22.5, 35.8)	0.0 (0.0, 0.0)
Uganda	347	18.1	313 (262, 370)	11.6 (9.7, 13.7)	2.9 (1.3, 5.0)	51.7 (42.8, 59.5)	25.0 (20.5, 30.1)	20.4 (12.1, 30.8)
Ukraine	659	7	673 (584, 781)	7.5 (6.5, 8.7)	49.4 (41.3, 55.2)	0.9 (0.7, 1.4)	48.1 (42.3, 56.3)	1.5 (0.4, 3.7)

	2014 total health spending		2030 expected health spending		2030 expected health spending by source			
	Per capita ($)	Per GDP (%)	Per capita ($)	Per GDP(%)	Government as a share of total (%)	Prepaid private as a share of total (%)	Out-of-pocket as a share of total (%)	Development assistance as a share of total (%)
United Arab Emirates	2561	3.6	3290 (2724, 4287)	4.2 (3.4, 5.4)	74.4 (68.4, 81.2)	9.3 (6.6, 12.2)	16.3 (11.7, 21.3)	0.0 (0.0, 0.0)
United Kingdom	3749	9.1	5002 (4276, 5803)	9.3 (7.9, 10.8)	83.1 (80.0, 85.8)	7.3 (6.0, 8.7)	9.7 (7.9, 11.9)	0.0 (0.0, 0.0)
United States	9237	16.6	12448 (11293, 13528)	17.7 (16.0, 19.2)	50.7 (45.7, 54.9)	38.7 (35.1, 43.0)	10.6 (9.3, 12.1)	0.0 (0.0, 0.0)
Uruguay	1837	8.6	2766 (2289, 3130)	8.9 (7.4, 10.1)	73.3 (67.5, 77.3)	12.7 (10.5, 16.0)	14.0 (11.3, 17.5)	0.0 (0.0, 0.0)
Uzbekistan	397	5.9	802 (648, 1024)	7.2 (5.8, 9.2)	63.7 (55.3, 72.6)	1.8 (1.3, 2.3)	33.6 (25.2, 41.6)	0.9 (0.4, 1.7)
Vanuatu	149	5.4	214 (145, 331)	7.3 (5.0, 11.3)	64.8 (47.3, 81.0)	0.8 (0.5, 1.2)	4.2 (2.5, 6.1)	30.3 (15.0, 48.0)
Venezuela	1010	5.3	1125 (988, 1277)	5.7 (5.0, 6.5)	33.6 (27.0, 40.8)	6.3 (5.2, 8.0)	60.0 (53.2, 66.4)	0.0 (0.0, 0.0)
Vietnam	398	7	919 (740, 1123)	7.6 (6.1, 9.2)	62.8 (54.0, 71.2)	5.8 (4.6, 7.3)	30.4 (22.8, 38.3)	1.0 (0.3, 2.2)
Yemen	233	5.8	229 (179, 299)	7.0 (5.5, 9.1)	12.7 (6.2, 21.0)	1.4 (1.0, 1.9)	69.9 (56.3, 81.0)	16.0 (7.6, 30.0)
Zambia	216	5.4	287 (232, 363)	5.6 (4.5, 7.1)	40.5 (30.8, 50.6)	1.1 (0.7, 1.5)	27.2 (20.7, 34.2)	31.2 (19.1, 45.2)

FRONTIER ANALYSIS

Frontier analysis is an econometric method for determining the efficiency with which a country (or other unit) produces an output. By benchmarking the country's performance against the observed performance of others, the frontier describes the maximum potential output that one could achieve. In the present study, we used frontier analysis in two ways: 1) to describe the potential total health spending a country could achieve given their level of GDP per capita, and 2) to describe the potential government health spending a country could achieve under different policy scenarios. We provide a review of frontier methods we considered for this study and a more detailed explanation of how the results were calculated.

Approaches to frontier analysis

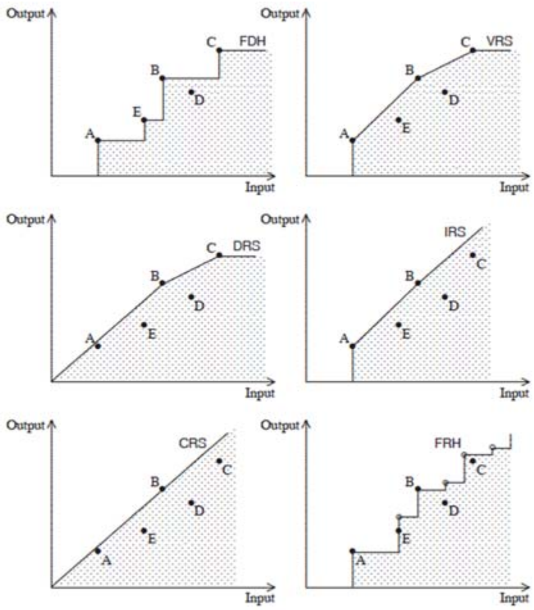
Methods for calculating a frontier generally fall into two categories: stochastic frontier analysis and data envelopment analysis.[29] Stochastic frontier analysis (SFA) can be understood intuitively as a modification to ordinary least squares regression. The frontier is defined by a set of parameters $\beta_0 \ldots \beta_n$, generally following the form

$$y_i = \beta_0 + \sum_n \beta_n x_{ni} + v_i - u_i$$

where *y* is the output of interest, *x* is an input, *v* represents random error, and *u* represents inefficiency. The random error term v_i has the same interpretation as the error term in OLS regression and is assumed to be normally distributed. The inefficiency term u_i describes the difference between each point and its efficient maximum, and may follow any distribution bounded by zero. Together, v_i minus u_i forms a compound error term that describes the departure of each point from the frontier. The inclusion of $-u_i$ pushes the fitted line higher on the y-axis, such that it describes a frontier rather than the central tendency of the data. Note that the analogy with ordinary least squares regression only applies to linear models; non-linear models require maximum likelihood estimation.

Data envelopment analysis (DEA) is a non-parametric alternative to SFA. An advantage of DEA is that it does not require a researcher to specify the functional form that relates the variables to each other (e.g., linear, Cobb-Douglas). It uses a deterministic algorithm, and does not attempt to describe the data using a probability distribution. Examples of different DEA algorithms are shown in Figure 8.[29] The main limitation of DEA is that, because it is non-parametric, it does not account for stochastic variation. Points high on the y-axis are assumed to represent a high level of the output, not random noise.

Figure 8. Comparison of DEA methods



Source: Bogetoft and Otto (2011), "Benchmarking with DEA, SFA, and R"

Key

FDH *– Free Disposability Hull assumes unnecessary input and unwanted outputs can be discarded. It does not assume that the hull is convex;* ***VRS*** *– Variable Returns to Scale assumes variable returns as inputs increase in scale, and the hull is convex;* ***DRS*** *– Decreasing Returns to Scale assumes decreasing returns as inputs increase in scale, and the hull is convex;* ***IRS*** *– Increasing Returns to Scale assumes increasing returns as inputs increase in scale, and the hull is convex;* ***CRS*** *– Constant Returns to Scale assumes constant returns as inputs increase in scale, and the hull is convex;* ***FRH*** *– Free Replicability Hull is used when peer units have disparate input combinations and it does not assume that the hull is convex*

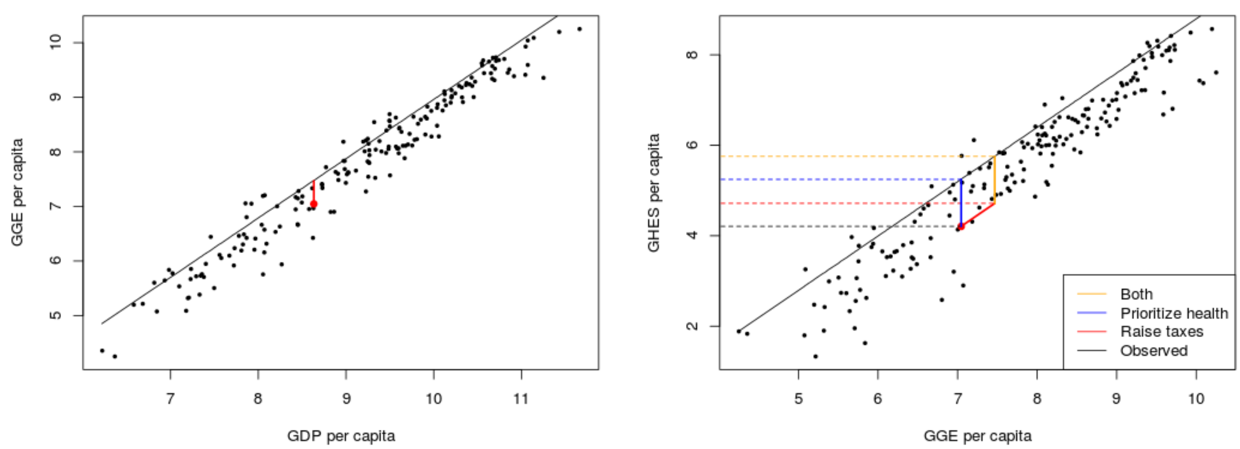
For the present analysis, we used stochastic frontier analysis with the inefficiency term u_i following a half-normal distribution. DEA was not suitable because the assumption of no stochastic variation does not hold for our data. The measures of interest, gross domestic product and health expenditure, inherently contain a degree of measurement error. Moreover, the relationship between our variables is linear, which is captured adequately with a linear functional form of SFA. Regarding the distribution of the inefficiency term, we considered using the truncated normal distribution because of its relative flexibility. It estimates two parameters (mean and variance) rather than one, as is the case with the half-normal and exponential distributions. The half-normal distribution is merely a special case of truncated normal in which the mean is zero. For each frontier, we ran models with truncated normal and found that the mean of the inefficiency term was not statistically different from zero. Because the extra flexibility of the truncated normal distribution was not needed, we proceeded with the half-normal distribution.

Analyses

To estimate a country's potential increase in total health expenditure, we fit a frontier with log-scale gross domestic product per capita (GDP) as the input and log-scale total health expenditure per capita as the output. The potential increase in total health expenditure is defined as the difference between each point and the frontier (after exponentiating both values). By using this approach, we assert that a below-average country could spend as much as an average country at its level of GDP, even in the absence of inefficiency. The "frontier" package in R is used to estimate the frontier.[30]

To estimate a country's potential increase in government health expenditure under different policy scenarios, we fit two frontiers. Figure 9 shows an example of these frontiers for India. First, we used GDP as the input and general government expenditure (GGE) as the output. The difference between each point and the frontier is the potential increase in GGE at the country's level of GDP (Plot 1, red line). For the second frontier, we used GGE as the input and government health expenditure (GHE) as the output. The difference between each point and the frontier is the potential increase in GHE at the country's level of general government expenditure (Plot 2, blue line). All differences were taken after exponentiating the values.

Figure 9. Potential government health expenditure; policy scenarios for India (illustrative example)



Plot 1 Plot 2

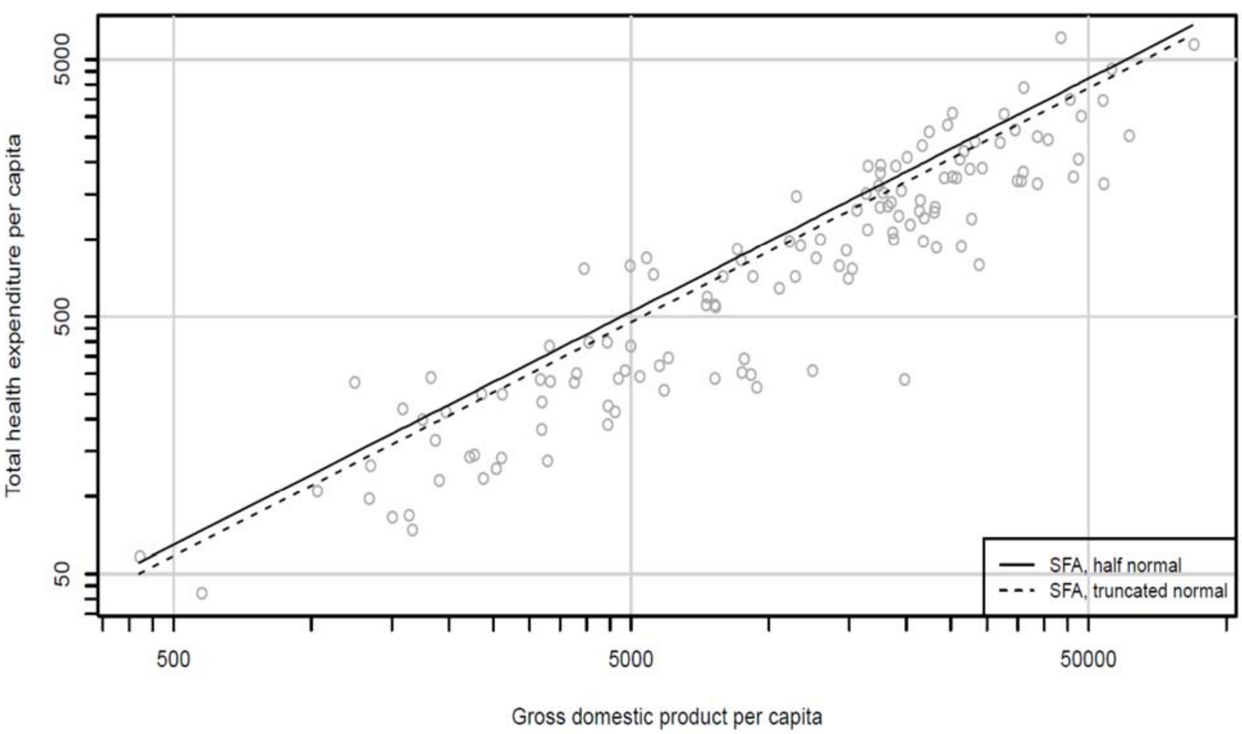
Together, these two frontiers can be used to model three policy scenarios and their effect on government health expenditure:

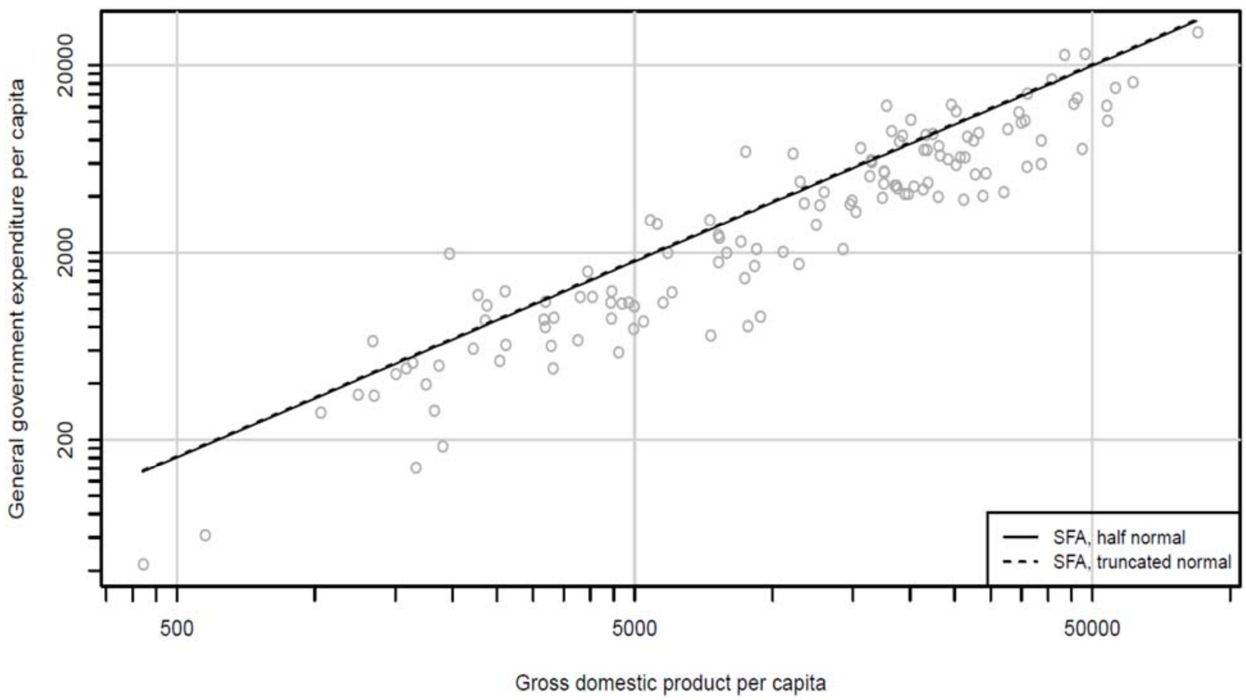
1) Potential increase due to prioritizing the health sector, calculated as the potential GHE at a country's current level of general government expenditure (Plot 2, blue line).
2) Potential increase due to increasing general government expenditure, calculated as the expected level of GHE at a country's potential level of general government expenditure (Plot 2, red line).
3) Potential increase due to both prioritizing the health sector and increasing general government expenditure, calculated as the potential GHE at a country's potential level of general government expenditure (Plot 2, red line and orange line combined).

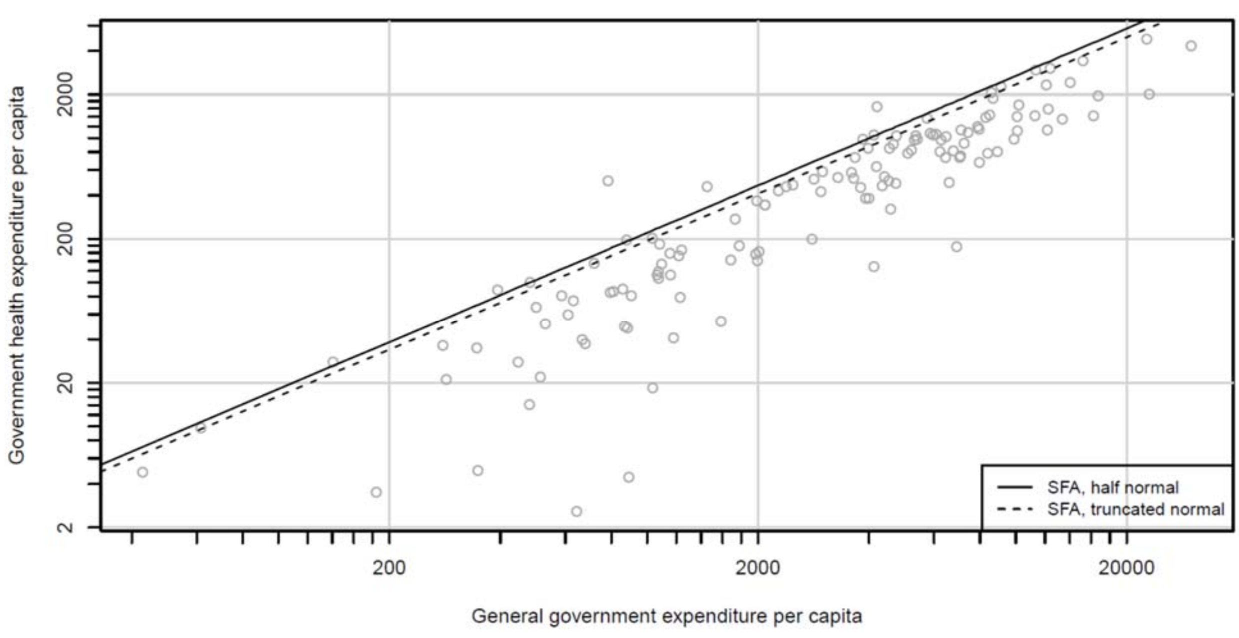
Robustness analysis

To examine the robustness of our results, we tested SFA with different distributional assumptions for the inefficiency term. The results are shown in Figure 10. The half-normal and truncated normal models produced similar frontiers. This result is consistent with Wald tests that assess whether the mean of the truncated normal efficiency distribution is equal to zero. None of the tests showed a statistically significant difference. With a mean of zero, the truncated normal model becomes half-normal, which is what we used in the final analysis.

Figure 10. Comparison of frontier methods







Additionally, we include figures that highlight the results of the policy simulation analysis for each low- and middle-income country. See figures after References.

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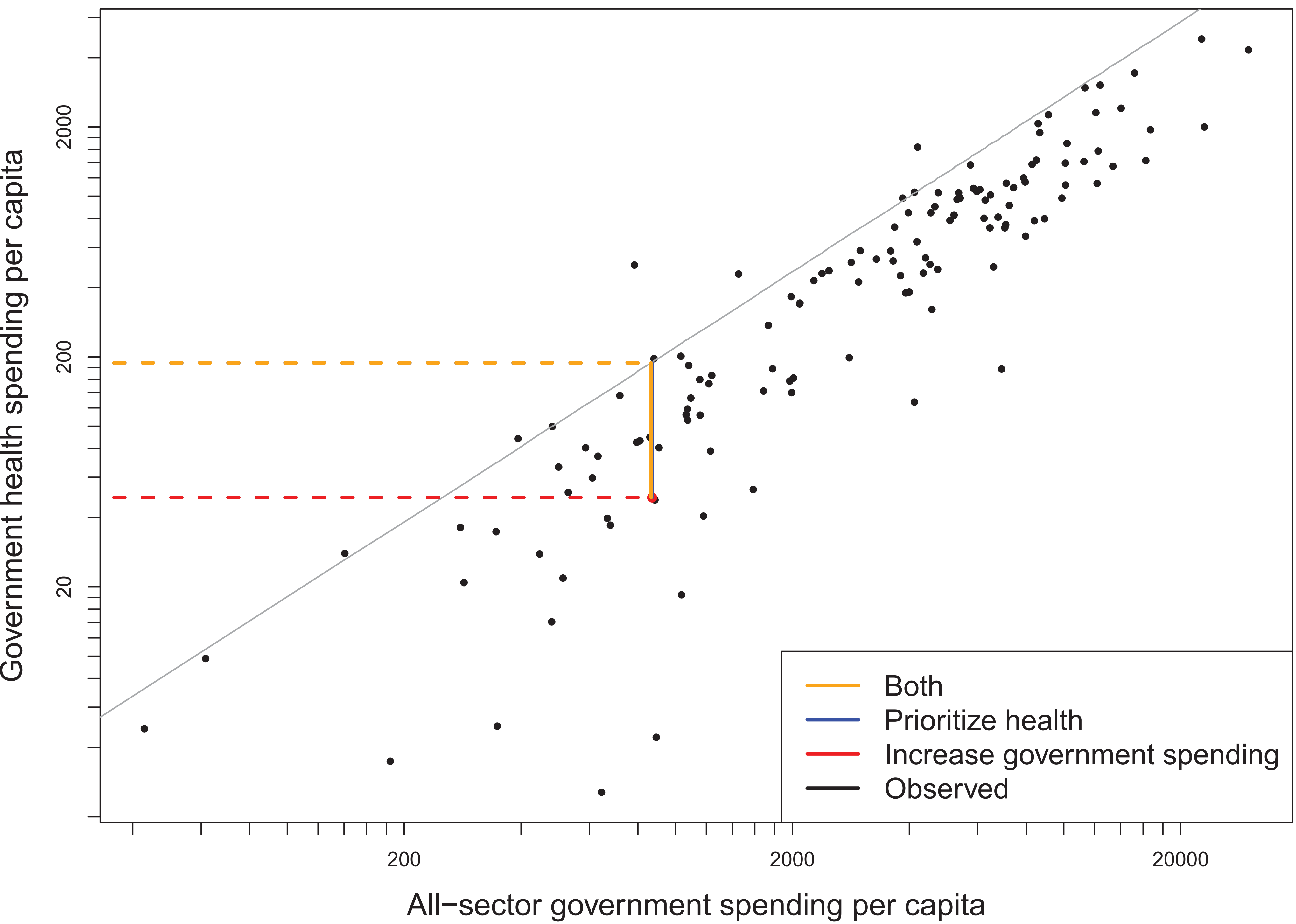
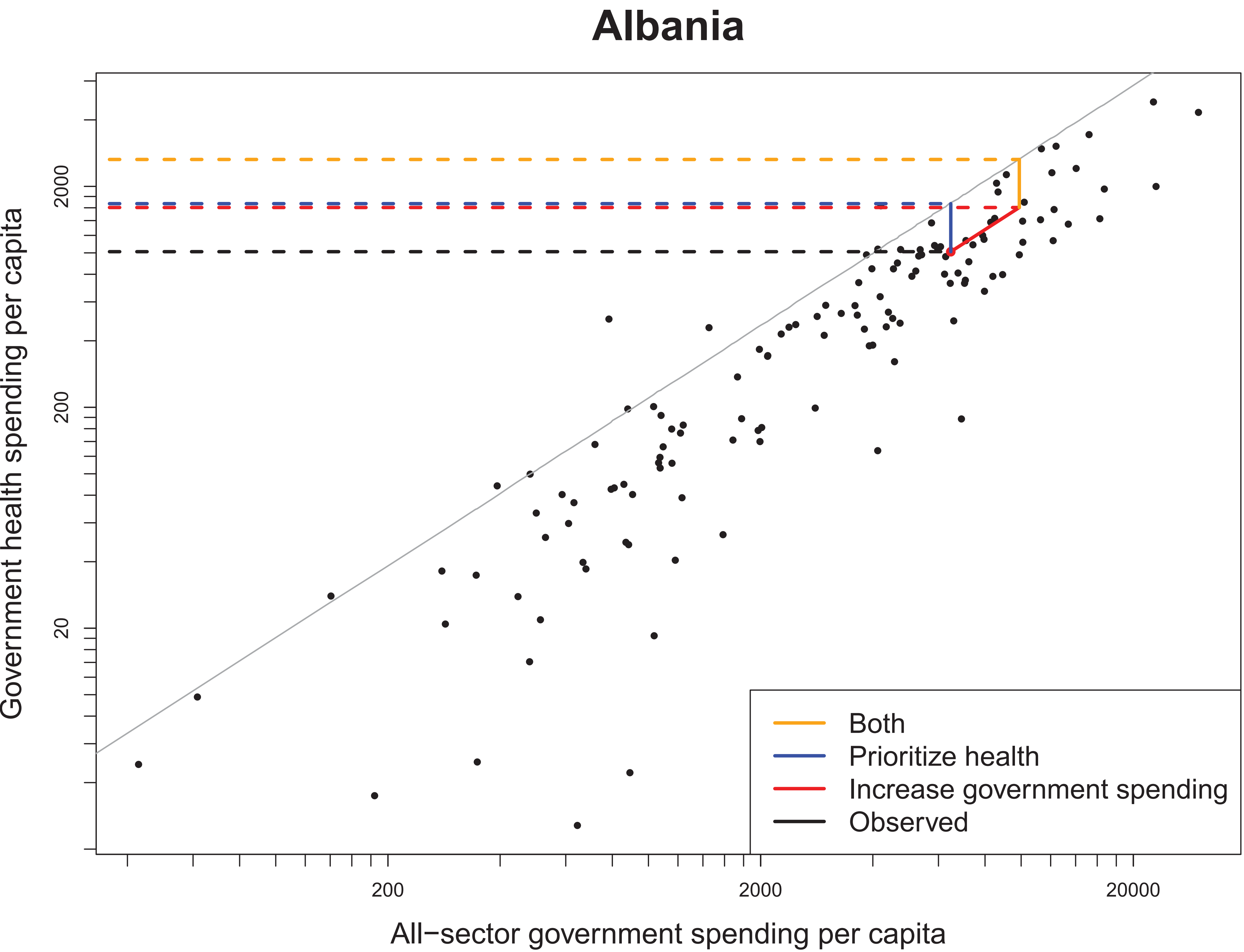
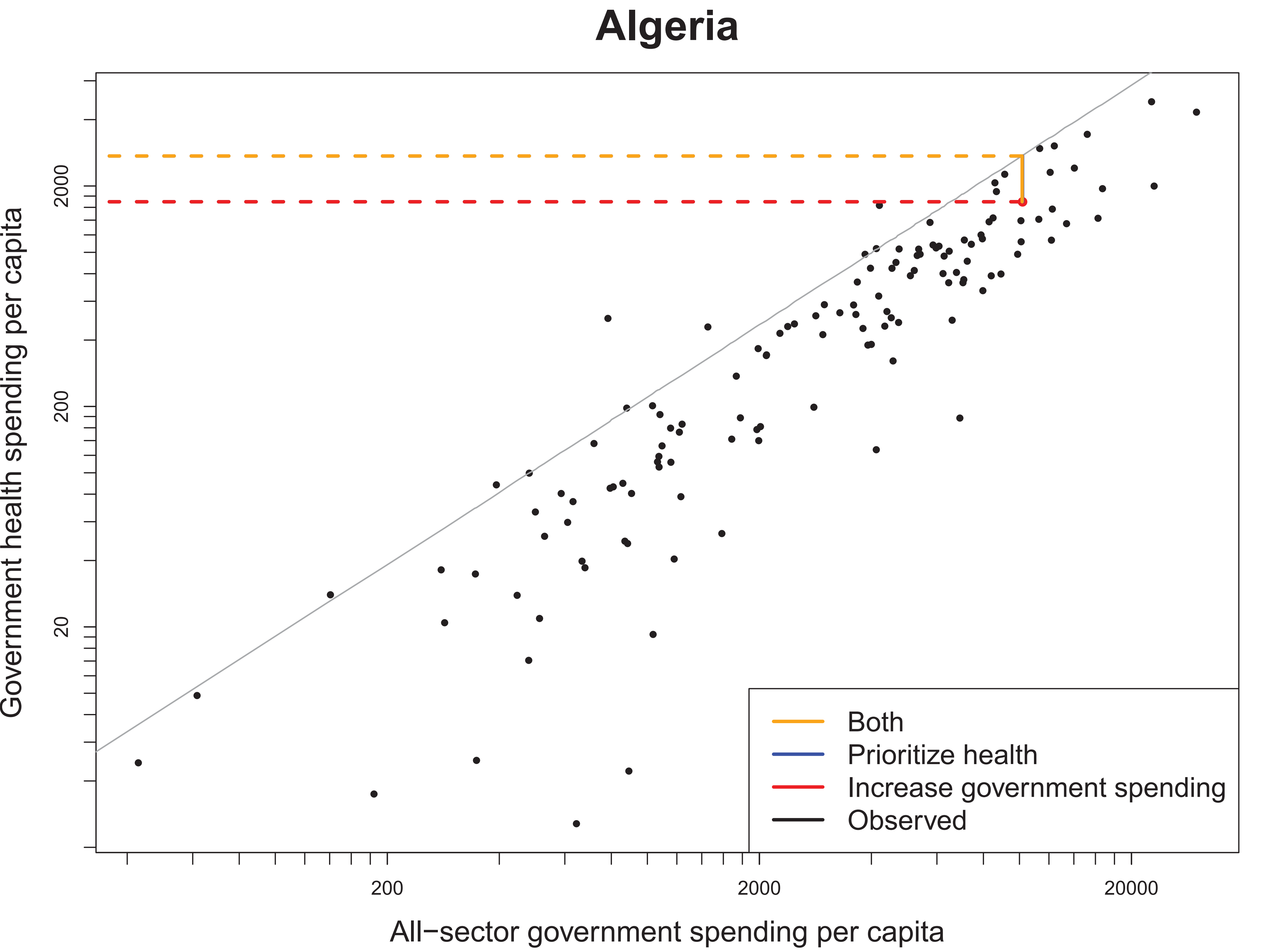
Country policy scenario figures

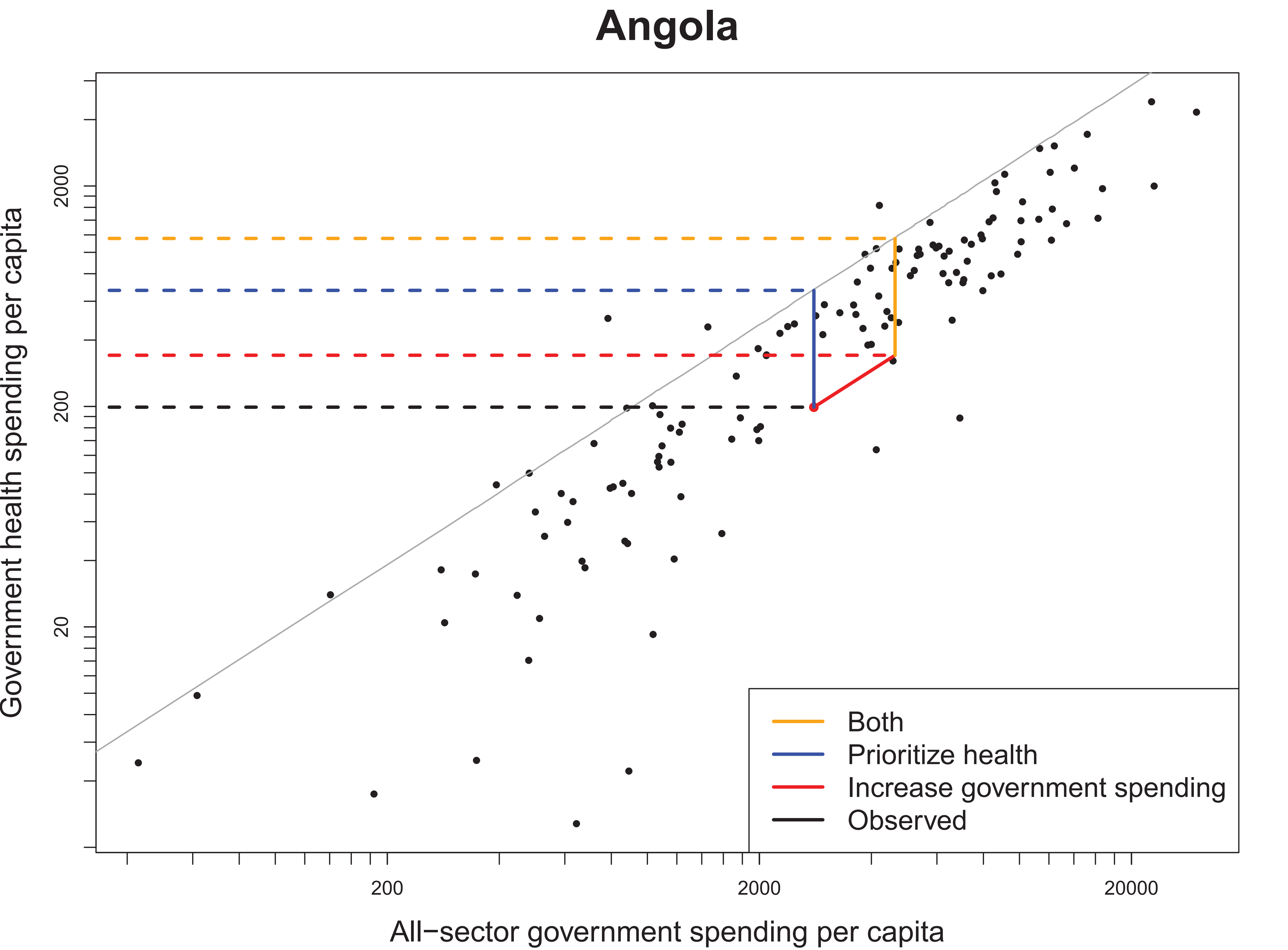
Afghanistan

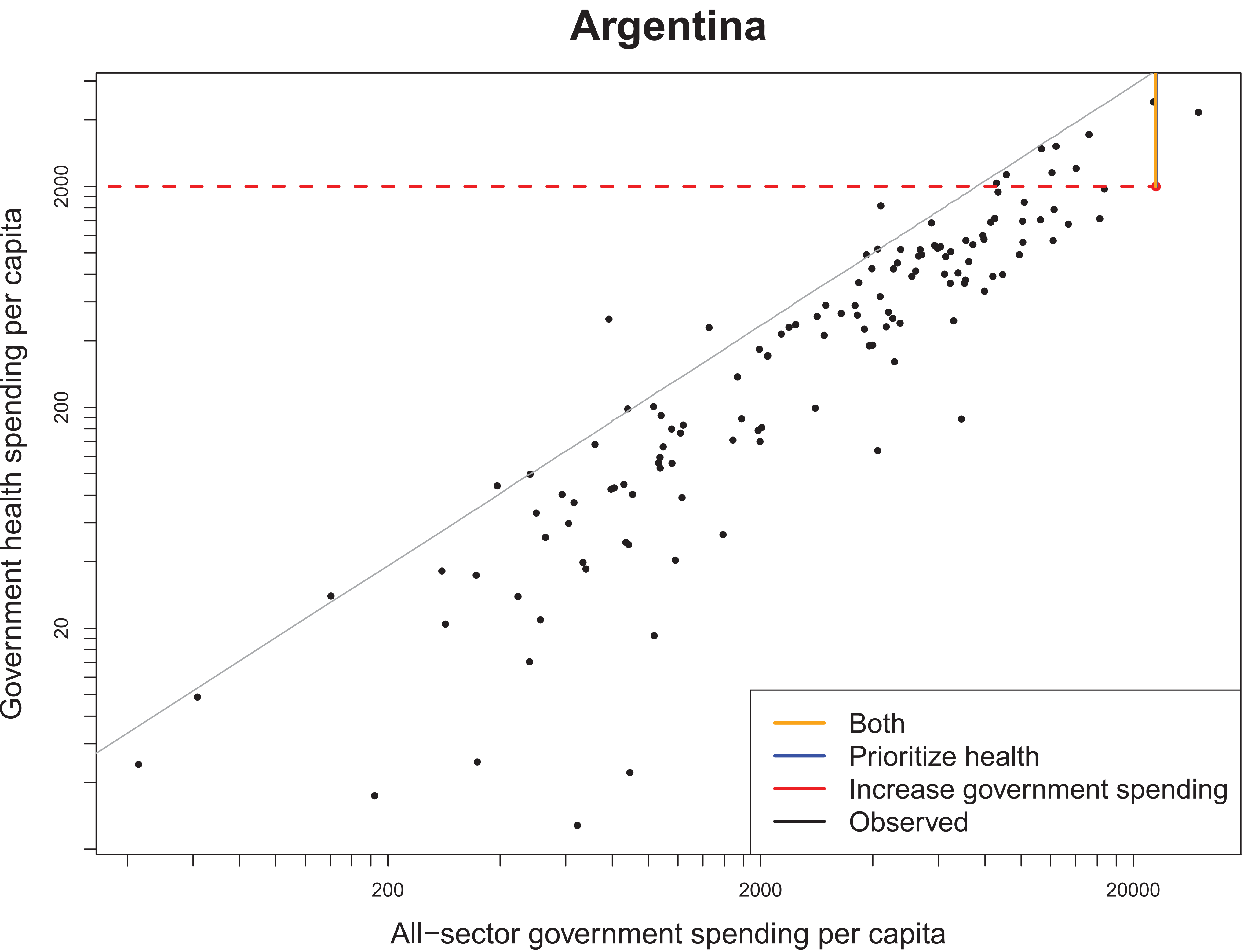


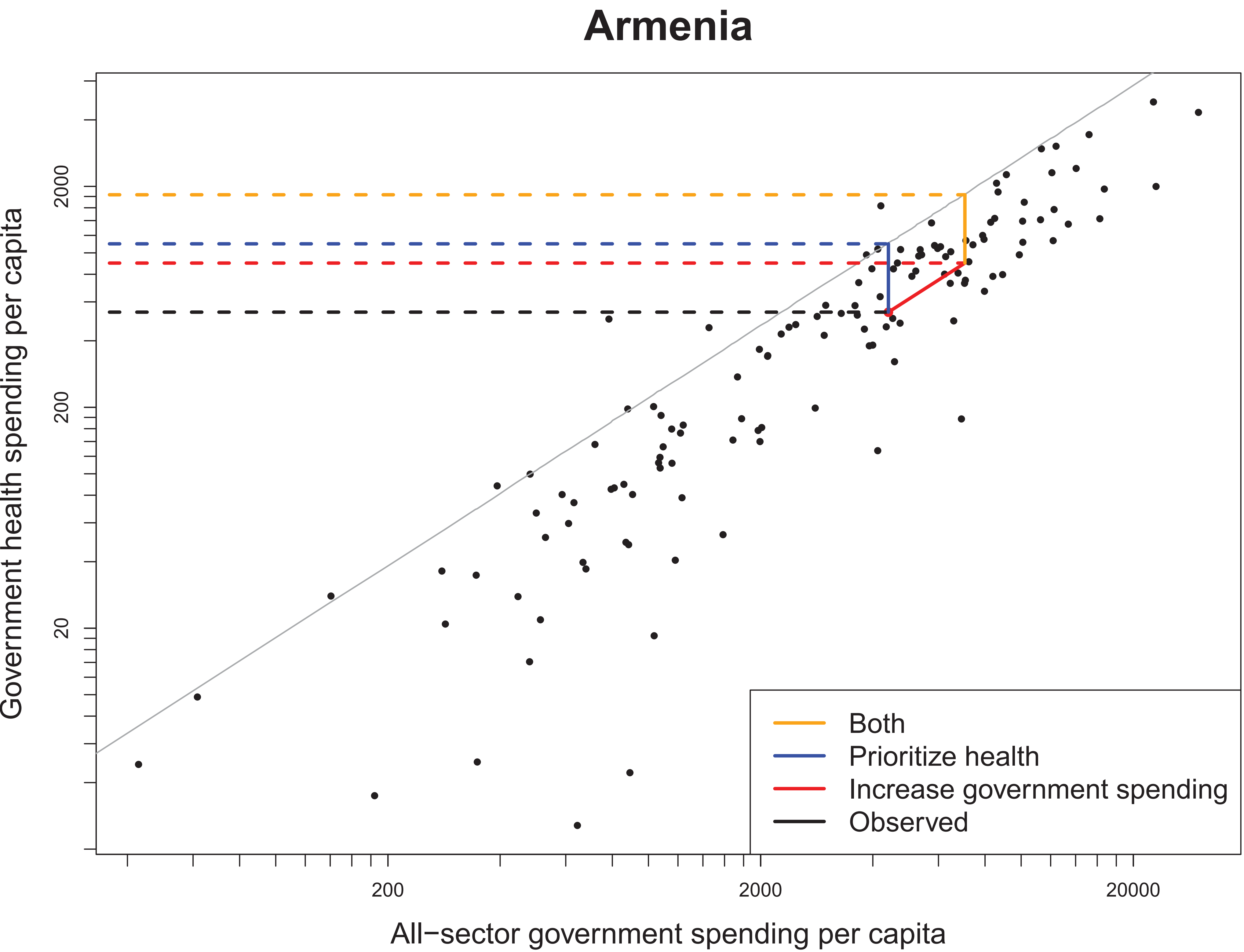


Albania
Both
Prioritize health
Increase government spending
Observed
2000
200
20
200
2000
20000
Government health spending per capita
All−sector government spending per capita

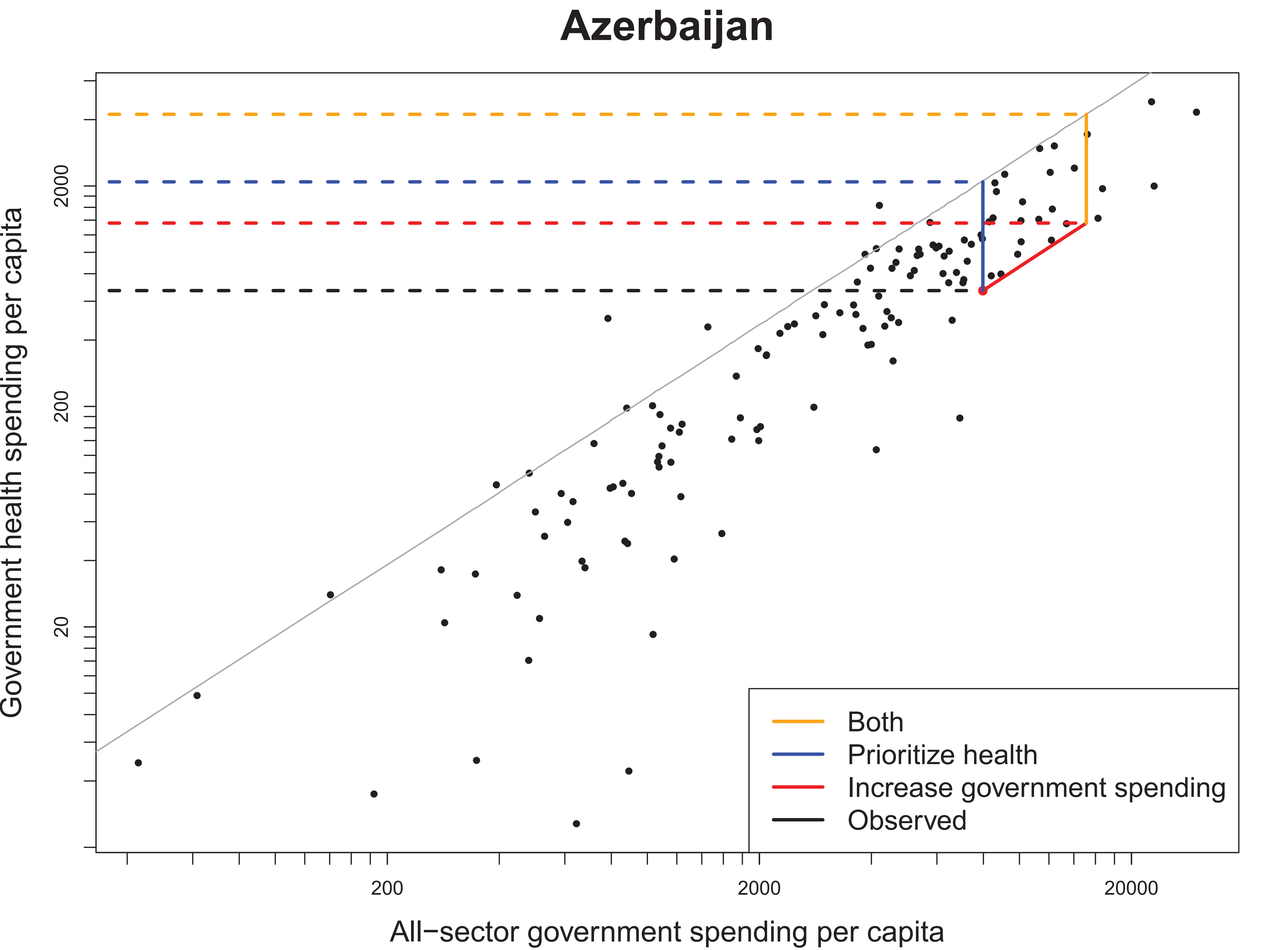

Algeria
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed


Angola
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

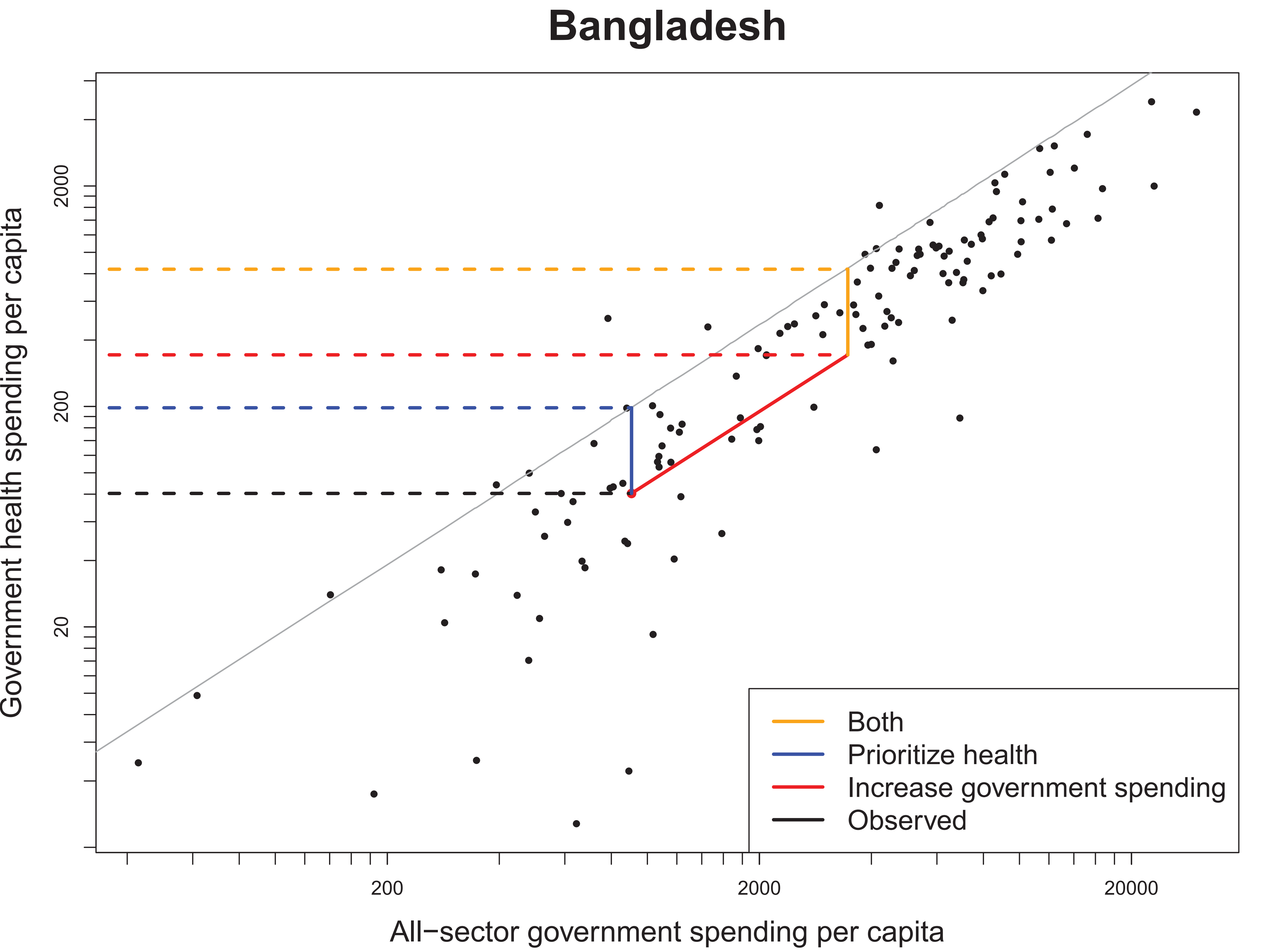

Argentina
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



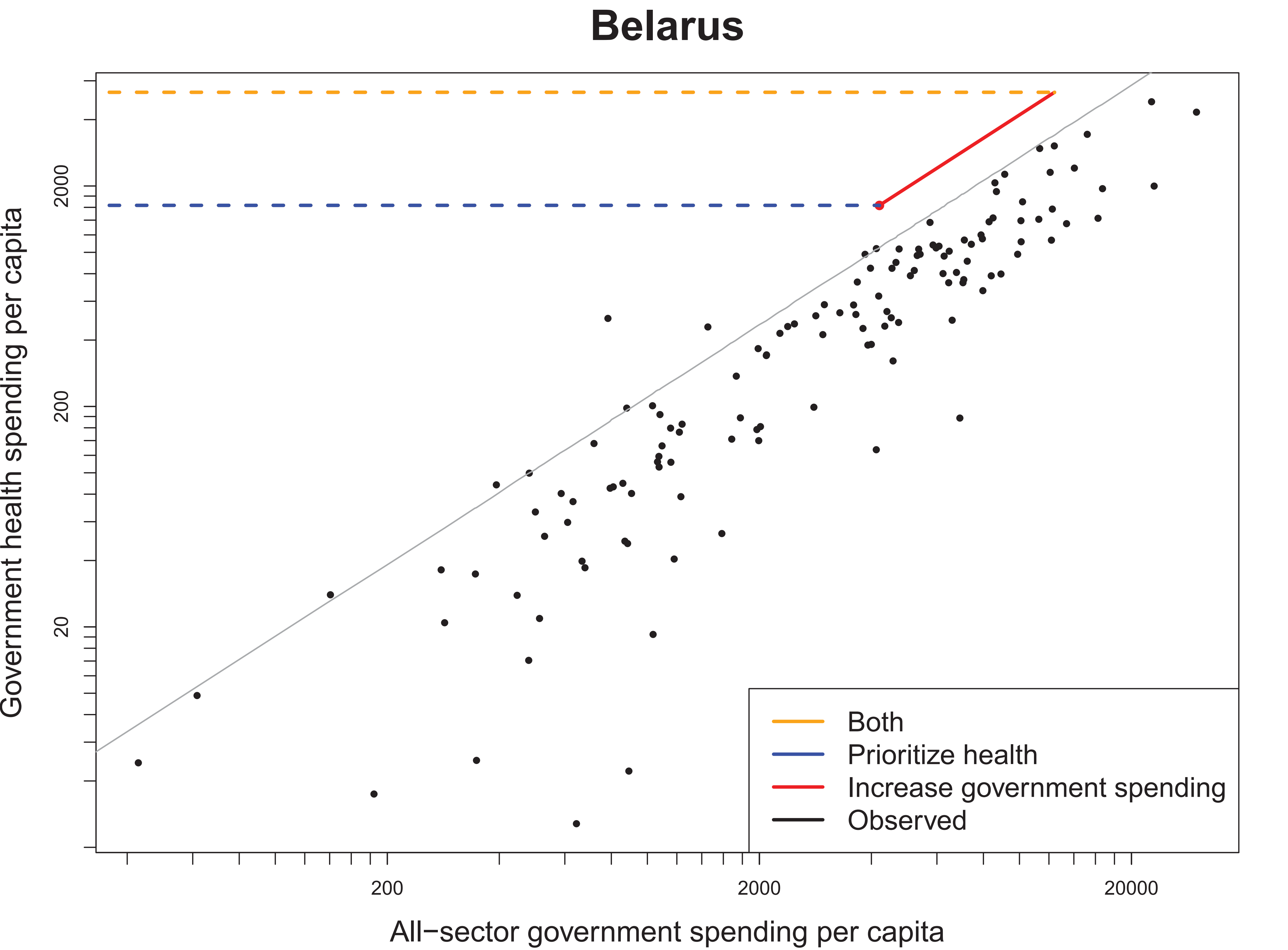
Armenia
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



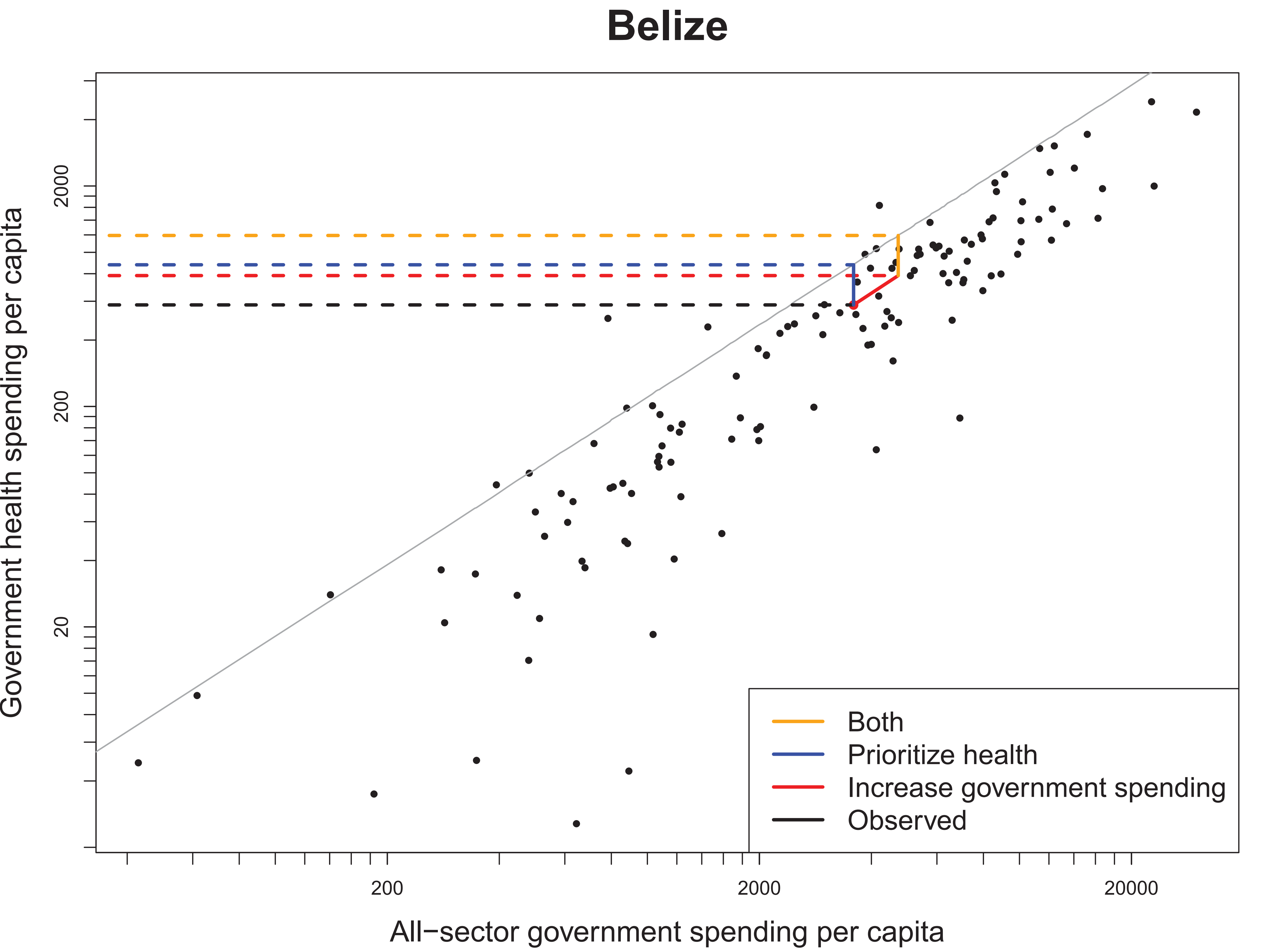
Azerbaijan
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



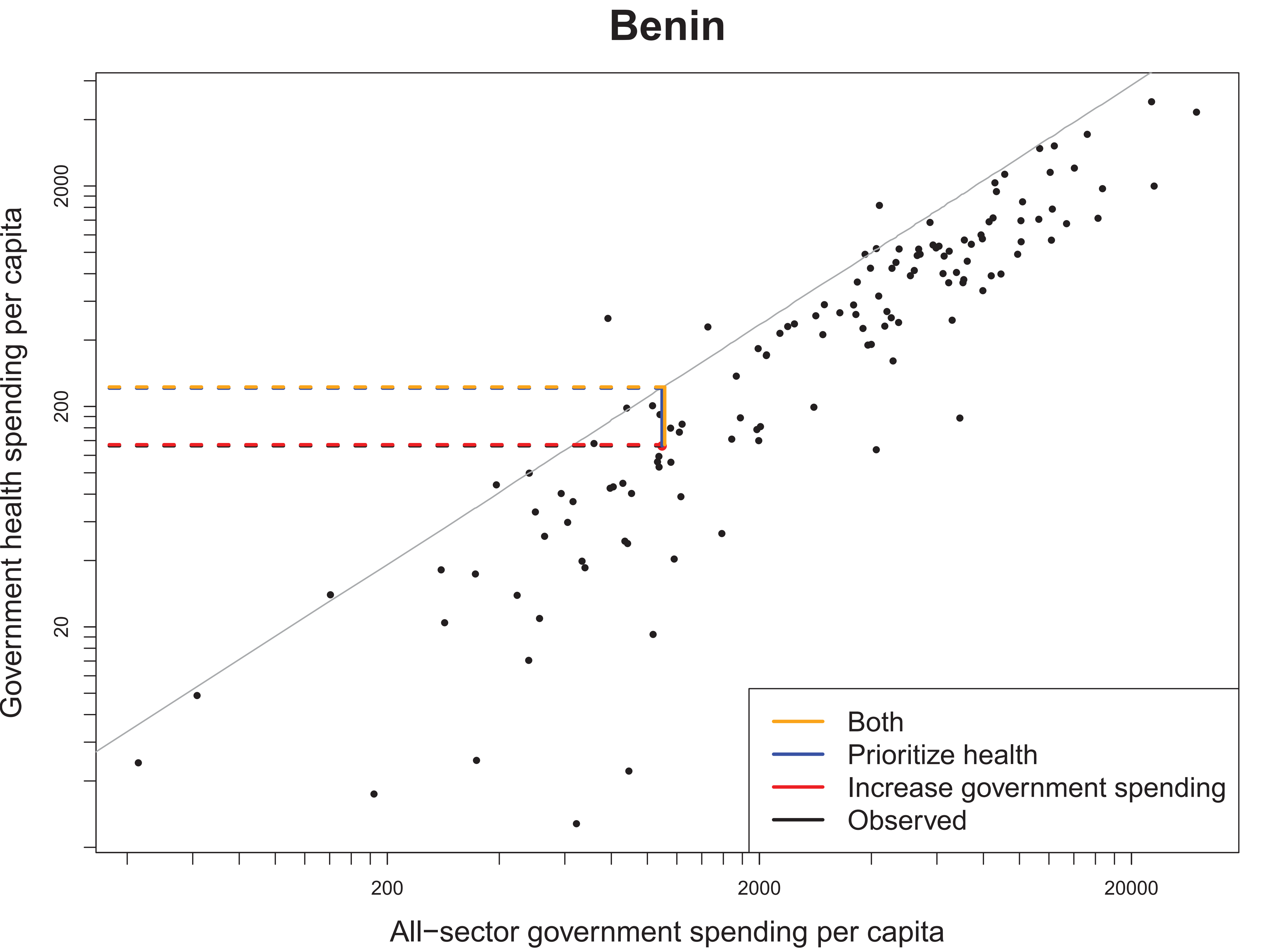
Bangladesh
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



Belarus
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



Belize
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed


Benin
Government health spending per capita
All−sector government spending per capita
2000
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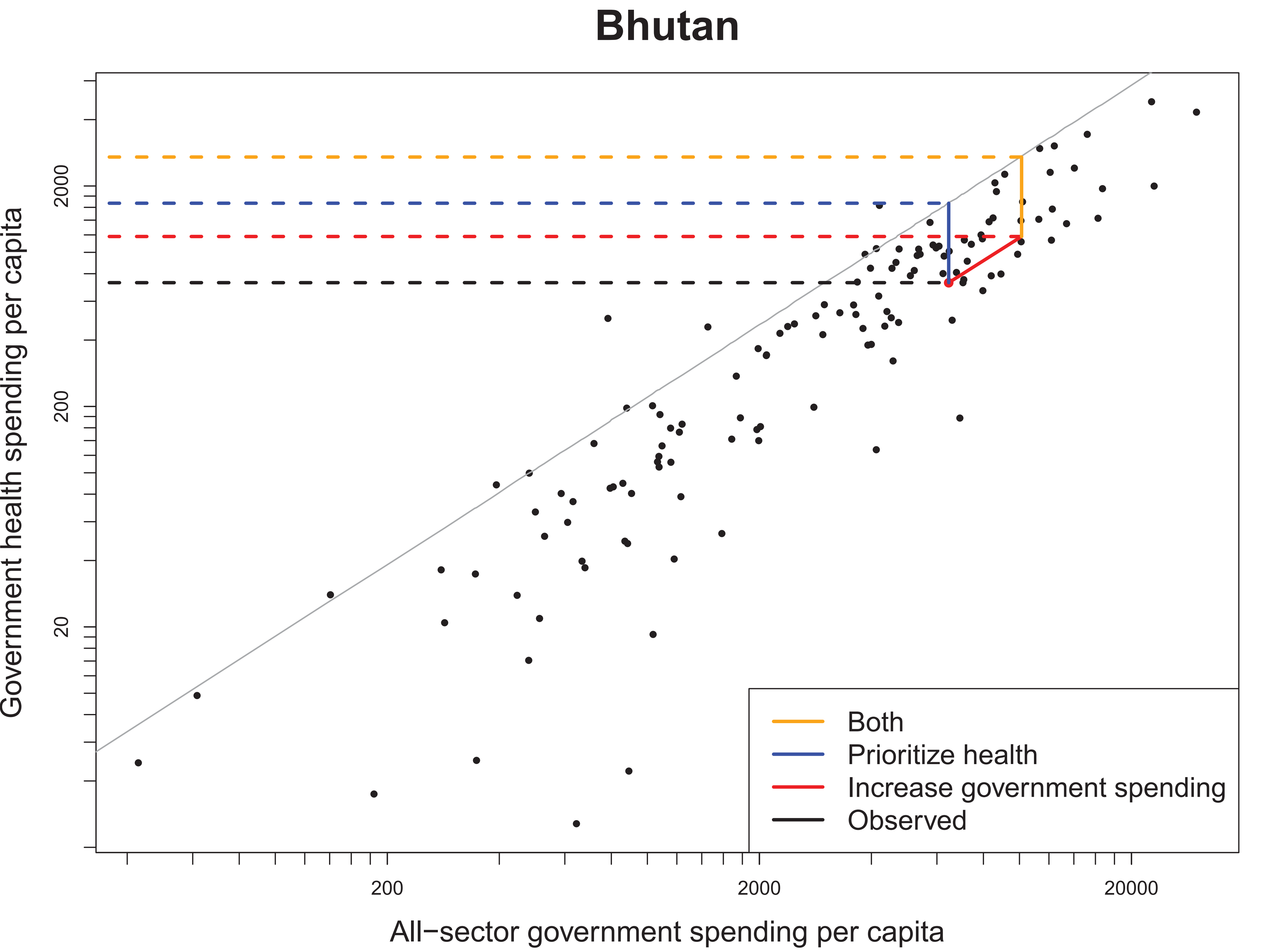
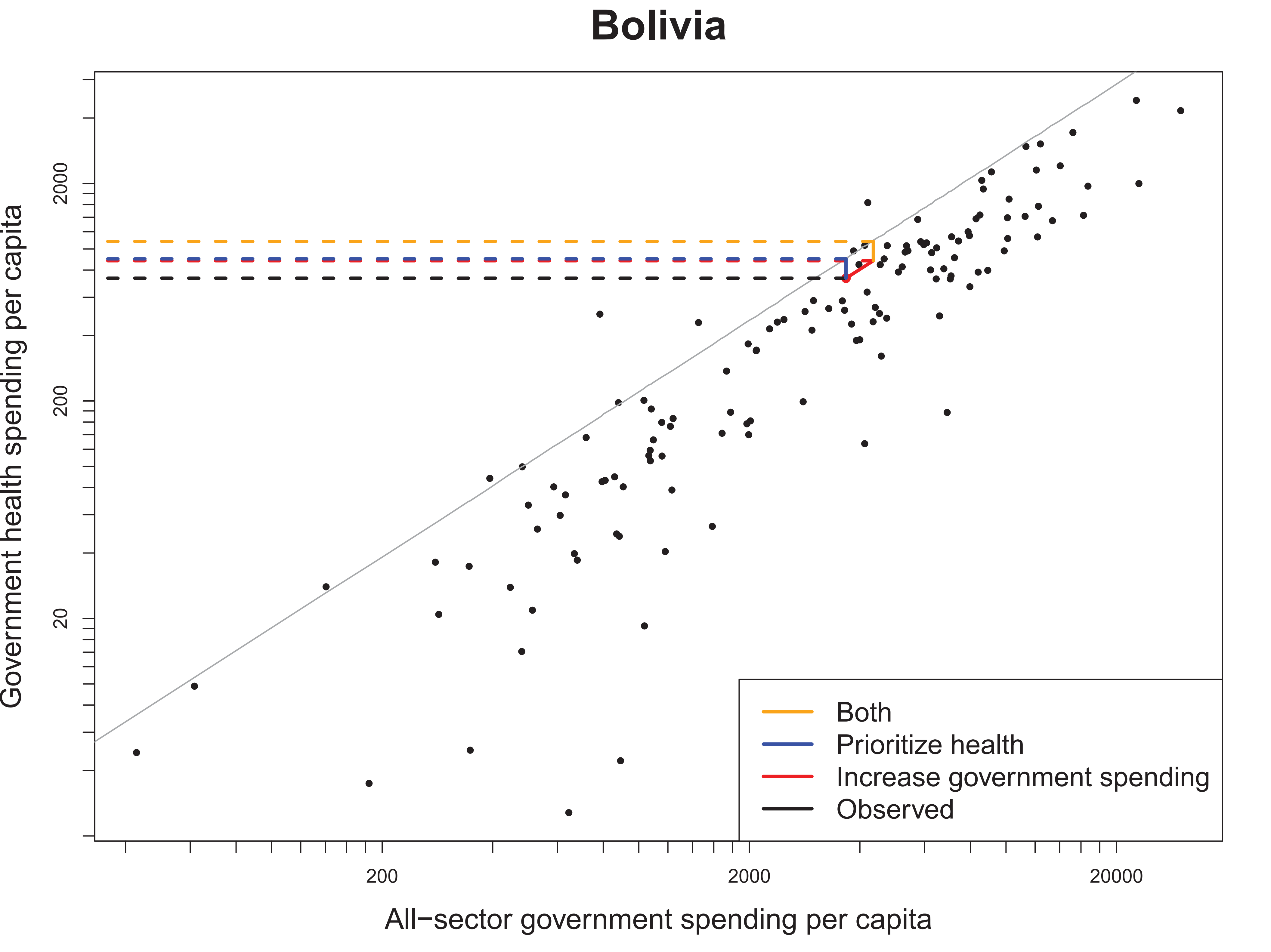
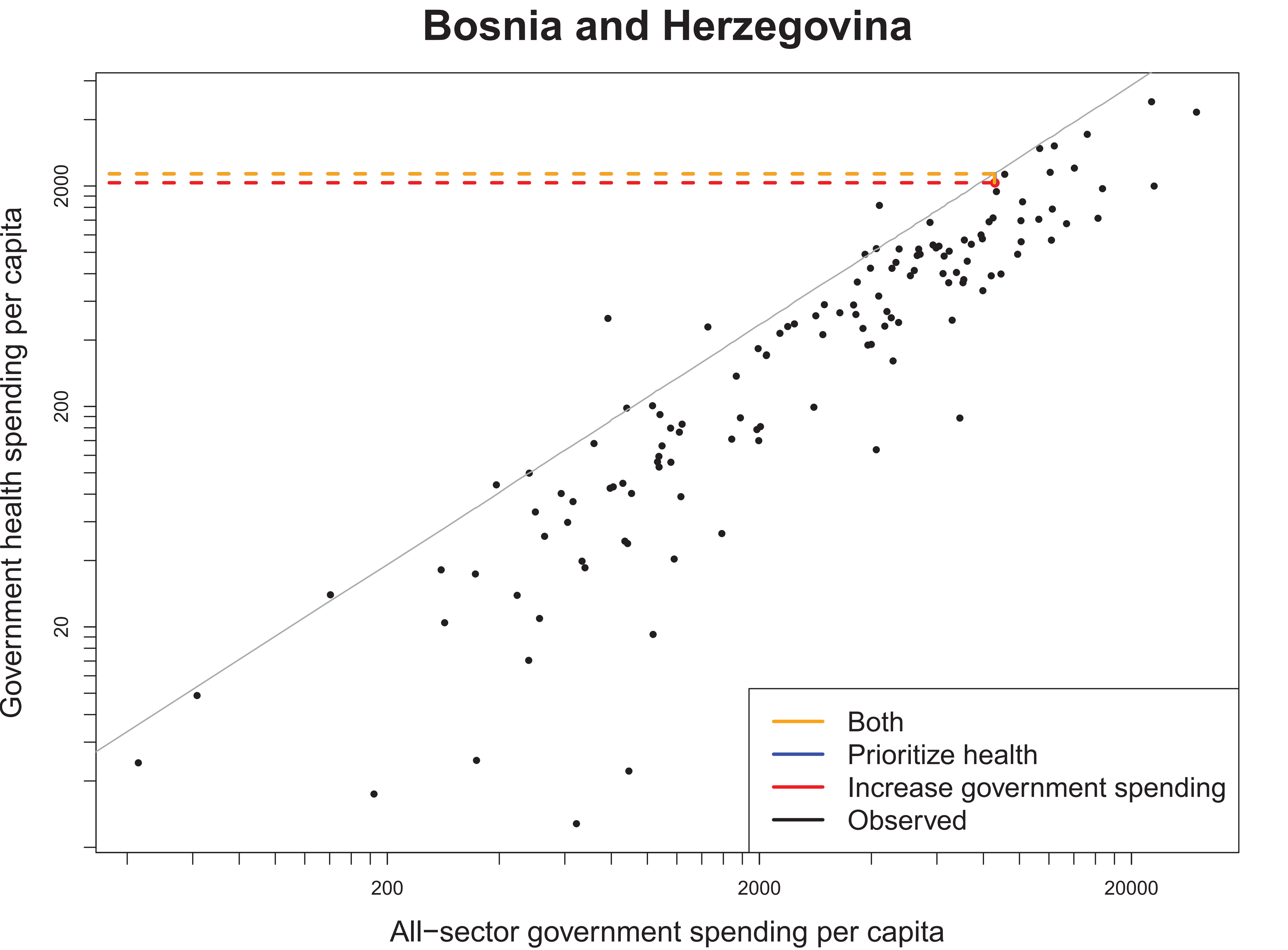
20000
Both
Prioritize health
Increase government spending
Observed


Bhutan
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



Bolivia
Government health spending per capita
All−sector government spending per capita
2000
200
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



Bosnia and Herzegovina
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
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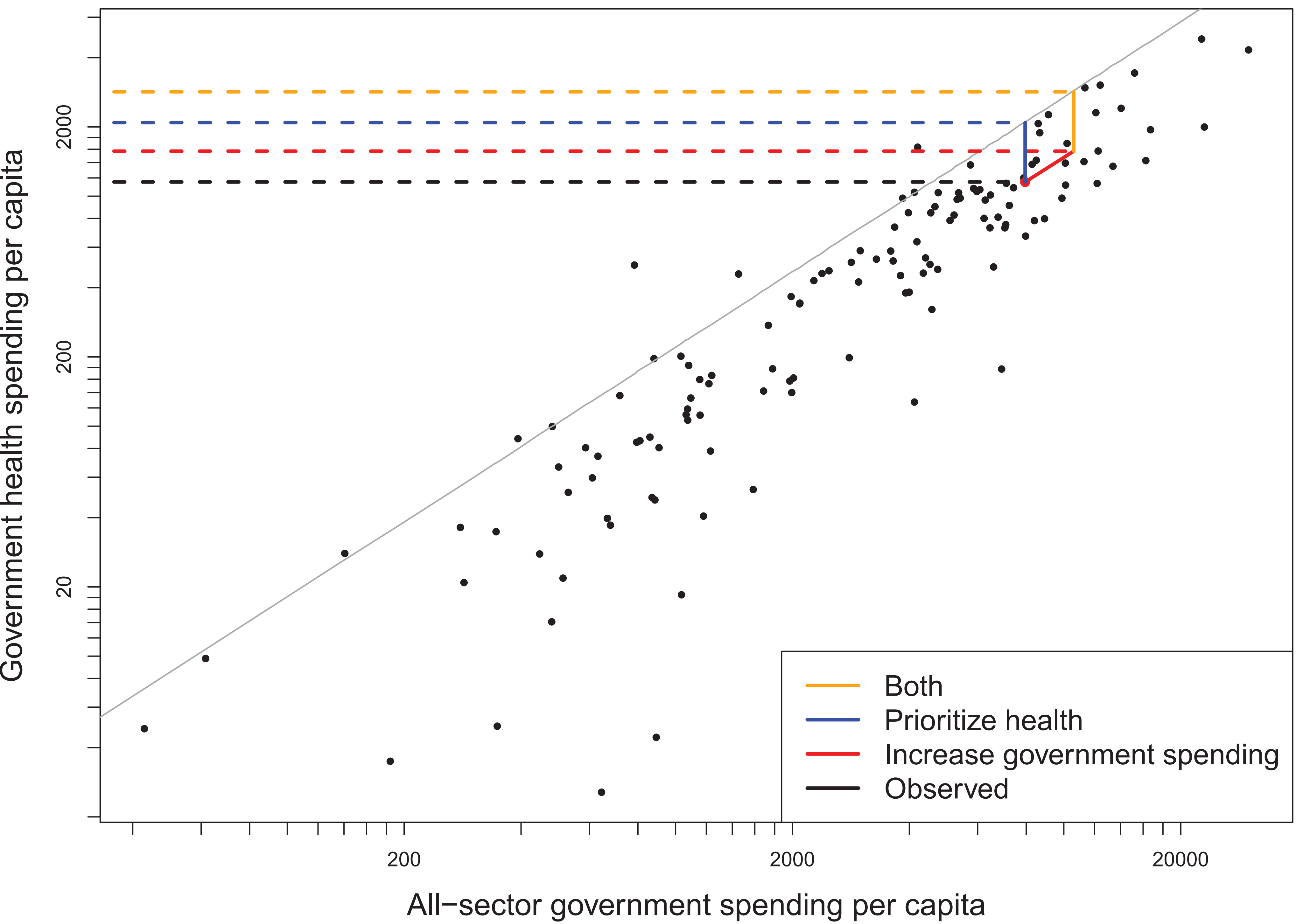
Both
Prioritize health
Increase government spending
Observed

Botswana



Government health spending per capita
2000
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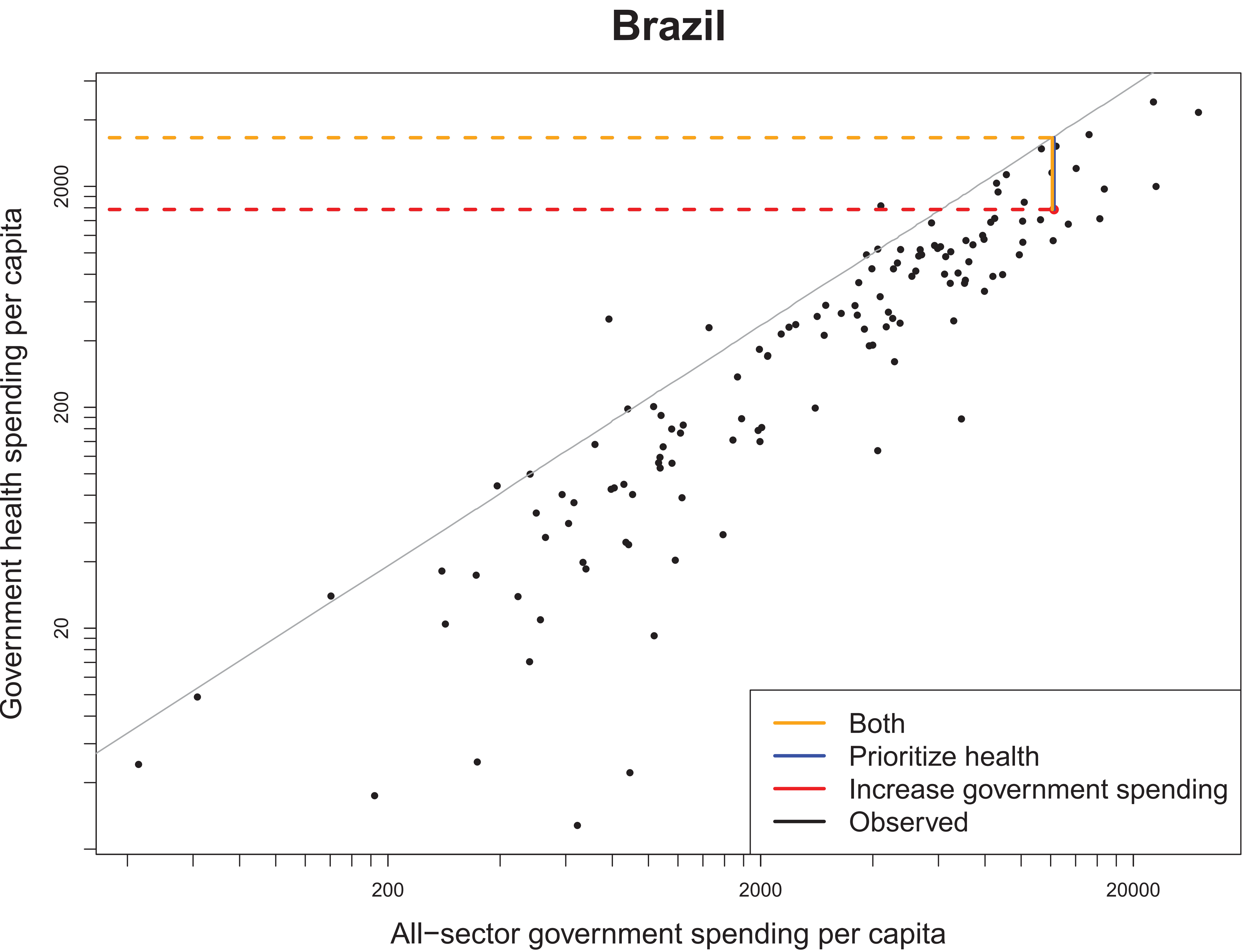
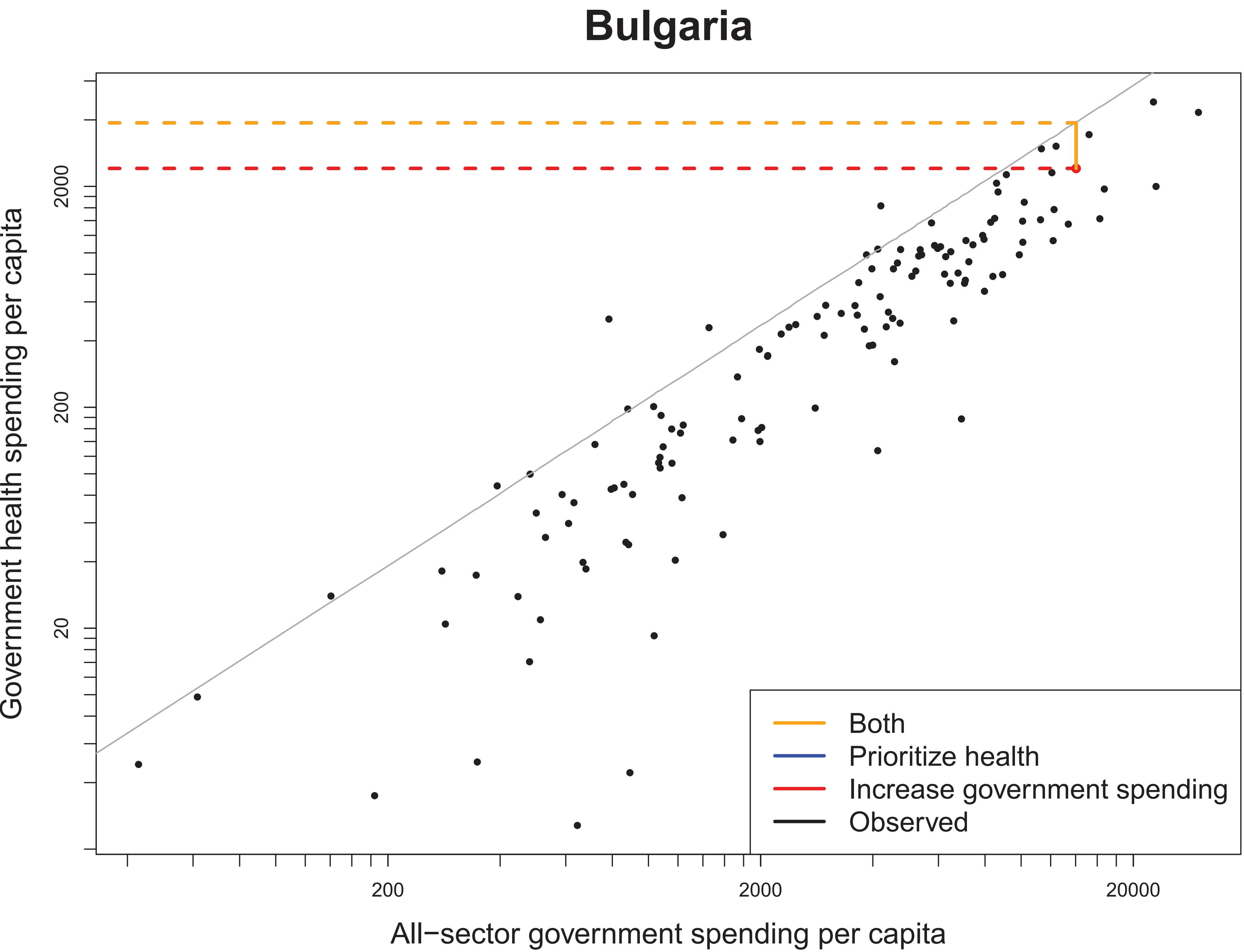
20000
All−sector government spending per capita
Both
Prioritize health
Increase government spending
Observed



Brazil
Both
Prioritize health
Increase government spending
Observed
2000
200
20
200
2000
20000
All−sector government spending per capita
Government health spending per capita



Bulgaria
Government health spending per capita
All−sector government spending per capita
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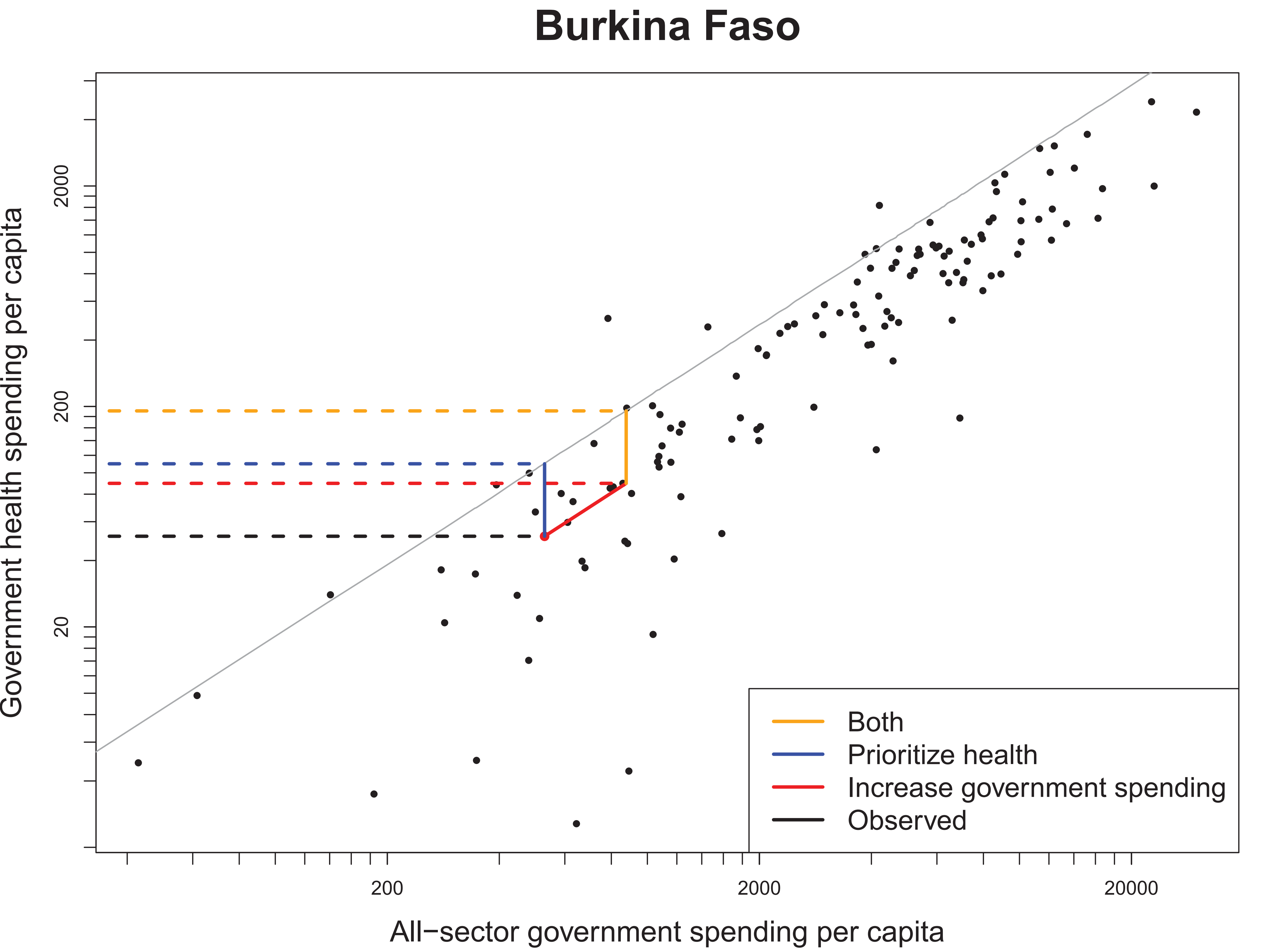
Both
Prioritize health
Increase government spending
Observed


Burkina Faso
Government health spending per capita
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All−sector government spending per capita
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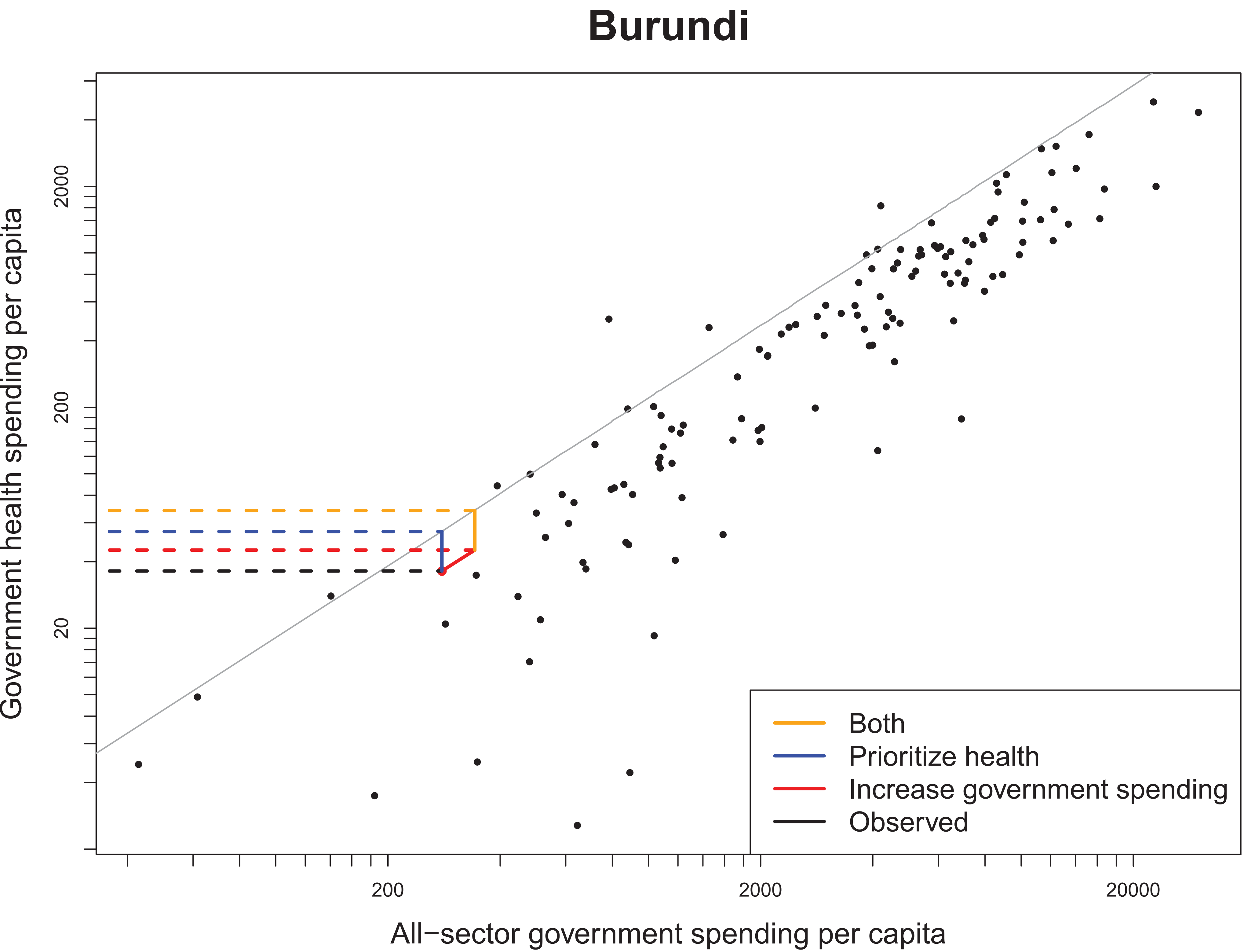
Both
Prioritize health
Increase government spending
Observed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Government health spending per capita
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All−sector government spending per capita
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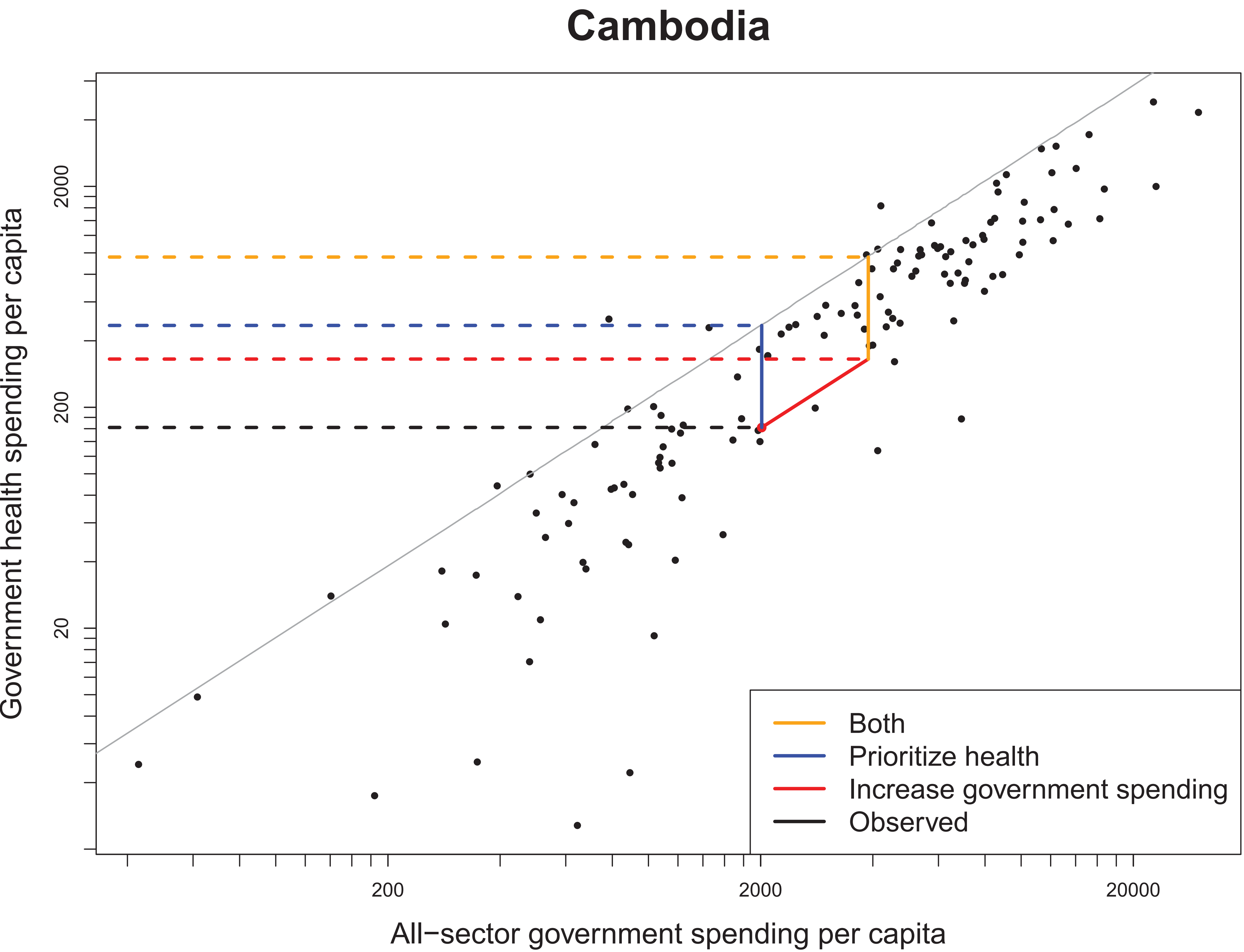
Prioritize health
Increase government spending
Observed


Cambodia
Government health spending per capita
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All−sector government spending per capita
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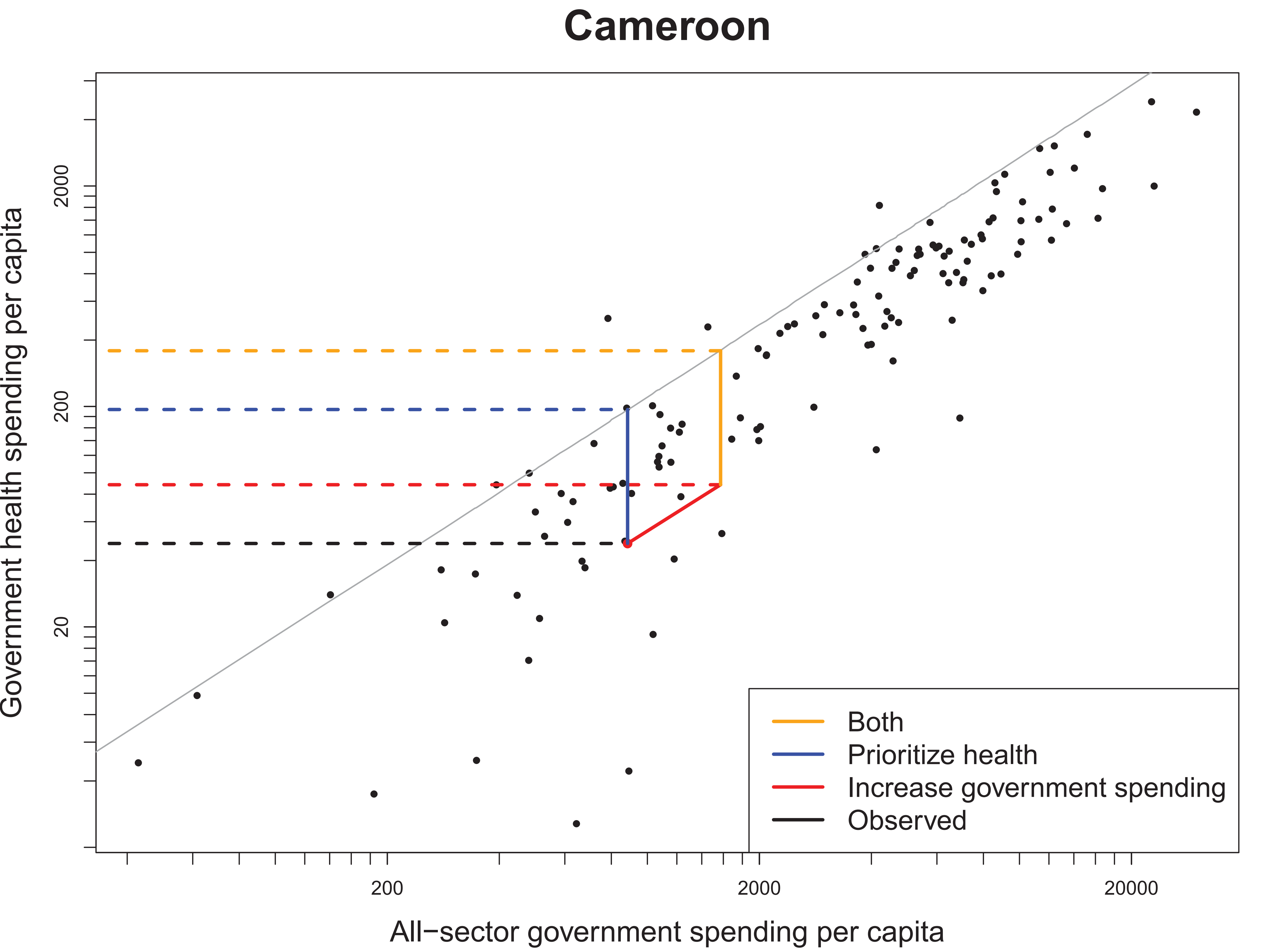
Prioritize health
Increase government spending
Observed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Government health spending per capita
All−sector government spending per capita
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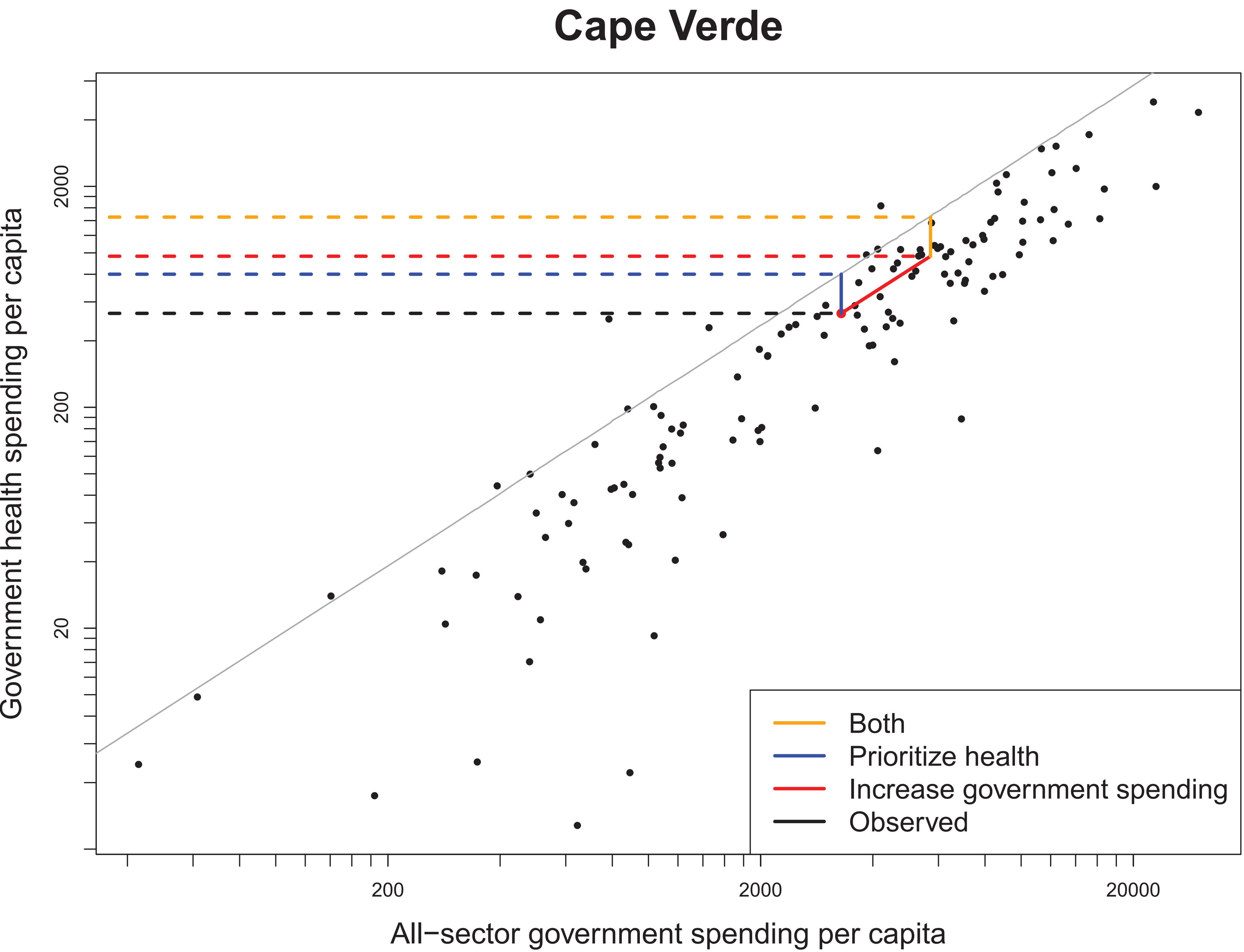
Prioritize health
Increase government spending
Observed


Cape Verde
Government health spending per capita
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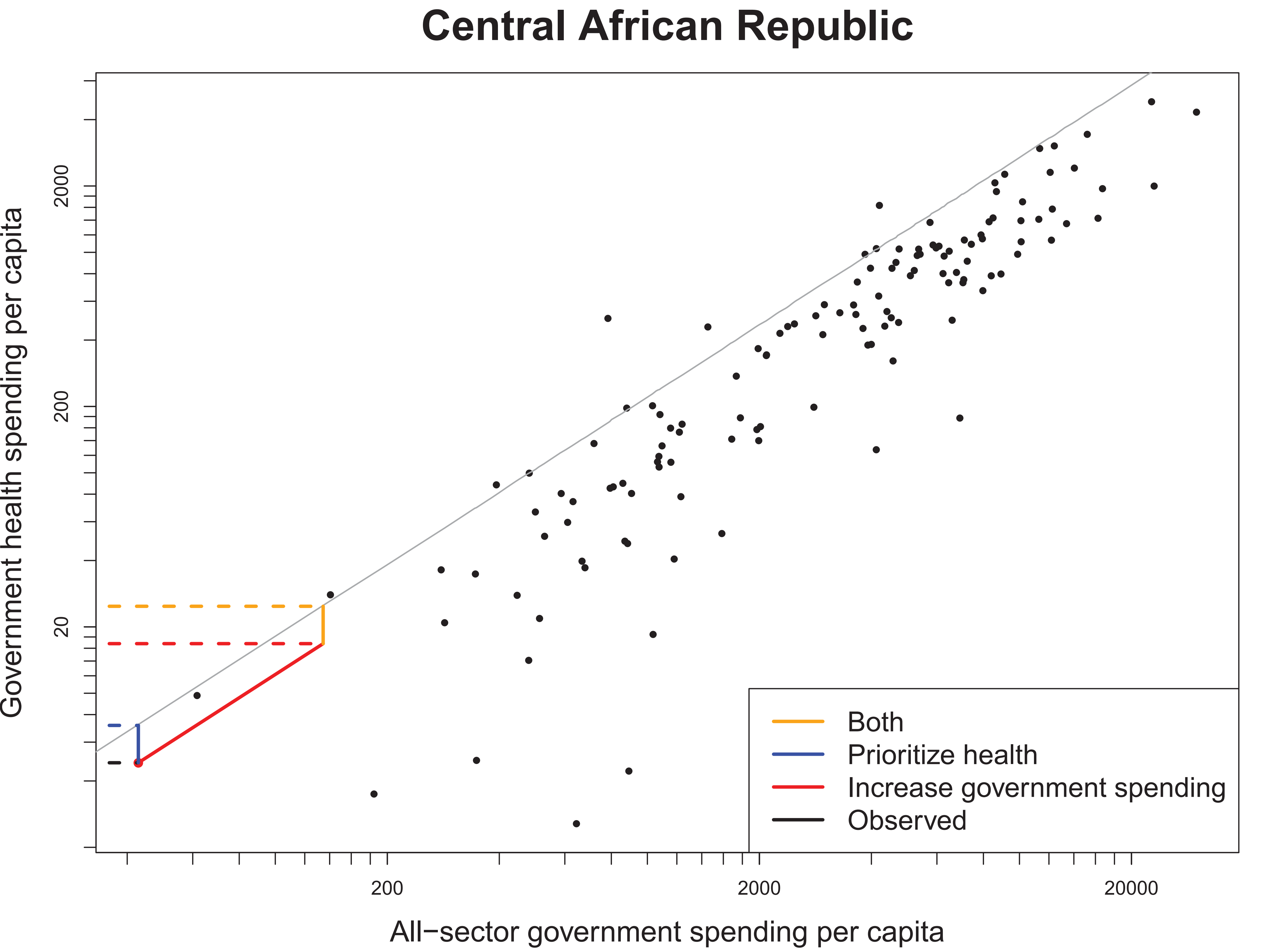
All−sector government spending per capita
Both
Prioritize health
Increase government spending
Observed


Central African Republic
Government health spending per capita
All−sector government spending per capita
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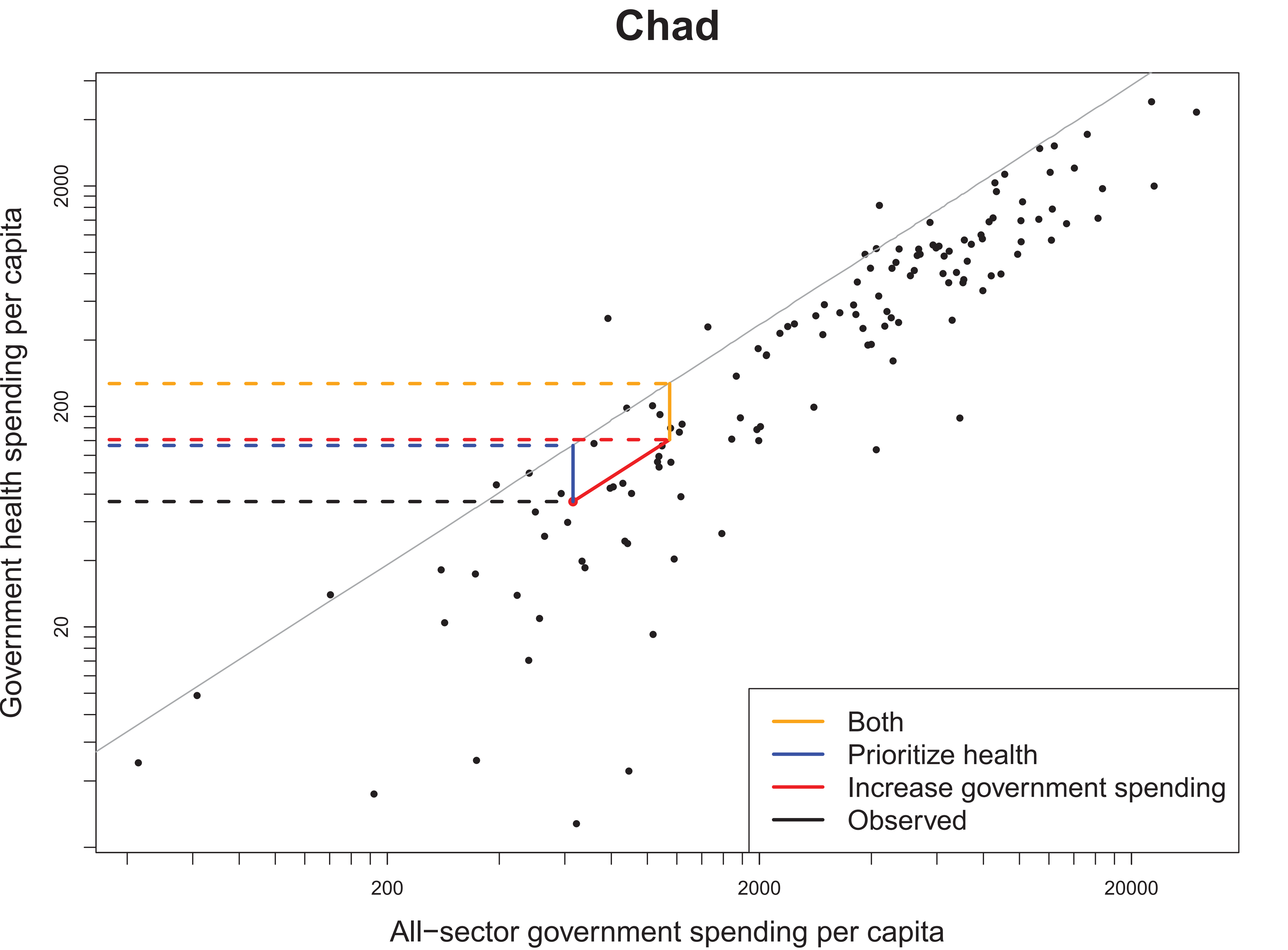
Prioritize health
Increase government spending
Observed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Government health spending per capita
All−sector government spending per capita
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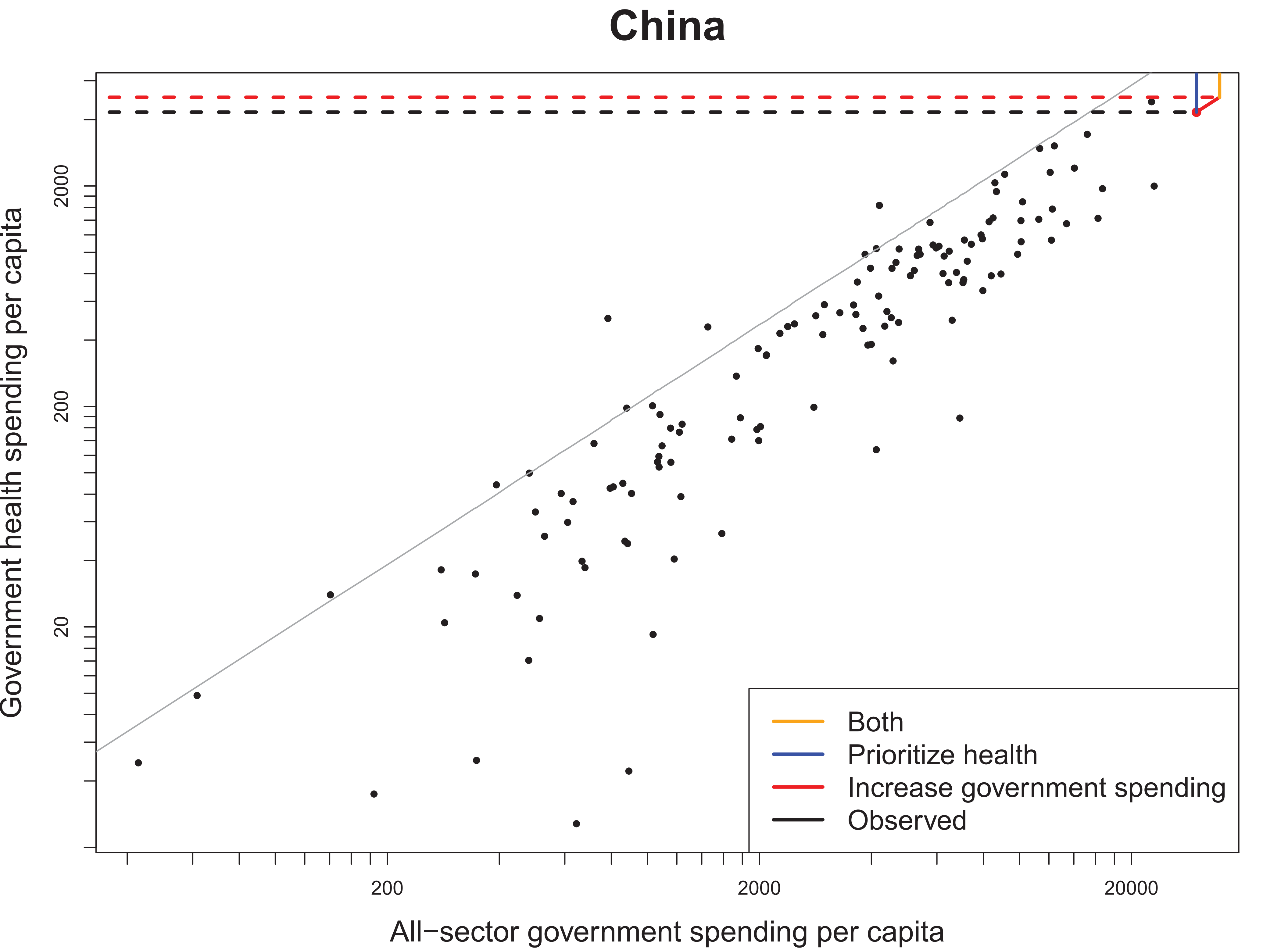
Both
Prioritize health
Increase government spending
Observed


China
Government health spending per capita
All−sector government spending per capita
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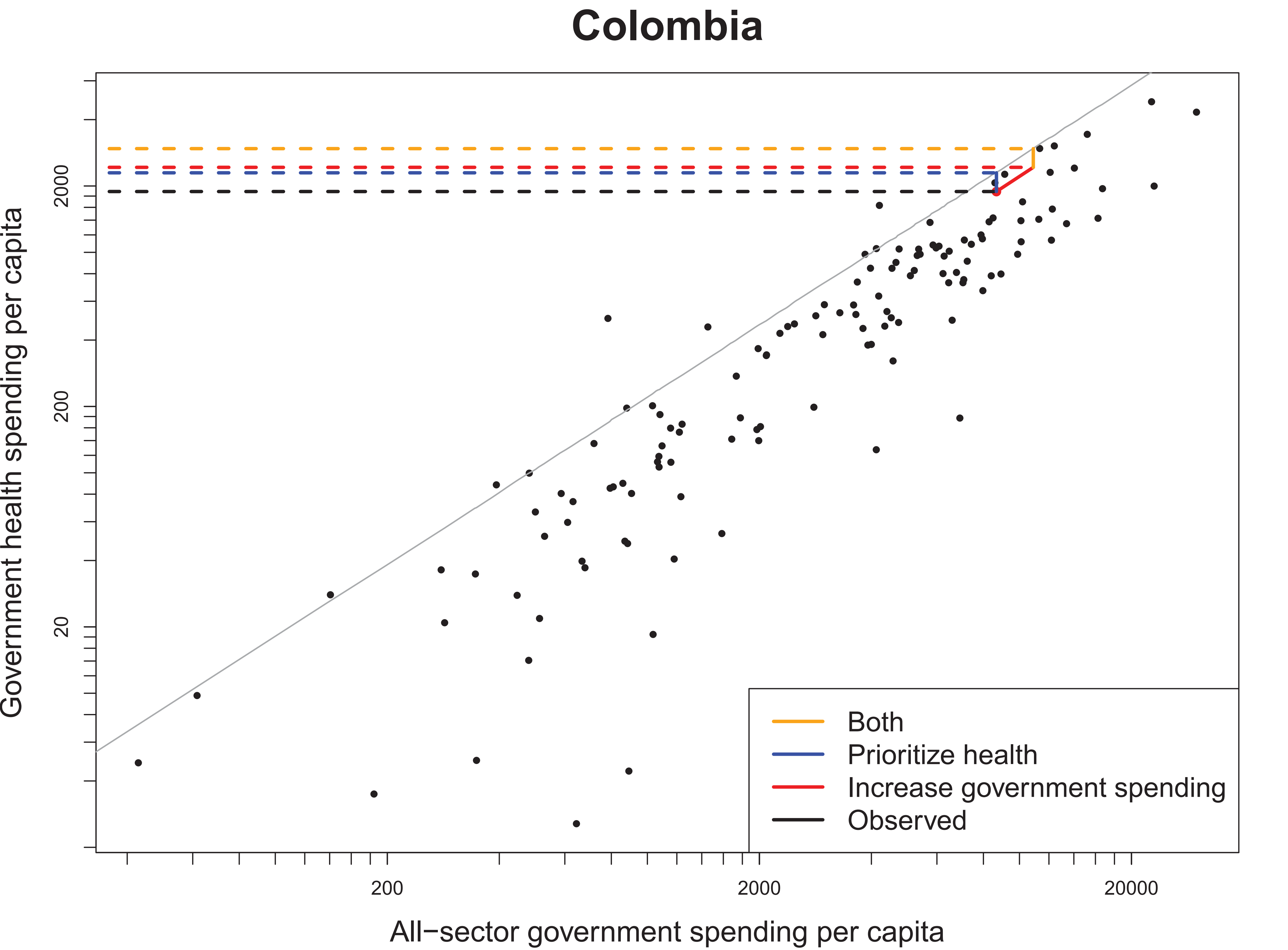
Prioritize health
Increase government spending
Observed



Colombia
Government health spending per capita
All−sector government spending per capita
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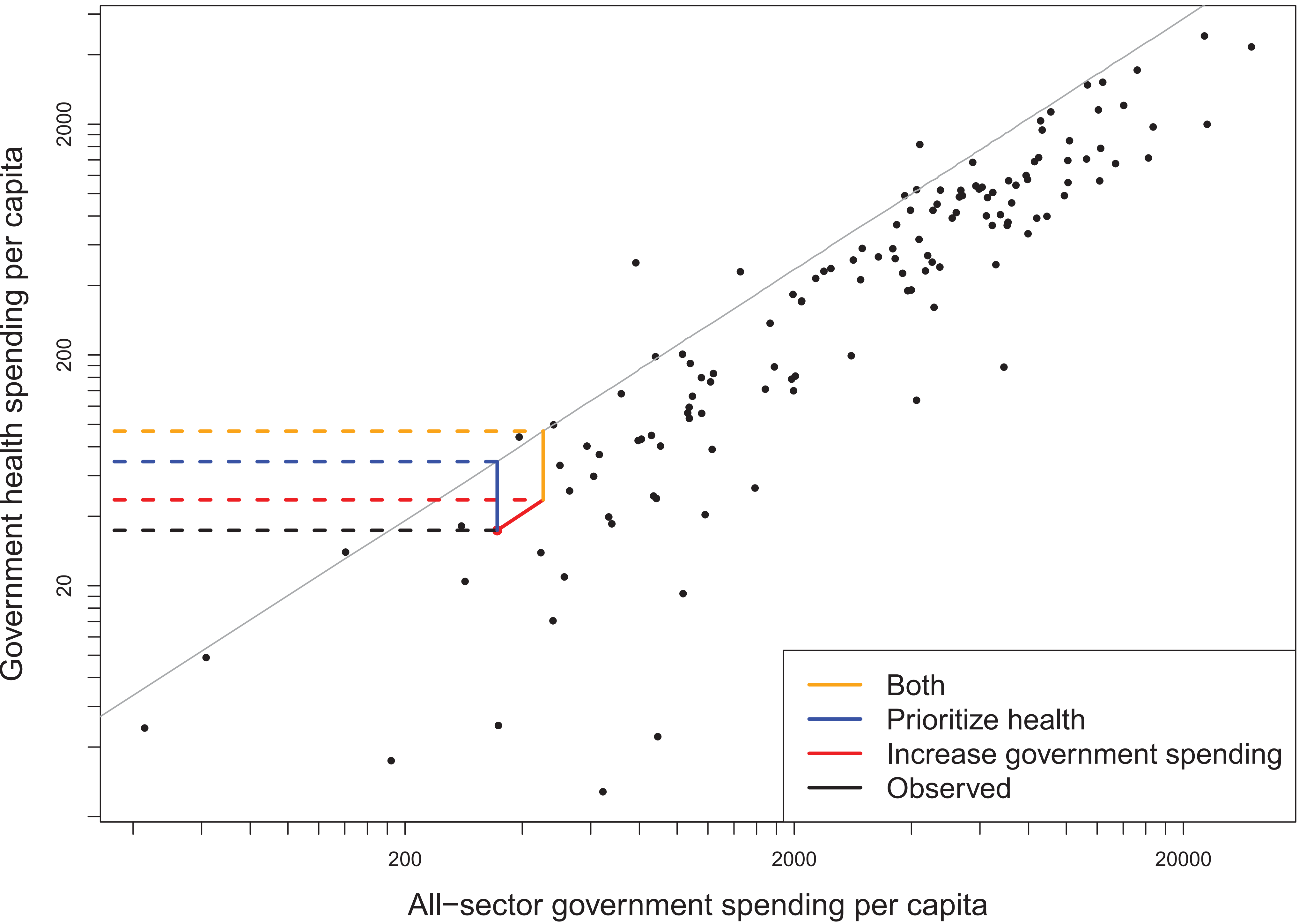
Both
Prioritize health
Increase government spending
Observed

Comoros



Government health spending per capita
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All−sector government spending per capita
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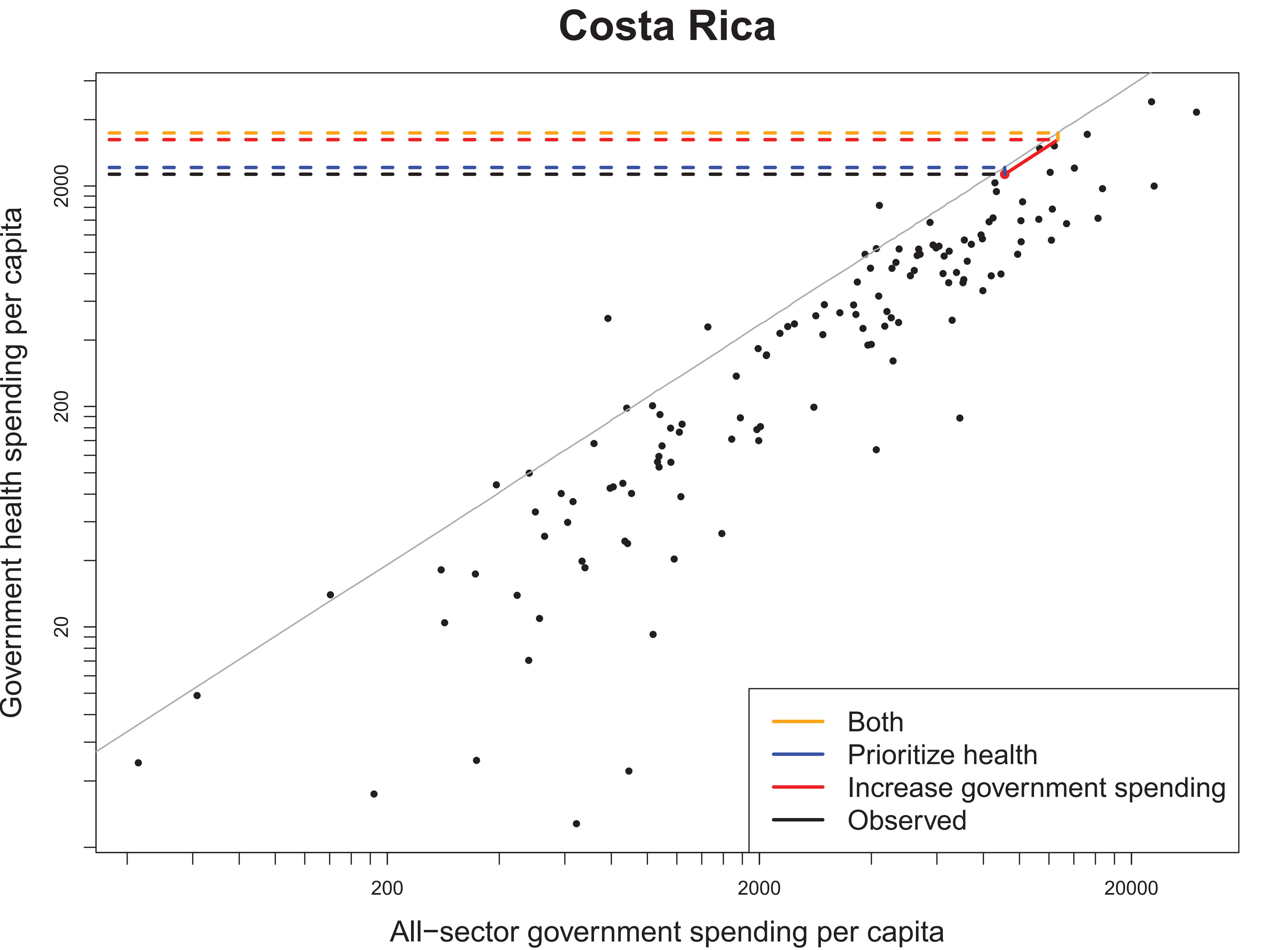
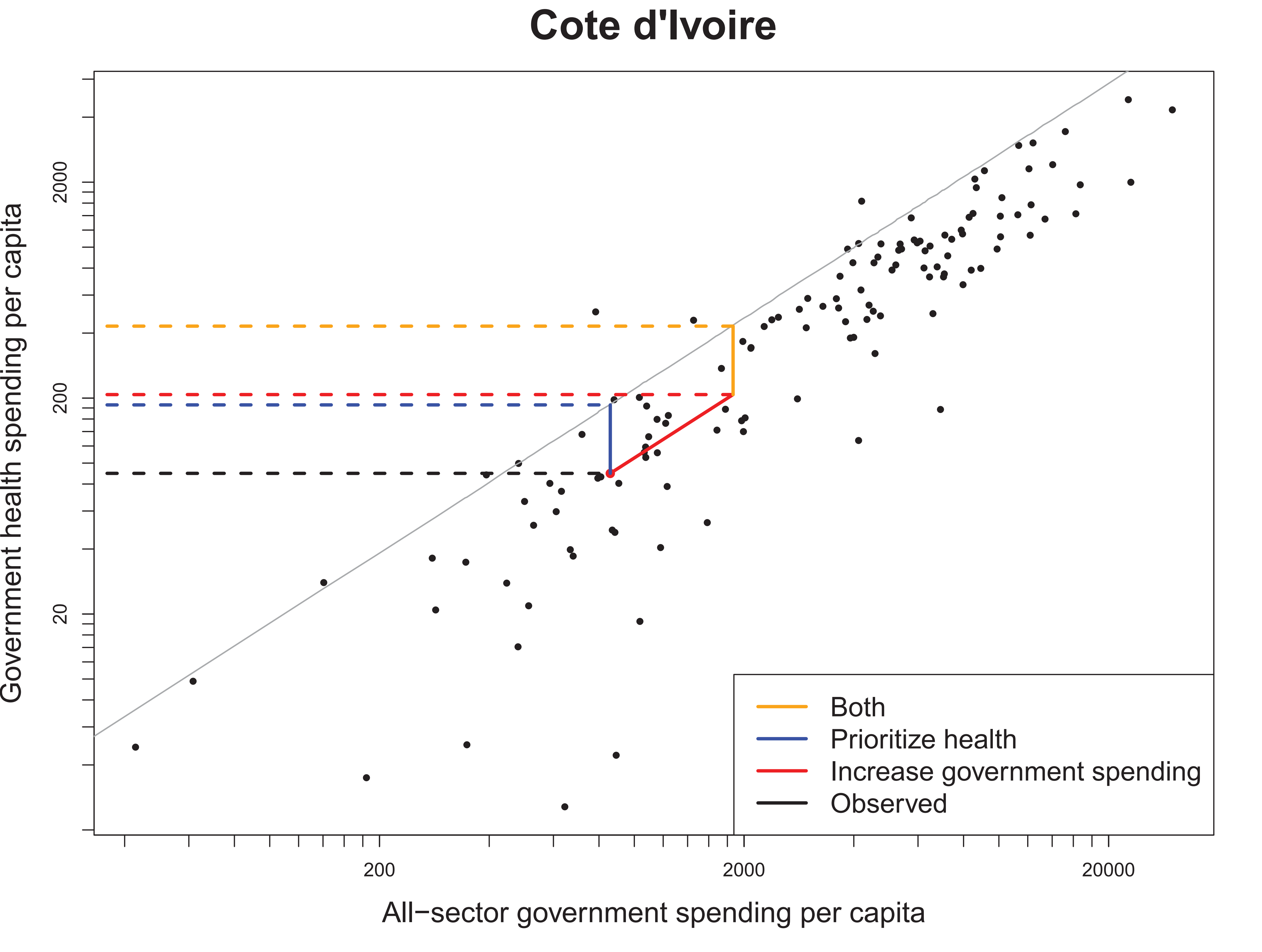
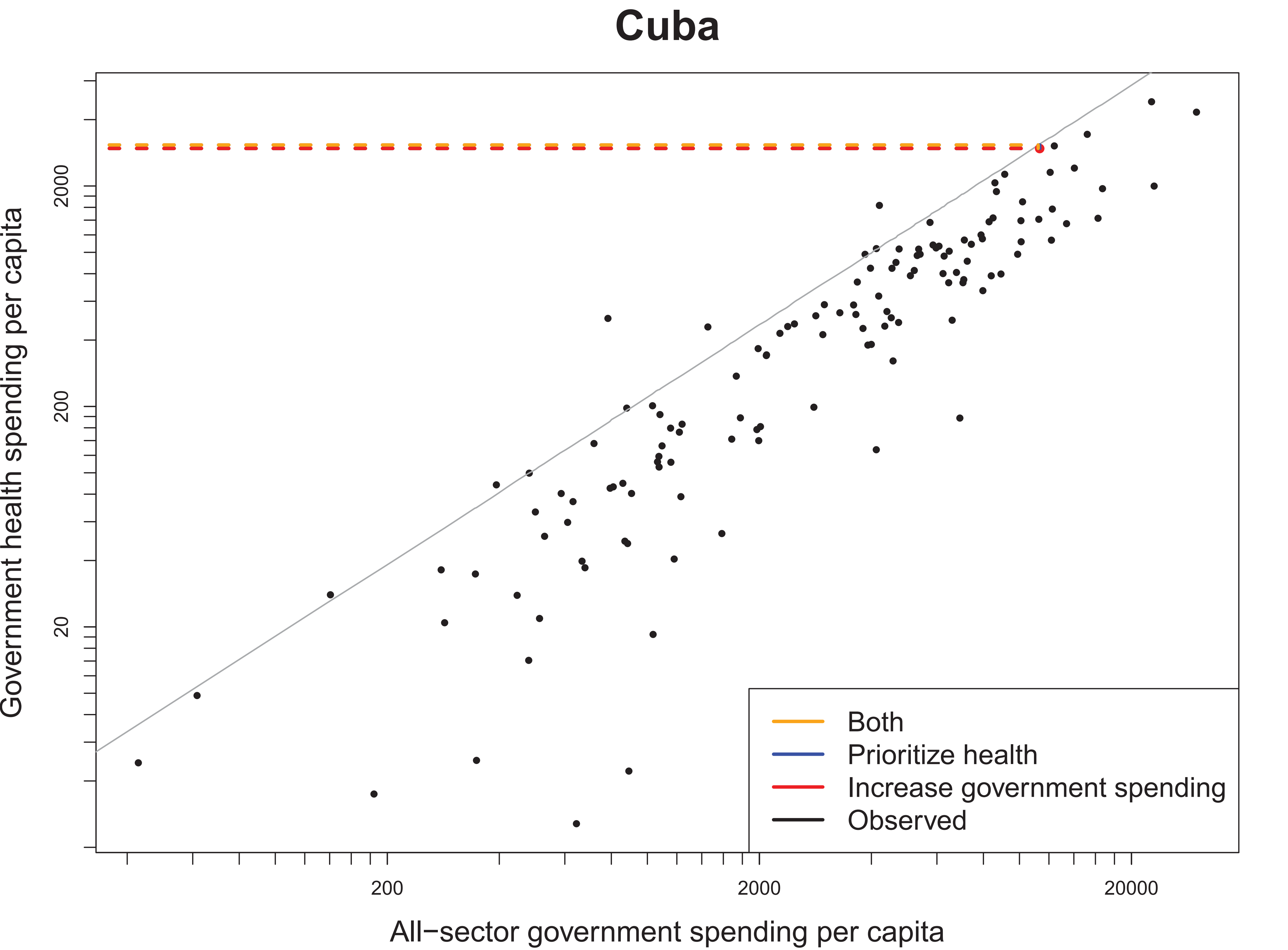
Prioritize health
Increase government spending
Observed

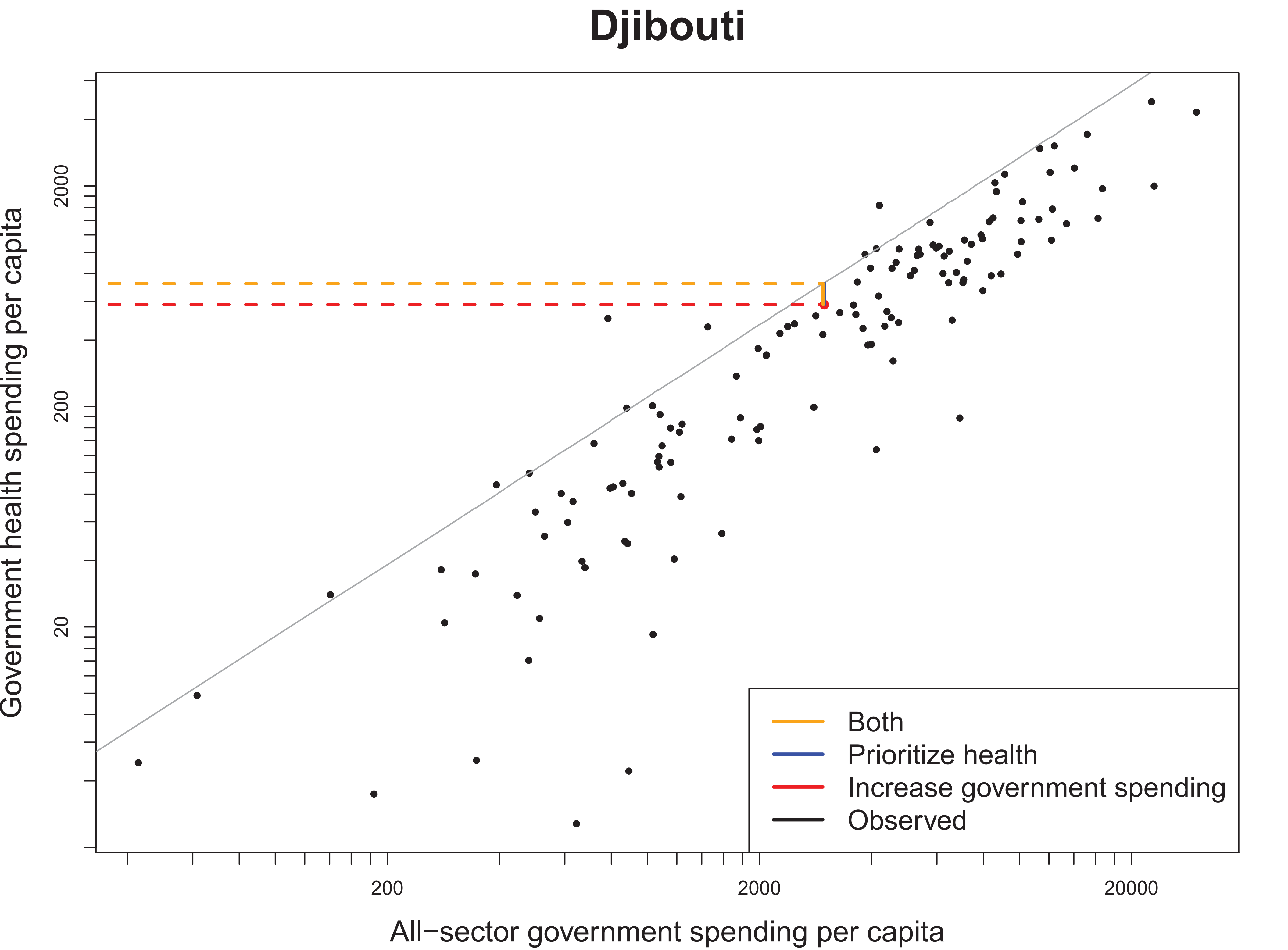


Costa Rica
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



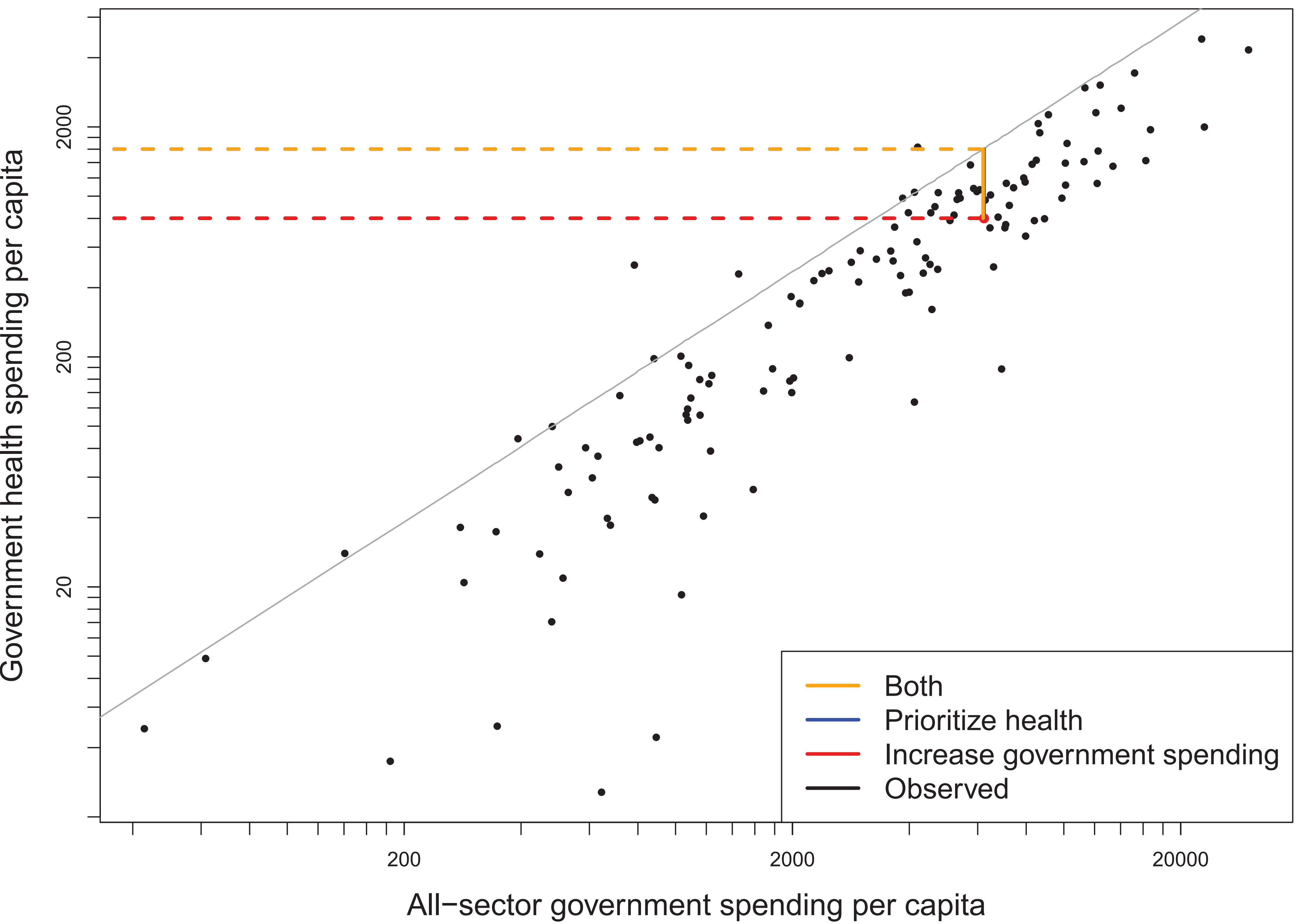
Cote d'Ivoire
Government health spending per capita
20
200
2000
200
2000
20000
All−sector government spending per capita
Both
Prioritize health
Increase government spending
Observed


Cuba
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



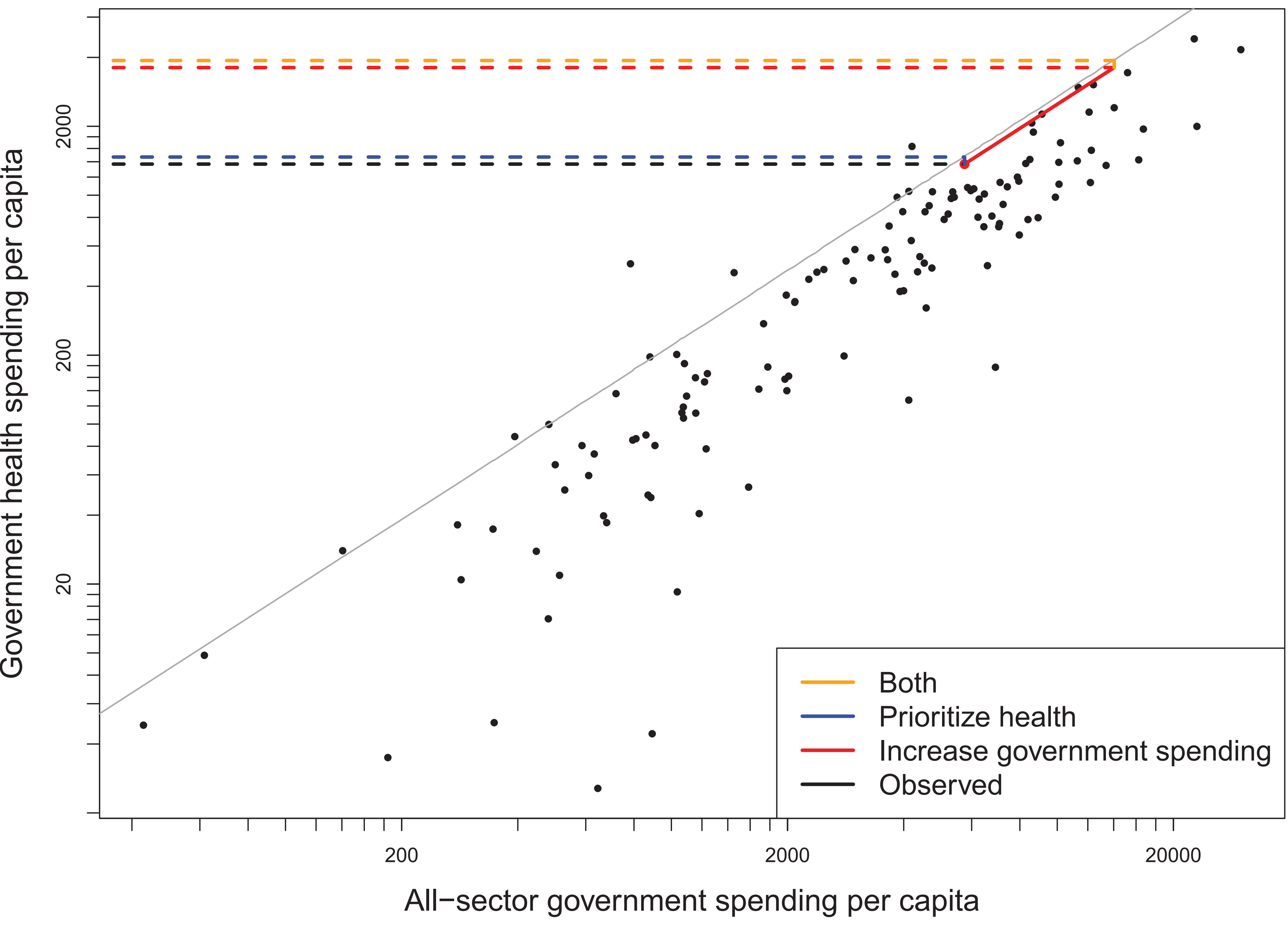
Djibouti
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

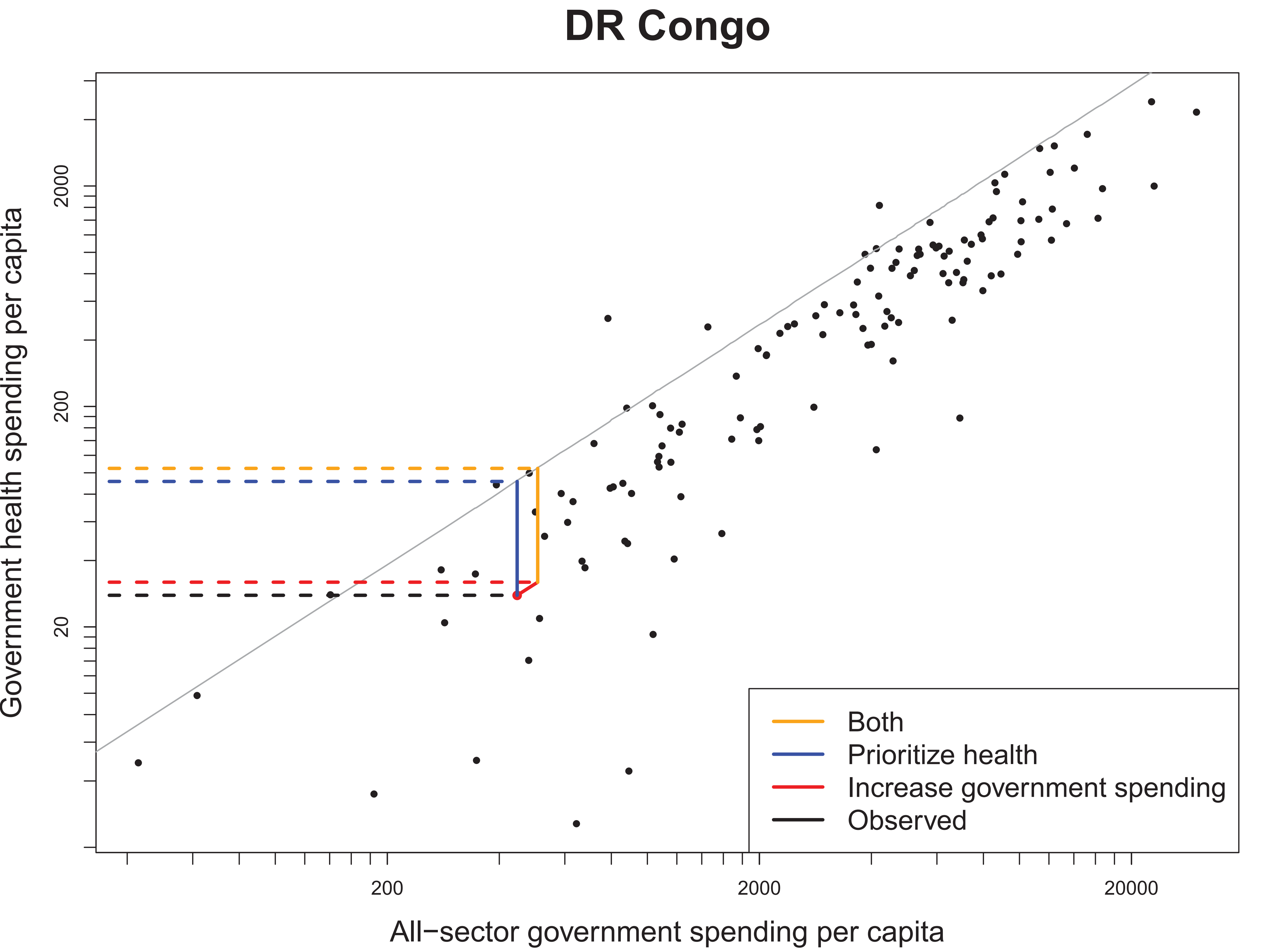
Dominica



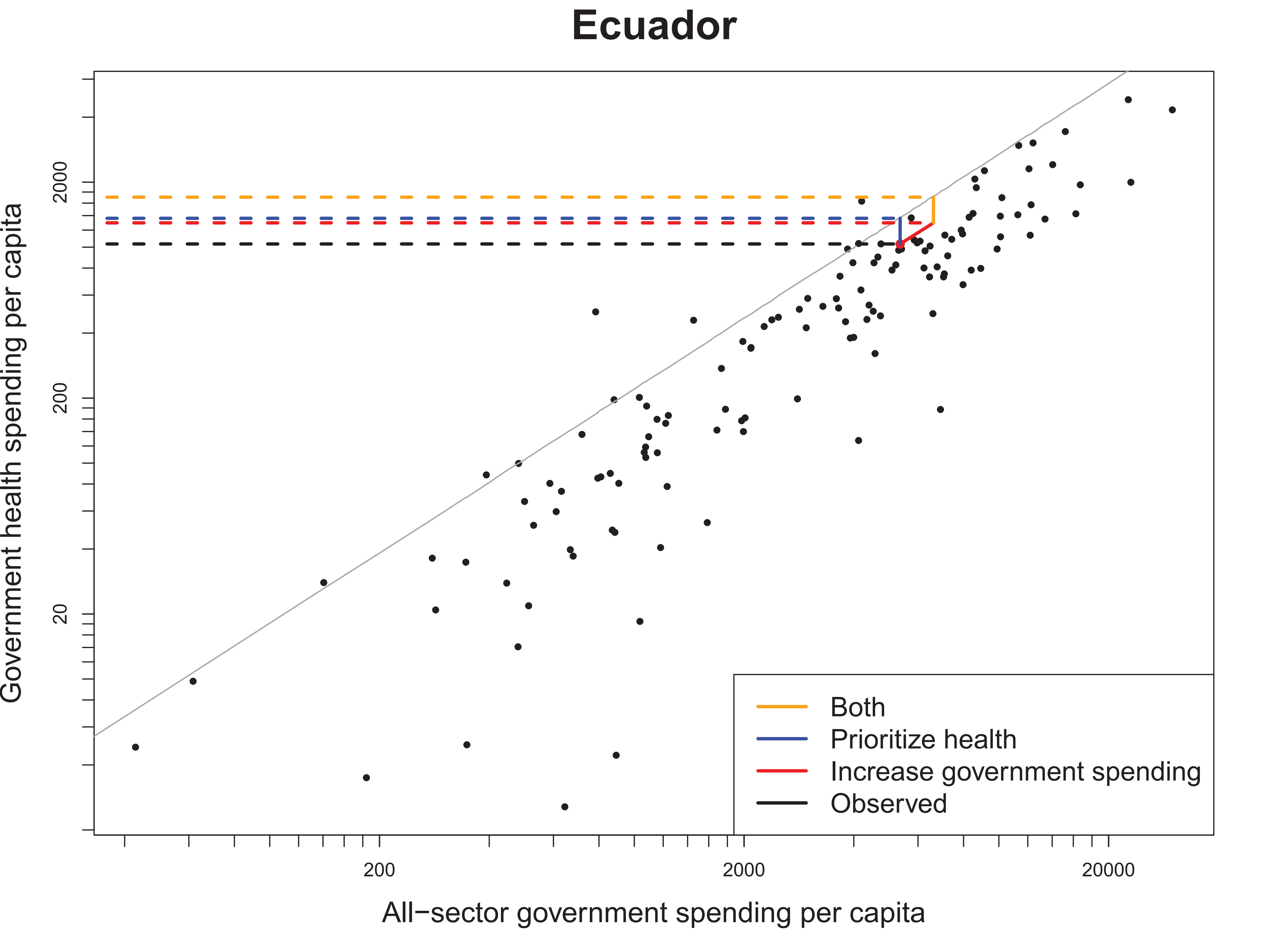
Government health spending per capita
2000
200
20
Both
Prioritize health
Increase government spending
Observed
200
2000
20000
All−sector government spending per capita

Dominican Republic

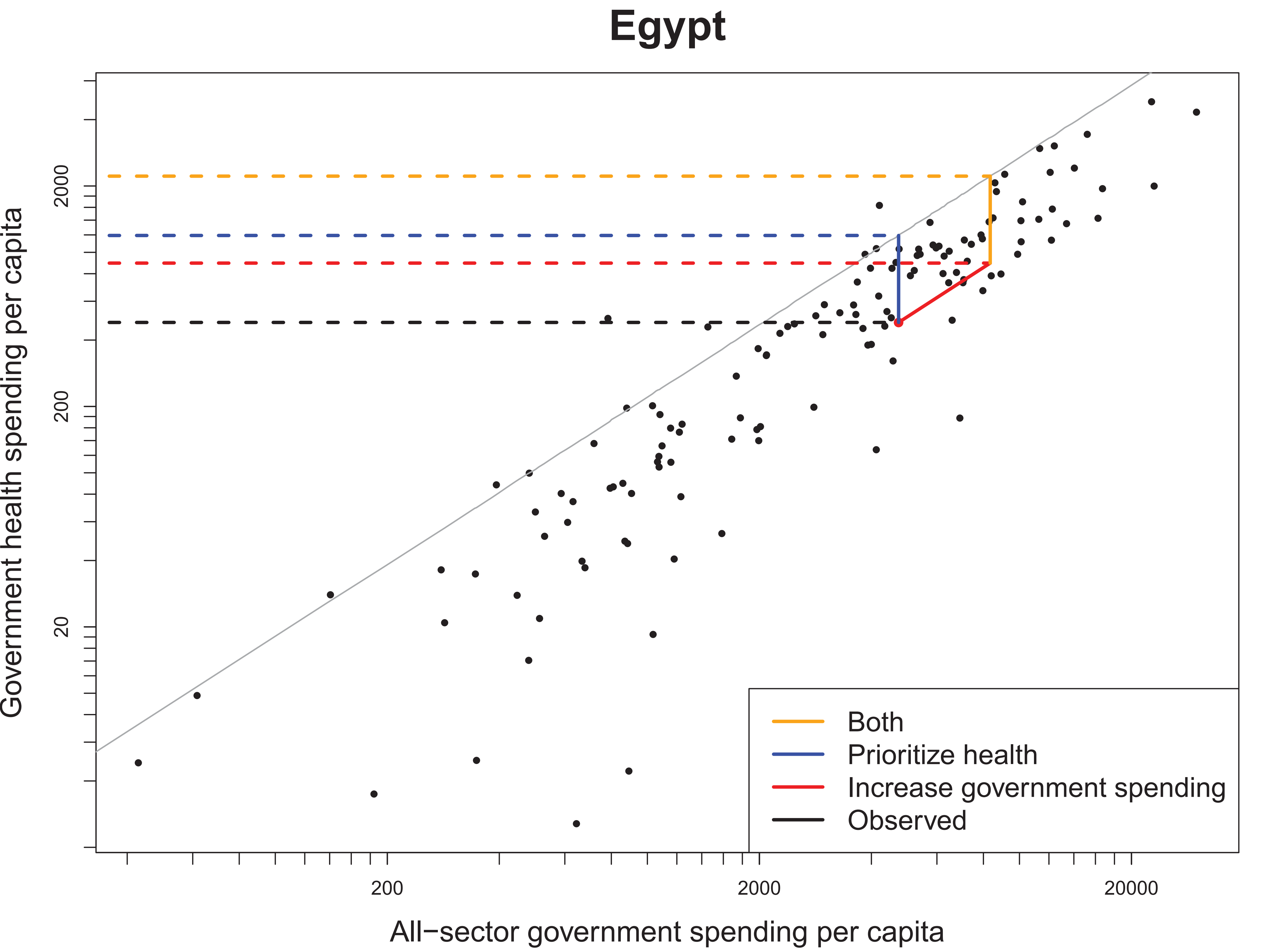




DR Congo
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

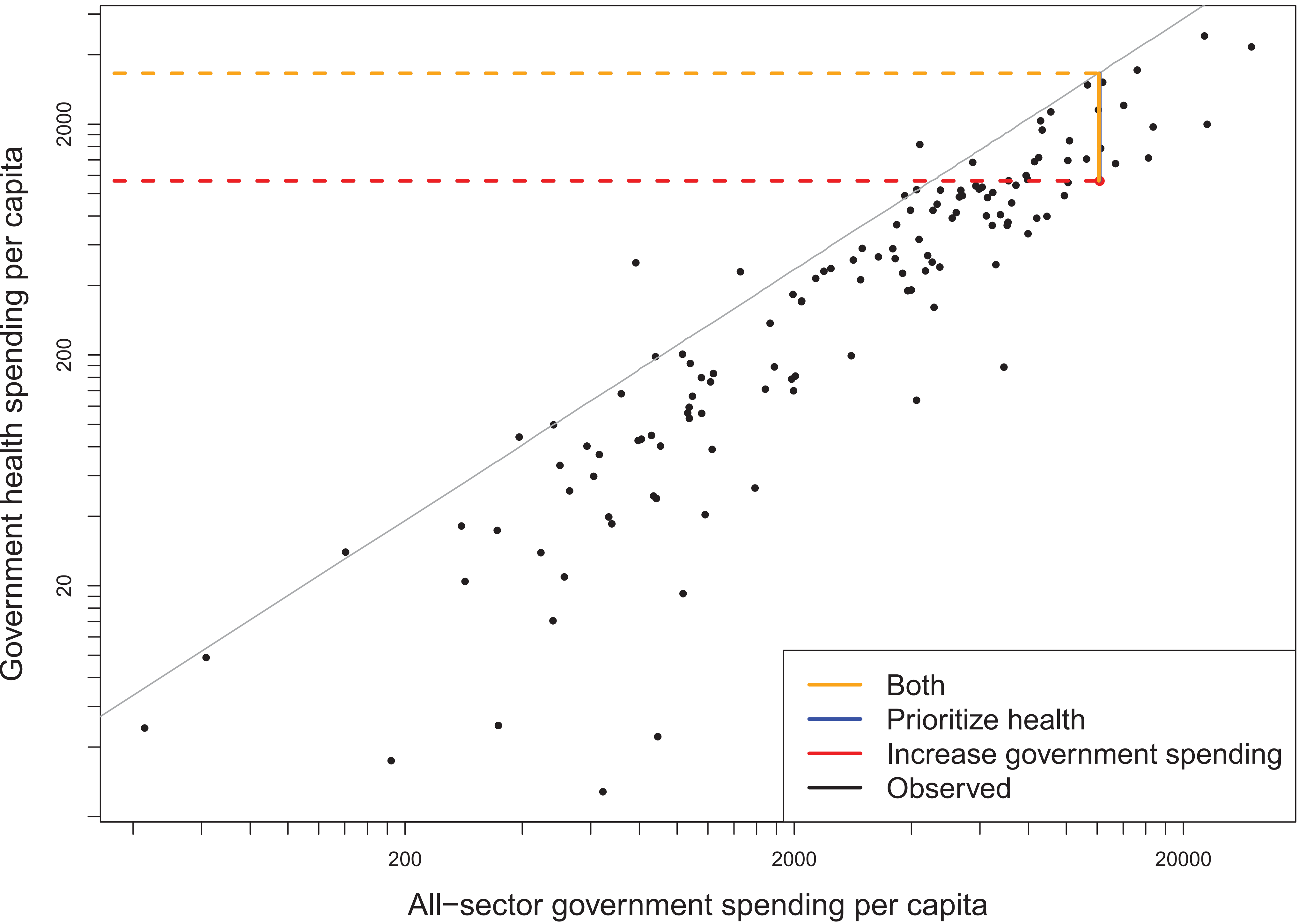


Ecuador
Government health spending per capita
All−sector government spending per capita
2000
200
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

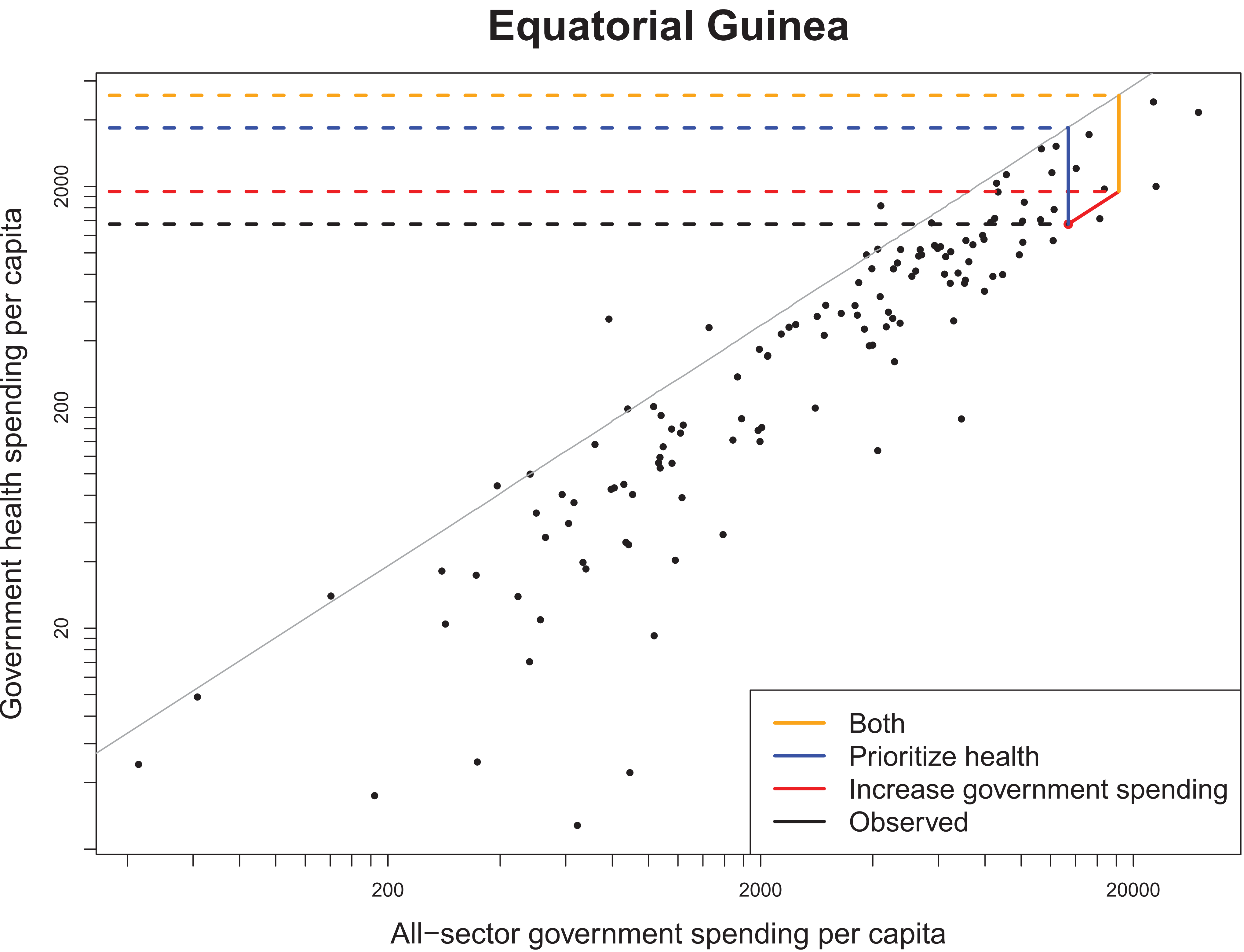


Egypt
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

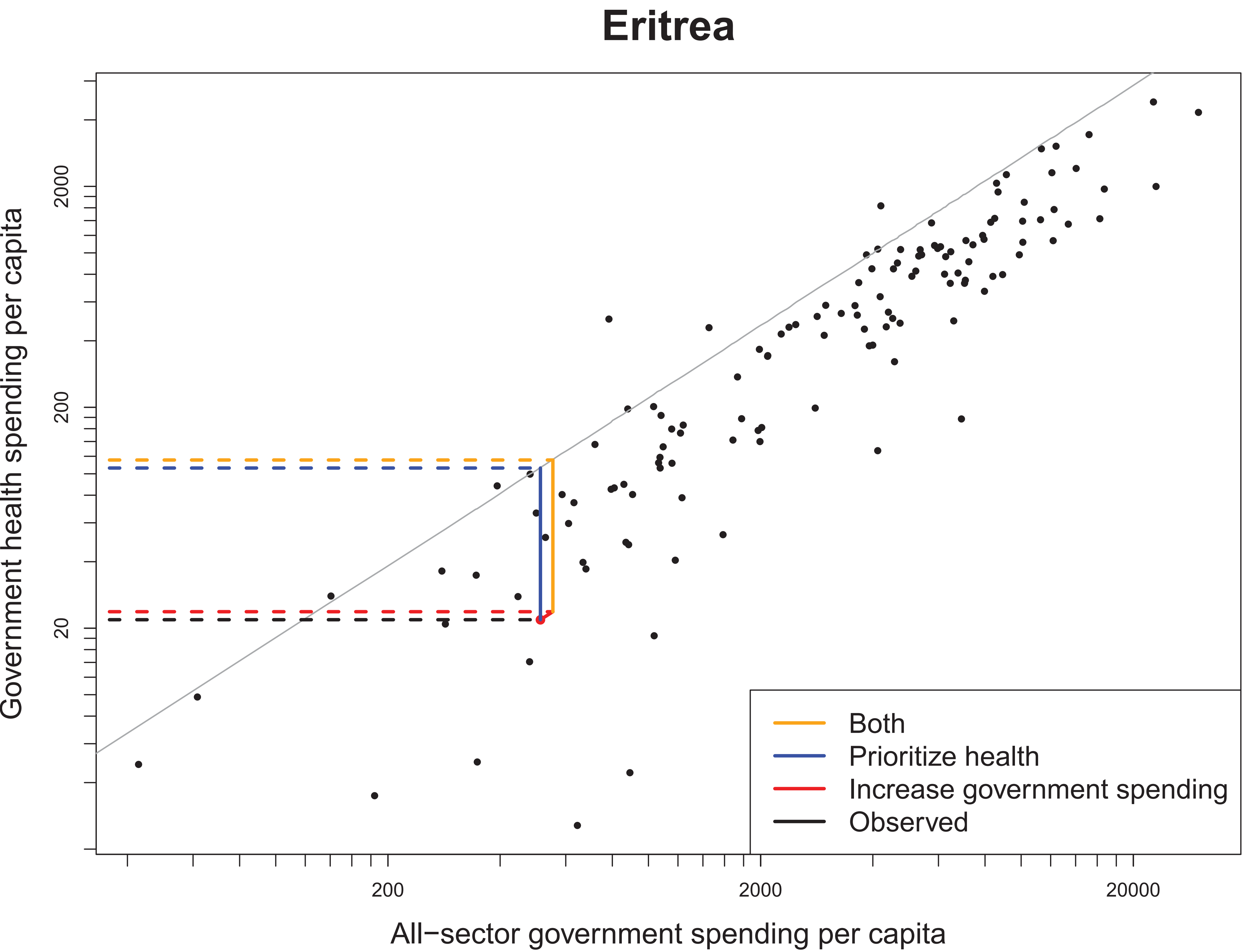
El Salvador

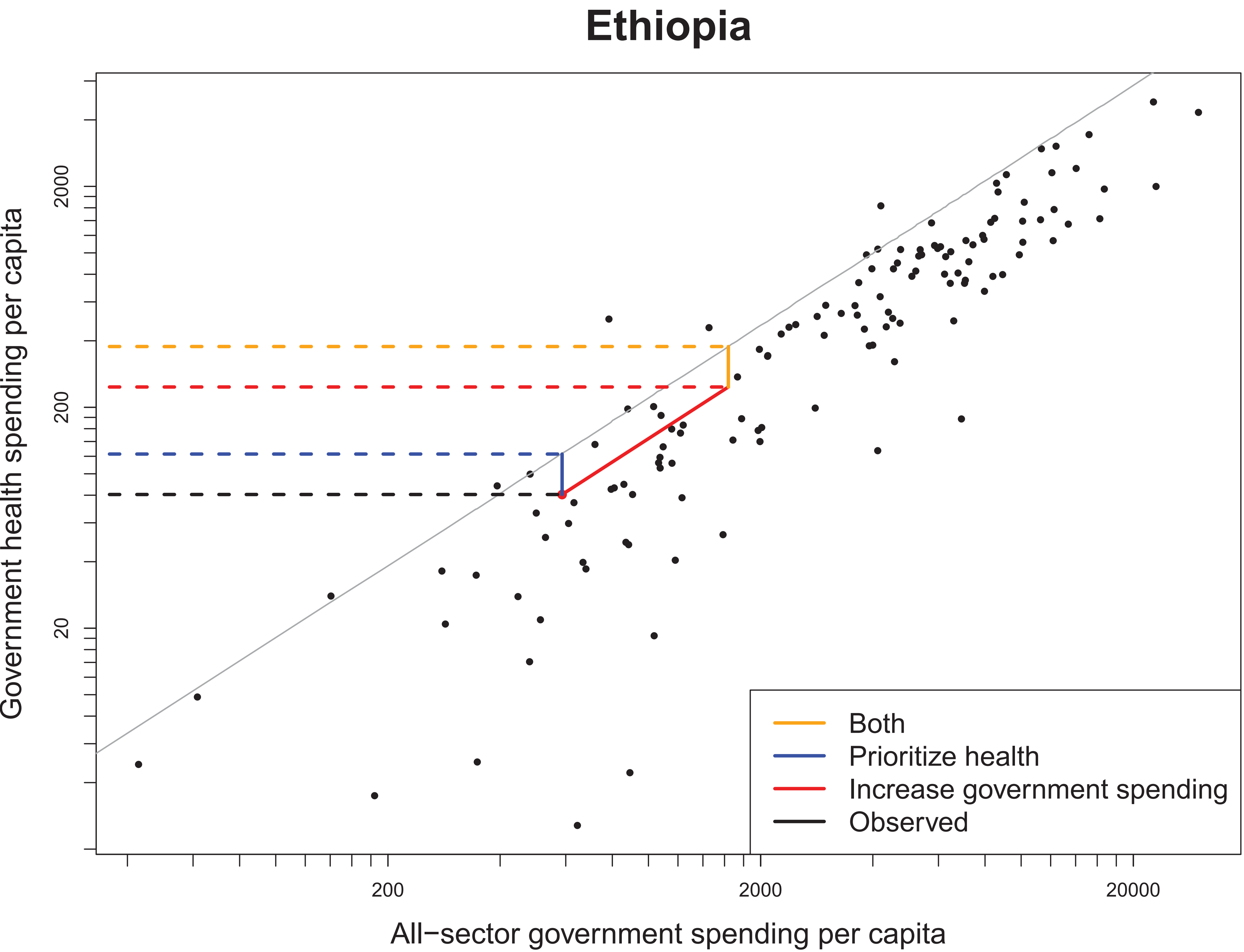


Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

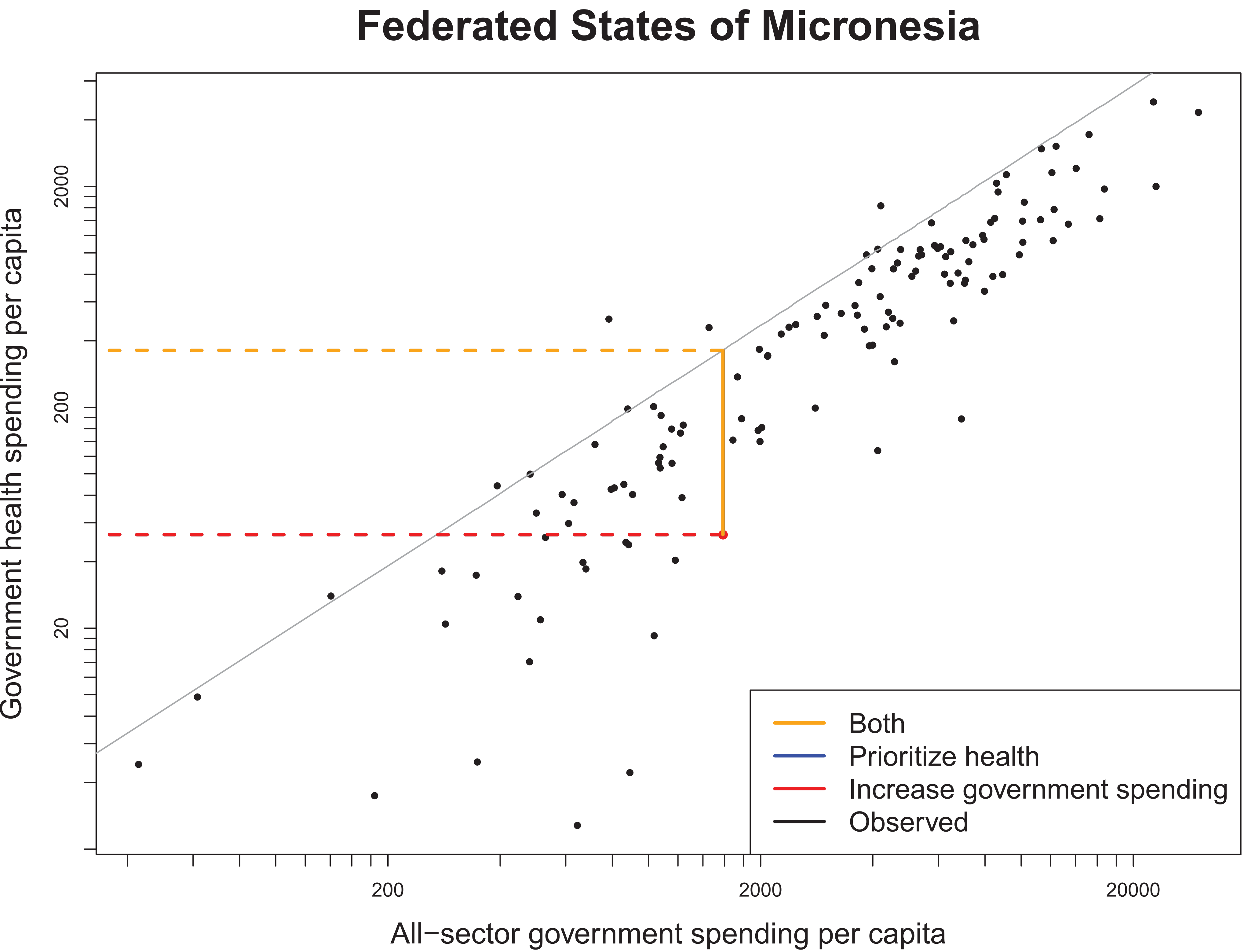


Equatorial Guinea
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

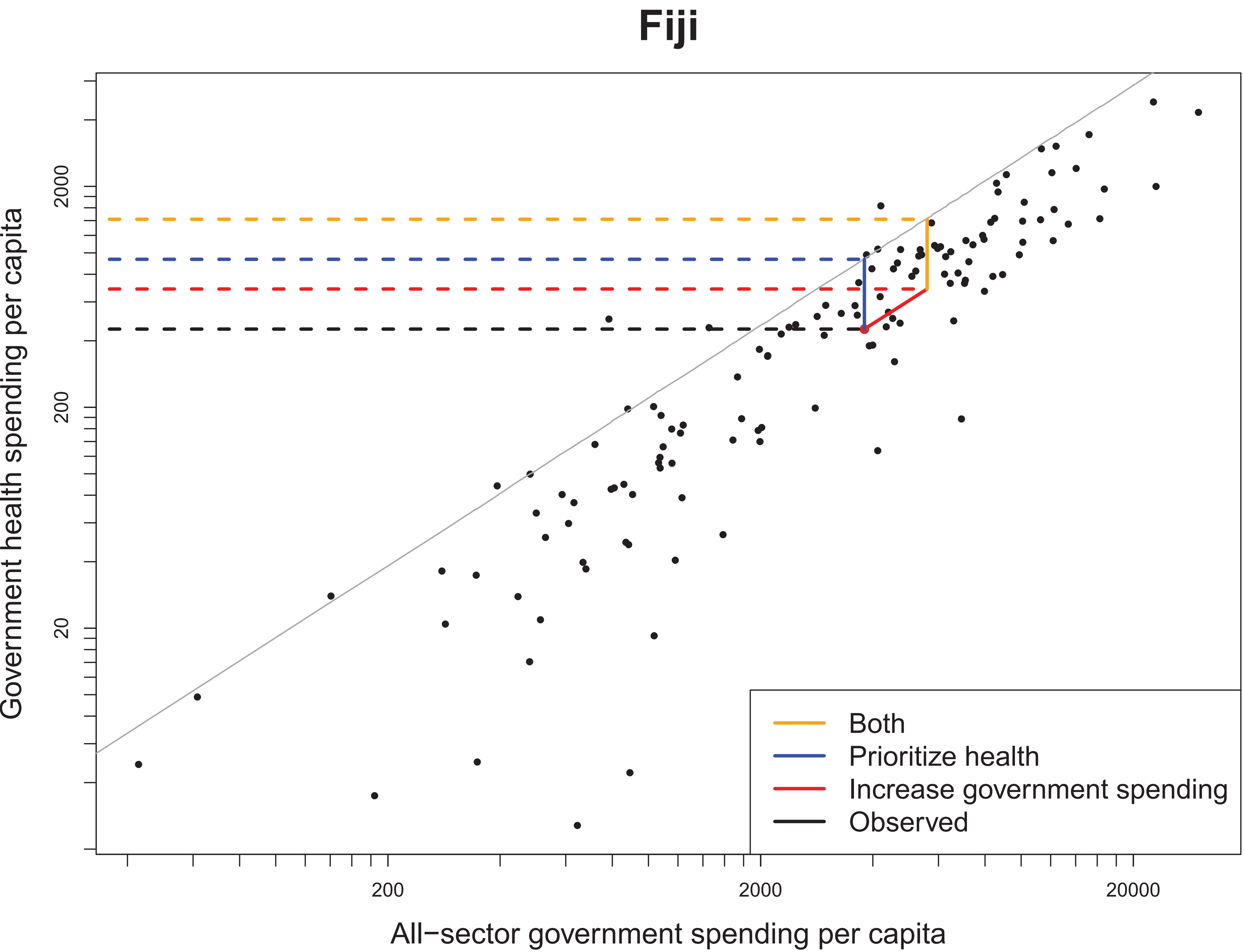

Eritrea
Government health spending per capita
20
200
2000
200
2000
20000
All−sector government spending per capita
Both
Prioritize health
Increase government spending
Observed



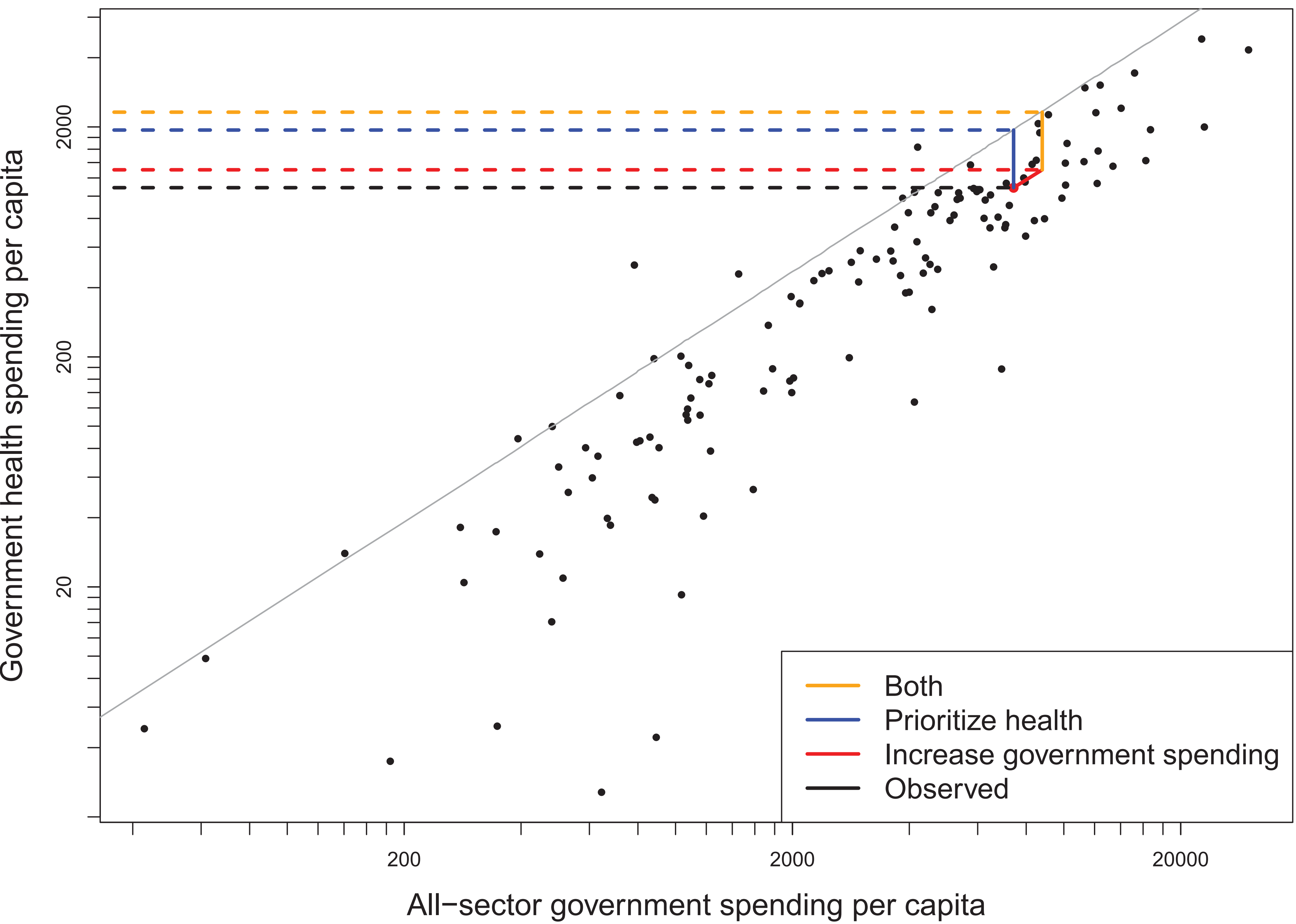
Ethiopia
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



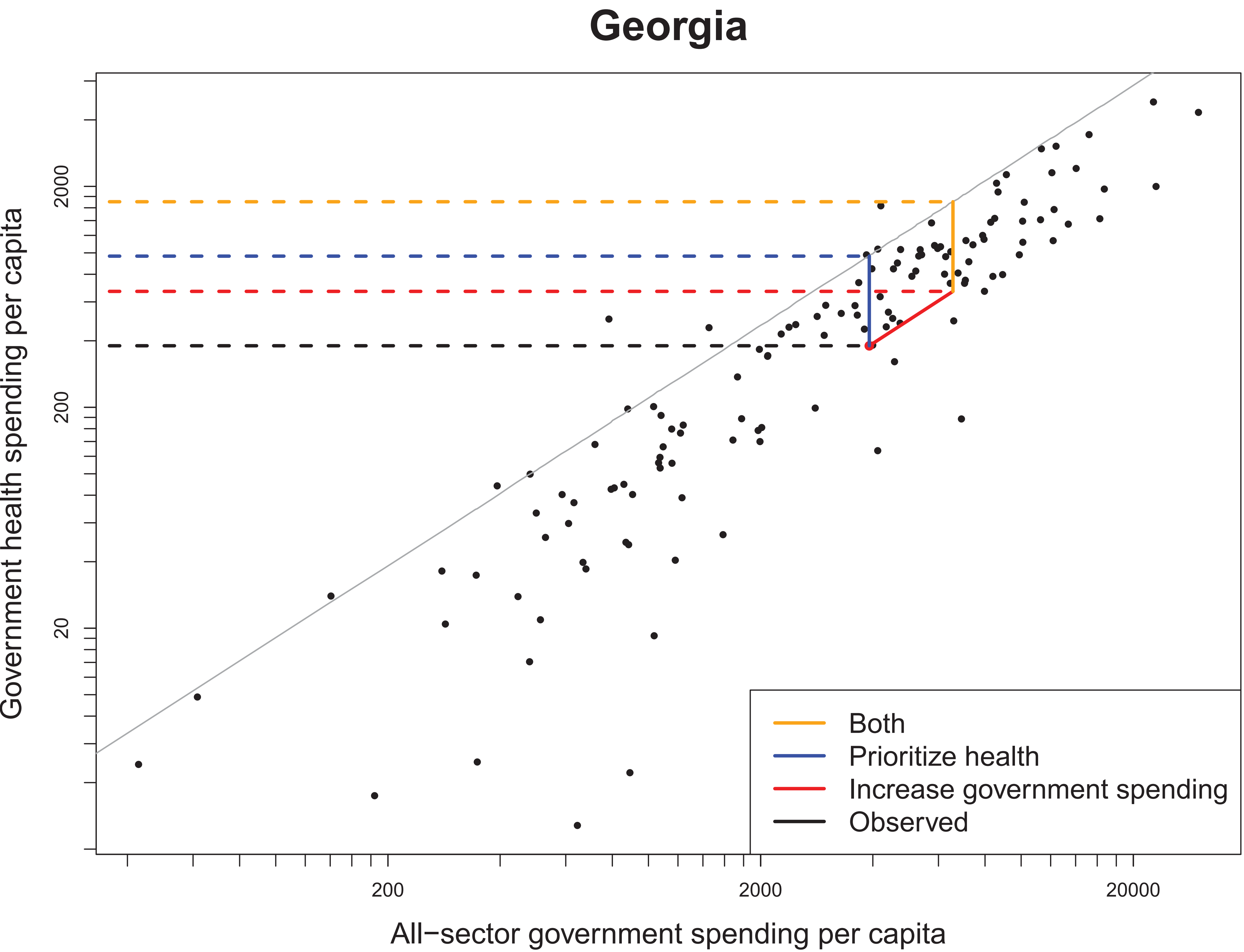
Federated States of Micronesia
Government health spending per capita
All−sector government spending per capita
2000
200
20
20000
Both
Prioritize health
Increase government spending
Observed

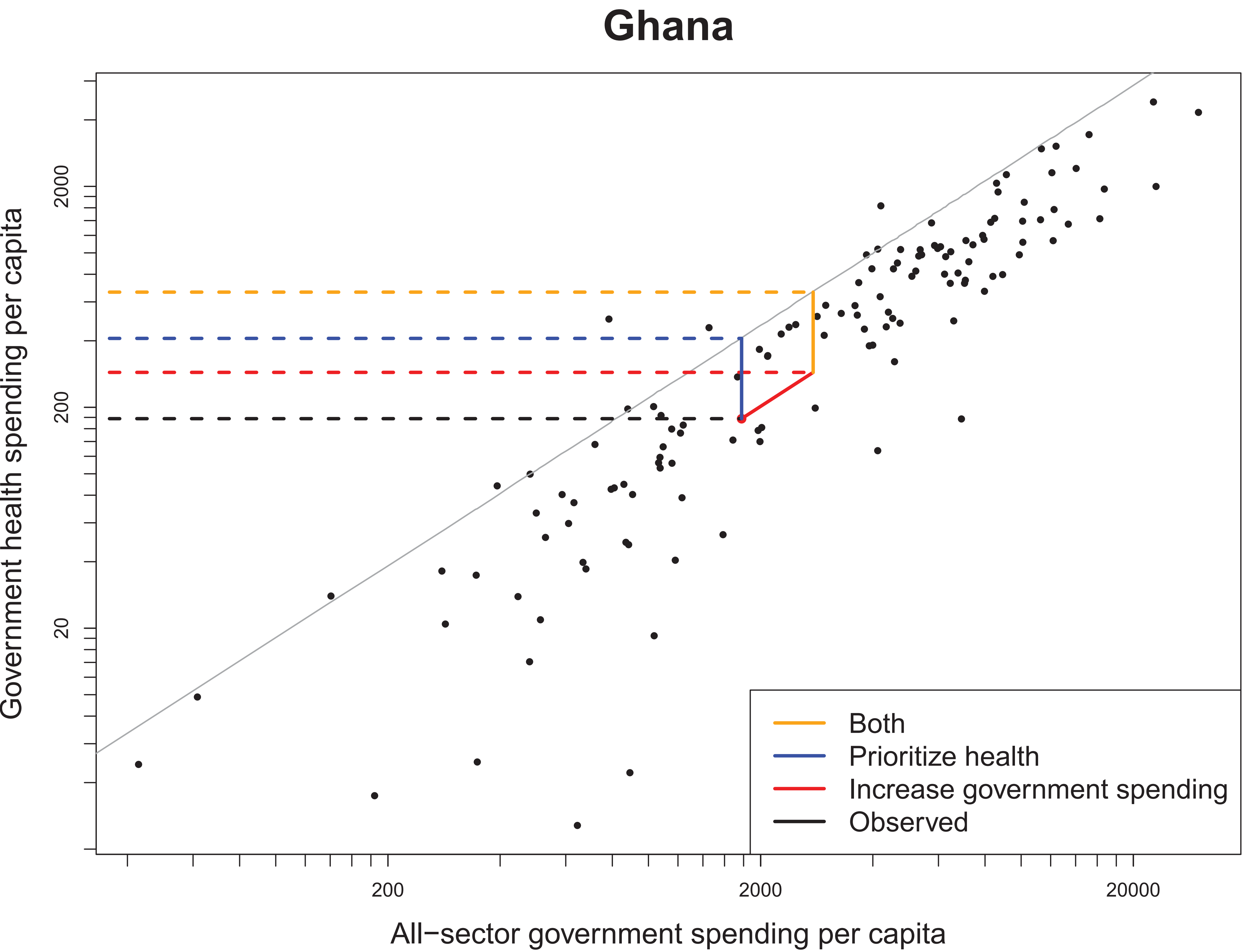

Fiji
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

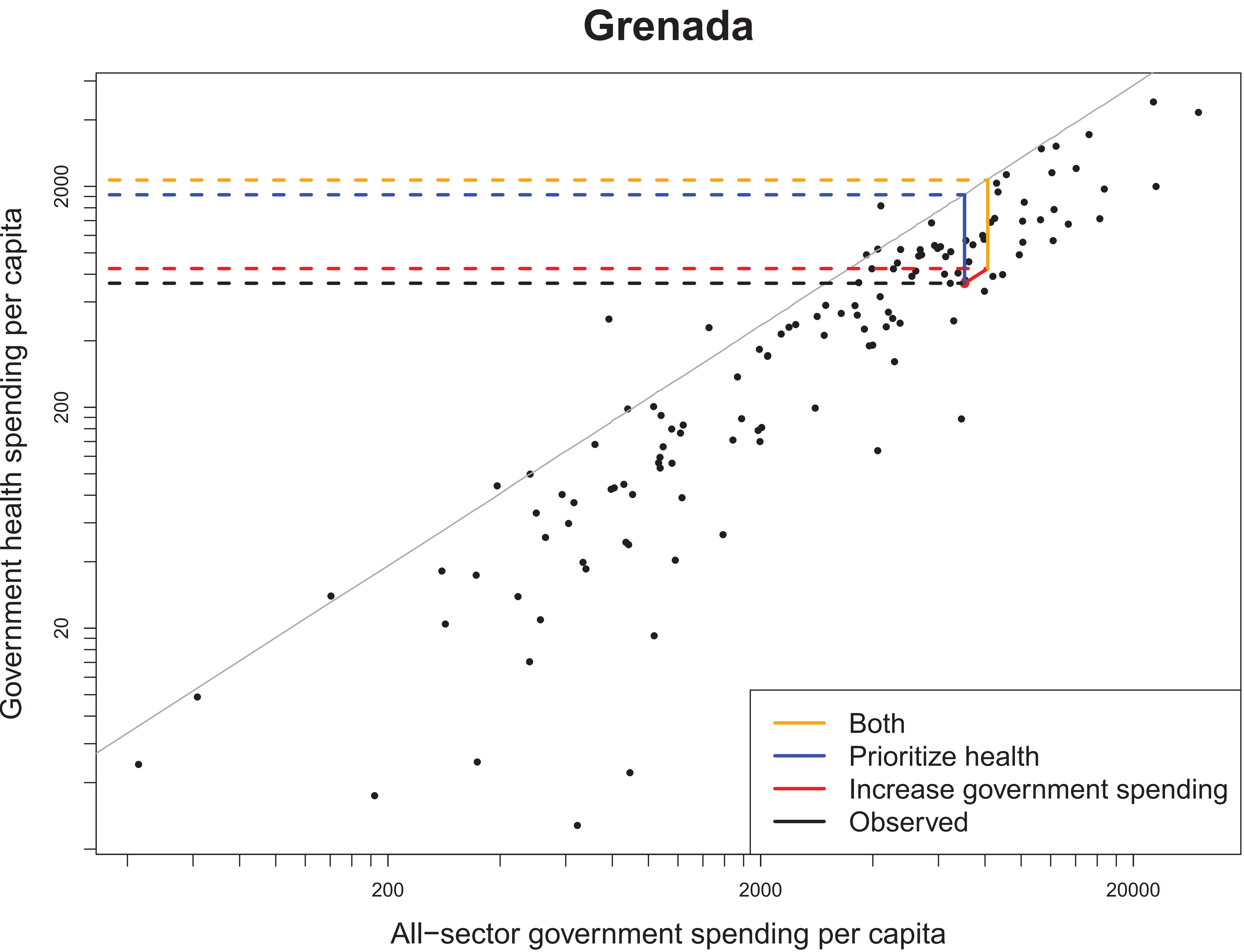
Gabon



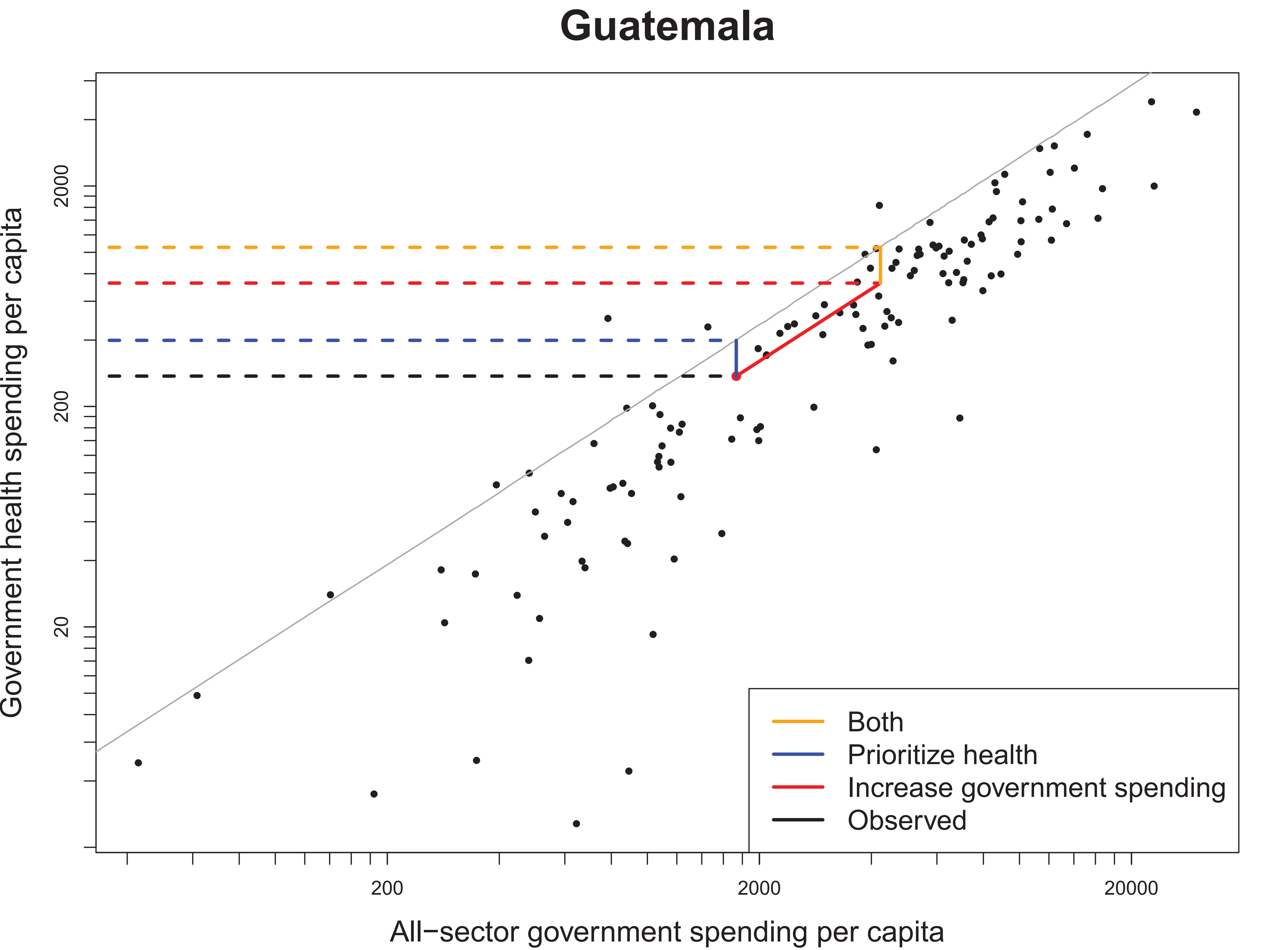
Government health spending per capita
2000
200
20
200
2000
20000
All−sector government spending per capita
Both
Prioritize health
Increase government spending
Observed


Georgia
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

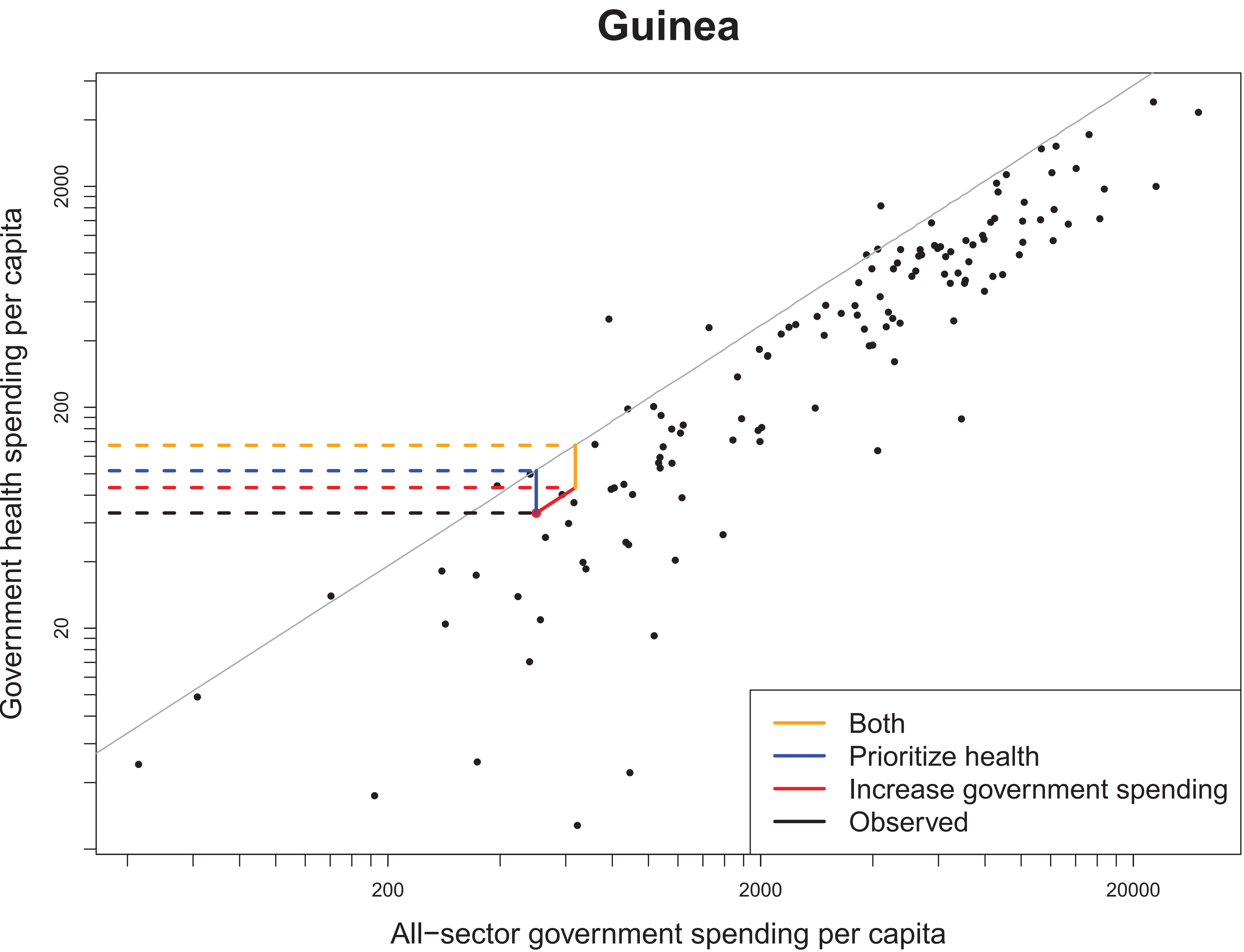

Ghana
Government health spending per capita
2000
200
20
200
2000
20000
All−sector government spending per capita
Both
Prioritize health
Increase government spending
Observed

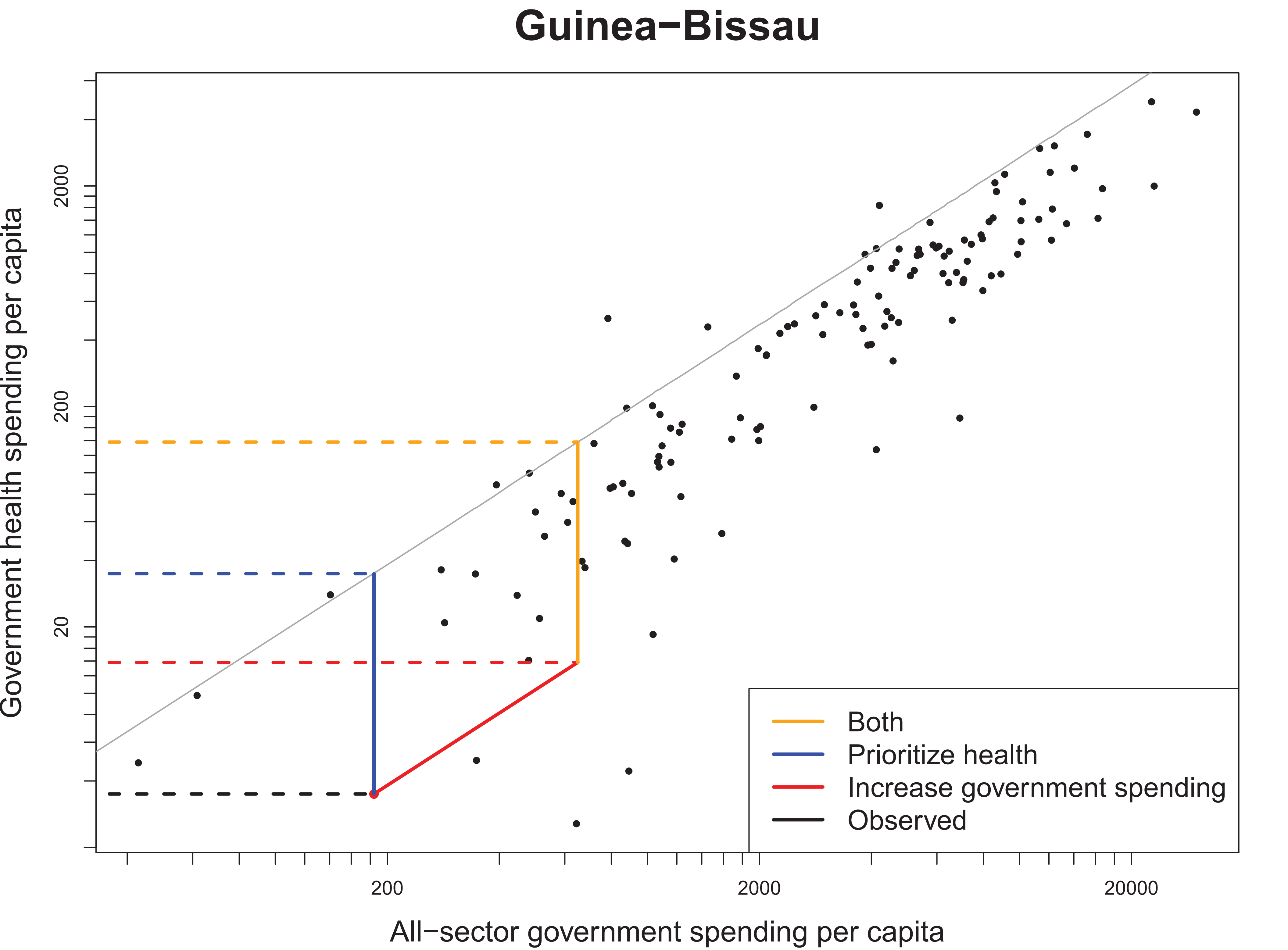


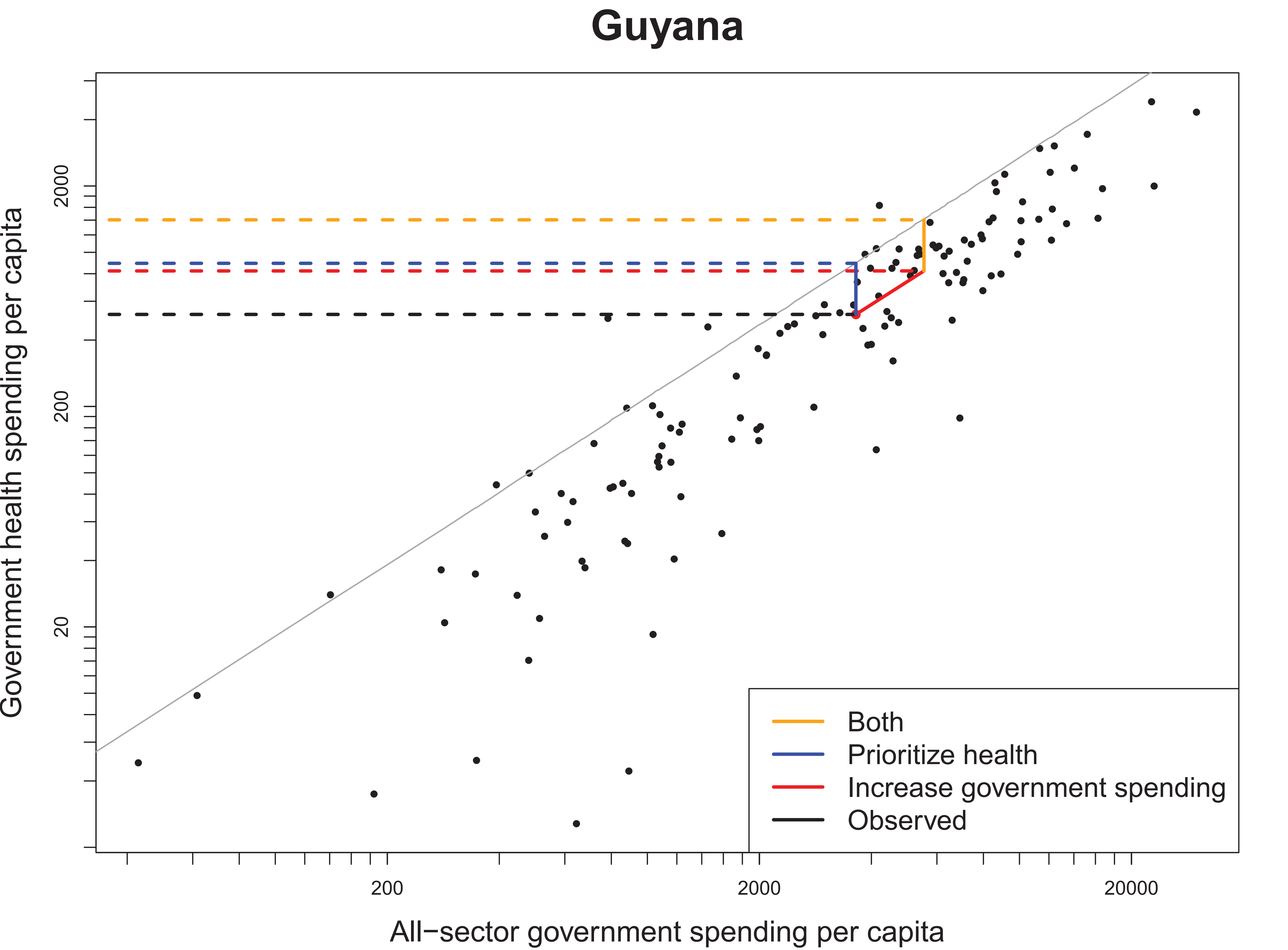
Grenada
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



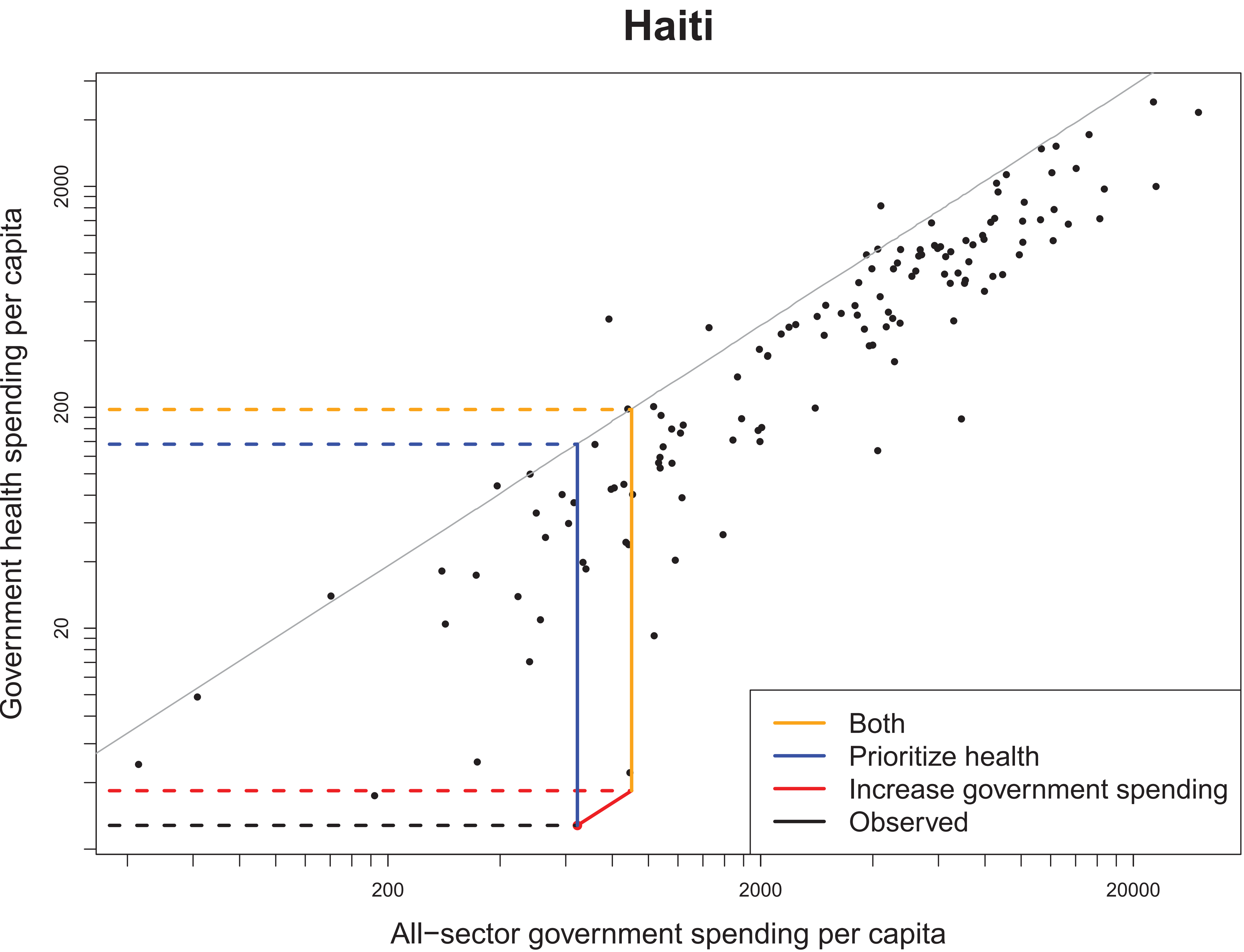
Guatemala
Government health spending per capita
2000
200
20
All−sector government spending per capita
Both
Prioritize health
Increase government spending
Observed


Guinea
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

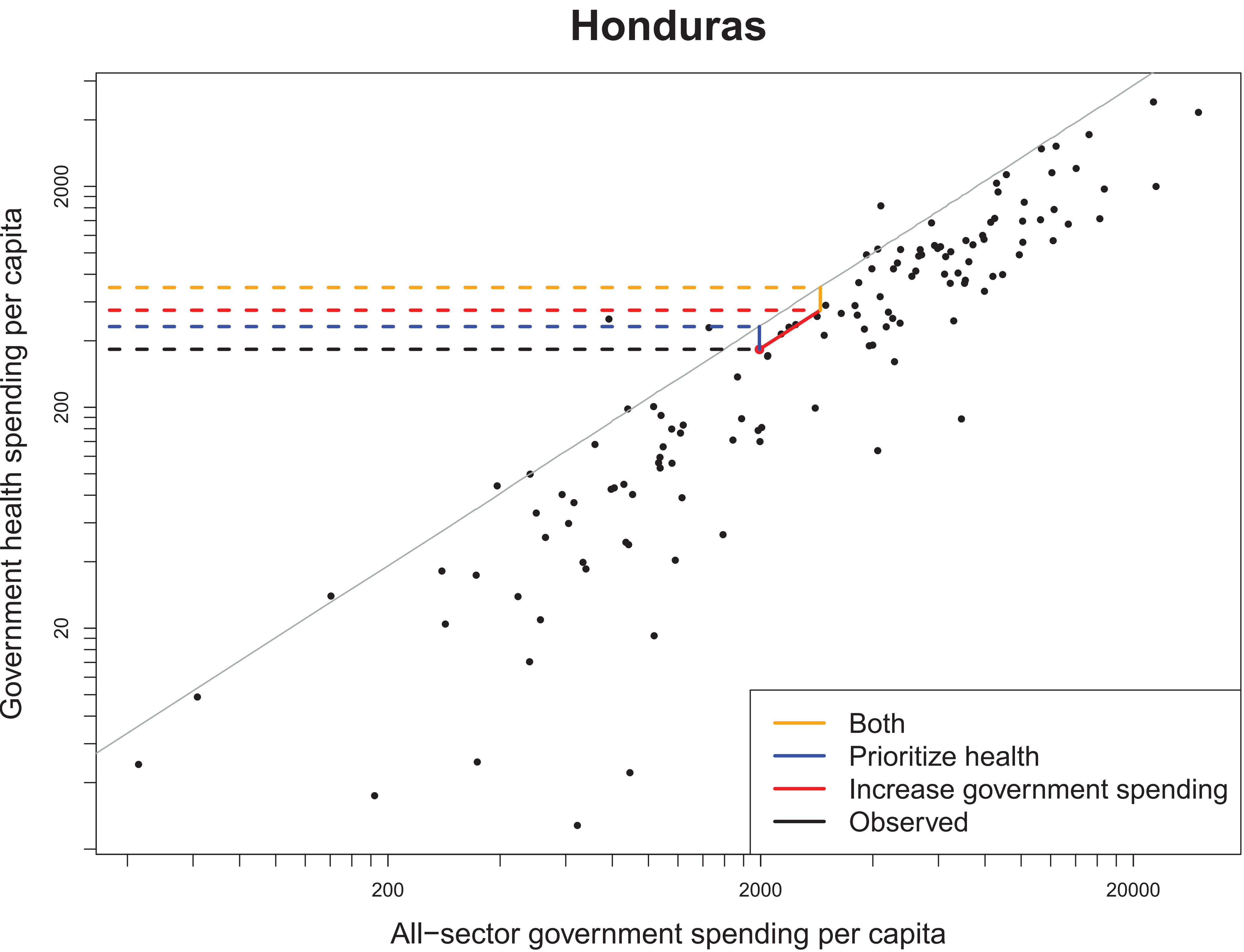

Guinea−Bissau
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



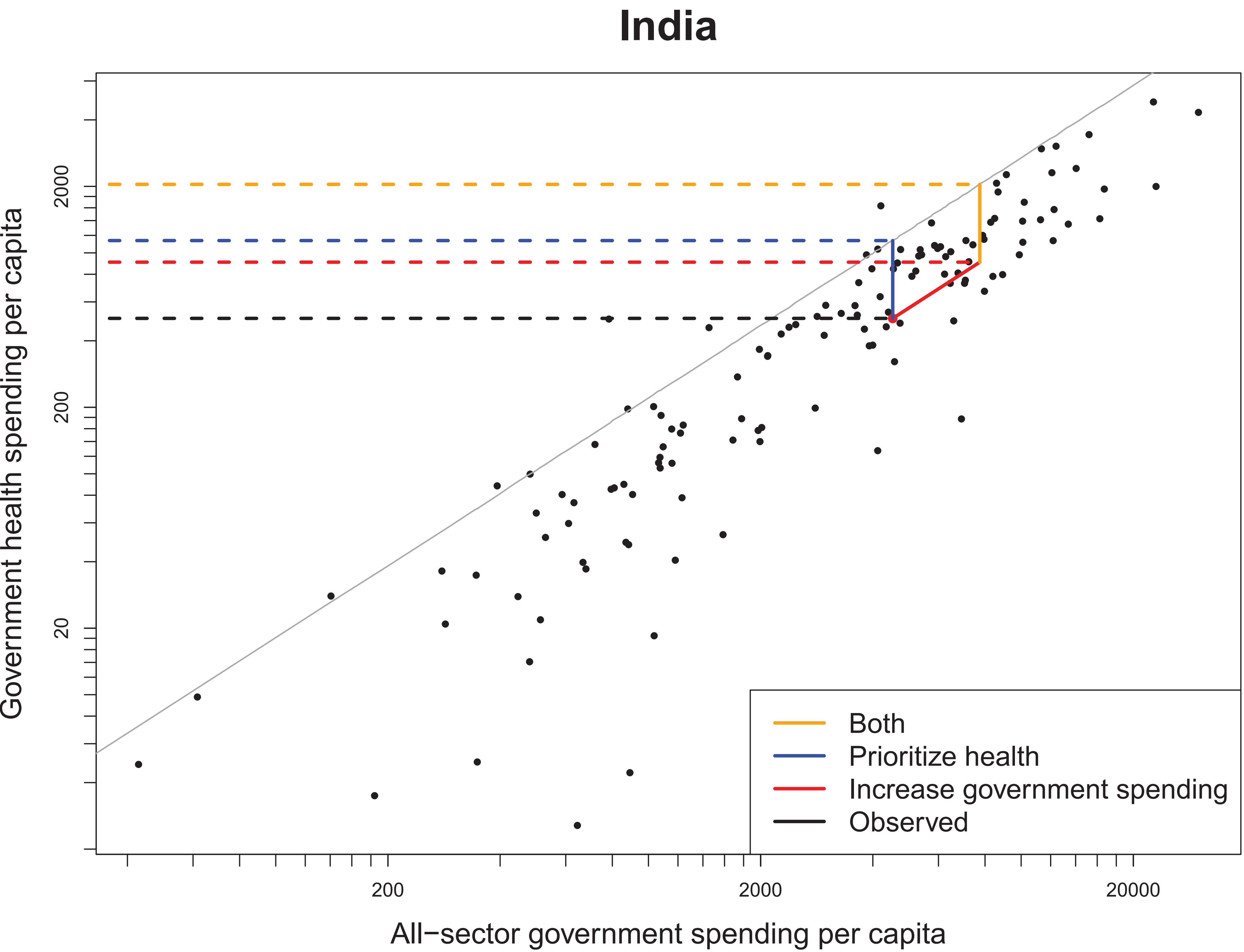
Guyana
Government health spending per capita
2000
200
20
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



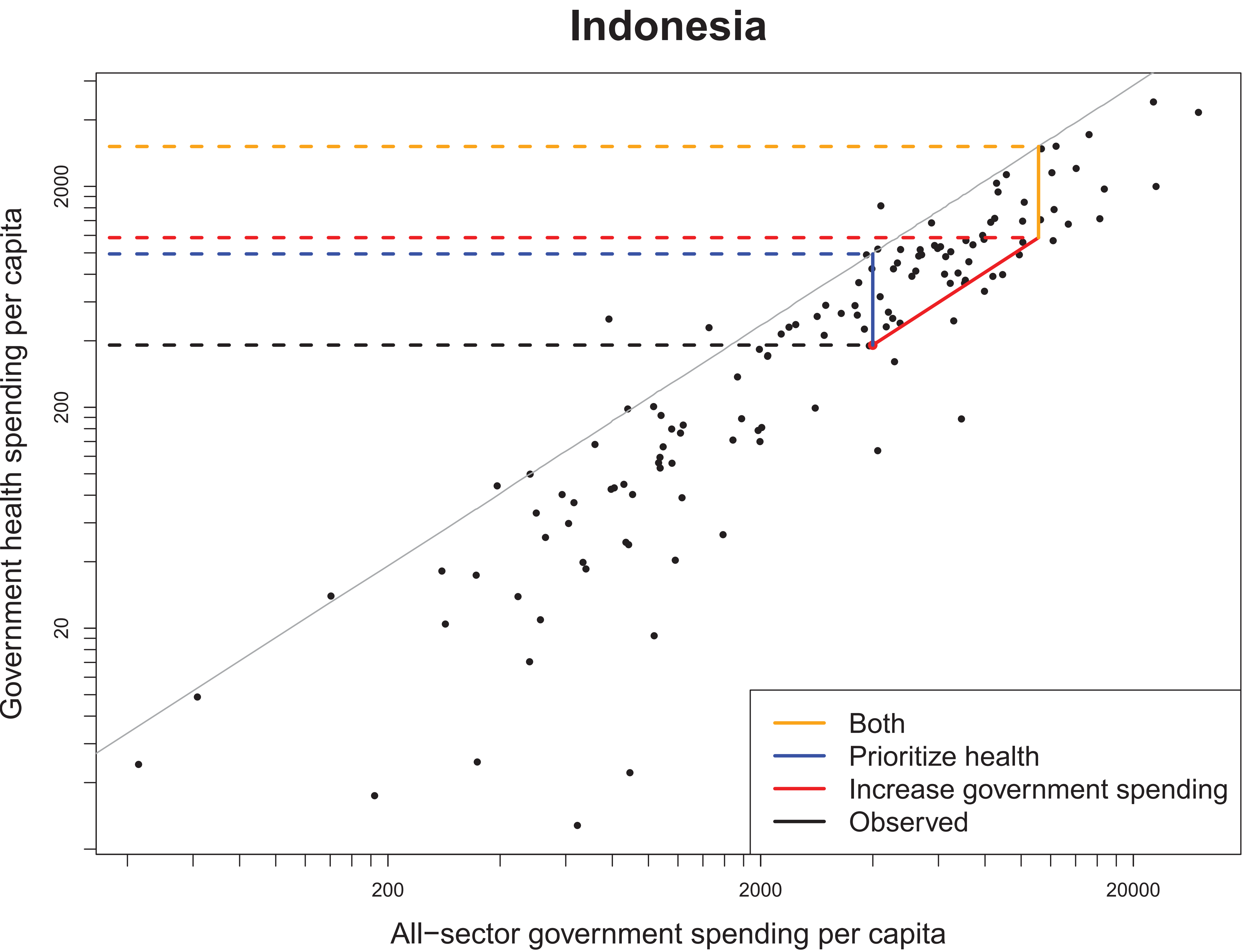
Haiti
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



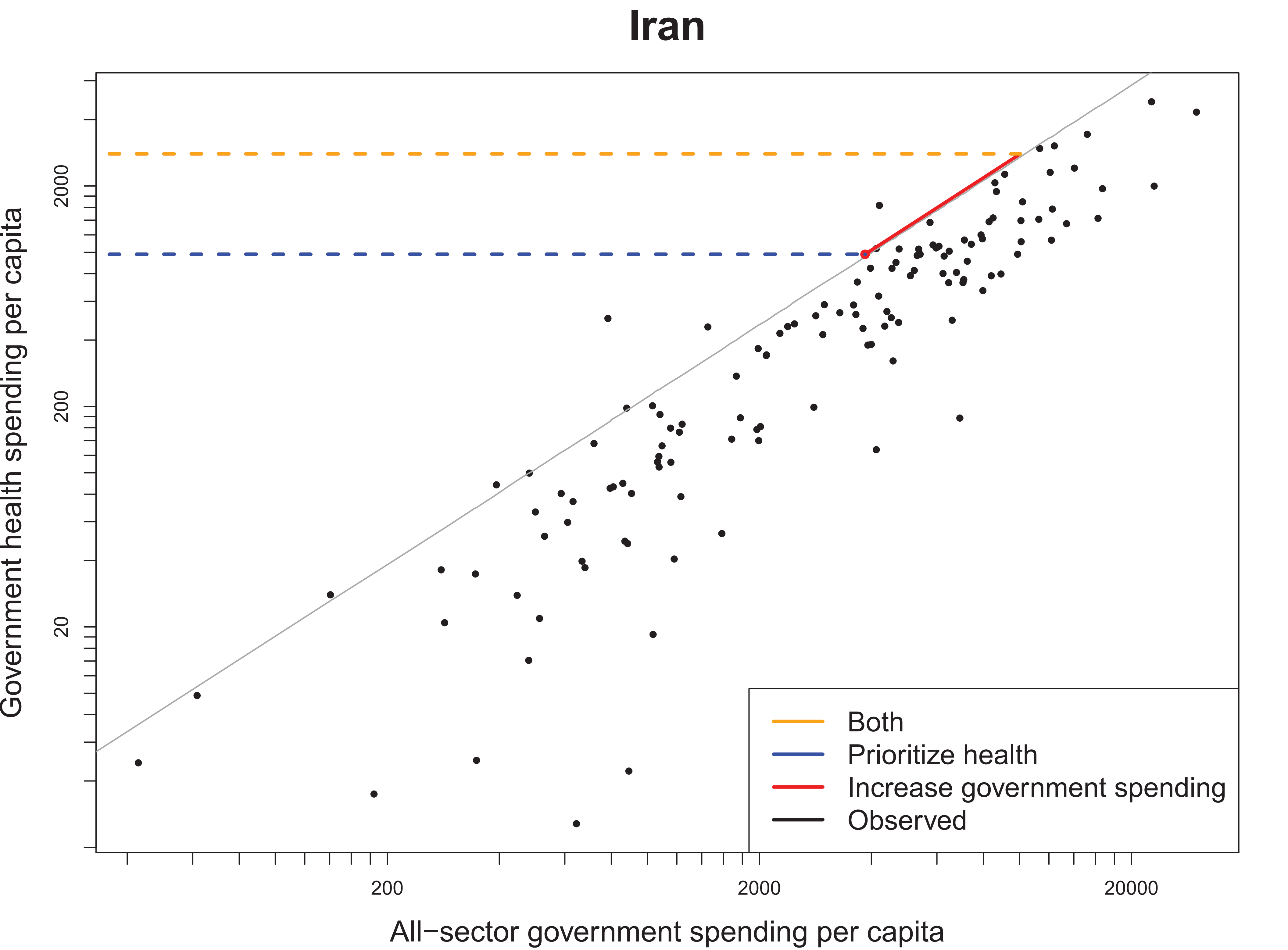
Honduras
Government health spending per capita
2000
200
20
200
2000
20000
All−sector government spending per capita
Both
Prioritize health
Increase government spending
Observed

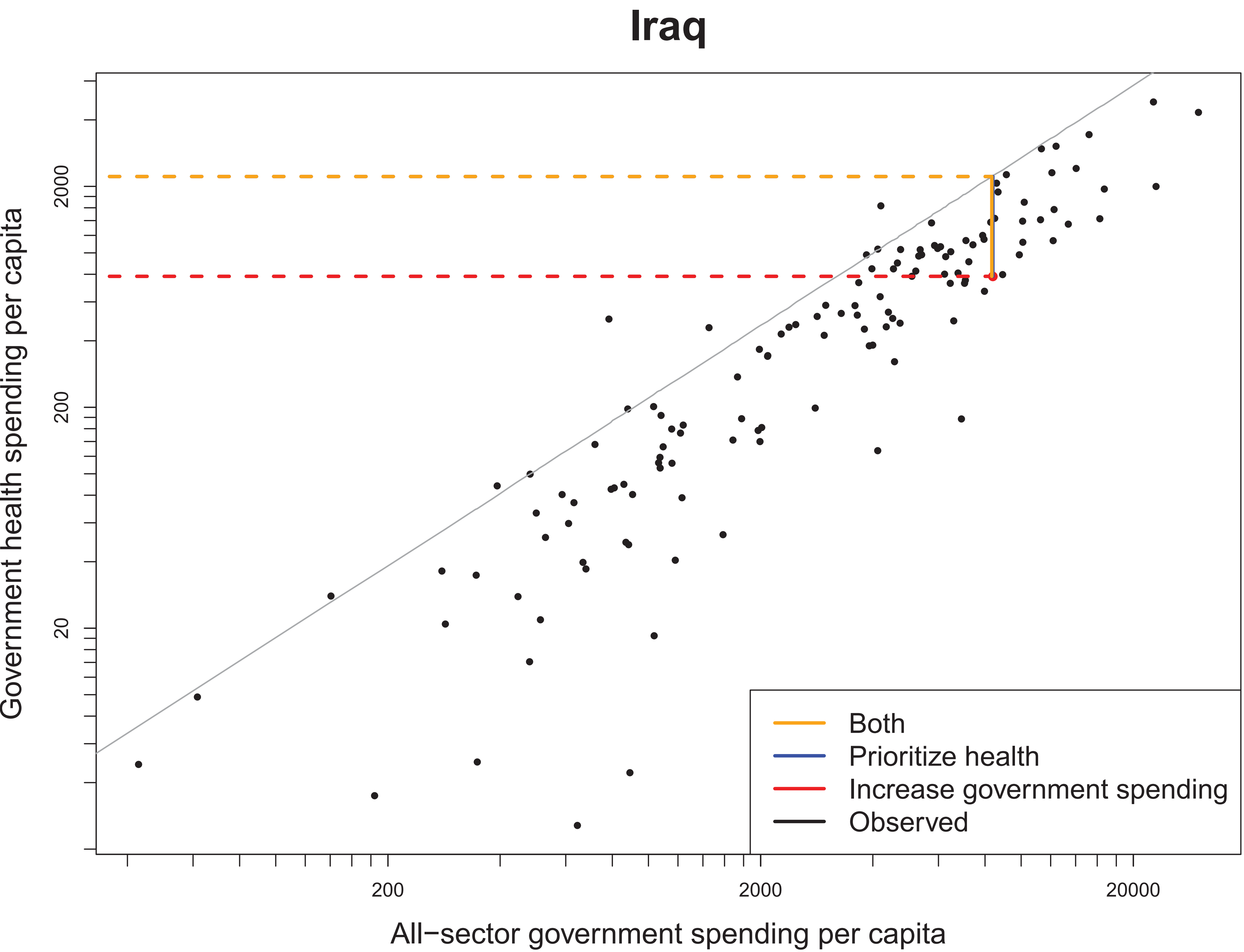


India
Both
Prioritize health
Increase government spending
Observed
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000

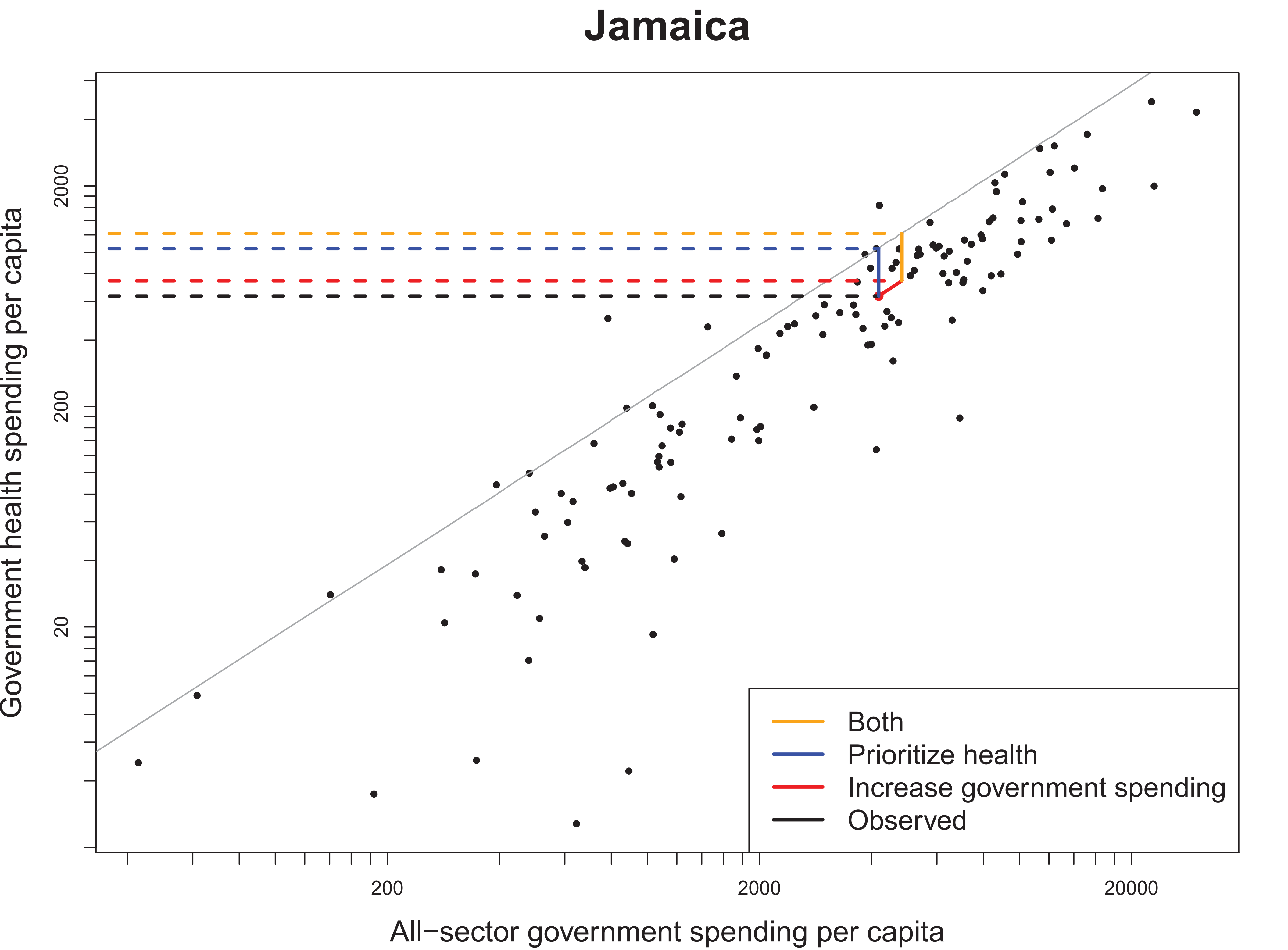


Indonesia
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

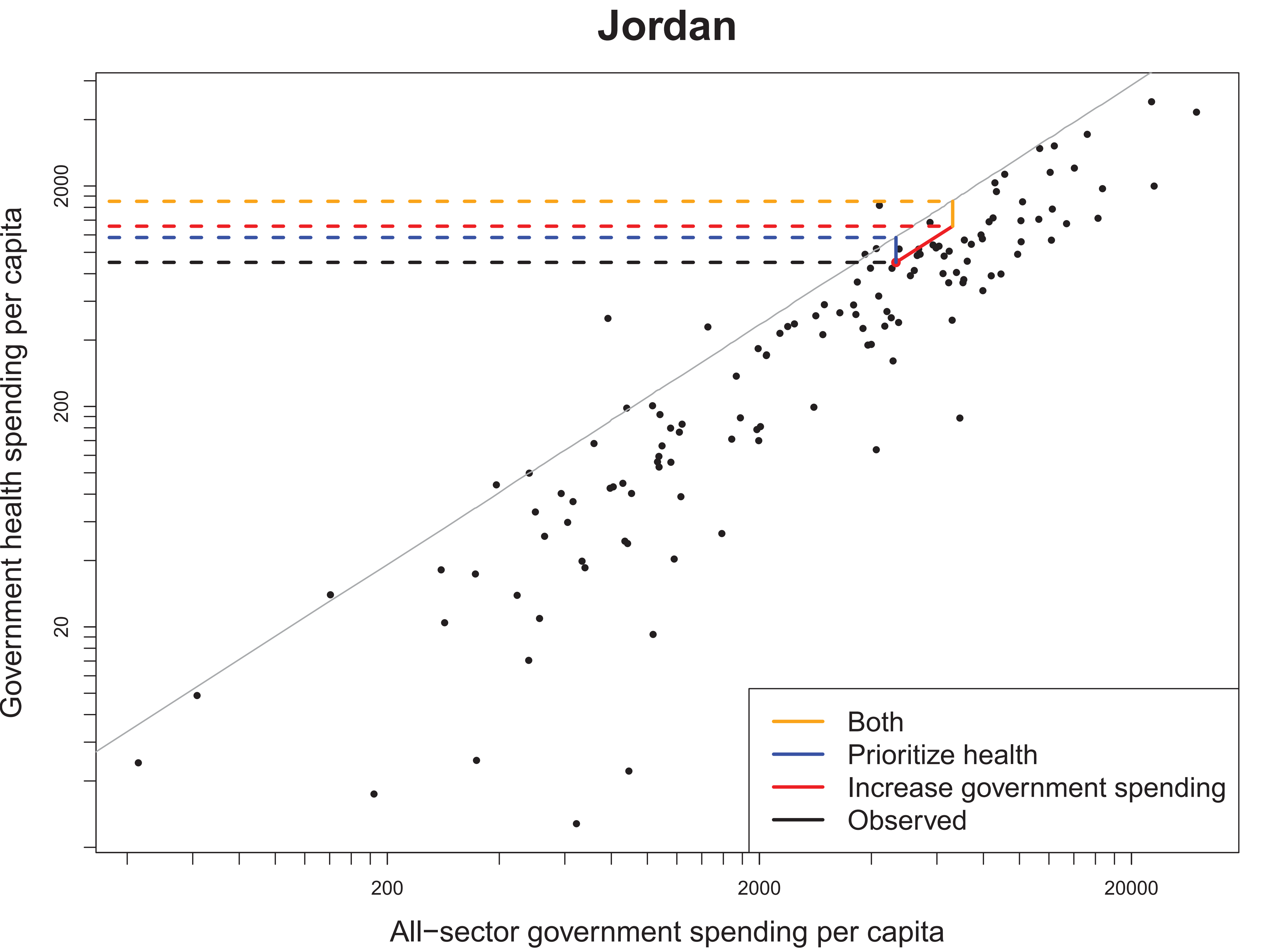

Iran
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



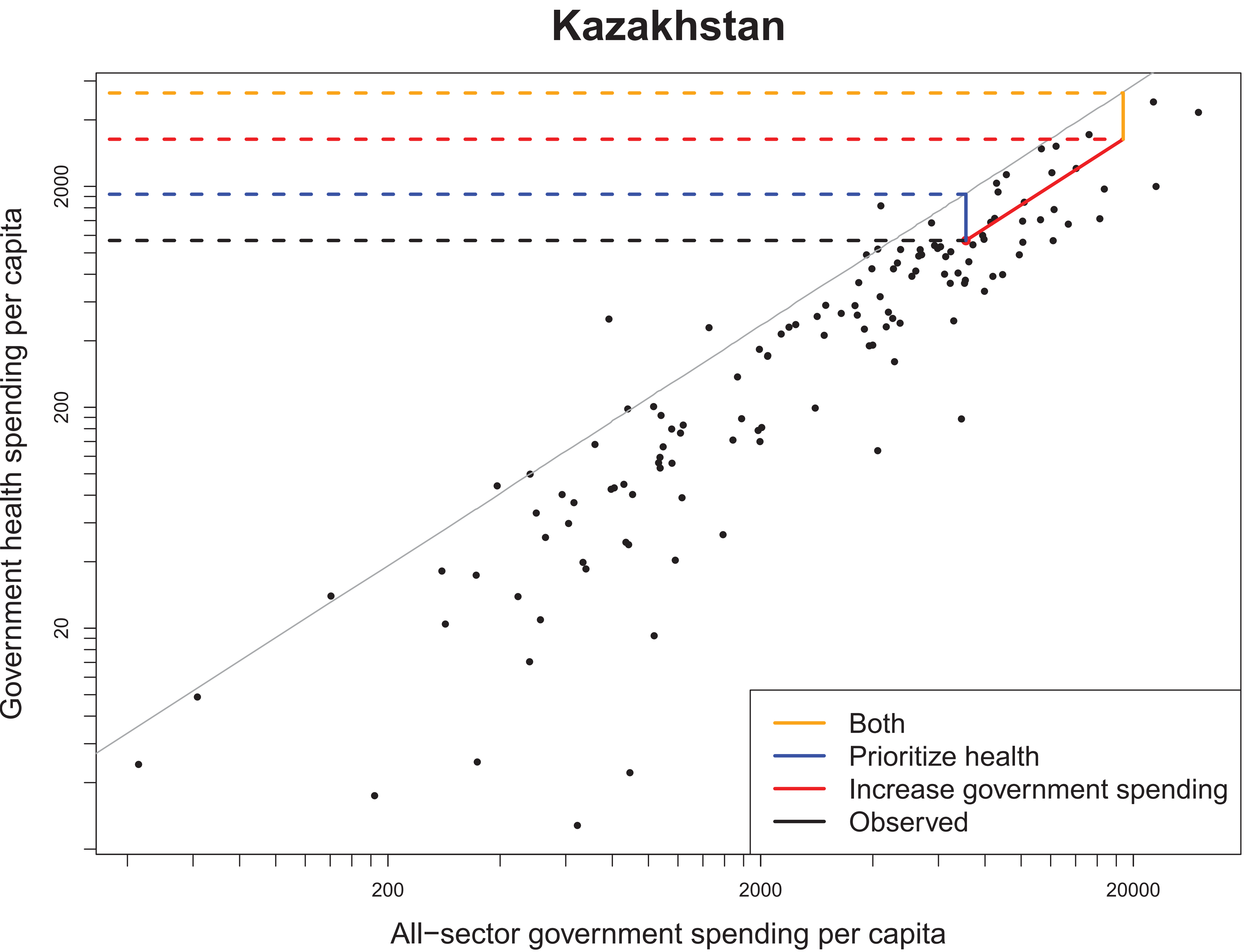
Iraq
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

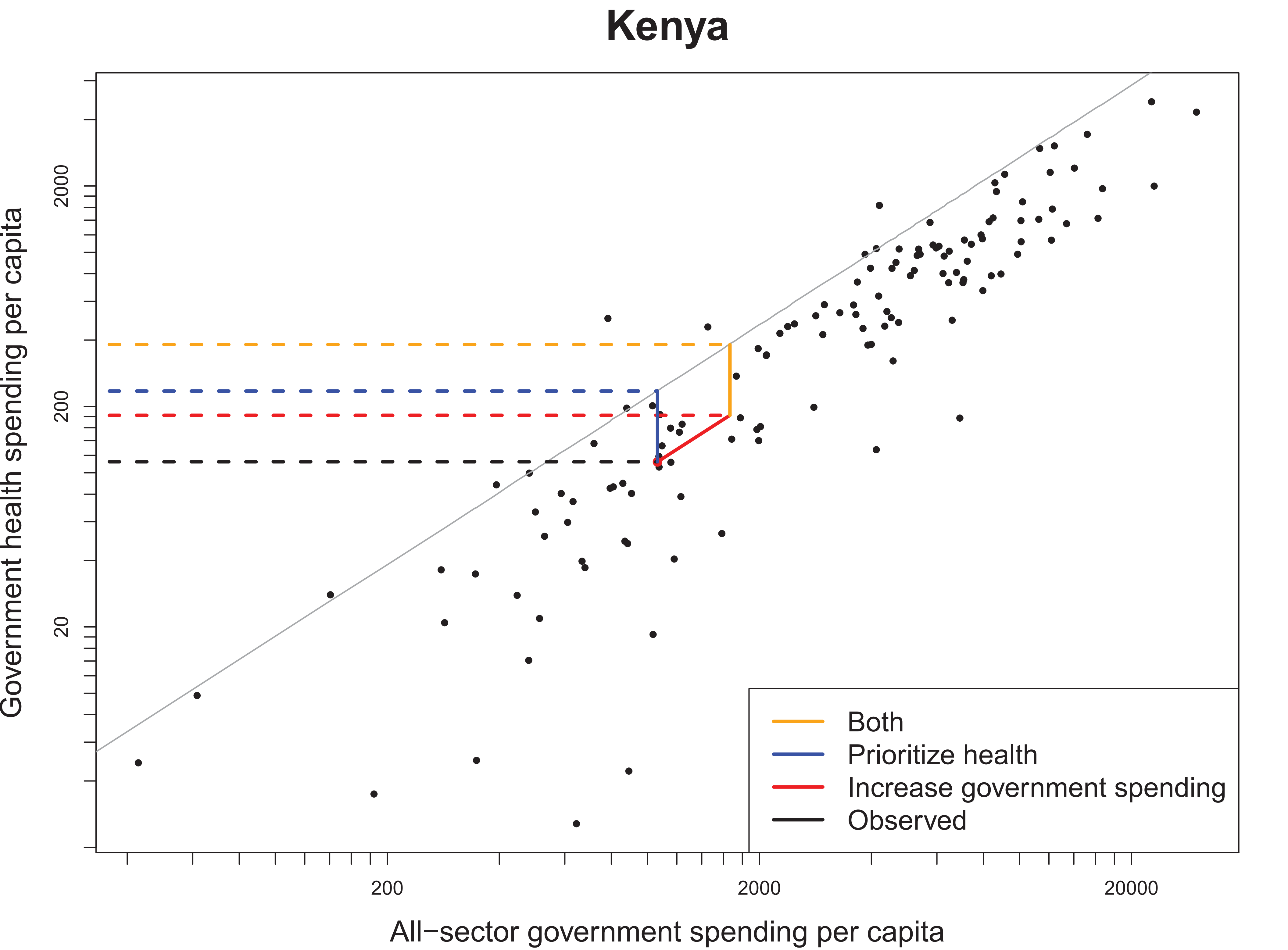


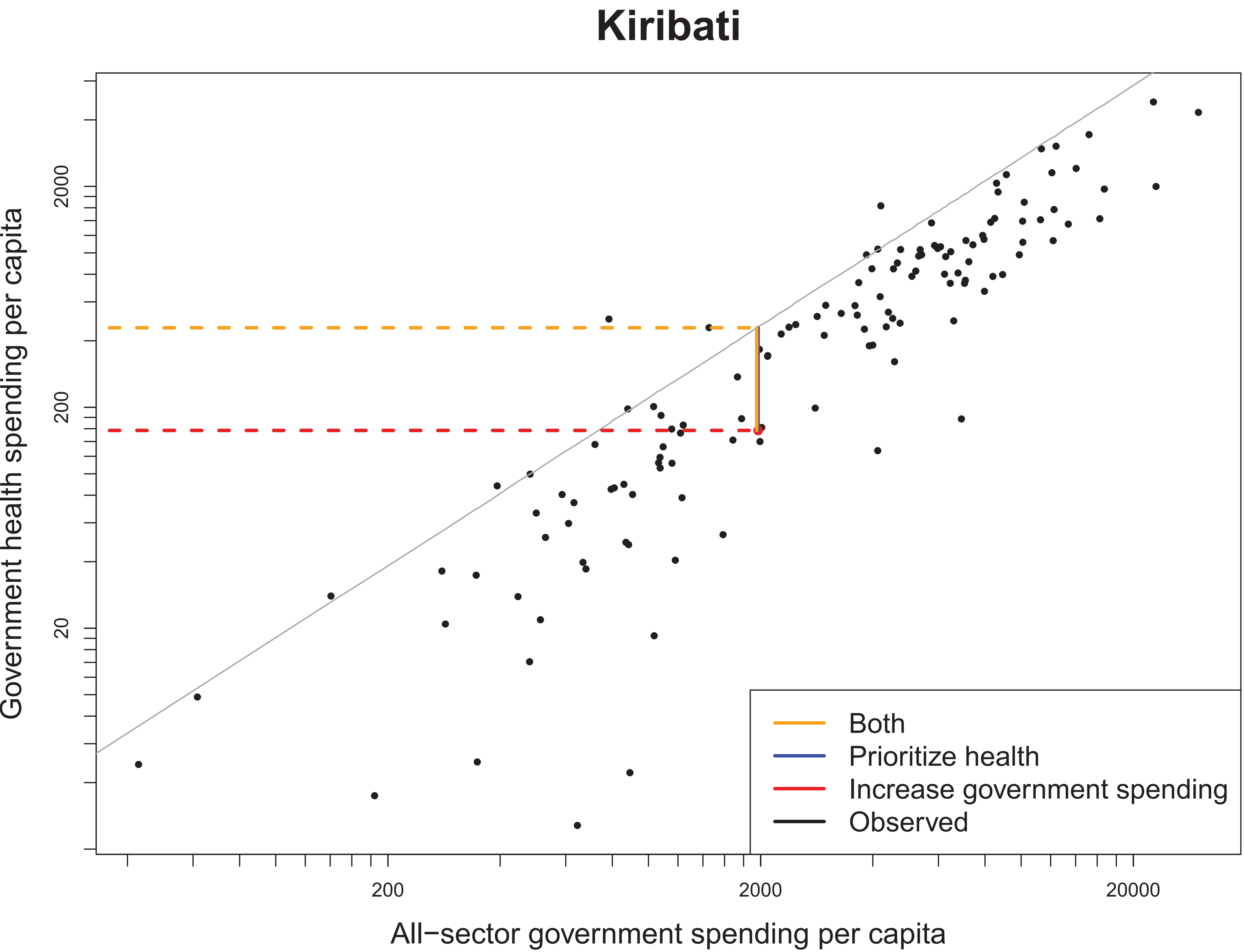
Jamaica
Government health spending per capita
2000
200
20
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



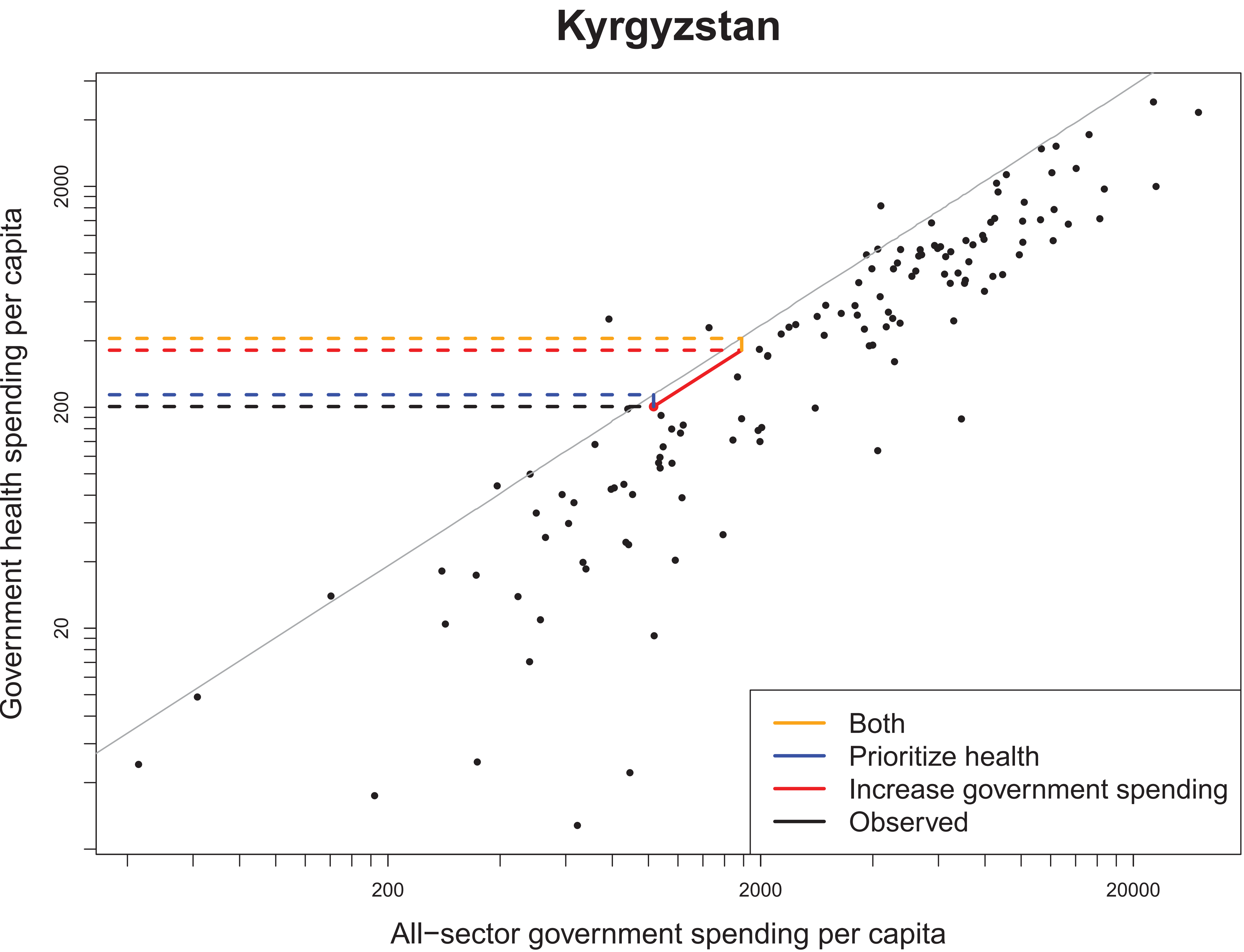
Jordan
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed


Kazakhstan
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

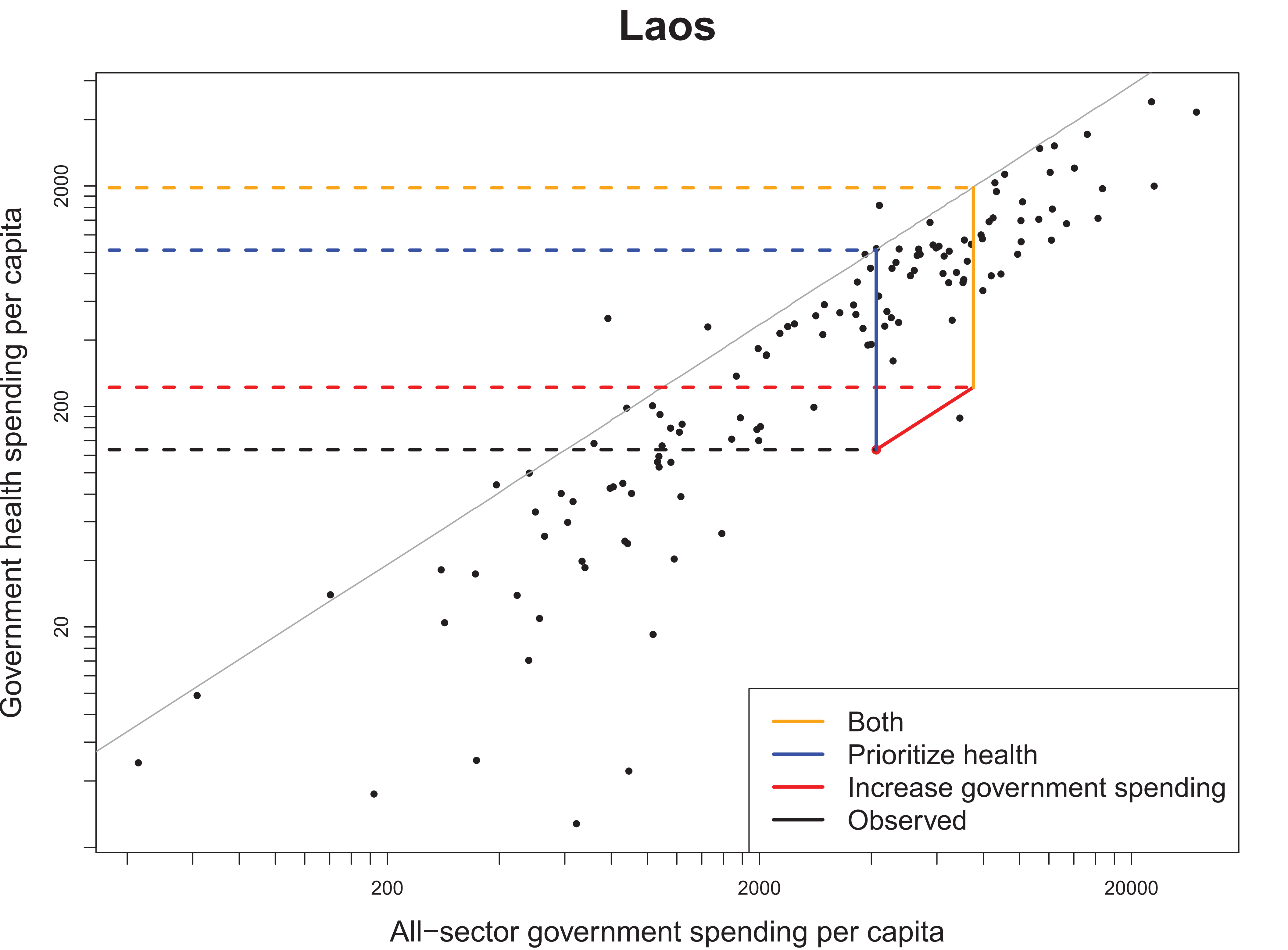

Kenya
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



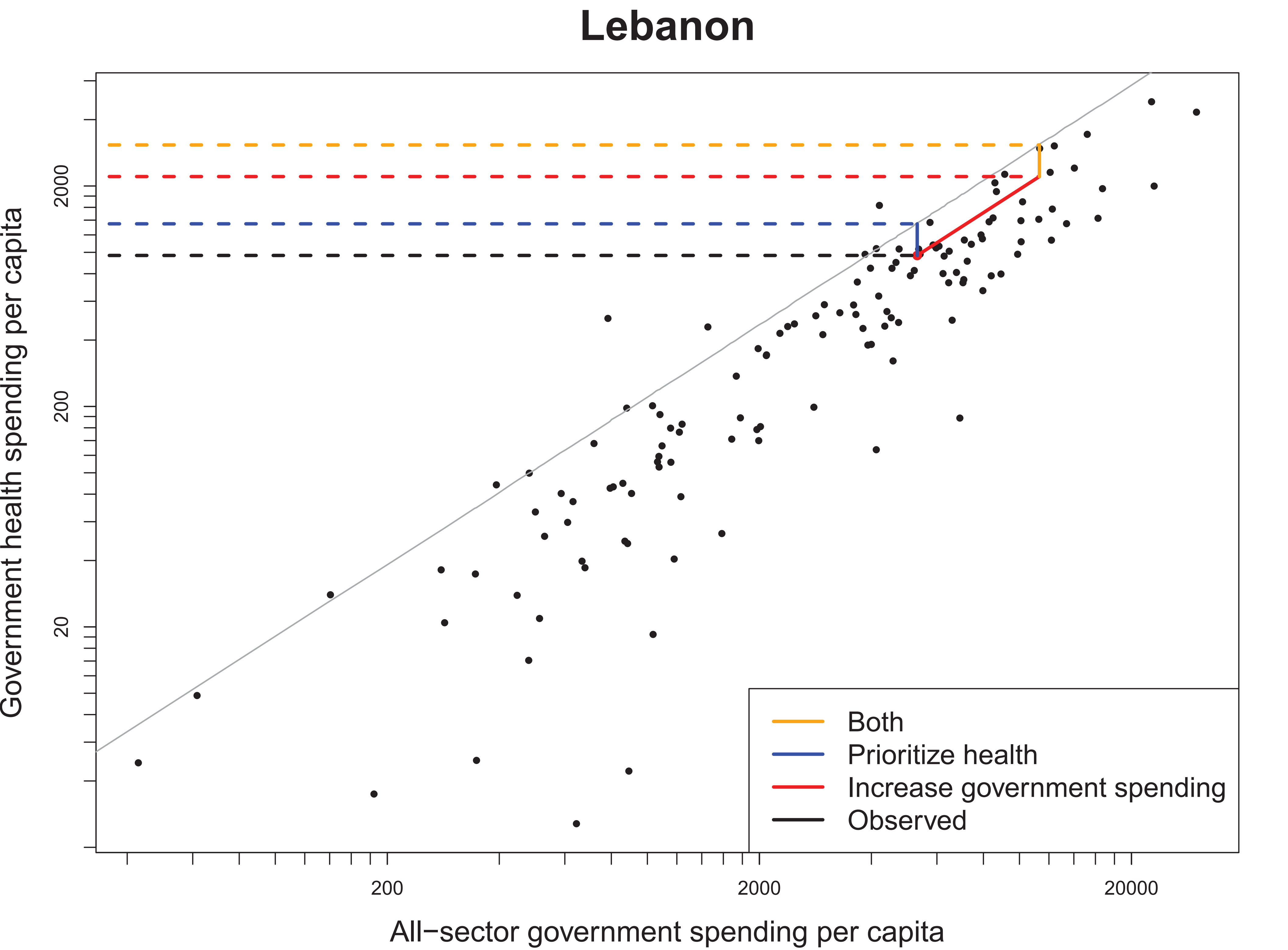
Kiribati
Government health spending per capita
20
200
2000
200
2000
20000
All−sector government spending per capita
Both
Prioritize health
Increase government spending
Observed



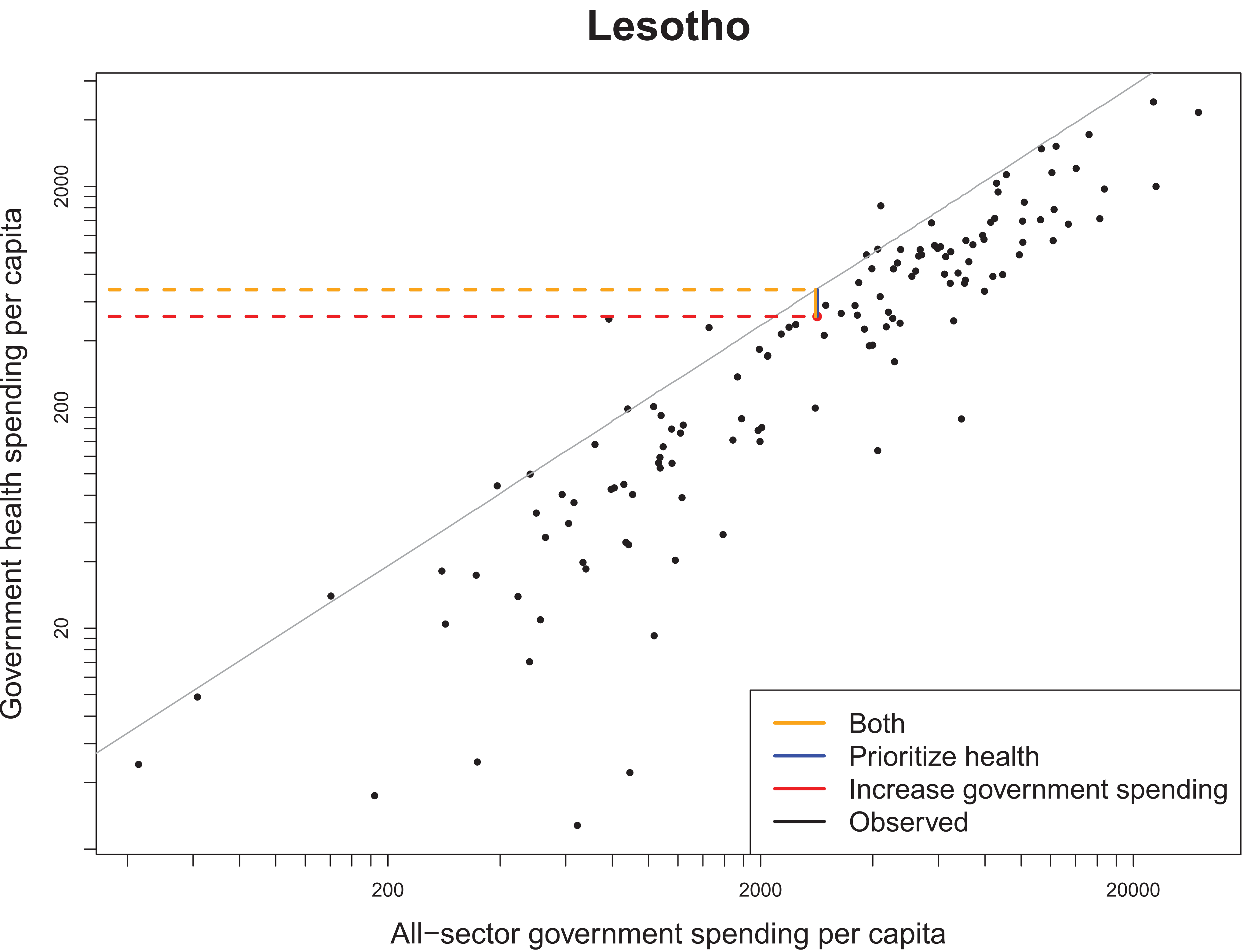
Kyrgyzstan
Government health spending per capita
All−sector government spending per capita
2000
200
20
20000
Both
Prioritize health
Increase government spending
Observed



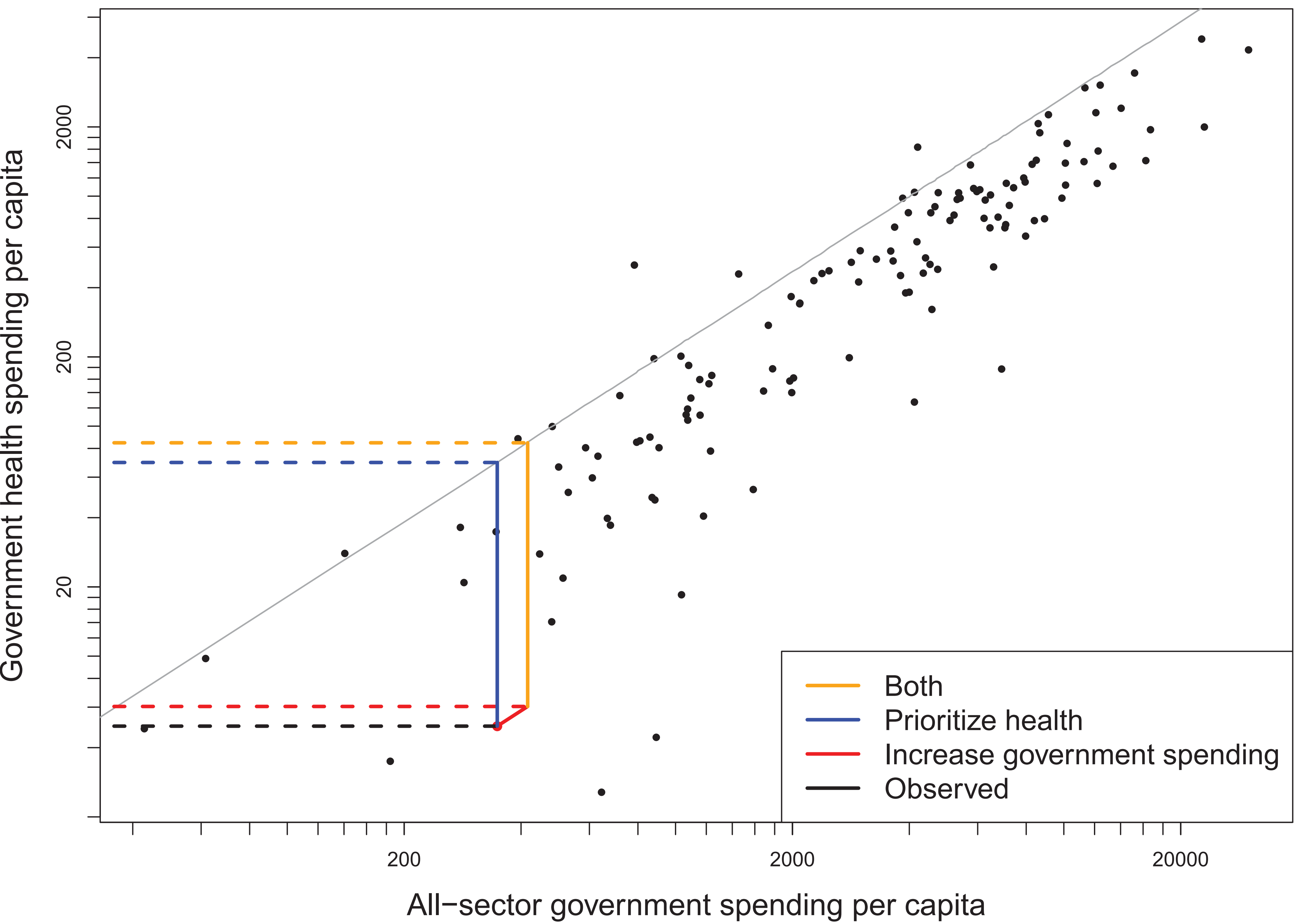
Laos
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



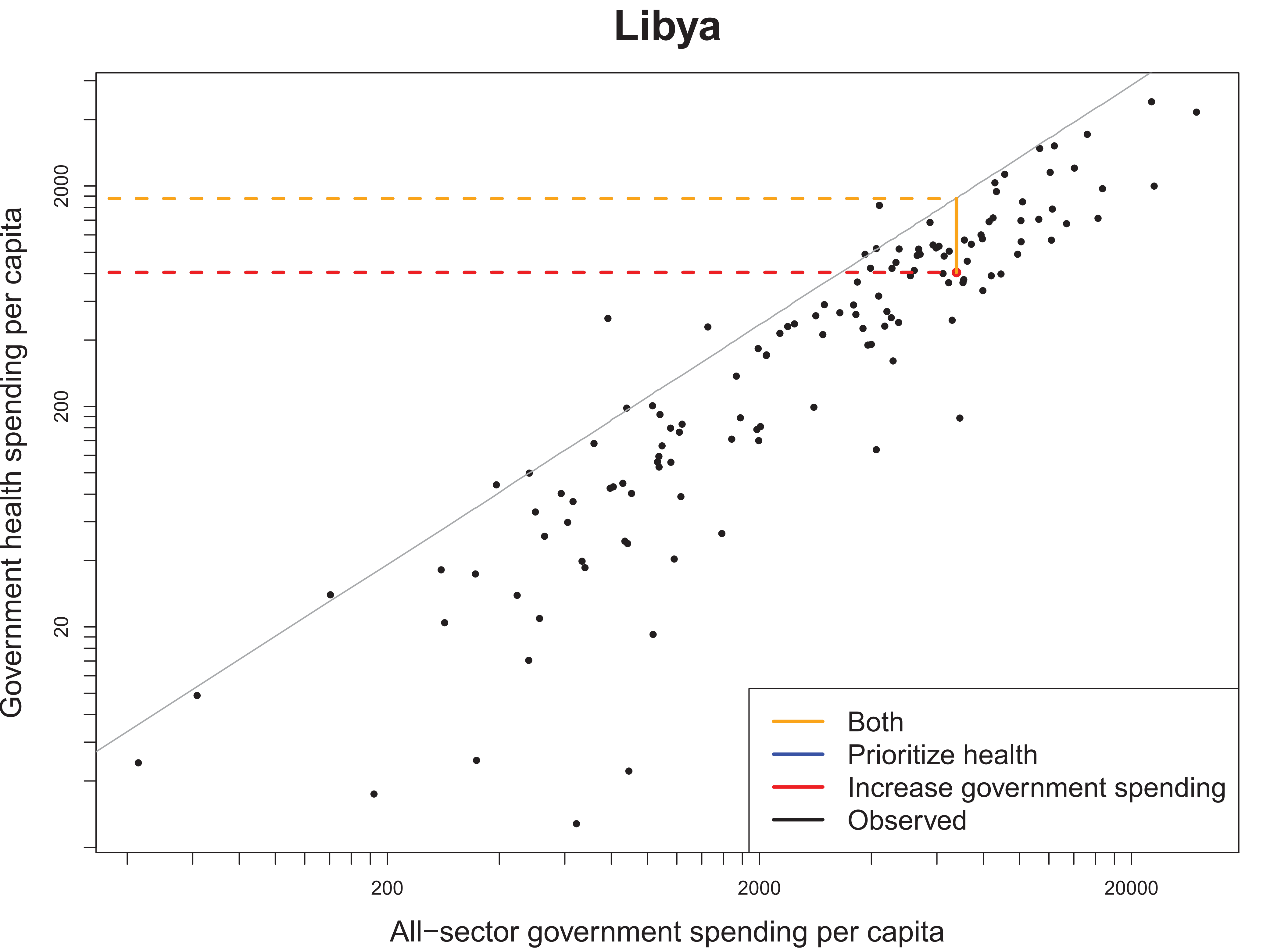
Lebanon
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

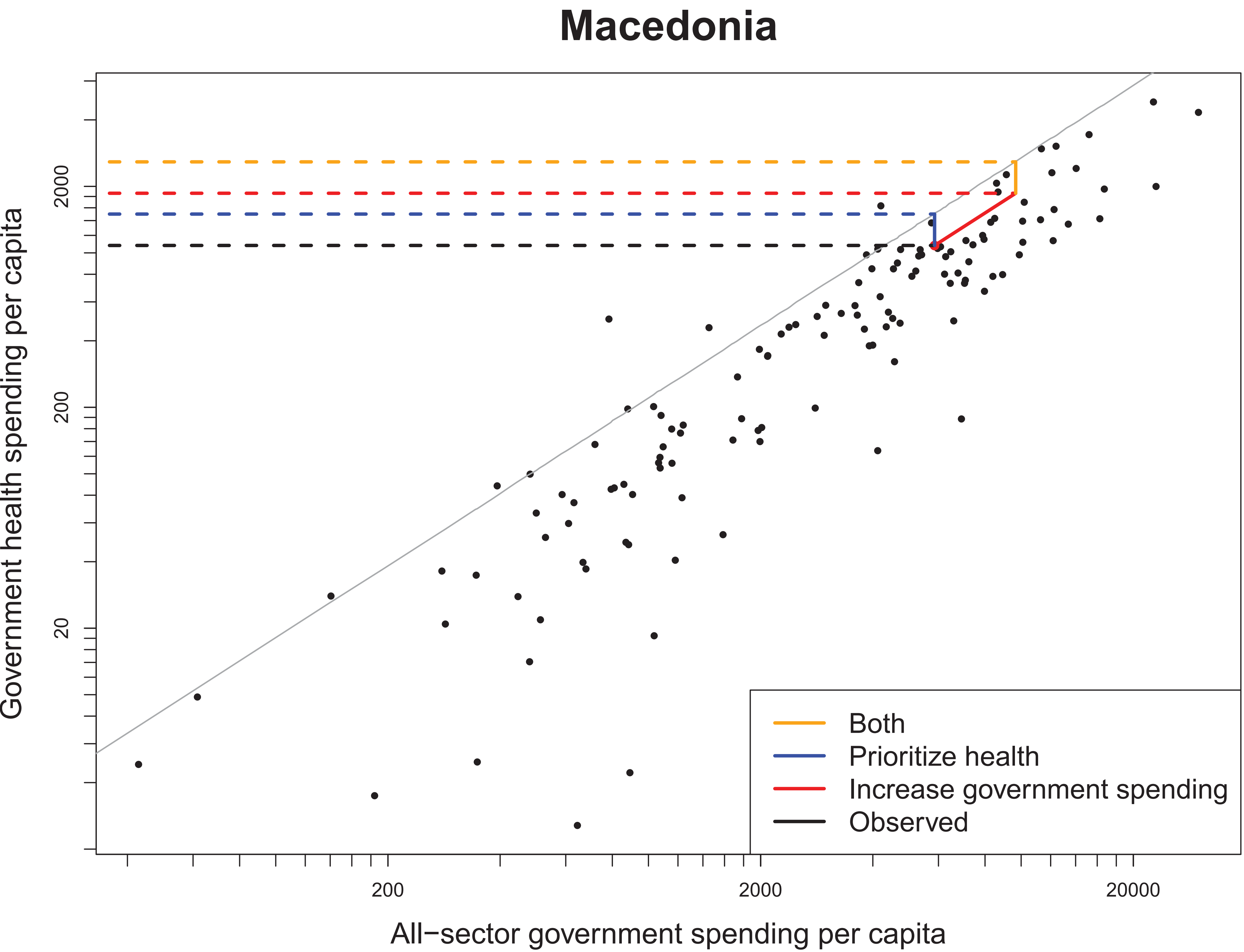

Lesotho
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

Liberia

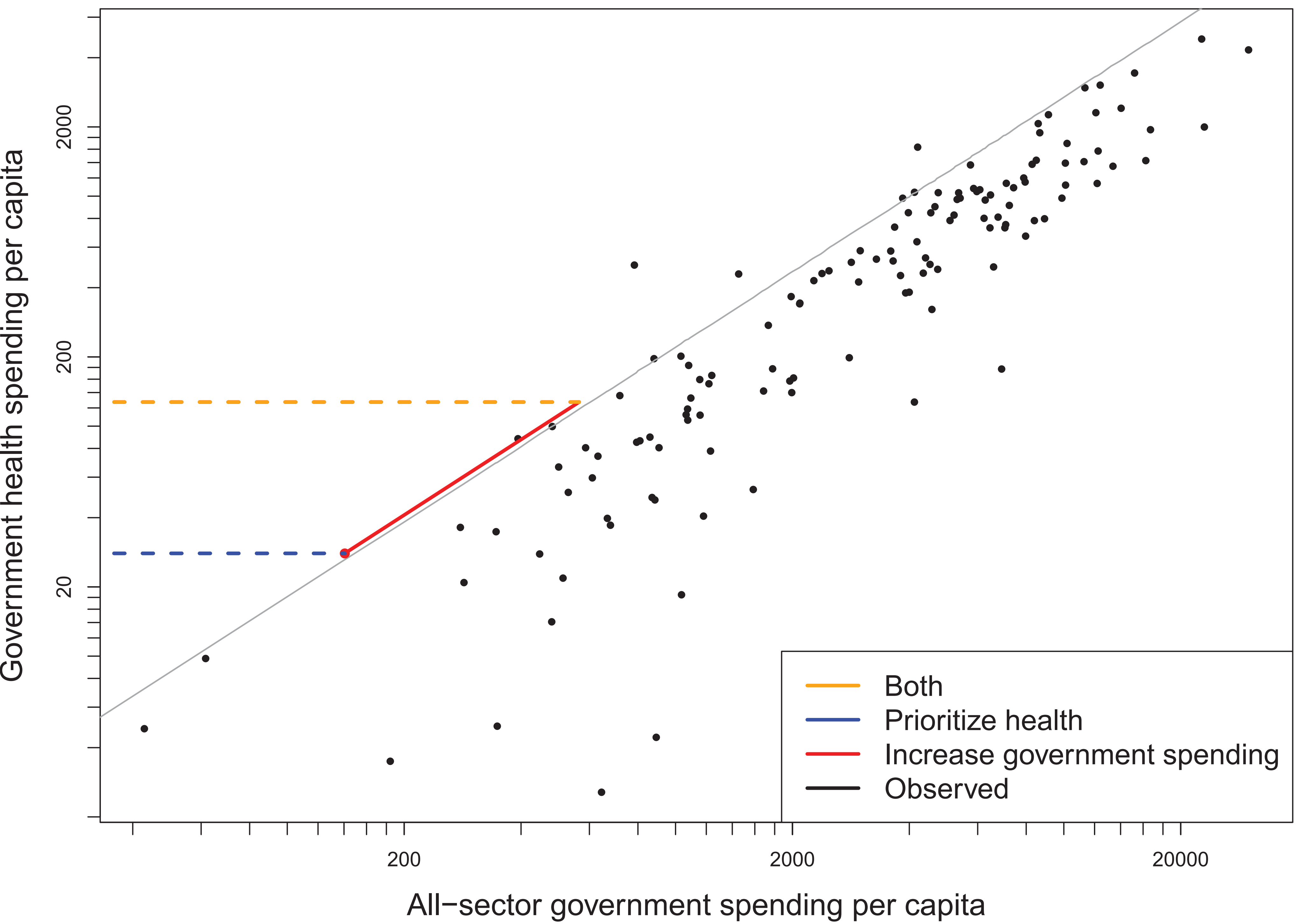


Government health spending per capita
2000
200
20
200
2000
20000
All−sector government spending per capita
Both
Prioritize health
Increase government spending
Observed

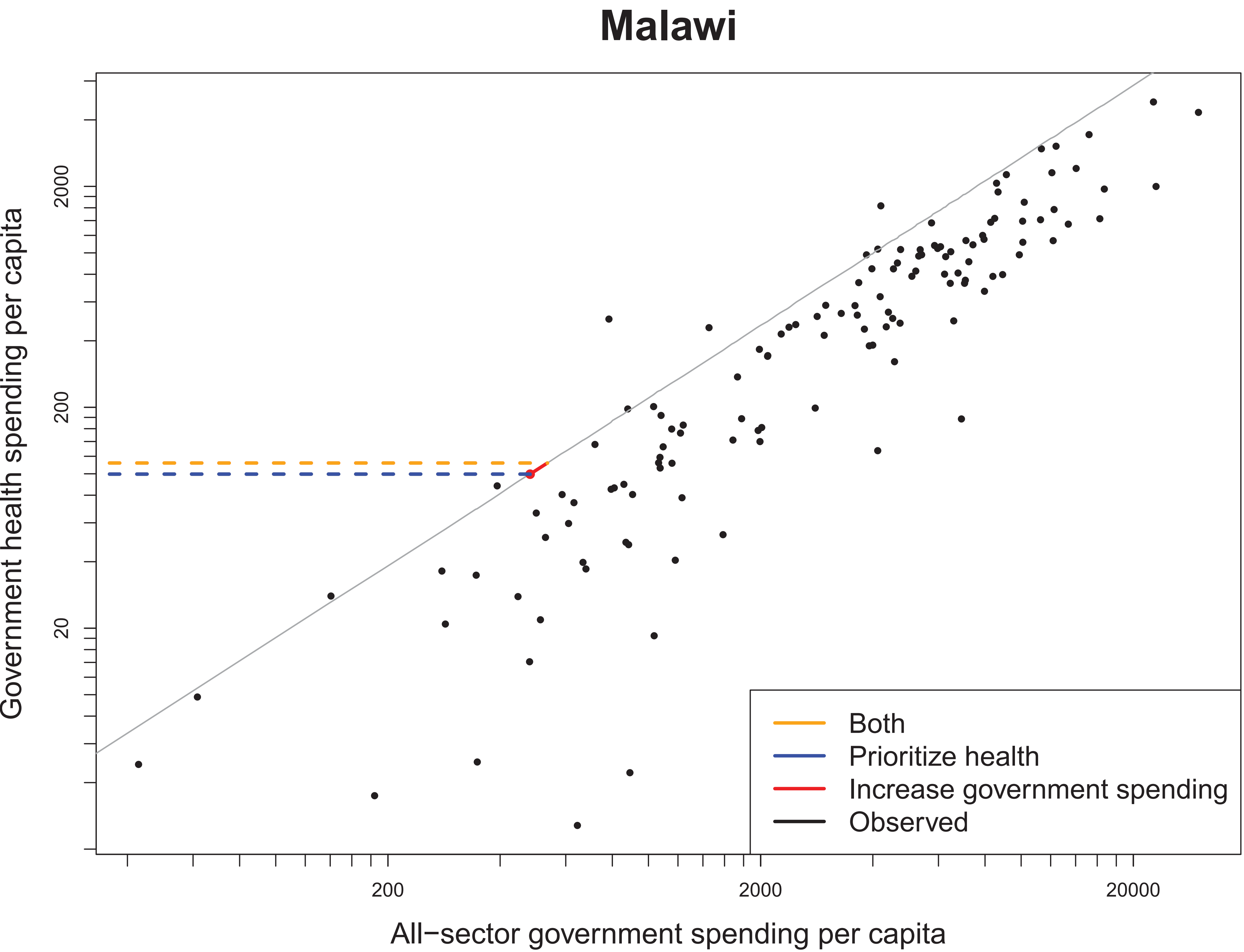

Libya
Government health spending per capita
2000
200
20
200
2000
20000
All−sector government spending per capita
Both
Prioritize health
Increase government spending
Observed

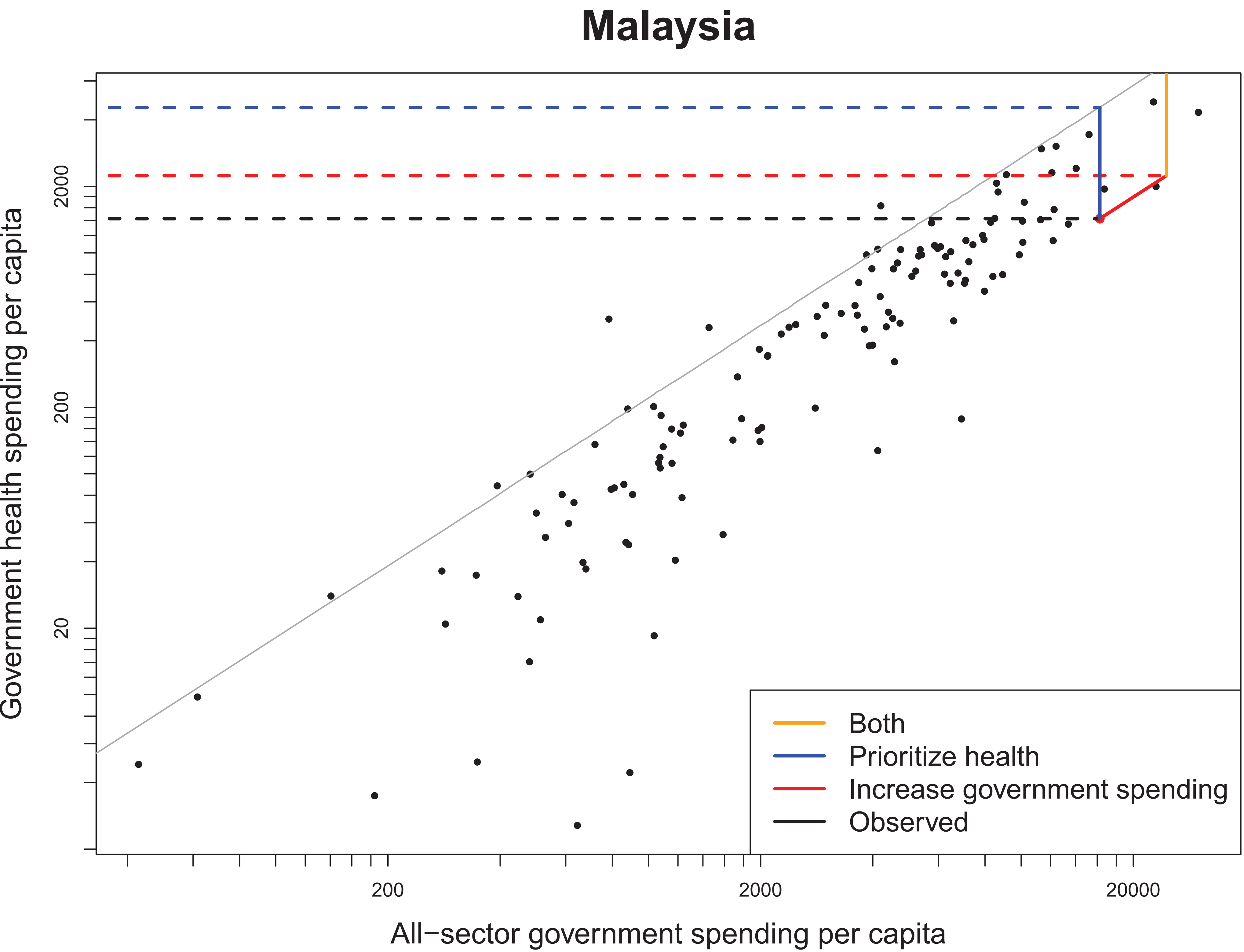

Macedonia
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

Madagascar

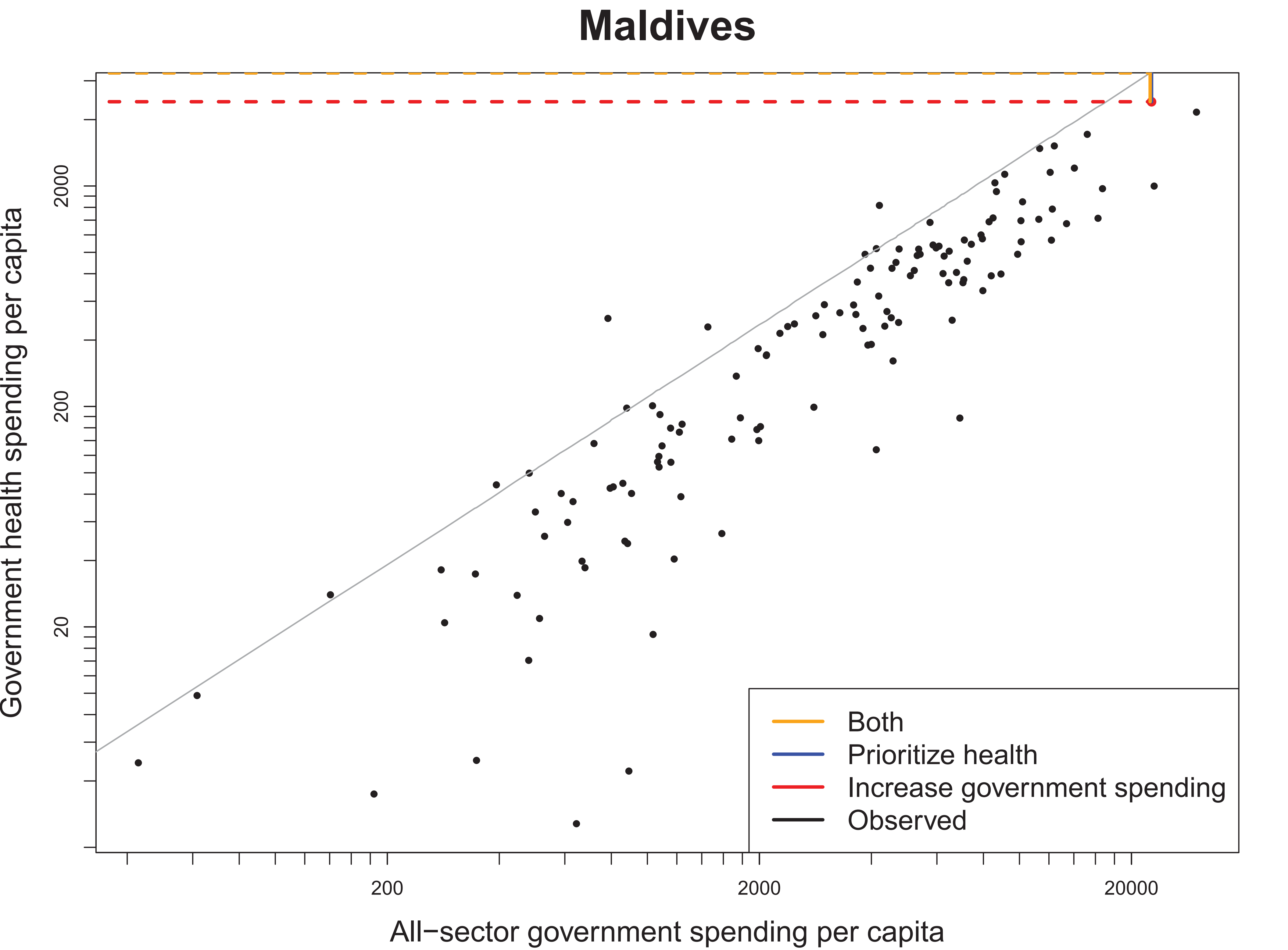


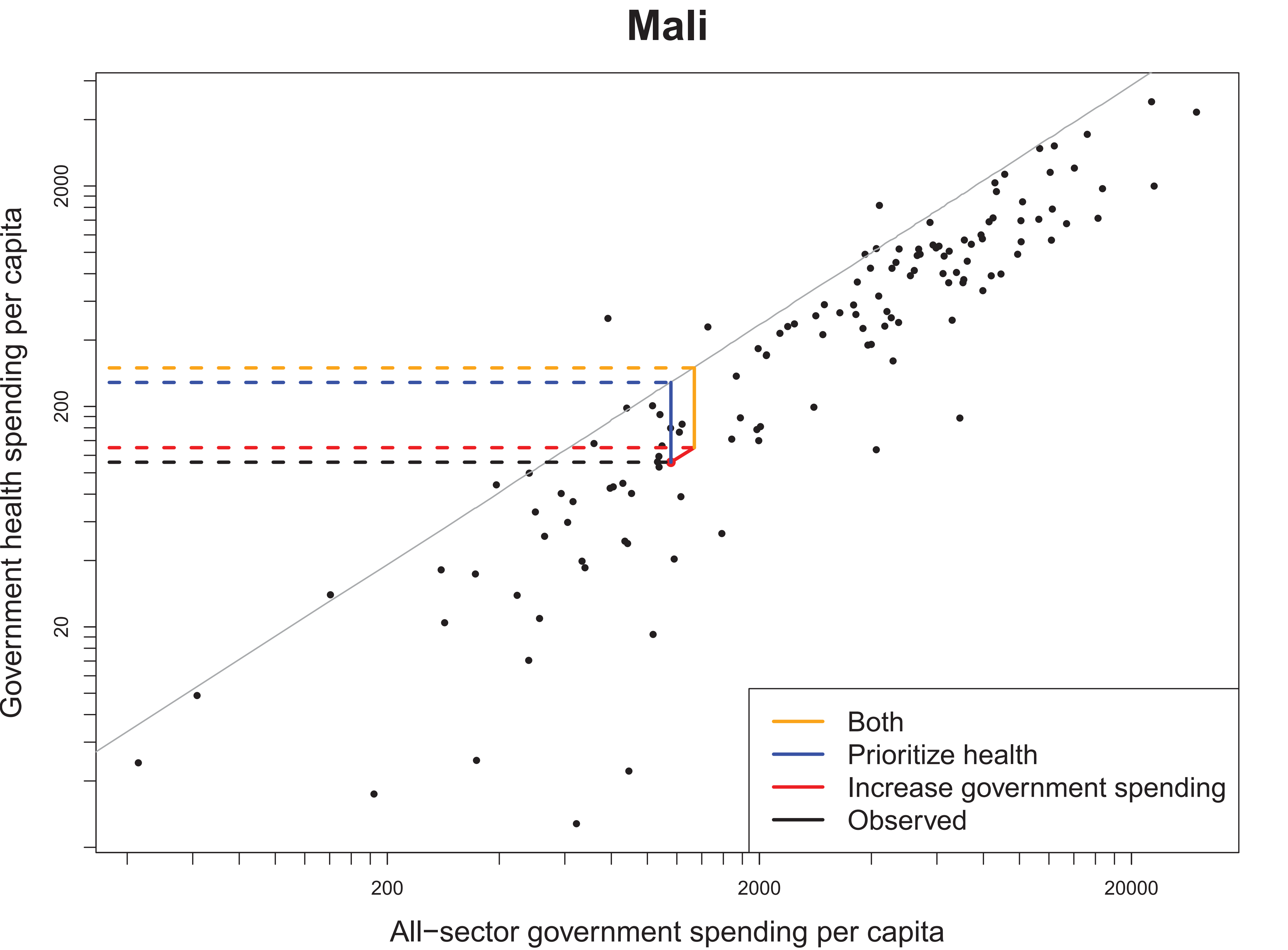
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

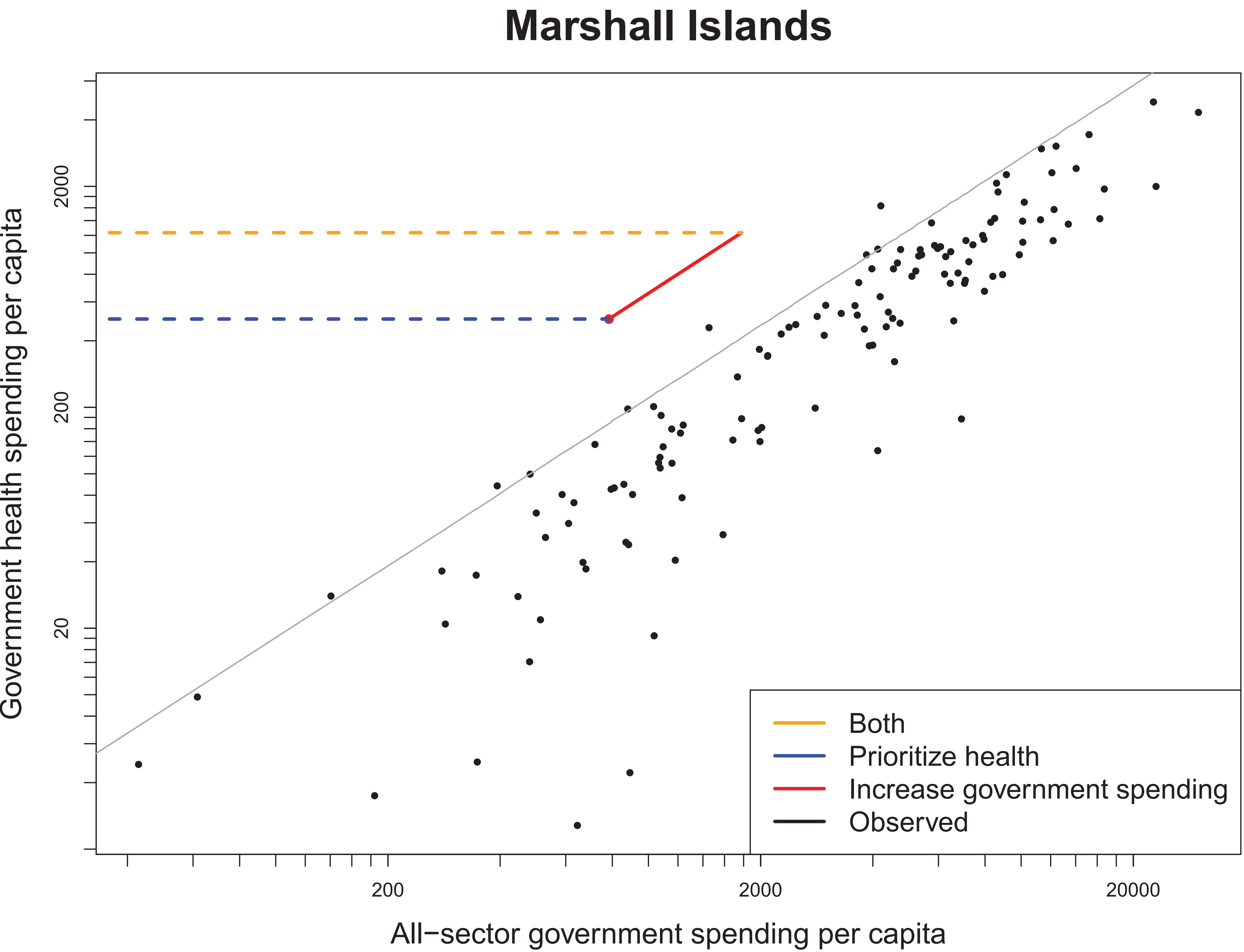

Malawi
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



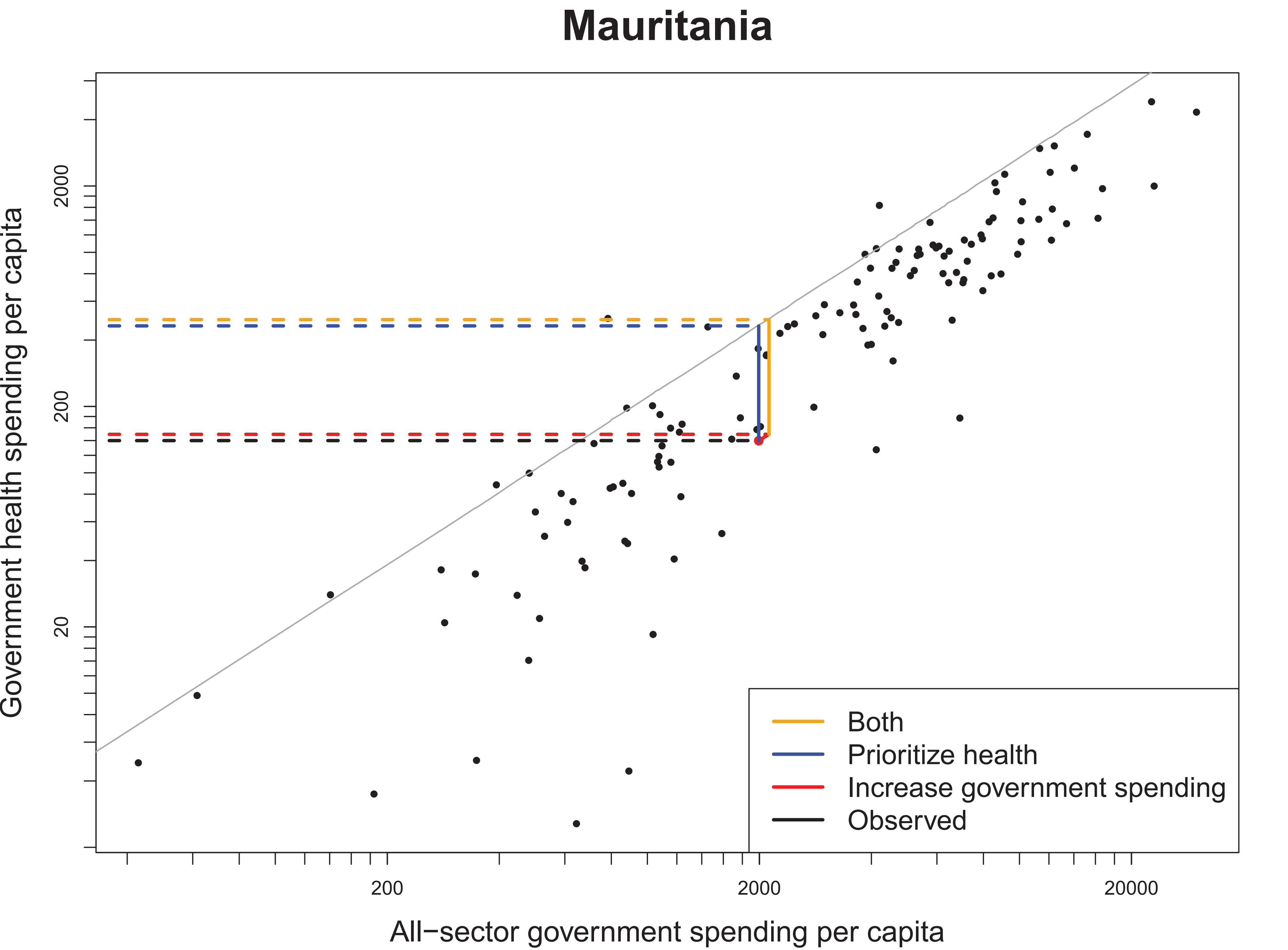
Malaysia
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed


Maldives
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed


Mali
Government health spending per capita
2000
200
20
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

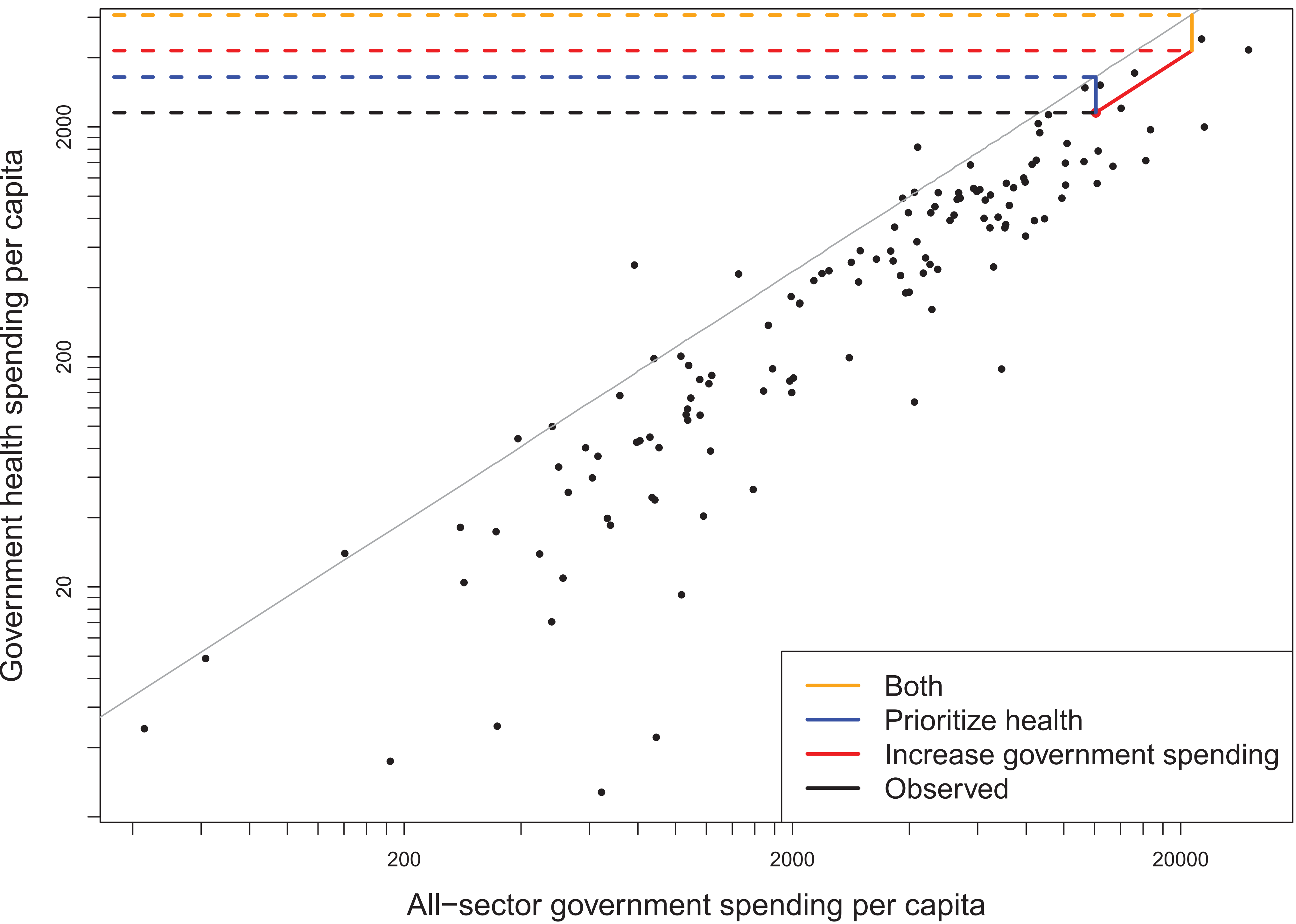


Marshall Islands
Government health spending per capita
All−sector government spending per capita
2000
200
20
20000
Both
Prioritize health
Increase government spending
Observed

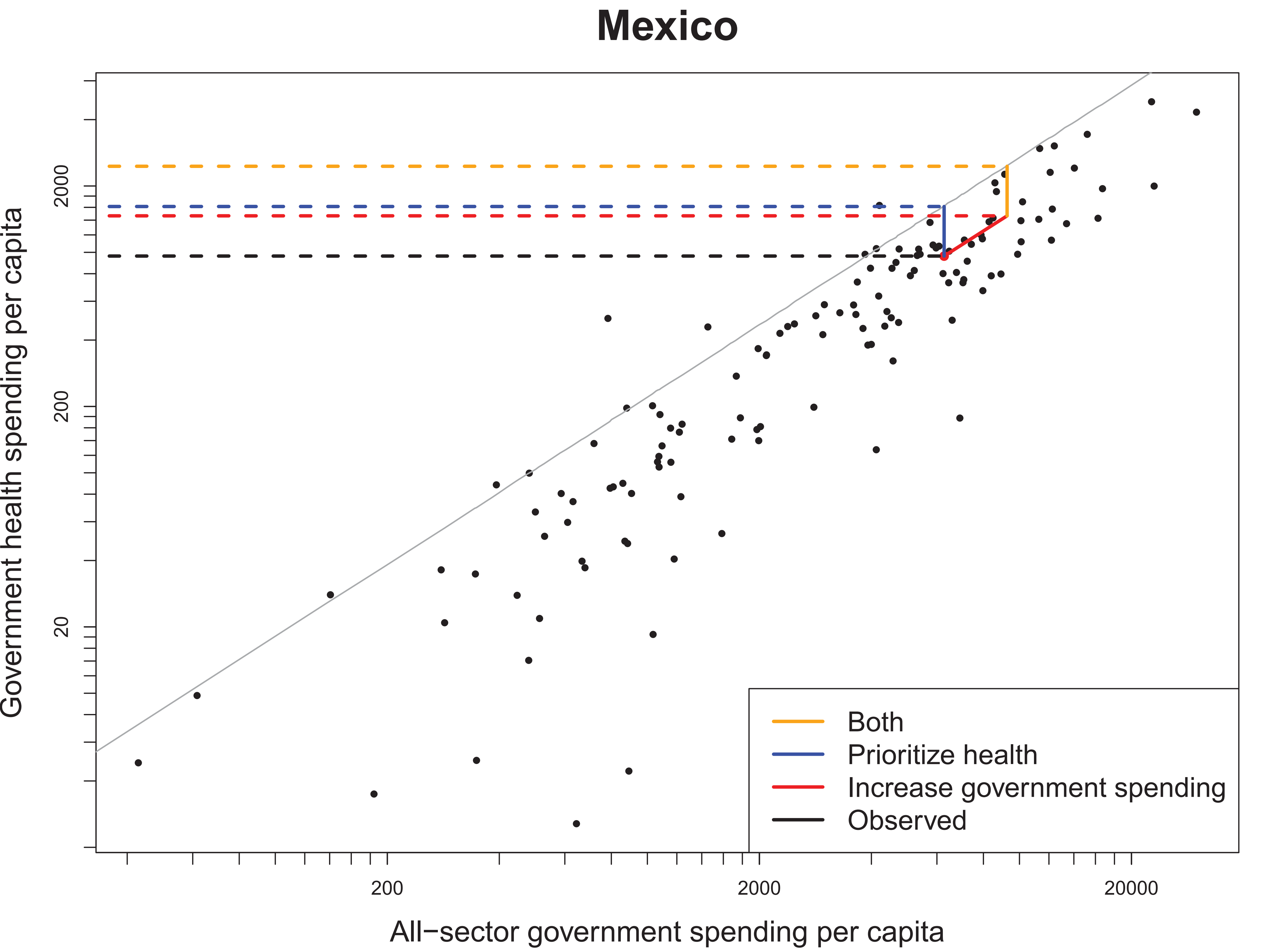


Mauritania
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

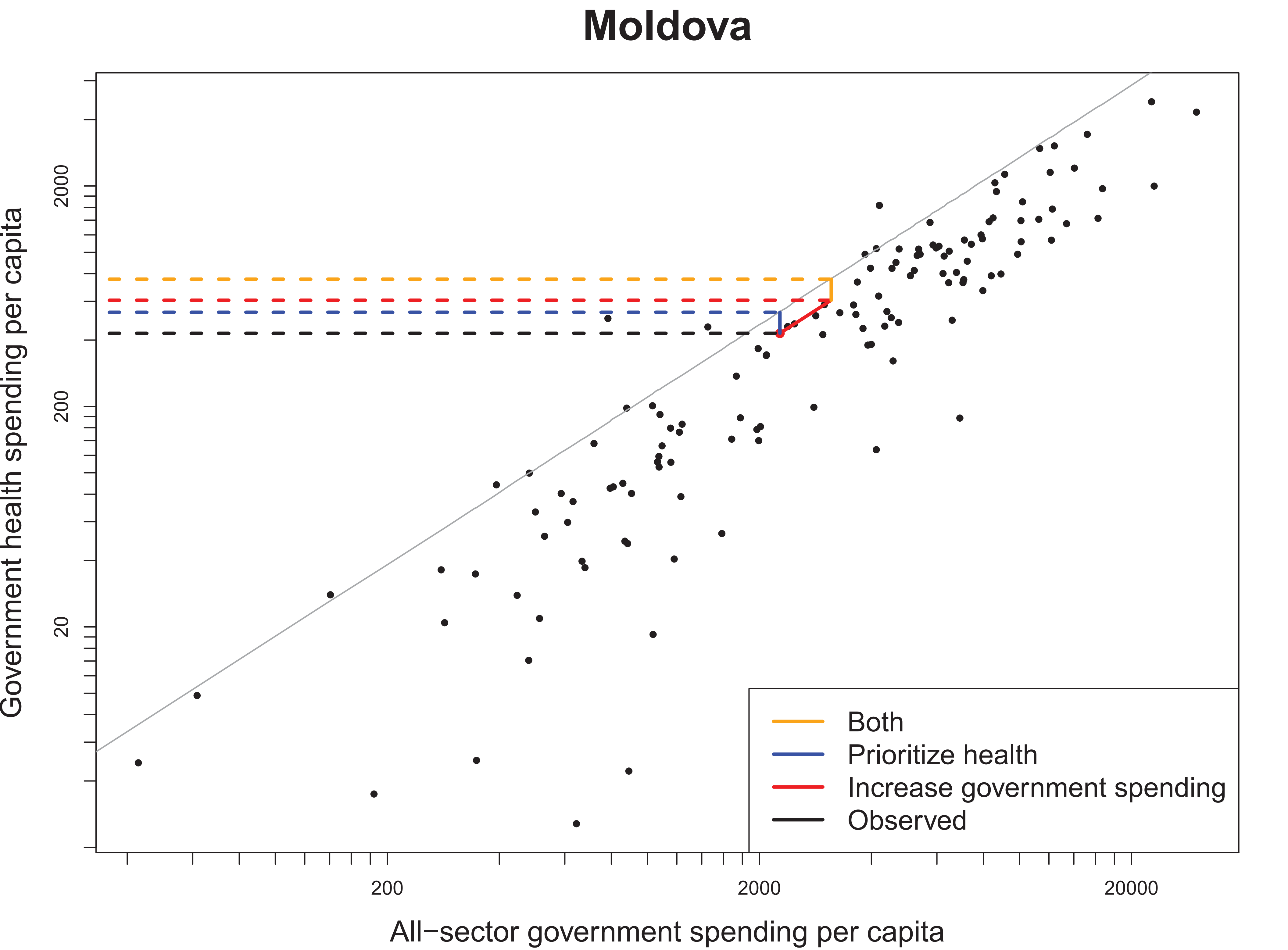
Mauritius

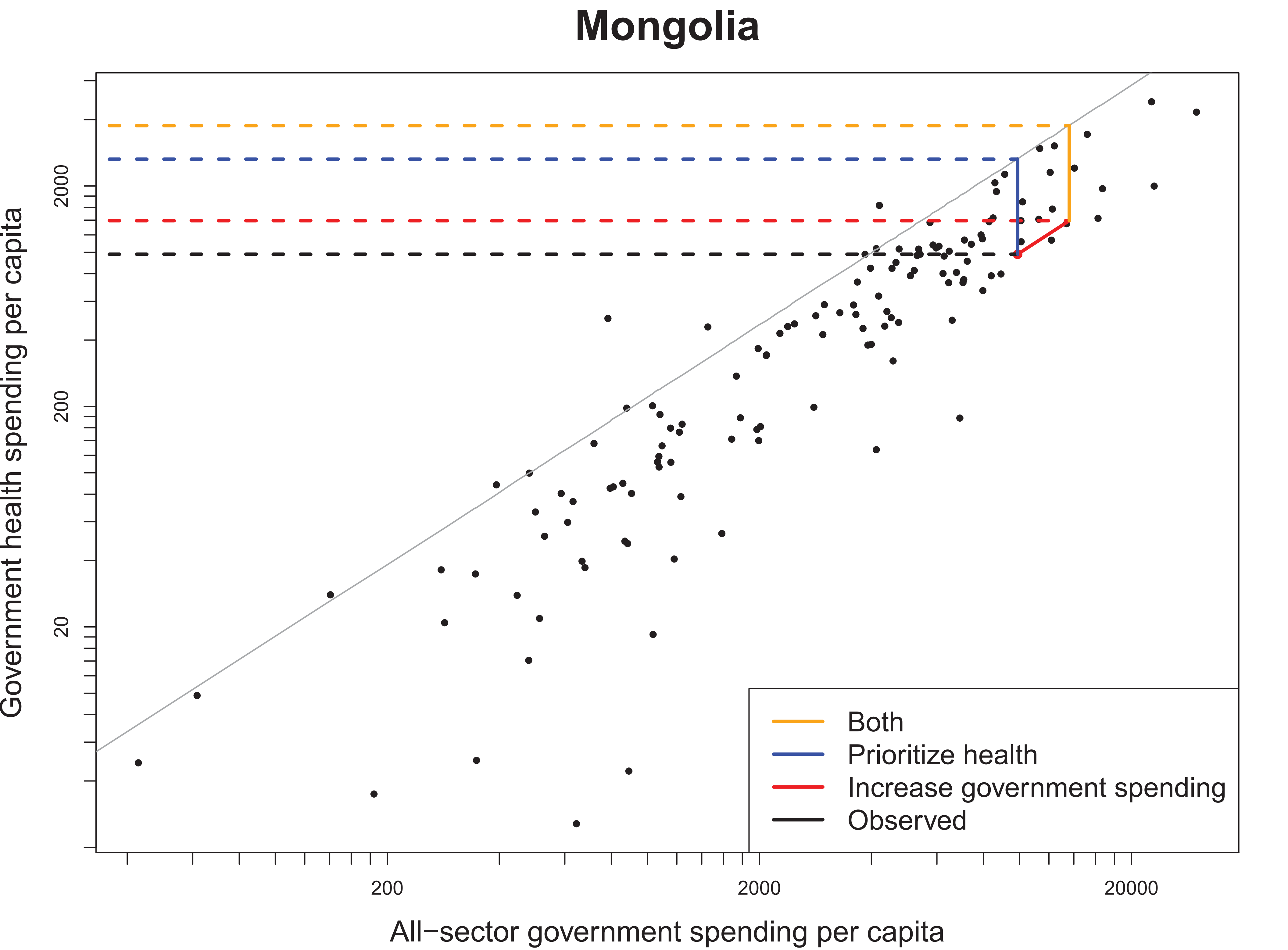


Both
Prioritize health
Increase government spending
Observed
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000

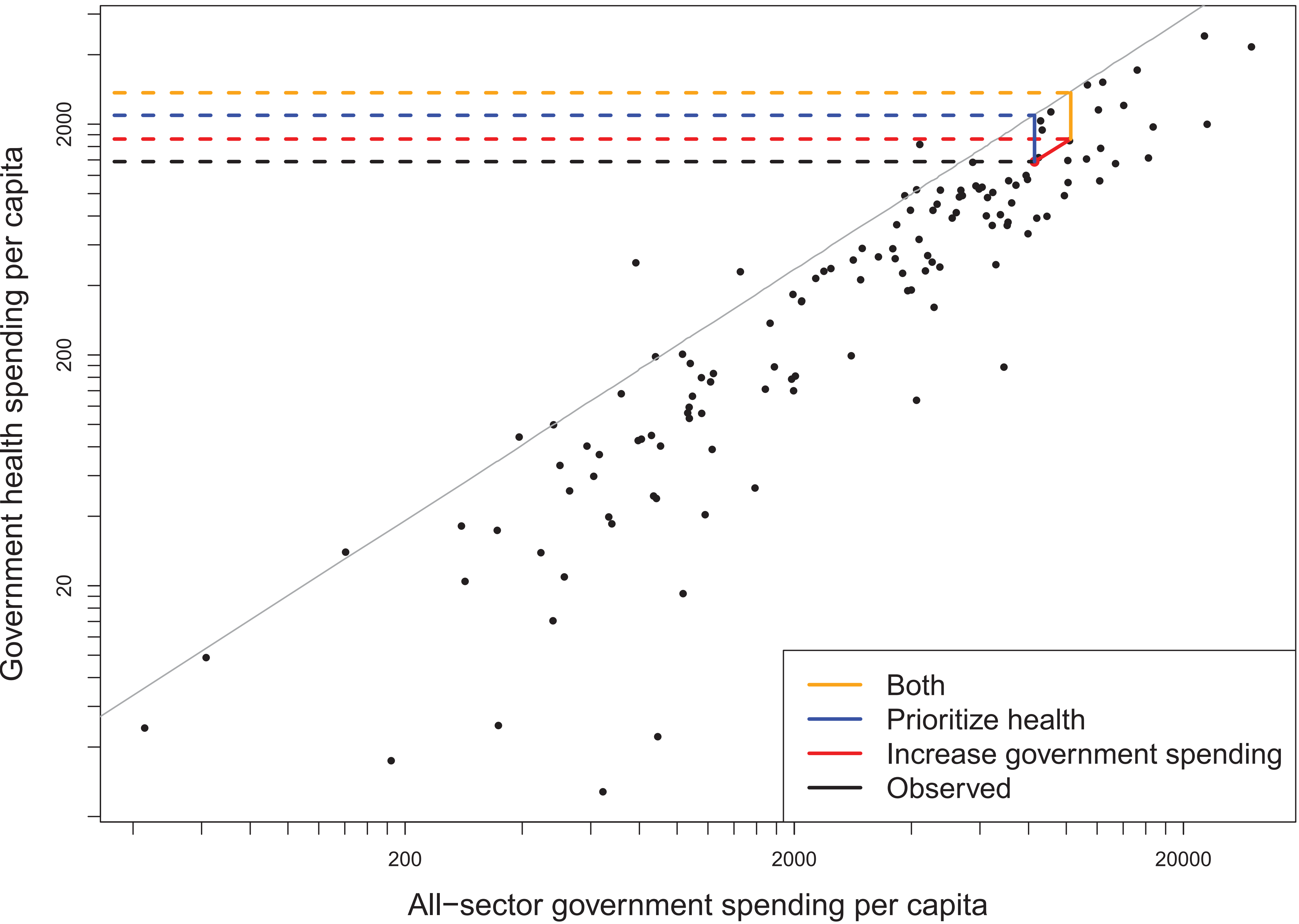


Mexico
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

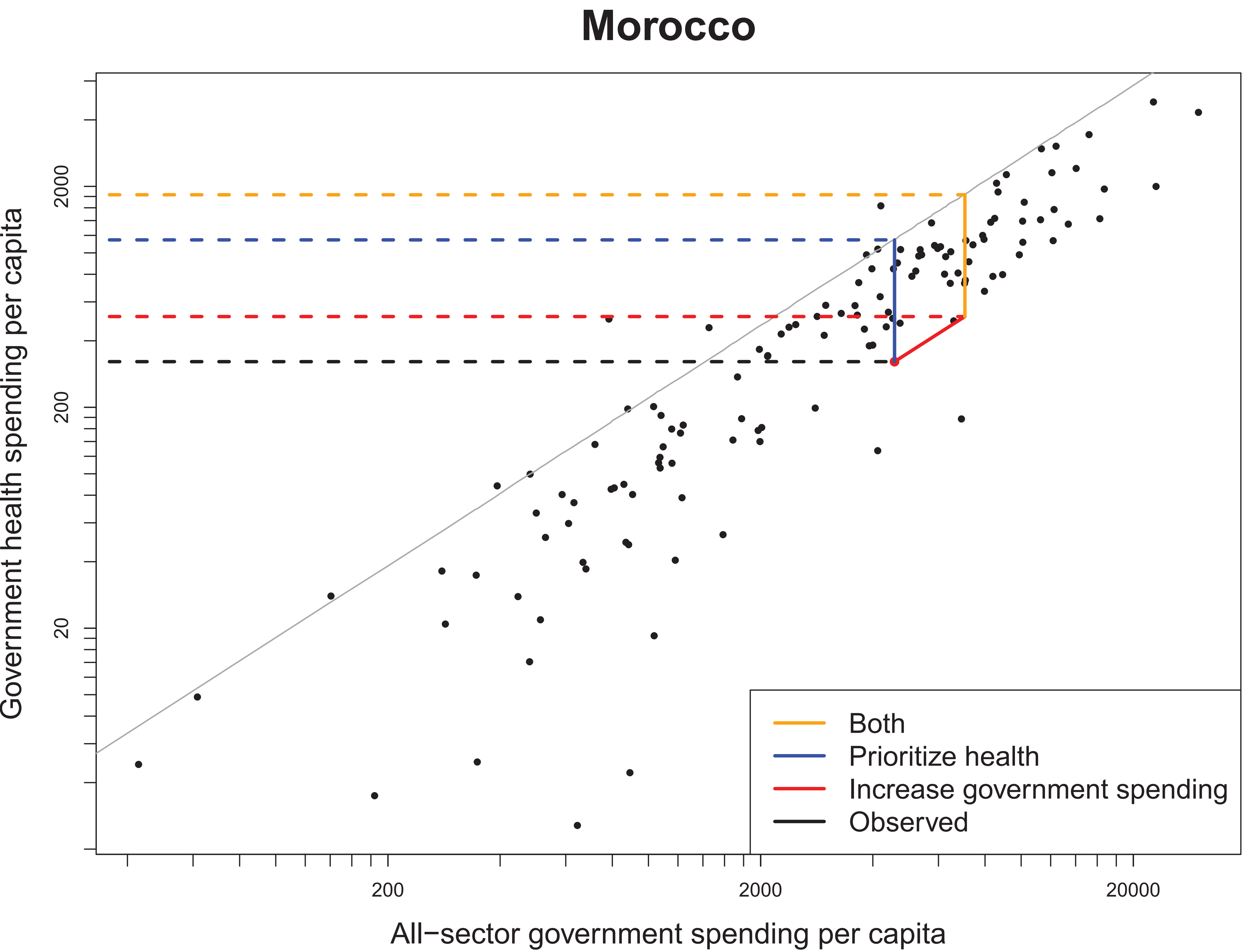

Moldova
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed


Mongolia
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

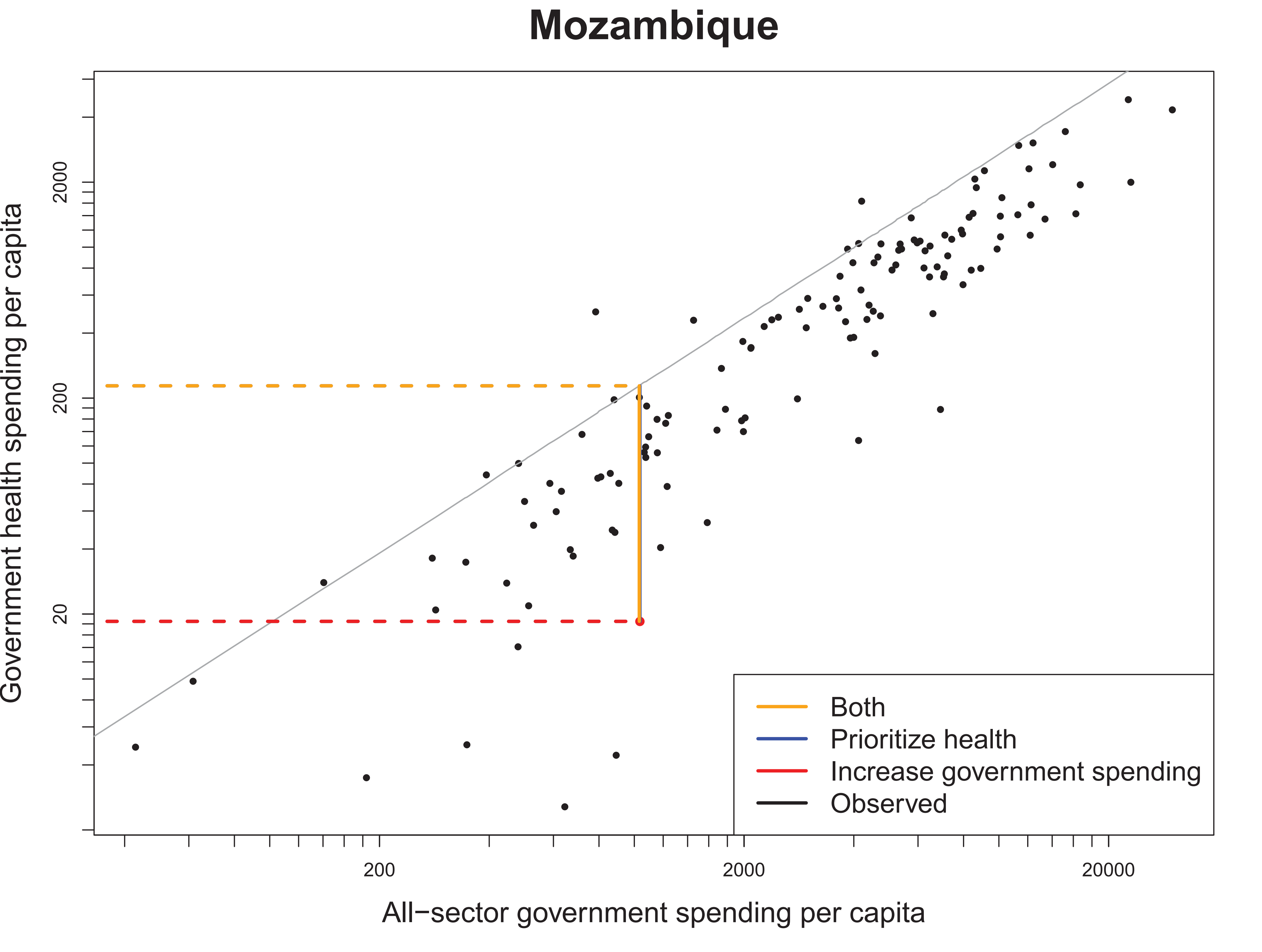
Montenegro



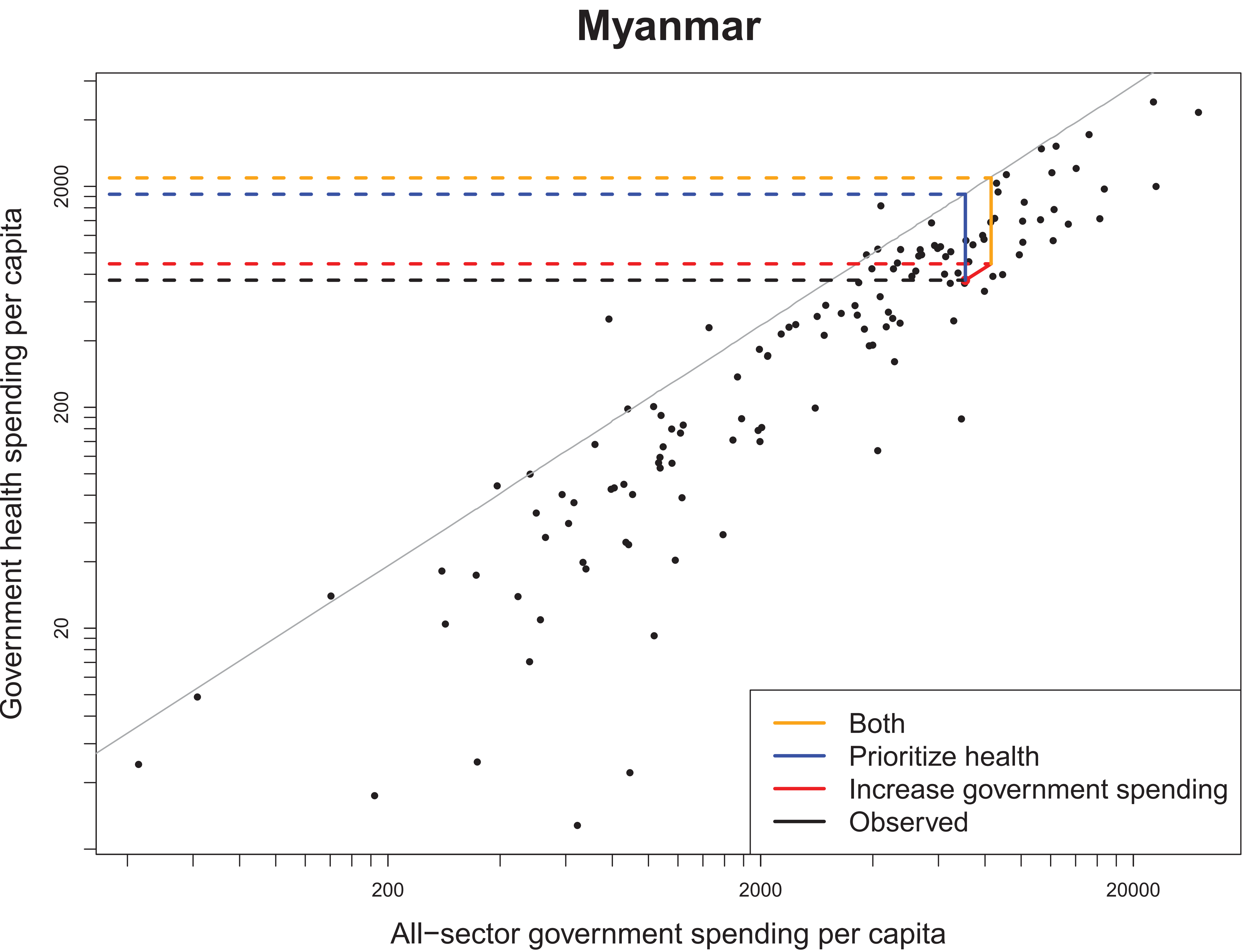
Government health spending per capita
2000
200
20
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



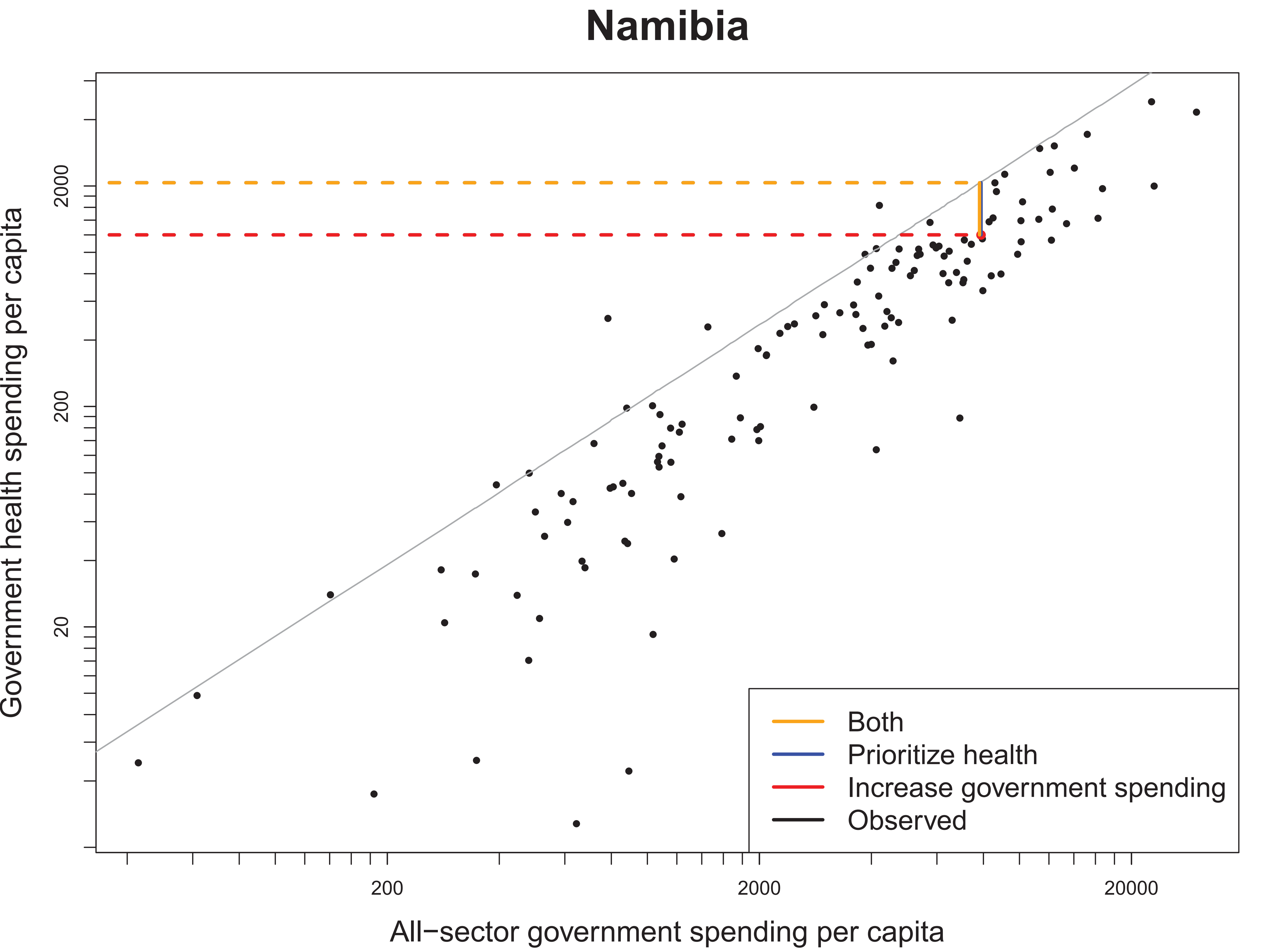
Morocco
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



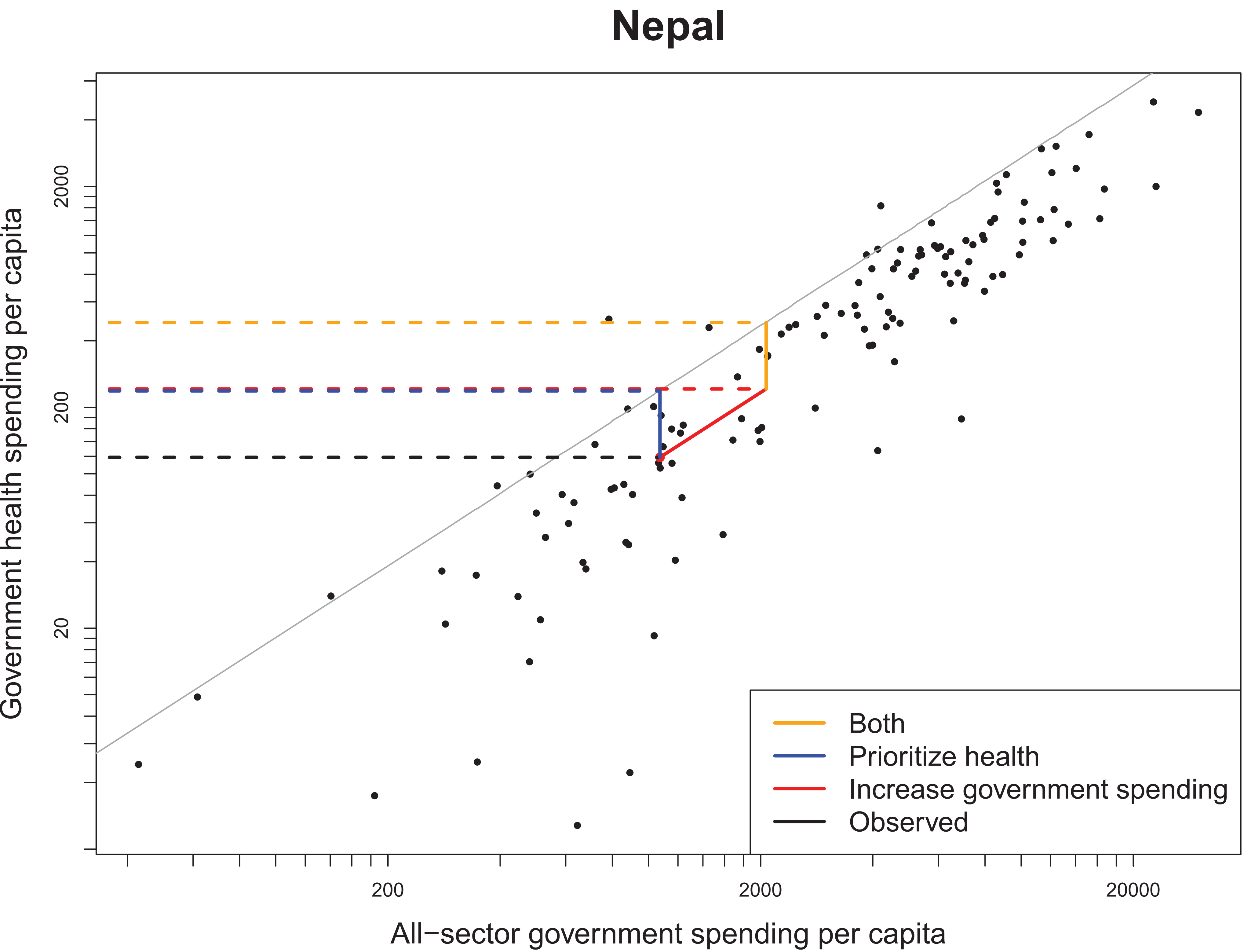
Mozambique
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



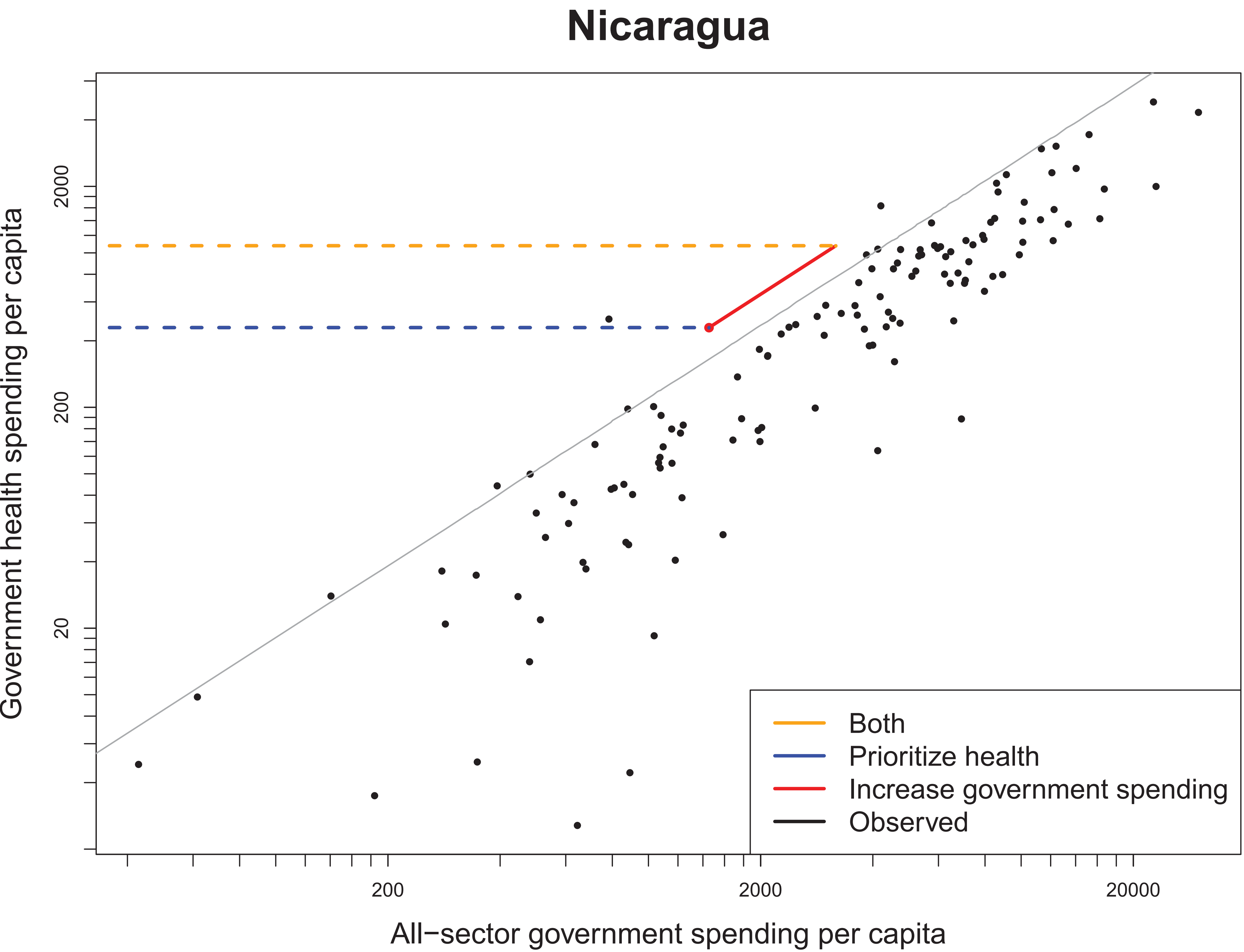
Myanmar
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



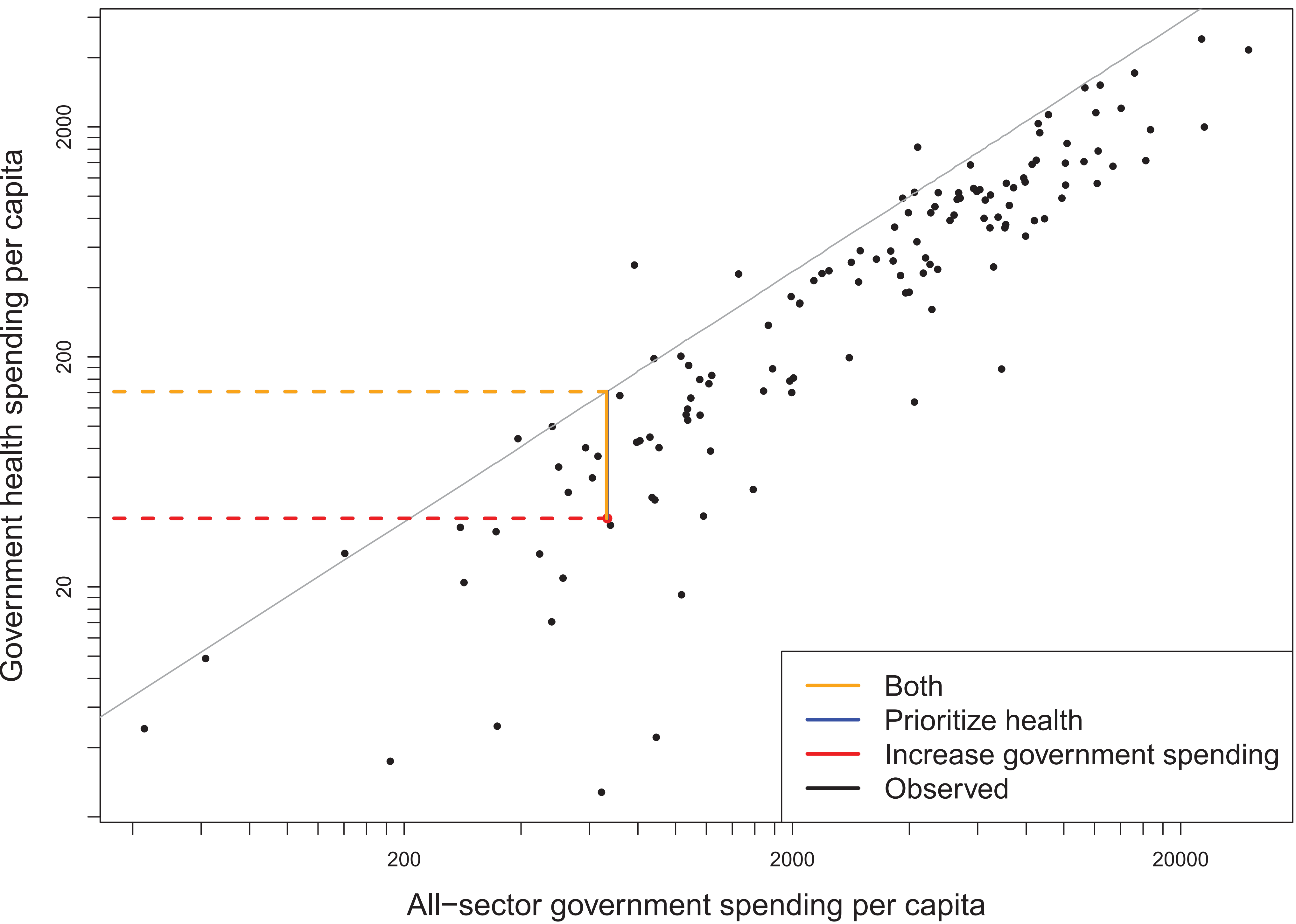
Namibia
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



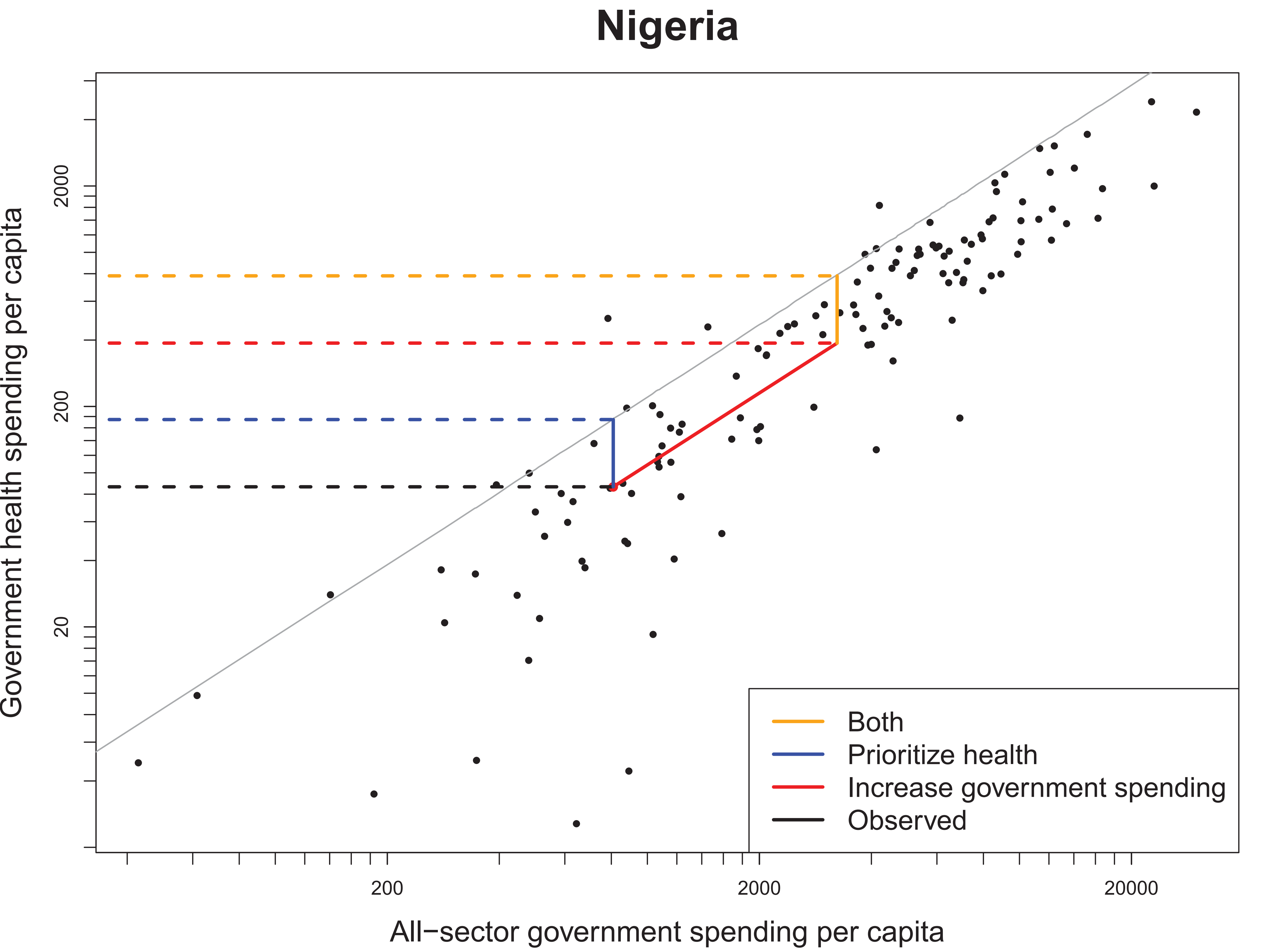
Nepal
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed


Nicaragua
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

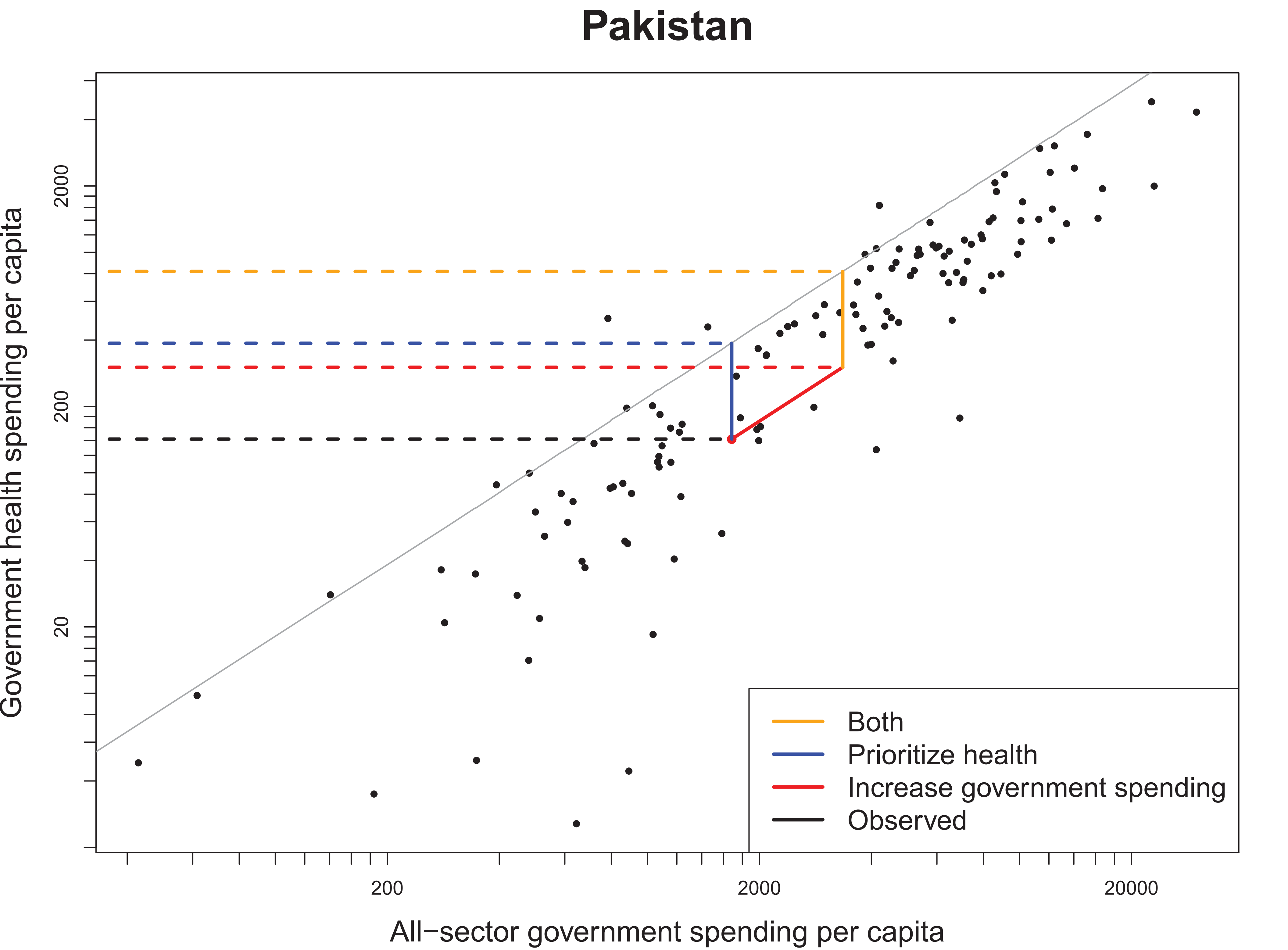
Niger



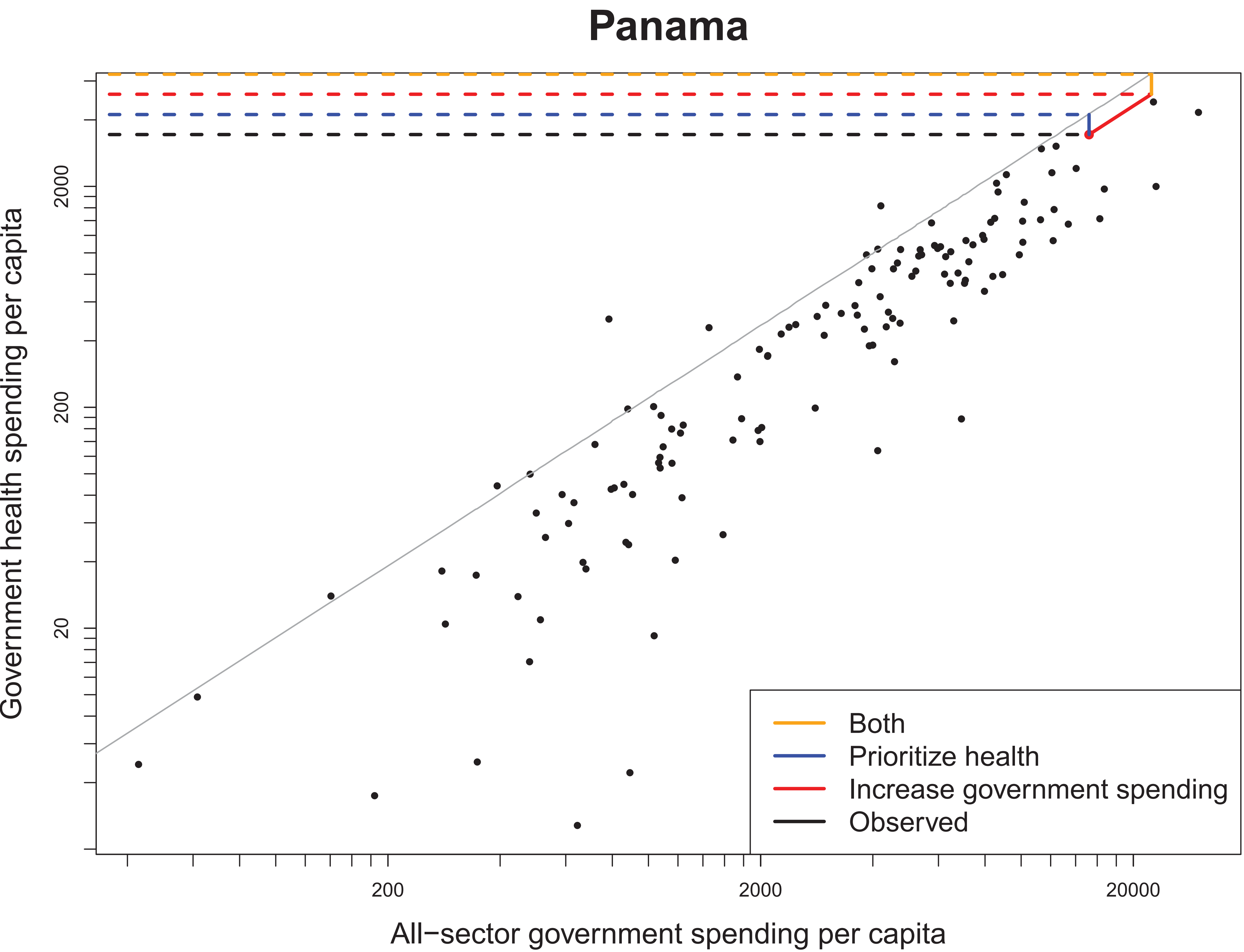
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

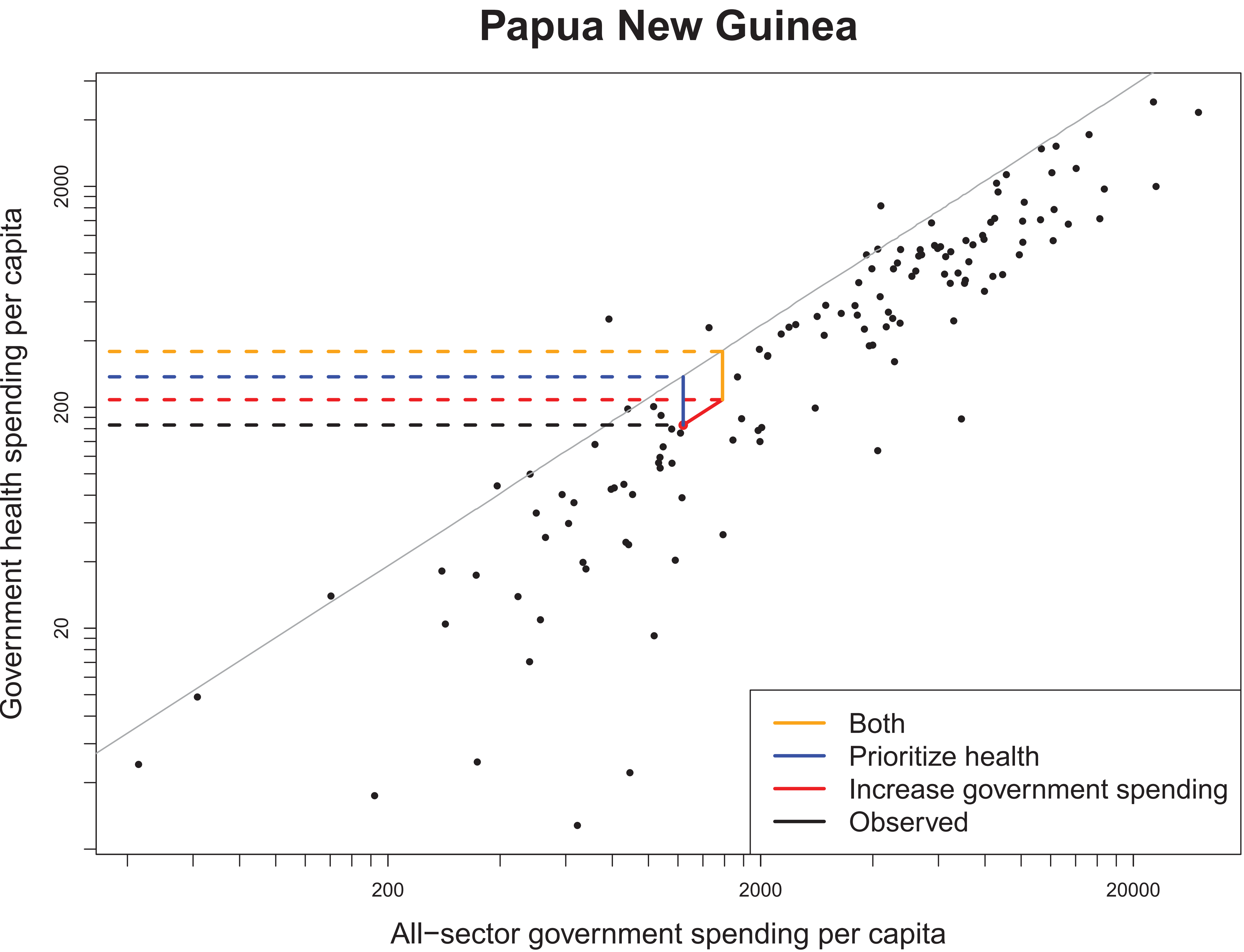


Nigeria
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

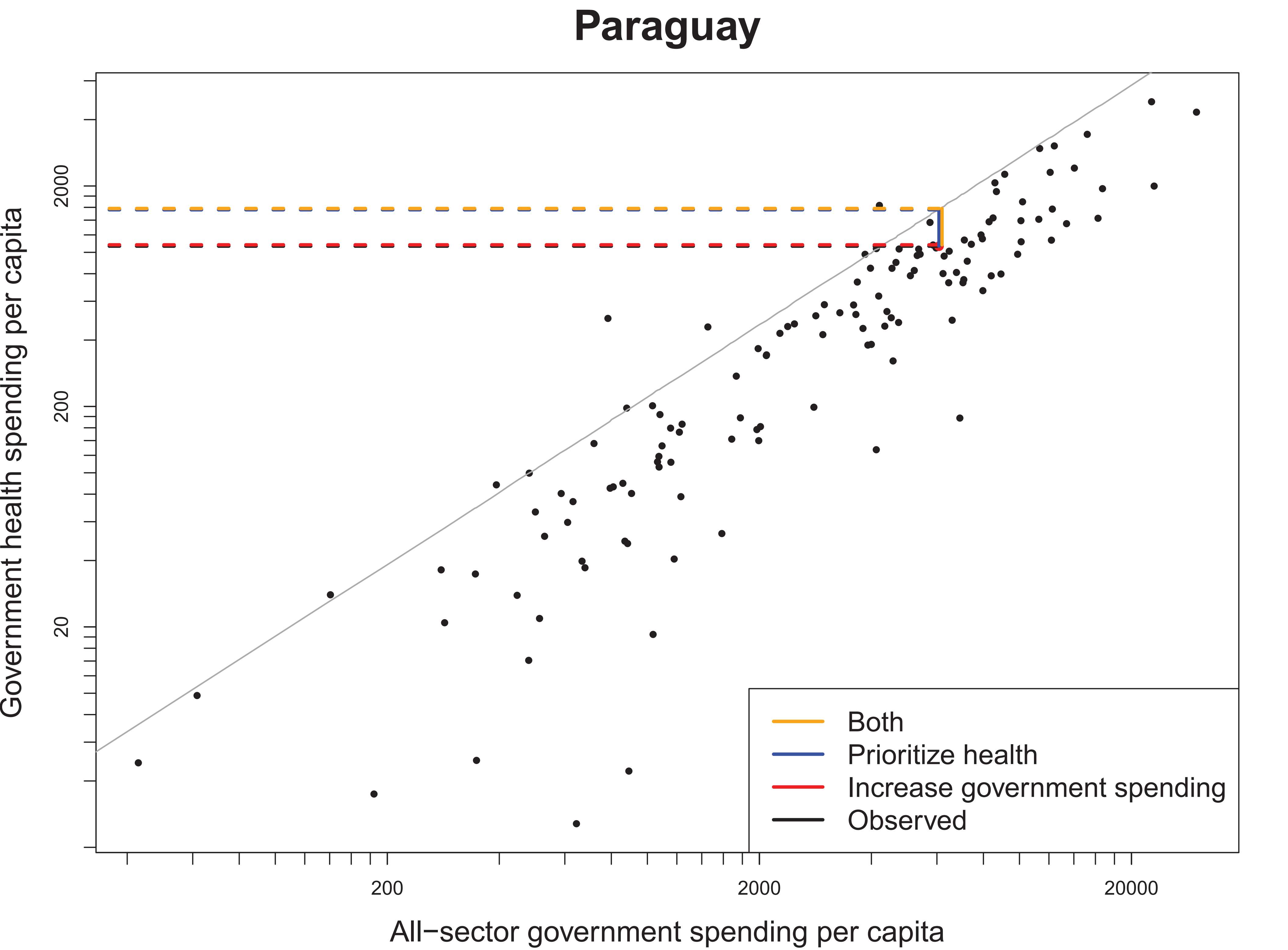


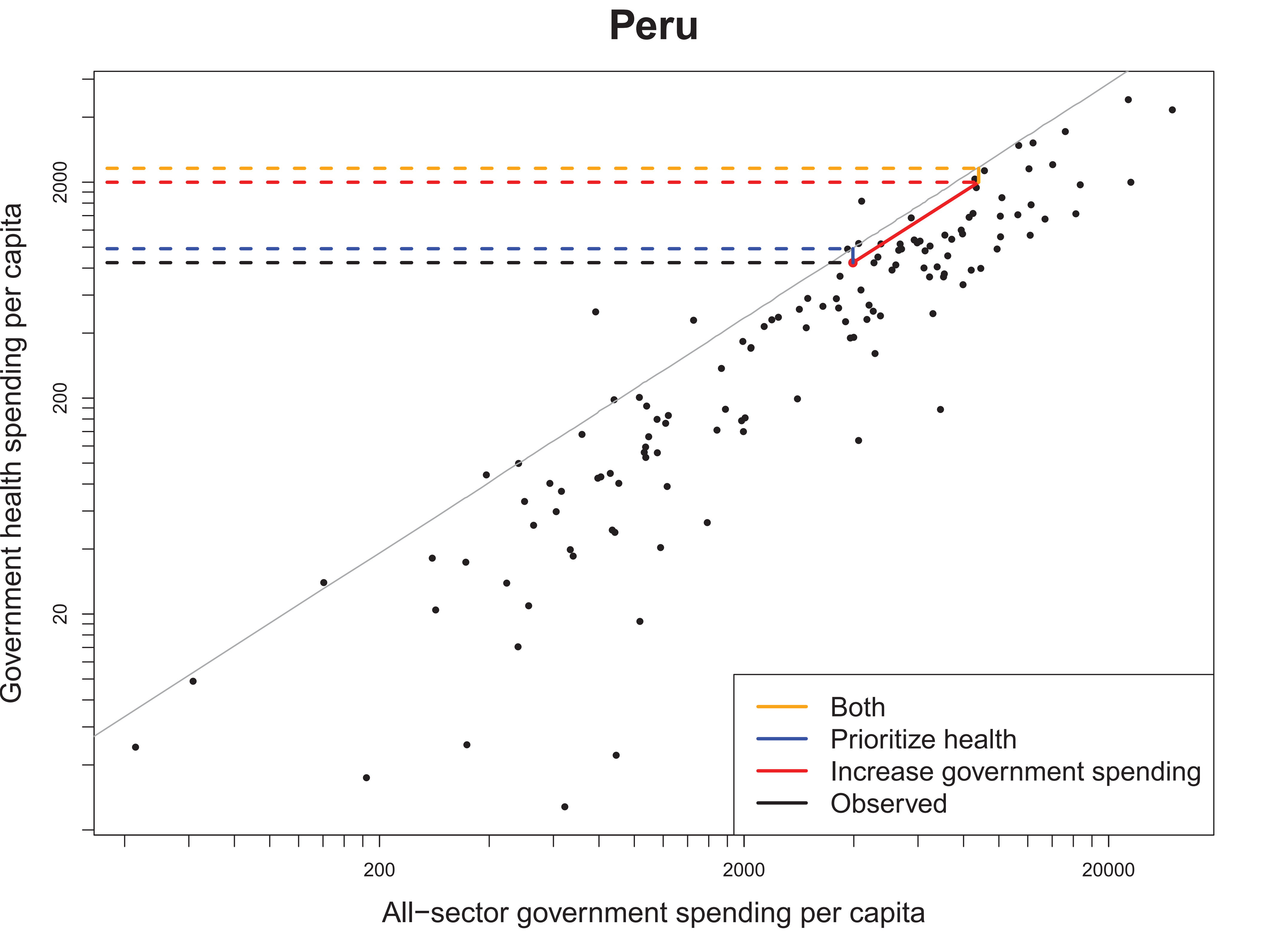
Pakistan
Both
Prioritize health
Increase government spending
Observed
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000

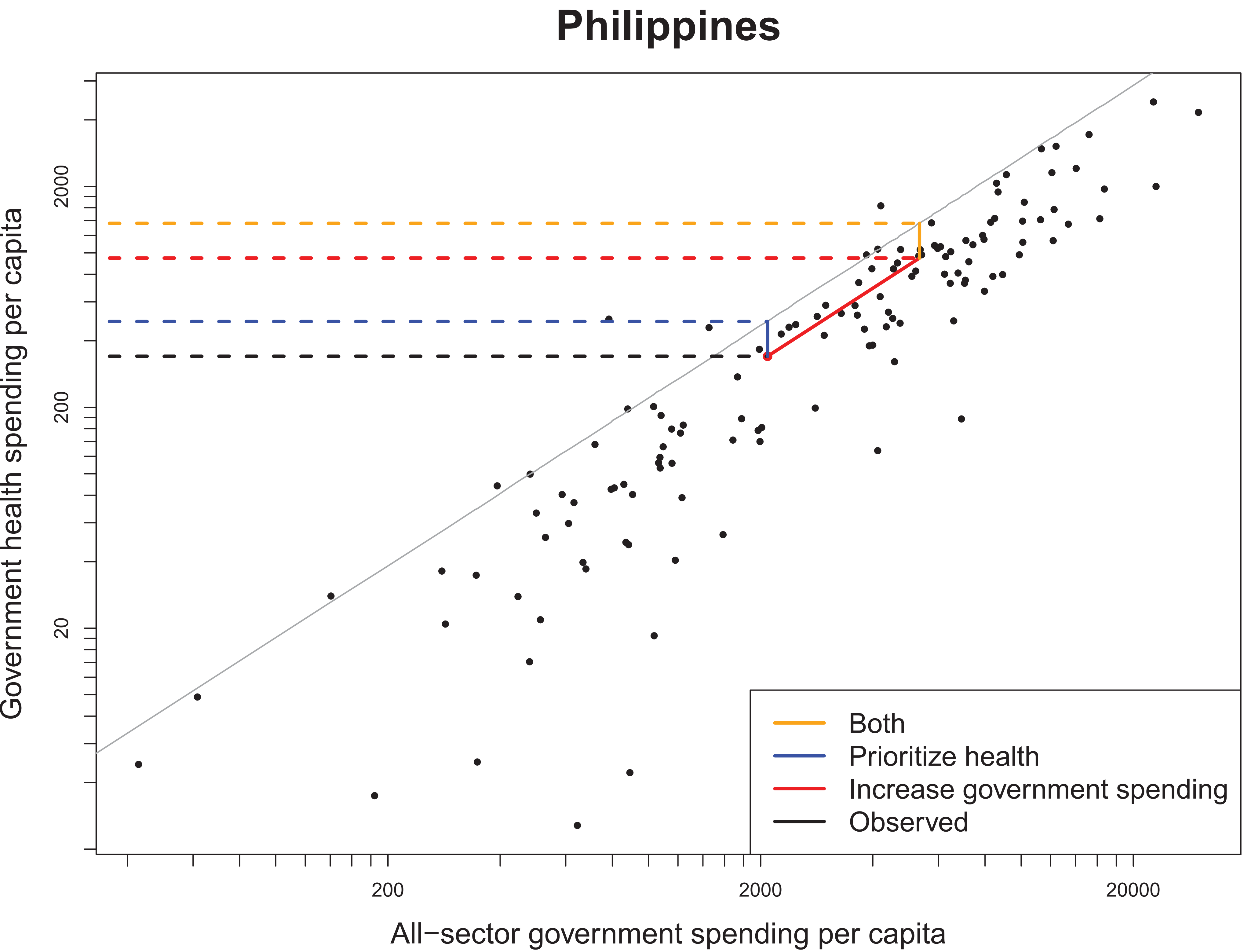

Panama
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



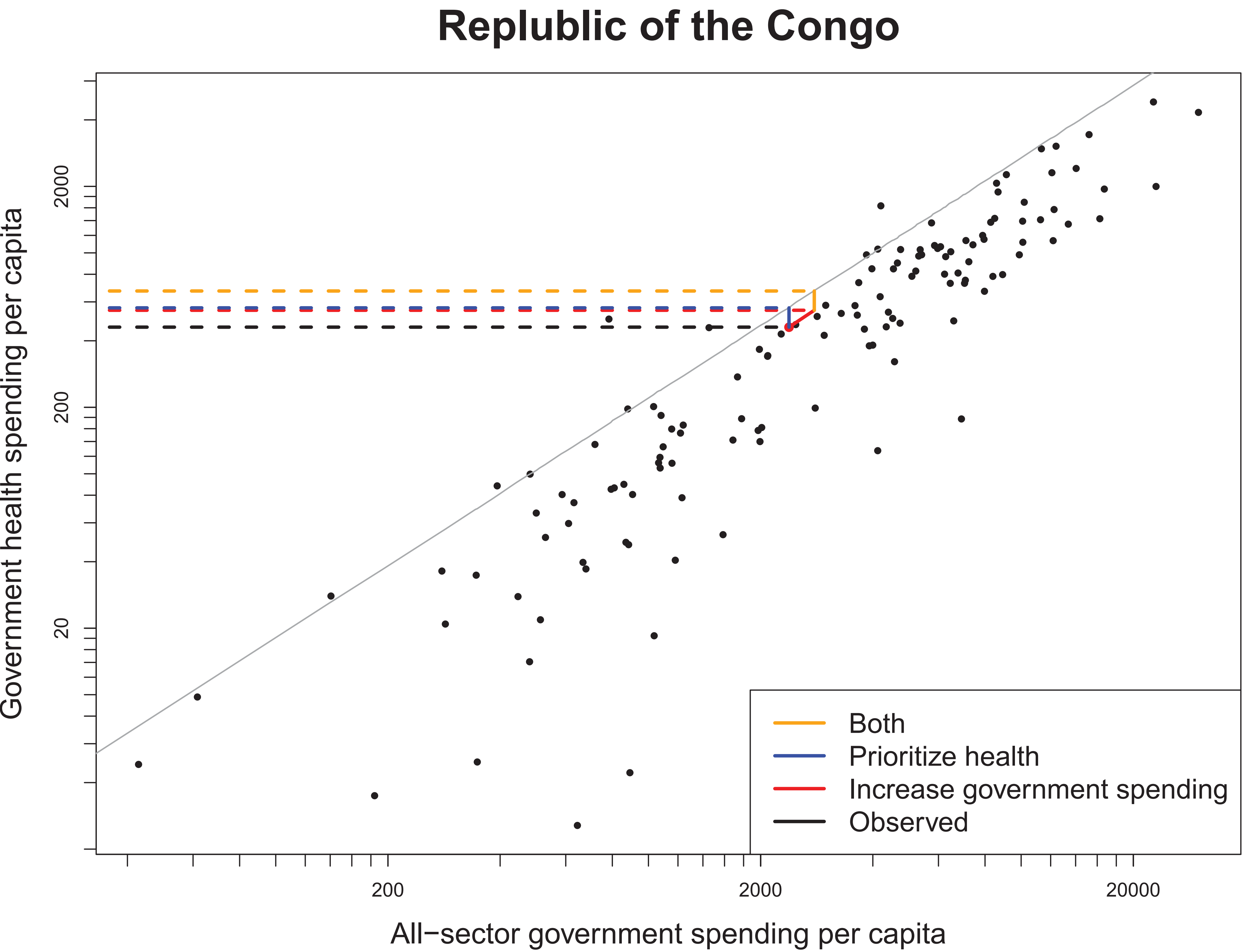
Papua New Guinea
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed


Paraguay
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

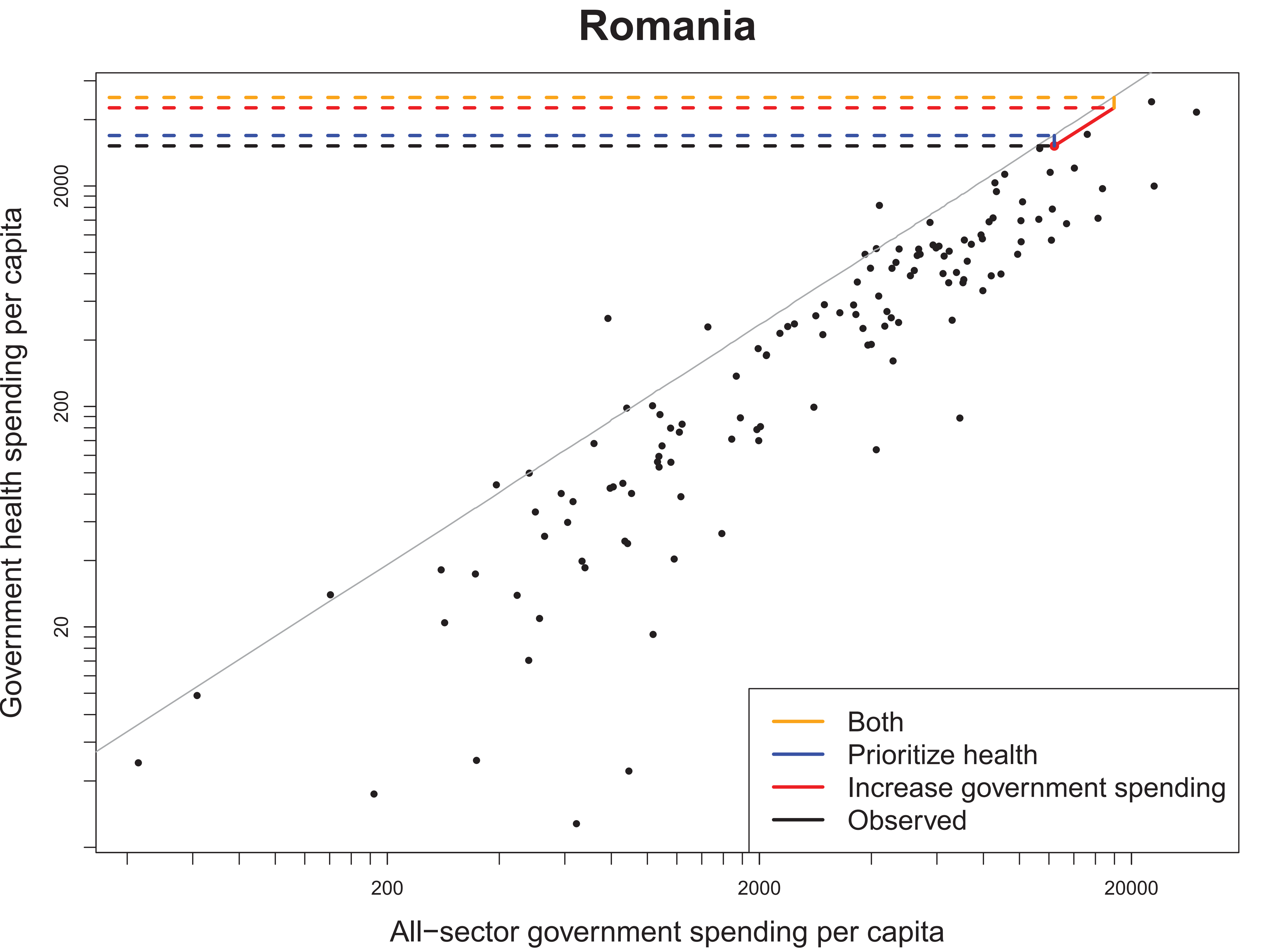

Peru
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

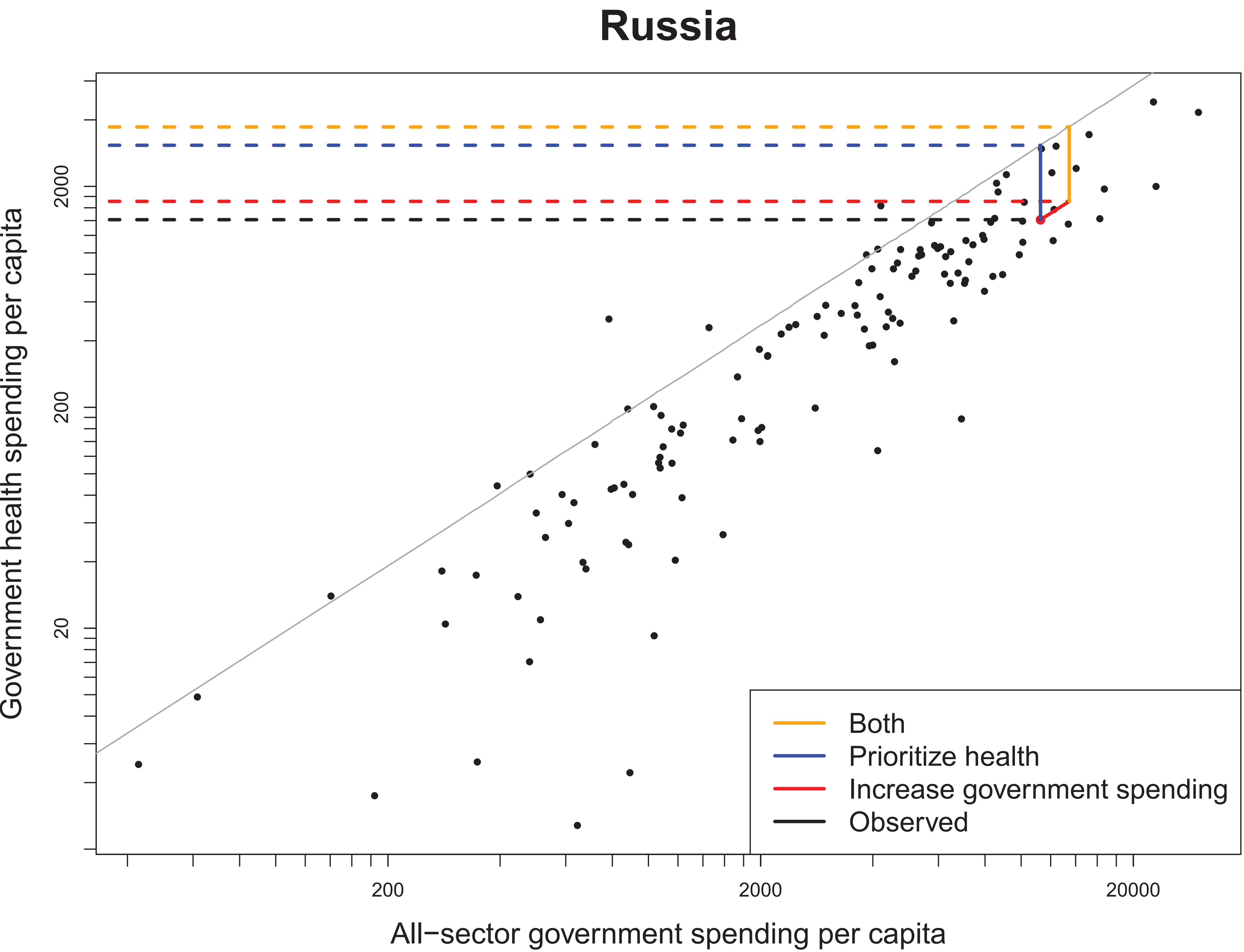


Philippines
2000
200
20
Government health spending per capita
200
2000
20000
All−sector government spending per capita
Both
Prioritize health
Increase government spending
Observed



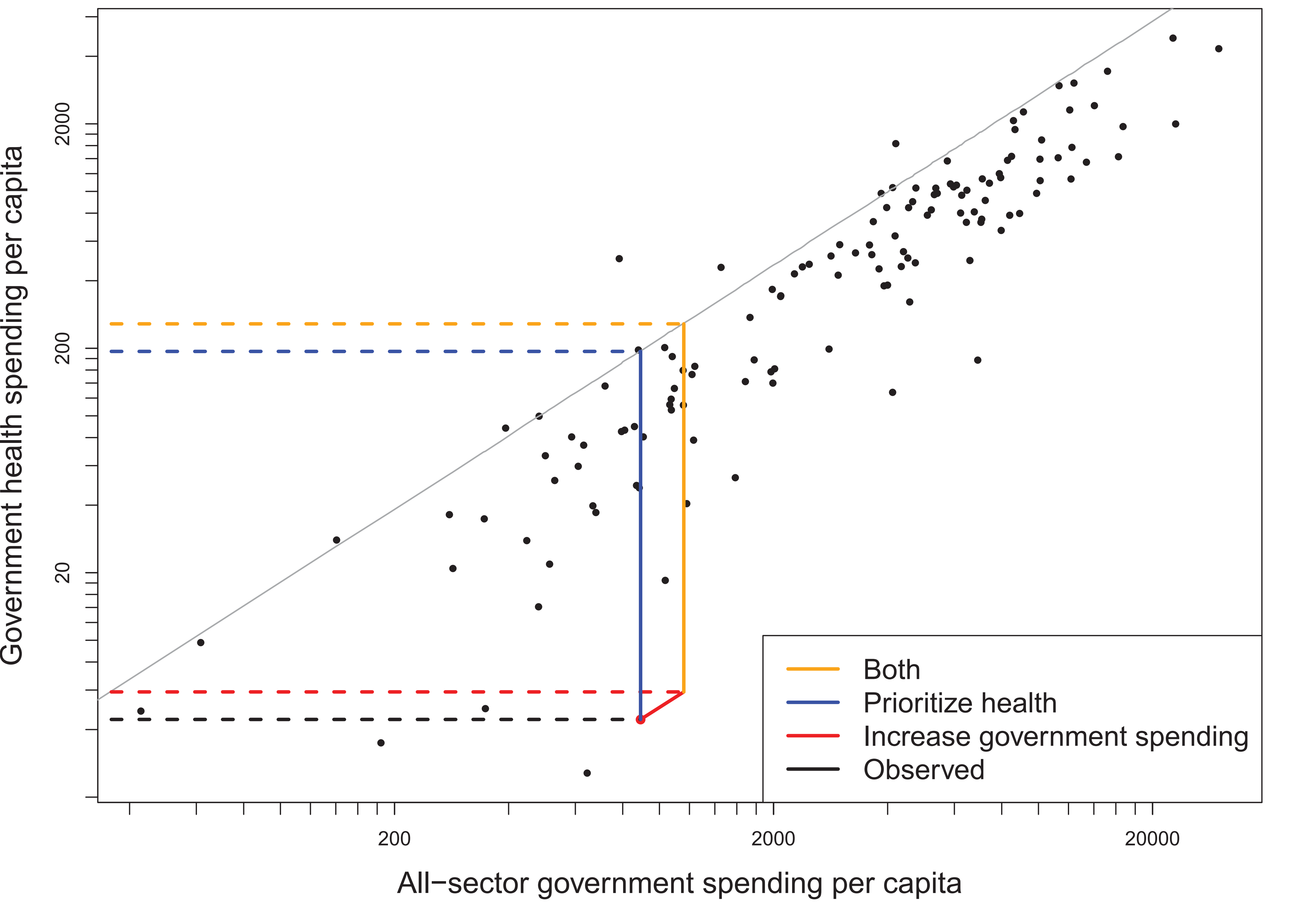
Replublic of the Congo
Government health spending per capita
All−sector government spending per capita
2000
200
20
20000
Both
Prioritize health
Increase government spending
Observed


Romania
Both
Prioritize health
Increase government spending
Observed
2000
200
20
200
2000
20000
Government health spending per capita
All−sector government spending per capita



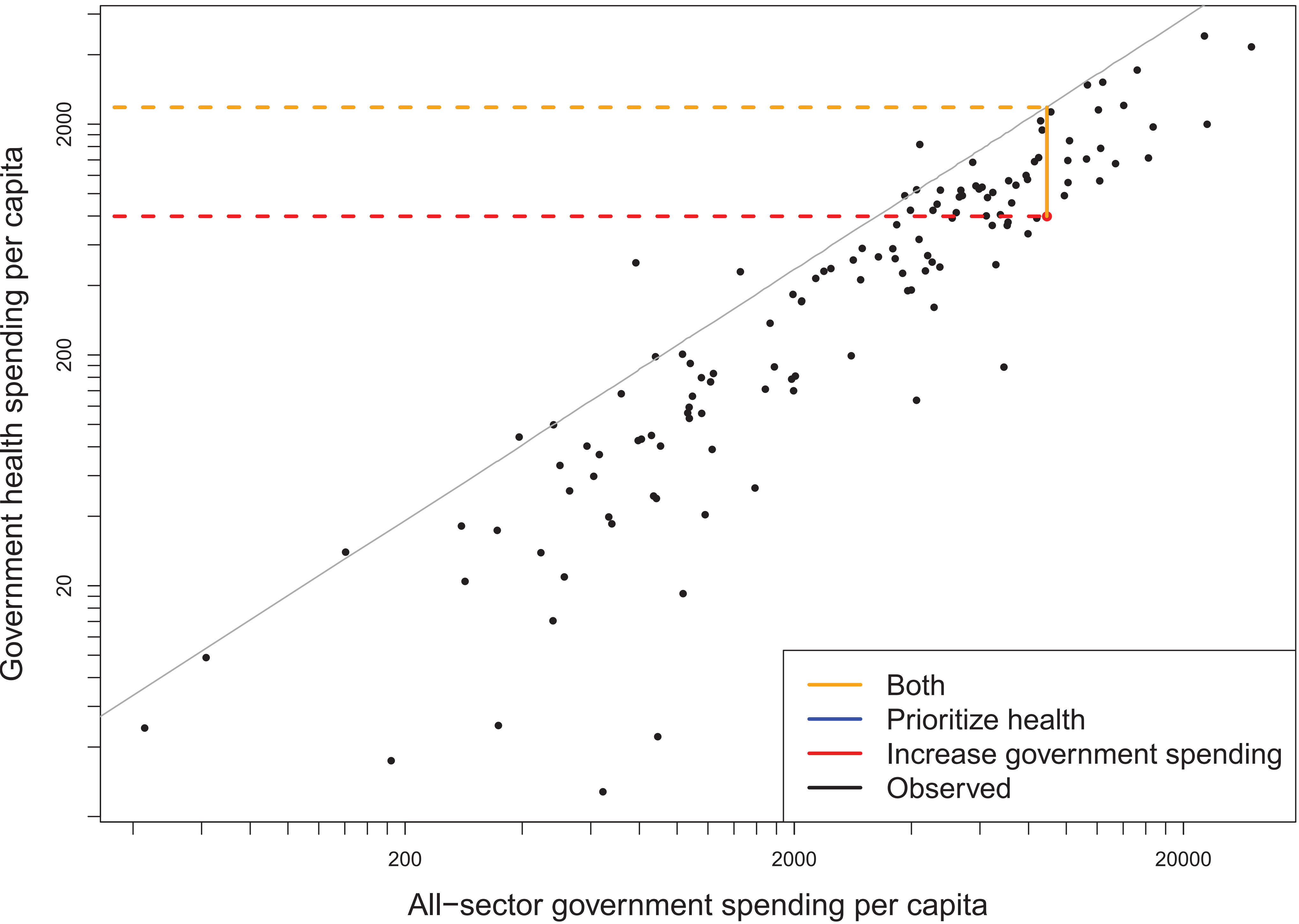
Russia
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

Rwanda

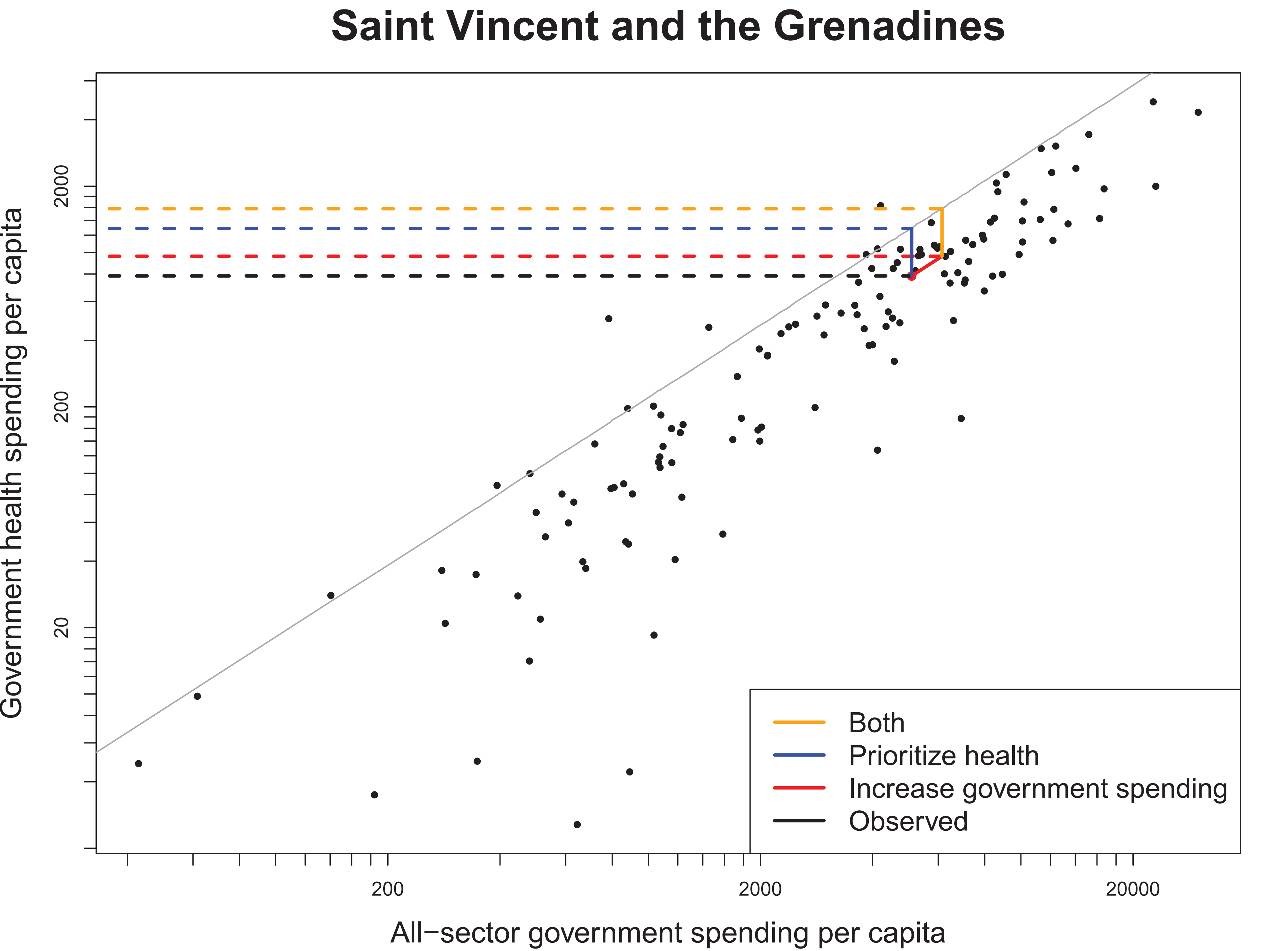


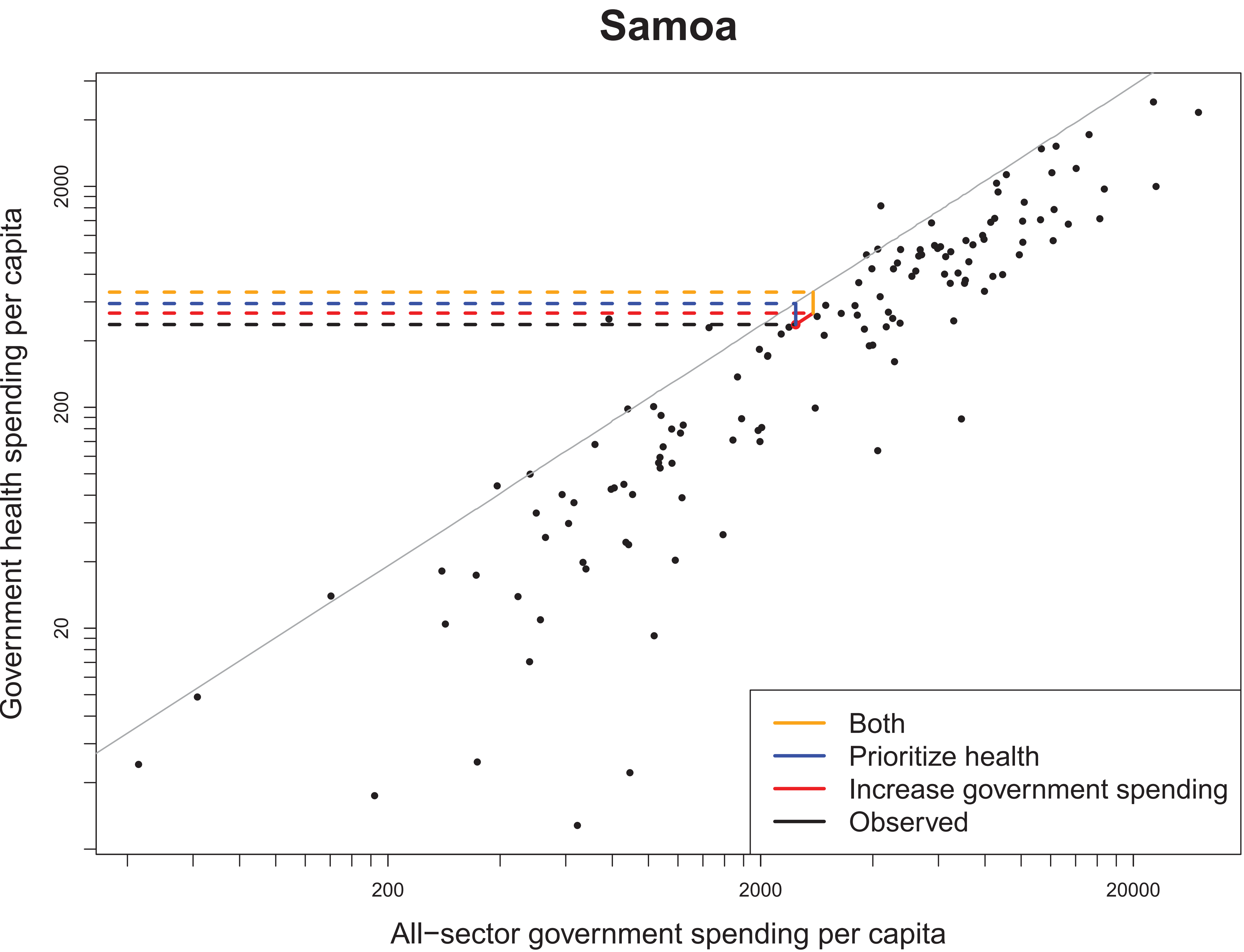
Government health spending per capita
All−sector government spending per capita
2000
200
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

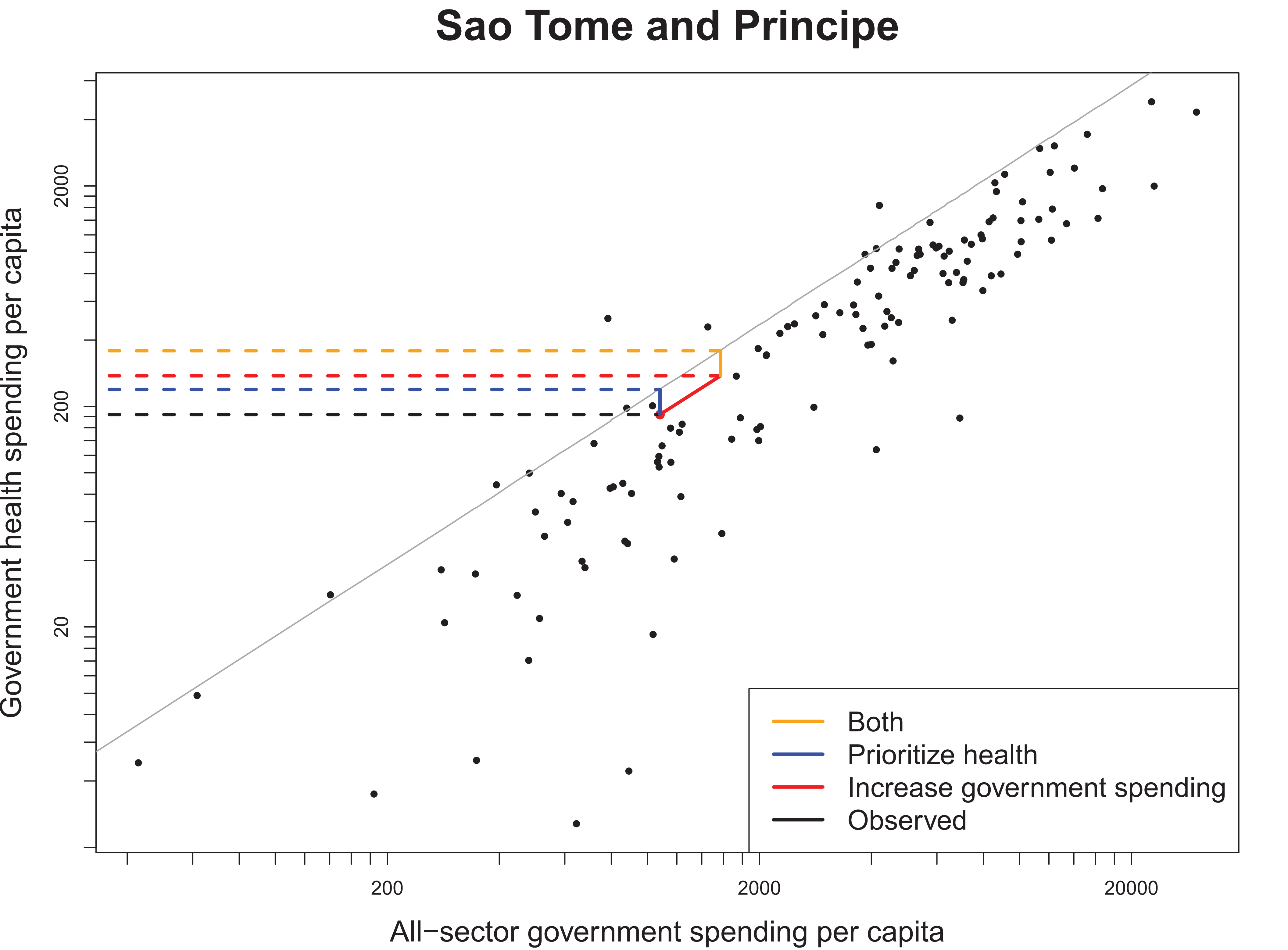
Saint Lucia



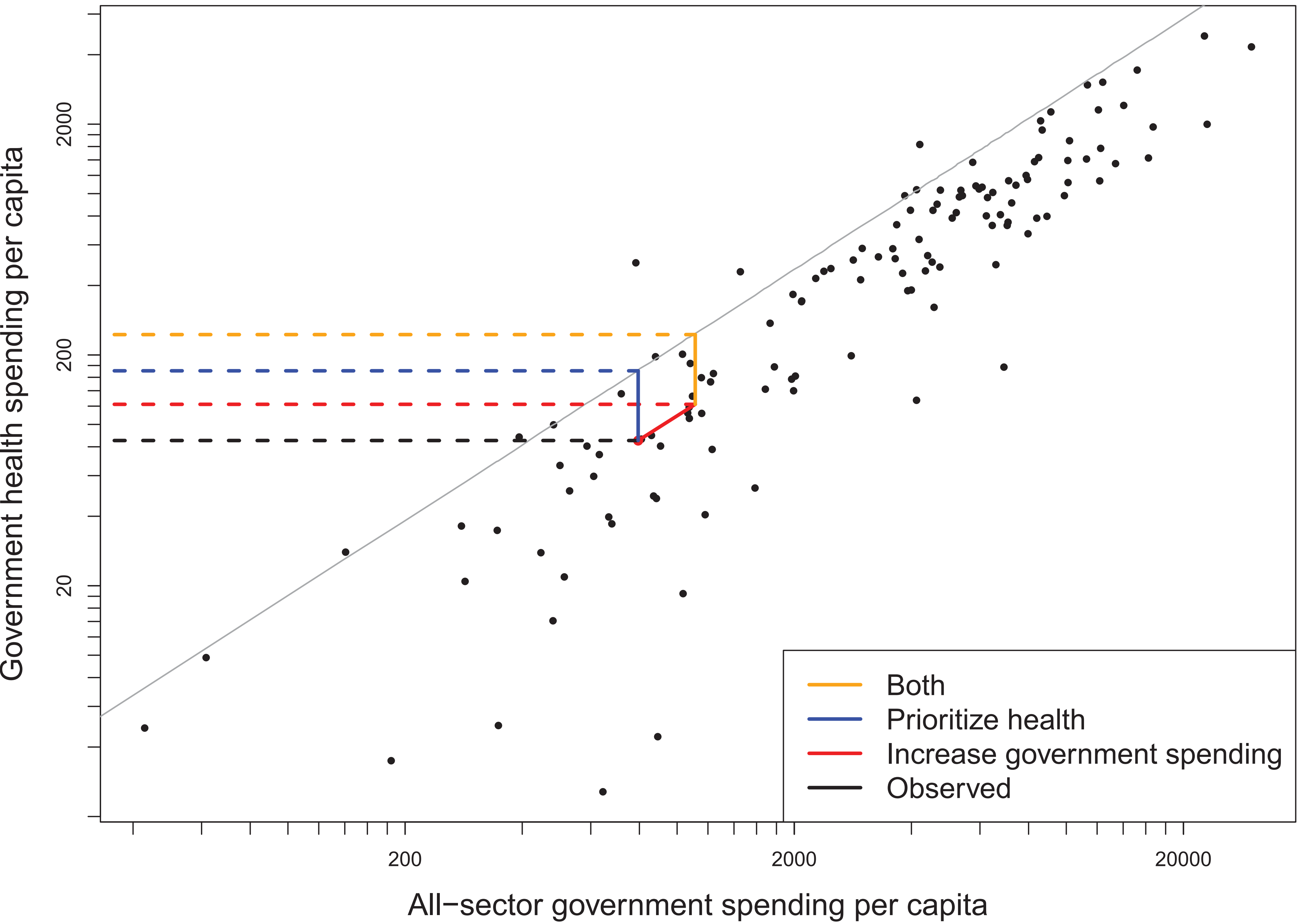
Government health spending per capita
2000
200
20
200
2000
20000
All−sector government spending per capita
Both
Prioritize health
Increase government spending
Observed


Saint Vincent and the Grenadines
Government health spending per capita
2000
200
20
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

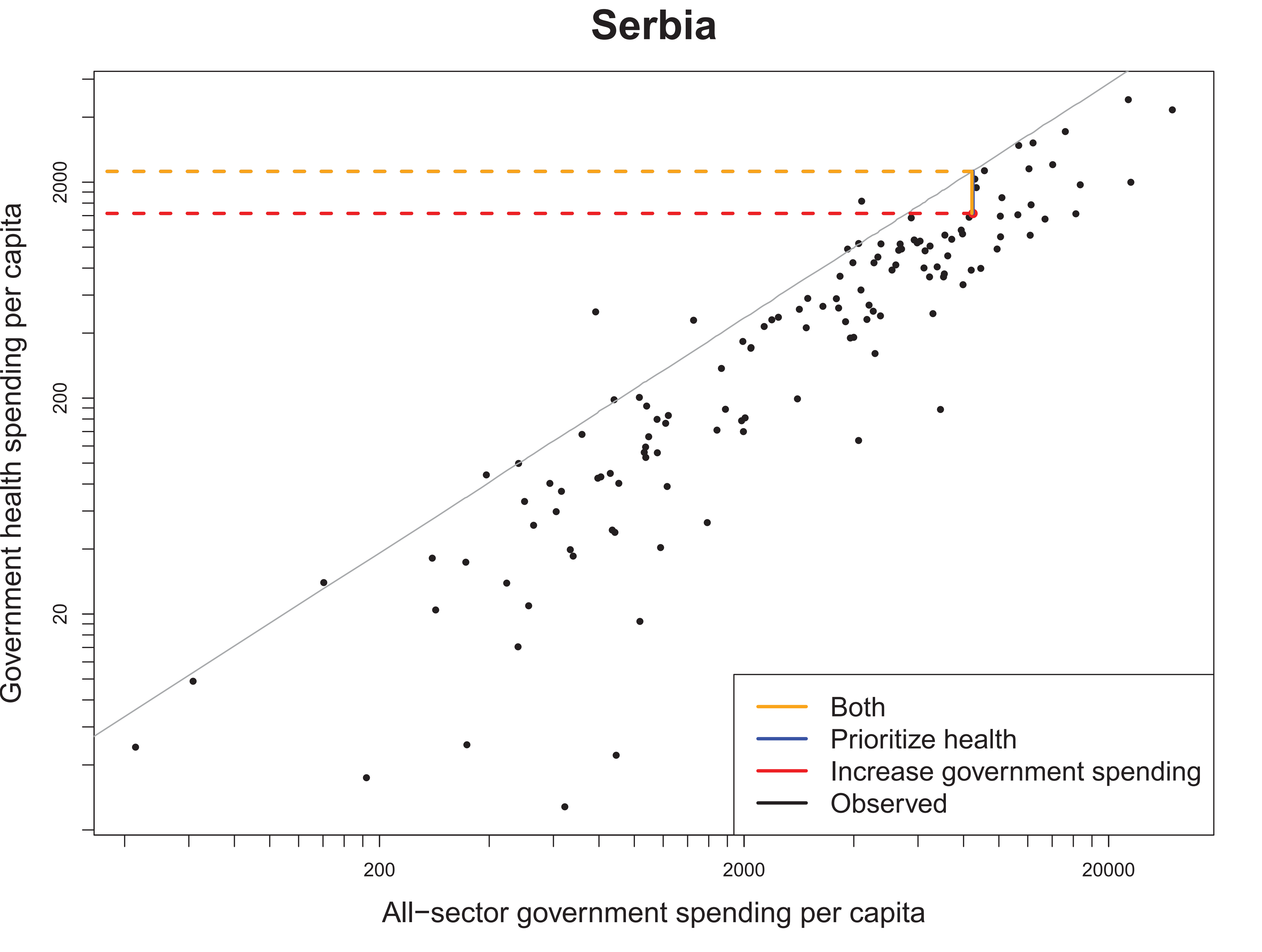

Samoa
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

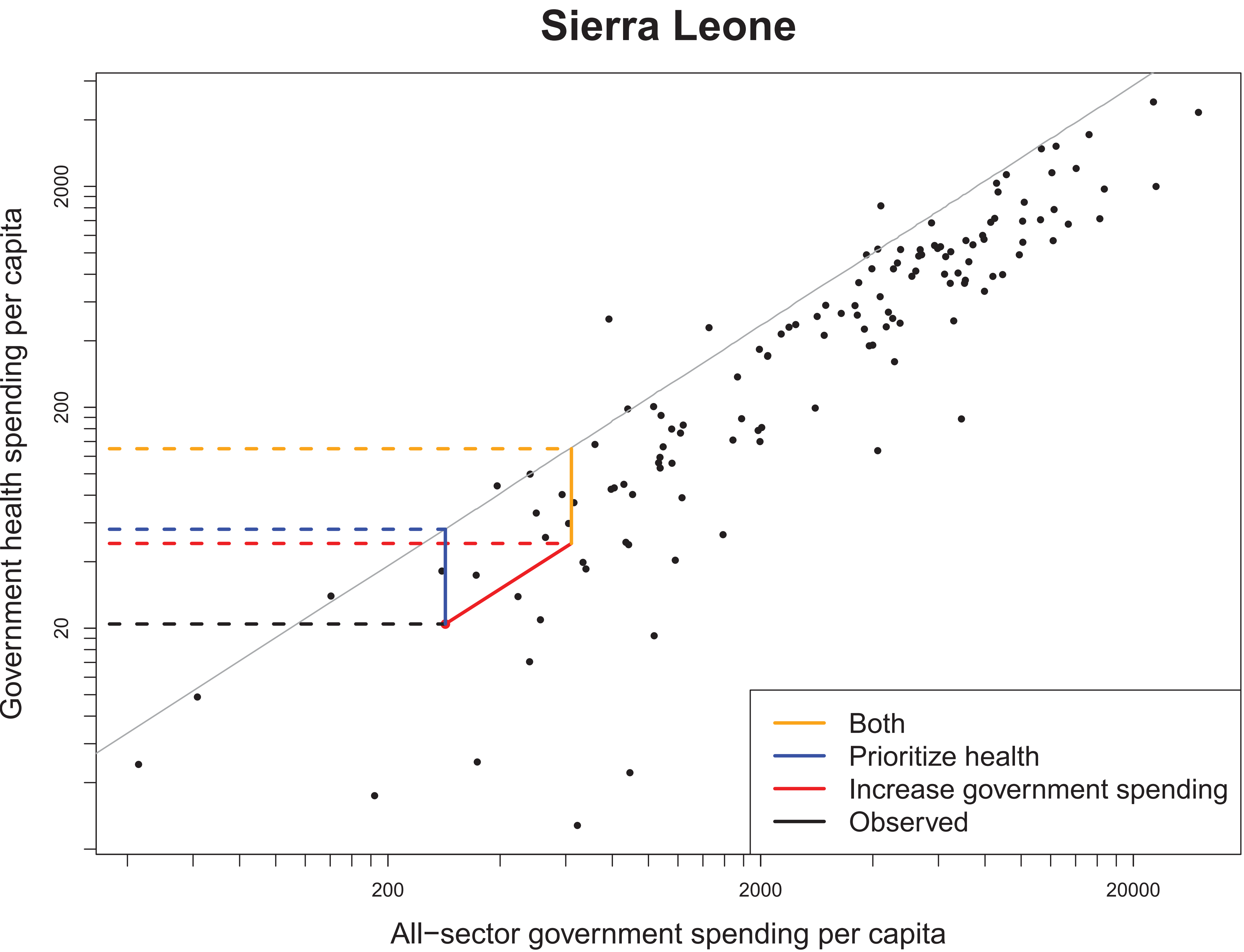

Sao Tome and Principe
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

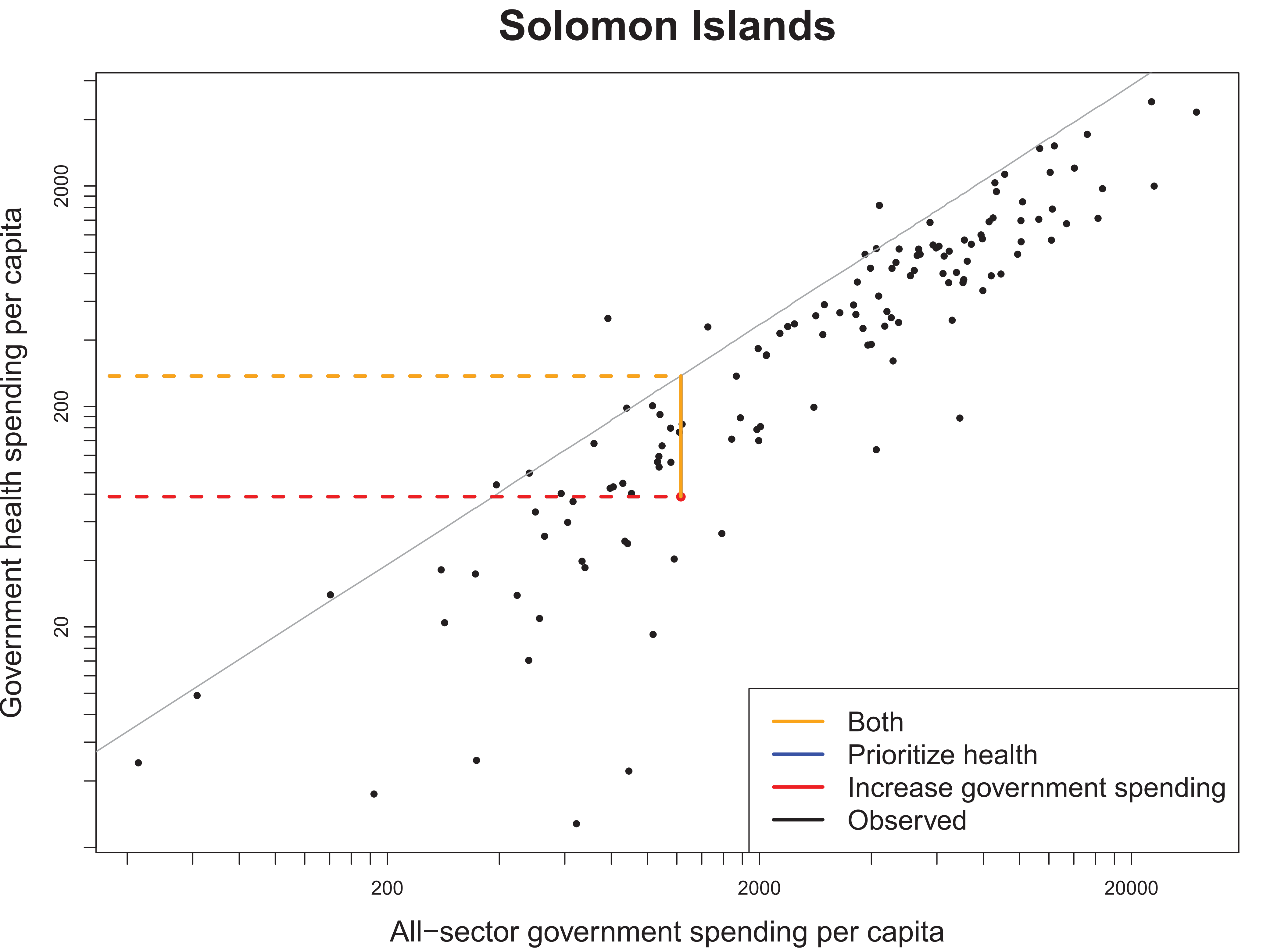
Senegal

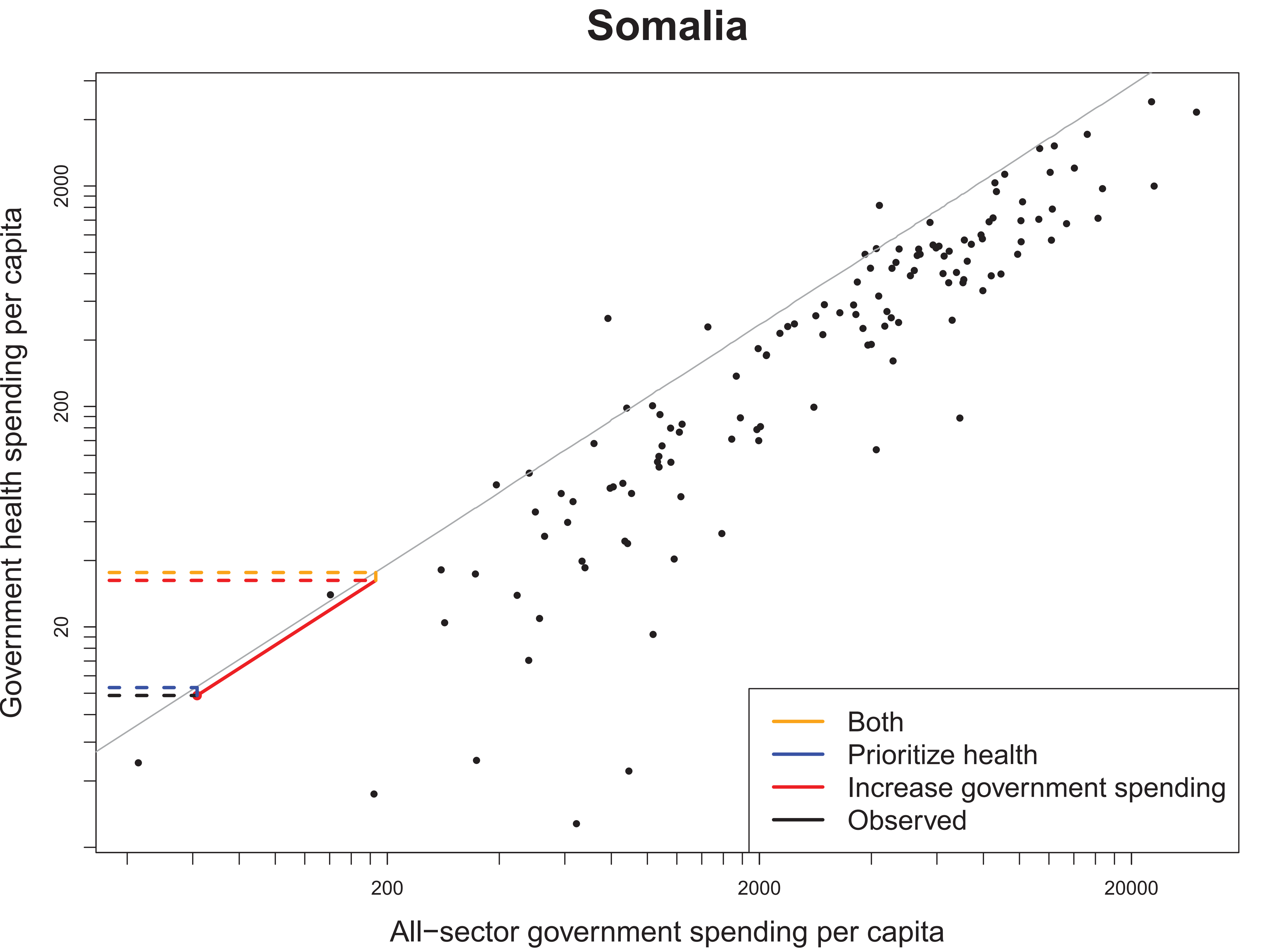


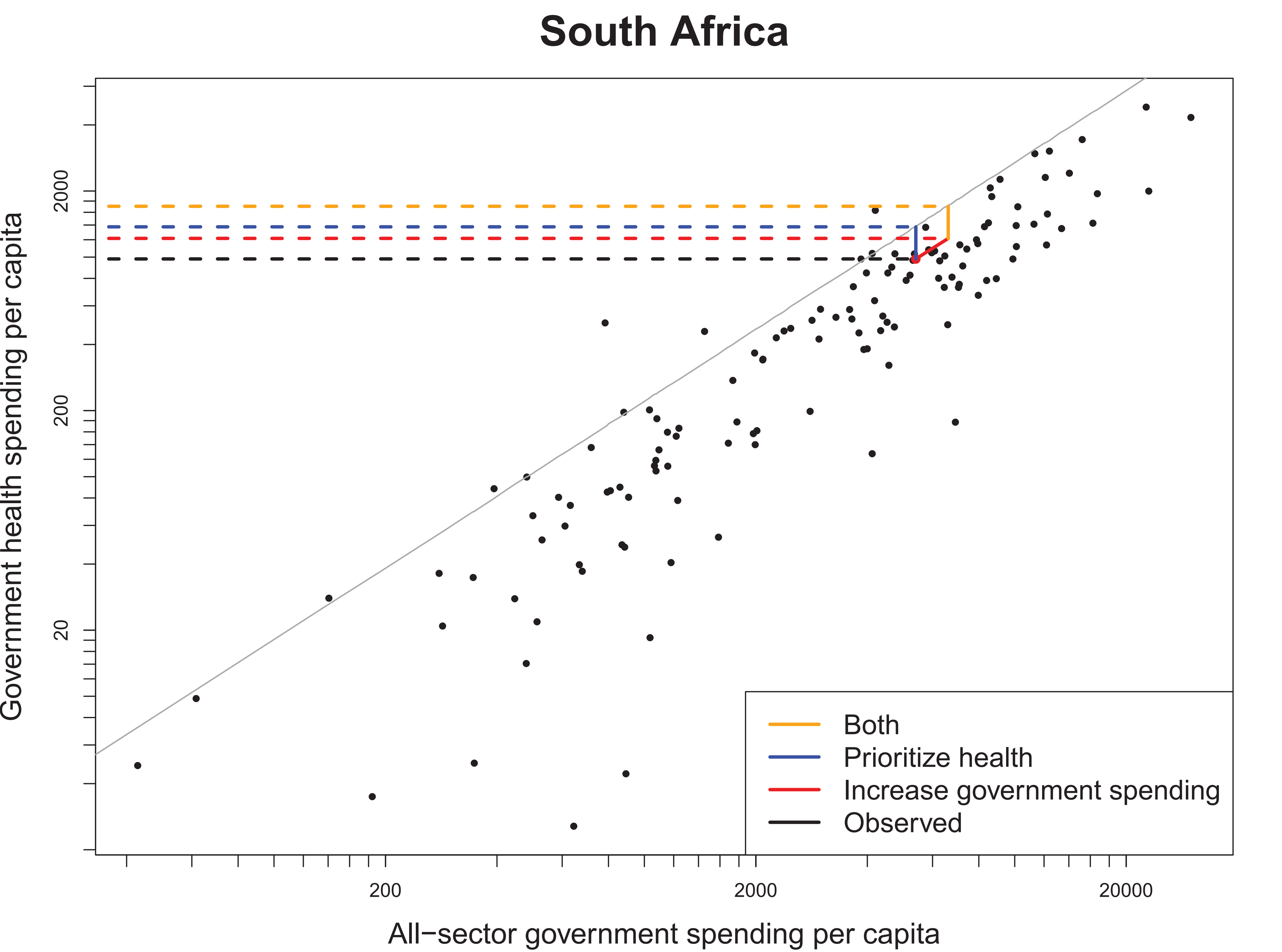
Government health spending per capita
2000
200
20
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed


Serbia
Both
Prioritize health
Increase government spending
Observed
200
2000
20000
20
200
2000
All−sector government spending per capita
Government health spending per capita


Sierra Leone
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

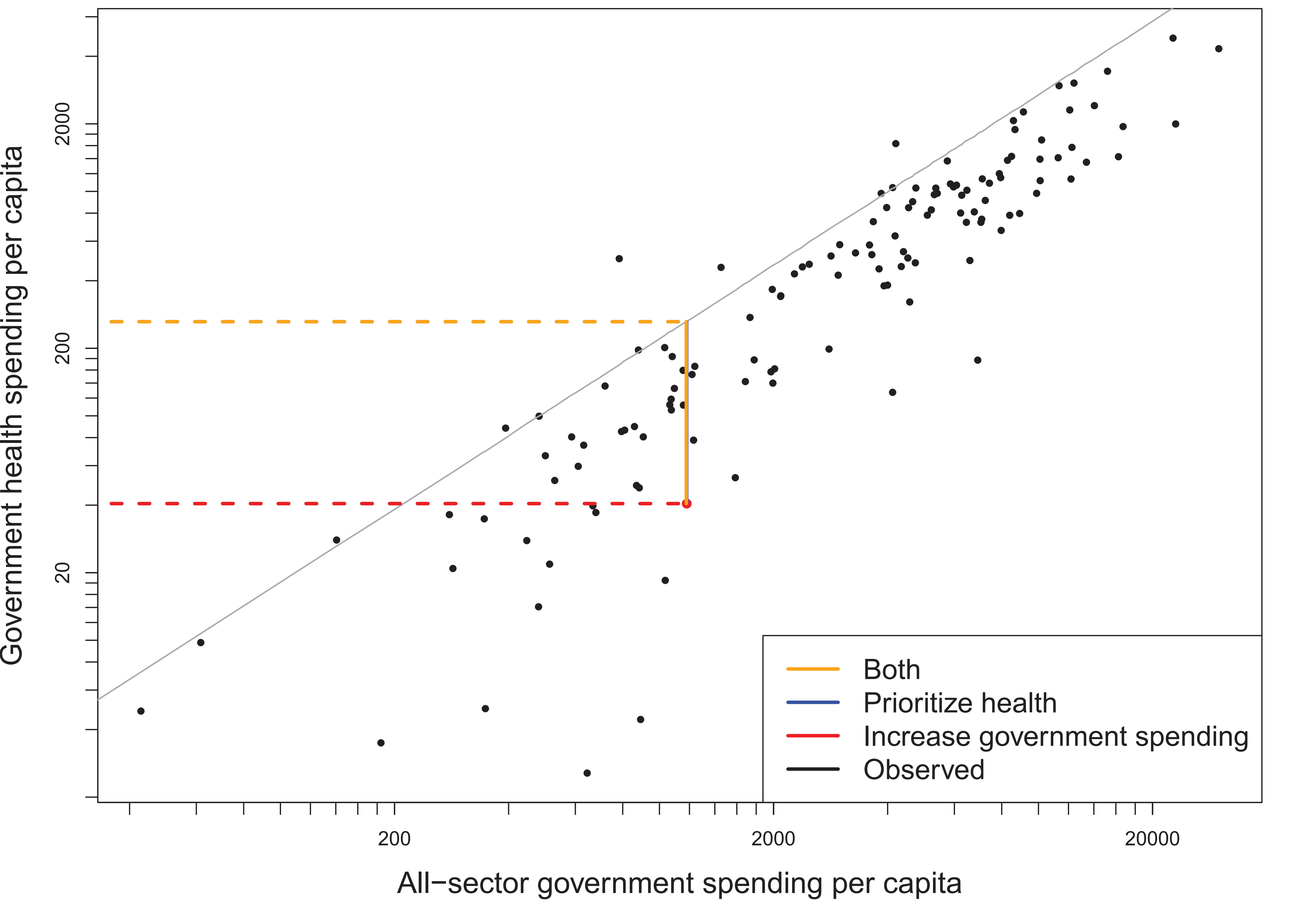

Solomon Islands
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed


Somalia
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

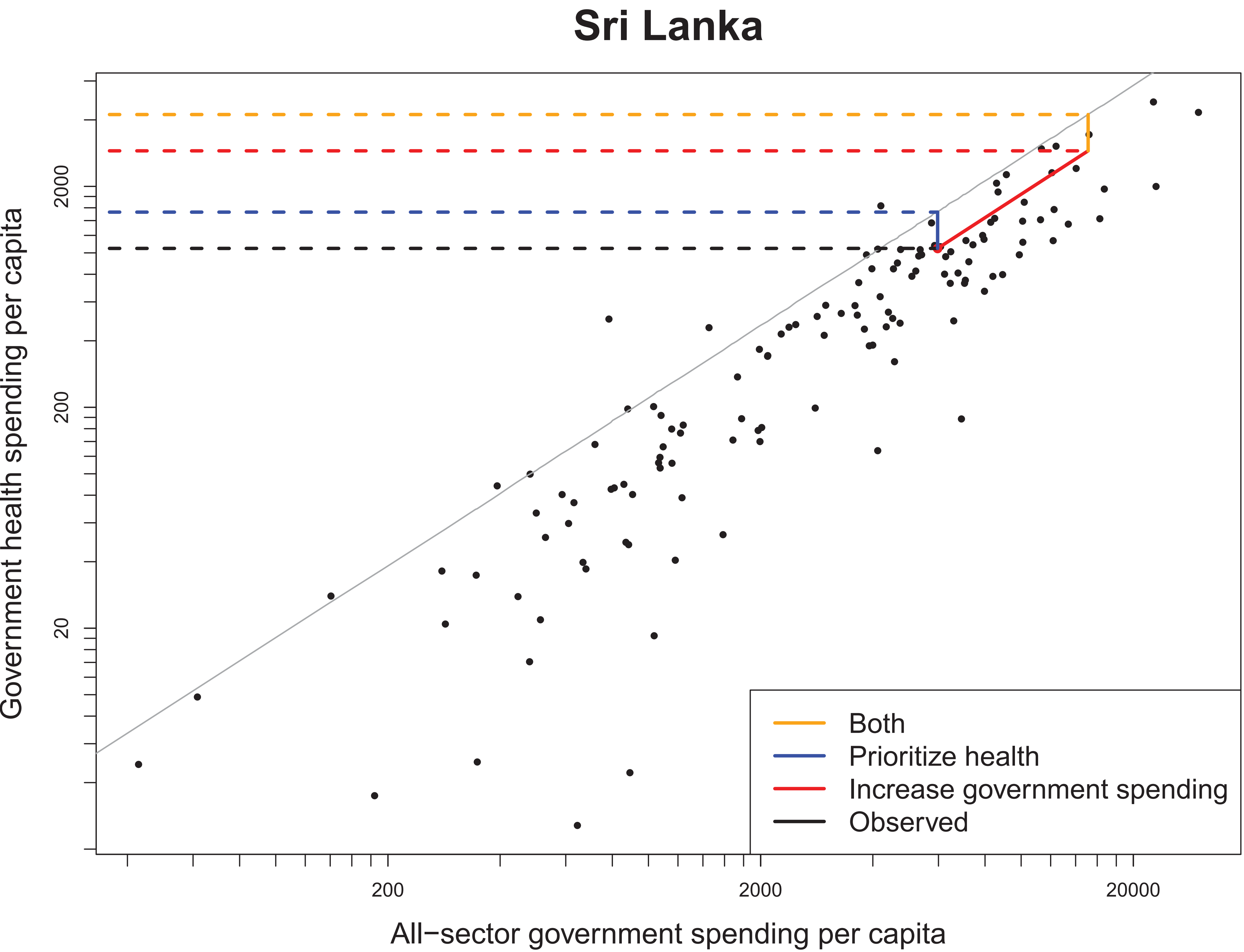


South Africa
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

South Sudan

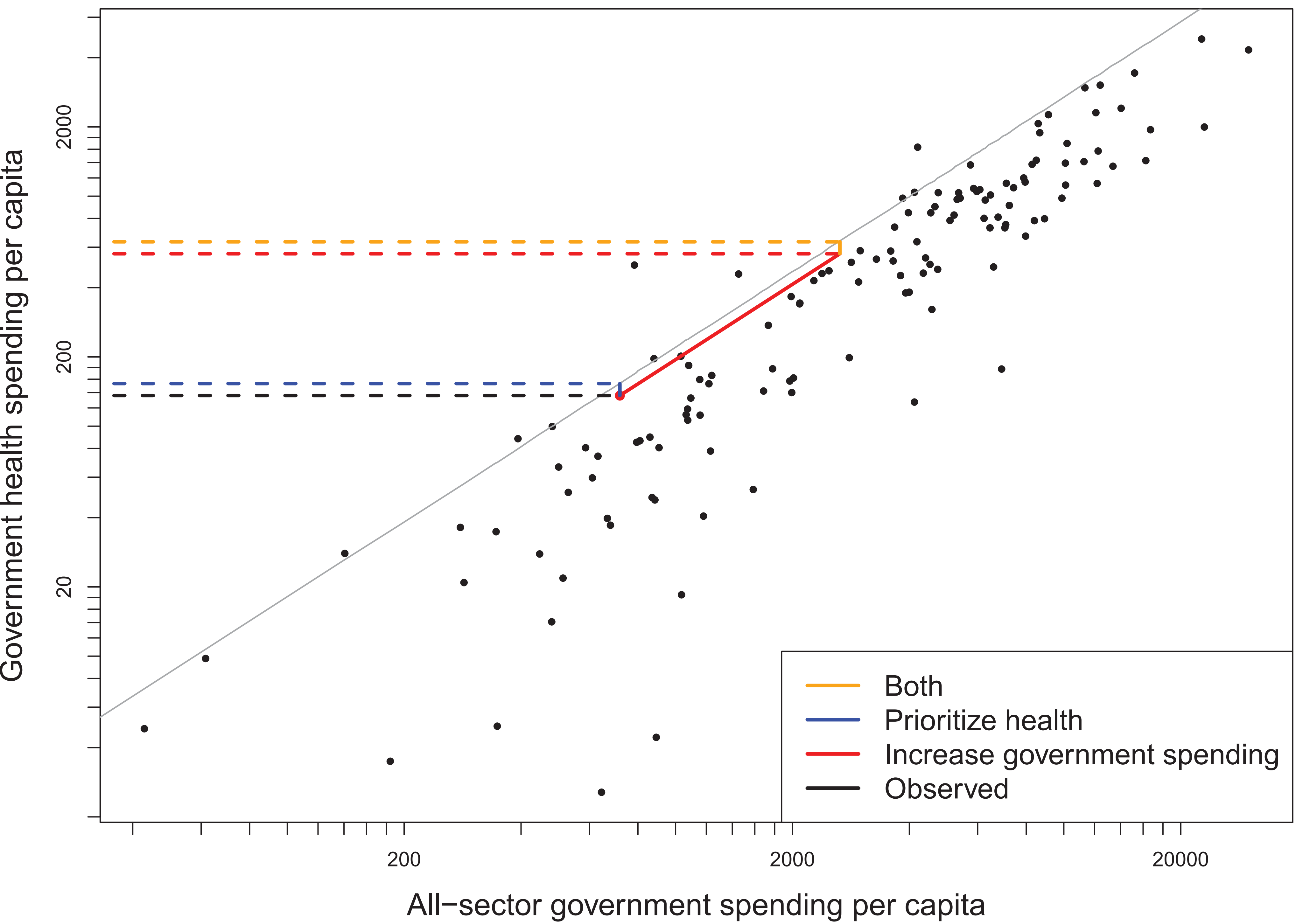


2000
200
20
Government health spending per capita
200
2000
20000
All−sector government spending per capita
Both
Prioritize health
Increase government spending
Observed

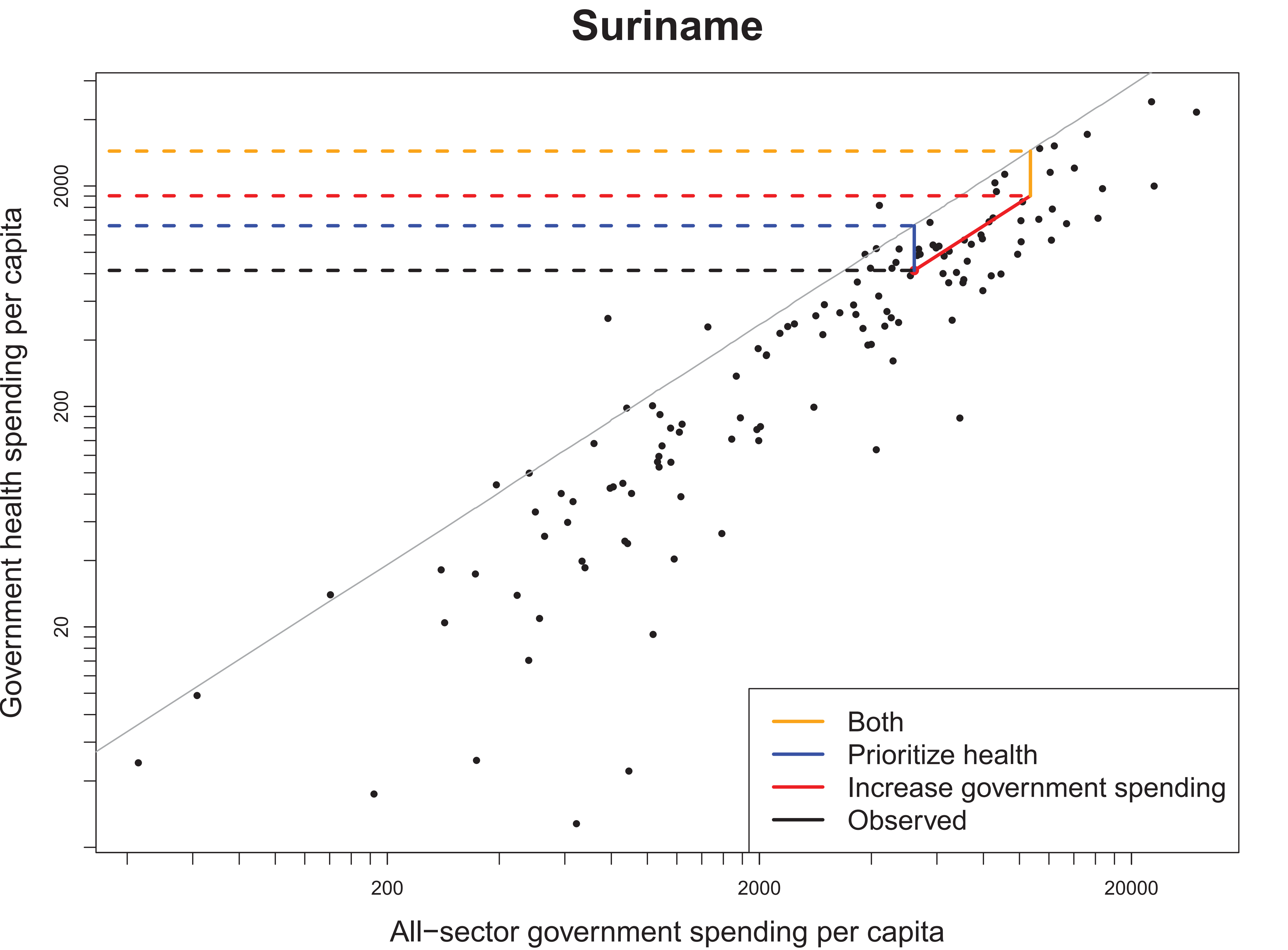


Sri Lanka
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

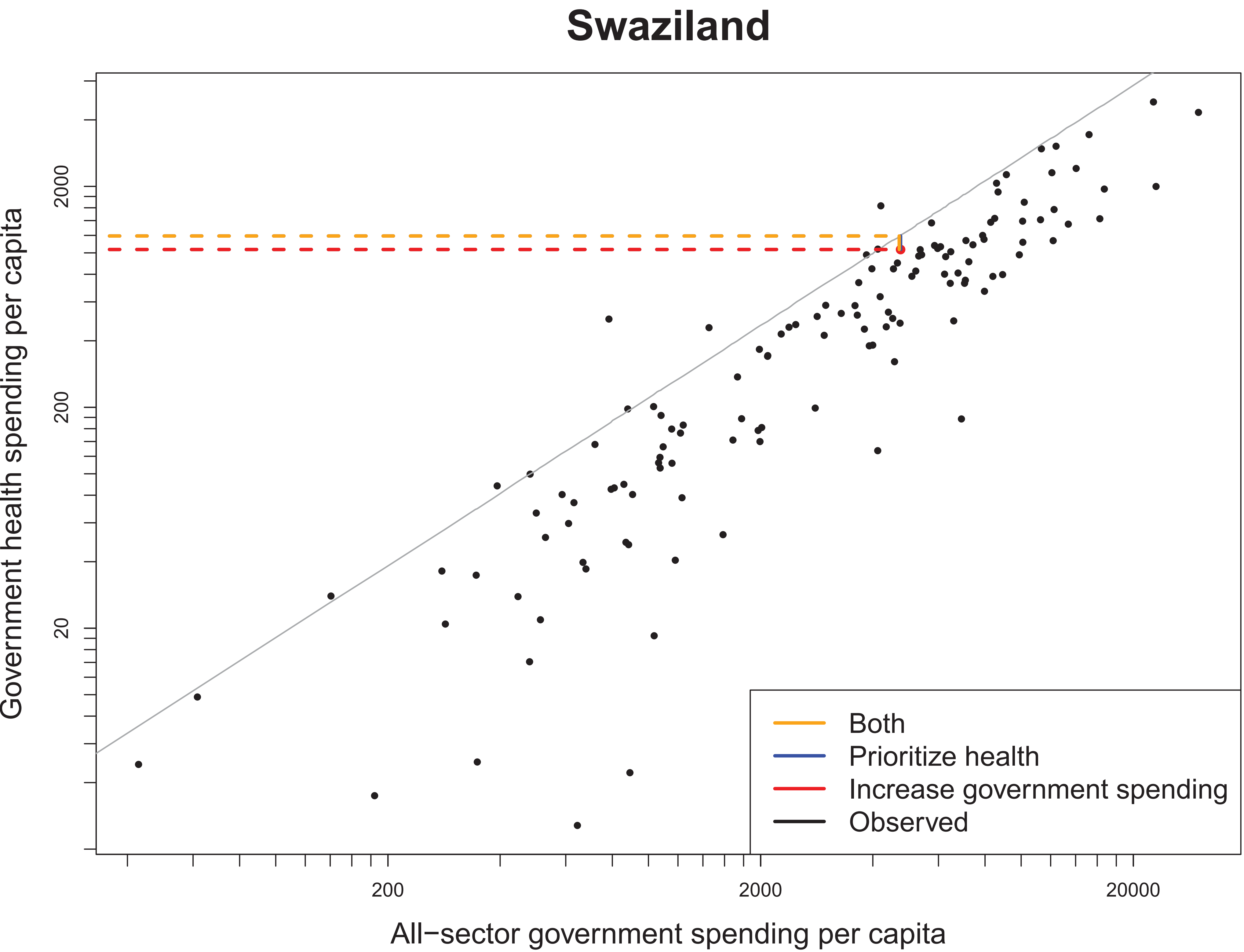
Sudan



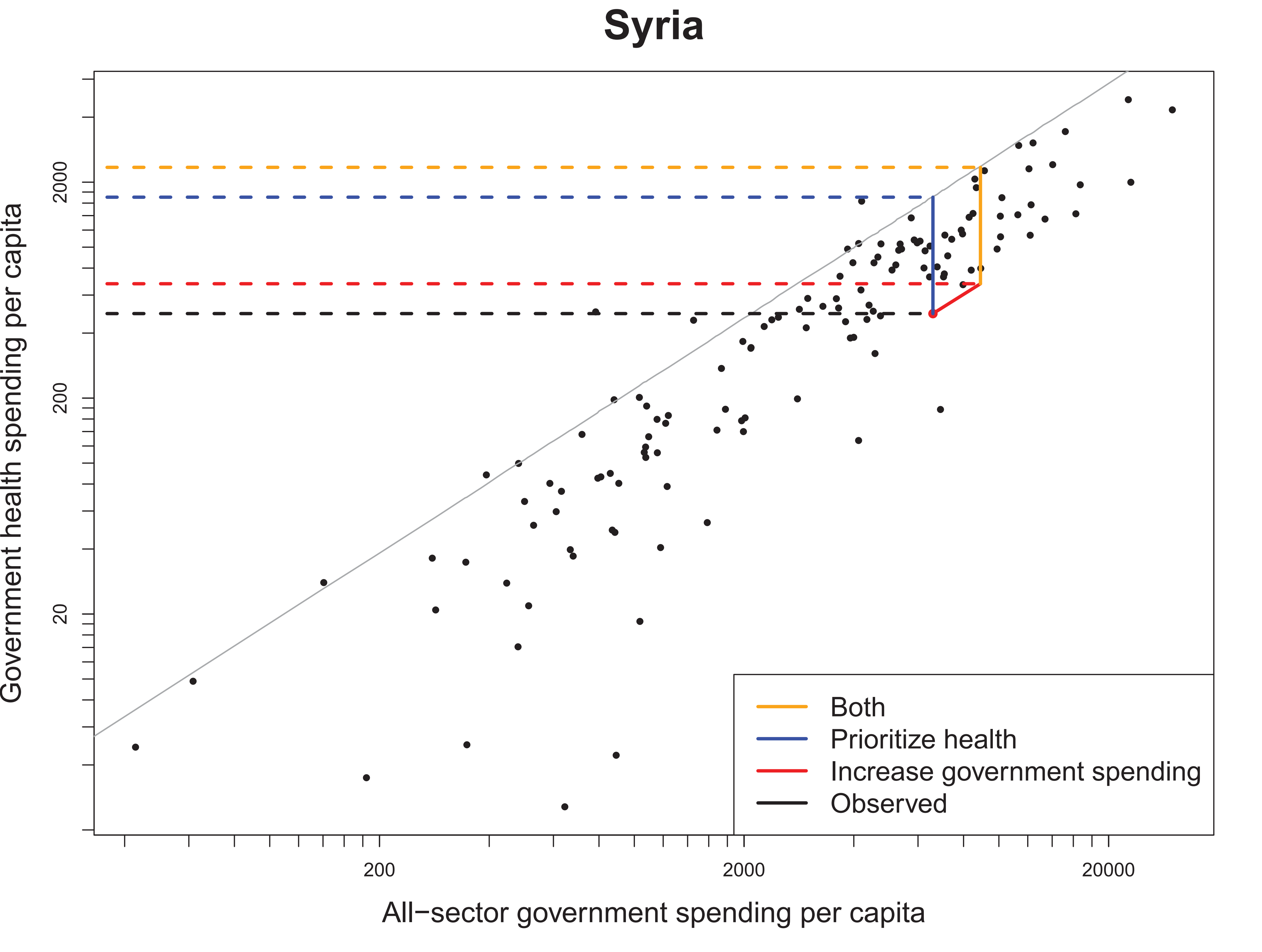
Government health spending per capita
2000
200
20
200
2000
20000
All−sector government spending per capita
Both
Prioritize health
Increase government spending
Observed

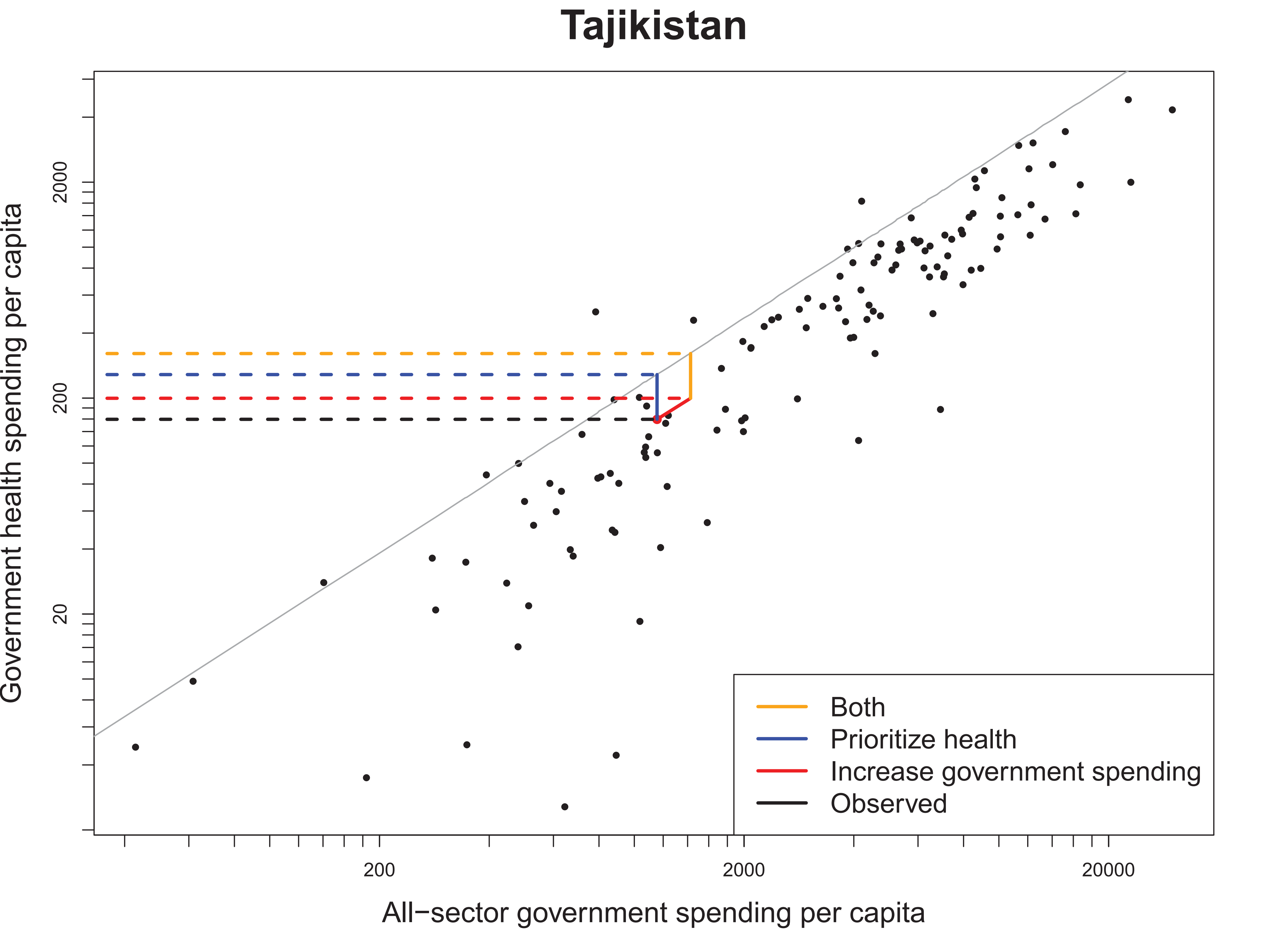


Suriname
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

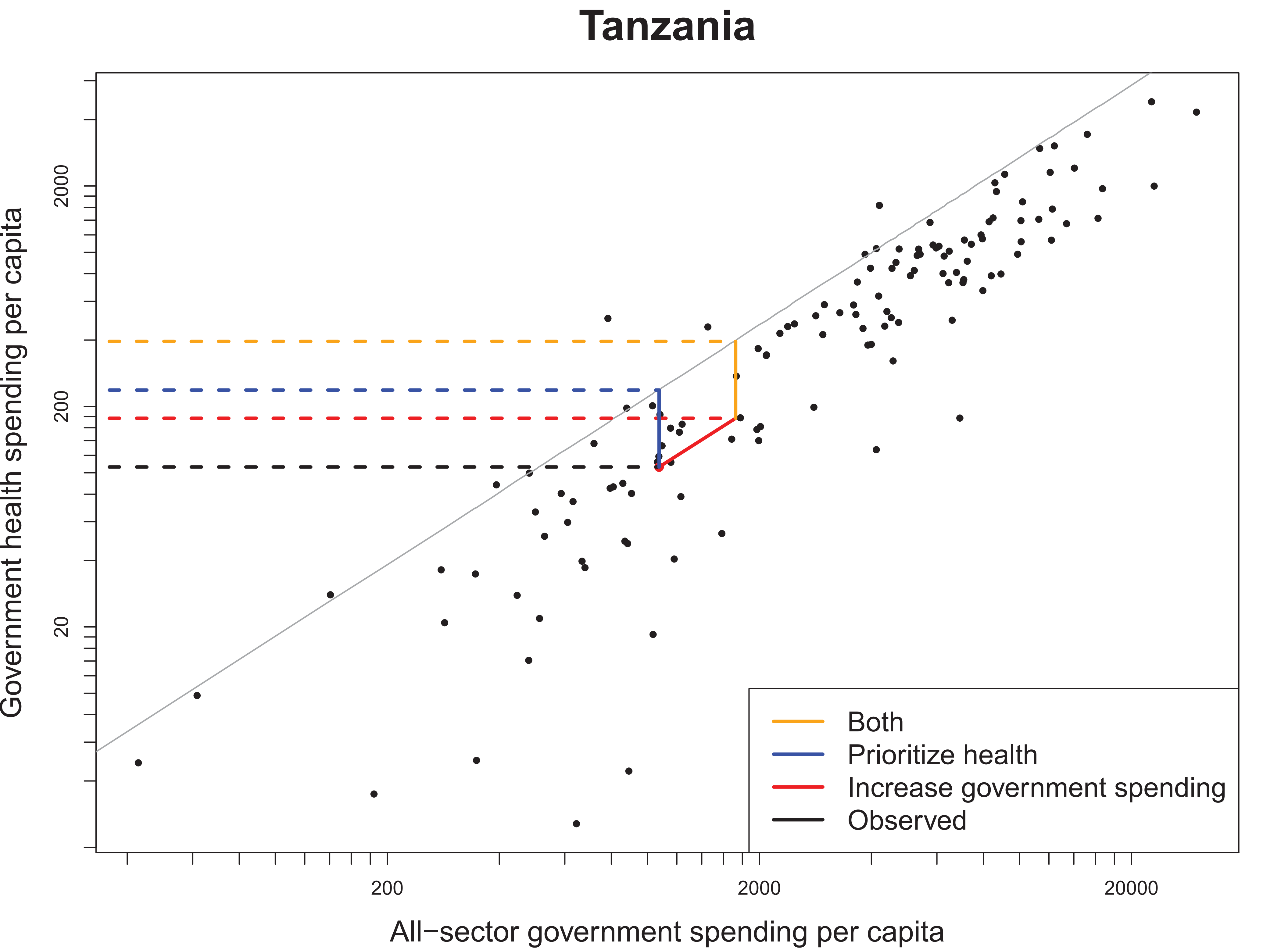


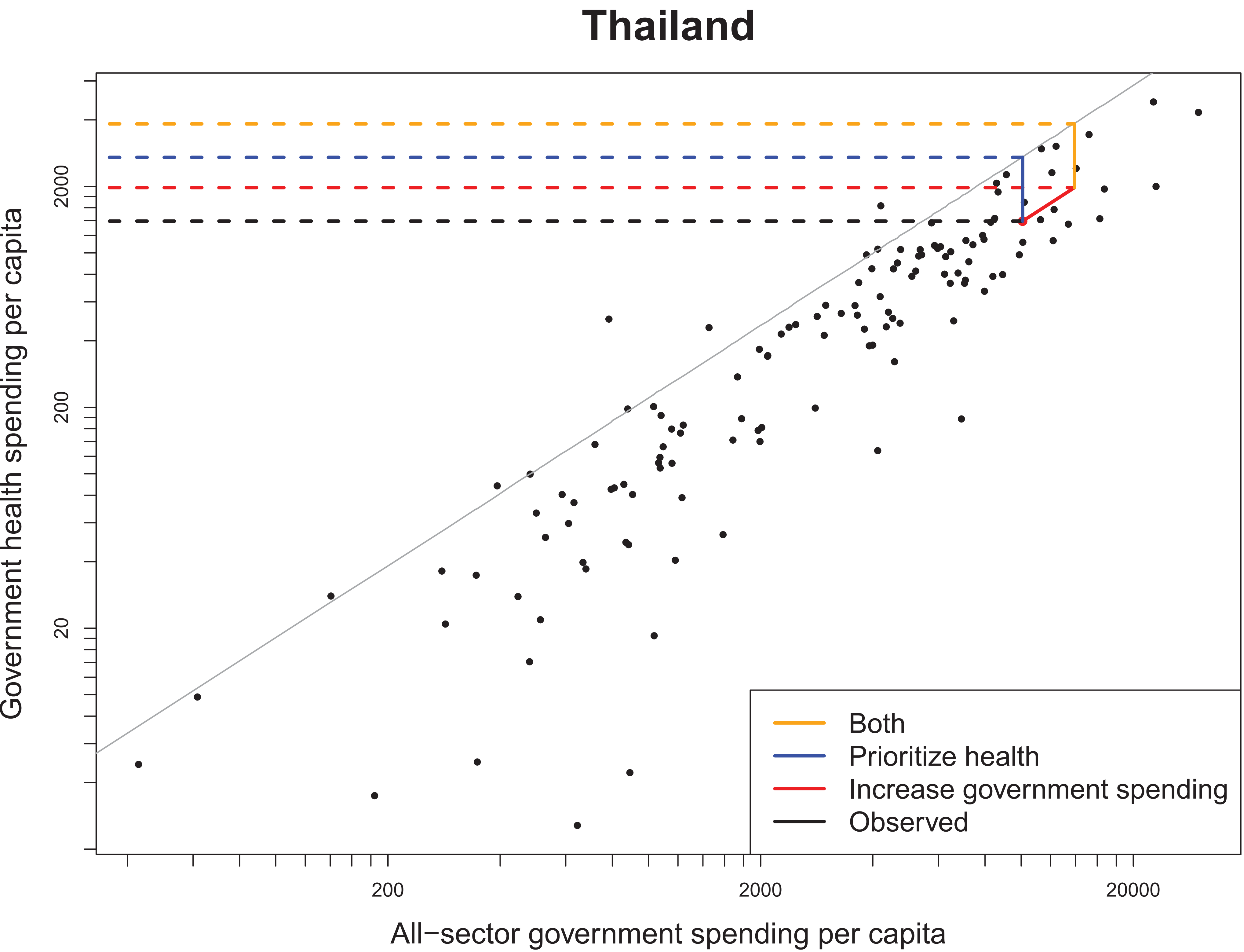
Swaziland
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

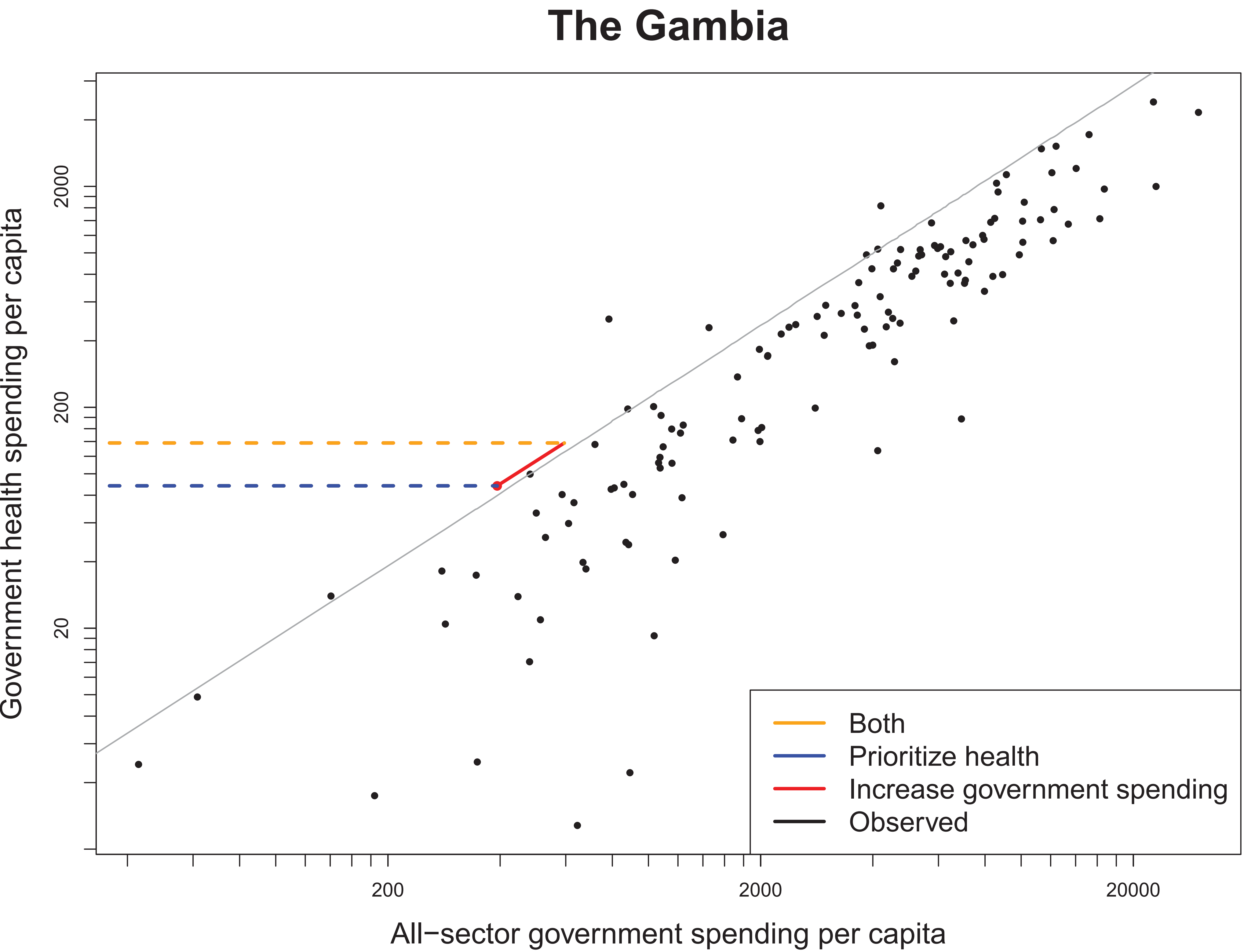

Syria
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

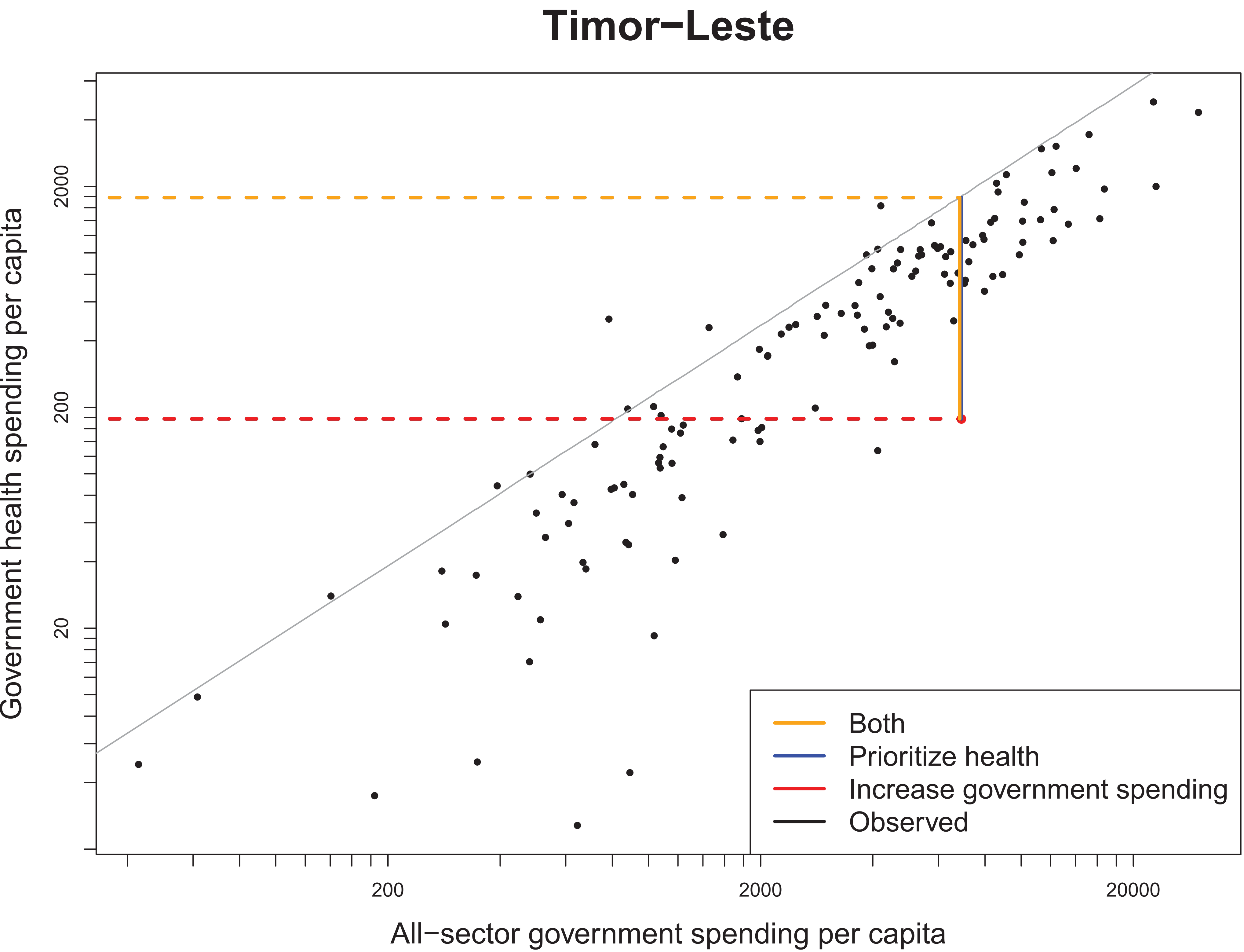


Tajikistan
Government health spending per capita
2000
200
20
All−sector government spending per capita
20000
2000
200
Both
Prioritize health
Increase government spending
Observed

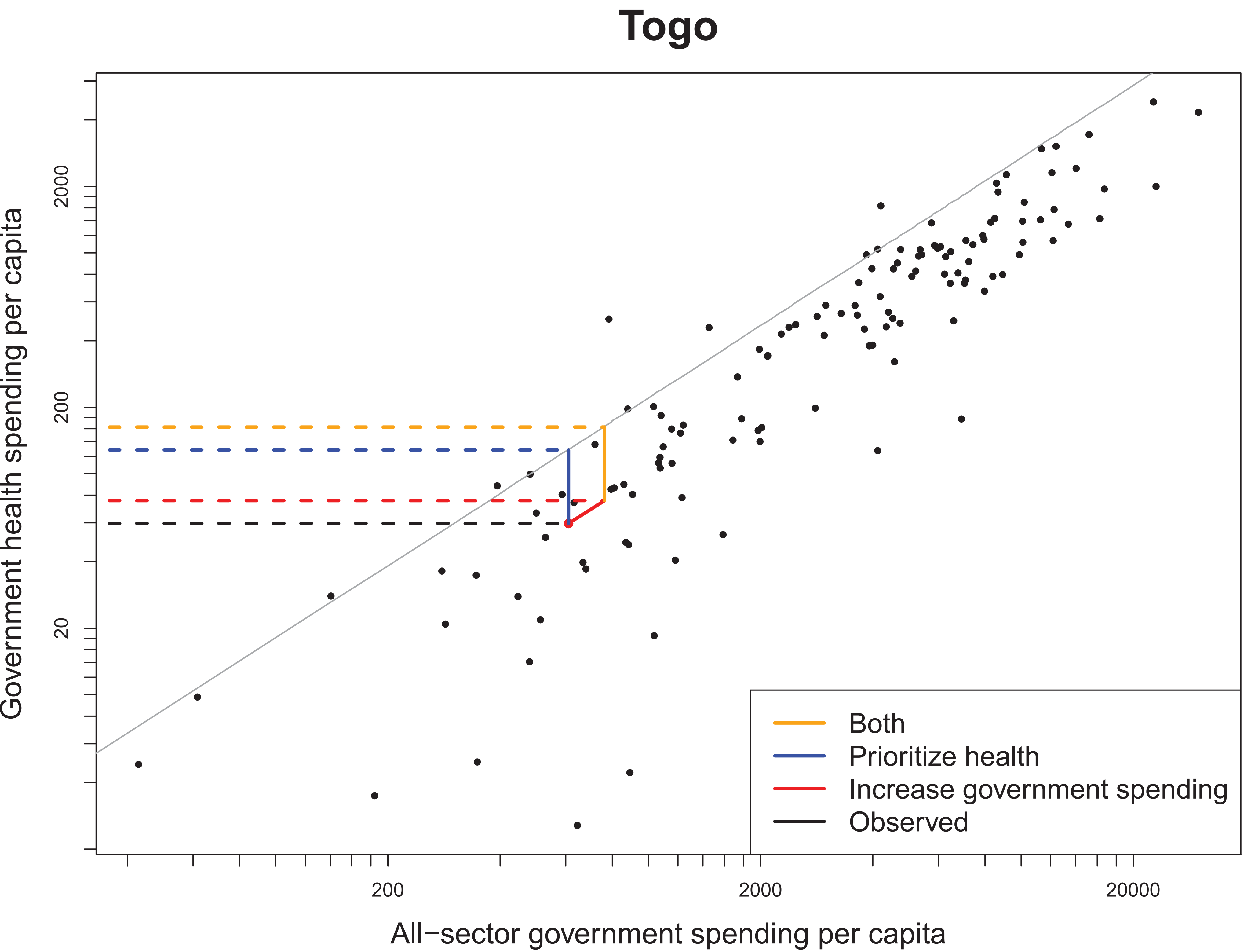

Tanzania
Government health spending per capita
20
200
2000
200
2000
20000
All−sector government spending per capita
Both
Prioritize health
Increase government spending
Observed

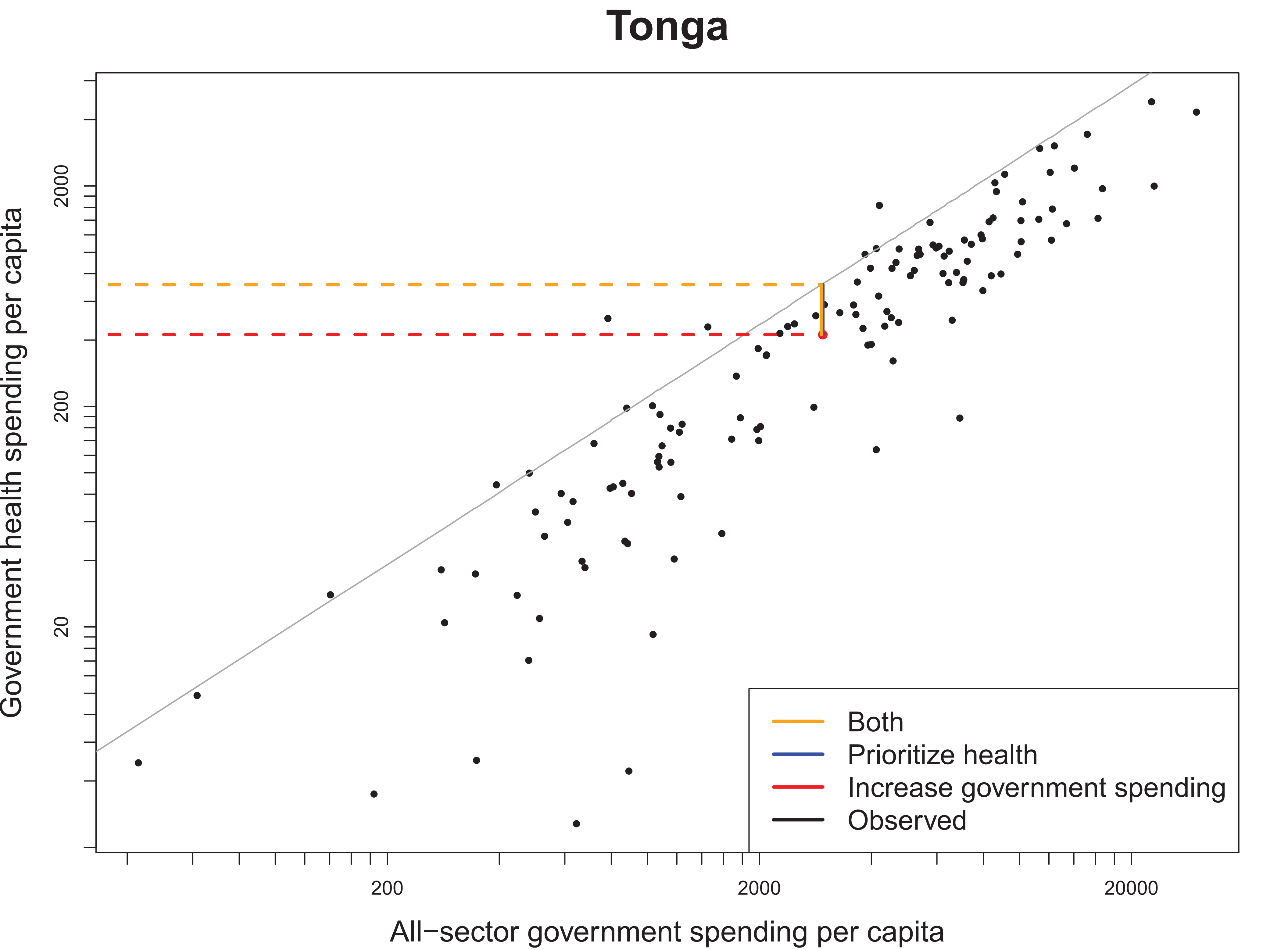

Thailand
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed


The Gambia
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

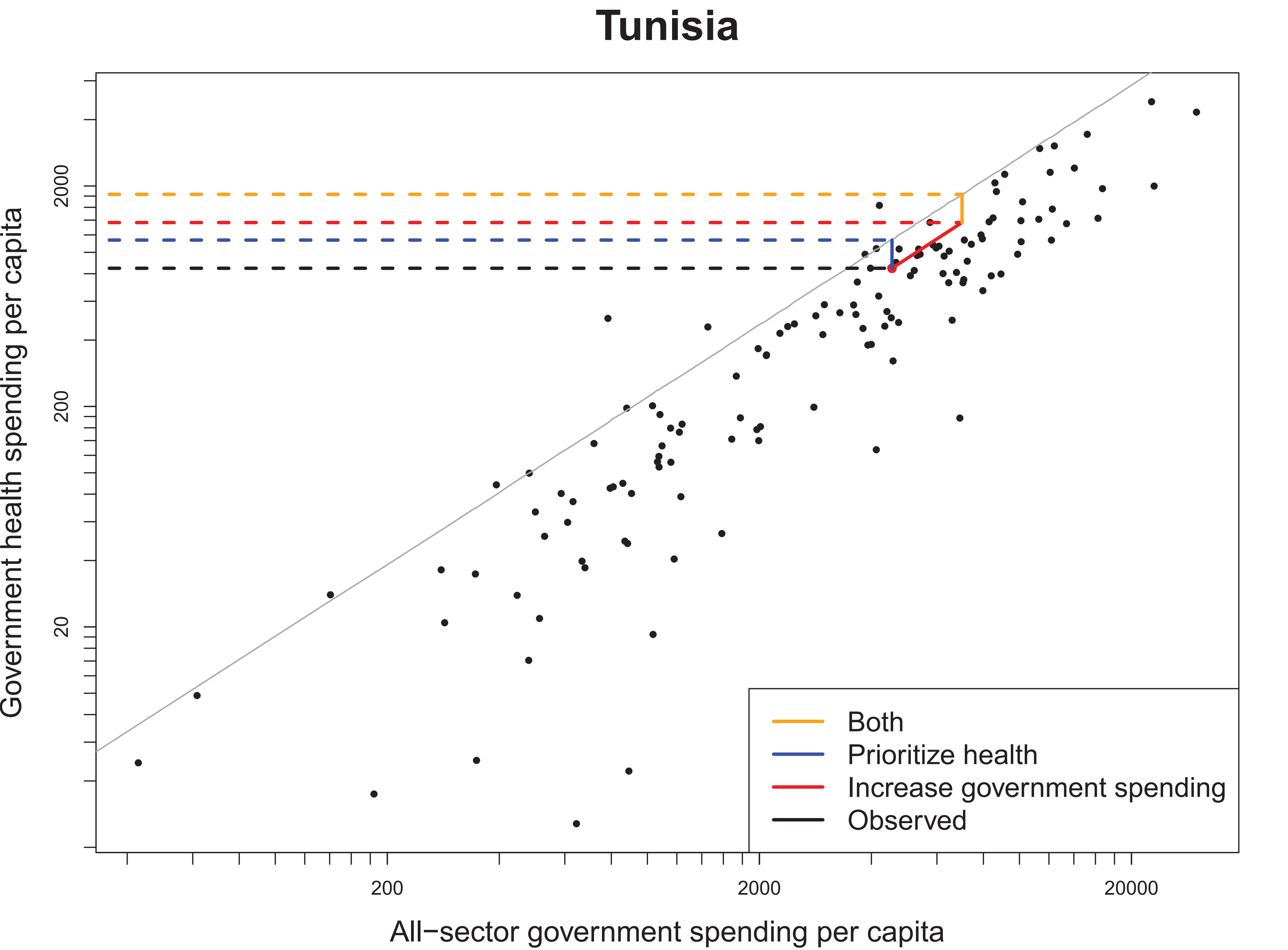


Timor−Leste
Government health spending per capita
All−sector government spending per capita
2000
200
20
20000
Both
Prioritize health
Increase government spending
Observed

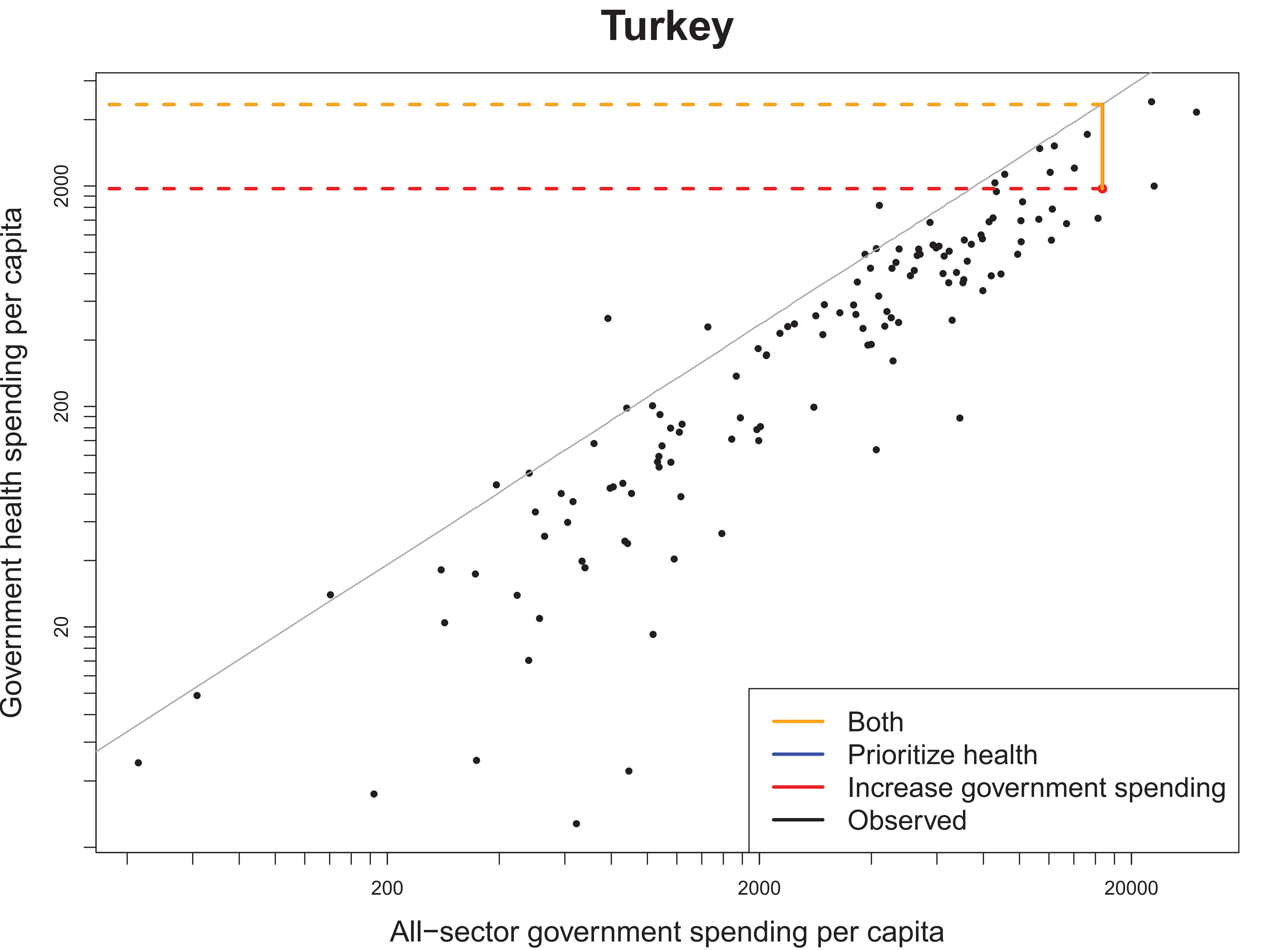

Togo
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



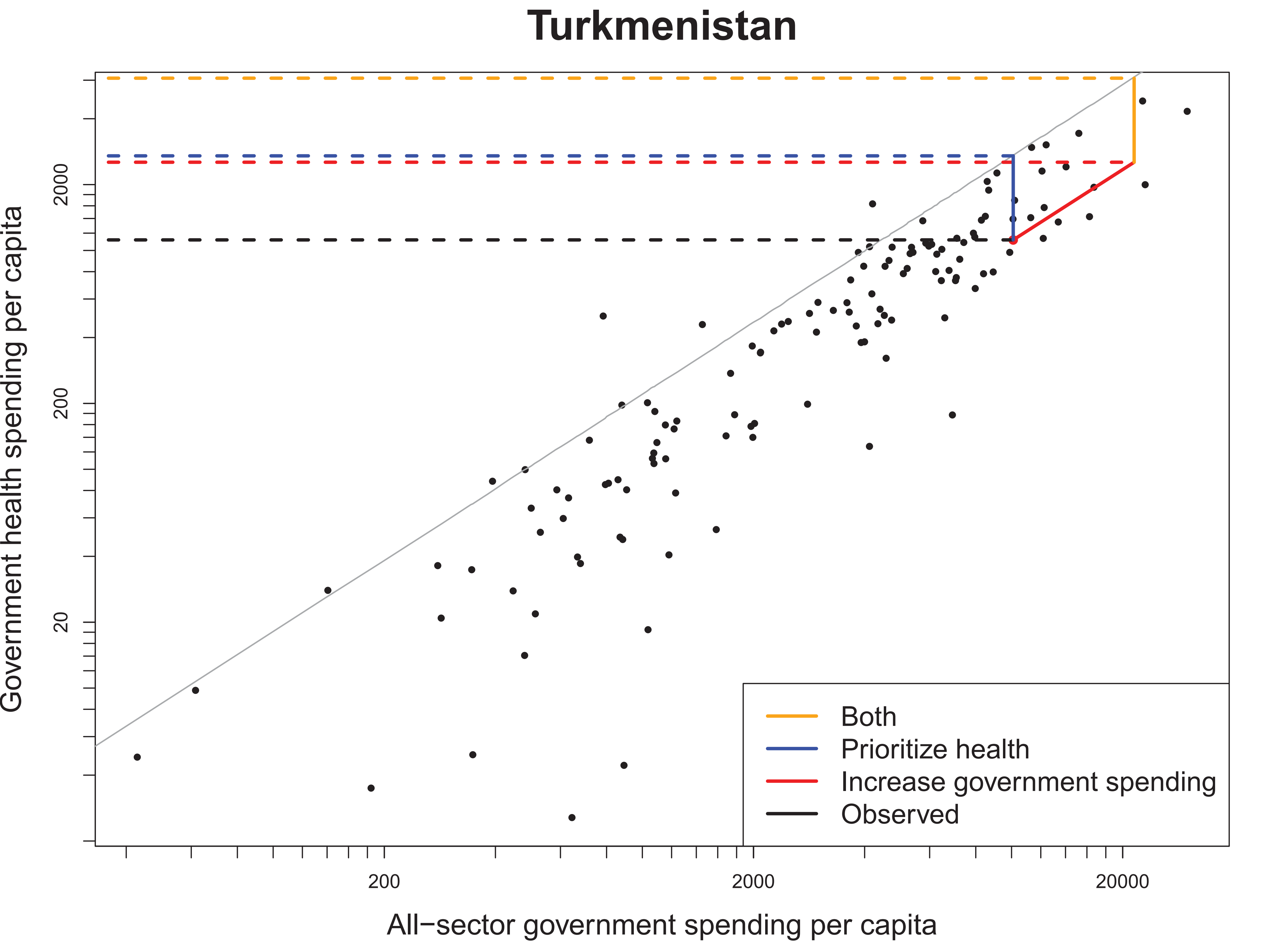
Tonga
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



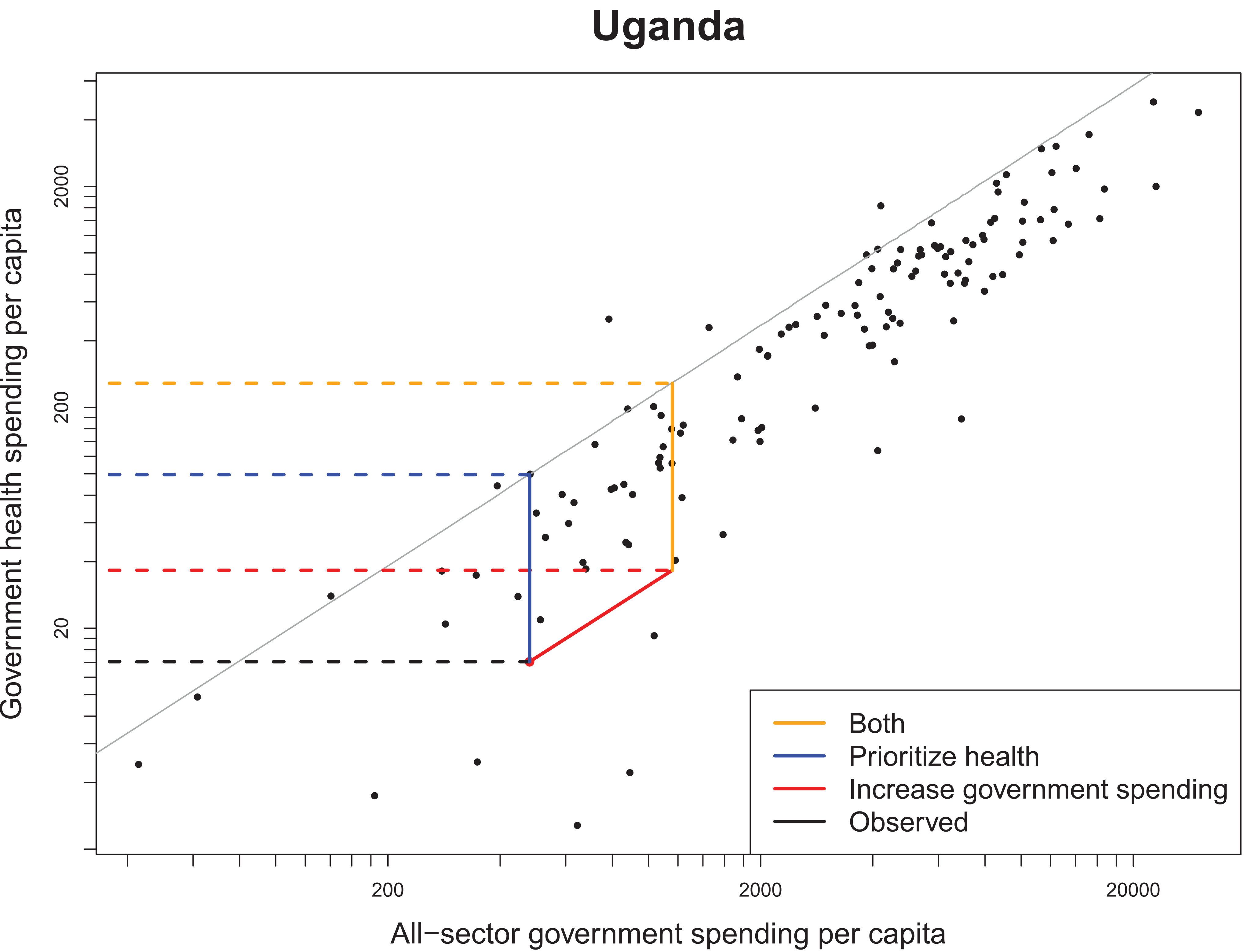
Tunisia
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

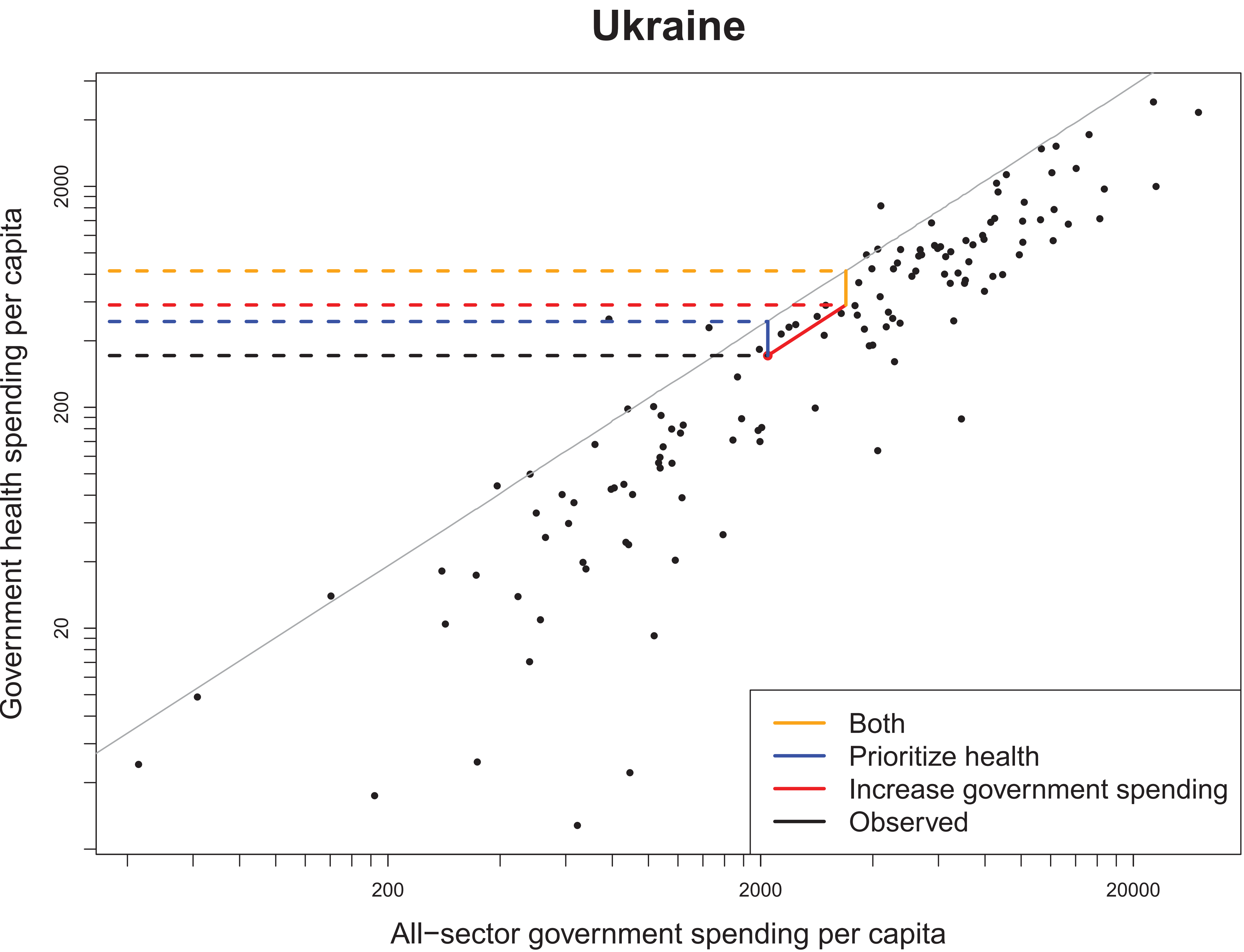


Turkey
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

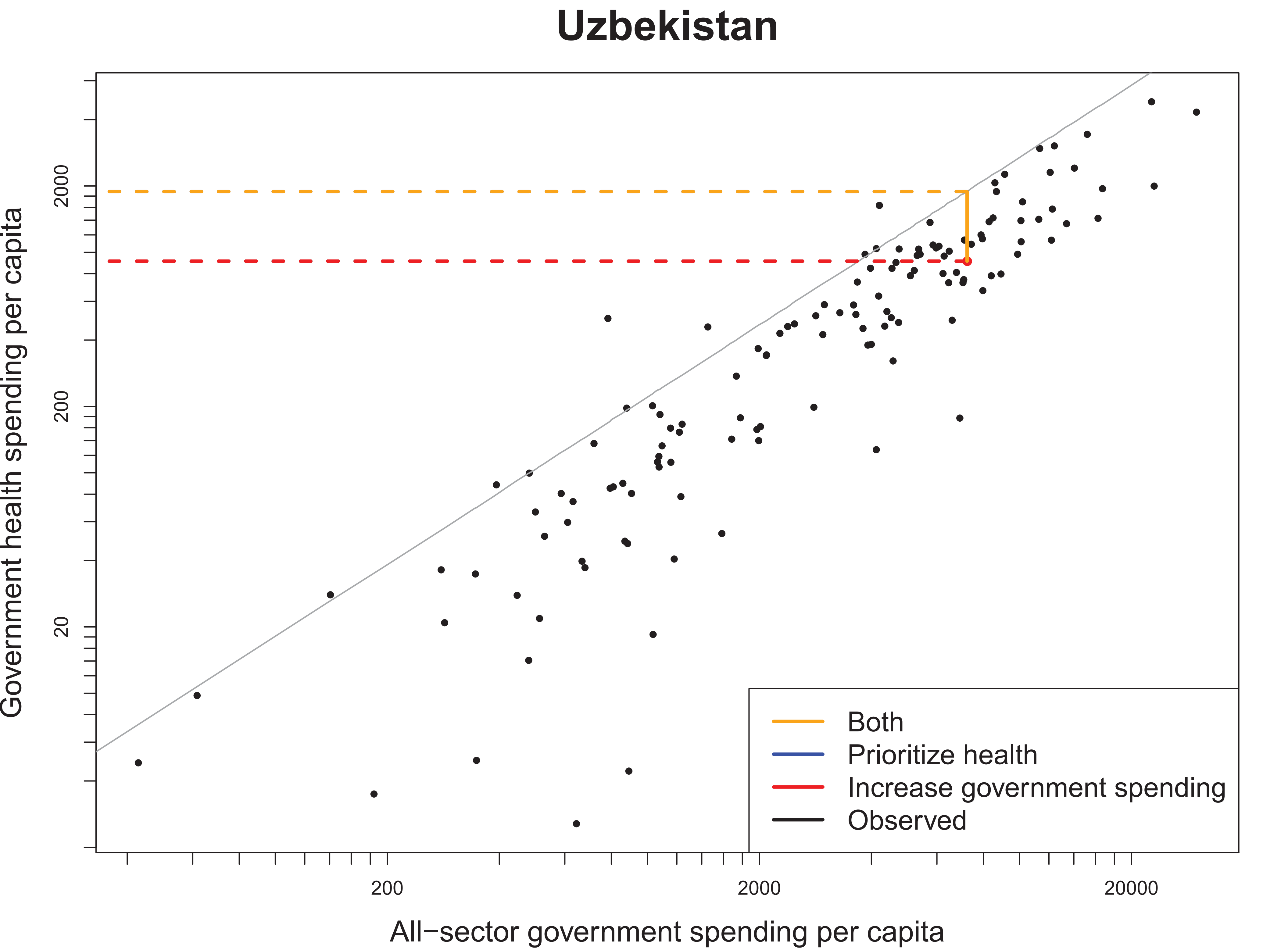


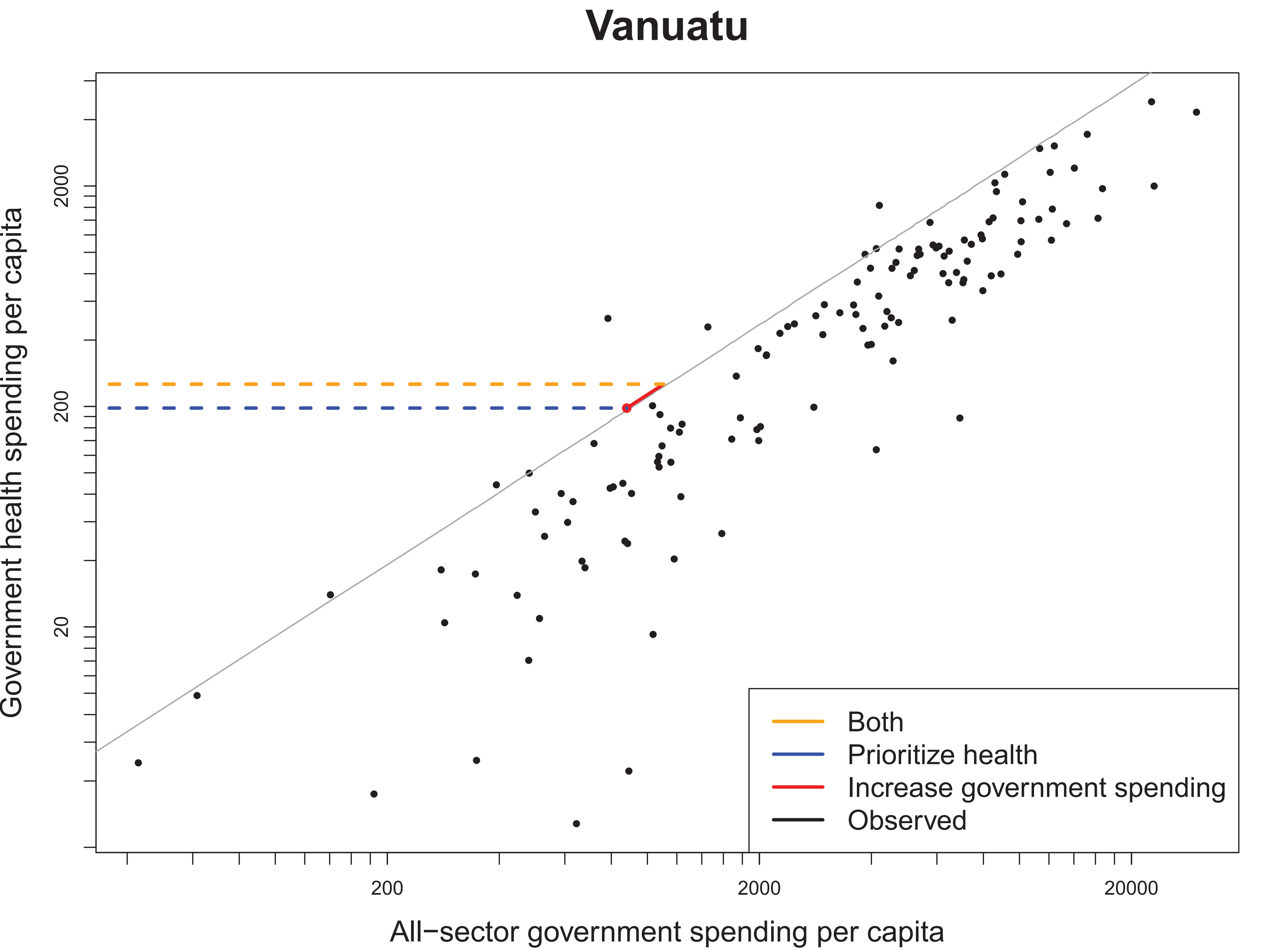
Turkmenistan
Government health spending per capita
All−sector government spending per capita
2000
200
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed


Uganda
Government health spending per capita
20
200
2000
200
2000
20000
All−sector government spending per capita
Both
Prioritize health
Increase government spending
Observed

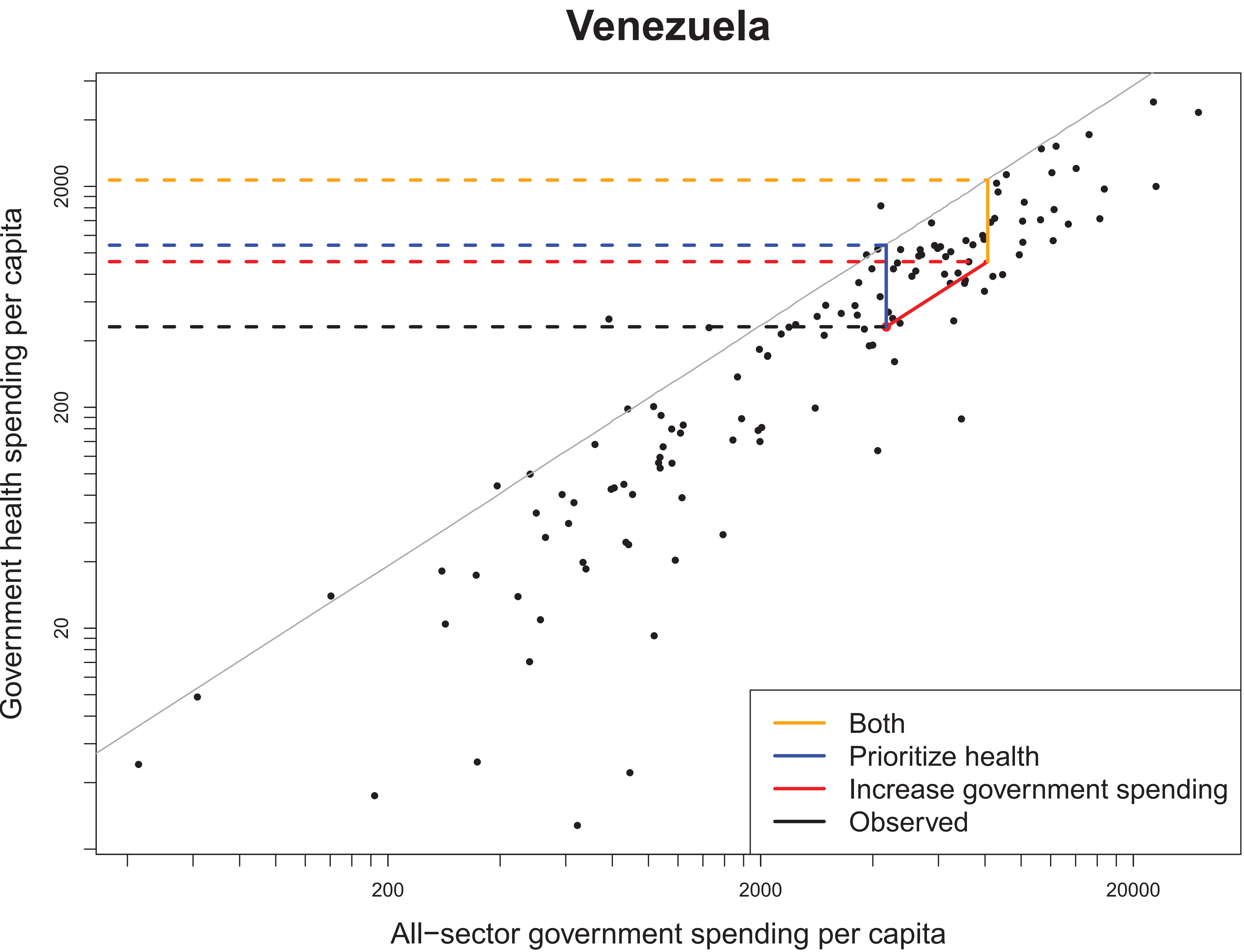


Ukraine
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

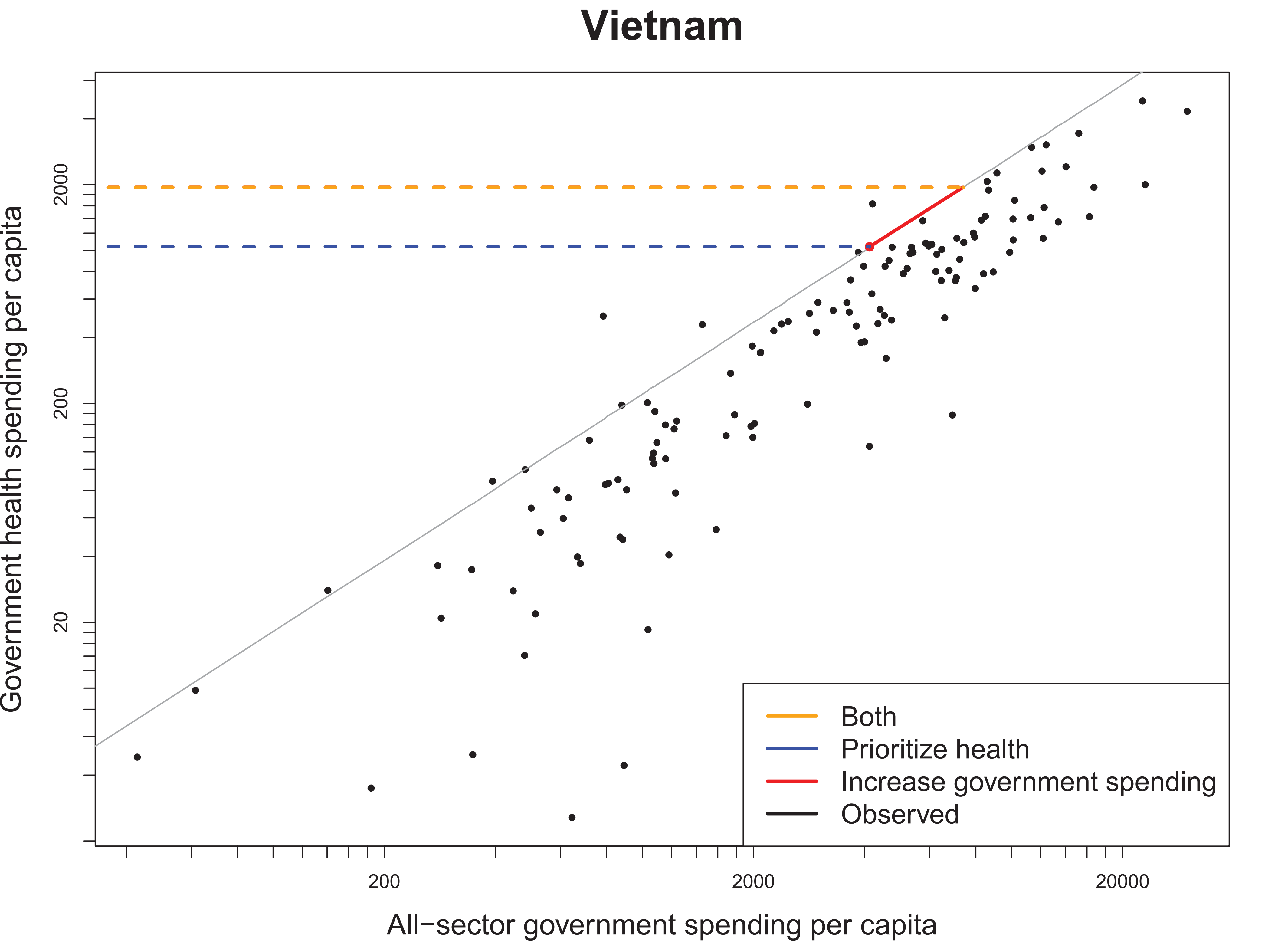

Uzbekistan
Government health spending per capita
2000
200
20
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed



Vanuatu
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

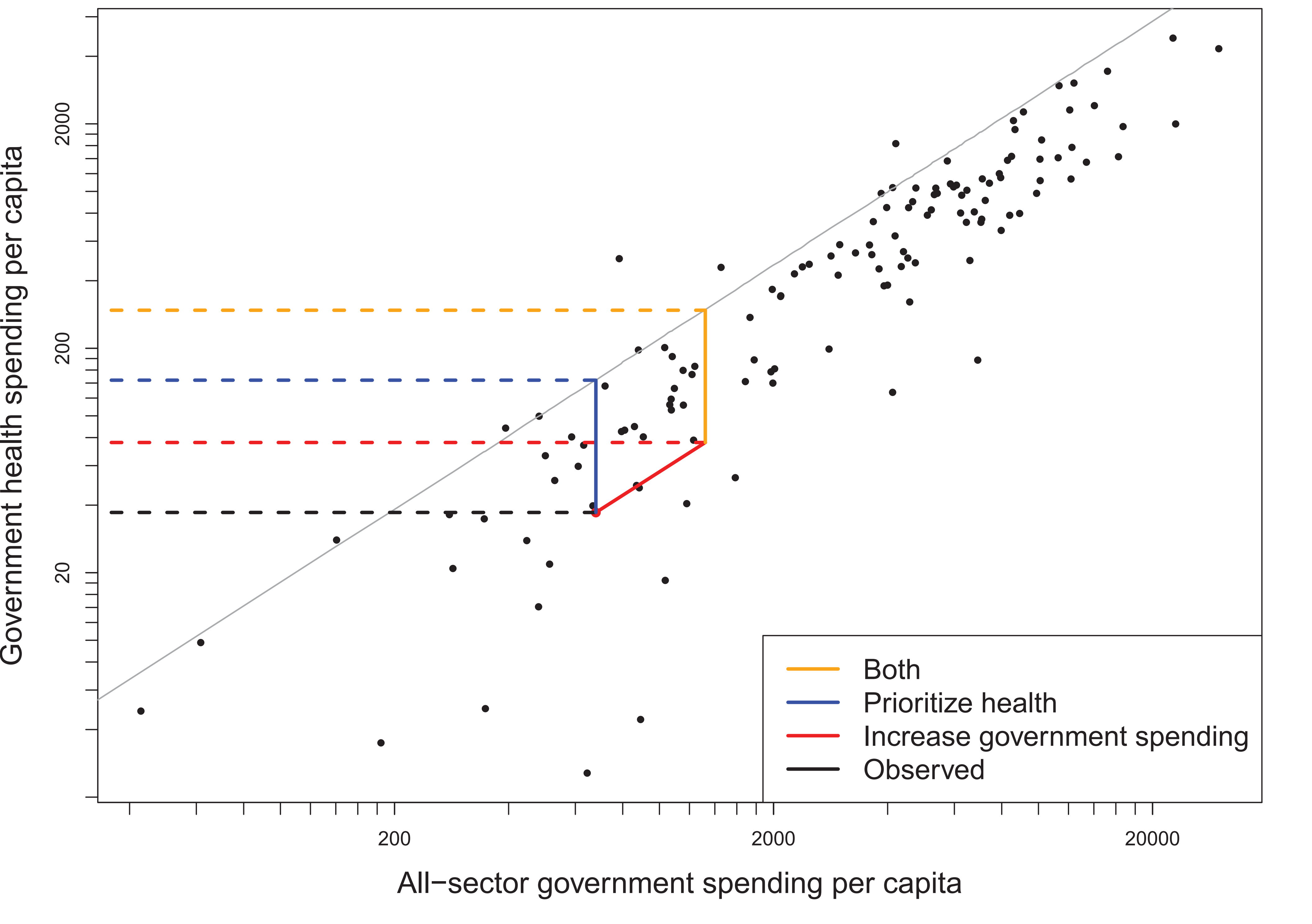


Venezuela
Government health spending per capita
All−sector government spending per capita
20
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

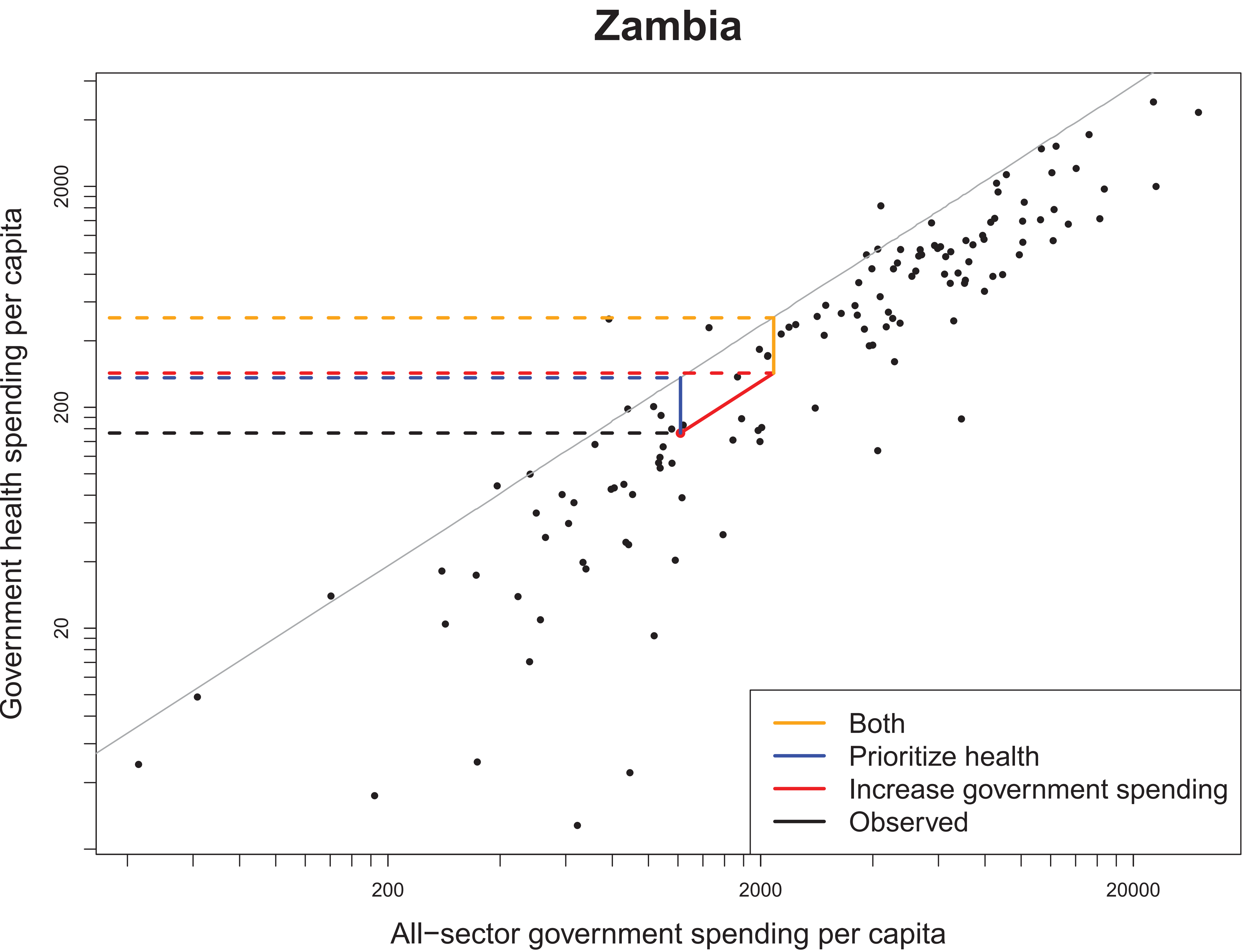


Vietnam
Government health spending per capita
20
200
2000
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed

Yemen



Government health spending per capita
2000
200
20
All−sector government spending per capita
200
2000
20000
Both
Prioritize health
Increase government spending
Observed


Zambia
Government health spending per capita
All−sector government spending per capita
20
200
2000
200
2000
20000
Both
Prioritize health
Increase government spending
Observed