Supplementary Appendix: Measuring Arms: Introducing the Global Military Spending Dataset

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January 26, 2024

Introduction to the Appendix

The supplementary material presented in this document provides additional details about the latent variable model developed in the article "Measuring Arms: Introducing the Global Military Spending Dataset". The main article makes reference to the materials contained here. The estimates presented in this appendix along with the code necessary to implement the measurement models in STAN will be made publicly available at a dataverse archive:

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Contents

1 Model Interpretation and Implementation **4**

2 Country-Year Unit Coverage **6**

3 Posterior prediction and observed values of countries by dataset, in constant values **10**

3.1 France . . . 11
3.2 Colombia . . . 12
3.3 Netherlands . . . 13
3.4 Spain . . . 14
3.5 Germany . . . 15
3.6 Italy . . . 16
3.7 Sweden . . . 17
3.8 Russia . . . 18
3.9 Brazil . . . 19
3.10 Iran . . . 20
3.11 Japan . . . 21
3.12 India . . . 22
3.13 Peoples' Republic of Korea . . . 23
3.14 Democratic Republic of Congo . . . 24
3.15 Democratic Republic of Vietnam . . . 25
3.16 Albania . . . 26
3.17 Pakistan . . . 27
3.18 Uganda . . . 28
3.19 Afghanistan . . . 29
3.20 Kosovo . . . 30
3.21 East Timor . . . 31
3.22 Eritrea . . . 32
3.23 Costa Rica . . . 33
3.24 Gambia . . . 34
3.25 Haiti . . . 35
3.26 Iceland . . . 36
3.27 Iraq . . . 37

3.28 Myanmar . . . 38
3.29 Nicaragua . . . 39
3.30 Yemen (Arab Republic of Yemen) . . . 40
3.31 Peru . . . 41
3.32 Somalia . . . 42
3.33 Trinidad and Tobago . . . 43
3.34 Uzbekistan . . . 44
3.35 Distributions for China, United Kingdom, and the USA (1990) . . . 45
3.36 Distributions for China, United Kingdom, and the USA (2010) . . . 48
3.37 Distributions for China, United Kingdom, and the USA (2019) . . . 51

4 Proportion of Coverage by Observed Variable 54

5 Country Plots with Normalized Posterior Prediction Intervals and Data Points 59

6 U.S. Military Expenditures for All Datasets 98
6.1 All Datasets, excluding IISS and WMEAT (constant) . . . 98
6.2 All Datasets, excluding IISS and WMEAT (current) . . . 99
6.3 IISS The Military Balance Issues (constant) . . . 100
6.4 IISS The Military Balance Issues (current, pre-2000) . . . 101
6.5 IISS The Military Balance Issues (current, post-2000) . . . 102
6.6 WMEAT Issues (constant) . . . 103
6.7 WMEAT Issues (current) . . . 104
6.8 Zimmerman (USSR) . . . 105
6.9 Peters (Sweden) . . . 106

7 Units with Observed Zeros 107

8 Replication of DiGiuseppe and Poast (2018) 110
8.1 Replication of regression analysis . . . 110
8.2 Replication of descriptive statistics for different historical time periods . . . 112

9 Correlations of Arming and other Variables of Interest Over Time 114

10 Predicting Levels of Arming 122

11 The Robustness of Military Burdens Over Time 124

12 Historic Arming Sources 135

1 Model Interpretation and Implementation

In the main manuscript, we present, estimate, and describe a latent variable model that links together observed dataset values from across many sources of military expenditure data.

We are interested in estimating is country-year military spending. Using military expenditure data presents several challenges because the datasets are incomplete, cover short periods of time, and are presented in many different monetary units-of-measurement. To overcome these challenges, we specify a dynamic latent variable measurement model that links all of the available information across different contemporary and historical sources of arms spending data. We essentially want to estimate the country-year distribution or simply the average of military spending across all the available observed dataset values so that we generate the best estimate of military spending for each of the country-year units.

The observed dataset values are linked together through the estimation of a country-year parameter or latent trait. However, the latent trait parameter itself is not directly of interest for inference because it does not have a direct monetary interpretation. This is because it is scaled by the item-specific intercept parameter which transforms the latent trait into the unit-of-measurement of any one of the originally observed military expenditure variables. The measurement model provides predictive intervals for each of the original observed variables on the original scales of these variables. Notationally, we represent the observed country-year dataset values as y_{itj} where i indexes countries, t indexes years of time, and j indexes the dataset. The model then produces posterior predictive distributions of y_{itj}, which we denote as $\tilde{y}_{itj}$. These are normally distributed values (on the natural log scale). We can therefore take the average of $\tilde{y}_{itj}$ as $E(\tilde{y}_{itj})$ or the standard deviation of $\tilde{y}_{itj}$ as $sd(\tilde{y}_{itj})$.

For the applications in the main manuscript and in this appendix, $\tilde{y}_{itj}$ is the key the quantity we care about. It is the estimated value of y_{itj}, conditional on all the other observed information about military spending for a given country-year unit, which is captured by the latent trait $\theta_{cur[it]}$ and then scaled by the item-specific intercept parameter α_j. Note that,

as described in the main manuscript, that we also account for the relationship between current and constant monetary values through inflation by this year scaling relationship: $\theta_{con[it]} = \beta_t * \theta_{cur[it]}$

We approximate the posterior distributions of $\tilde{y}_{itj}$ by taking repeated draws from Bayesian simulation model. Specifically, the measurement models are estimated with four MCMC chains to run for 2,000 iterations each using the Stan software (Stan Development Team, 2021). The first 1,000 iterations are thrown away as a burn-in or warmup period. The 4,000 remaining samples were thinned by a factor of 2 and are used to generate the posterior prediction intervals for the original observed variables. Diagnostics (i.e. trace plots, effective sample size, and R-hats) all suggest convergence (Gelman and Hill, 2007).

So in the end, we have a normally distributed, posterior prediction interval: $\tilde{y}_{itj}$ for every country-year dataset. We can then compare the observed dataset values to these prediction intervals to see how well the model is doing at approximating these observed dataset values. We learn a lot from these descriptive comparisons as we demonstrate in the main manuscript and in additional detail in the rest of this appendix. Ultimately, these comparisons help us validate the resulting estimates relative to other estimates. Even the original data represents historic and government estimates, so such validation efforts are essential, especially when comparing long term historical trends and making predictions about the future.

2 Country-Year Unit Coverage

In the main manuscript, we present information about nine published dataset projects that cover a total of 76 variables of arming. Here we present a breakdown of country-year unit coverage by dataset and US dollar type in Table 1. Below, in Table 2 and Table 3, we present the breakdown of country-year unit coverage by dataset and year from 1948 to the present (only the NMC dataset and the Peters Sweden dataset provide coverage of country-year units in years prior to 1948).

	Constant Dollars	Current Dollars
IISS	3373	12202
MDED	0	535
NCD	5222	0
NMC (COW)	12430	12430
Peters/Sweden	103	0
SIPRI	7807	8044
SIRE NATDAT	0	2656
WMEAT	9270	9822
Zimmerman/USSR	0	87

Table 1: Observed country-year units by Publisher and Dollar Type

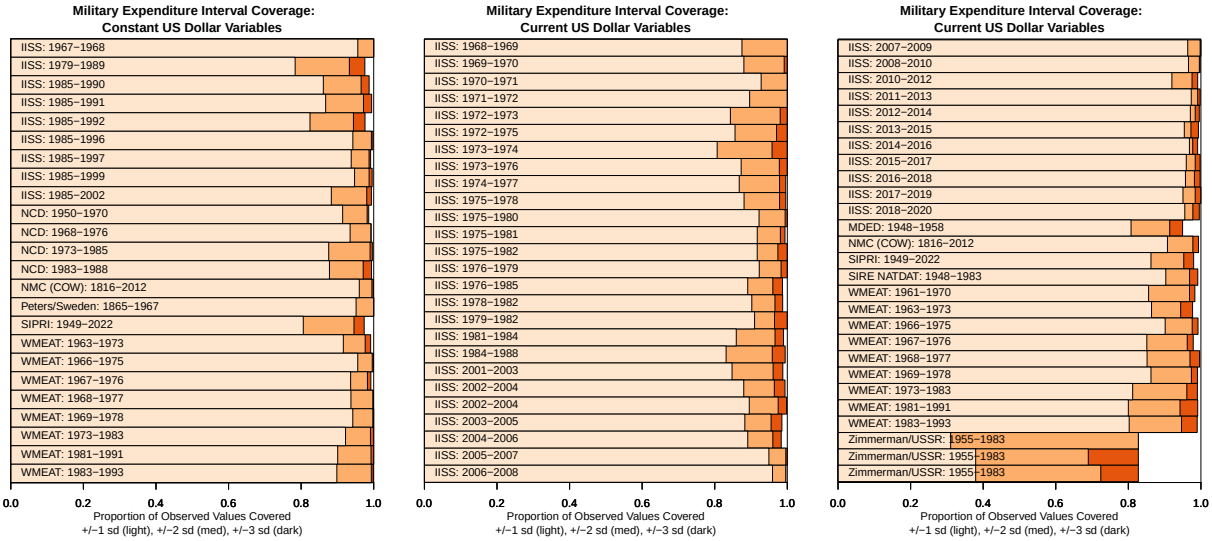

Figure 1: Proportion of observed dataset values that fall within ± 1, ± 2, and ± 3 standard deviation(s) of the posterior distribution.

	IISS	MDED	NCD	NMC (COW)	SIPRI	SIRE NATDAT	WMEAT
1948	0	38	0	120	0	65	0
1949	0	41	0	116	28	68	0
1950	0	46	49	132	36	68	0
1951	0	45	52	126	46	68	0
1952	0	45	53	136	50	69	0
1953	0	49	57	136	61	69	0
1954	0	49	55	138	53	70	0
1955	0	55	56	146	62	72	0
1956	0	54	61	146	76	72	0
1957	0	57	67	162	93	73	0
1958	0	56	68	162	104	73	0
1959	0	0	71	162	102	73	0
1960	0	0	100	198	117	73	0
1961	0	0	107	220	126	75	50
1962	0	0	112	228	134	76	51
1963	0	0	113	234	140	76	160
1964	0	0	115	238	141	76	162
1965	0	0	117	242	148	76	162
1966	0	0	117	244	148	76	403
1967	57	0	117	244	151	76	645
1968	109	0	241	248	163	76	815
1969	119	0	242	250	162	76	1058
1970	111	0	225	252	177	76	1077
1971	108	0	127	260	181	76	1045
1972	167	0	129	262	184	76	1060
1973	232	0	254	266	194	76	1278
1974	239	0	254	268	192	76	1204
1975	420	0	255	270	192	76	1216
1976	227	0	245	268	199	76	907
1977	176	0	124	272	207	76	662
1978	197	0	126	272	205	76	496
1979	315	0	126	276	208	76	246
1980	298	0	125	278	216	75	242
1981	509	0	124	284	220	75	505
1982	372	0	124	280	211	75	486
1983	248	0	247	280	211	75	756

Table 2: Observed country-year units by Publisher and Year (Constant and Current)

	IISS	MDED	NCD	NMC (COW)	SIPRI	SIRE NATDAT	WMEAT
1984	255	0	242	286	221	0	520
1985	949	0	236	282	229	0	496
1986	115	0	115	274	222	0	480
1987	94	0	97	274	231	0	492
1988	2	0	77	276	231	0	482
1989	105	0	0	278	233	0	496
1990	214	0	0	270	241	0	489
1991	213	0	0	276	238	0	463
1992	139	0	0	278	266	0	256
1993	0	0	0	298	278	0	232
1994	0	0	0	322	282	0	0
1995	164	0	0	330	276	0	0
1996	328	0	0	330	280	0	0
1997	163	0	0	330	283	0	0
1998	165	0	0	334	273	0	0
1999	165	0	0	332	279	0	0
2000	0	0	0	332	283	0	0
2001	326	0	0	332	285	0	0
2002	643	0	0	318	291	0	0
2003	639	0	0	322	300	0	0
2004	632	0	0	316	301	0	0
2005	473	0	0	318	302	0	0
2006	473	0	0	316	292	0	0
2007	464	0	0	314	290	0	0
2008	462	0	0	306	302	0	0
2009	320	0	0	318	294	0	0
2010	317	0	0	310	292	0	0
2011	312	0	0	320	290	0	0
2012	448	0	0	298	301	0	0
2013	445	0	0	0	306	0	0
2014	432	0	0	0	309	0	0
2015	430	0	0	0	299	0	0
2016	443	0	0	0	303	0	0
2017	447	0	0	0	303	0	0
2018	446	0	0	0	307	0	0
2019	298	0	0	0	301	0	0
2020	150	0	0	0	301	0	0
2021	0	0	0	0	301	0	0
2022	0	0	0	0	297	0	0

Table 3: Observed country-year units by Publisher and Year (Constant and Current)

3 Posterior prediction and observed values of countries by dataset, in constant values

In the main manuscript, we present prediction intervals for arming for three country cases of interest: China, the United States, and the United Kingdom. Here we present many additional country examples (France, Colombia, Netherlands, Spain, Germany, Italy, Sweden, Russia/USSR, Brazil, Iran, Japan, India, South Korea, Democratic Republic of Congo (DRC), Vietnam/North Vietnam, Albania, Pakistan, Uganda, Afghanistan, Kosovo, East Timor, Eritrea, Costa Rica, Gambia, Haiti, Iceland, Iraq, Myanmar, Nicaragua, Yemen (Arab Republic of Yemen), Peru, Somalia, Trinidad and Tobago, and Uzbekistan).

We presented four variables in constant US dollars: IISS, NMC (COW), SIPRI, and WMEAT. Please note that for the following plots, we use the most recent WMEAT and IISS variable from those dataset projects published in 1993 and 2003 respectively.

Finally we zoom to show single year distributions for three countries (China, the United Kingdom, and the USA) in 1990 and 2010.

3.1 France

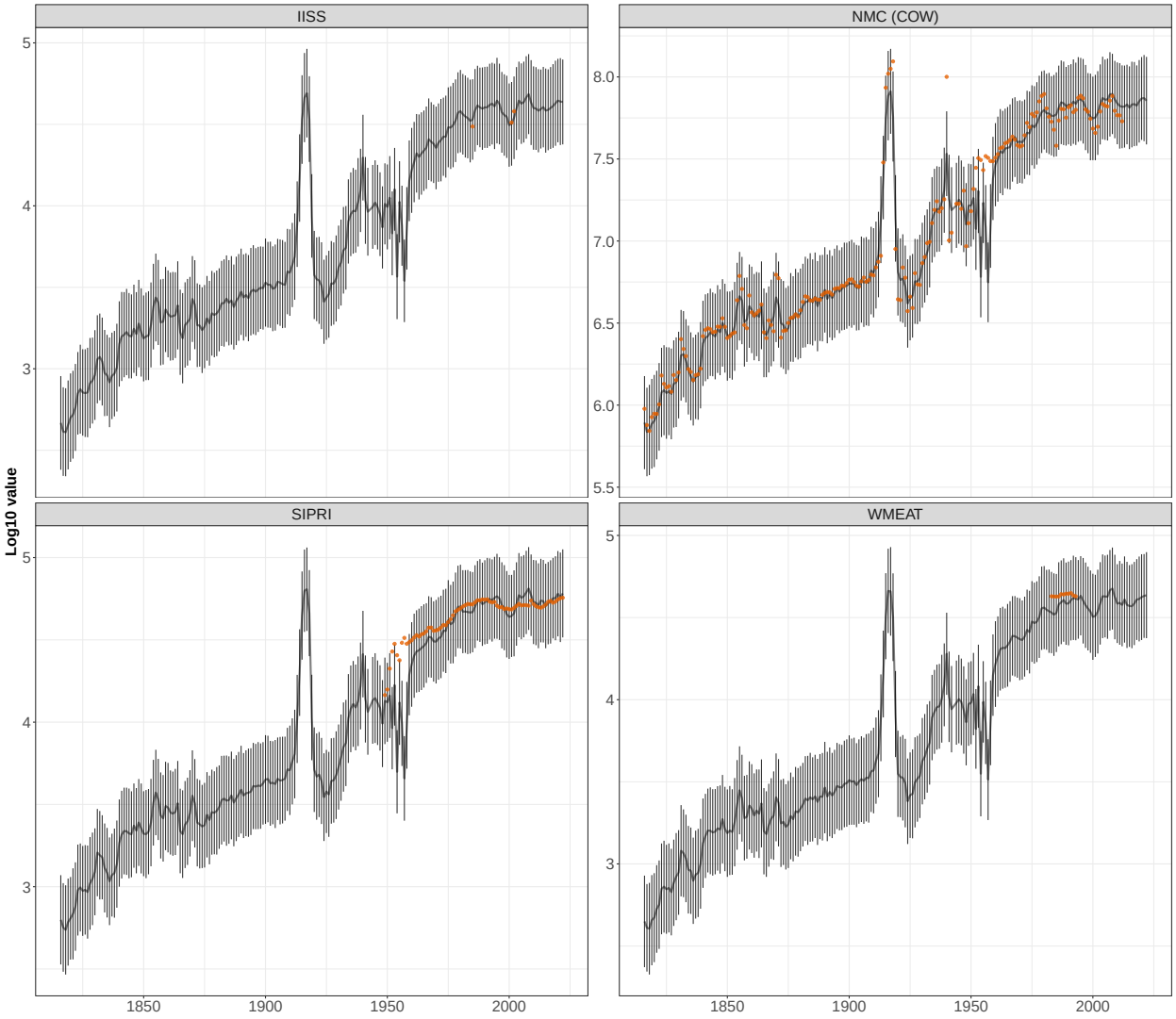

Figure 2: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for France.

3.2 Colombia

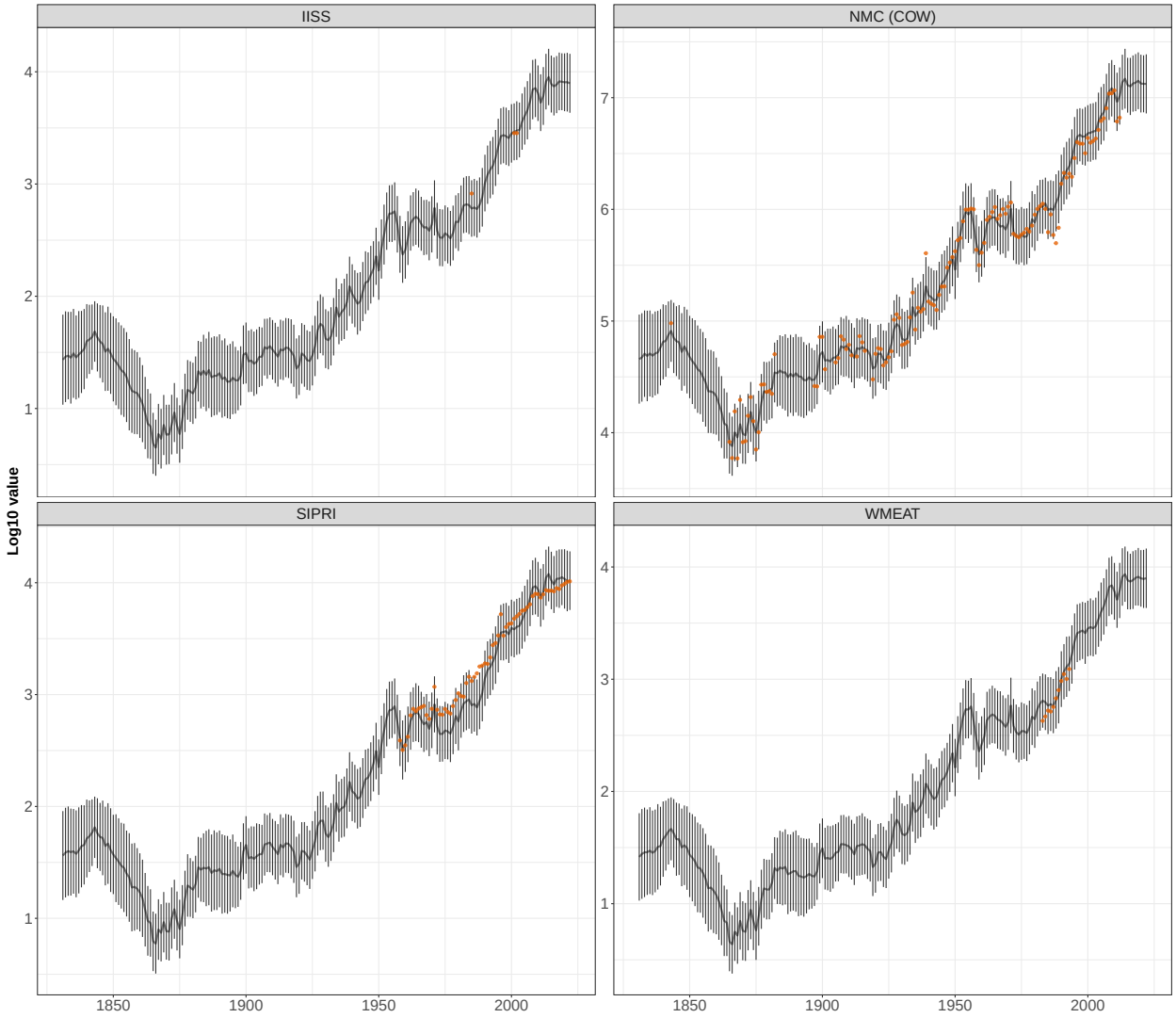

Figure 3: Posterior prediction intervals (gray lines) with± 1 standard deviation confidence bands and observed variables (orange points) for Colombia.

3.3 Netherlands

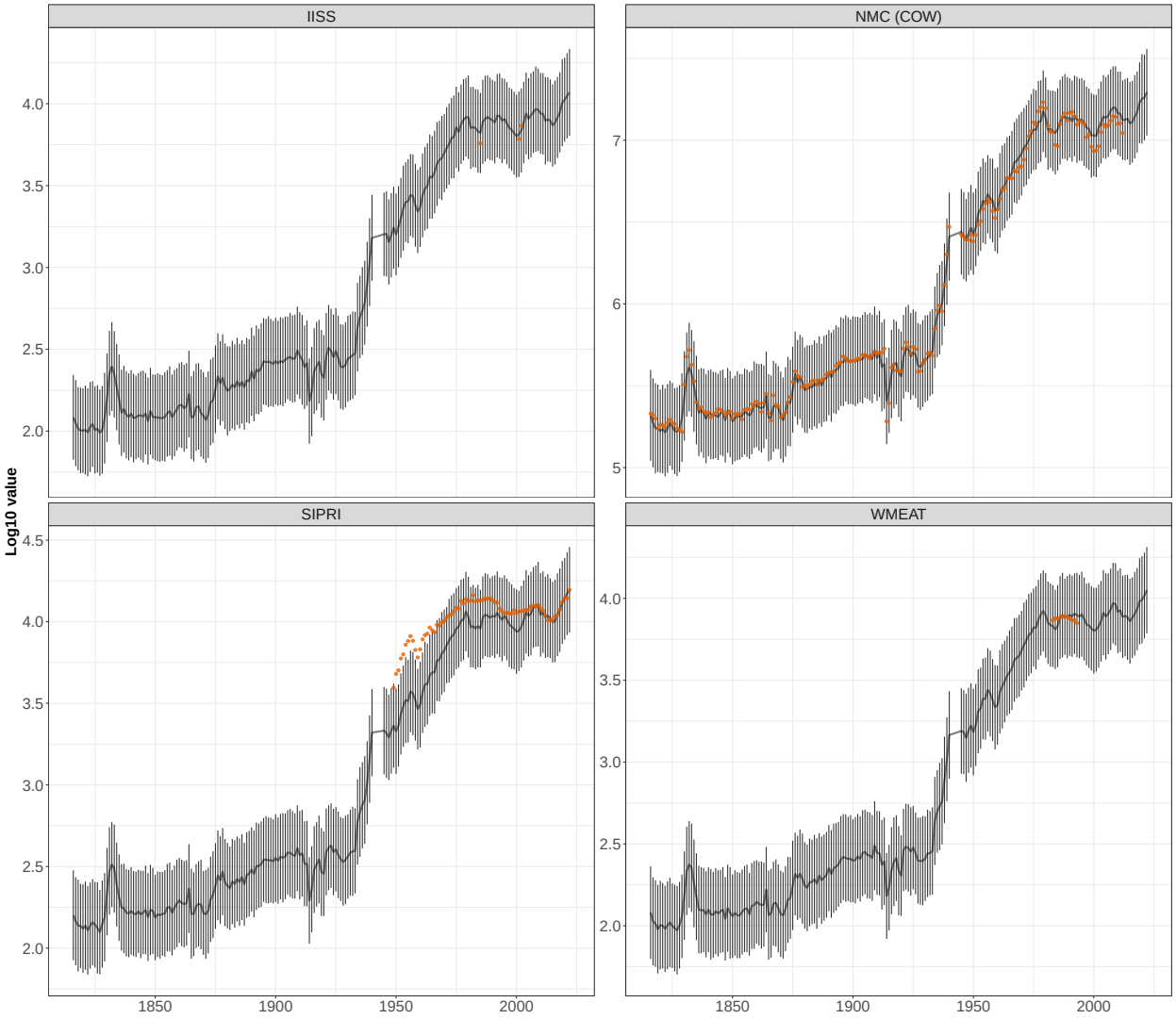

Figure 4: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for the Netherlands.

3.4 Spain

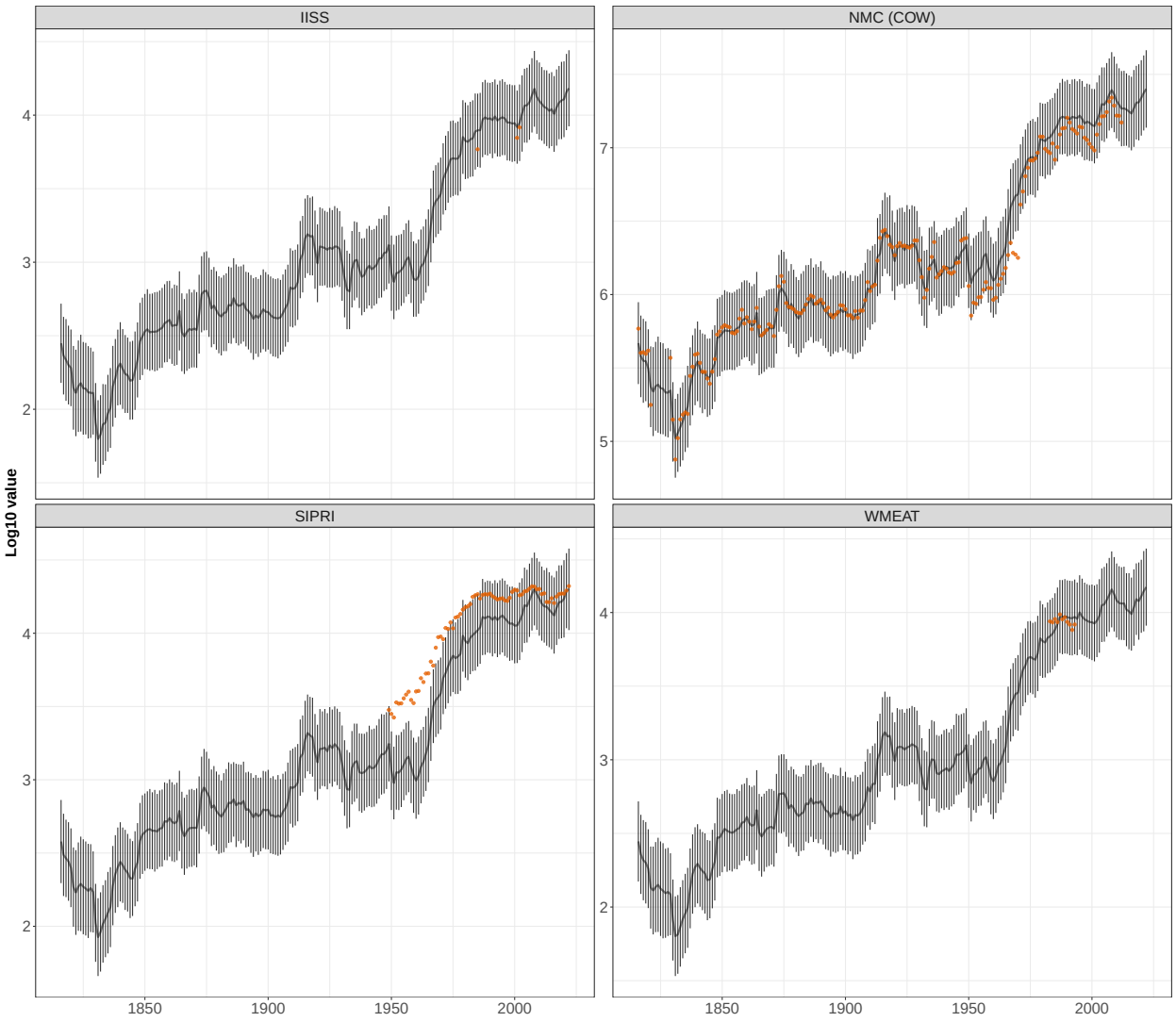

Figure 5: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Spain.

3.5 Germany

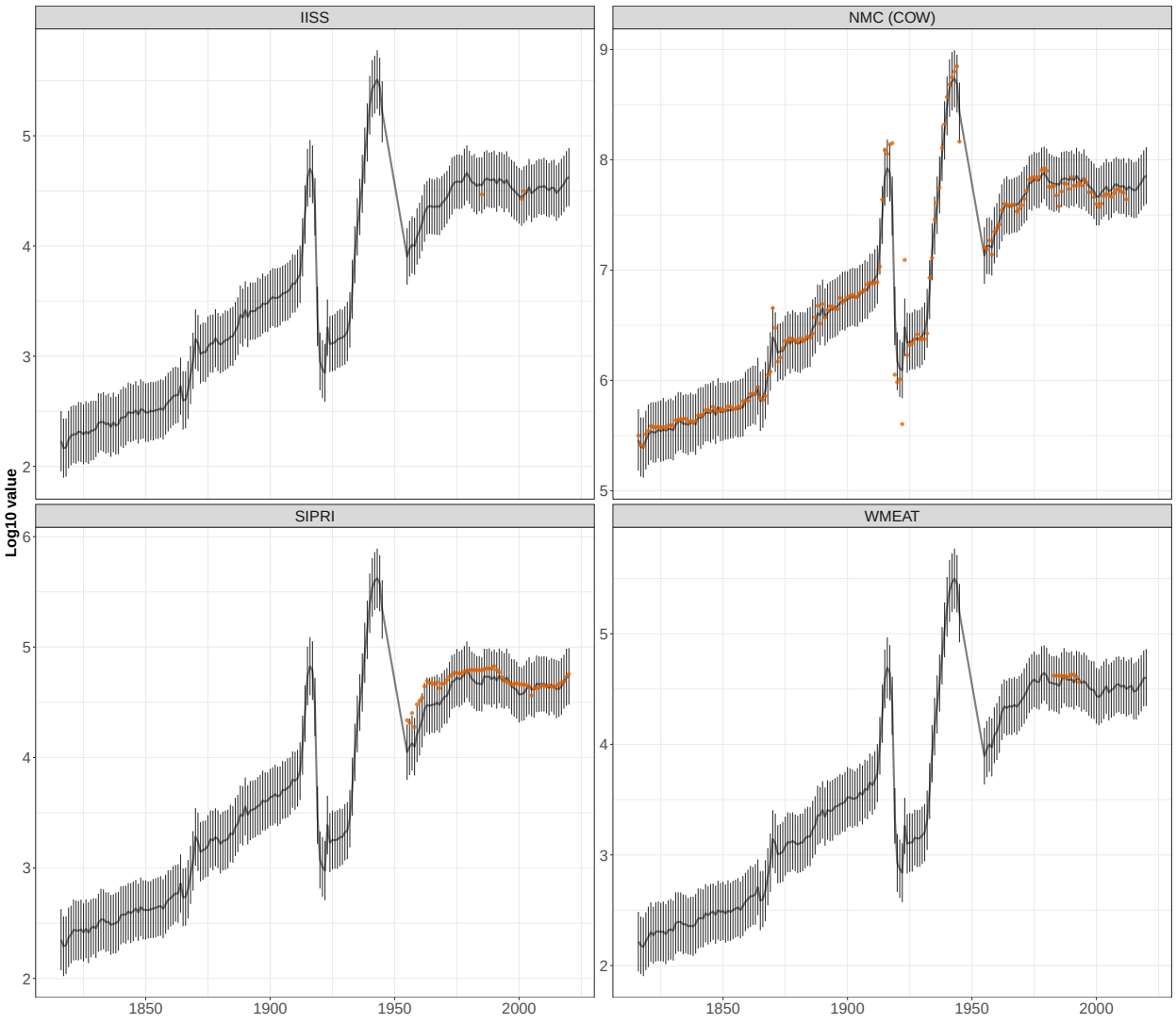

Figure 6: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Germany.

3.6 Italy

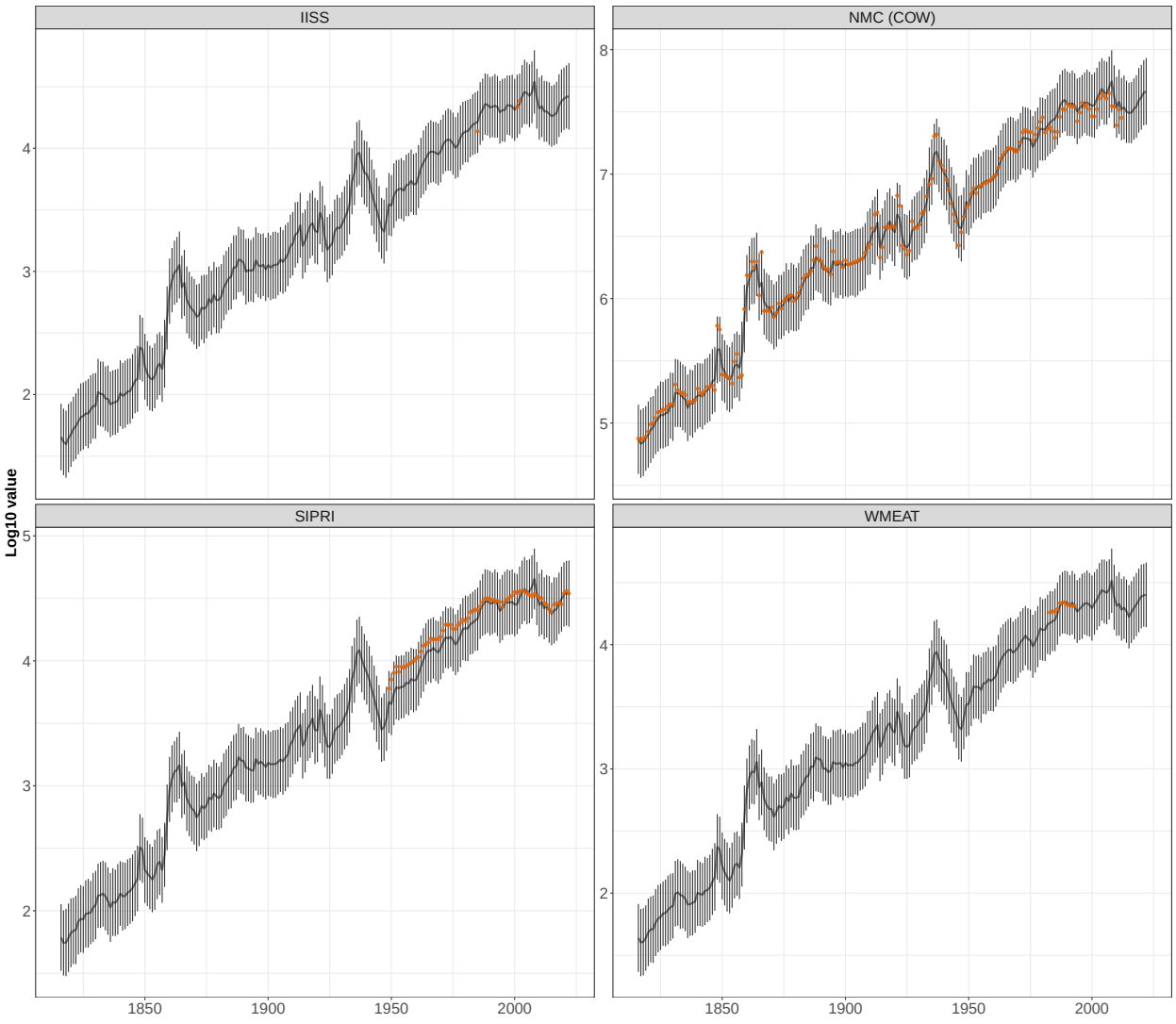

Figure 7: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Italy.

3.7 Sweden

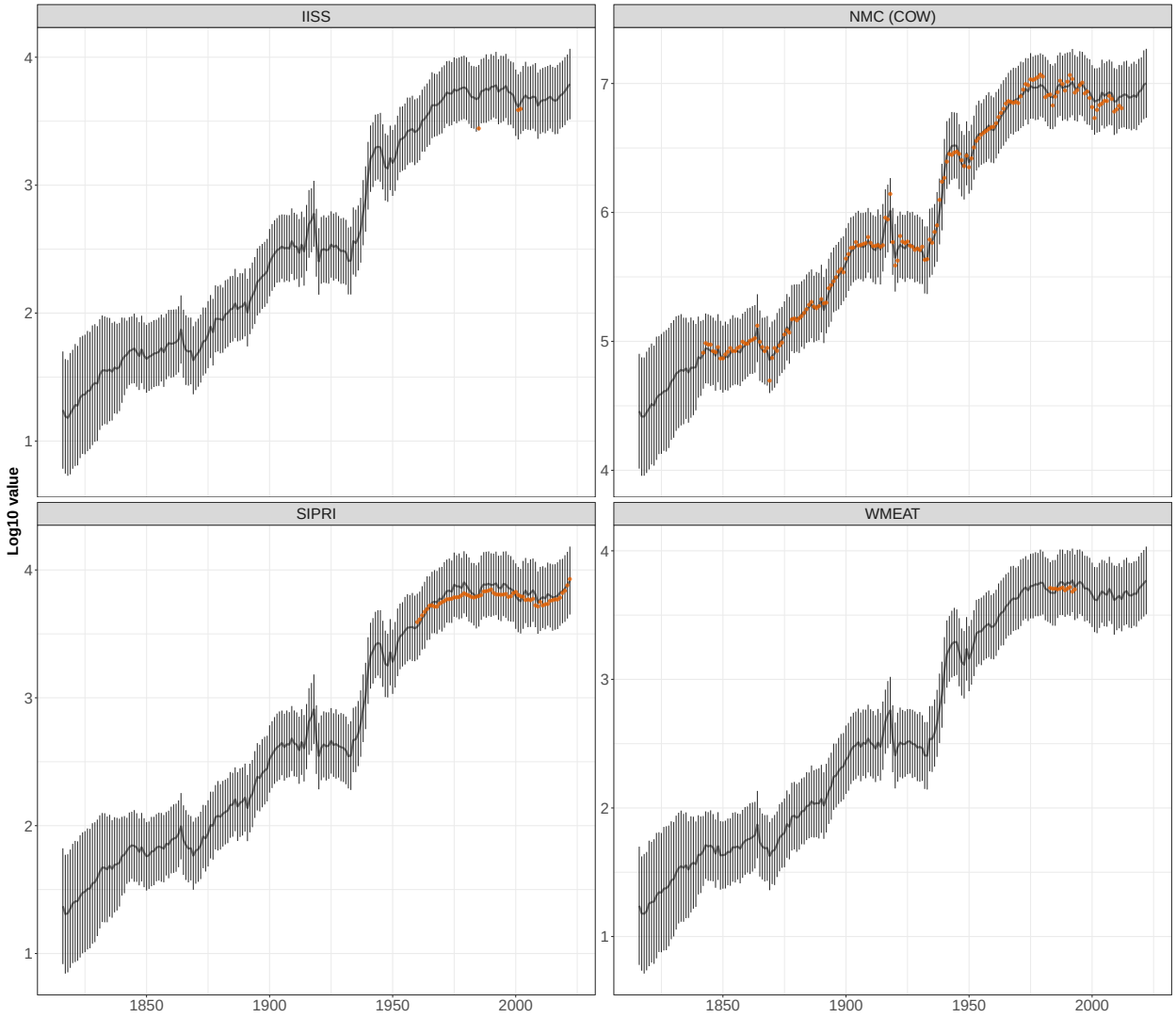

Figure 8: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Sweden.

3.8 Russia

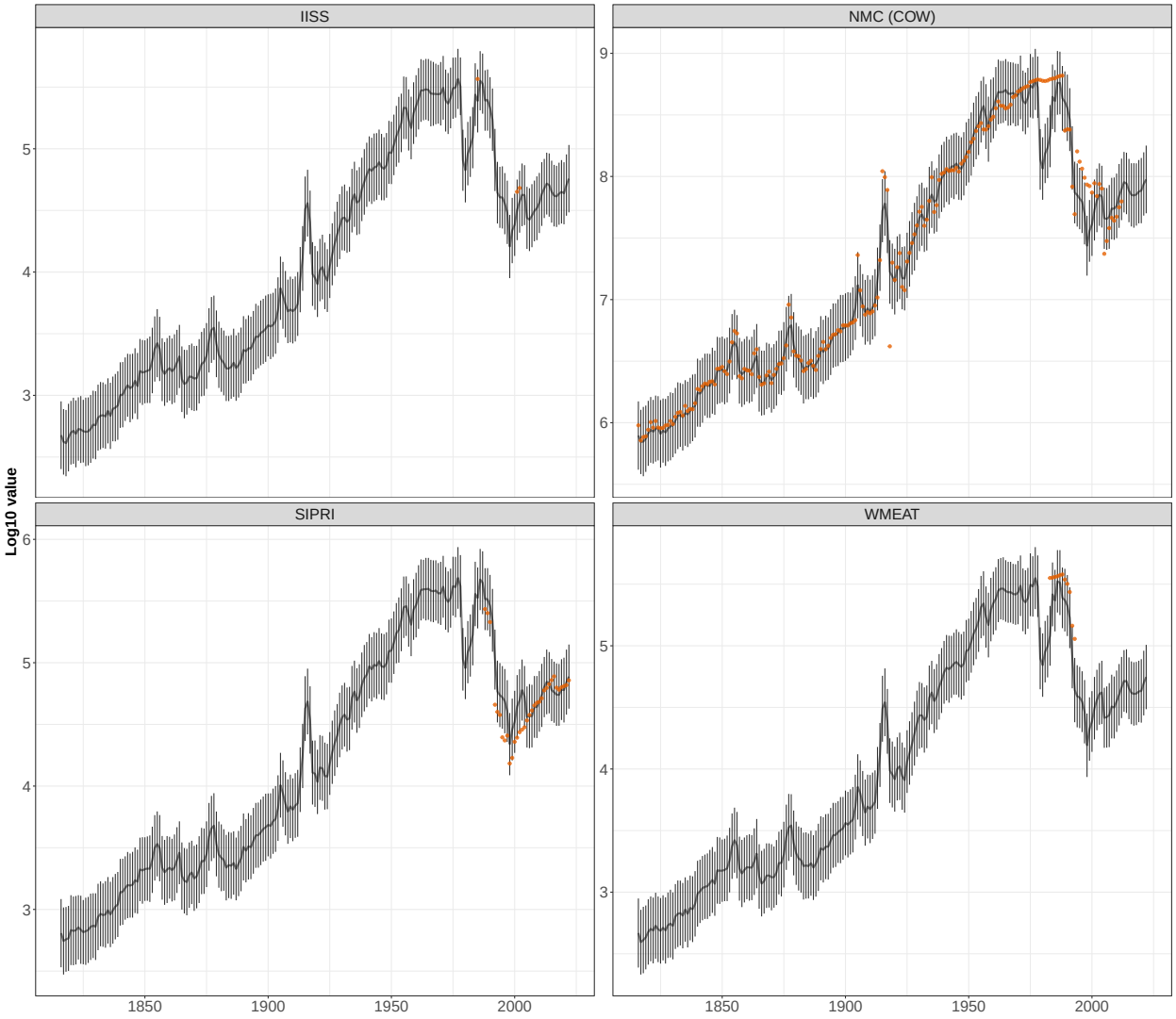

Figure 9: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Russia.

3.9 Brazil

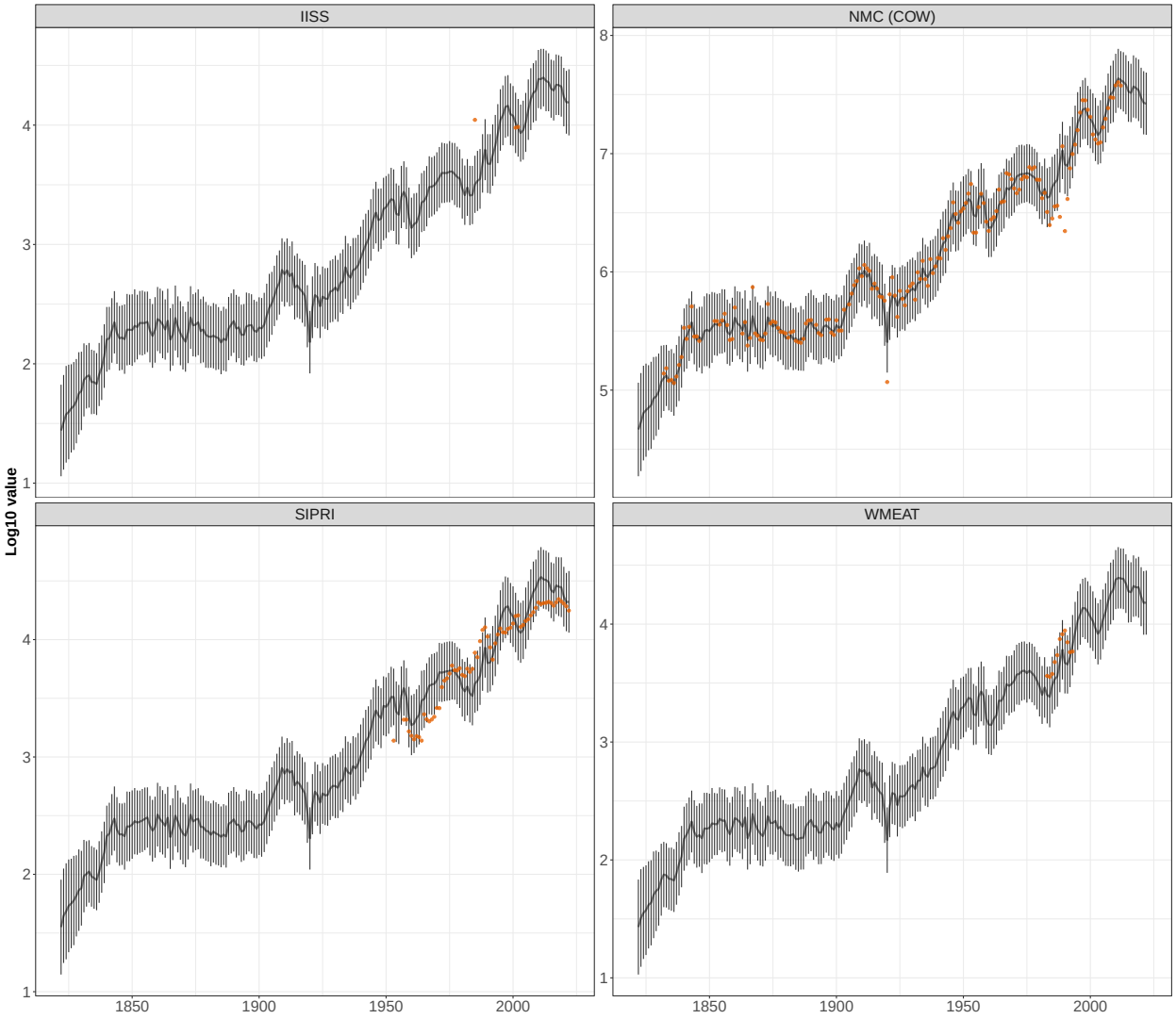

Figure 10: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Brazil.

3.10 Iran

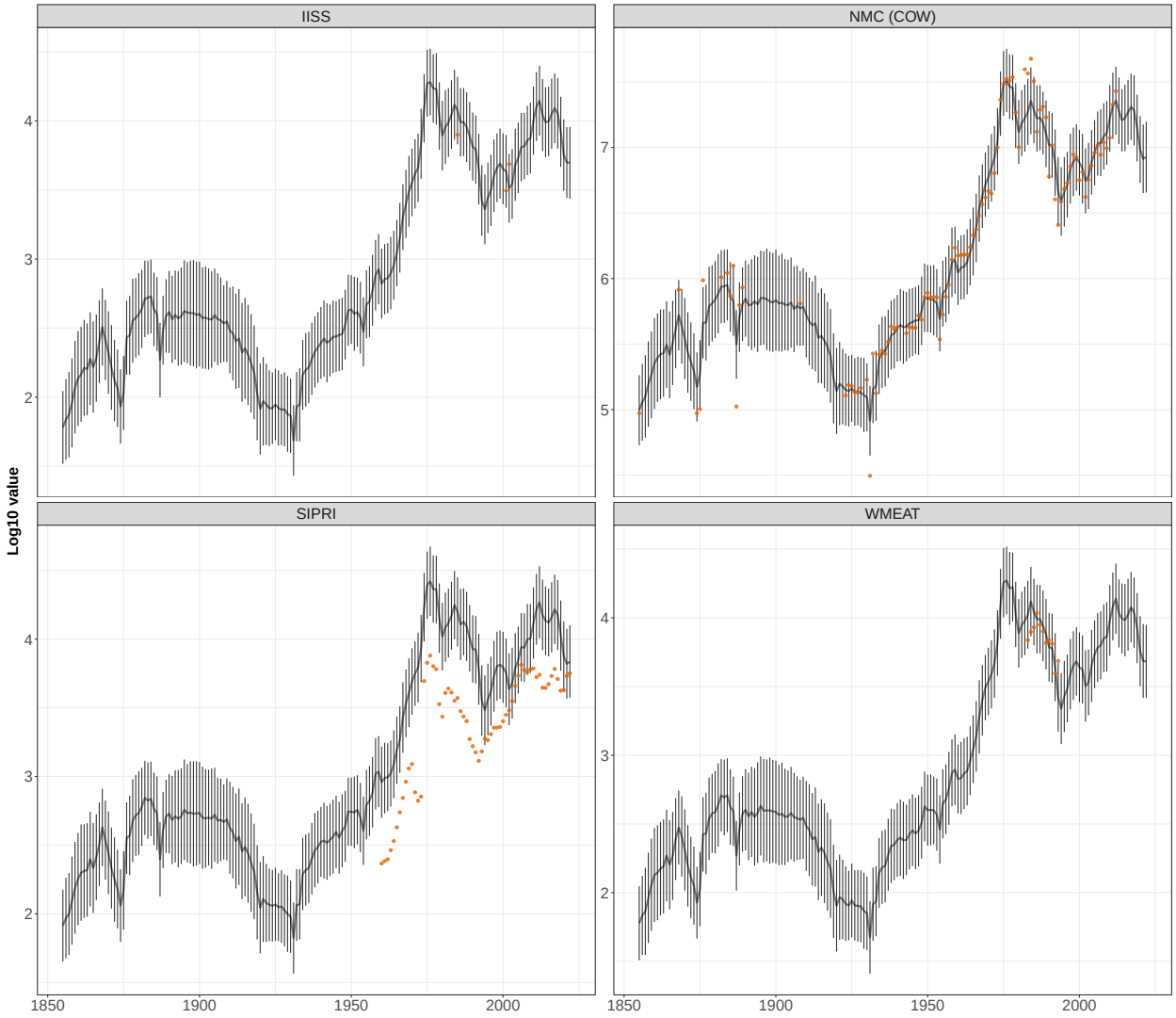

Figure 11: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Iran.

3.11 Japan

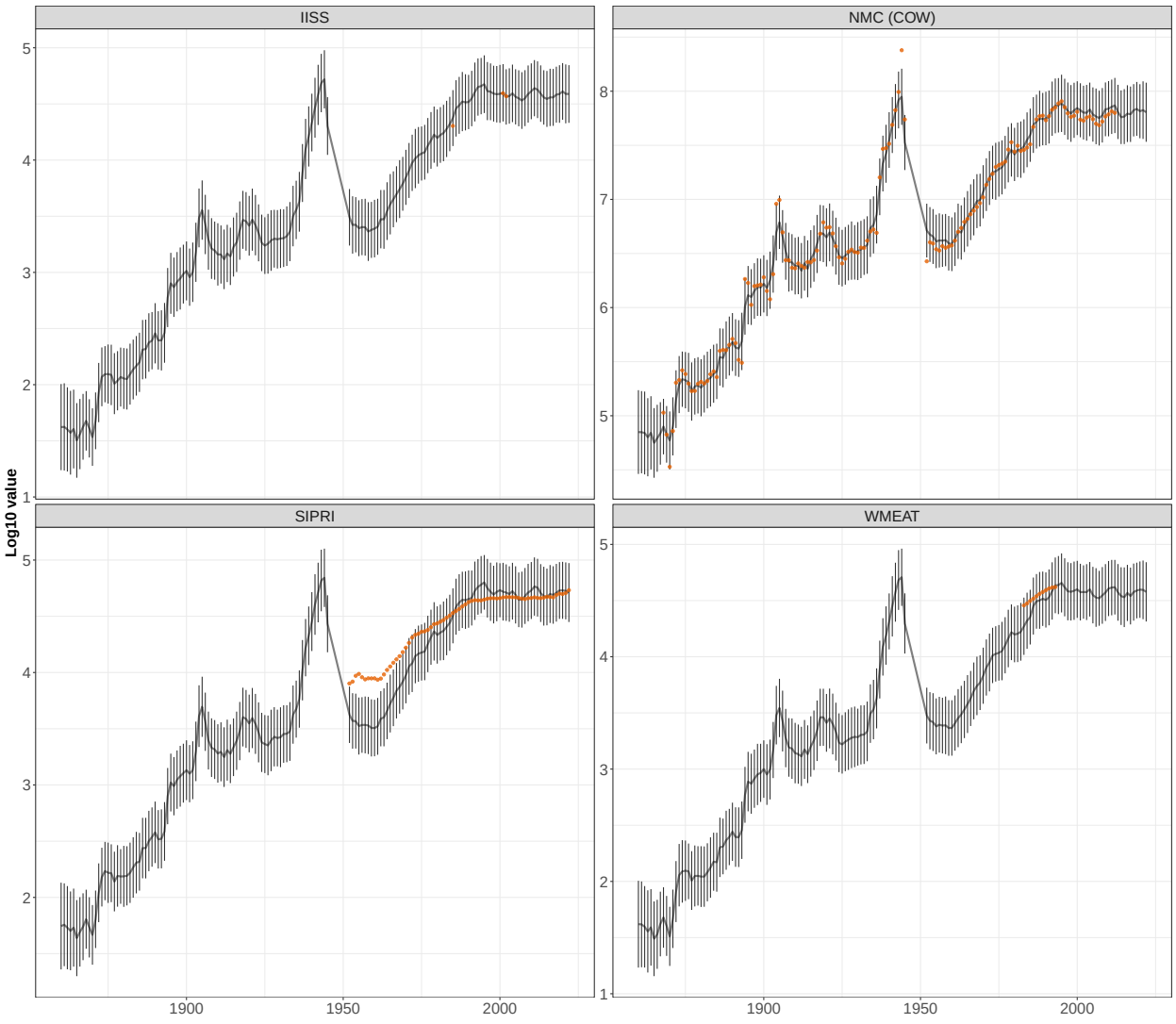

Figure 12: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Japan.

3.12 India

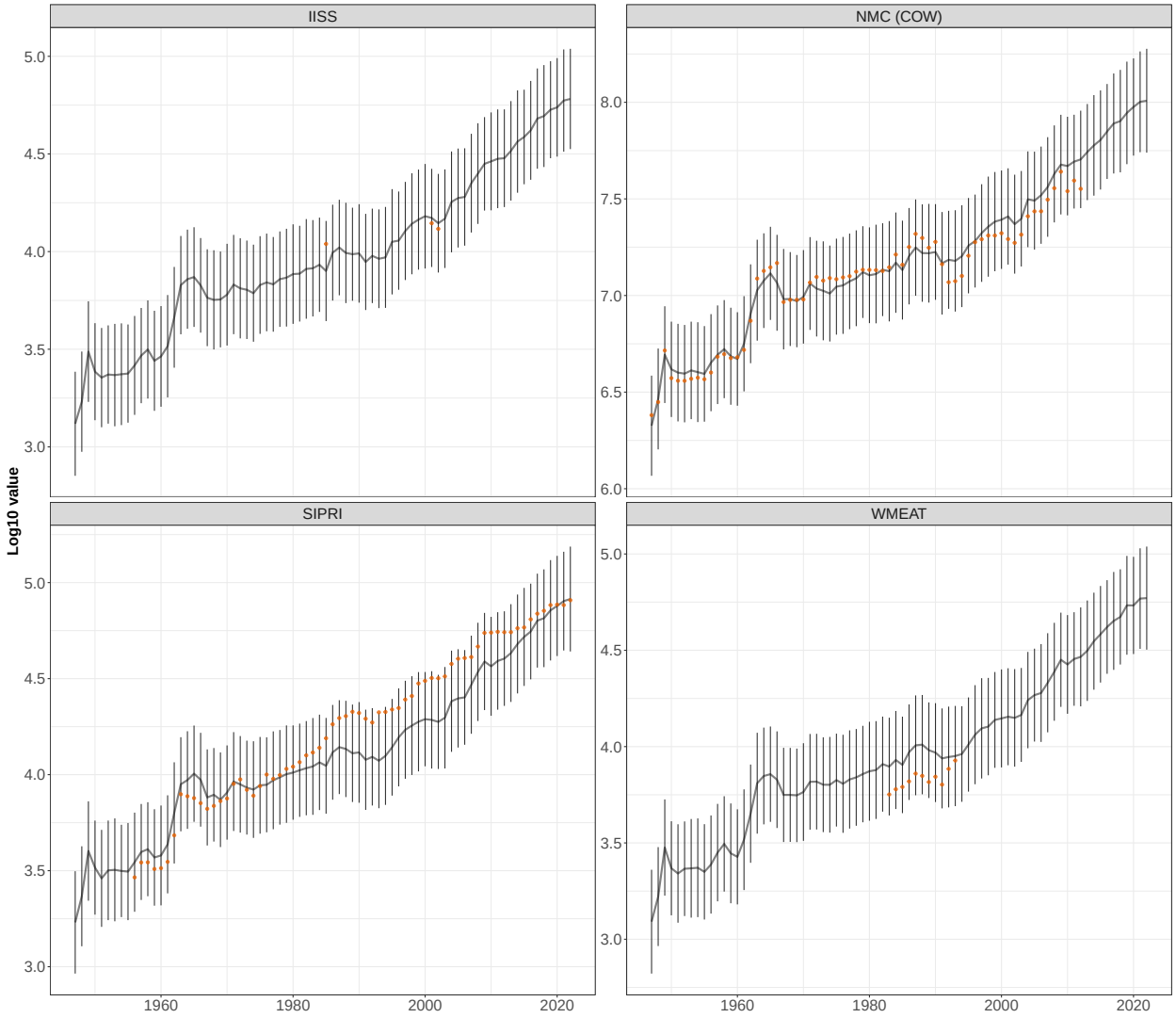

Figure 13: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for India.

3.13 Peoples' Republic of Korea

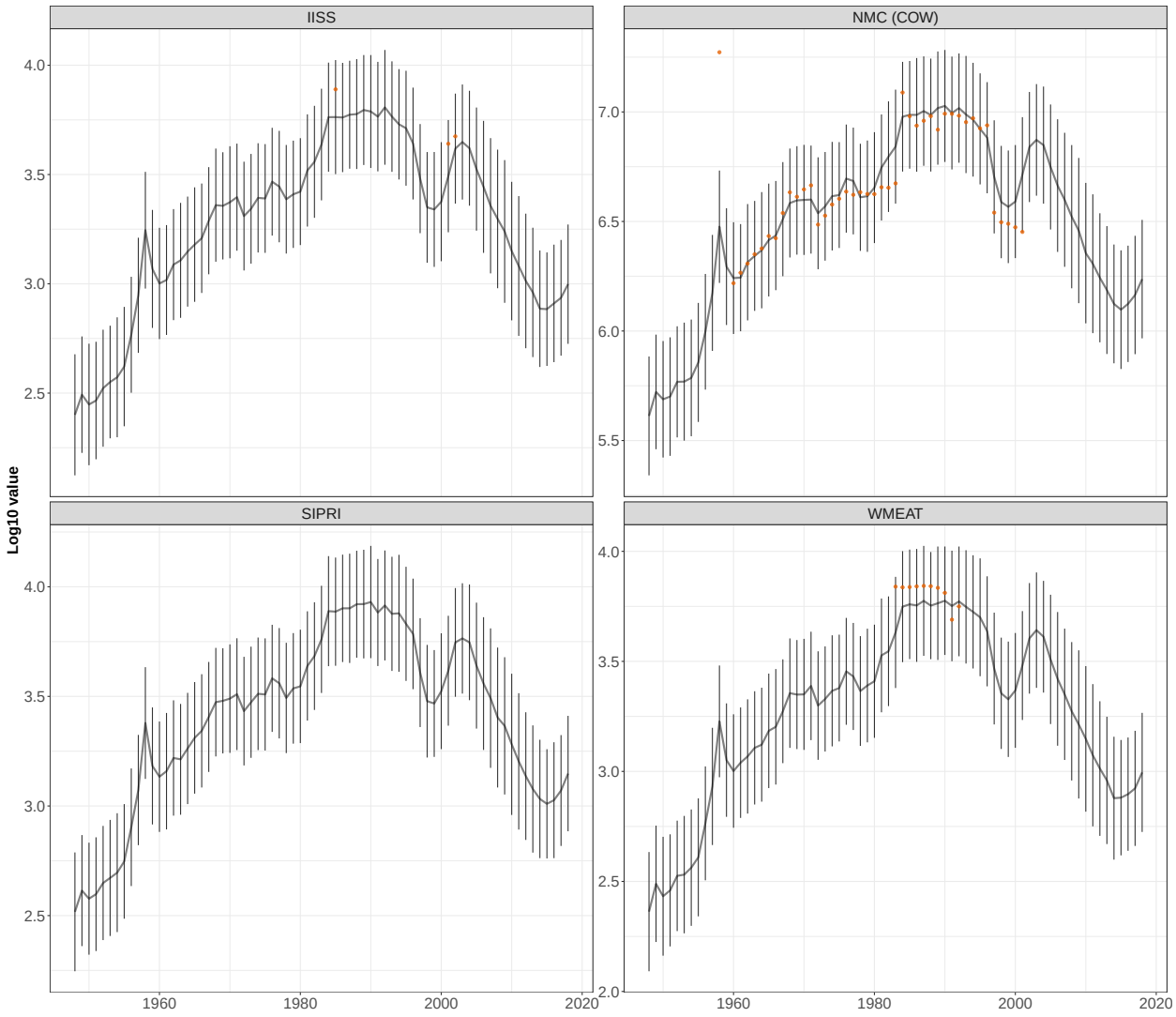

Figure 14: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for People's Republic of Korea.

3.14 Democratic Republic of Congo

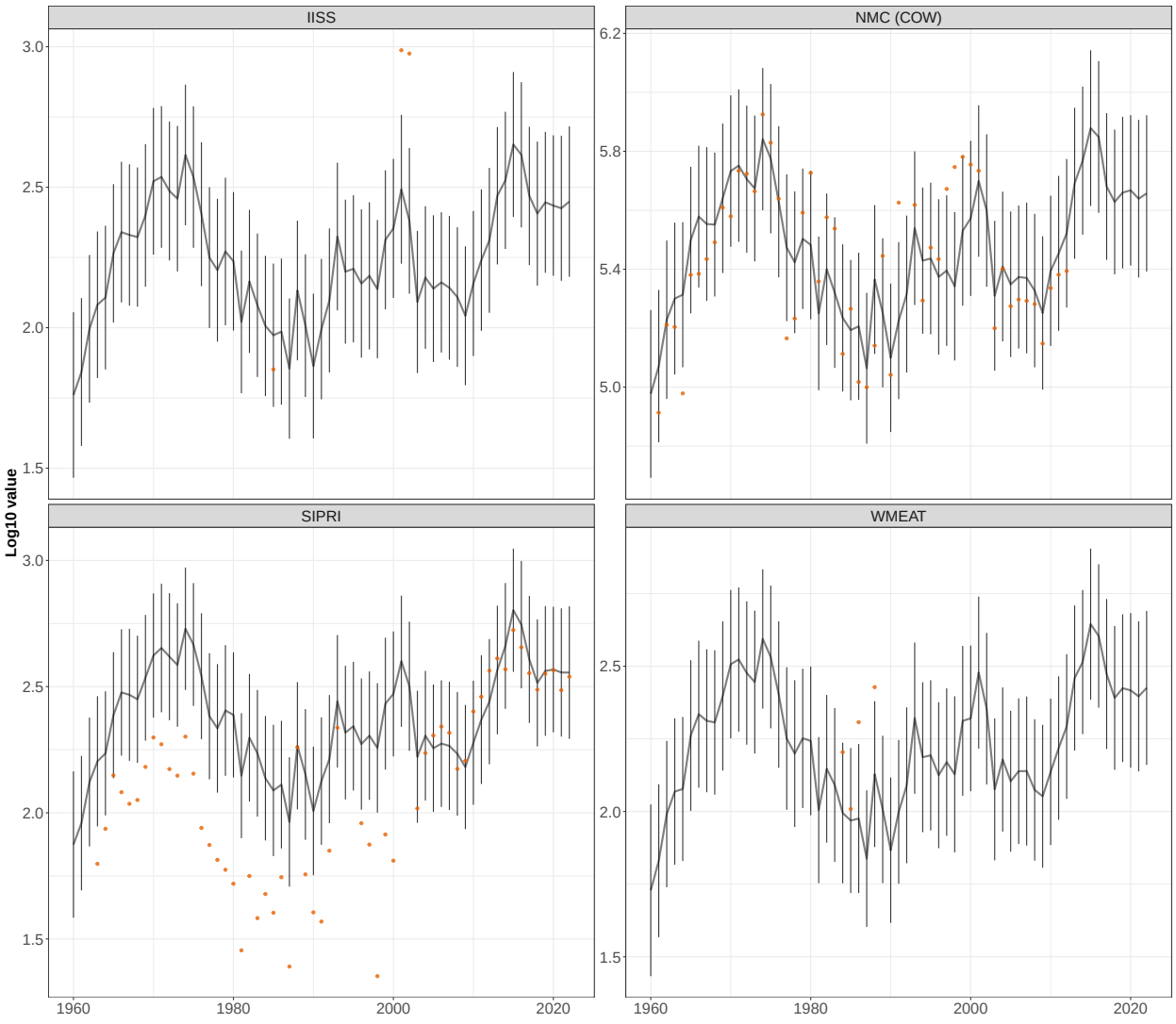

Figure 15: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for the Democratic Republic of Congo.

3.15 Democratic Republic of Vietnam

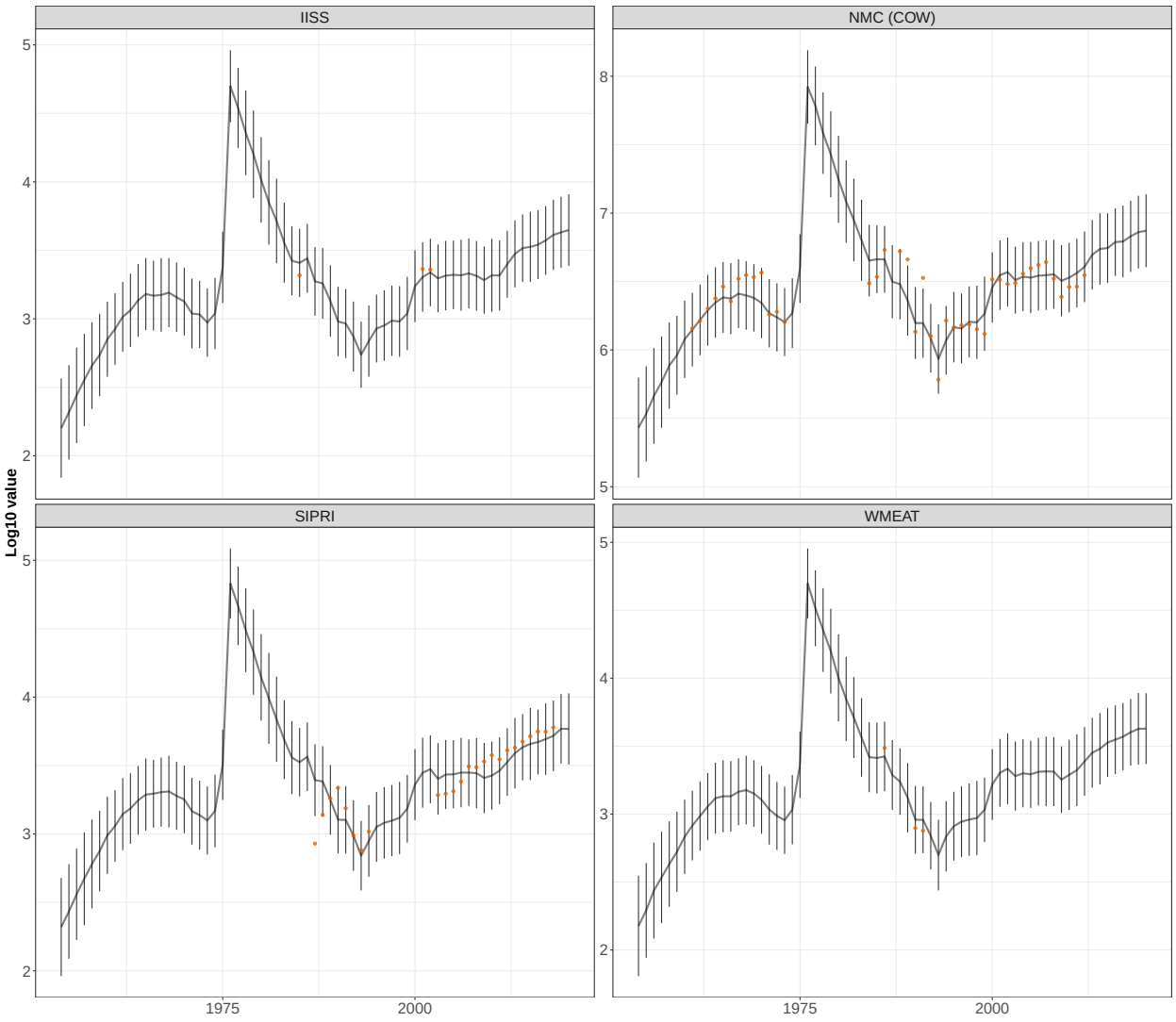

Figure 16: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Democratic Republic of Vietnam.

3.16 Albania

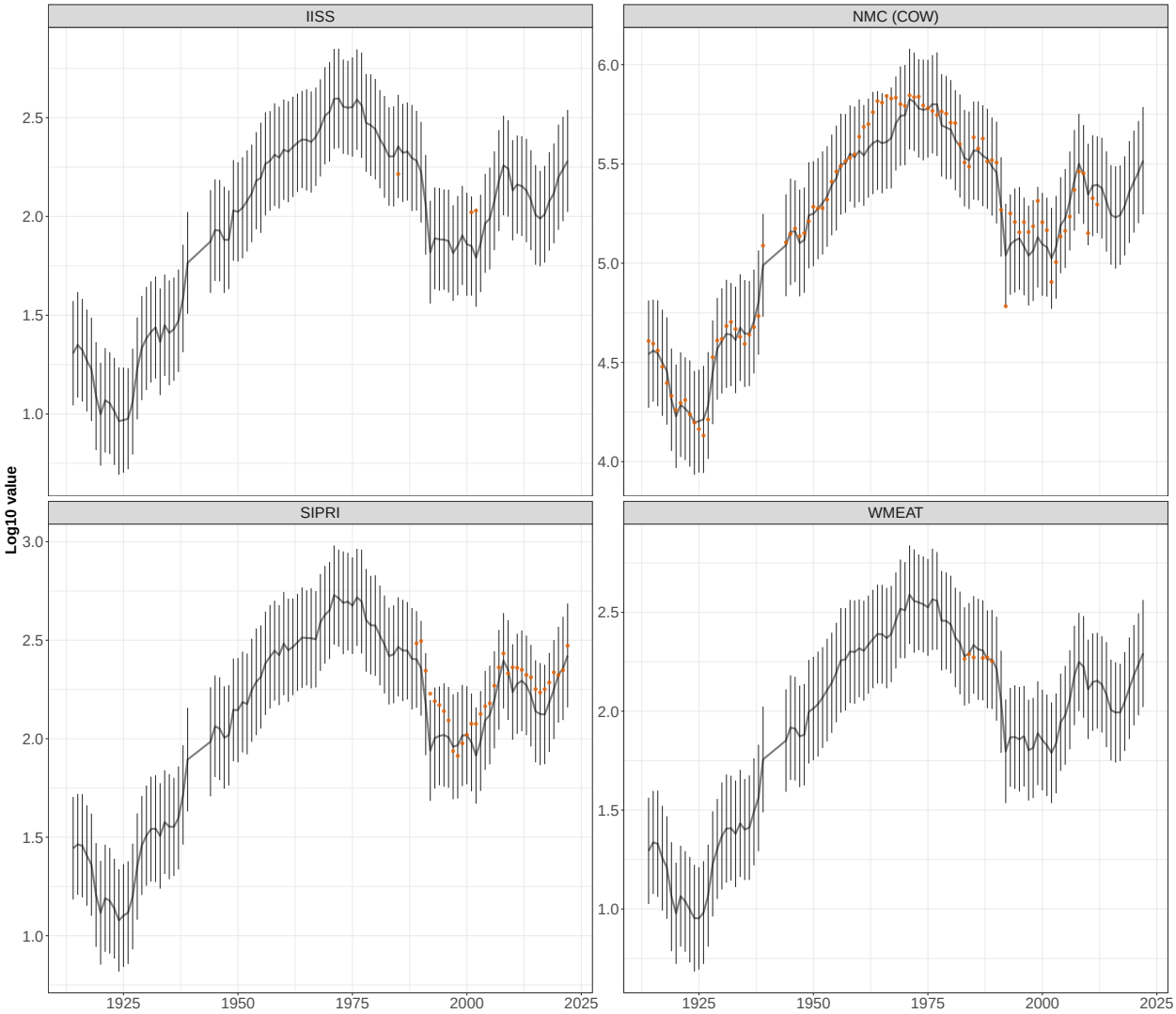

Figure 17: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Albania.

3.17 Pakistan

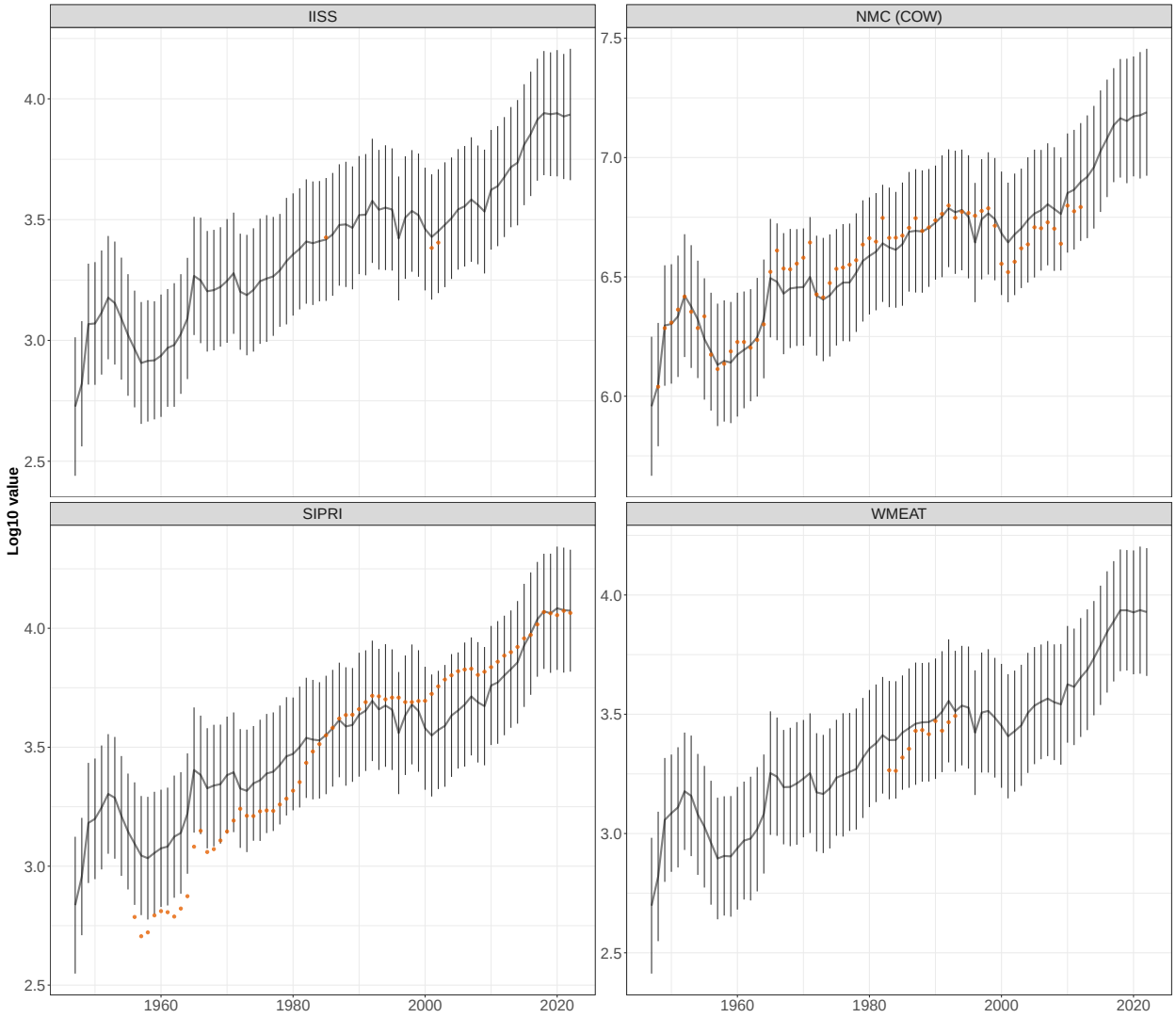

Figure 18: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Pakistan.

3.18 Uganda

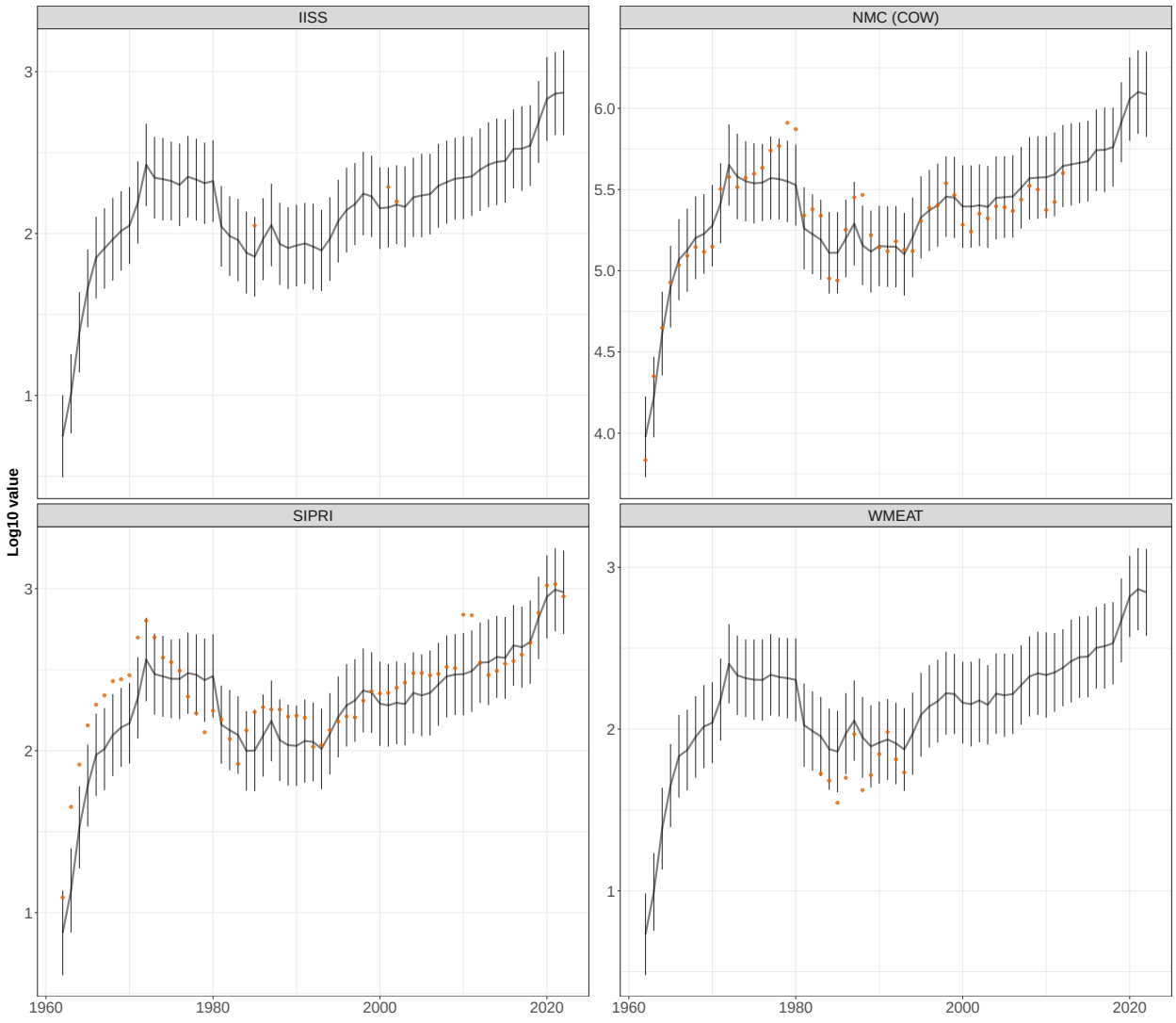

Figure 19: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Uganda.

3.19 Afghanistan

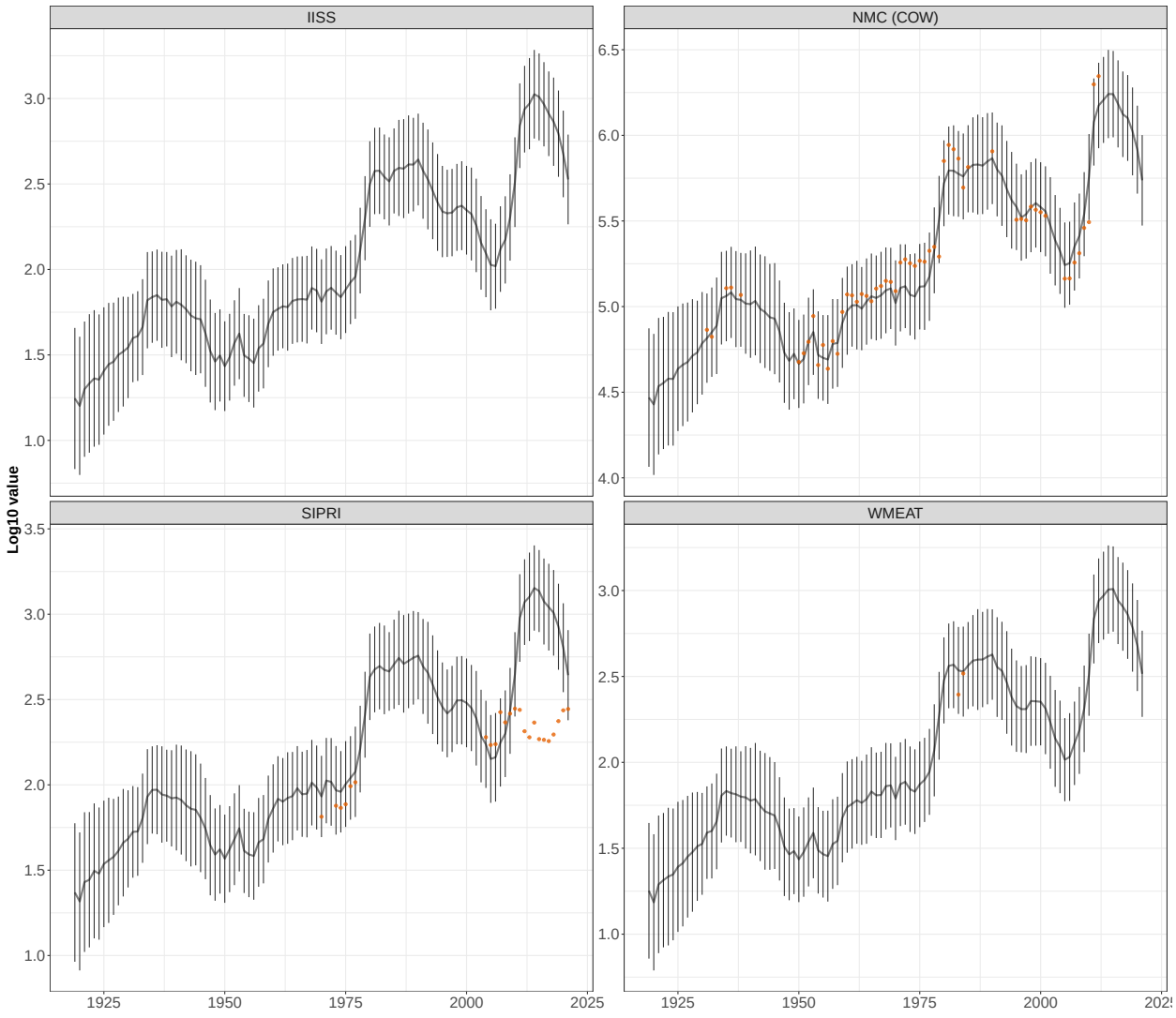

Figure 20: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Afghanistan.

3.20 Kosovo

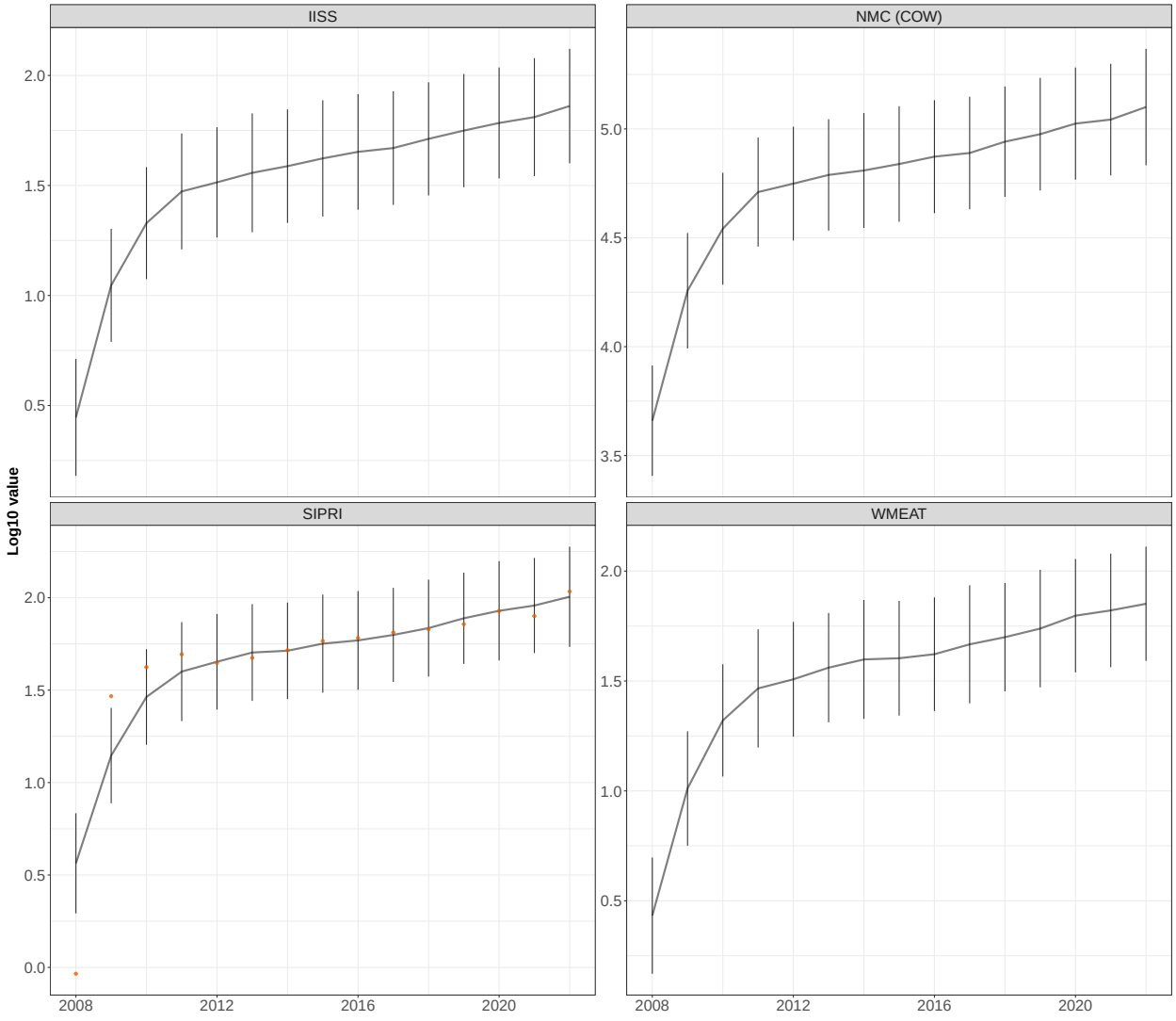

Figure 21: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Kosovo.

3.21 East Timor

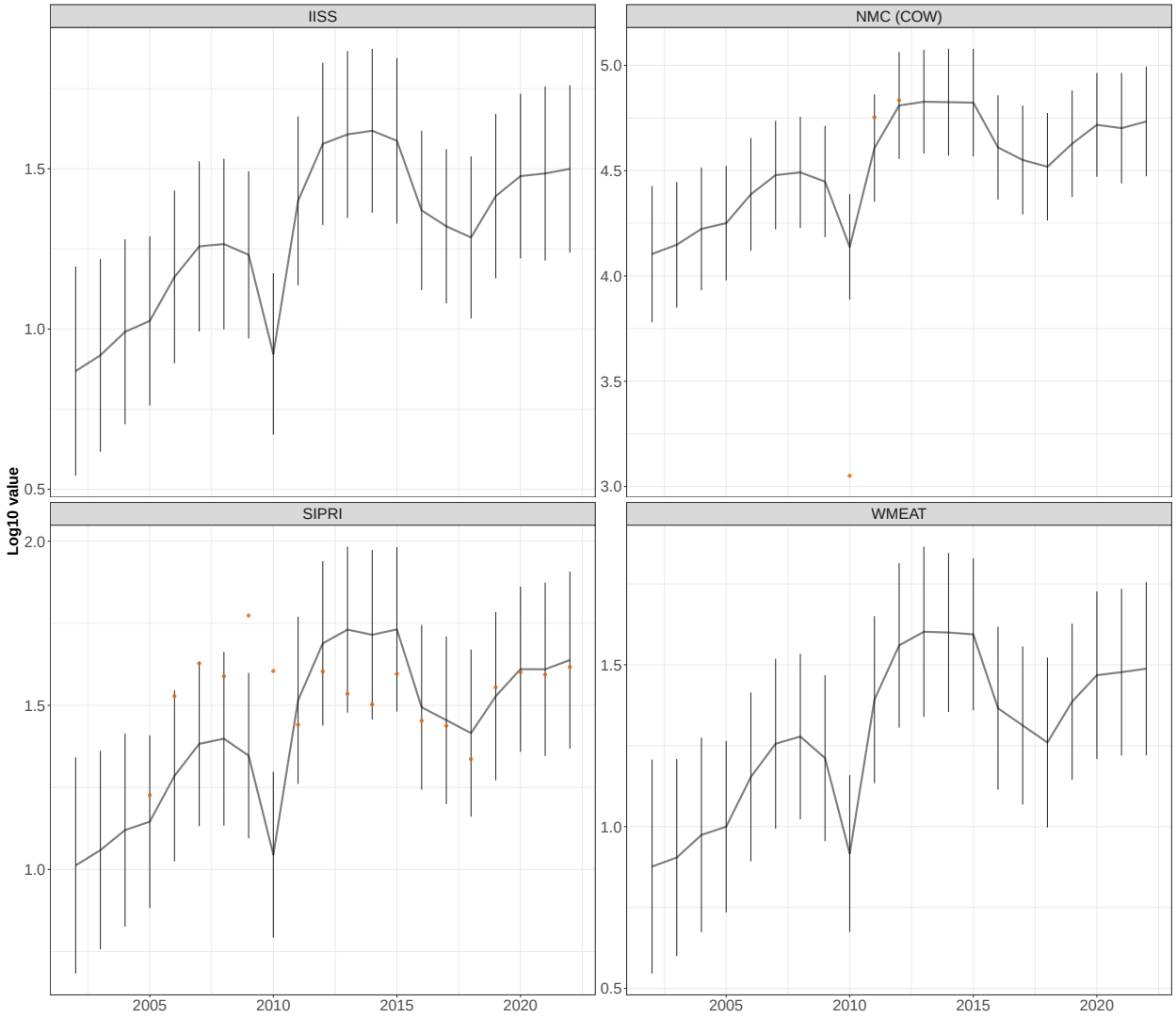

Figure 22: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for East Timor.

3.22 Eritrea

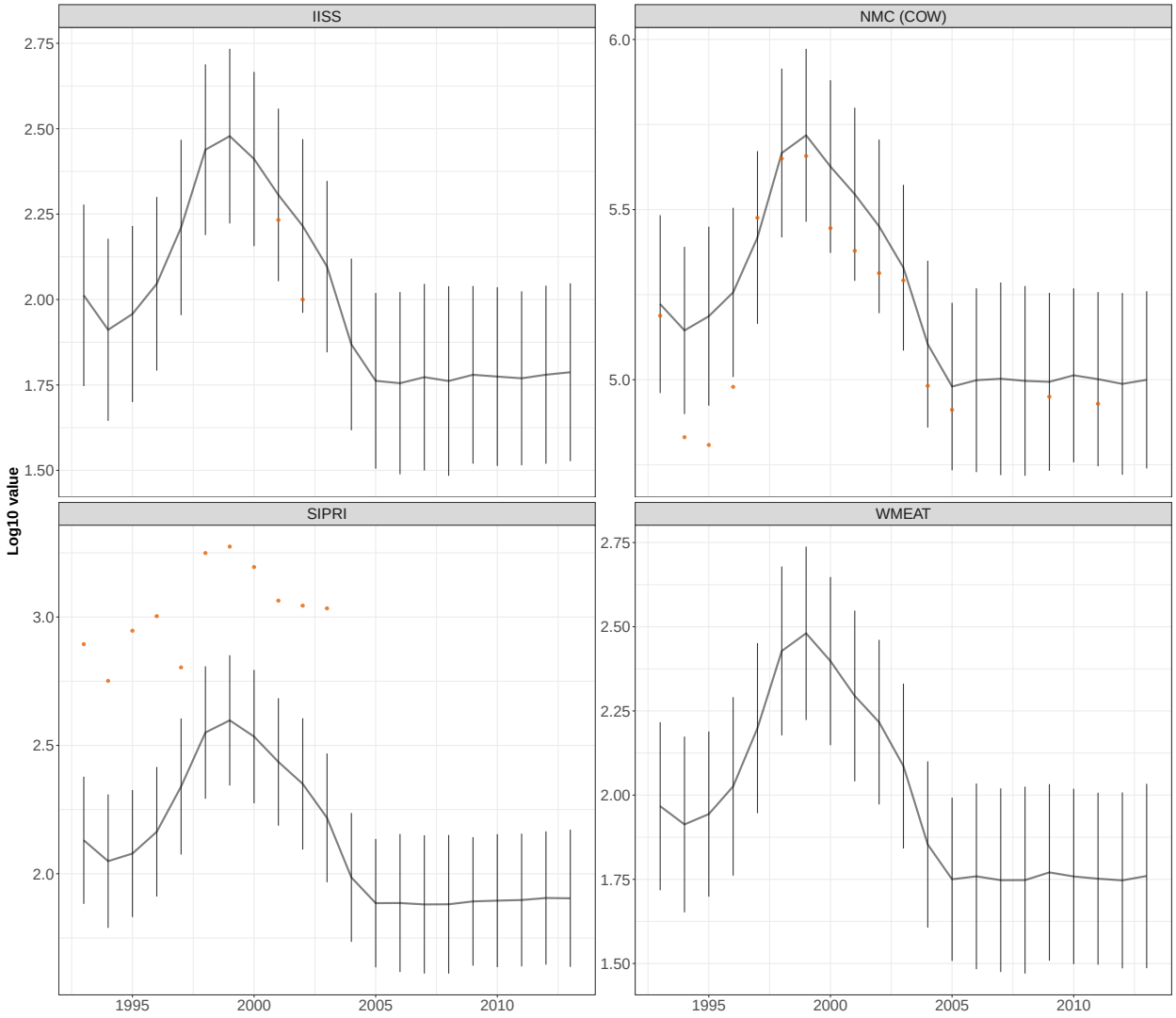

Figure 23: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Eritrea.

3.23 Costa Rica

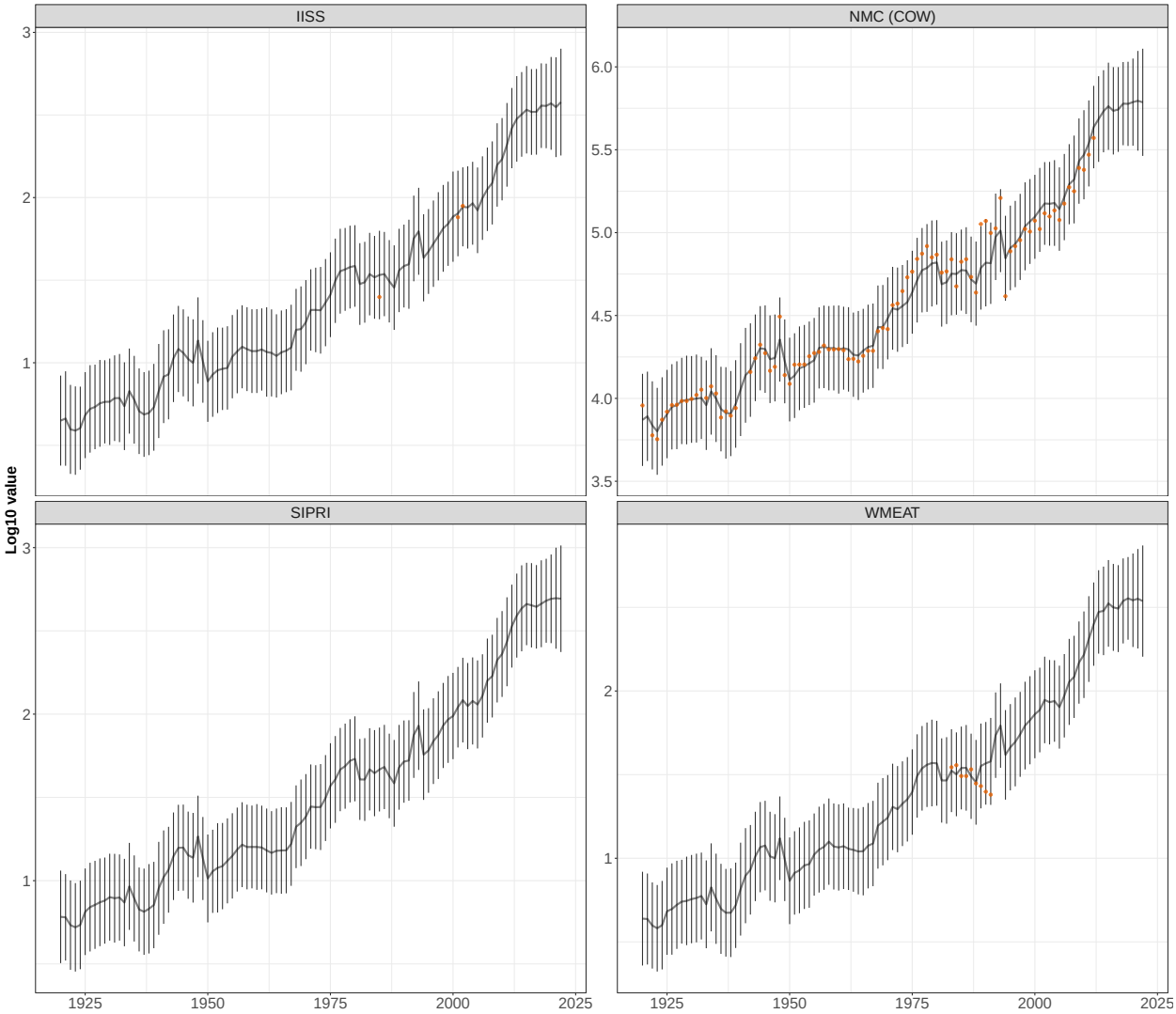

Figure 24: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Costa Rica.

3.24 Gambia

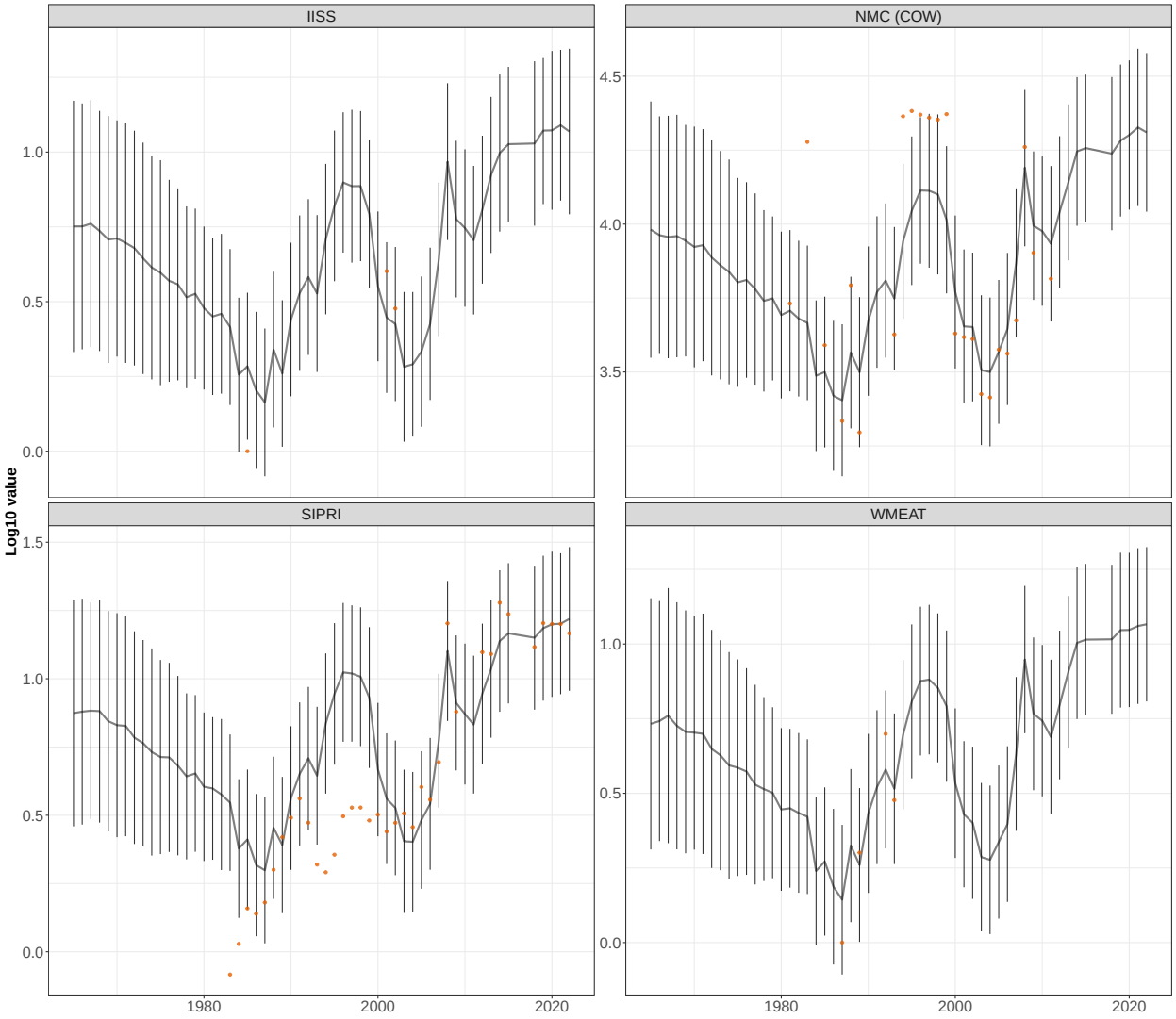

Figure 25: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Gambia.

3.25 Haiti

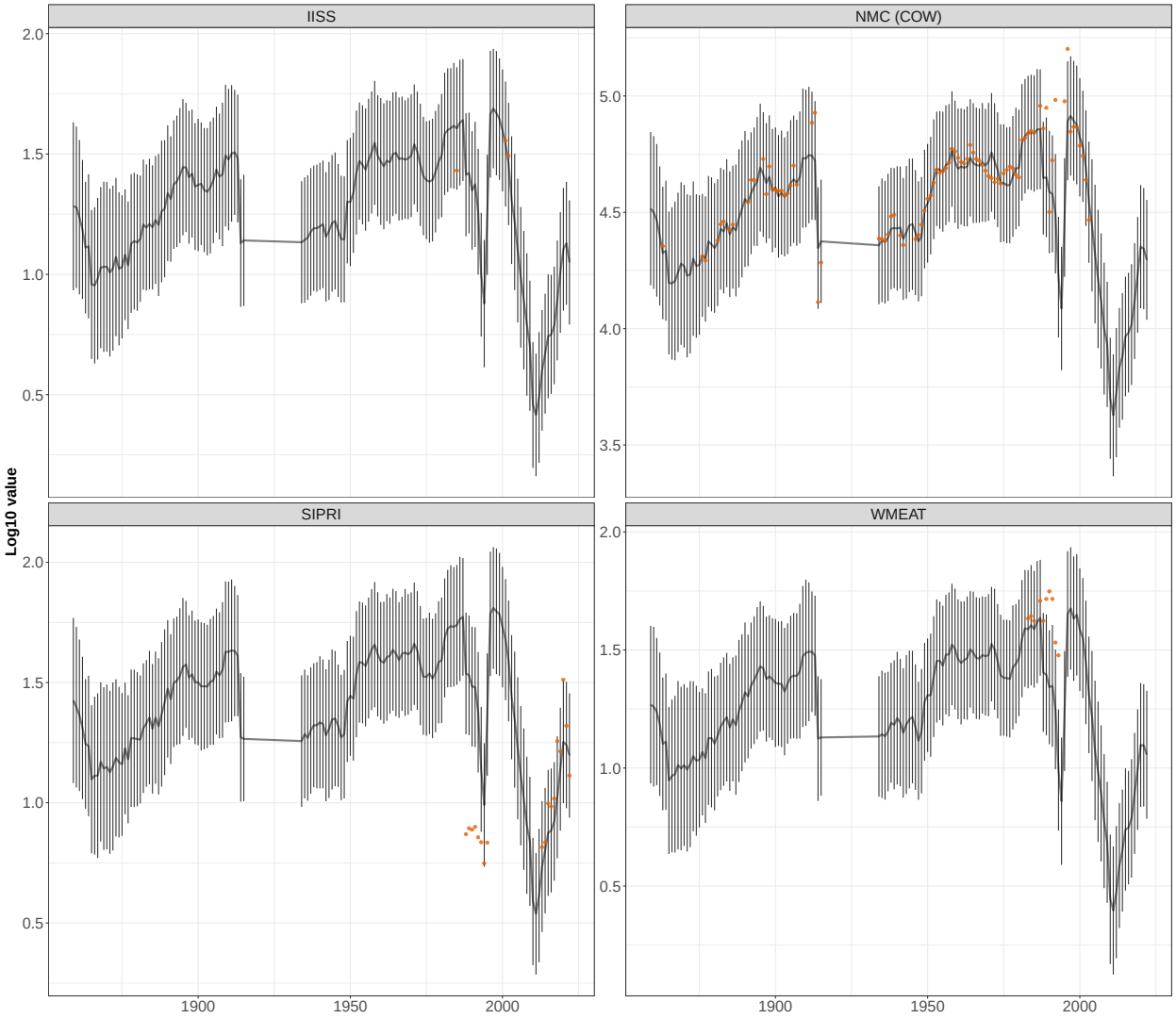

Figure 26: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Haiti.

3.26 Iceland

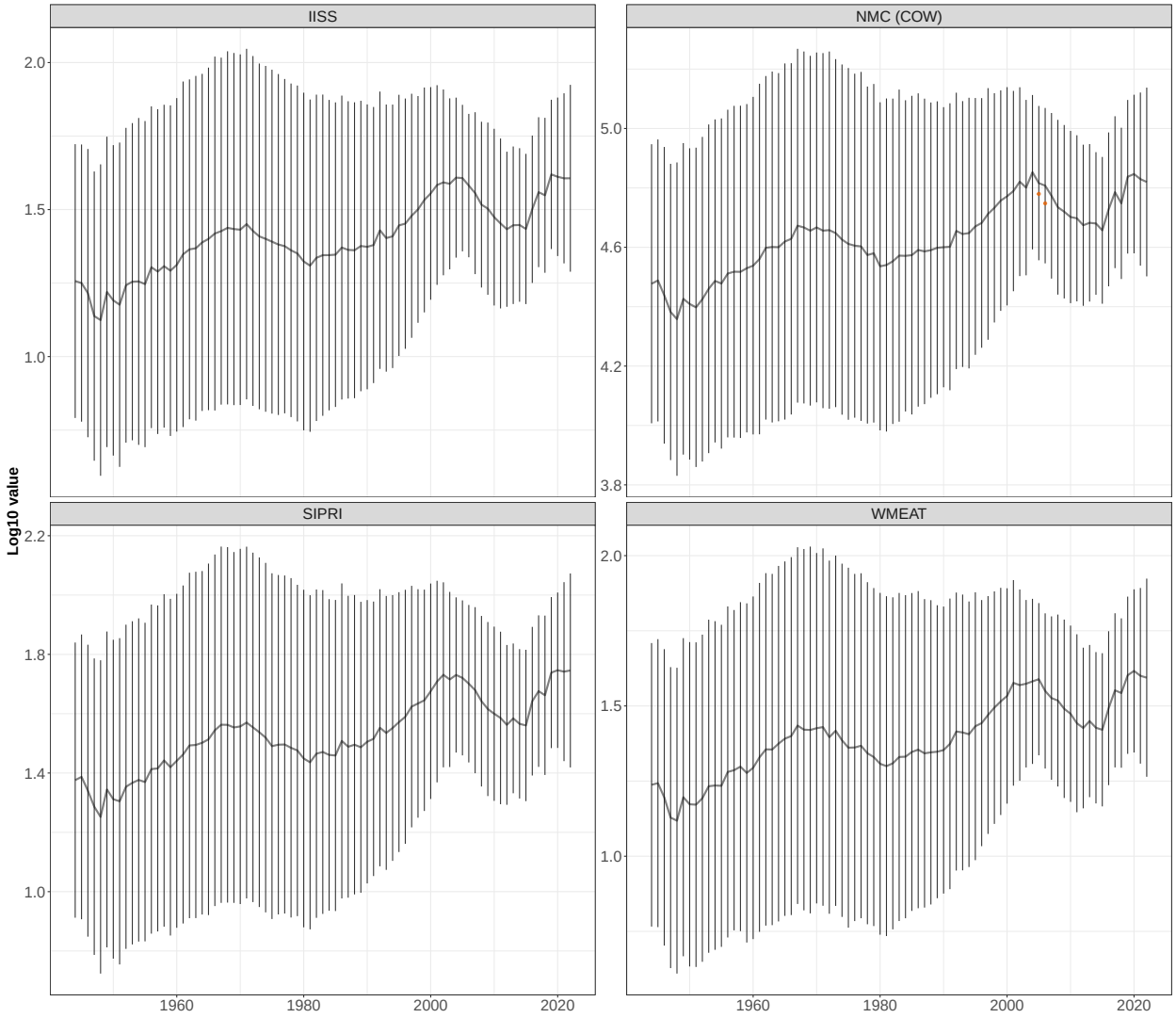

Figure 27: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Iceland.

3.27 Iraq

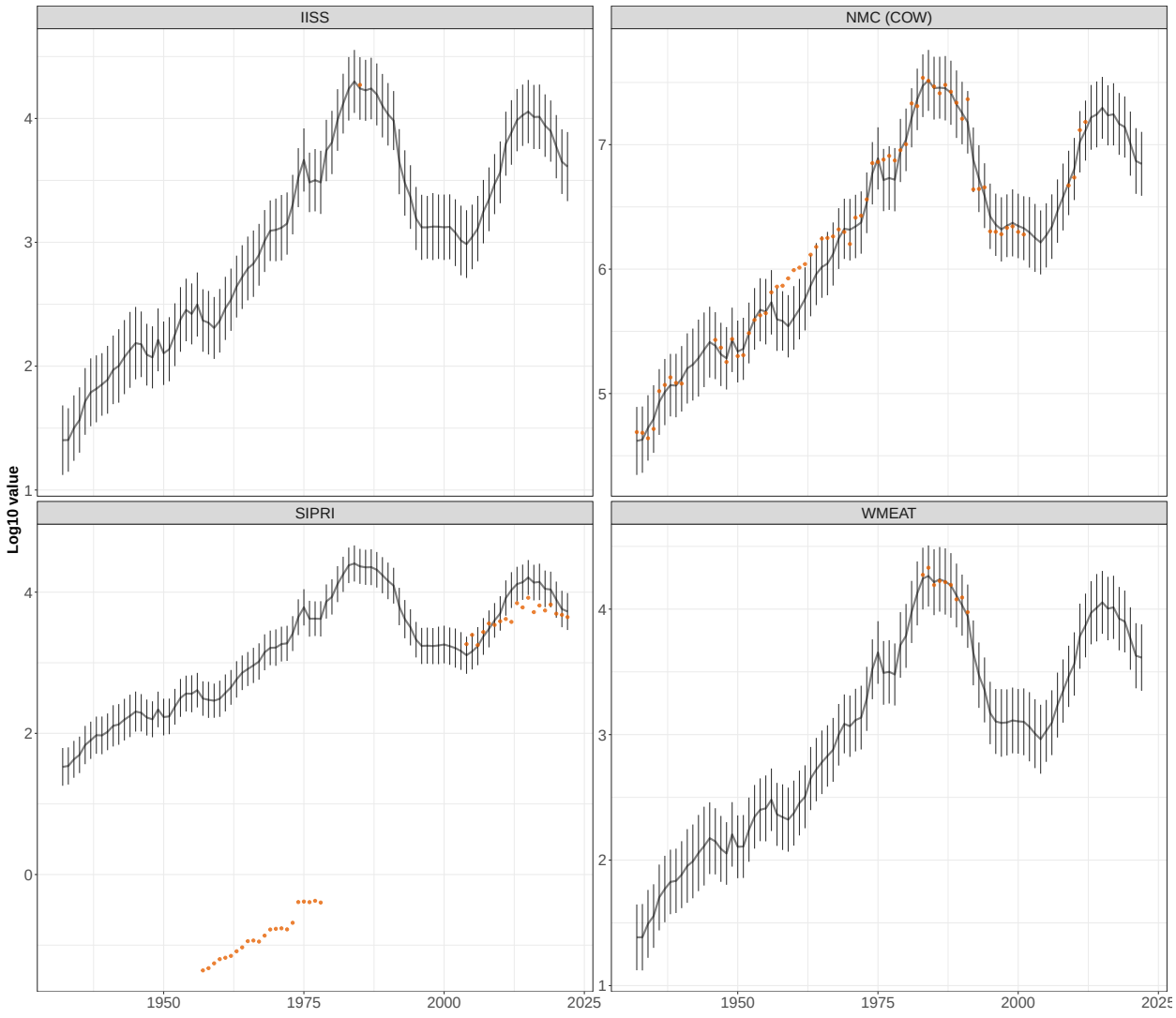

Figure 28: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Iraq.

3.28 Myanmar

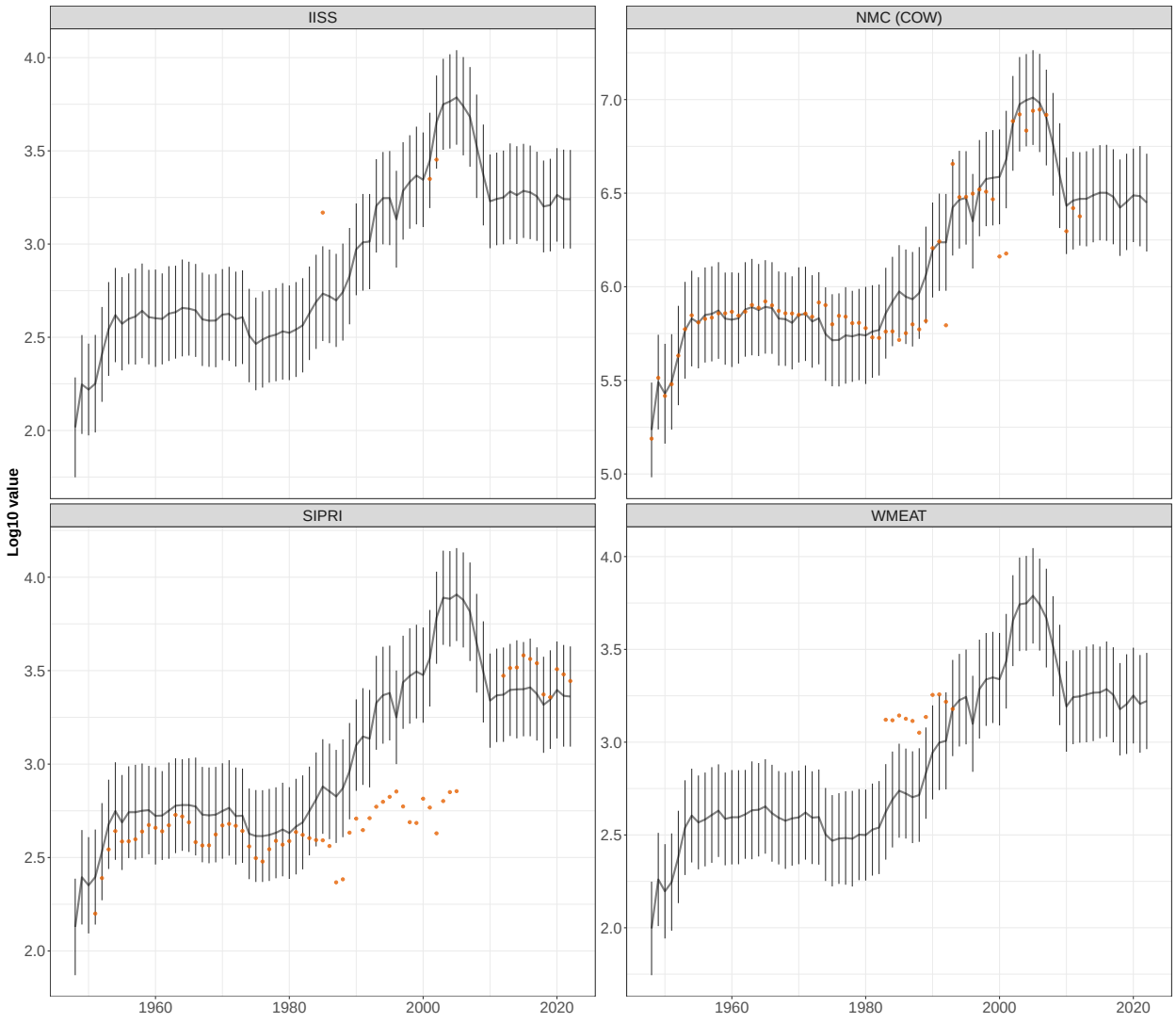

Figure 29: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Myanmar.

3.29 Nicaragua

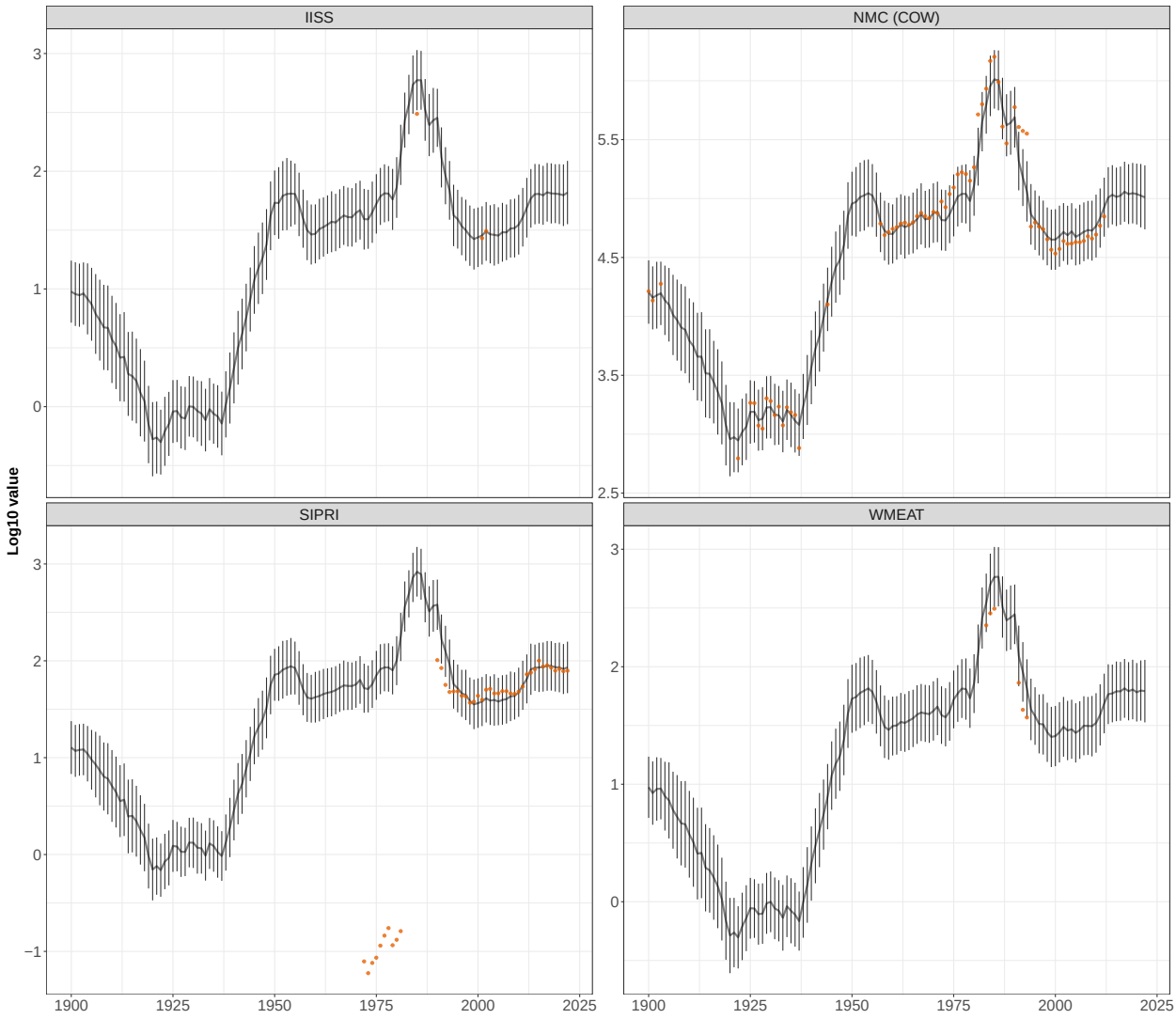

Figure 30: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Nicaragua.

3.30 Yemen (Arab Republic of Yemen)

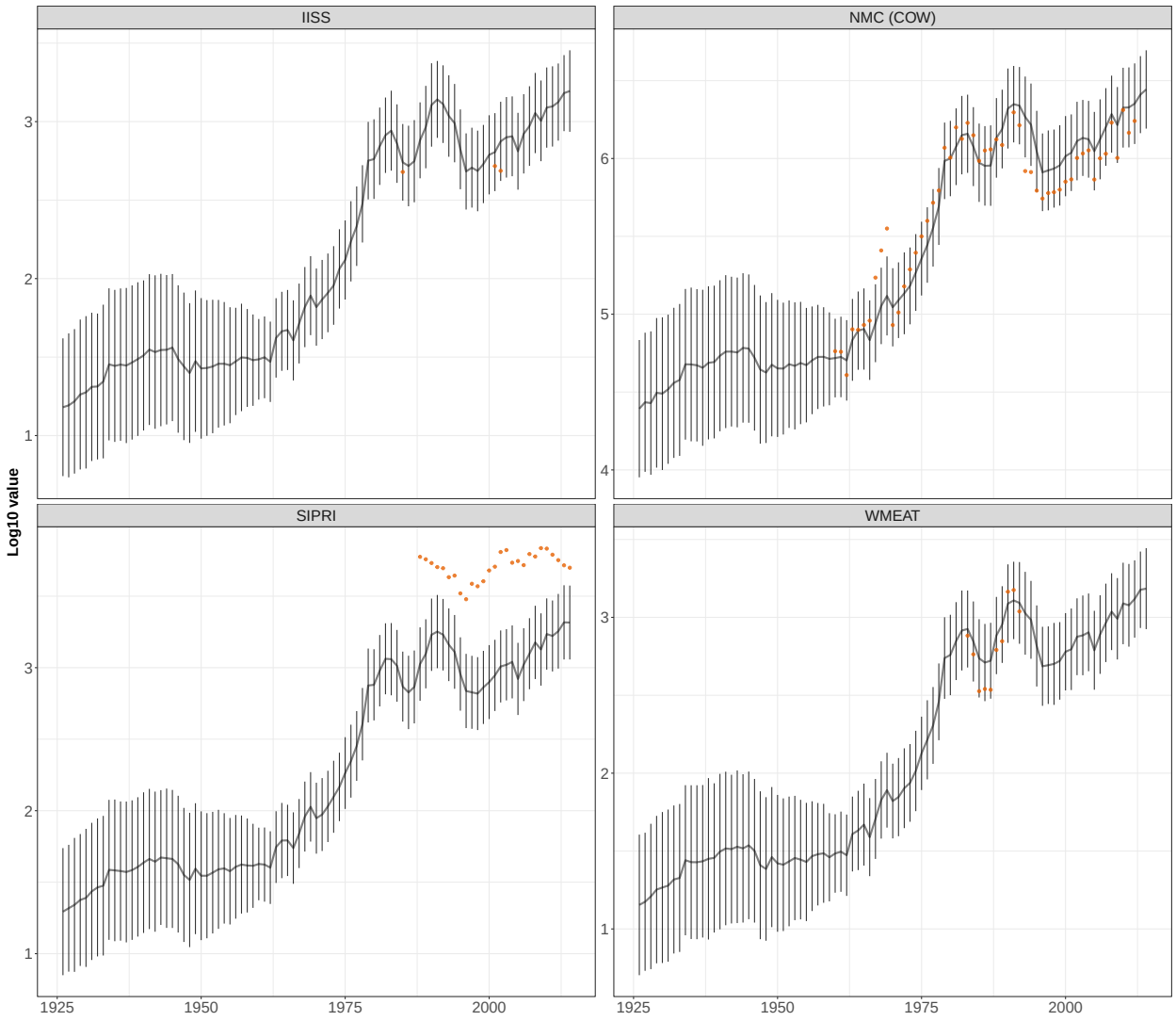

Figure 31: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Arab Republic of Yemen

3.31 Peru

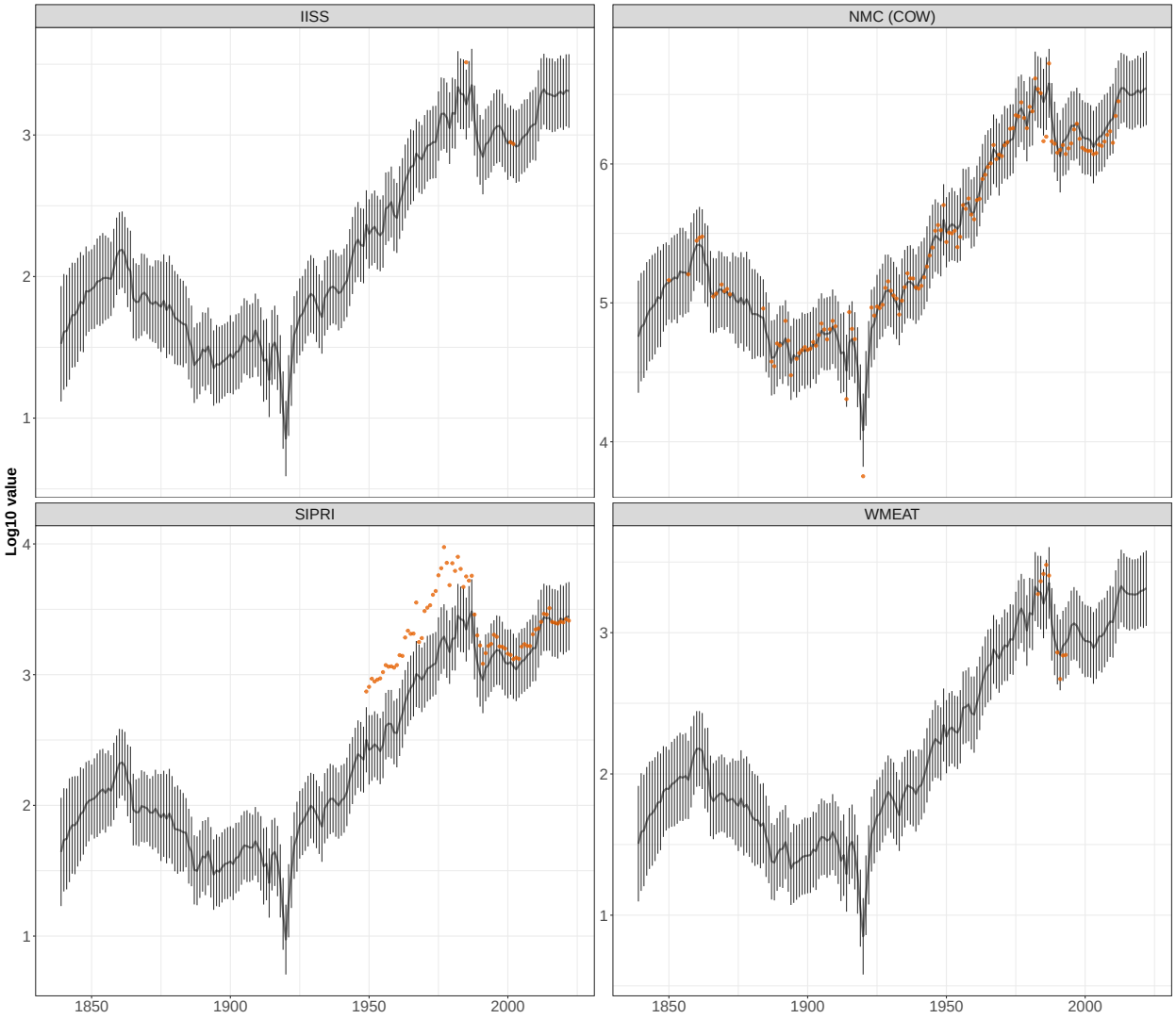

Figure 32: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Peru.

3.32 Somalia

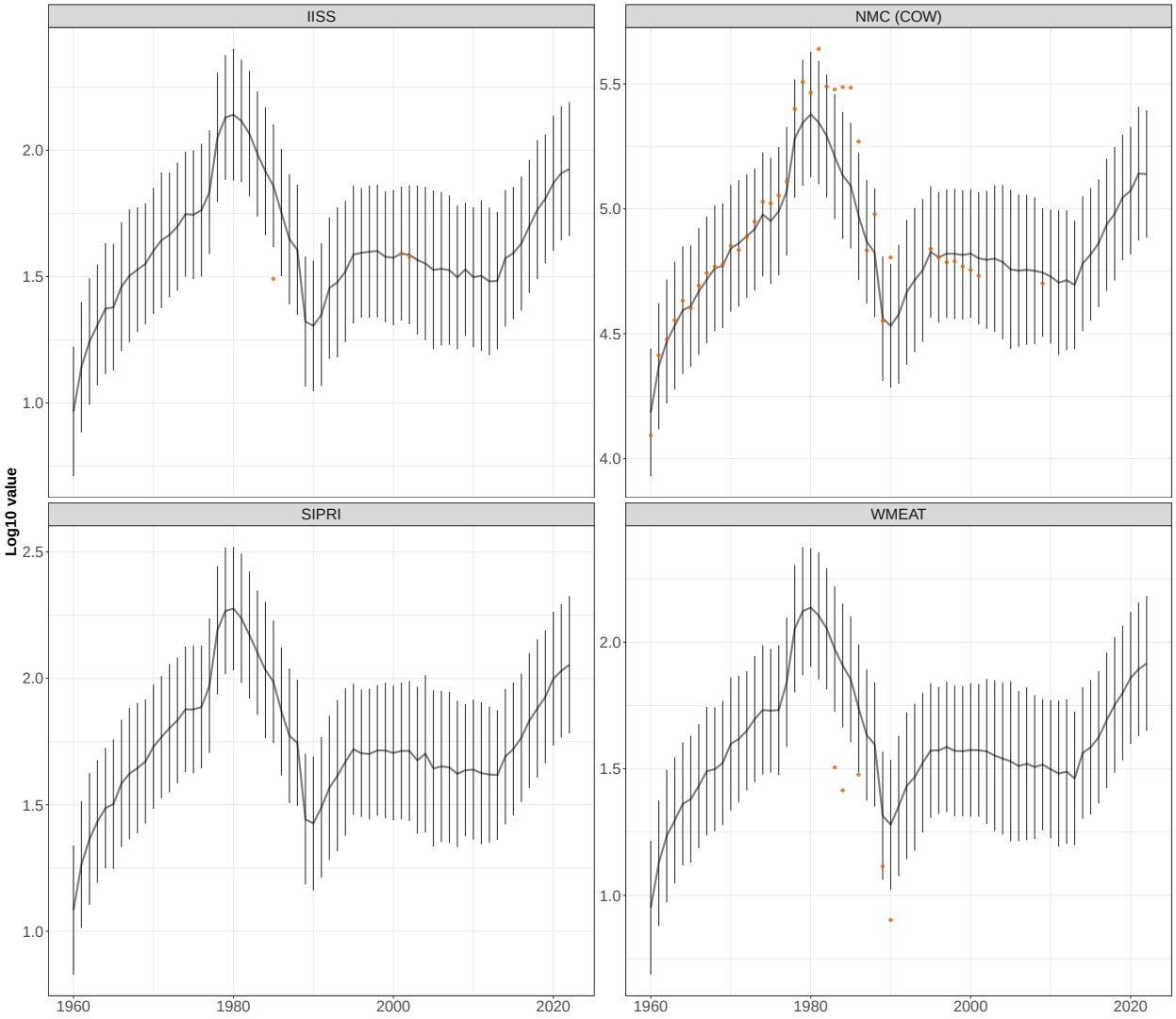

Figure 33: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Somalia.

3.33 Trinidad and Tobago

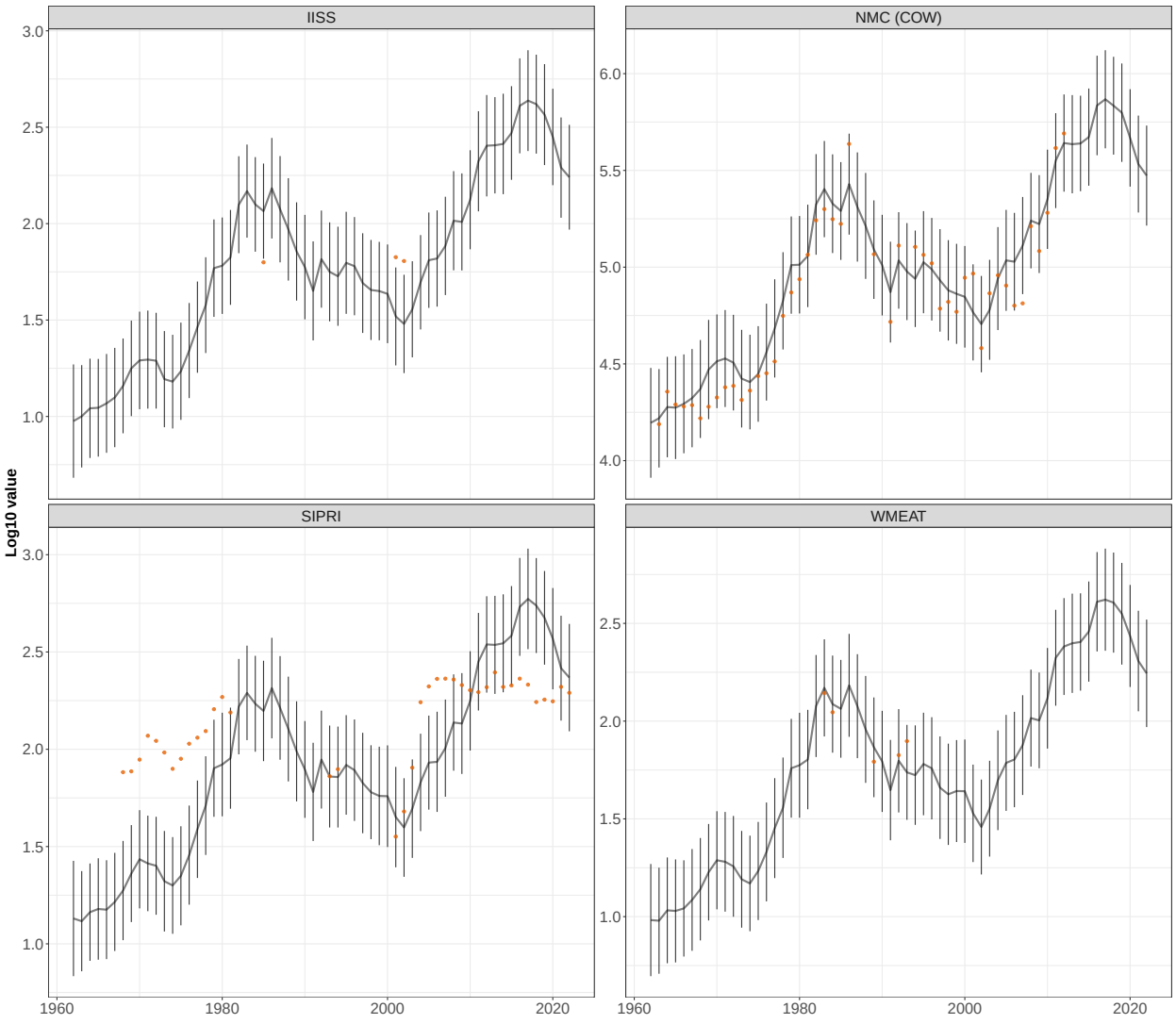

Figure 34: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Trinidad and Tobago.

3.34 Uzbekistan

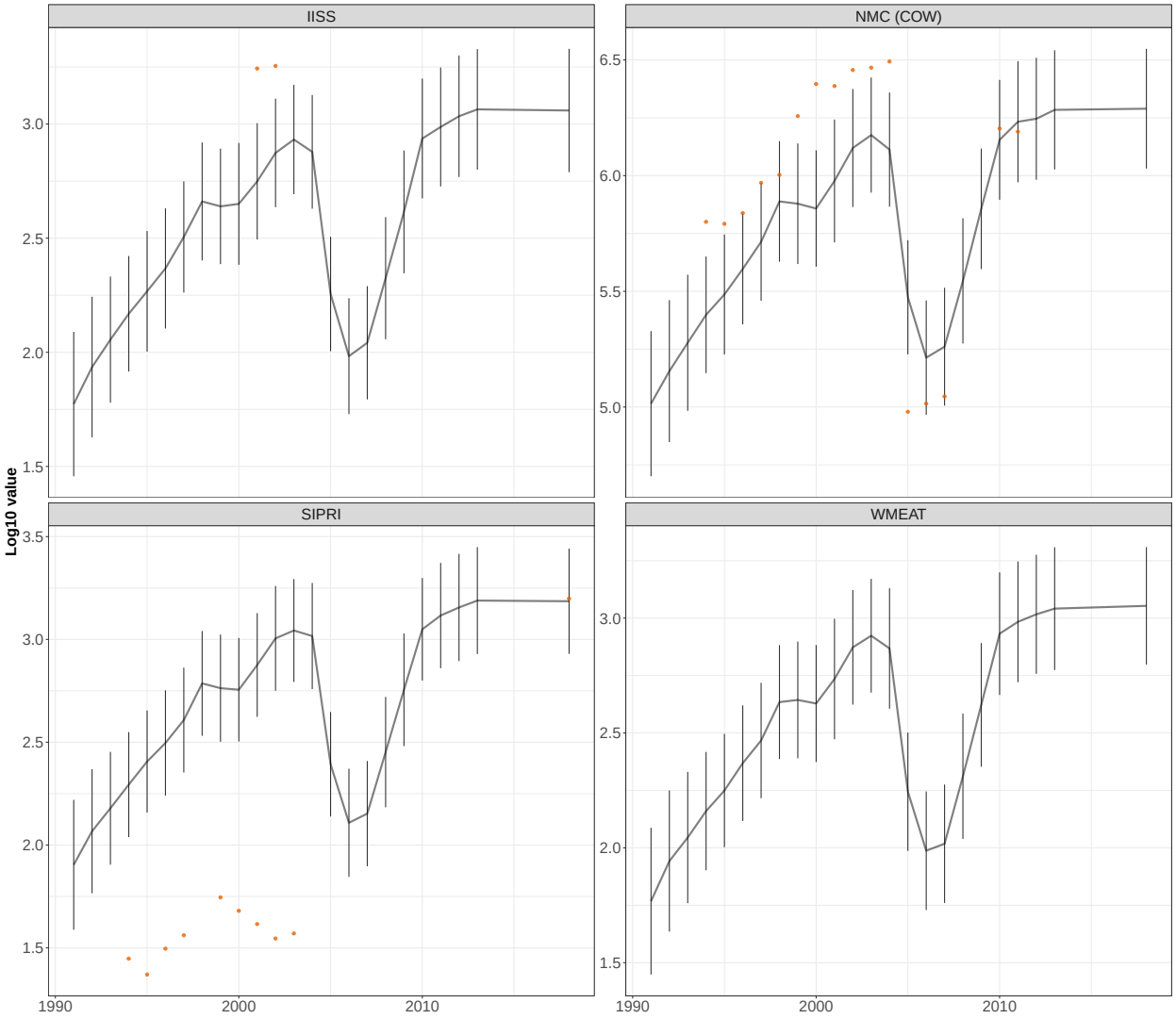

Figure 35: Posterior prediction intervals (gray lines) with ± 1 standard deviation confidence bands and observed variables (orange points) for Uzbekistan.

3.35 Distributions for China, United Kingdom, and the USA (1990)

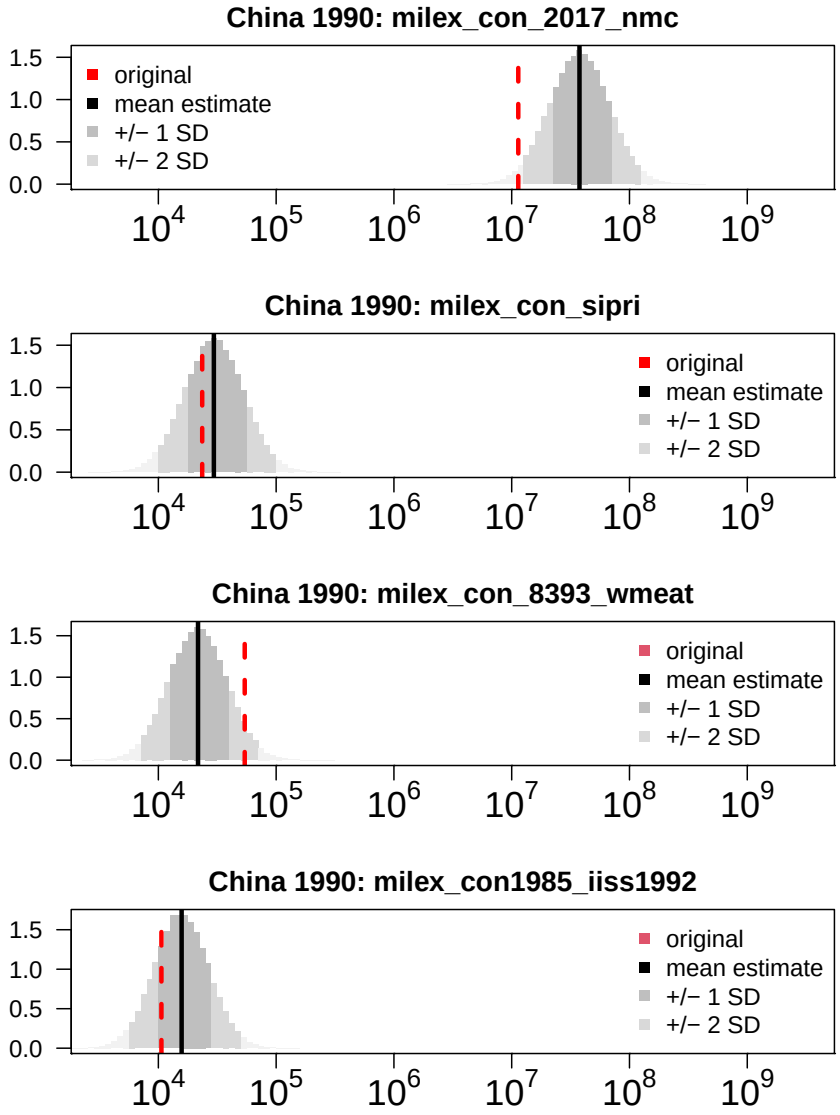

Figure 36: Example posterior prediction distributions and observed dataset values (red line) for 1990. The observed dataset values (red line) are plotted along with the range of estimates for the country-year cases derived from the latent variable model. The dataset values are from four distinct datasets which use different monetary units-of-measurement. Importantly, our latent variable model allow us to generate the posterior prediction distributions in terms of these original monetary units-of-measurement as function of the latent variable itself. The plots also illustrates the relative amount of disagreement between estimated distribution and the observed dataset value which we can characterize with a simple Z-score.

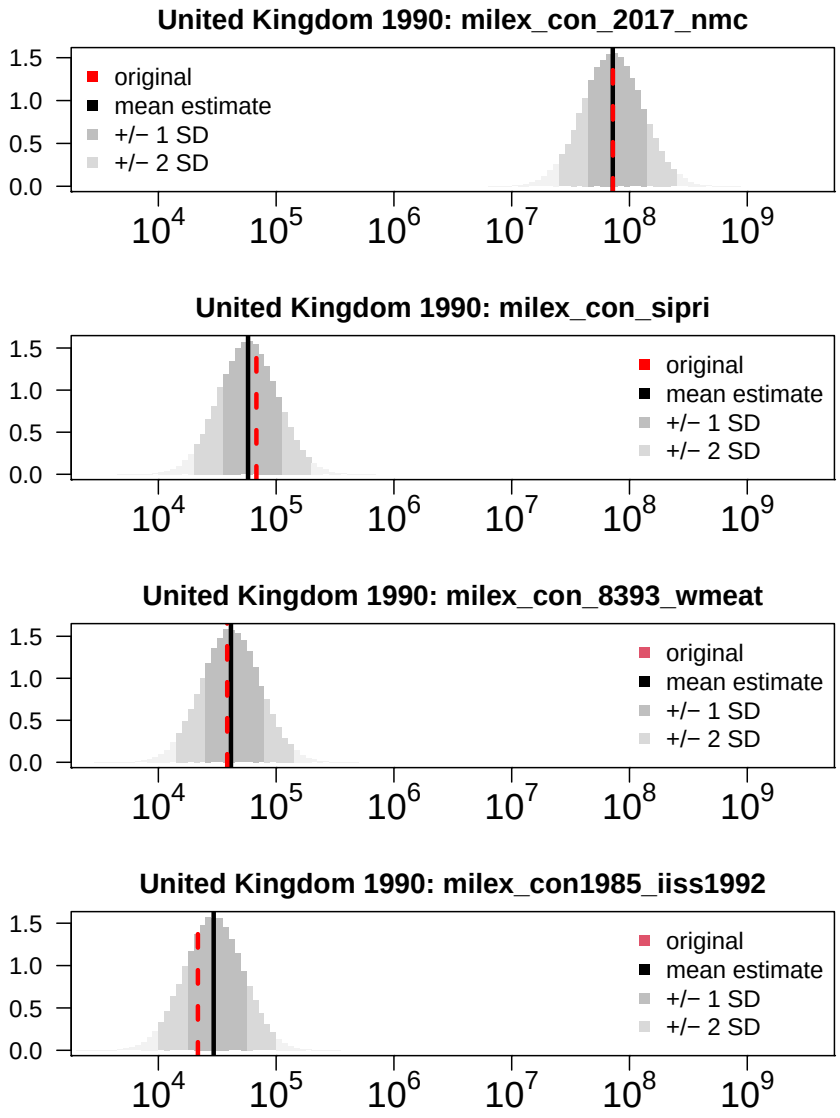

Figure 37: Example posterior prediction distributions and observed dataset values (red line) for 1990. Same information as above.

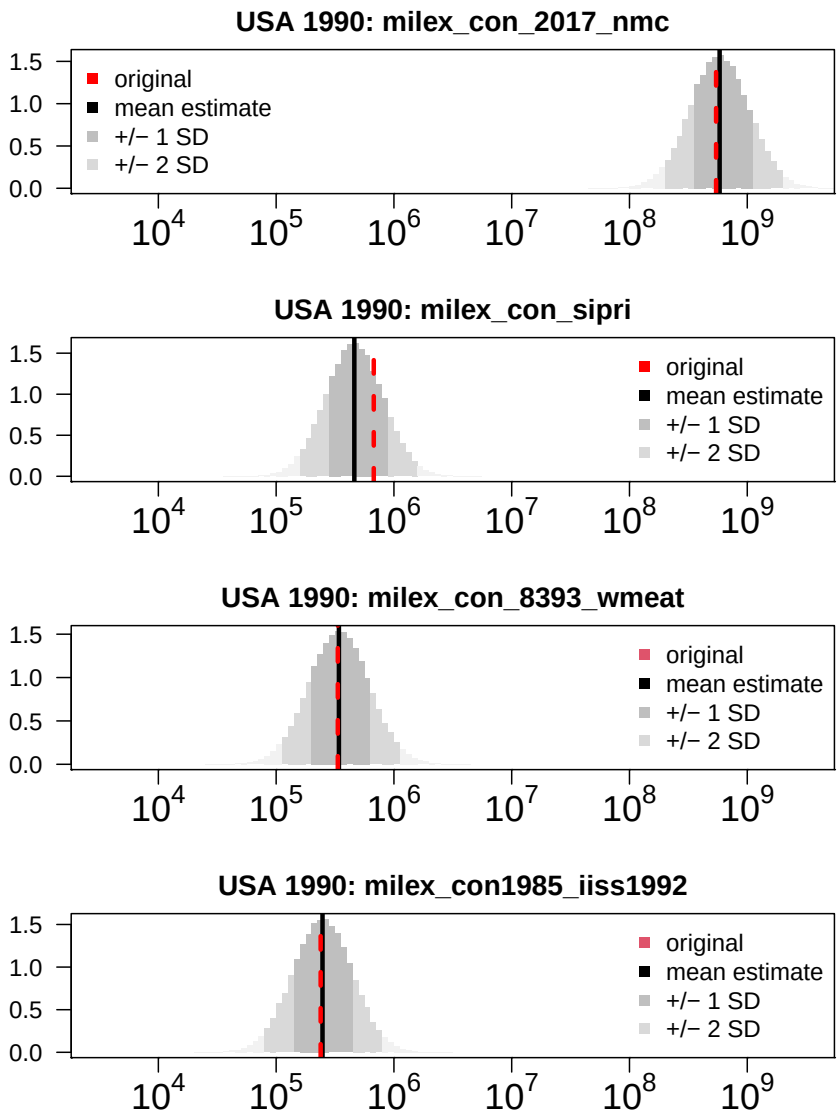

Figure 38: Example posterior prediction distributions and observed dataset values (red line) for 1990. Same information as above.

3.36 Distributions for China, United Kingdom, and the USA (2010)

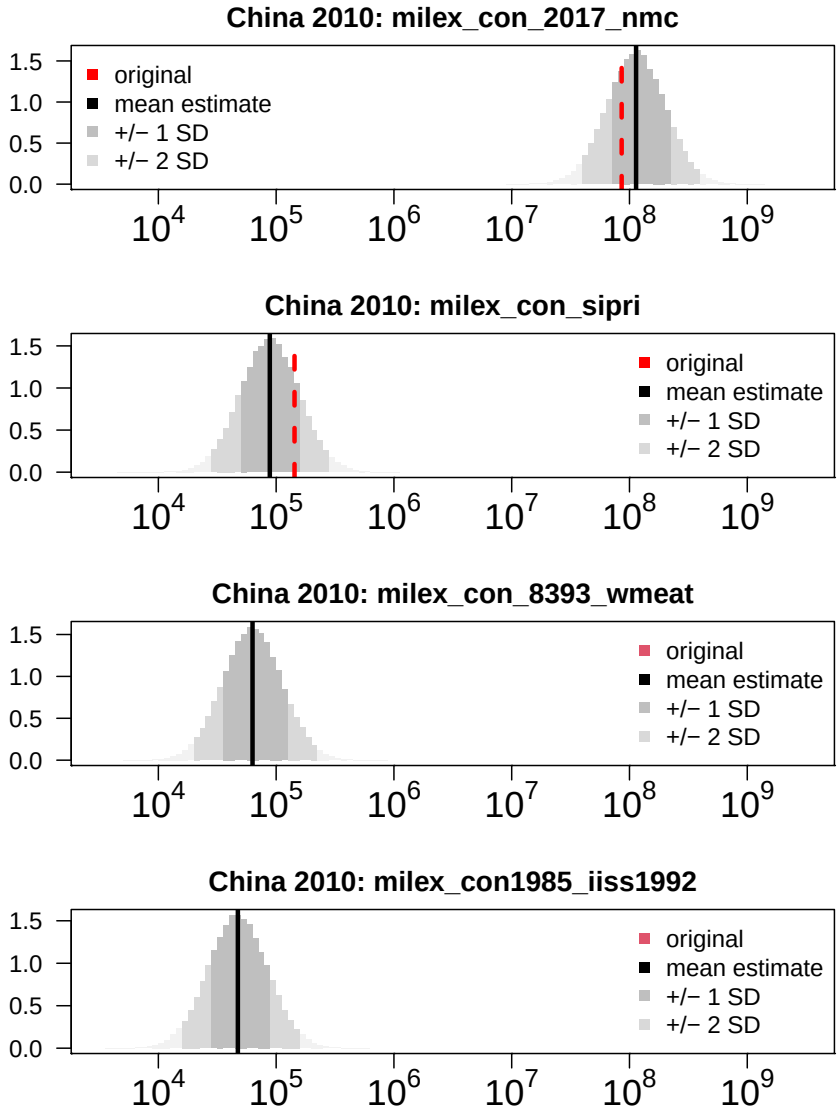

Figure 39: Example posterior prediction distributions and observed dataset values (red line) for 2010 Same information as above. Note also that only 2 of country-year-items is observed. This is because not all dataset values need to be observed for the latent variable model to estimate a distribution.

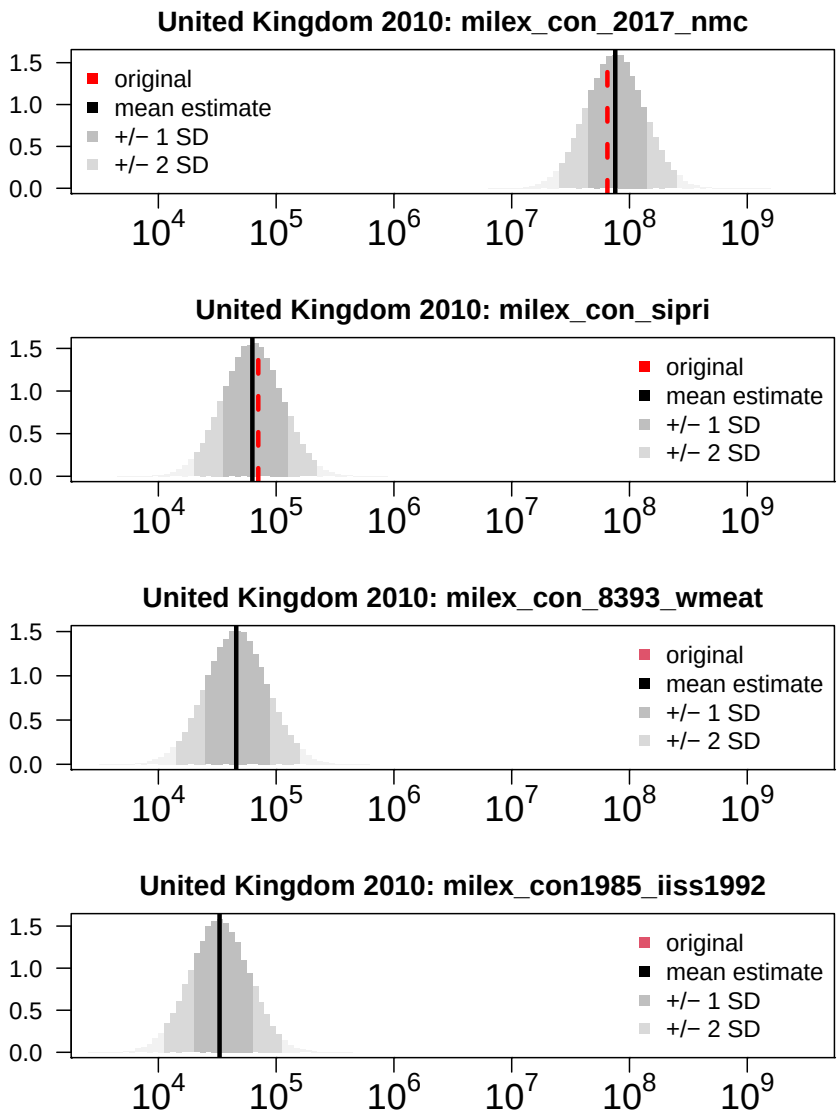

Figure 40: Example posterior prediction distributions and observed dataset values (red line) for 2010 Same information as above. Note also that only 2 of country-year-items is observed. This is because not all dataset values need to be observed for the latent variable model to estimate a distribution.

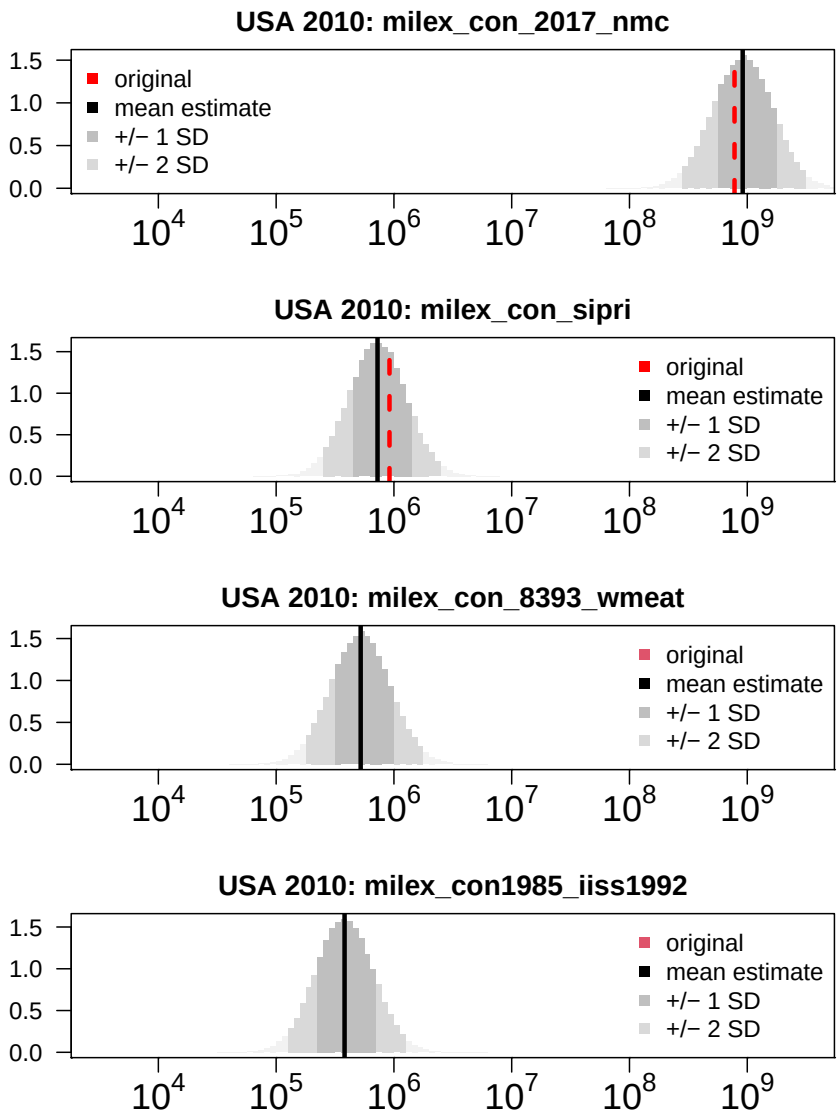

Figure 41: Example posterior prediction distributions and observed dataset values (red line) for 2010 Same information as above. Note also that only 2 of country-year-items is observed. This is because not all dataset values need to be observed for the latent variable model to estimate a distribution.

3.37 Distributions for China, United Kingdom, and the USA (2019)

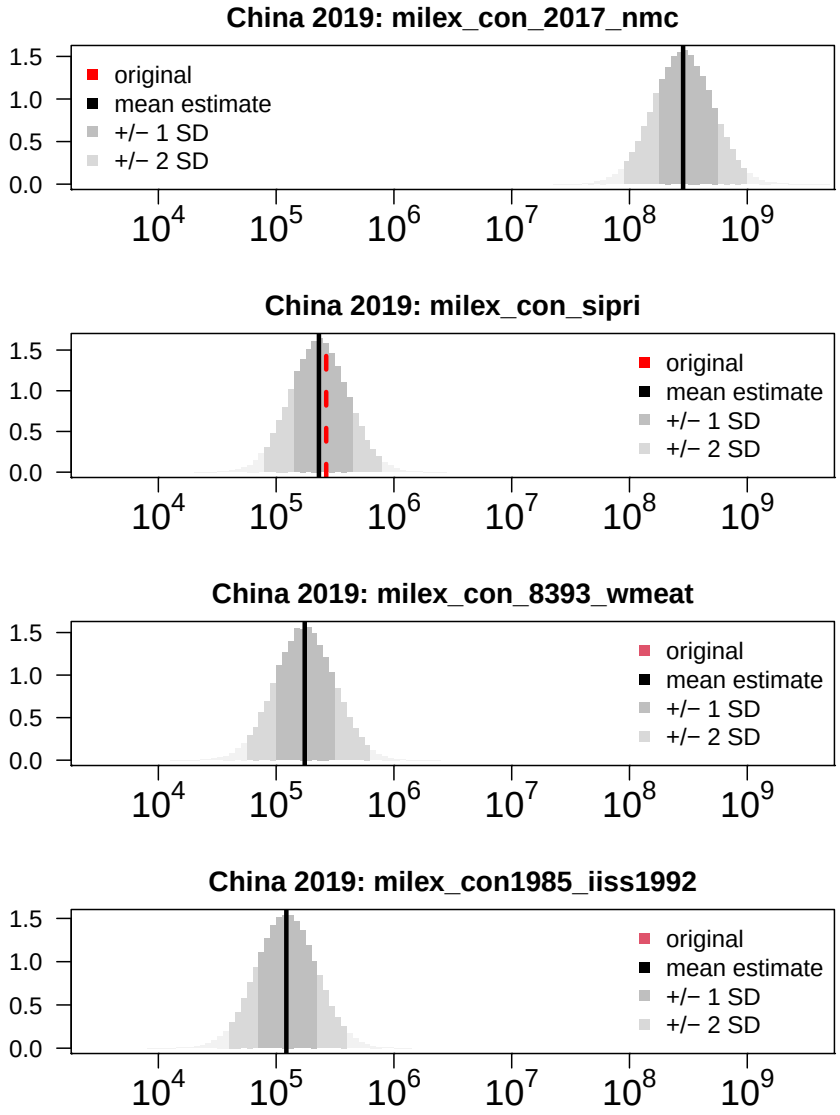

Figure 42: Example posterior prediction distributions and observed dataset values (red line) for 2019. Same information as above. Note also that only 1 of country-year-items is observed. This is because not all dataset values need to be observed for the latent variable model to estimate a distribution.

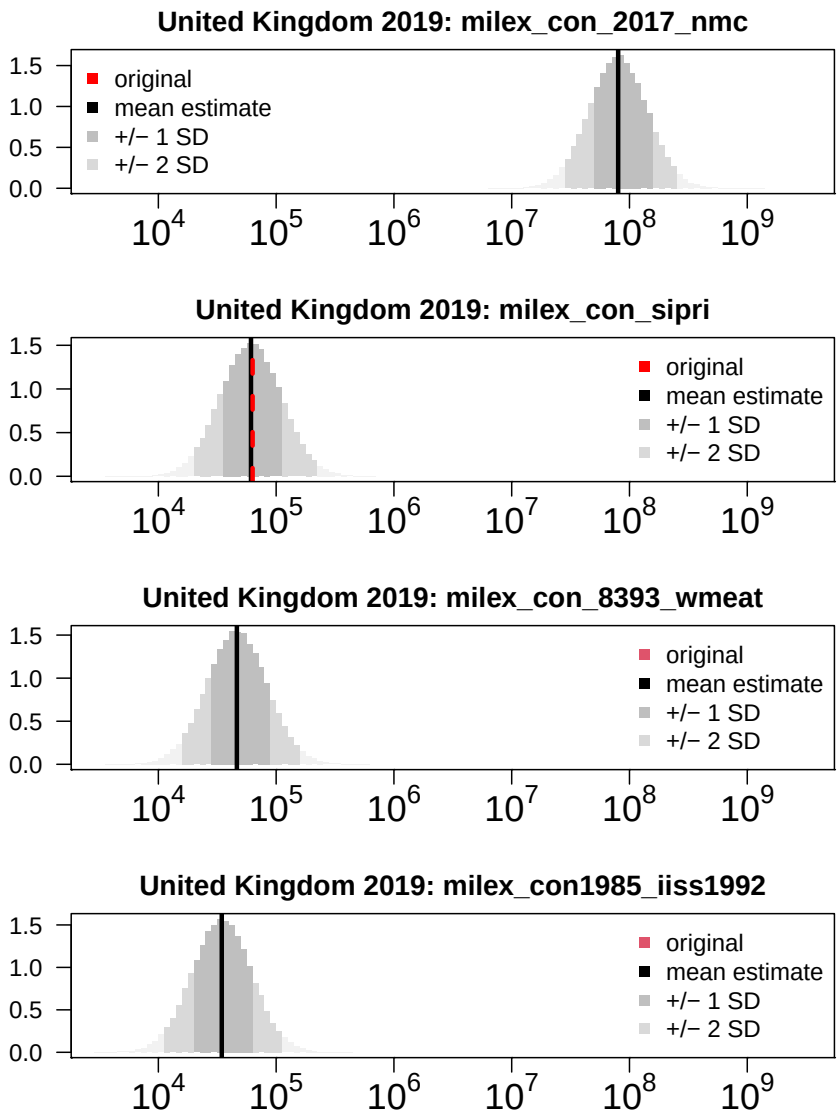

Figure 43: Example posterior prediction distributions and observed dataset values (red line) for 2019. Same information as above. Note also that only 1 of country-year-items is observed. This is because not all dataset values need to be observed for the latent variable model to estimate a distribution.

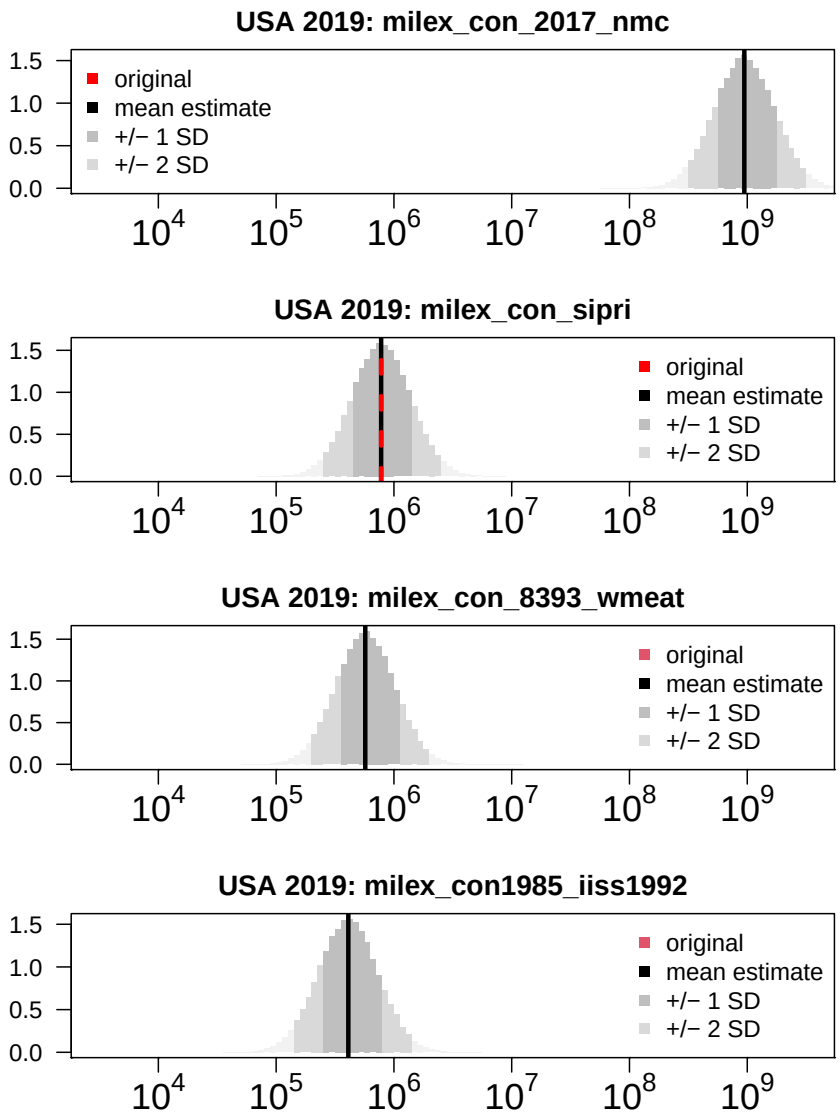

Figure 44: Example posterior prediction distributions and observed dataset values (red line) for 2019. Same information as above. Note also that only 1 of country-year-items is observed. This is because not all dataset values need to be observed for the latent variable model to estimate a distribution.

4 Proportion of Coverage by Observed Variable

In the main manuscript, we discuss how closely do our country-year intervals correspond to the observed dataset values and what does it mean when they do not? To do so, we first calculated country-year Z-scores for every observed dataset value: $z_{itj} = \frac{(y_{itj} - E(\tilde{y}_{itj}))}{(\sigma_{y_{itj}})}$. These Z-scores tell us how far away an observed dataset value y_{itj} is from the center $E(\tilde{y}_{itj})$ of the estimated country-year distribution, which is then standardized by the overall size of the country-year distribution $\sigma_{y_{itj}}$. Where $\tilde{y}_{itj}$ are the estimated country-year-item distributions for each of the observed dataset values.

We use these country-year Z-scores to tell us where the observed dataset values reside relative to the estimated country-year distributions from the latent variable model. The proportions in the tables below tell us how many of the observed dataset values fall within ± 1, ± 2, or ± 3 standard deviations of the estimated country-year ranges (credible intervals), which we calculate using the country-year Z-scores above.

	Publisher	Variable	1sd	2sd	3sd	Units	Start	End
1	IISS	milex_con1968?_iiss1968	0.956	1.000	1.000	114	1967	1968
2	IISS	milex_con1985_iiss1989	0.784	0.933	0.976	328	1979	1989
3	IISS	milex_con1985_iiss1991	0.861	0.965	0.987	317	1985	1990
4	IISS	milex_con1985_iiss1992	0.868	0.972	0.994	355	1985	1991
5	IISS	milex_con1985_iiss1993	0.824	0.944	0.976	376	1985	1992
6	IISS	milex_con1995_iiss1997	0.943	0.994	0.998	470	1985	1996
7	IISS	milex_con1997_iiss1998	0.938	0.987	0.991	468	1985	1997
8	IISS	milex_con1999_iiss2000	0.947	0.987	0.996	474	1985	1999
9	IISS	milex_con2000_iiss2003	0.883	0.981	0.994	471	1985	2002
10	NCD	milex_con_1960_ncd	0.914	0.982	0.986	1823	1950	1970
11	NCD	milex_con_1973_ncd	0.935	0.992	0.993	1138	1968	1976
12	NCD	milex_con_1980_ncd	0.876	0.990	0.996	1605	1973	1985
13	NCD	milex_con_1986_ncd	0.878	0.971	0.994	656	1983	1988
14	NMC (COW)	milex_con_2017_nmc	0.960	0.995	0.999	12430	1816	2012
15	Peters/Sweden	milex_con1967_swd	0.951	1.000	1.000	103	1865	1967
16	SIPRI	milex_con_sipri	0.806	0.946	0.974	7807	1949	2022
17	WMEAT	milex_con_6373_wmeat	0.916	0.977	0.992	597	1963	1973
18	WMEAT	milex_con_6675_wmeat	0.956	0.996	0.999	1251	1966	1975
19	WMEAT	milex_con_6776_wmeat	0.936	0.983	0.992	1274	1967	1976
20	WMEAT	milex_con_6877_wmeat	0.937	0.998	0.999	829	1968	1977
21	WMEAT	milex_con_6978_wmeat	0.942	0.998	1.000	1249	1969	1978
22	WMEAT	milex_con_7383_wmeat	0.922	0.991	1.000	1340	1973	1983
23	WMEAT	milex_con_8191_wmeat	0.901	0.993	1.000	1361	1981	1991
24	WMEAT	milex_con_8393_wmeat	0.898	0.993	0.999	1369	1983	1993

Table 4: Estimated Military Expenditure Interval Coverage: Constant US Dollar Variables

	Publisher	Variable	1sd	2sd	3sd	Units	Start	End
25	IISS	milex_cur_iiss1969	0.875	1.000	1.000	104	1968	1969
26	IISS	milex_cur_iiss1970	0.880	0.991	1.000	117	1969	1970
27	IISS	milex_cur_iiss1971	0.928	1.000	1.000	111	1970	1971
28	IISS	milex_cur_iiss1972	0.896	1.000	1.000	106	1971	1972
29	IISS	milex_cur_iiss1973	0.843	0.980	1.000	102	1972	1973
30	IISS	milex_cur_iiss1975	0.856	0.970	1.000	236	1972	1975
31	IISS	milex_cur_iiss1974	0.807	0.958	1.000	119	1973	1974
32	IISS	milex_cur_iiss1976	0.873	0.978	1.000	228	1973	1976
33	IISS	milex_cur_iiss1977	0.868	0.979	0.996	234	1974	1977
34	IISS	milex_cur_iiss1978	0.881	0.979	0.996	235	1975	1978
35	IISS	milex_cur_iiss1980	0.922	0.994	1.000	167	1975	1980
36	IISS	milex_cur_iiss1981	0.917	0.981	0.994	157	1975	1981
37	IISS	milex_cur_iiss1982	0.917	0.974	1.000	193	1975	1982
38	IISS	milex_cur_iiss1979	0.923	0.983	1.000	233	1976	1979
39	IISS	milex_cur_iiss1985	0.891	0.960	0.987	376	1976	1985
40	IISS	milex_cur_iiss1983	0.902	0.966	0.987	235	1978	1982
41	IISS	milex_cur_iiss1984	0.910	0.965	1.000	255	1979	1982
42	IISS	milex_cur_iiss1986	0.859	0.966	0.990	384	1981	1984
43	IISS	milex_cur_iiss1988	0.831	0.959	0.994	338	1984	1988
44	IISS	milex_cur_iiss2004	0.848	0.961	0.988	486	2001	2003
45	IISS	milex_cur_iiss2005	0.880	0.964	0.994	475	2002	2004
46	IISS	milex_cur_iiss2006	0.895	0.975	0.998	477	2002	2004
47	IISS	milex_cur_iiss2007	0.883	0.955	0.985	470	2003	2005
48	IISS	milex_cur_iiss2008	0.891	0.960	0.983	477	2004	2006
49	IISS	milex_cur_iiss2009	0.949	0.996	1.000	473	2005	2007
50	IISS	milex_cur_iiss2010	0.959	0.996	0.996	466	2006	2008

Table 5: Estimated Military Expenditure Interval Coverage: Current US Dollar Variables part 1

	Publisher	Variable	1sd	2sd	3sd	Units	Start	End
51	IISS	milex_cur_iiss2011	0.964	0.998	1.000	468	2007	2009
52	IISS	milex_cur_iiss2012	0.966	0.996	0.998	467	2008	2010
53	IISS	milex_cur_iiss2013	0.920	0.976	0.991	450	2010	2012
54	IISS	milex_cur_iiss2014	0.973	0.991	0.998	451	2011	2013
55	IISS	milex_cur_iiss2015	0.971	0.984	0.996	446	2012	2014
56	IISS	milex_cur_iiss2016	0.954	0.973	0.993	437	2013	2015
57	IISS	milex_cur_iiss2017	0.968	0.977	0.991	442	2014	2016
58	IISS	milex_cur_iiss2018	0.960	0.984	0.998	446	2015	2017
59	IISS	milex_cur_iiss2019	0.957	0.982	0.998	446	2016	2018
60	IISS	milex_cur_iiss2020	0.951	0.984	1.000	445	2017	2019
61	IISS	milex_cur_iiss2021	0.956	0.978	0.996	450	2018	2020
62	MDED	milex_cur_mded	0.807	0.914	0.950	535	1948	1958
63	NMC (COW)	milex_cur_nmc	0.908	0.978	0.993	12430	1816	2012
64	SIPRI	milex_cur_sipri	0.862	0.953	0.980	8044	1949	2022
65	SIRE NATDAT	milex_cur_snd	0.903	0.969	0.991	2656	1948	1983
66	WMEAT	milex_cur_6170_wmeat	0.856	0.969	0.983	541	1961	1970
67	WMEAT	milex_cur_6373_wmeat	0.864	0.944	0.977	610	1963	1973
68	WMEAT	milex_cur_6675_wmeat	0.902	0.976	0.992	1249	1966	1975
69	WMEAT	milex_cur_6776_wmeat	0.851	0.962	0.979	1275	1967	1976
70	WMEAT	milex_cur_6877_wmeat	0.852	0.970	0.996	829	1968	1977
71	WMEAT	milex_cur_6978_wmeat	0.862	0.974	0.990	1257	1969	1978
72	WMEAT	milex_cur_7383_wmeat	0.812	0.961	0.990	1340	1973	1983
73	WMEAT	milex_cur_8191_wmeat	0.800	0.942	0.991	1355	1981	1991
74	WMEAT	milex_cur_8393_wmeat	0.802	0.947	0.990	1366	1983	1993
75	Zimmerman/USSR	milex_cur_cw_soviet	0.310	0.828	0.828	29	1955	1983
76	Zimmerman/USSR	milex_cur_high_soviet	0.379	0.690	0.828	29	1955	1983
77	Zimmerman/USSR	milex_cur_low_soviet	0.379	0.724	0.828	29	1955	1983

Table 6: Estimated Military Expenditure Interval Coverage: Current US Dollar Variables part 2

	Publisher	Variable	1sd	2sd	3sd	Units	Start	End
1	NMC (COW)	milex_con_2017_nmc	0.988	0.999	1.000	4077	1816	1947
2	Peters/Sweden	milex_con1967_swd	0.940	1.000	1.000	83	1865	1947
3	NMC (COW)	milex_cur_nmc	0.959	0.994	0.999	4077	1816	1947

Table 7: Estimated Military Expenditure Interval Coverage for units prior to 1948 (Constant or Current)

5 Country Plots with Normalized Posterior Prediction Intervals and Data Points

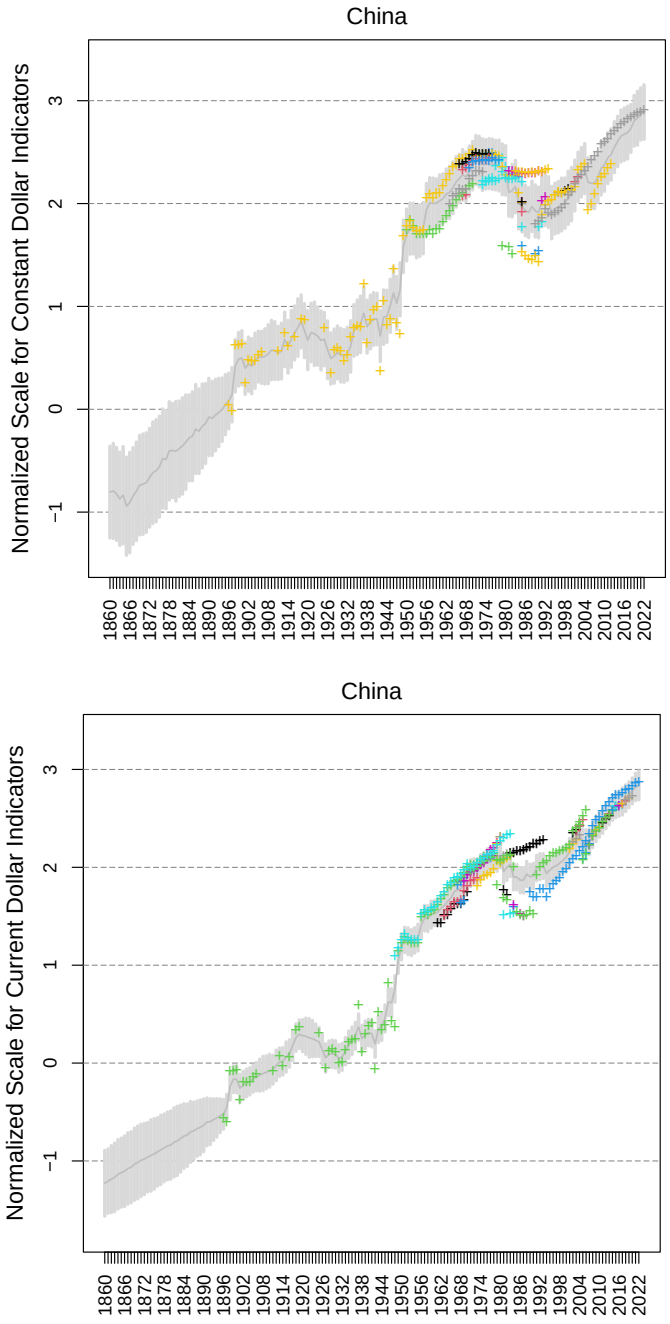

Figure 45: Constant series and data in the upper plot. Current series and data in the lower plot.

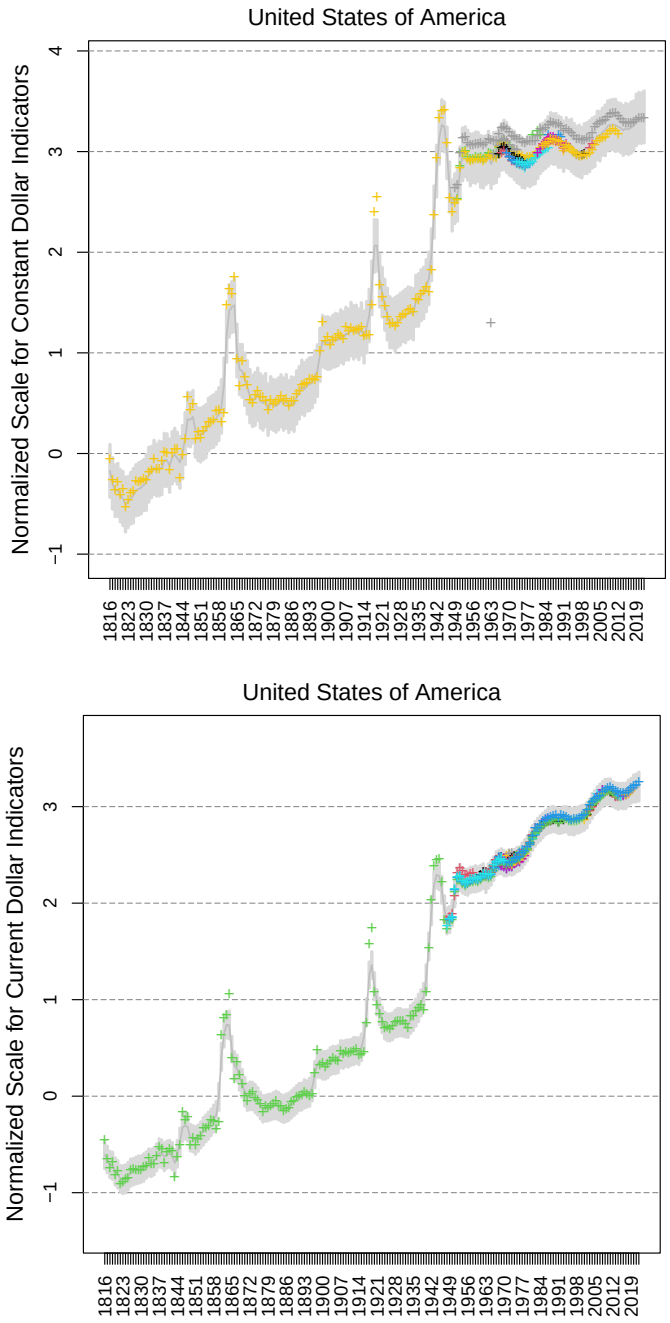

Figure 46: Constant series and data in the upper plot. Current series and data in the lower plot.

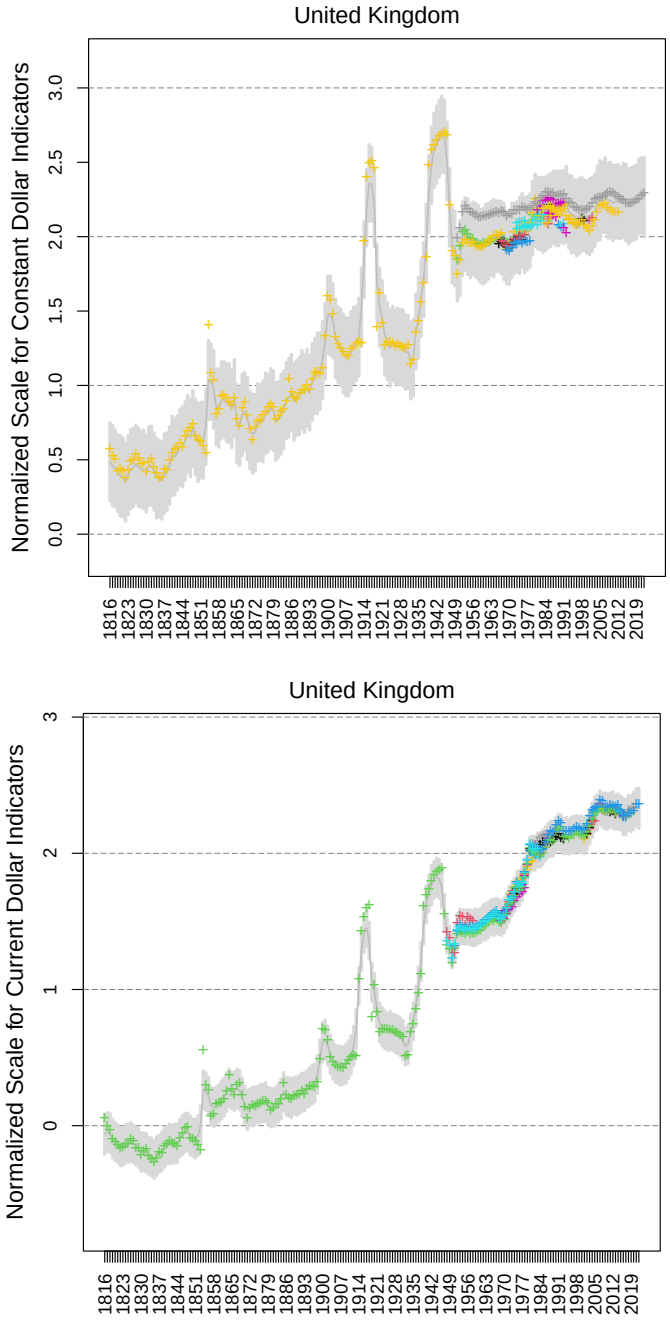

Figure 47: Constant series and data in the upper plot. Current series and data in the lower plot.

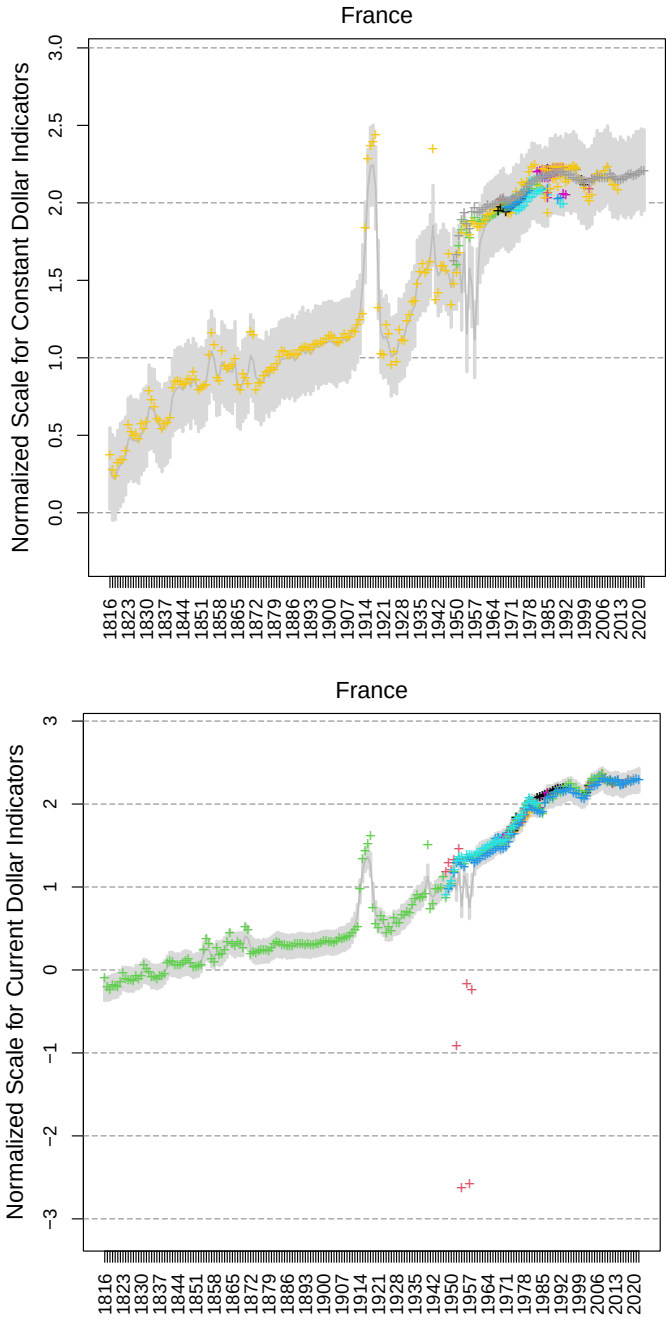

Figure 48: Constant series and data in the upper plot. Current series and data in the lower plot.

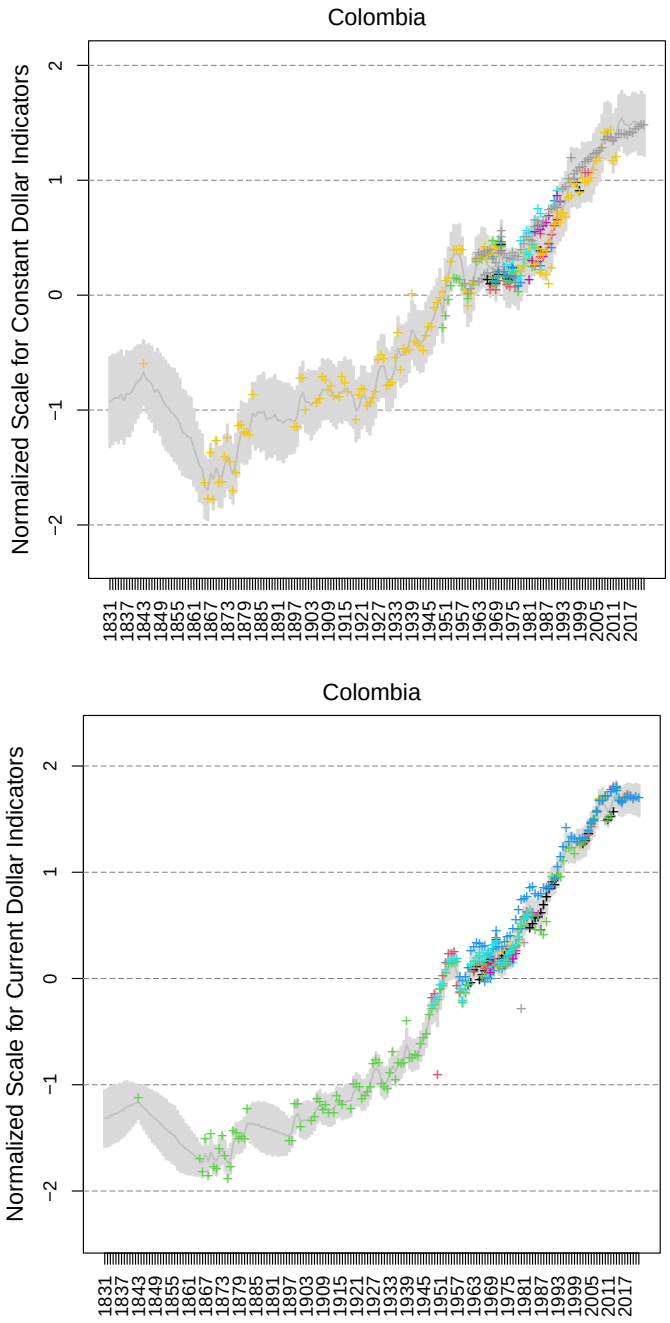

Figure 49: Constant series and data in the upper plot. Current series and data in the lower plot.

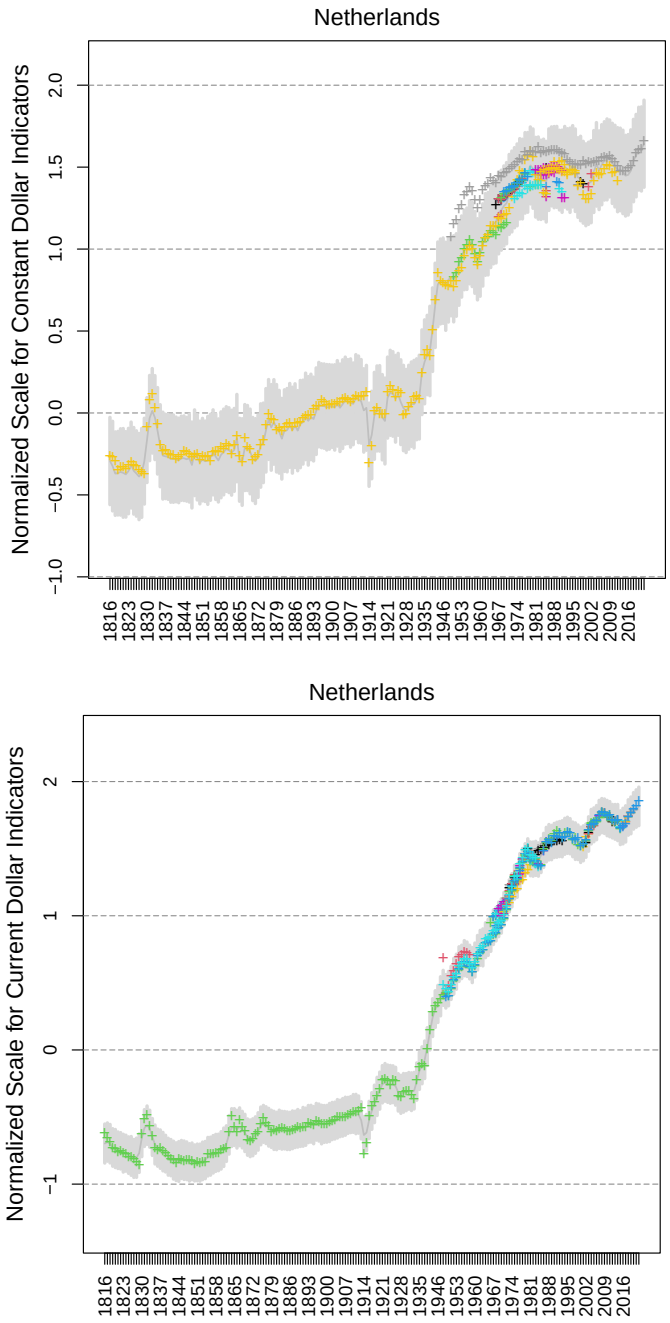

Figure 50: Constant series and data in the upper plot. Current series and data in the lower plot.

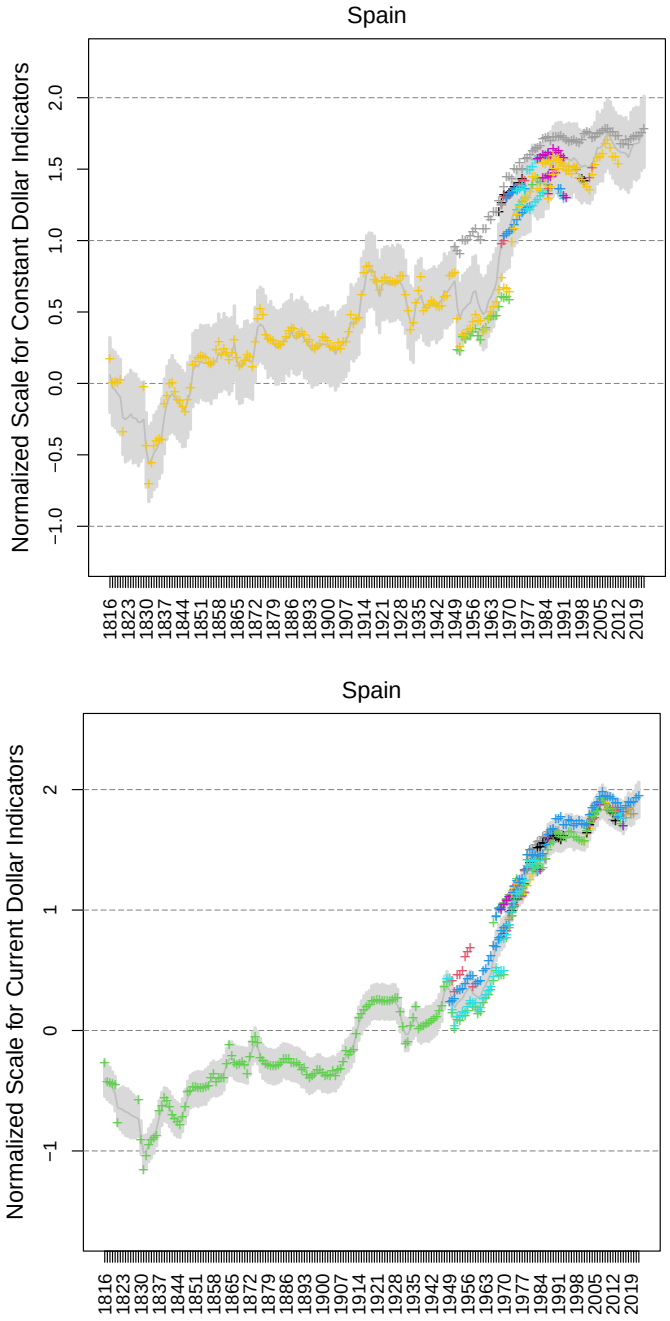

Figure 51: Constant series and data in the upper plot. Current series and data in the lower plot.

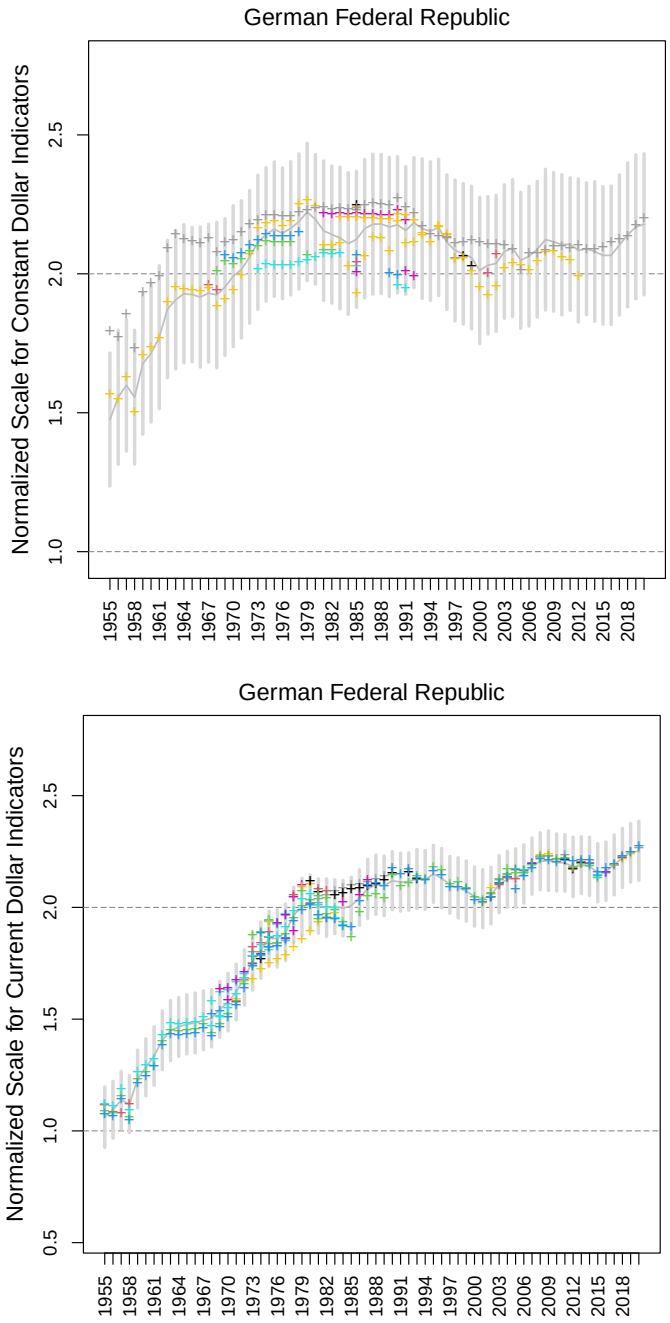

Figure 52: Constant series and data in the upper plot. Current series and data in the lower plot.

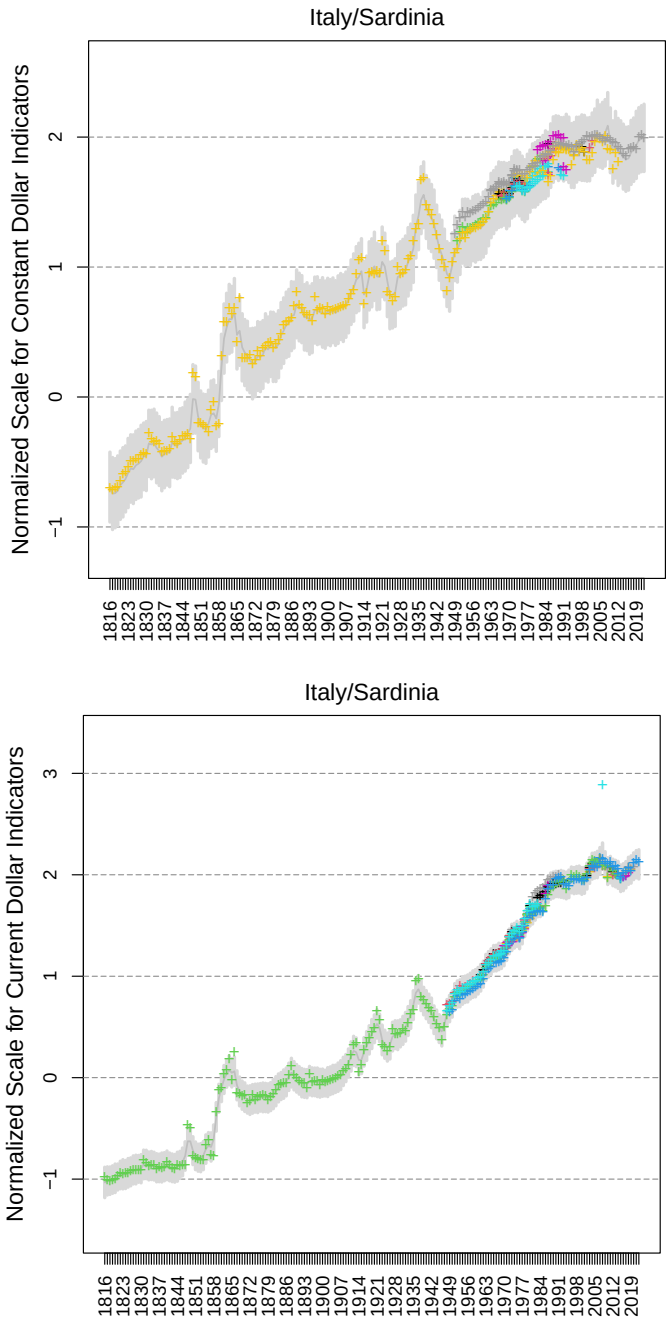

Figure 53: Constant series and data in the upper plot. Current series and data in the lower plot.

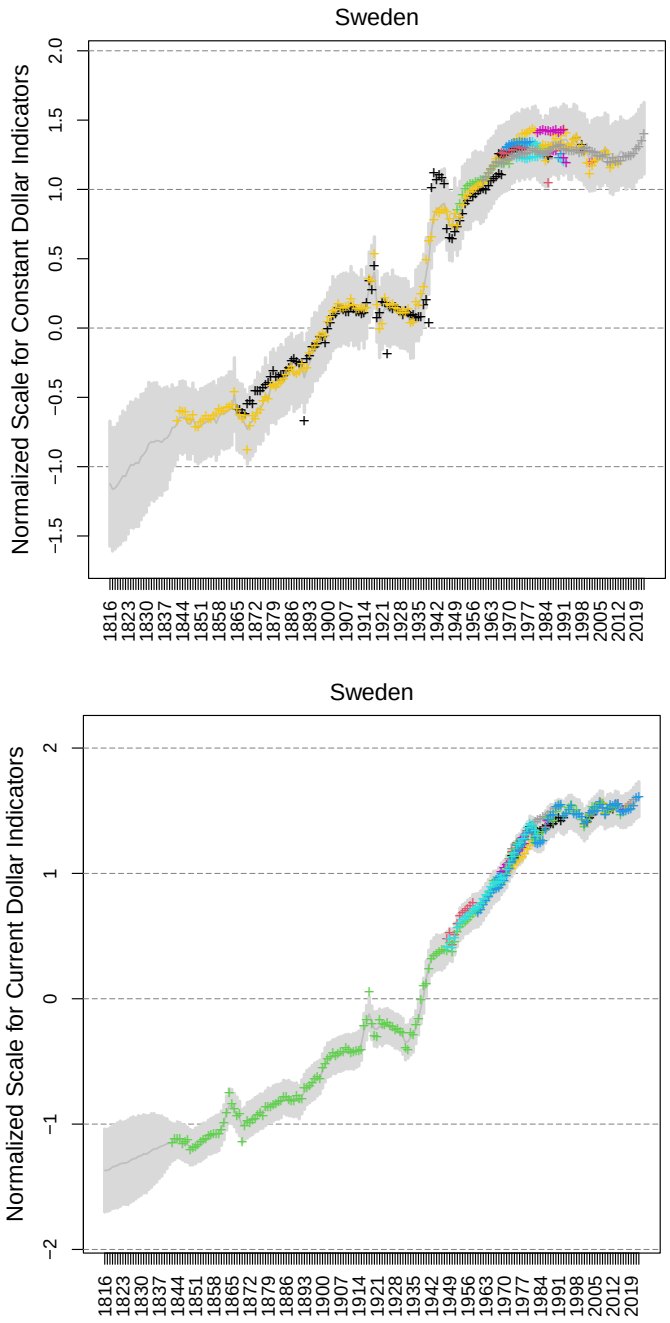

Figure 54: Constant series and data in the upper plot. Current series and data in the lower plot.

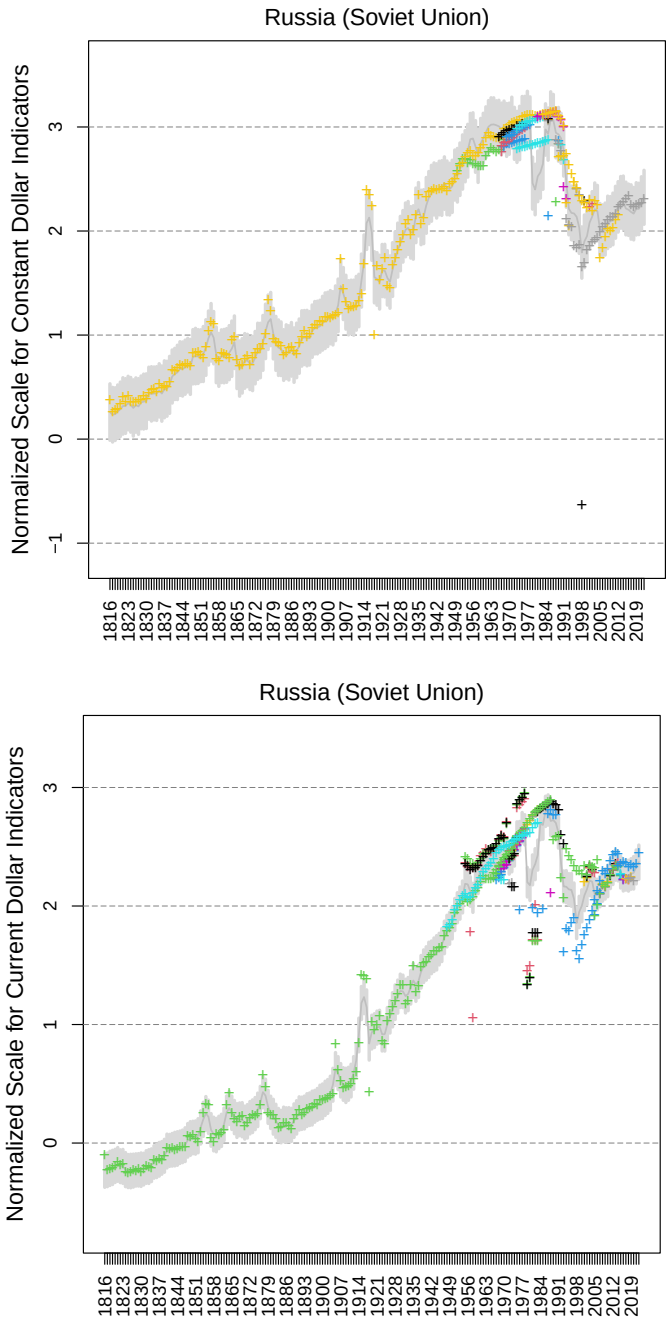

Figure 55: Constant series and data in the upper plot. Current series and data in the lower plot.

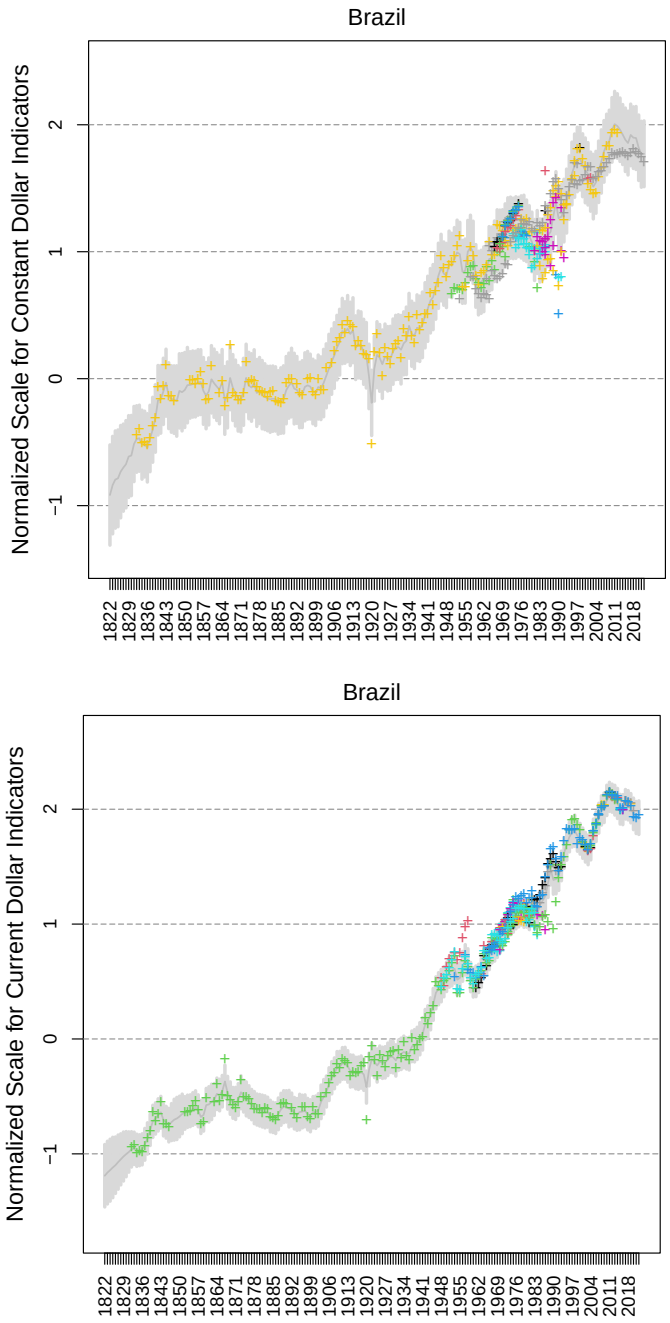

Figure 56: Constant series and data in the upper plot. Current series and data in the lower plot.

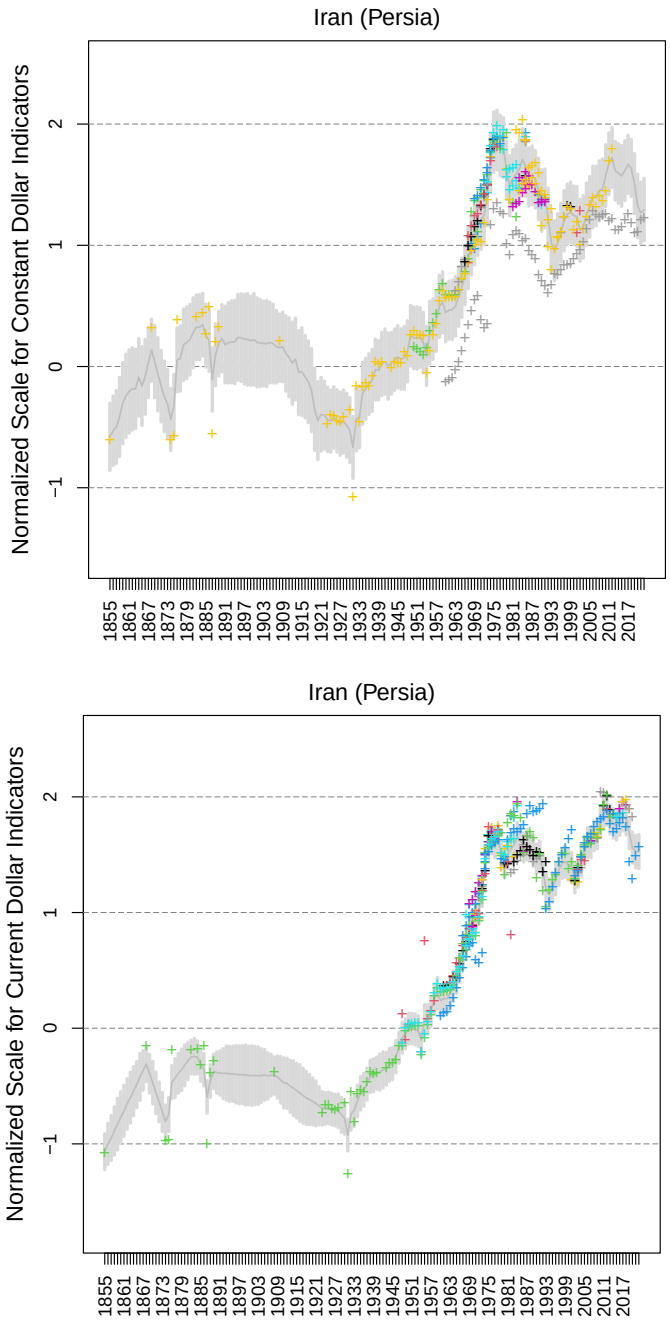

Figure 57: Constant series and data in the upper plot. Current series and data in the lower plot.

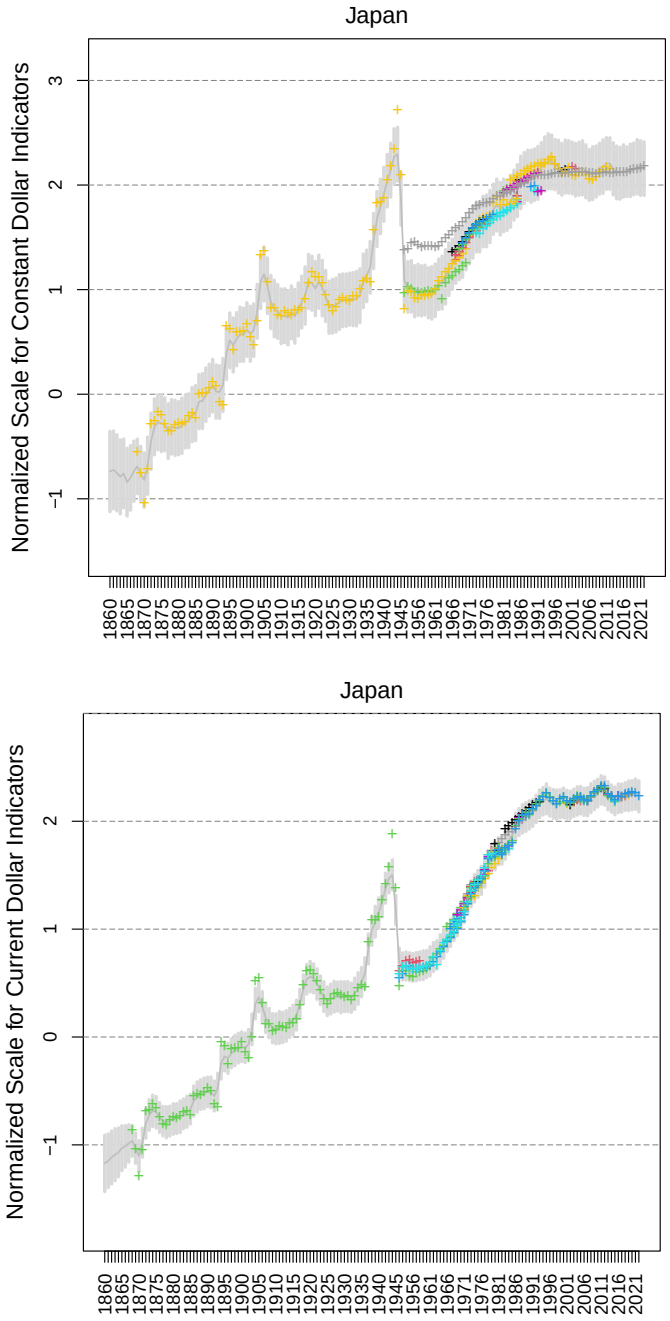

Figure 58: Constant series and data in the upper plot. Current series and data in the lower plot.

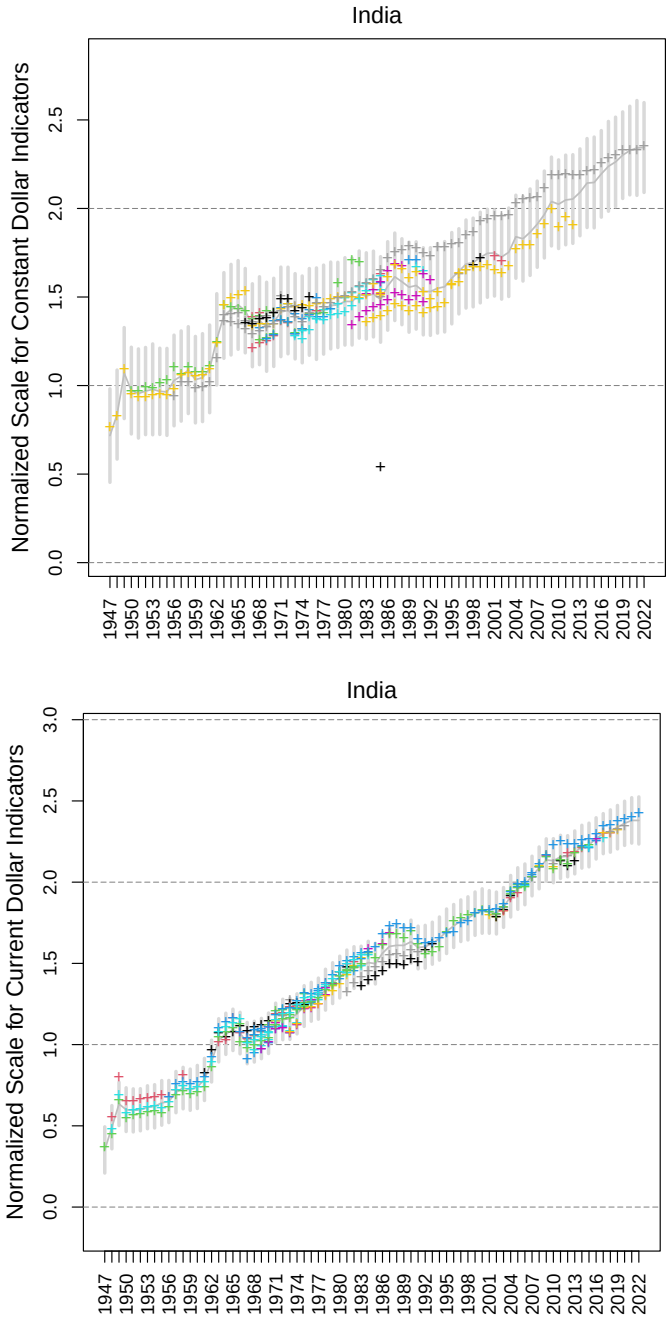

Figure 59: Constant series and data in the upper plot. Current series and data in the lower plot.

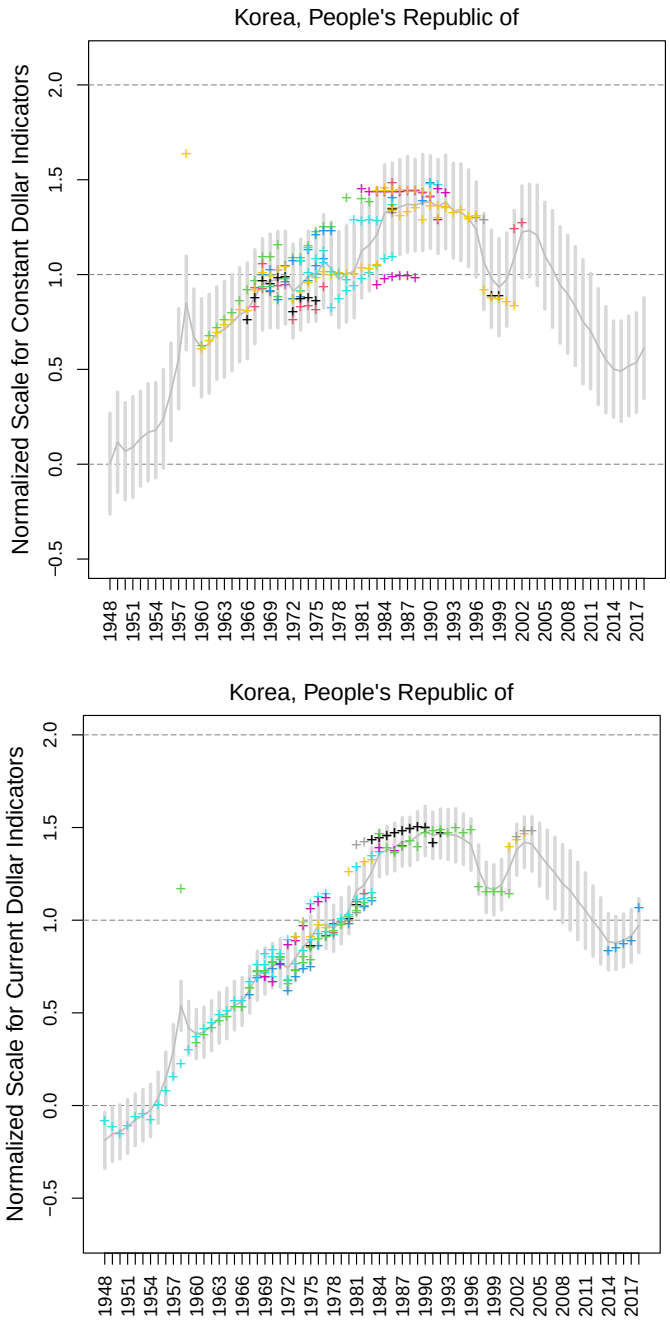

Figure 60: Constant series and data in the upper plot. Current series and data in the lower plot.

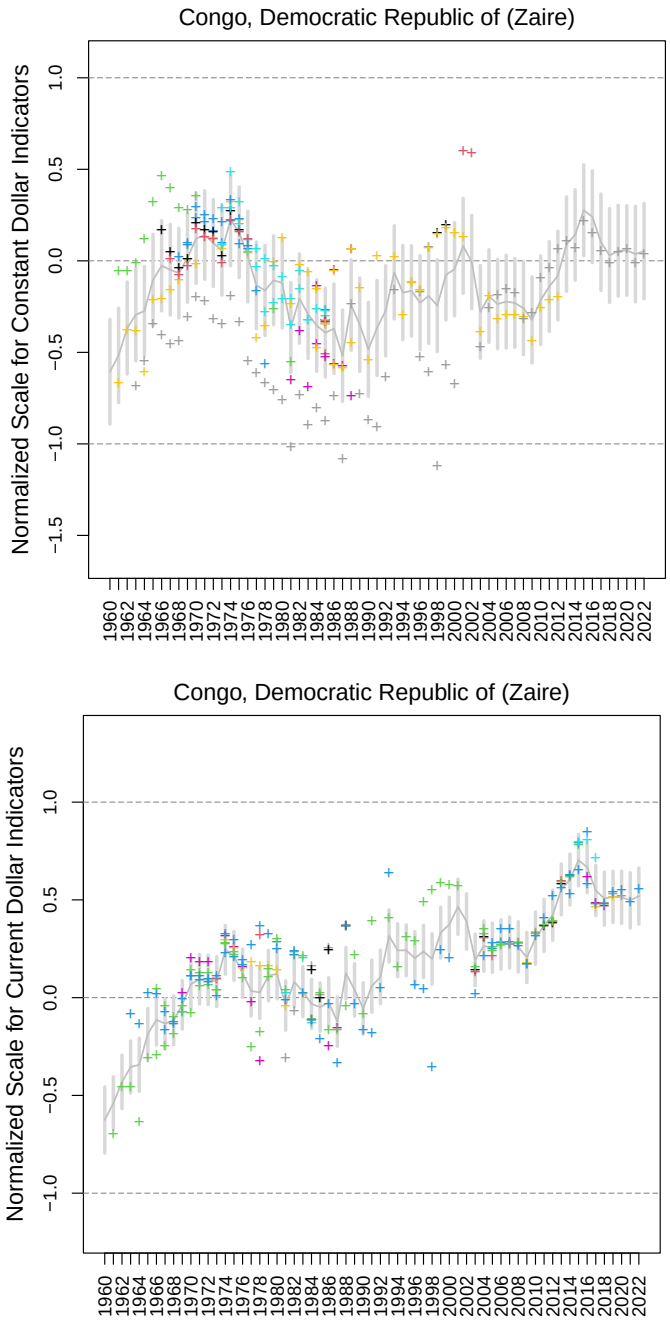

Figure 61: Constant series and data in the upper plot. Current series and data in the lower plot.

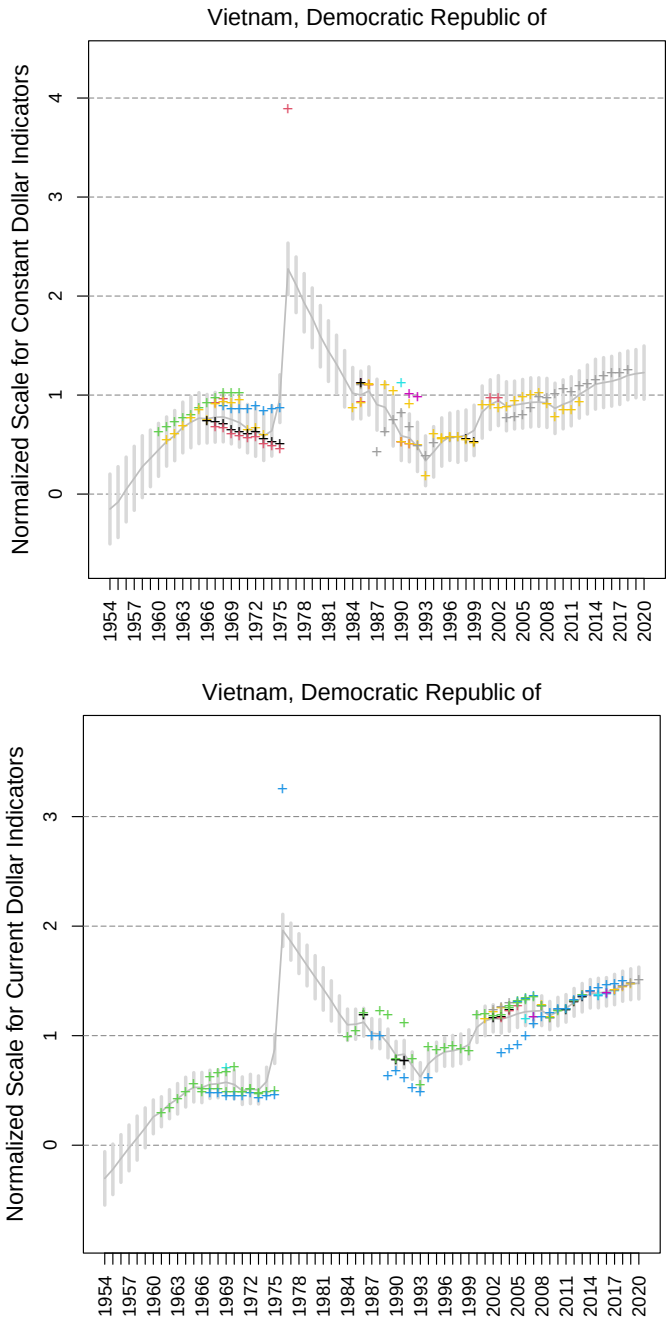

Figure 62: Constant series and data in the upper plot. Current series and data in the lower plot.

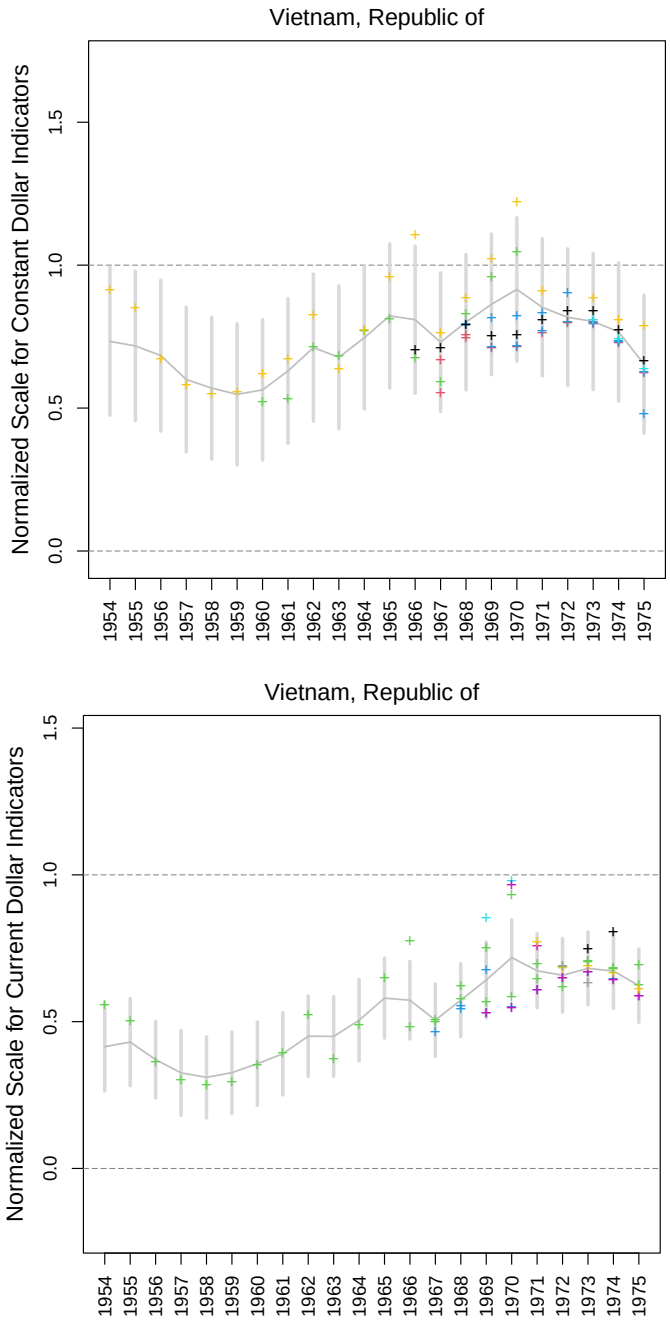

Figure 63: Constant series and data in the upper plot. Current series and data in the lower plot.

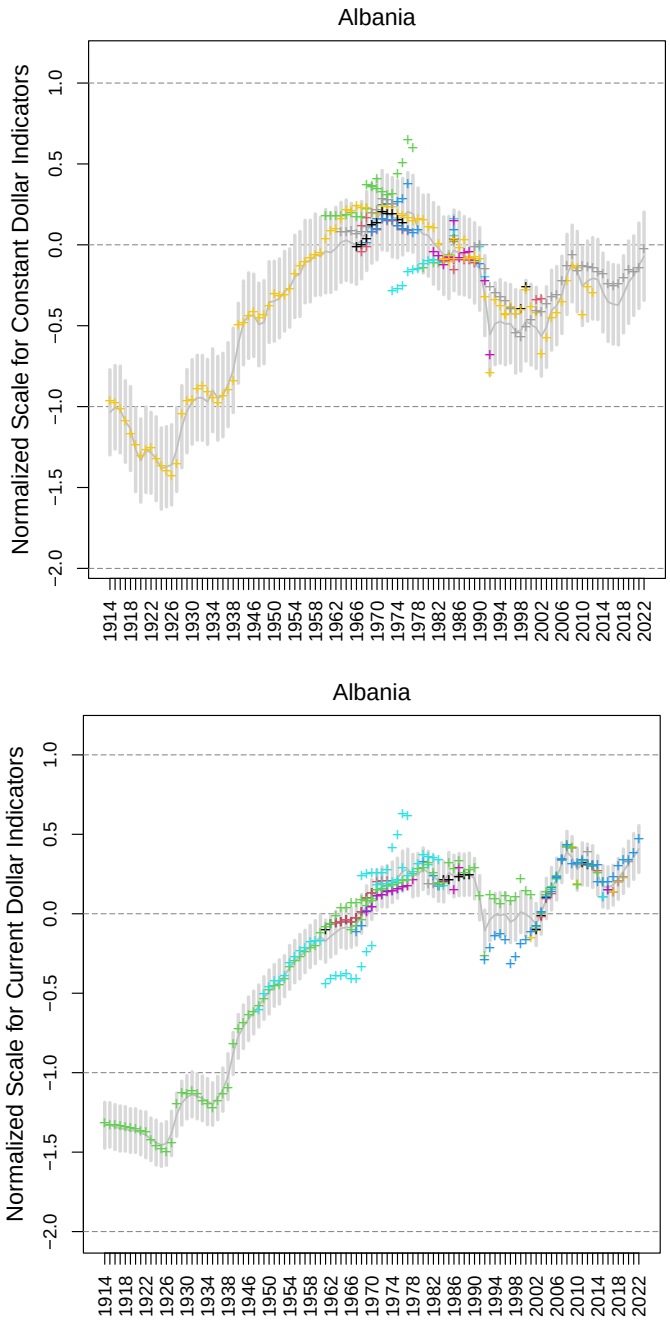

Figure 64: Constant series and data in the upper plot. Current series and data in the lower plot.

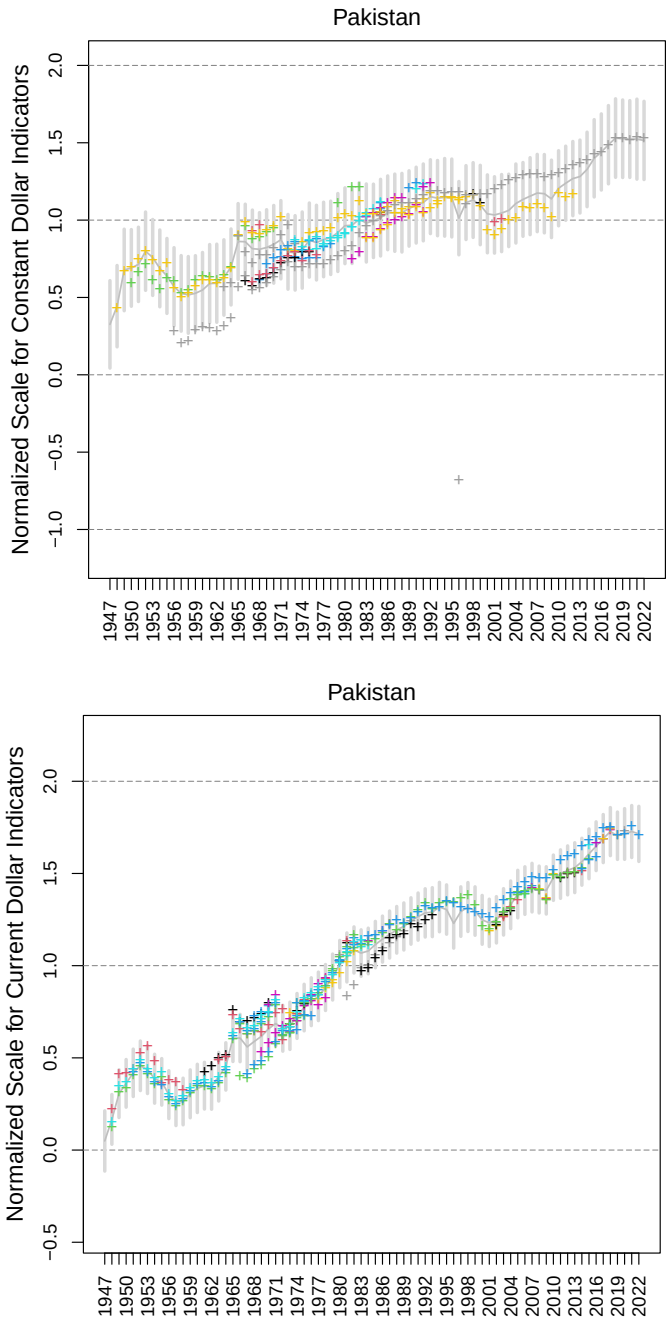

Figure 65: Constant series and data in the upper plot. Current series and data in the lower plot.

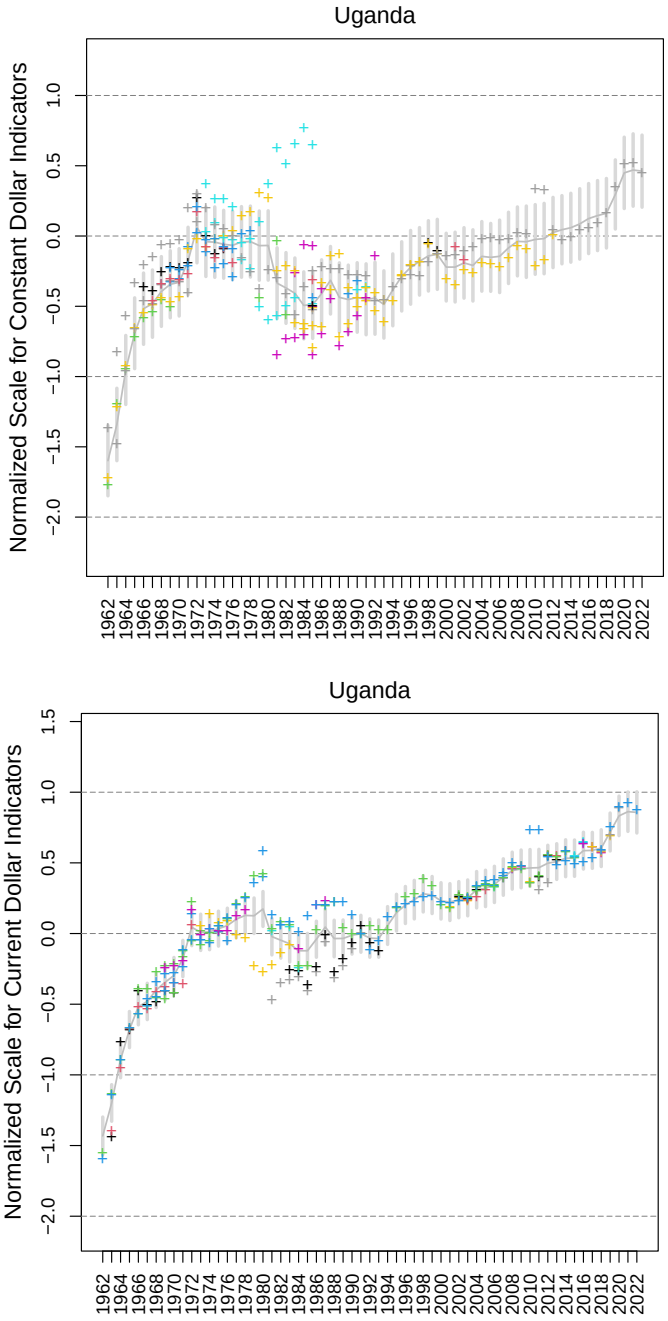

Figure 66: Constant series and data in the upper plot. Current series and data in the lower plot.

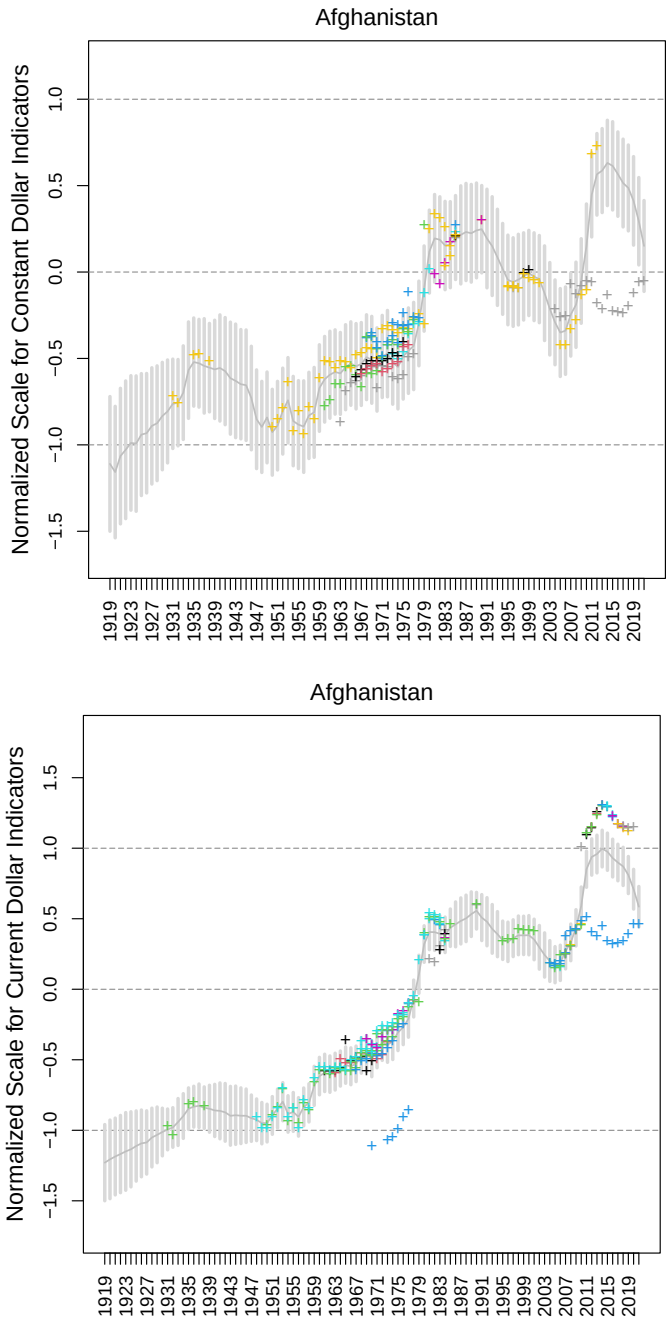

Figure 67: Constant series and data in the upper plot. Current series and data in the lower plot.

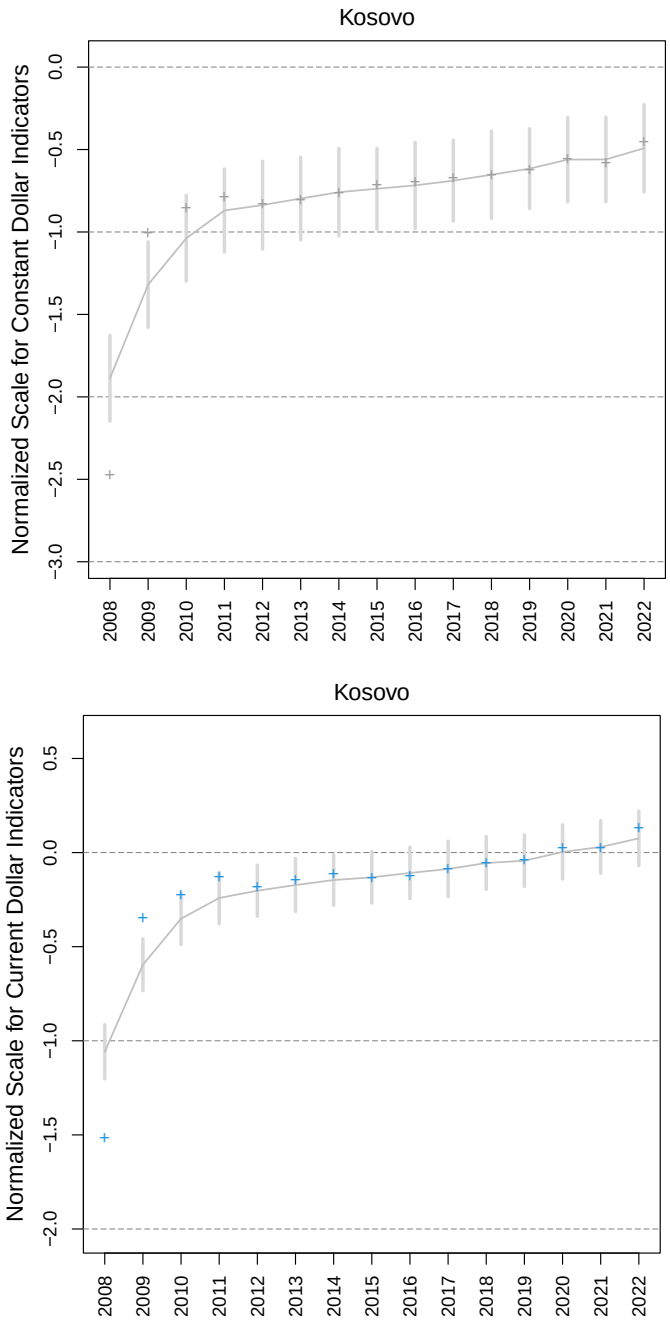

Figure 68: Constant series and data in the upper plot. Current series and data in the lower plot.

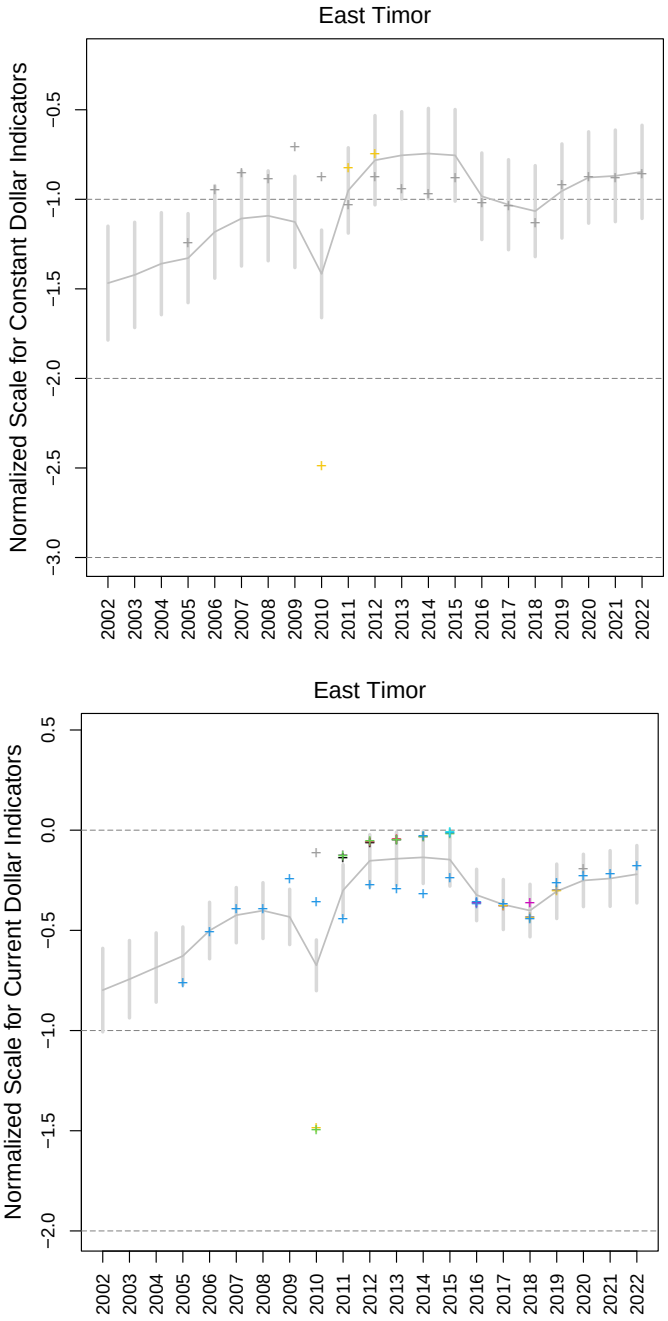

Figure 69: Constant series and data in the upper plot. Current series and data in the lower plot.

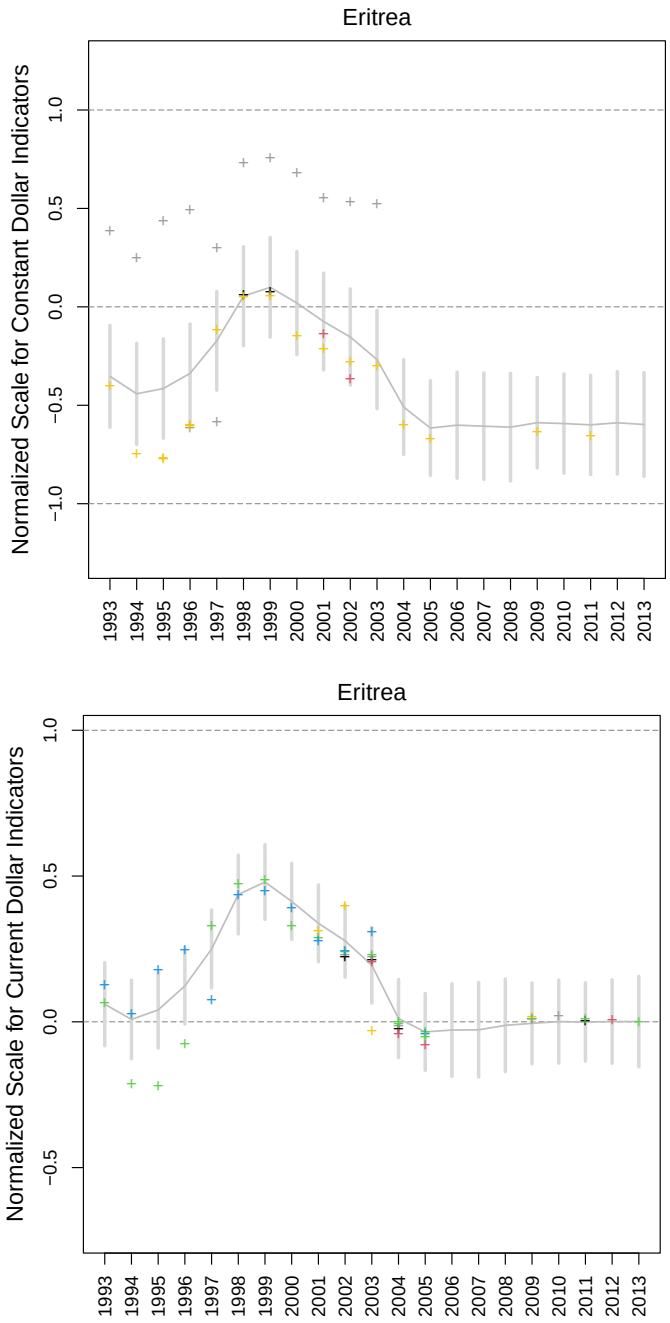

Figure 70: Constant series and data in the upper plot. Current series and data in the lower plot.

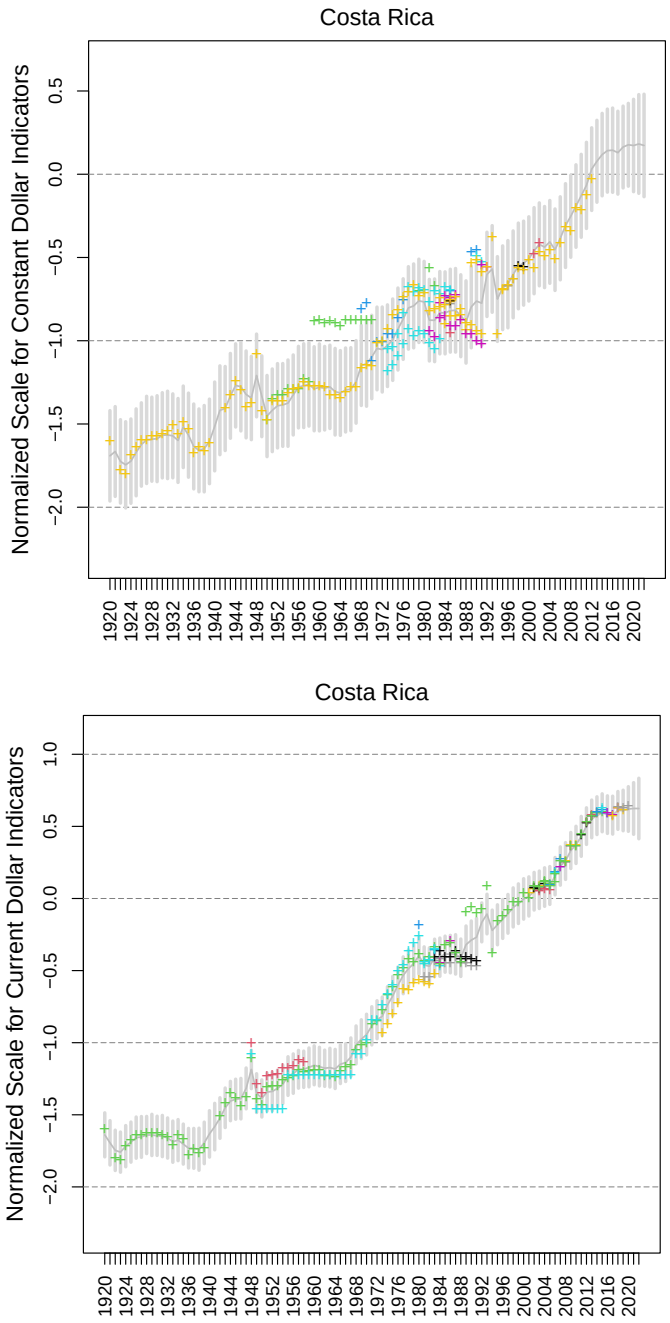

Figure 71: Constant series and data in the upper plot. Current series and data in the lower plot.

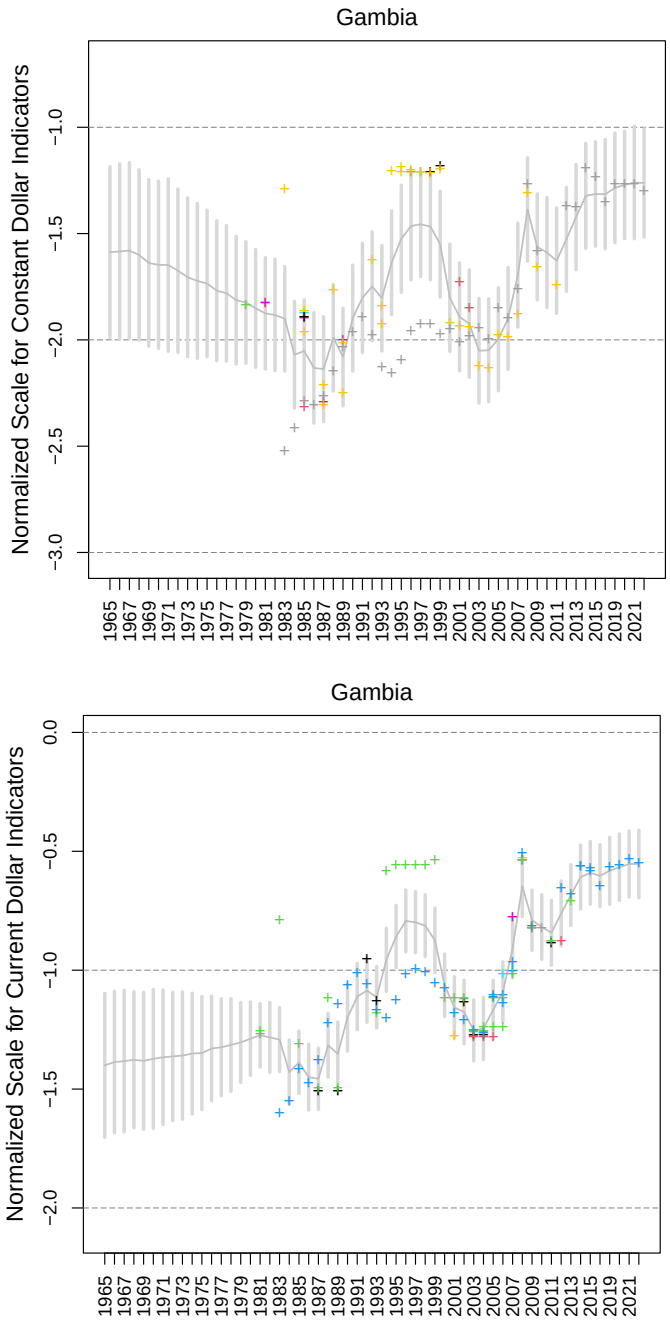

Figure 72: Constant series and data in the upper plot. Current series and data in the lower plot.

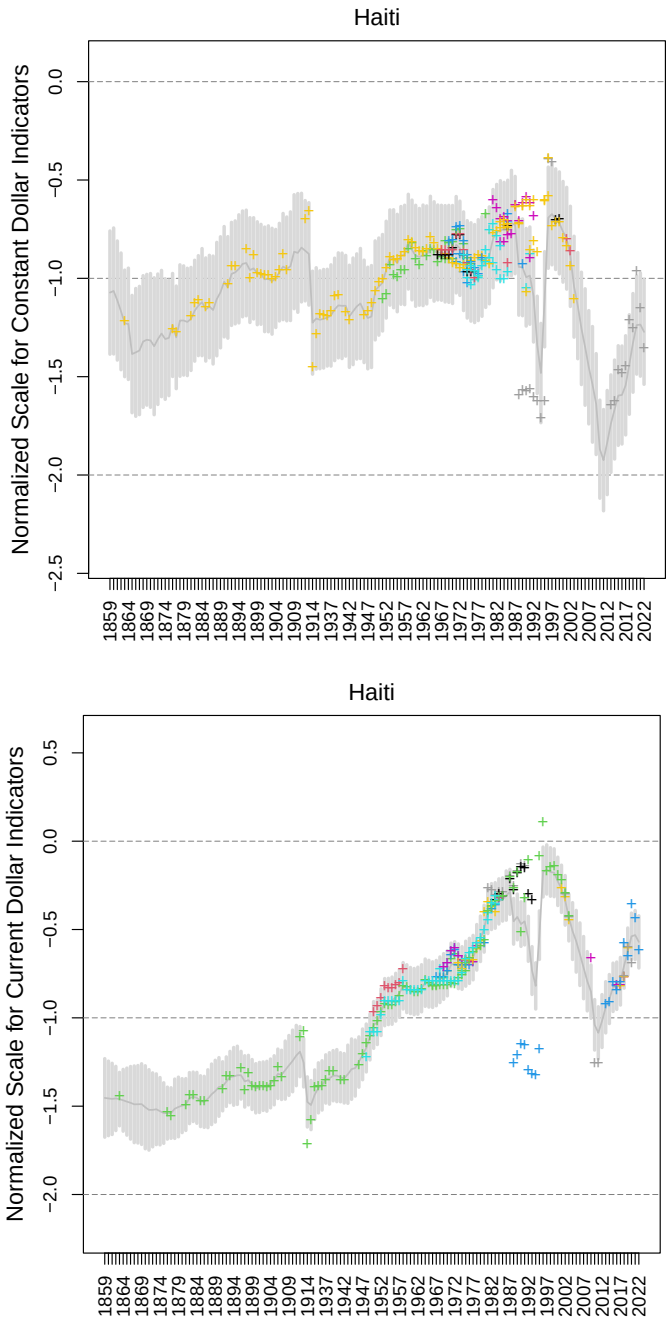

Figure 73: Constant series and data in the upper plot. Current series and data in the lower plot.

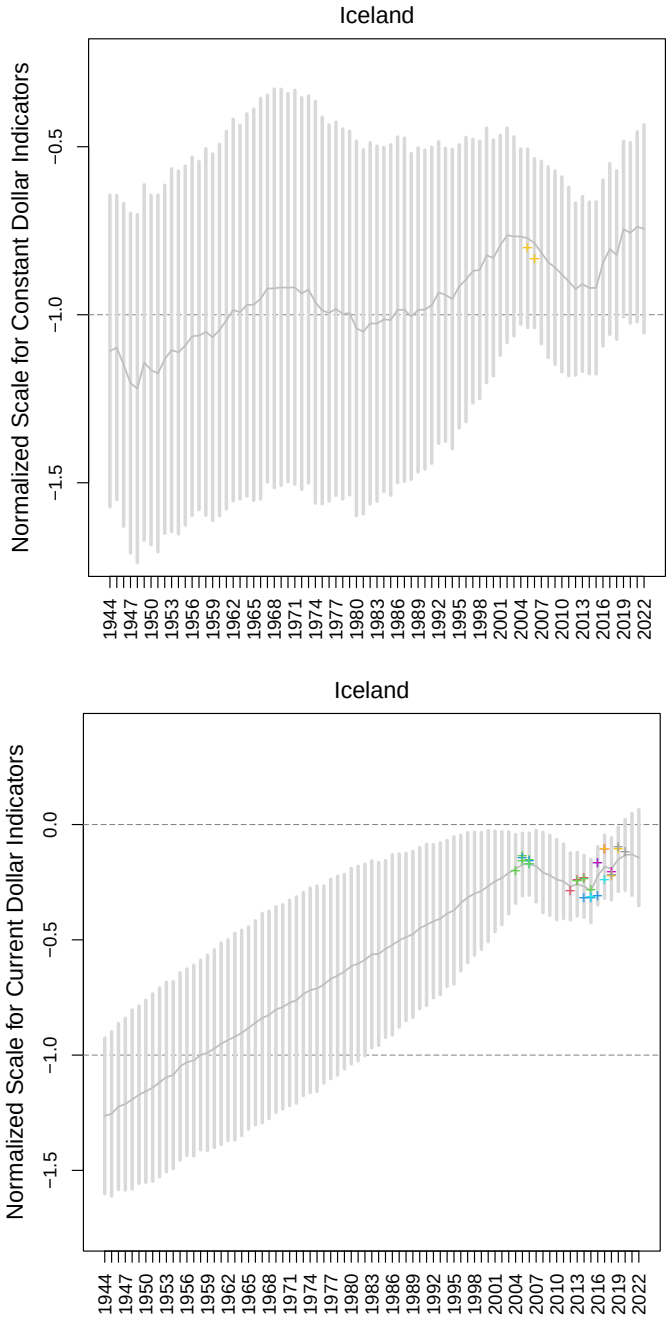

Figure 74: Constant series and data in the upper plot. Current series and data in the lower plot.

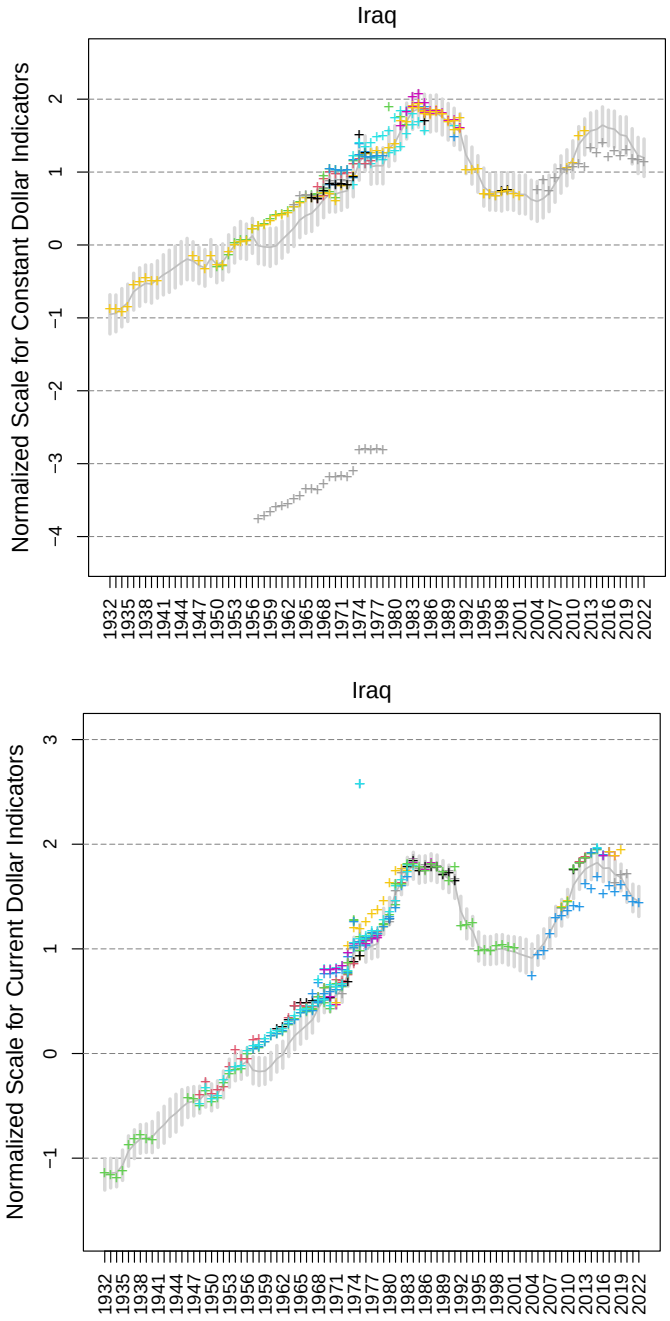

Figure 75: Constant series and data in the upper plot. Current series and data in the lower plot.

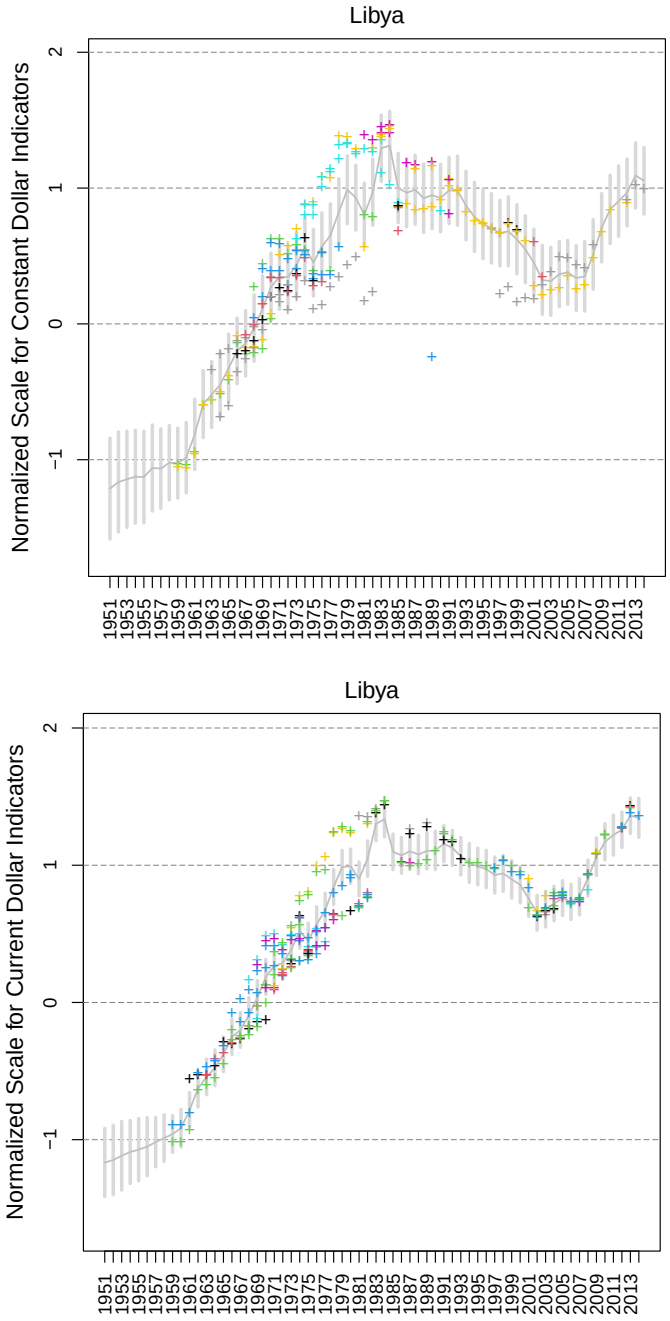

Figure 76: Constant series and data in the upper plot. Current series and data in the lower plot.

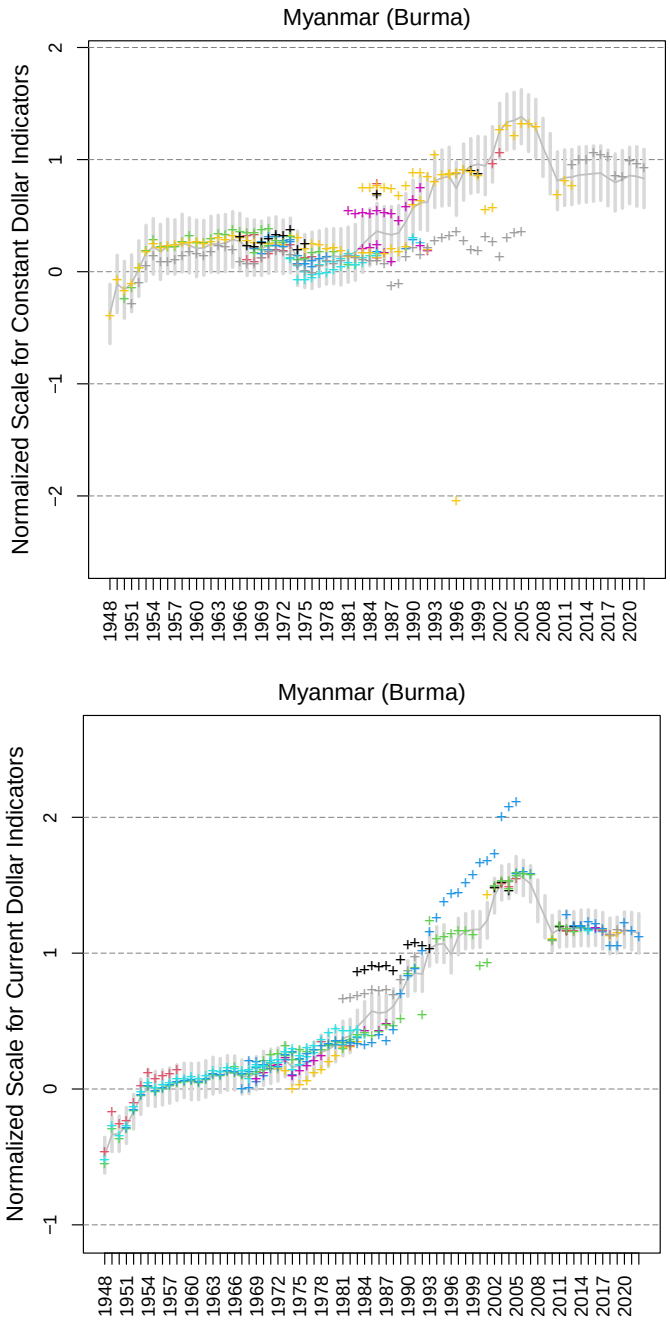

Figure 77: Constant series and data in the upper plot. Current series and data in the lower plot.

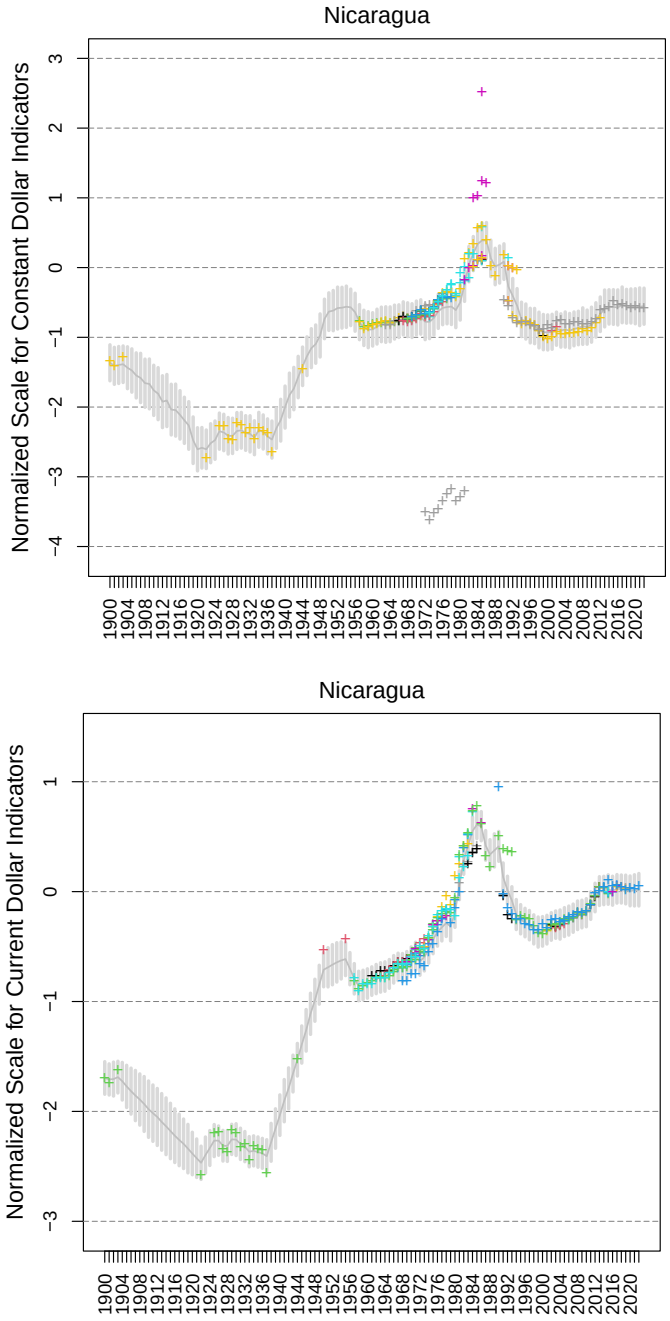

Figure 78: Constant series and data in the upper plot. Current series and data in the lower plot.

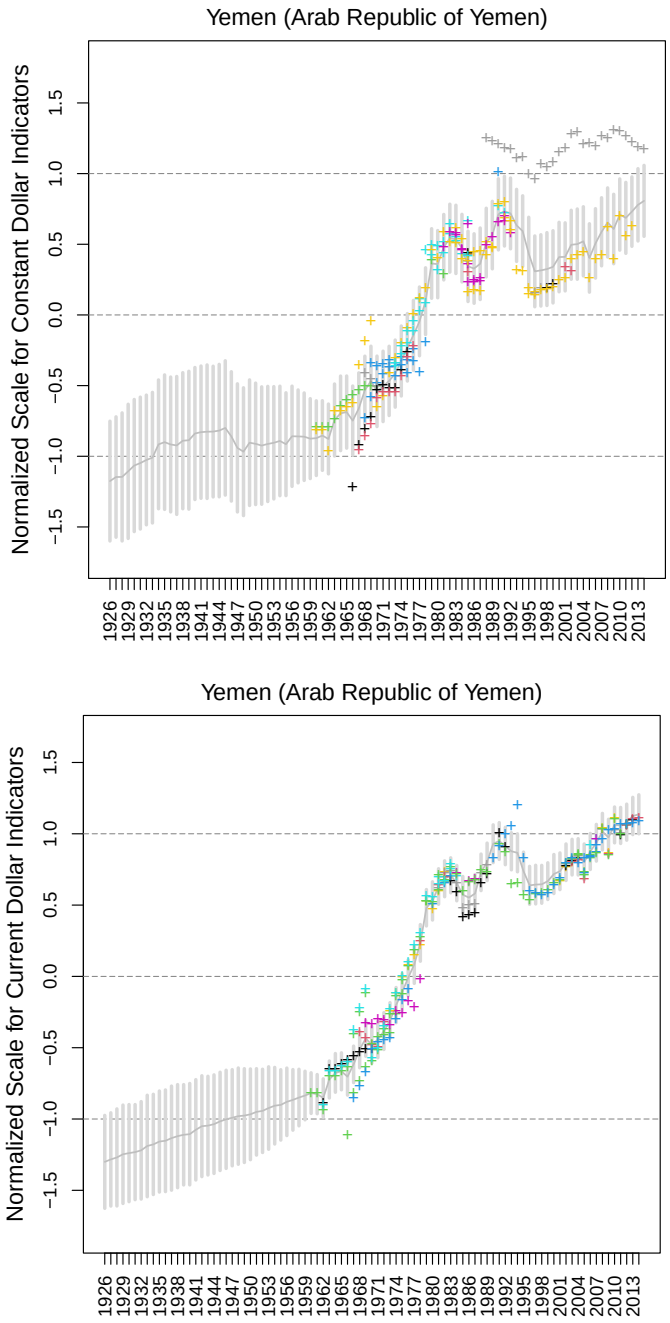

Figure 79: Constant series and data in the upper plot. Current series and data in the lower plot.

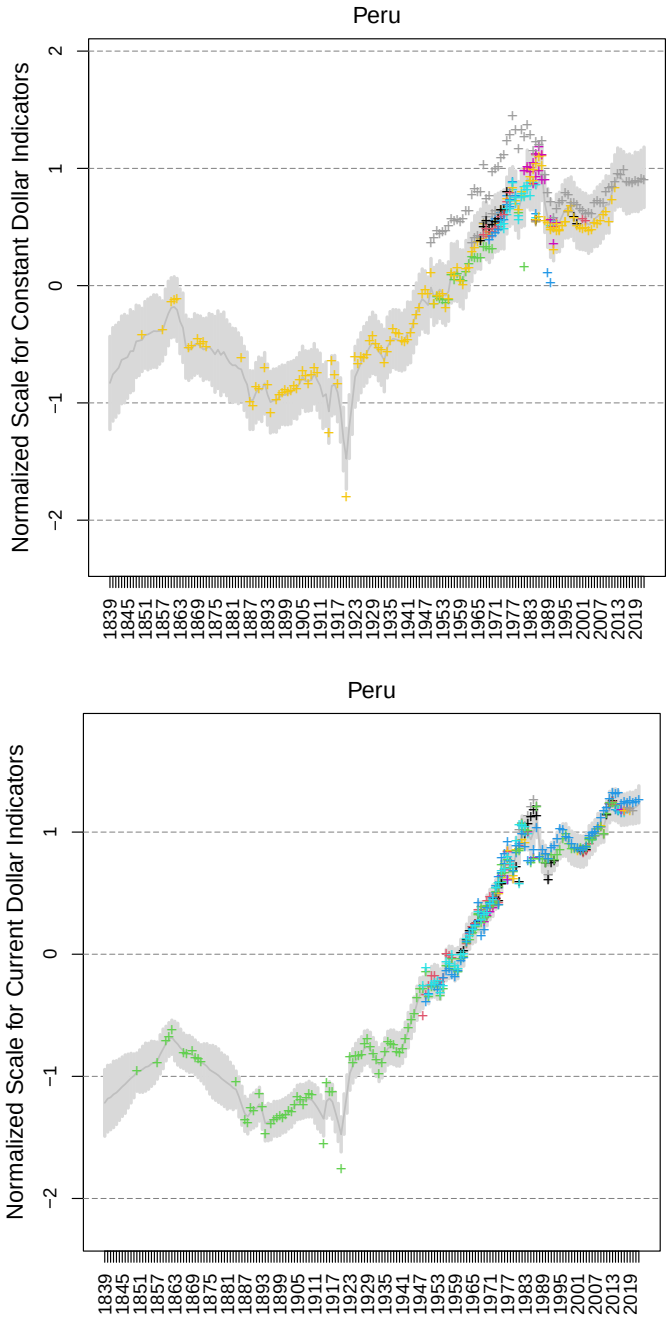

Figure 80: Constant series and data in the upper plot. Current series and data in the lower plot.

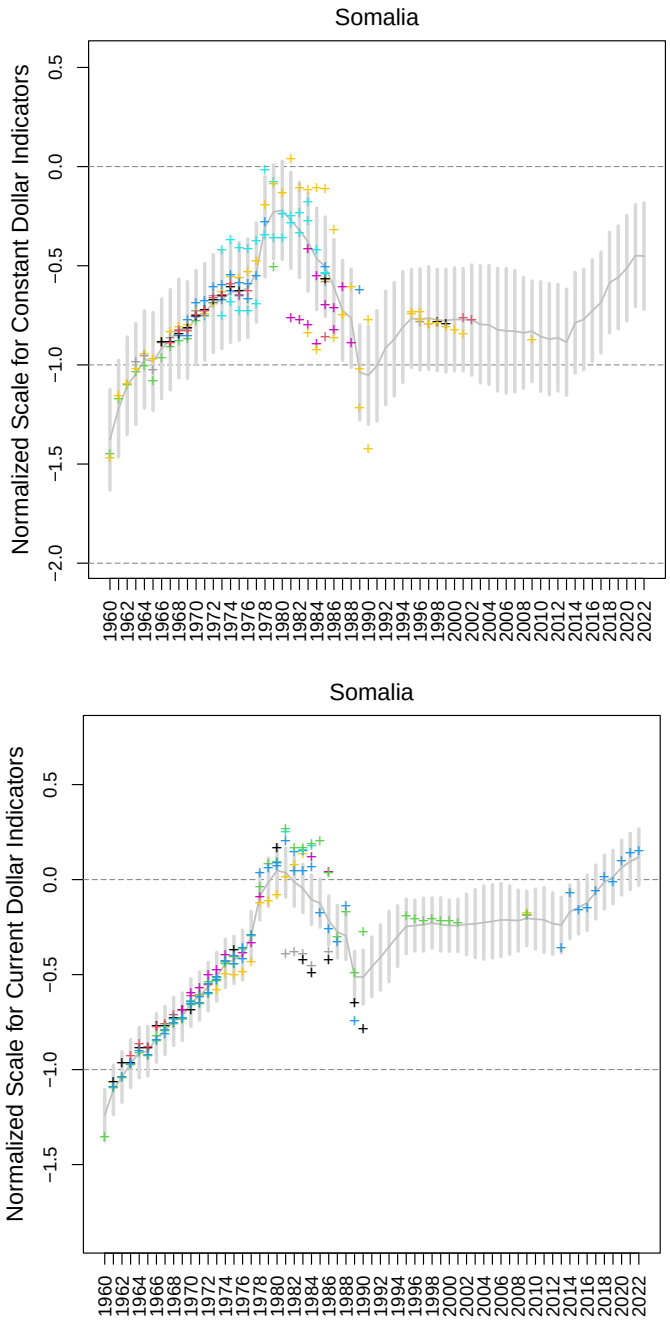

Figure 81: Constant series and data in the upper plot. Current series and data in the lower plot.

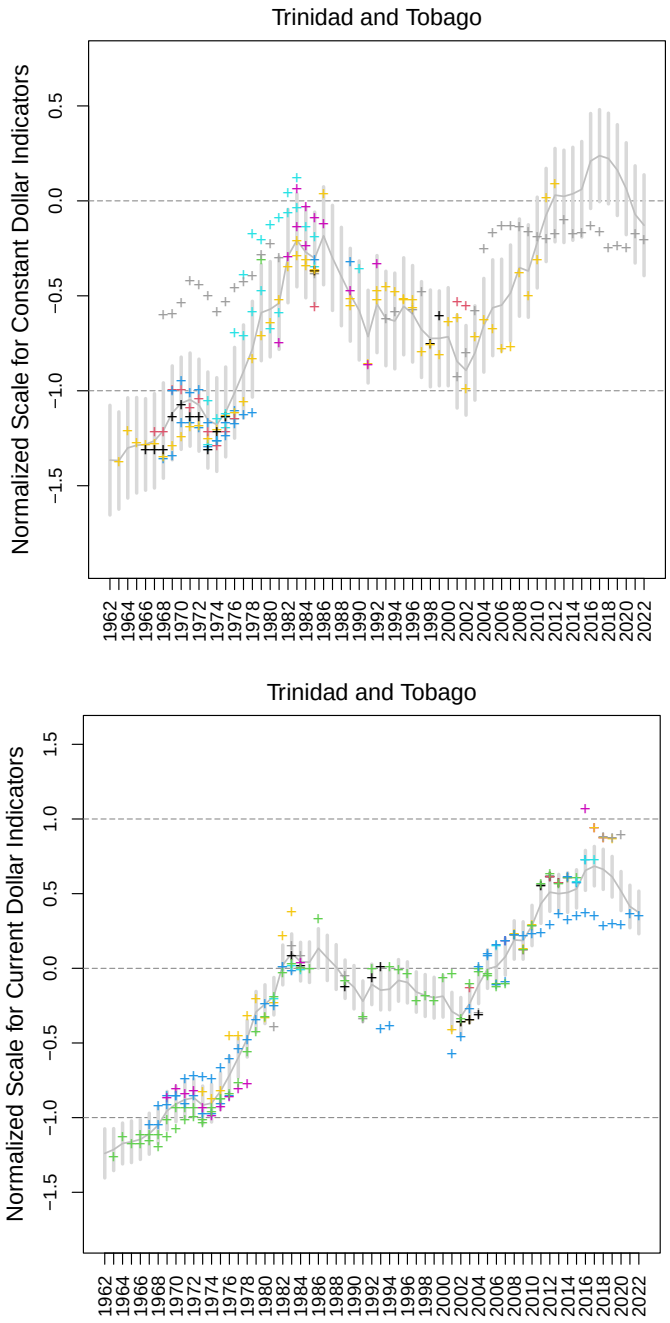

Figure 82: Constant series and data in the upper plot. Current series and data in the lower plot.

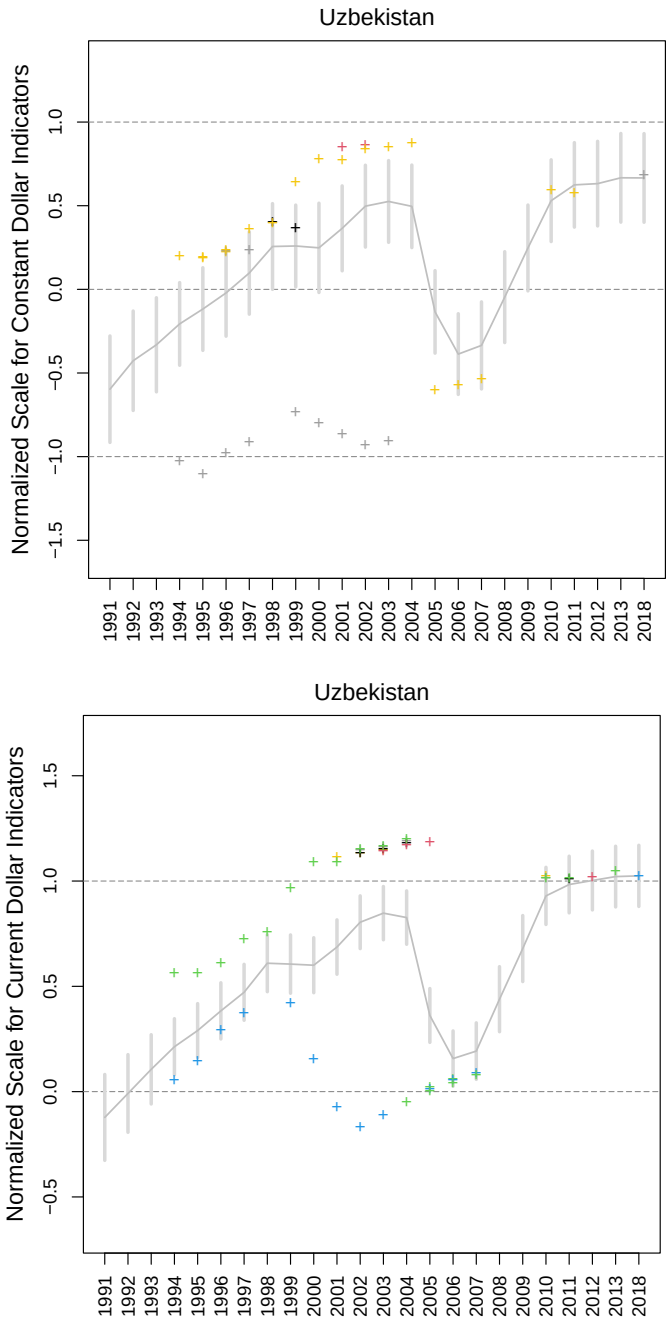

Figure 83: Constant series and data in the upper plot. Current series and data in the lower plot.

6 U.S. Military Expenditures for All Datasets

Most of the country time-series graphs we have shown only include four variables. Here we present the time-series graphs for all available dataset variables for the United States. Overall, the measurement model does well and placing the center of the estimated interval near the observed dataset values. Note that the Zimmerman/USSR and Peters/Sweden variables are excluded in this example because these are single country datasets that do not focus on the United States.

6.1 All Datasets, excluding IISS and WMEAT (constant)

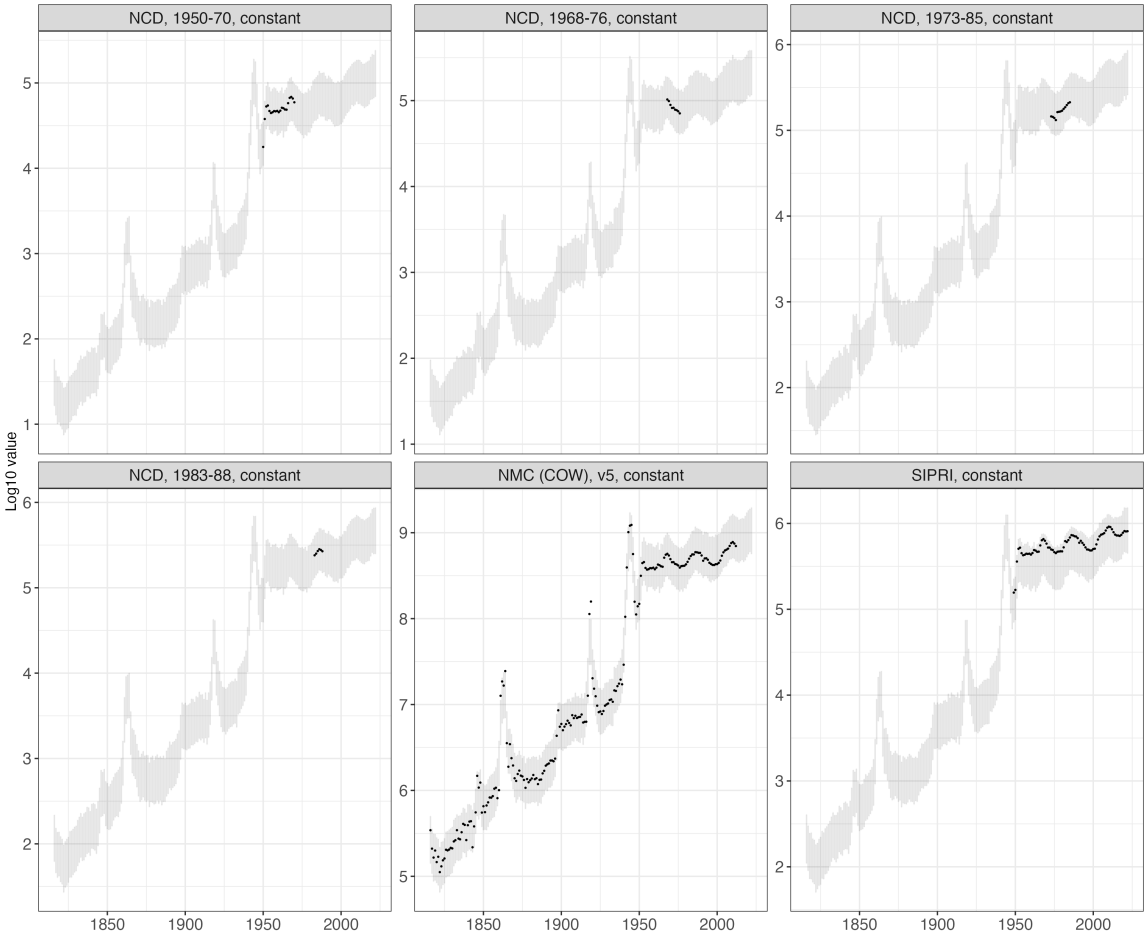

Figure 84: Observed variables (orange points) for the U.S.

6.2 All Datasets, excluding IISS and WMEAT (current)

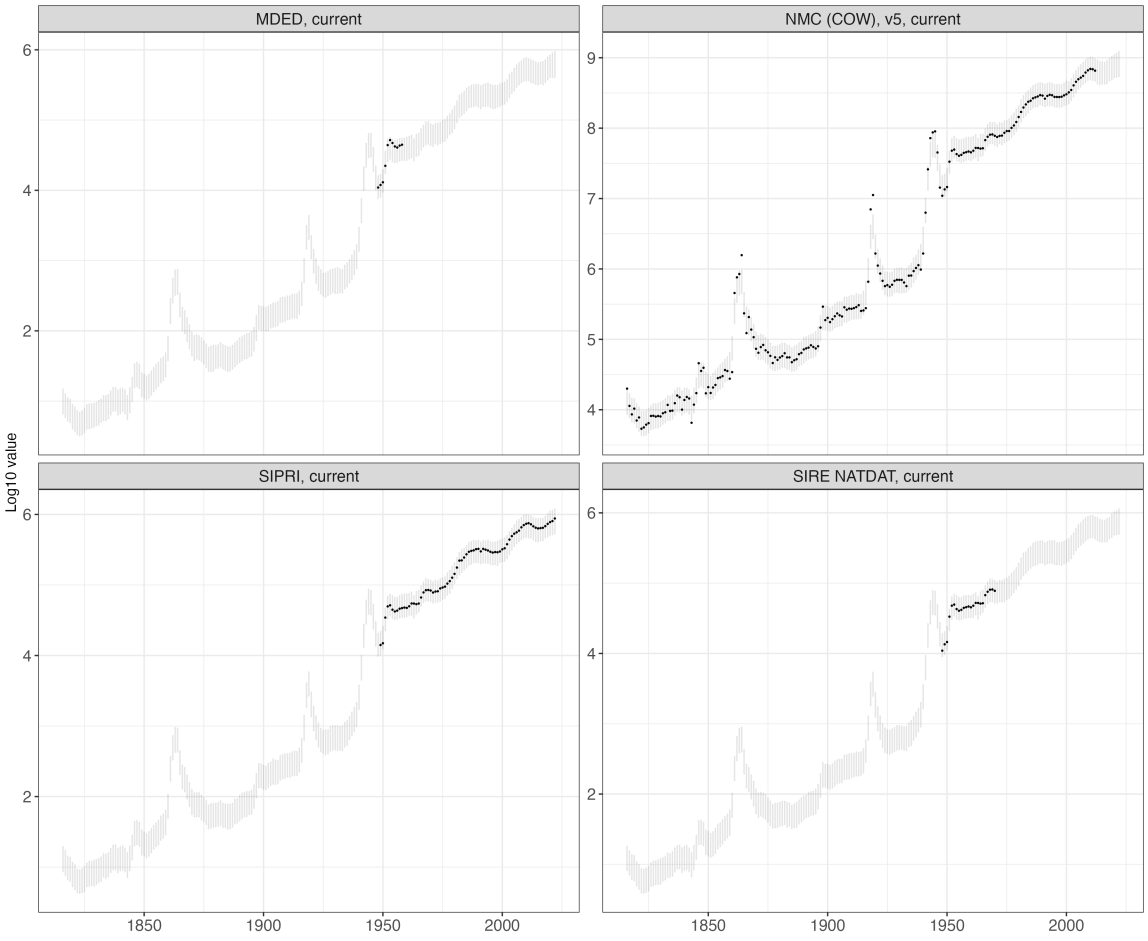

Figure 85: Observed variables (orange points) for the U.S.

6.3 IISS The Military Balance Issues (constant)

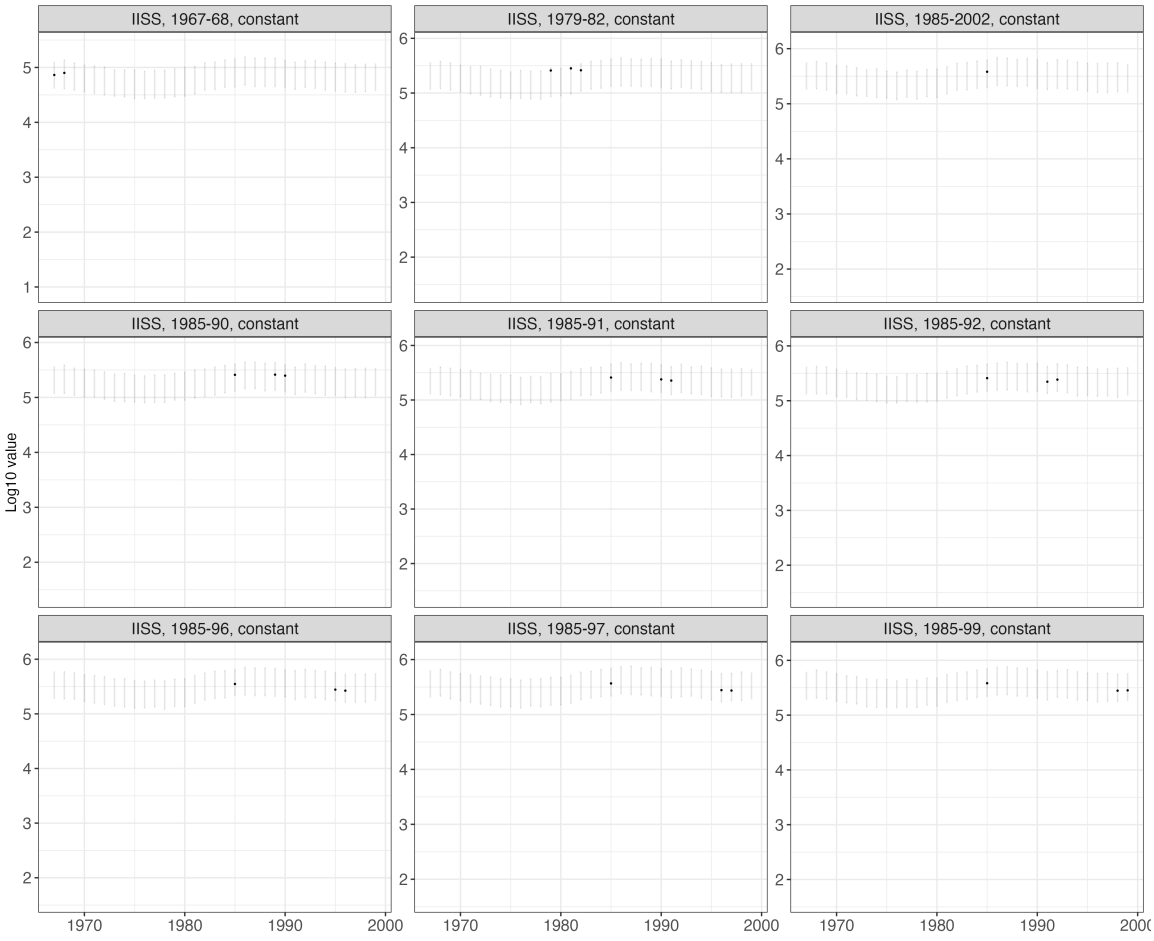

Figure 86: Observed variables (orange points) for the U.S.

6.4 IISS The Military Balance Issues (current, pre-2000)

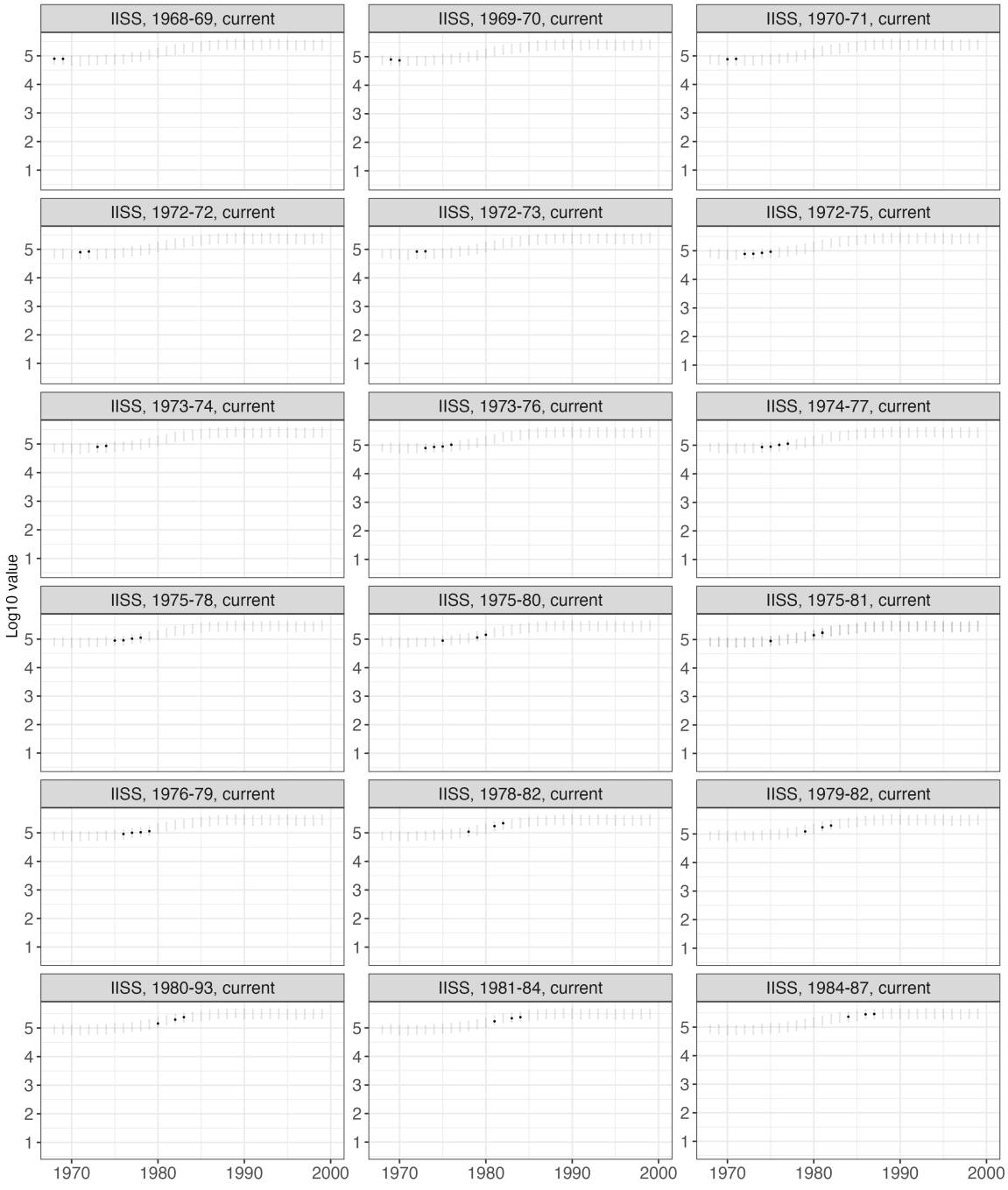

Figure 87: Observed variables (orange points) for the U.S.

6.5 IISS The Military Balance Issues (current, post-2000)

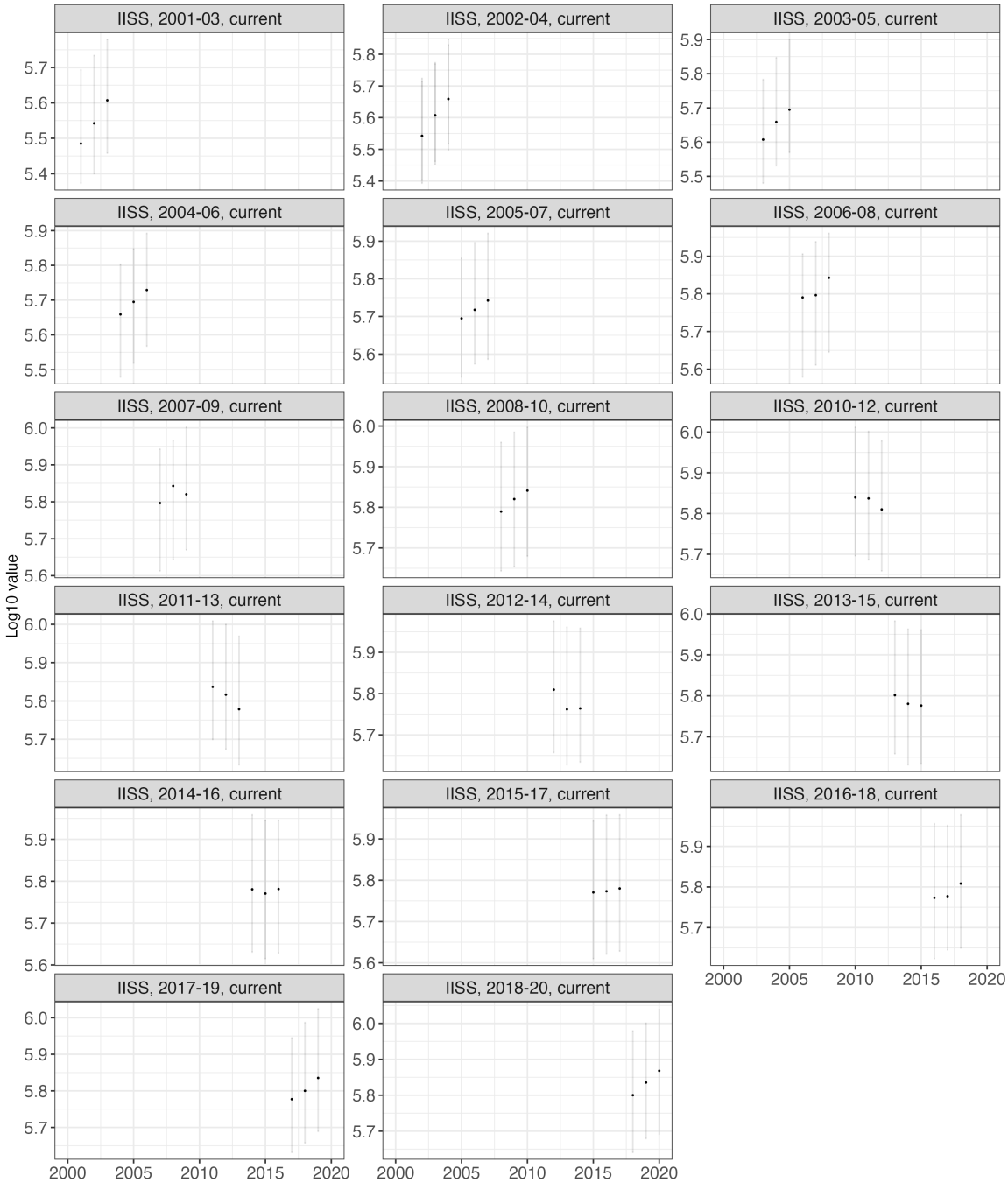

Figure 88: Observed variables (orange points) for the U.S.

6.6 WMEAT Issues (constant)

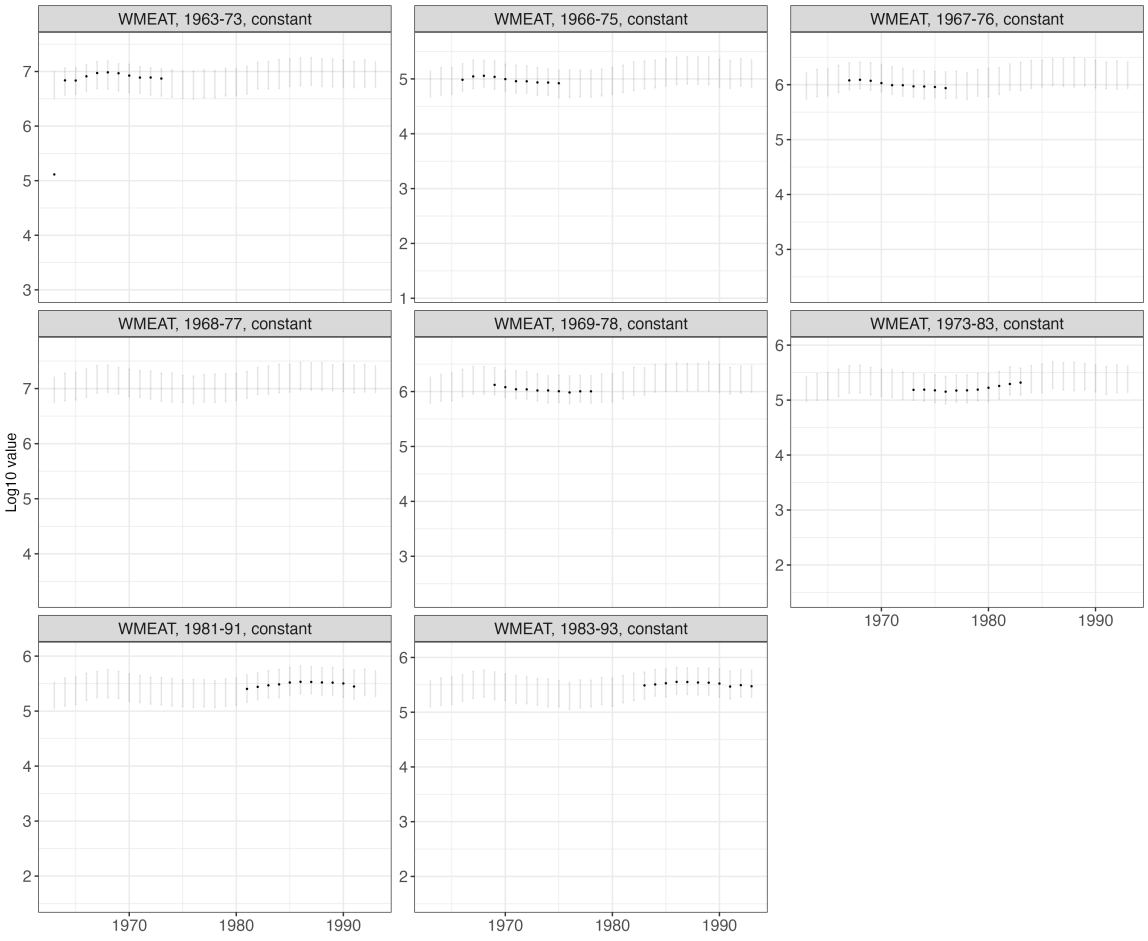

Figure 89: Observed variables (orange points) for the U.S.

6.7 WMEAT Issues (current)

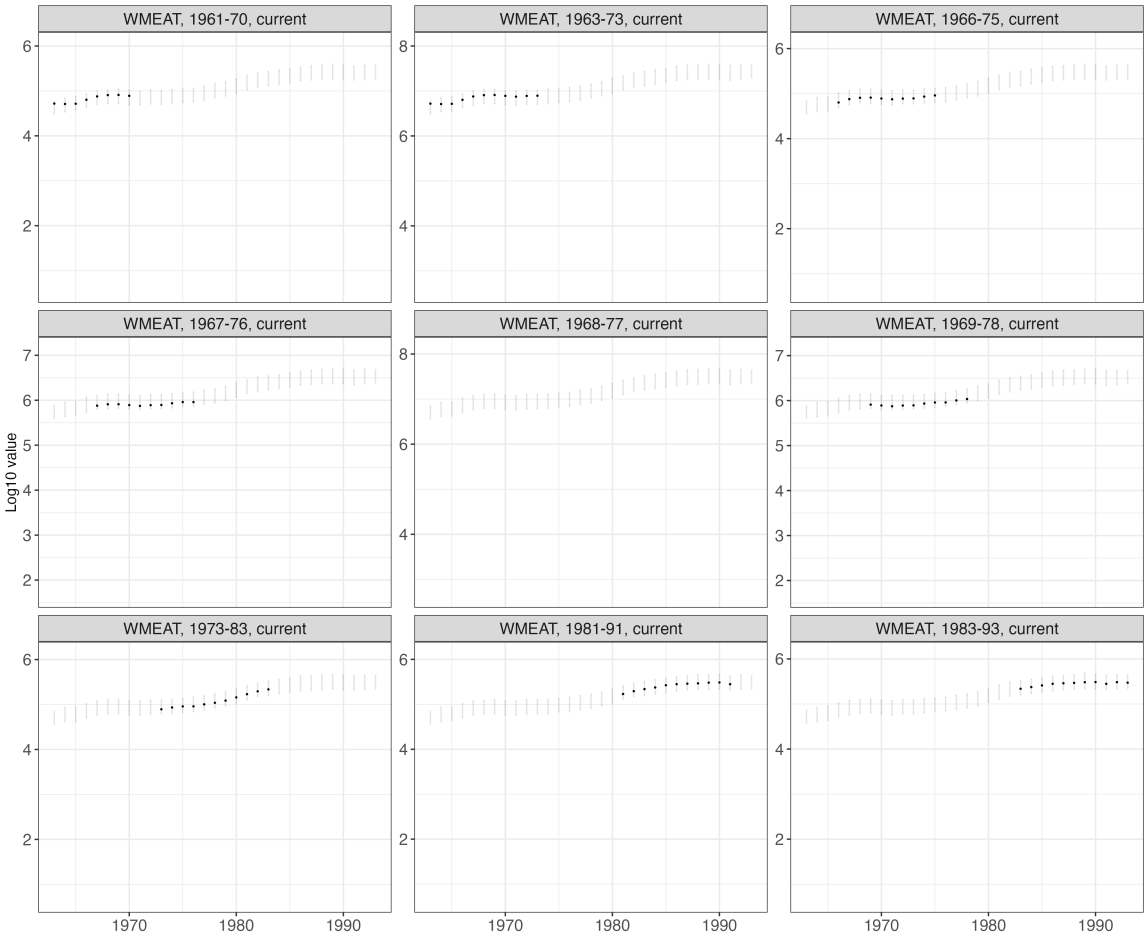

Figure 90: Observed variables (orange points) for the U.S.

6.8 Zimmerman (USSR)

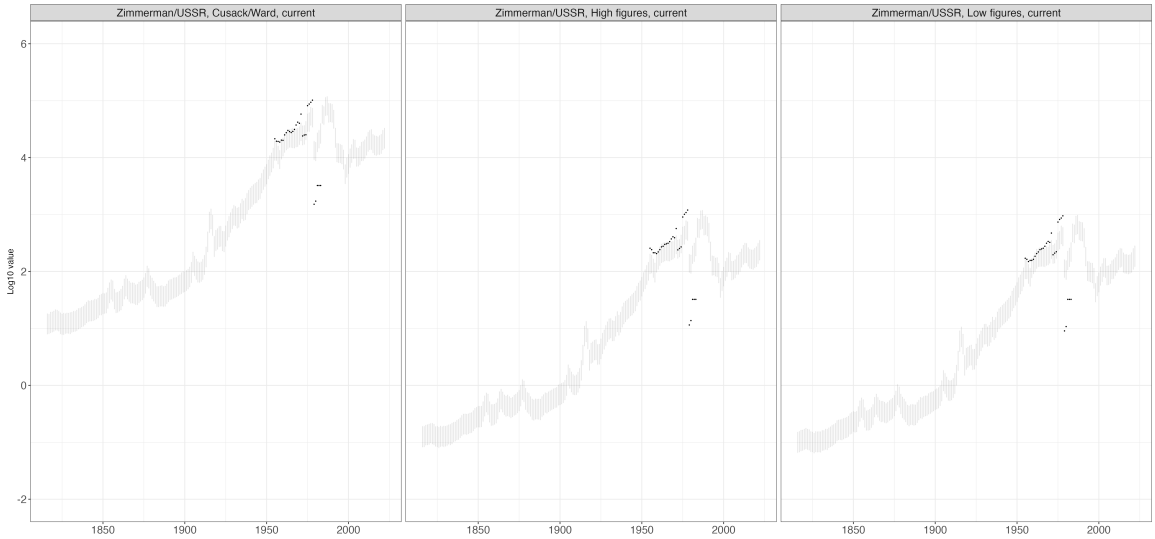

Figure 91: Observed variables (orange points) for the USSR.

6.9 Peters (Sweden)

Figure 92: Observed variables (orange points) for Sweden.

7 Units with Observed Zeros

There are some observed ZEROs in the datasets we cover. 421 country-years have some (but not all) observed dataset values that are 0. This means that these country-years have some positive dollar values in the coverage of certain datasets but not all datasets. For all these cases we have treated these observed ZEROs as missing values and estimate them as such. Note that these estimates are all for relatively small levels of military spending (a few hundred thousand to millions of dollars). Because of this choice, there is additional uncertainty associated with the estimated posterior distributions, which is a useful feature since the datasets disagree on these observations.

Also, 187 country-years have all their observed dataset values recorded as ZERO. Note that this is out of 17,855 total country-year observations. Nearly half of the countries that are part of this list 187 country-years only have one year in which there are all ZERO entries for military expenditures. These country-years are the first year for many independent states that decolonized in 1960 or other years from 1948 to the present.

There are some additional cases with more than one cases of all ZERO observed values. For example, Malta has 6 years with all ZERO values. These years for Malta occur during a period of transition between independence from Britain and the founding of its current military in 1973. However there was a defense force in operation during this transition period. So for these cases, there appears to be a conceptual issue with some datasets and the transition from colony to independent state and the accounting of military expenditures during these transition periods.

The country with the most years of all ZERO data is Iceland (67 years). Iceland too spends annually on defense primarily through its Coast Guard but this is not recorded by most datasets (possibly because it is a very small number, but there is clearly military spending occurring on an annual basis).

There are some other substantively interesting cases: The Gambia has 16 years of all ZERO data, during a period when it was part of a confederation with Senegal, which com-

pletely surrounds it. Haiti has 6 years of all ZERO data, occurring after a coup attempt. So again, these cases are about transition periods and we treat the values as missing instead of ZERO. This again increases the uncertainty around the estimated posterior distributions.

For all these cases we have treated these observed ZEROs as missing values and estimated non-ZERO values for these country-year units using the models. Because of this choice, there are not any issues with log transforming the dollar spend values from the observed dataset values. For all these missing values, most of our estimates range from a few hundred-thousand US dollars to a few million to 10s of millions of US dollars. All very small sums of military expenditures compared to nearly all the other country-years in the dataset.

The table below shows the country and years for units that have all ZERO entries.

gwcode	country	count	range	years
395	Iceland	67	1944-2022	1944-2003, 2007-2011, 2021, 2022
420	Gambia	16	1965-1982	1965-1978, 1980, 1982
95	Panama	14	1948-2022	1948-1959, 2021, 2022
571	Botswana	11	1966-1976	1966-1976
570	Lesotho	10	1966-1975	1966-1975
450	Liberia	9	1948-1956	1948-1956
731	North Korea	9	2005-2013	2005-2013
781	Maldives	8	1986-1993	1986-1993
41	Haiti	6	2004-2012	2004-2008, 2012
338	Malta	6	1964-1969	1964-1969
53	Barbados	5	1966-1970	1966-1970
115	Surinam	4	1975-1978	1975-1978
31	Bahamas	3	1973-1975	1973-1975
94	Costa Rica	2	2021-2022	2021, 2022
540	Angola	2	1976-1977	1976, 1977
811	Cambodia	2	1976-1977	1976, 1977

52	Trinidad and Tobago	1	1962-1962	1962
404	Guinea-Bissau	1	1975-1975	1975
411	Equatorial Guinea	1	1977-1977	1977
438	Guinea	1	1976-1976	1976
482	CAR	1	1960-1960	1960
483	Chad	1	1960-1960	1960
490	DR Congo	1	1960-1960	1960
517	Rwanda	1	1962-1962	1962
522	Djibouti	1	1977-1977	1977
581	Comoros	1	1975-1975	1975
713	Taiwan	1	1949-1949	1949
770	Pakistan	1	1947-1947	1947
816	Vietnam	1	1954-1954	1954

Table 8: Country-year units where all observed items are zero. For each country, the table gives the total number of years where all observed items are zero, the year range where observed zeros occur, and the specific years that have all observed zeros.

8 Replication of DiGiuseppe and Poast (2018)

8.1 Replication of regression analysis

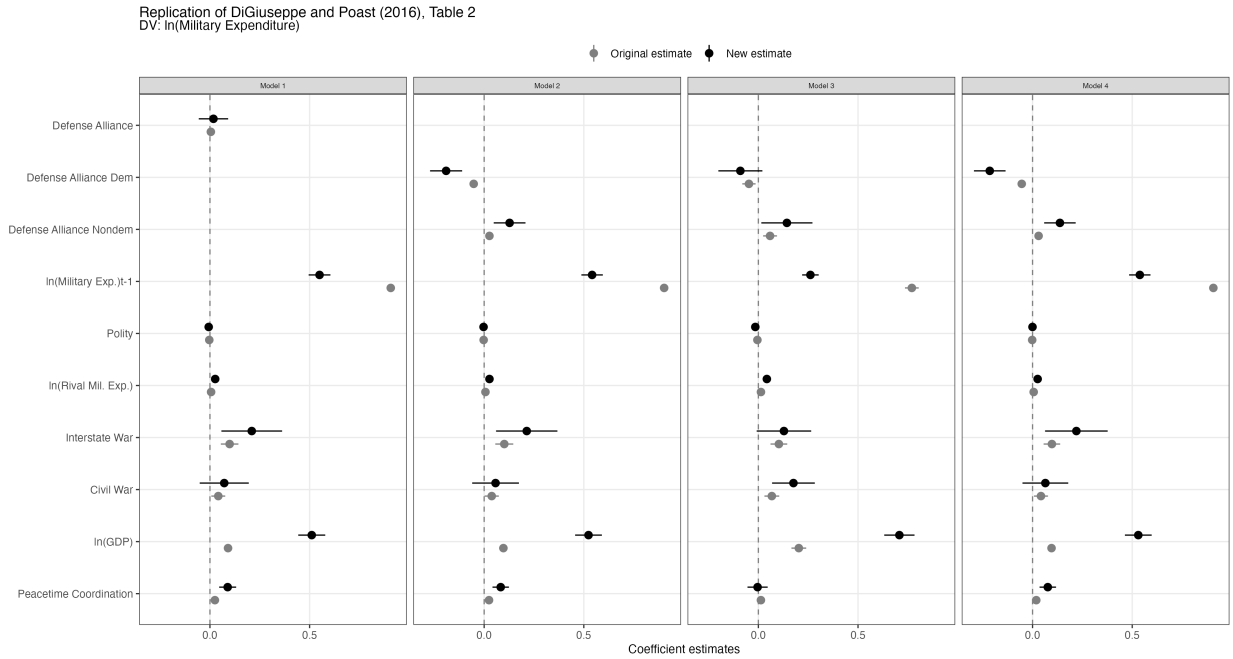

Figure 93: Coefficient estimates from replication of DiGiuseppe and Poast (2018), Table 2, Model 2. Estimates from the original paper are shown in gray. Estimates using new military expenditure data from the GMSD are shown in black. The latent variable approach of the GMSD allows us to incorporate measurement uncertainty into the estimation process.

	Model 1	Model 2	Model 3	Model 4
Defense Alliance	0.02			
	(0.04)			
Defense Alliance Dem		-0.19^{***}	-0.08	-0.21^{***}
		(0.04)	(0.06)	(0.04)
Defense Alliance Nondem		0.13^{**}	0.14^{*}	0.14^{**}
		(0.04)	(0.06)	(0.04)
ln(Military Exp.)_t-1	0.55^{***}	0.54^{***}	0.26^{***}	0.54^{***}
	(0.03)	(0.03)	(0.02)	(0.03)
ln(Rival Mil. Exp.)	0.03^{***}	0.03^{***}	0.04^{***}	0.03^{***}
	(0.00)	(0.00)	(0.01)	(0.00)
Interstate War	0.21^{**}	0.22^{**}	0.12	0.22^{**}
	(0.07)	(0.07)	(0.07)	(0.08)
Civil War	0.06	0.05	0.17^{**}	0.06
	(0.06)	(0.06)	(0.06)	(0.06)
ln(GDP)	0.51^{***}	0.52^{***}	0.71^{***}	0.53^{***}
	(0.03)	(0.03)	(0.04)	(0.03)
Peacetime Coordination	0.09^{***}	0.08^{***}	-0.01	0.08^{***}
	(0.02)	(0.02)	(0.03)	(0.02)
Fixed Effects	No	No	Country	Year
AR1	Yes	Yes	Yes	Yes
mean r^2	0.89	0.89	0.92	0.90

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 9: Replication of DiGiuseppe and Poast (2018). Models include the same covariates as Models 1-4, respectively, from Table 2 in DiGiuseppe and Poast, "Arms versus Democratic Allies." Military spending data is from the GMSD. To incorporate measurement uncertainty in the regression models, we take m = 100 random draws from the posterior distribution of military expenditure (using the posterior predictive interval for the SIPRI indicator), estimate m = 100 regression models, and combine the results. OLS regression coefficients with panel corrected standard errors in parentheses.

8.2 Replication of descriptive statistics for different historical time periods

	Variable	obs	mean	stdev
1	All states	2922	0.03	0.06
2	No defense pact	2156	0.03	0.06
3	Any defense pact	766	0.05	0.04
4	Defense pact with non-democracy and no democratic defense pact	638	0.06	0.04

	Variable	obs	mean	stdev
1	All states	2792	0.04	0.08
2	No defense pact	1880	0.02	0.06
3	Any defense pact	912	0.06	0.11
4	Defense pact with democracy and no nondemocratic defense pact	44	0.03	0.03
5	Defense pact with non-democracy and no democratic defense pact	318	0.09	0.10

	Variable	obs	mean	stdev
1	All states	6949	0.06	0.14
2	No defense pact	2195	0.06	0.14
3	Any defense pact	4754	0.05	0.13
4	Defense pact with democracy and no nondemocratic defense pact	505	0.02	0.01
5	Defense pact with non-democracy and no democratic defense pact	1574	0.09	0.18

	Variable	obs	mean	stdev
1	All states	3483	0.03	0.10
2	No defense pact	409	0.10	0.26
3	Any defense pact	3074	0.03	0.07
4	Defense pact with democracy and no nondemocratic defense pact	520	0.01	0.01
5	Defense pact with non-democracy and no democratic defense pact	616	0.06	0.15

9 Correlations of Arming and other Variables of Interest Over Time

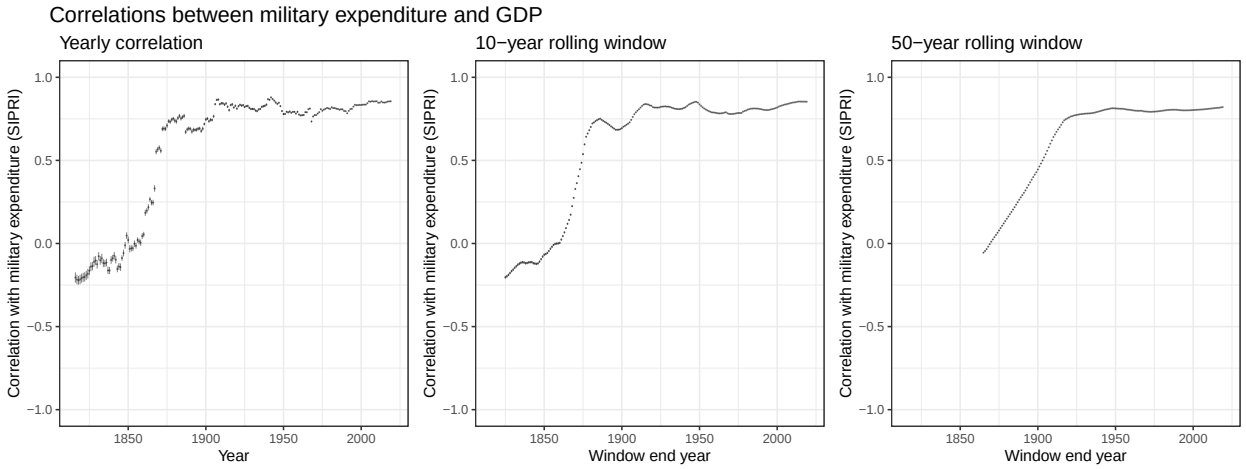

Figure 94: Distribution of Spearman rank-order correlation between the latent arming variable and GDP. Correlations are calculated for each 1-year period, 10-year period, and 50-year period. Note that we only estimate a correlation coefficient for year-periods with at least 10 country-year units.

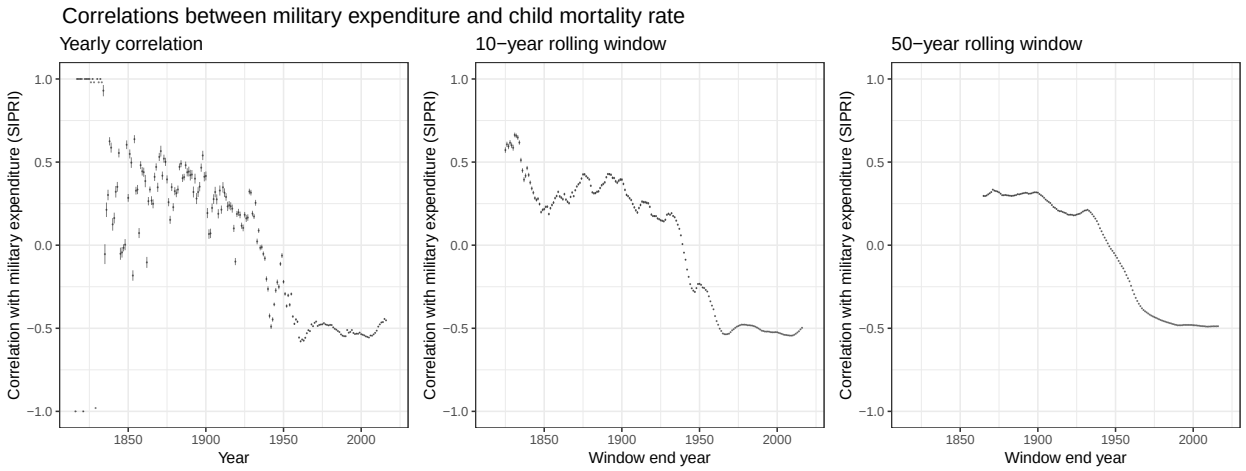

Figure 95: Distribution of Spearman rank-order correlation between the latent arming variable and child mortality. Correlations are calculated for each 1-year period, 10-year period, and 50-year period. Note that we only estimate a correlation coefficient for year-periods with at least 10 country-year units.

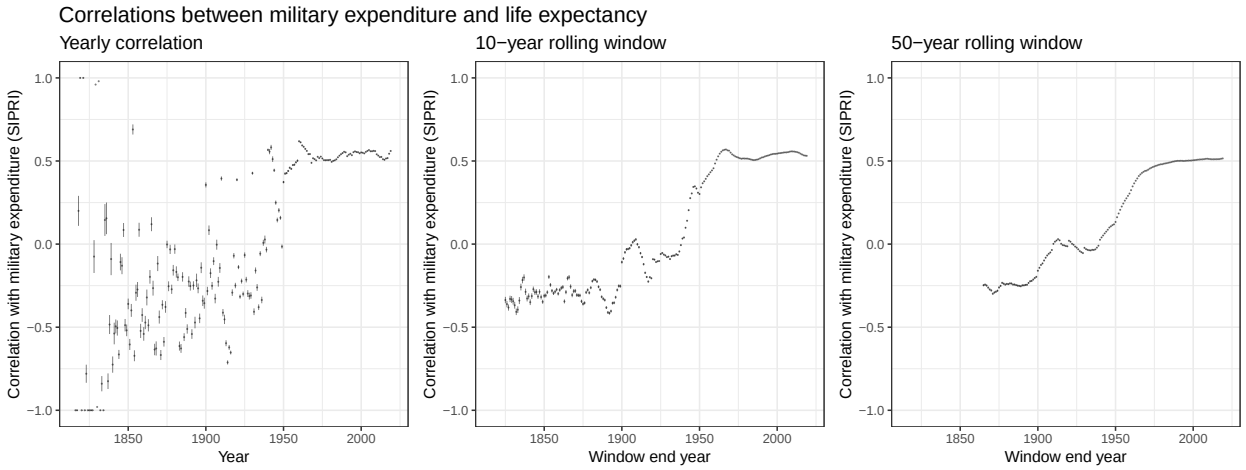

Figure 96: Distribution of Spearman rank-order correlation between the latent arming variable and life expectancy. Correlations are calculated for each 1-year period, 10-year period, and 50-year period. Note that we only estimate a correlation coefficient for year-periods with at least 10 country-year units.

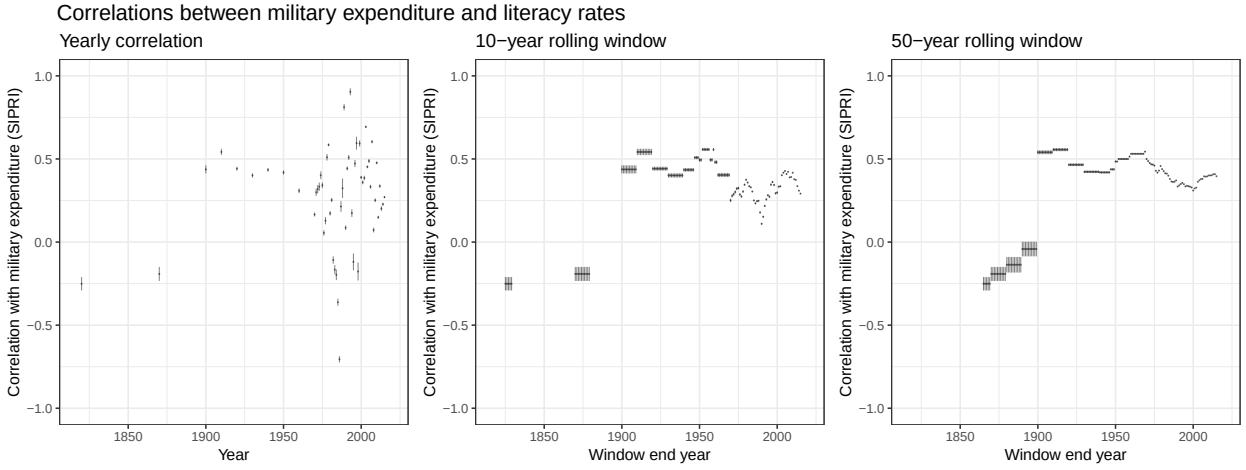

Figure 97: Distribution of Spearman rank-order correlation between the latent arming variable and literacy rates. Correlations are calculated for each 1-year period, 10-year period, and 50-year period. Note that we only estimate a correlation coefficient for year-periods with at least 10 country-year units.

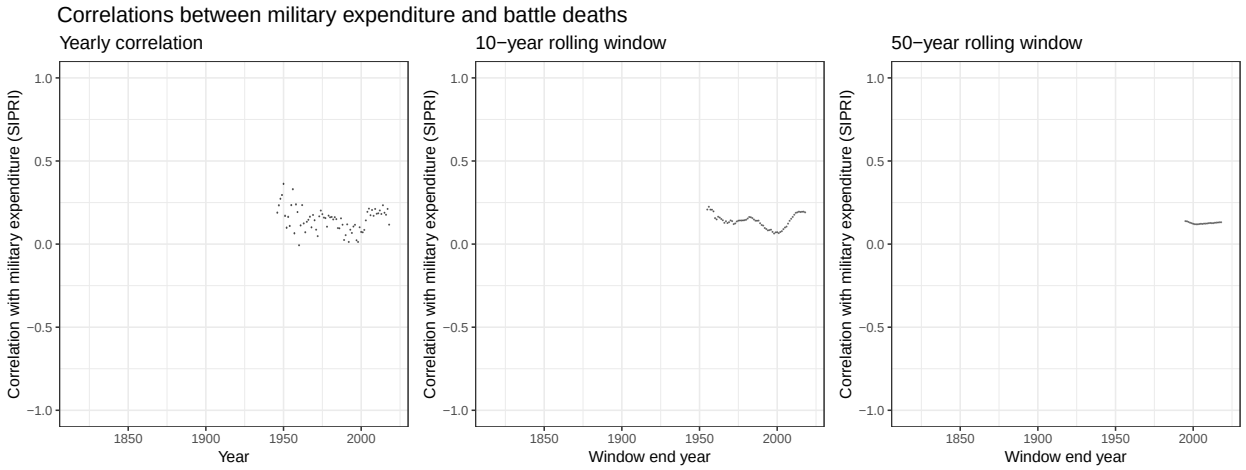

Figure 98: Distribution of Spearman rank-order correlation between the latent arming variable and battle deaths. Correlations are calculated for each 1-year period, 10-year period, and 50-year period. Note that we only estimate a correlation coefficient for year-periods with at least 10 country-year units.

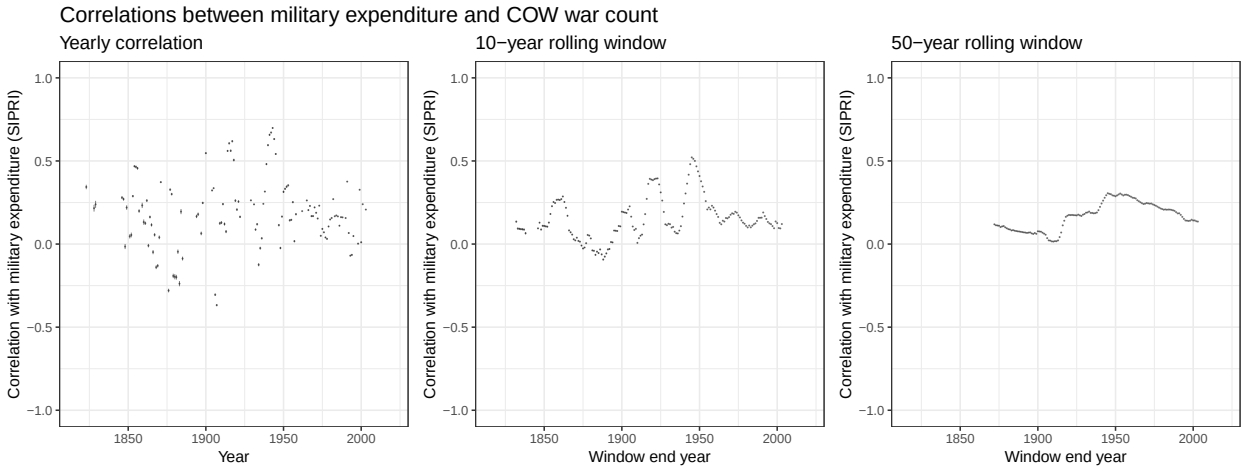

Figure 99: Distribution of Spearman rank-order correlation between the latent arming variable and war. Correlations are calculated for each 1-year period, 10-year period, and 50-year period. Note that we only estimate a correlation coefficient for year-periods with at least 10 country-year units.

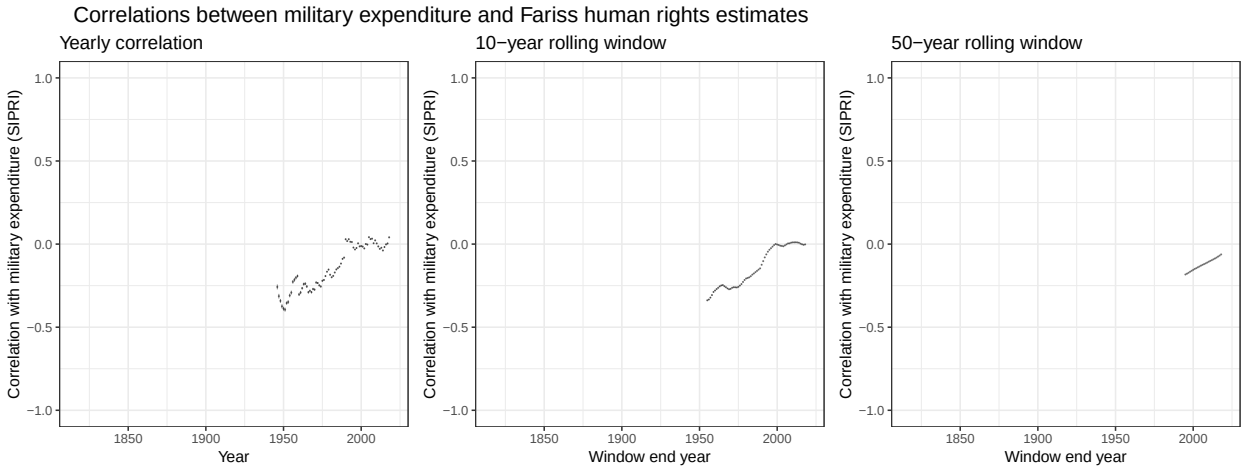

Figure 100: Distribution of Spearman rank-order correlation between the latent arming variable and human rights. Correlations are calculated for each 1-year period, 10-year period, and 50-year period. Note that we only estimate a correlation coefficient for year-periods with at least 10 country-year units.

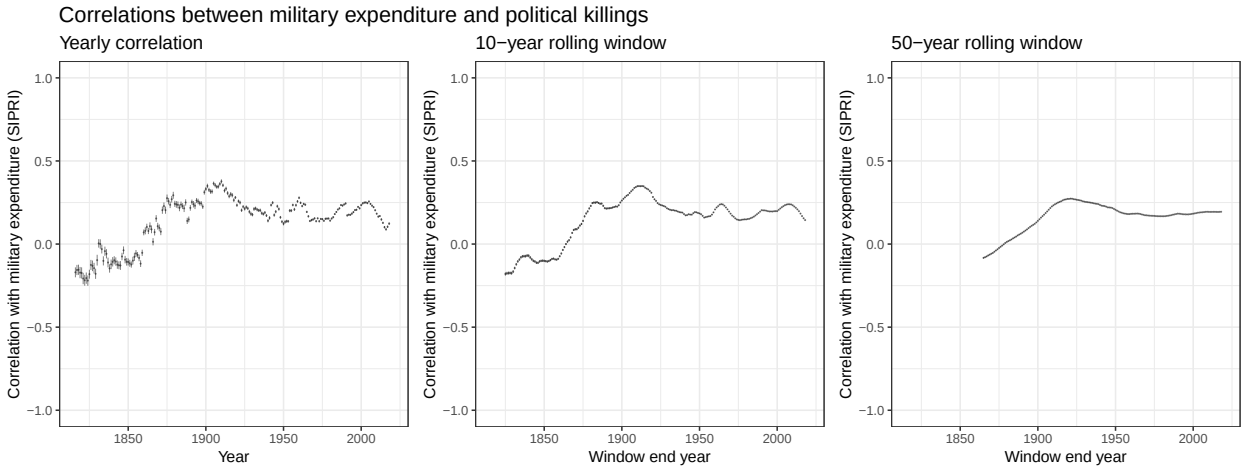

Figure 101: Distribution of Spearman rank-order correlation between the latent arming variable and VDEM killing. Correlations are calculated for each 1-year period, 10-year period, and 50-year period. Note that we only estimate a correlation coefficient for year-periods with at least 10 country-year units.

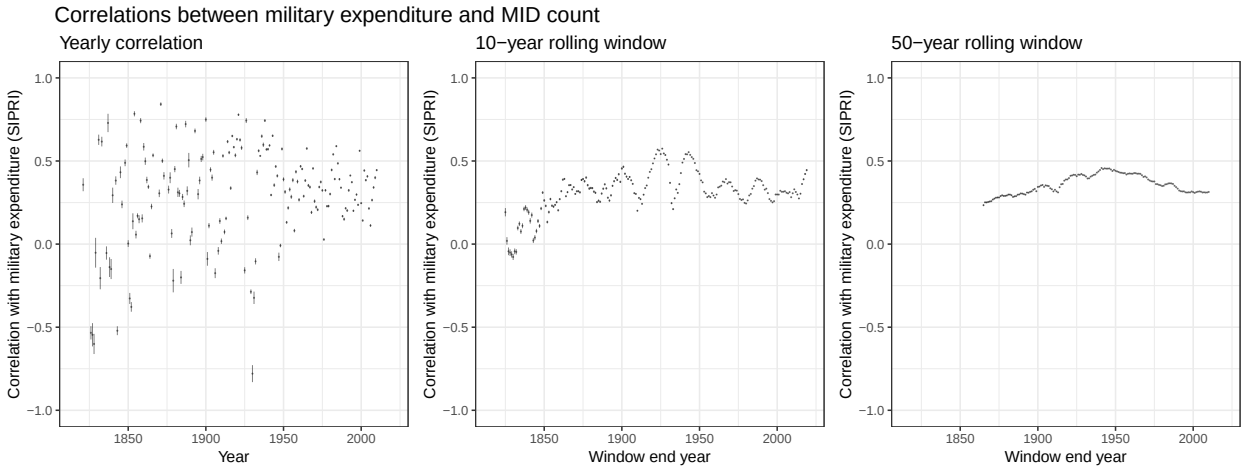

Figure 102: Distribution of Spearman rank-order correlation between the latent arming variable and MIDs. Correlations are calculated for each 1-year period, 10-year period, and 50-year period. Note that we only estimate a correlation coefficient for year-periods with at least 10 country-year units.

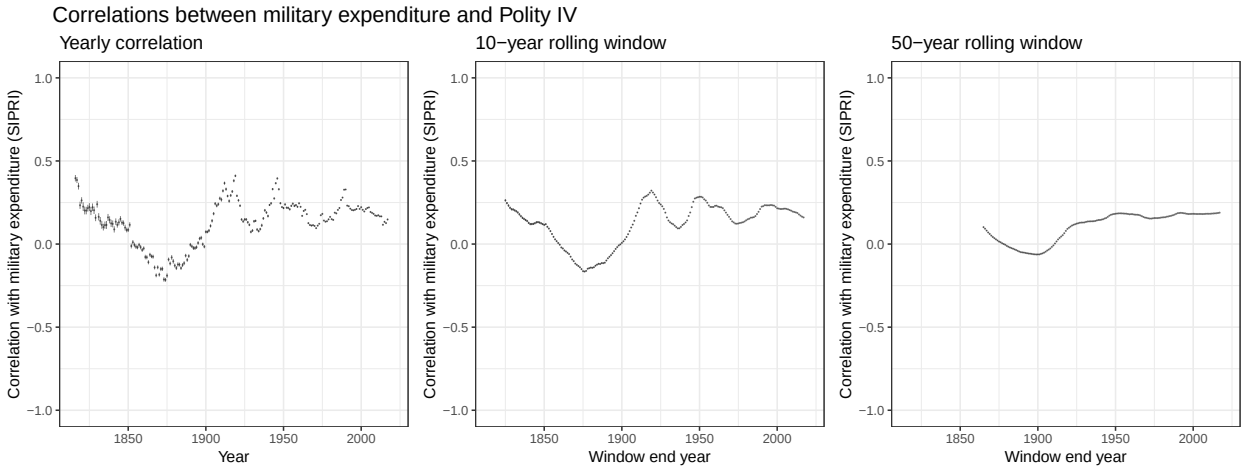

Figure 103: Distribution of Spearman rank-order correlation between the latent arming variable and democracy from the polity2 variable. Correlations are calculated for each 1-year period, 10-year period, and 50-year period. Note that we only estimate a correlation coefficient for year-periods with at least 10 country-year units.

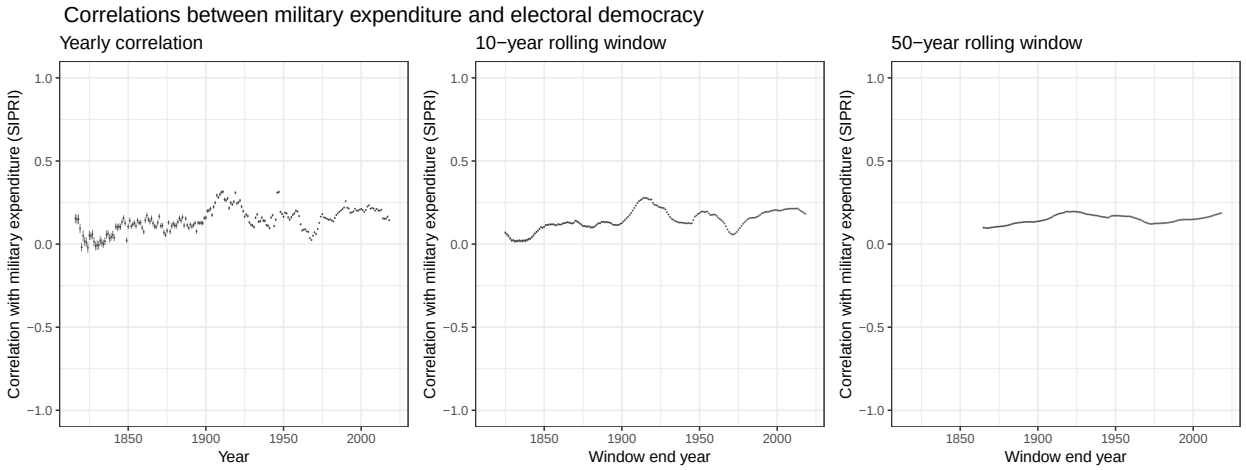

Figure 104: Distribution of Spearman rank-order correlation between the latent arming variable and democracy. Correlations are calculated for each 1-year period, 10-year period, and 50-year period. Note that we only estimate a correlation coefficient for year-periods with at least 10 country-year units.

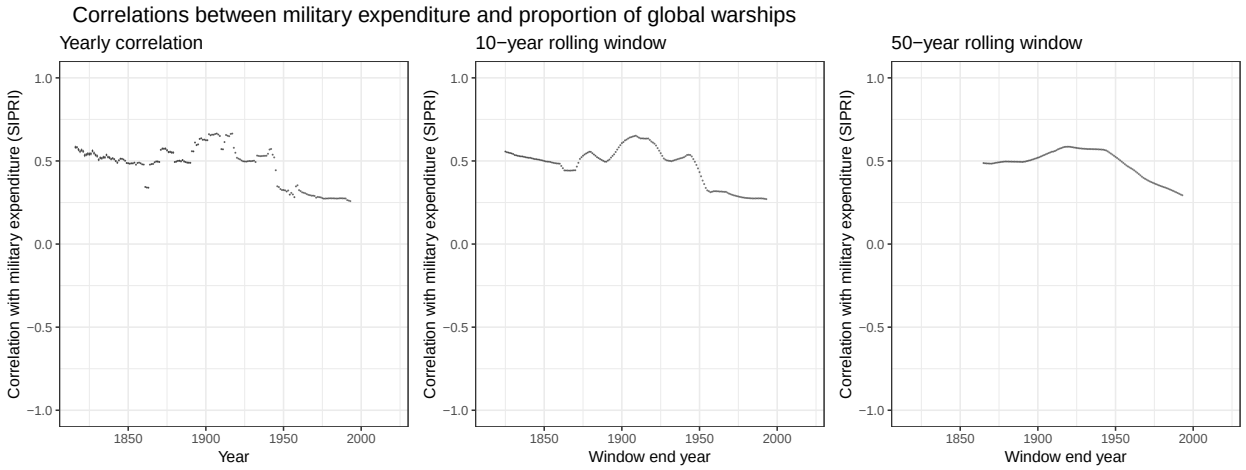

Figure 105: Distribution of Spearman rank-order correlation between the latent arming variable and naval ships proportion. Correlations are calculated for each 1-year period, 10-year period, and 50-year period. Note that we only estimate a correlation coefficient for year-periods with at least 10 country-year units.

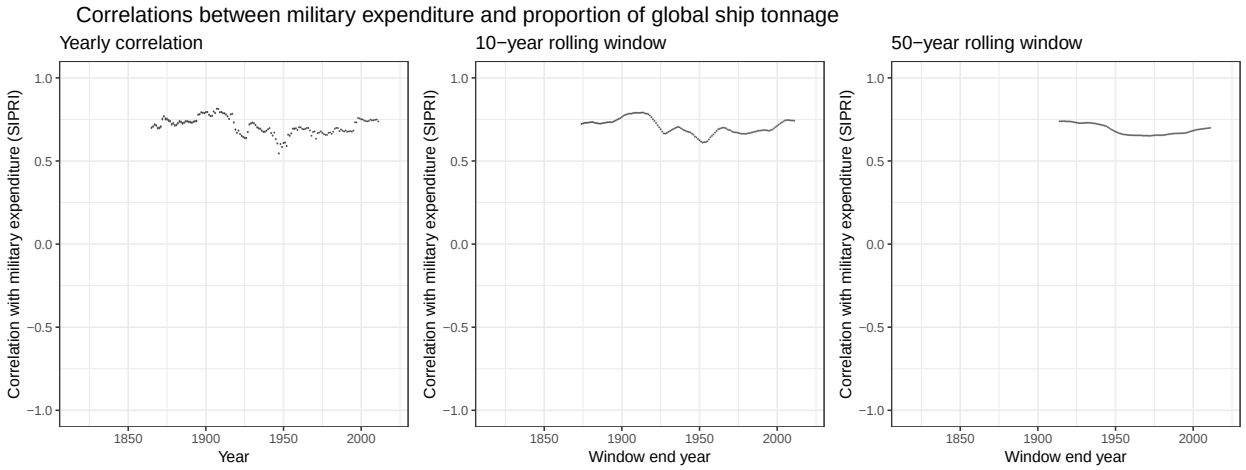

Figure 106: Distribution of Spearman rank-order correlation between the latent arming variable and naval tonnage. Correlations are calculated for each 1-year period, 10-year period, and 50-year period. Note that we only estimate a correlation coefficient for year-periods with at least 10 country-year units.

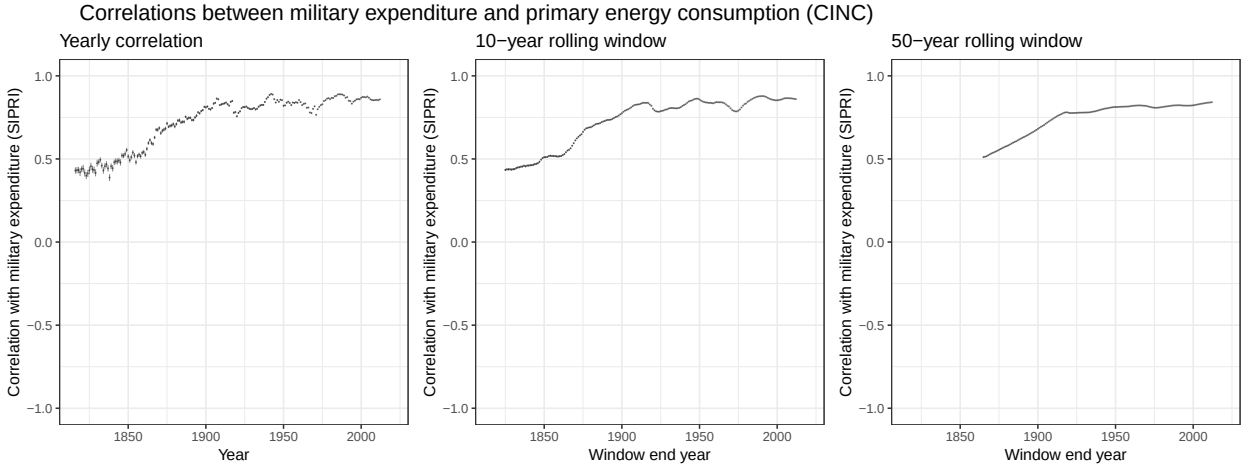

Figure 107: Distribution of Spearman rank-order correlation between the latent arming variable and energy production. Correlations are calculated for each 1-year period, 10-year period, and 50-year period. Note that we only estimate a correlation coefficient for year-periods with at least 10 country-year units.

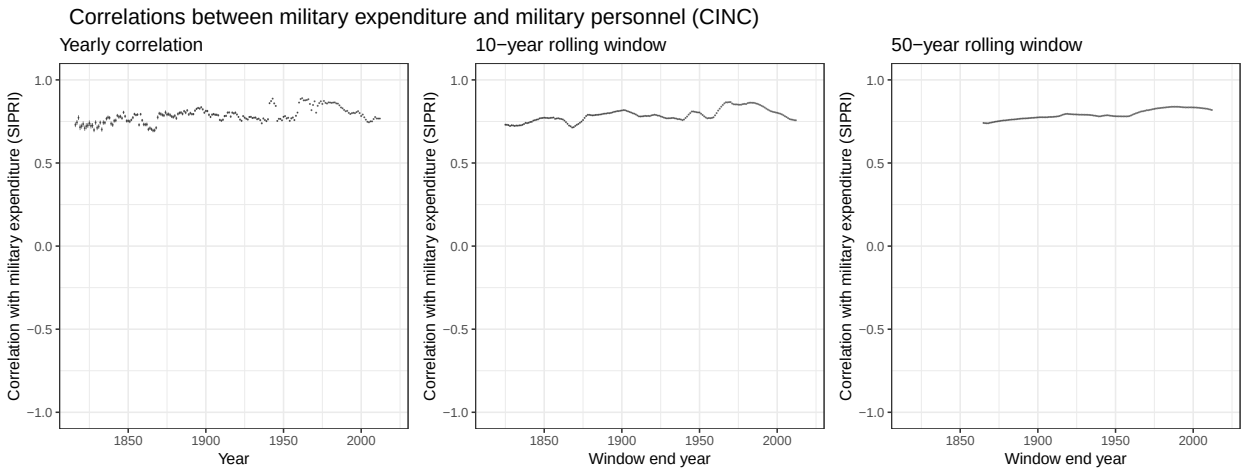

Figure 108: Distribution of Spearman rank-order correlation between the latent arming variable and military personnel. Correlations are calculated for each 1-year period, 10-year period, and 50-year period. Note that we only estimate a correlation coefficient for year-periods with at least 10 country-year units.

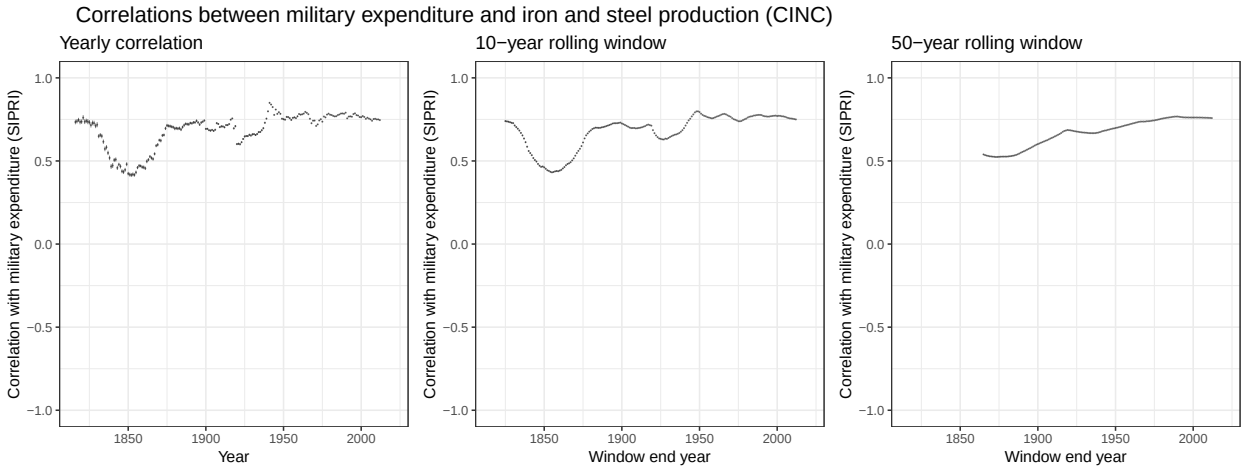

Figure 109: Distribution of Spearman rank-order correlation between the latent arming variable and iron and steal production. Correlations are calculated for each 1-year period, 10-year period, and 50-year period. Note that we only estimate a correlation coefficient for year-periods with at least 10 country-year units.

10 Predicting Levels of Arming

Here, we present some preliminary forecasting models in which we show the predictive relationship of SDP from Anders, Fariss, and Markowitz (2020) and potential threat (geopolitical competition) on the new measure of arming we develop in this paper. We present linear regression models with our measure of arming as the dependent variable. The model specifications vary and include an (1) intercept-only model, (2) intercept + SDP, (3) intercept + potential threat, and (4) intercept + SDP + potential threat. Models (5) - (8) are the same as (1) - (4) with the addition of a 1-year lagged measure of arming. Figure 18 presents the RMSE (root mean square error) for each model. Note that we present distributions for these statistics, which we are able to estimate because we estimate the model 100 times, by taking draws from the arming dependent variable and the other variables that also have uncertainty estimates (i.e., the lagged dependent variables, SDP). We also estimate these models using a leave-one-out procedure in which we predict each country?s values of arming based on a fitted linear regression model that does not include the specific country being predicted.

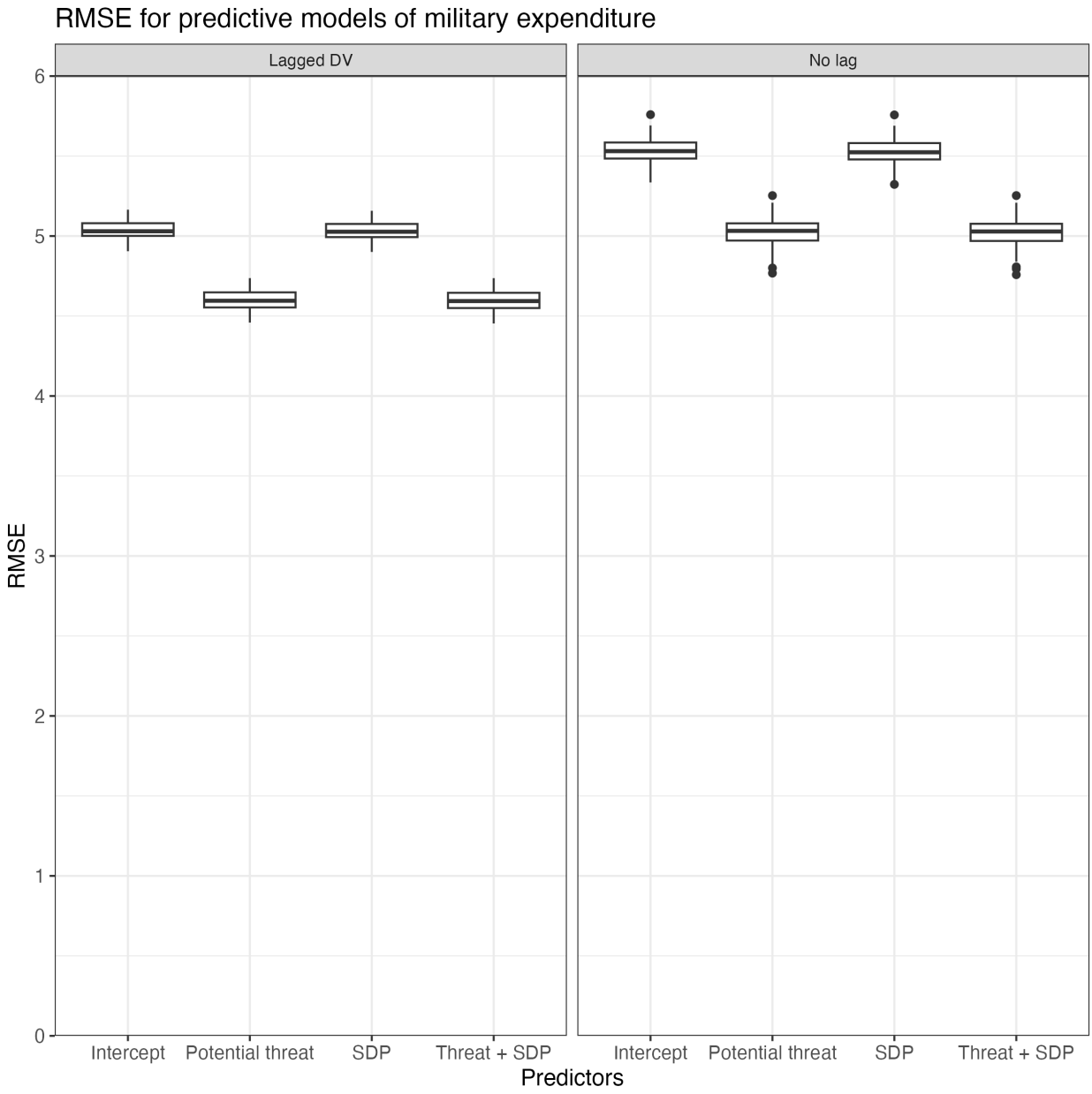

Figure 110: Comparison of root mean square error for predictive models of arming. Models in the left panel include the lagged dependent variable as a predictor, while those in the right panel do not. Other predictors include Surplus Domestic Product (calculated using a $2 per day subsistence threshold), and a measure of potential threat.

11 The Robustness of Military Burdens Over Time

Military burdens the ratio of states spending on arming to available monetary resources are an important area of research for international relations scholars (Anders, Fariss and Markowitz, 2020; Cappella Zielinski, 2016; Fearon, 2018; Lind, 2011; Norloff and Wohlforth, 2019). Here we consider the military burdens of several countries and regions over time, building on results published by Anders, Fariss and Markowitz (2020).

Anders, Fariss, and Markowitz demonstrate that surplus domestic product (SDP) is a better conceptual representation of the economic resources available to states to invest in arming than gross domestic product (GDP), previously the default measure (see e.g., Fearon, 2018; Khanna, Sandler and Shimizu, 1998; Rasler and Thompson, 1985). Thus, we measure military burdens in two ways: as ratios of spending to SDP and to GDP. To compute SDP for each state i in year t, we subtract from GDP the economic resources that the population consumes to survive, such that $SDP_{it} = GDP_{it} - ((365 * \tau) * Population_{it})$, where is the subsistence threshold (SDP is truncated to 0 if the resources needed for subsistence exceed GDP). Anders, Fariss, and Markowitz (2020) primarily use a subsistence threshold of $3 per day per person (and thresholds at $2, $1, and $0). In order to facilitate comparisons with previous results, we show military burdens at the $3 threshold. However, we also show results using a $2 per day subsistence threshold, as we are particularly interested in analyzing arming levels and military burdens in earlier historical time periods (facilitated by our new estimates of arming expenditures). Consistent with Anders, Fariss, and Markowitz (2020), we show here that when scaling military expenditures by SDP, the military burdens of poor states are much higher than the conventional measure (scaled by GDP).

We make two notable improvements to the calculation of military burdens in this paper. First, by including our new estimates of arms spending, we are able to incorporate uncertainty about expenditure values into the estimate of military burdens. Second, we include updated estimates of GDP from a recent article by Fariss et al. (2022), which also include uncertainty estimates, and recalculate SDP based on those estimates. In sum, we are able

to bring together the most up-to-date estimates of military burdens component measures, and showcase key patterns for important states and regions over time.

The expanded coverage of our estimates reveals additional information about historical military burdens. Figure 12 illustrates the evolution of military burdens over time for selected states. It provides additional evidence that supports previous findings from Anders, Fariss and Markowitz (2020) that suggest that until recently, military burdens were high for many developing countries. For example, the reason that there is a big difference between the military burdens measured as a share of SDP vs. GDP for China and India in comparison to other large countries, such as Russia, is that the former have a large population but are poor and have very little surplus domestic product. As a result, military burdens are much higher when measured as a share of their SDP compared to their GDP. If anything, our new data reveal that Andres et al., in fact, underestimated China military burdens in the first half of the 20th century, and that they were even higher than previous estimates suggest. China was so poor that, with $3 per person per day subsistence income, military expenditures consumed between 80-95% of their surplus income. However, for other countries such as Brazil, our new estimate suggests that, for much of the late 19th century, military expenditures were much lower than previous data suggested, and therefore military burdens during this time are also much lower than previously estimated. This highlights the importance of generating higher quality military expenditure estimates.

The figures below showcase trends in military burdens at the regional level. Our new data reinforce previous findings regarding the speed and extent of the decline in military burdens in recent decades, while also altering our understanding of historical trends in the average level of states' military burdens in earlier time periods.

Our data support previous findings that sub-Saharan Africa currently has the highest military burdens of any region, particularly when measured as a proportion of SDP. This further under-cuts Fearon's claims that there is "not much tragedy generated by conditions of international anarchy today because military burdens are only a couple of percentages

of GDP for more countries these days" (Fearon 2018, 555). However, if military burdens are measured as a share of the surplus income that could be spent on improving welfare (i.e., using SDP not GDP), there is in fact an enormous amount of tragedy. The average military burden for a sub-Saharan African state is 13.3% of SDP in 2019, which is much more tragic than Fearon's preferred measure of 1.2% of GDP would suggest. For context, this is approximately as high as the peak military burdens that the U.S. experienced during the Cold War in 1952 when the U.S. was fighting the Korean War and undergoing a massive rearmament.

While our data are consistent with previous estimates of high military burdens in sub-Saharan Africa during the 1990s (likely driven by the explosion in civil conflicts during this period), they also reveal that burdens were, on average, much higher during the 1950s than previously estimated, peaking around 40% of SDP and 16% of GDP. During this time period, our data includes estimates for military spending in many newly independent states, which were more sparsely covered in previous arming data. Sub-Saharan Africa is the only region where there has not been a steady uninterrupted decline in military burdens since the 1960s.

For the Middle East and North Africa (MENA), our new data allows us to calculate military burdens prior to 1850, and alters our understanding of historical trends. While average burdens were high in the 1800s, they were not nearly as high as previous data suggested (peaking at 29% of SDP in 1845, rather than being over 80% in 1850). Turning to the twentieth century, our data also reveal that, rather than spiking during WWII and the Iran-Iraq war, average burdens were actually highest in the late 1960s, likely driven by Arab conflicts with Israel. As a result, the data show that military burdens in the Middle East have followed a similar pattern to other regions and generally steadily decreased since the 1960s. However, our data reinforce previous findings which suggest that military burdens in the Middle East have fallen more slowly than in other regions and remain relatively high today, as a proportion of both SDP and GDP. One potential explanation for this trend is that, in contrast to other regions, much of the Middle East has grown richer from sources

of wealth (oil and gas) that are insensitive to appropriation. Because these resources would enrich anyone who succeeded in taking them by force, governing regimes face much greater incentives to maintain high levels of arms to deter internal and external threats to that wealth.

For Europe, our new data capture important features of historical trends in burdens that do not show up in Anders, Fariss and Markowitz (2020) estimates. Previous estimates suggest that average military burdens peaked at nearly 50% of SDP or approximately 38% of GDP in the early 1850s during the Crimean War. This is implausible given that they exceed average military burdens during the Napoleonic Wars. As the Napoleonic Wars were wars of survival for many European countries; we would expect military burdens to be much higher than during the Crimean War. Our new estimates match this expectation and provide a useful correction to the Anders, Fariss and Markowitz (2020) estimates. Our data suggest that average military burdens in Europe during the Crimean War (1853-1856) were approximately 3% of GDP or 5% of SDP. This is in line with existing estimates for the United Kingdom, one of the few countries where we have historical sources based on high-quality government data, which estimate the U.K. peaked at roughly 22% of GDP during the Napoleonic Wars as opposed to approximately 6% of GDP during Crimea. Insofar as the United Kingdom is representative of other countries in the region, this suggests that military burdens should have been much higher during the Napoleonic Wars than during the war in Crimea, which is exactly what our new data show. Furthermore, in contrast to previous estimates, our new data capture a dip in military burdens during the interwar period, giving us greater confidence that the new data paint a more accurate picture of Europe's military burdens over time.

For Asia, our new data show military burdens increasing throughout the first half of the 20th century, peaking for both SDP and GDP in the 1950s. This is plausible given that historical accounts suggest World War II was a far more intense military competition than any of the arms races and conflicts occurring in Asia since 1816 (and that this competition

extended into the postwar period and the Korean War), but contrasts with previous results from Anders, Fariss and Markowitz (2020), which show a peak in Asian military burdens in 1900. However, our data reinforce previous findings which suggest that, while Asia had higher peak military burdens since WWII than any other region (peaking in 1952 at just over 50% of SDP or 13.6% of GDP), burdens in Asia decreased faster than in any other region. Average military burdens were around 17.4% of SDP in 1990, down to 13.3% of SDP in 2000, and had fallen to 6.2% of SDP by 2019. While consistent with Anders, Fariss, and Markowitz (2020), this finding contradicts the narrative that Asia is growing more militaristic and that a regional arms race is intensifying.

Finally, our new data suggest that military burdens in the Americas were historically far higher and peaked earlier than previously understood, likely peaking around 47% rather than 30% of SDP in 1847. Average military burdens appear higher because our new data provide military spending estimates for a number of poorer countries that were missing from existing datasets in earlier time periods.

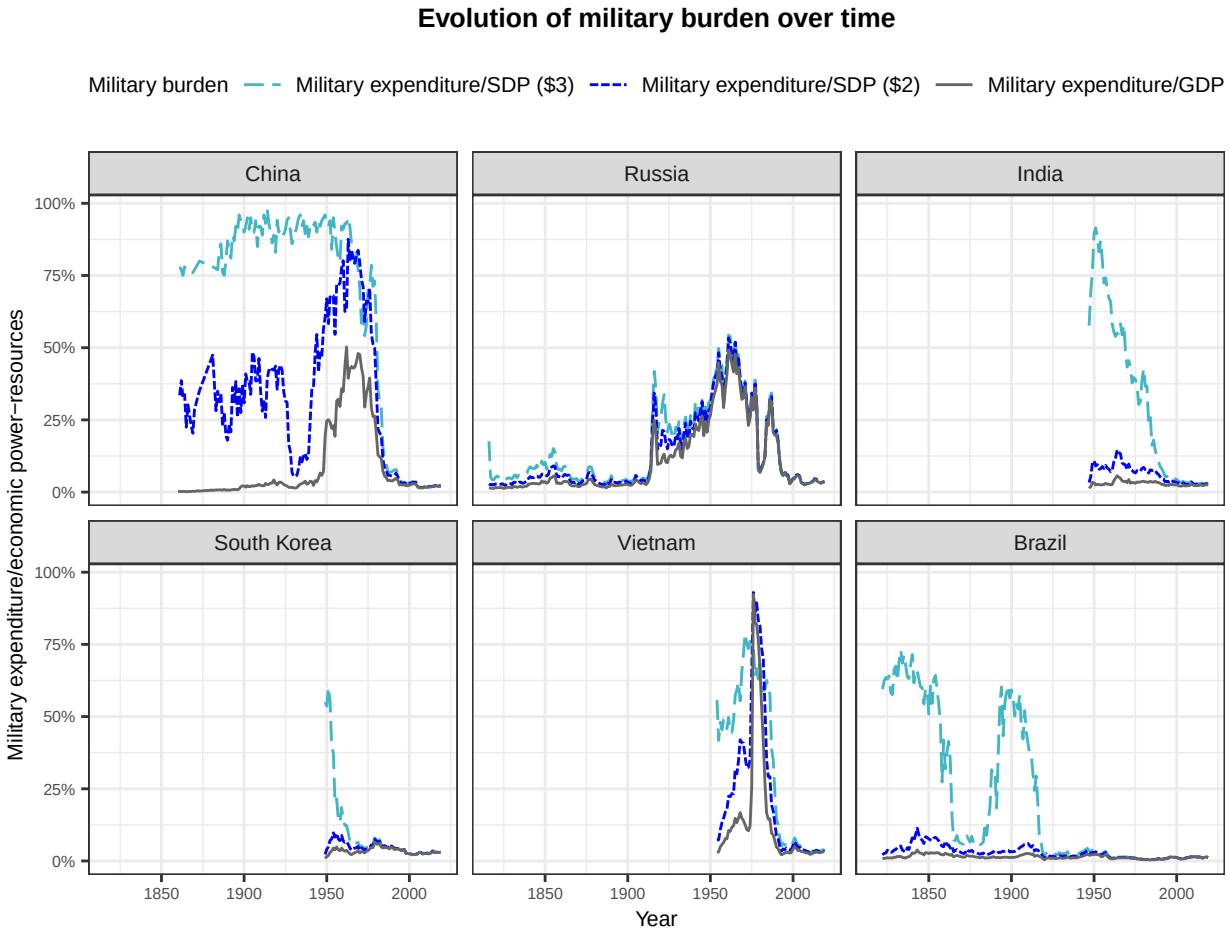

Figure 111: Change in military burden over time for select countries. Lines represent three indicators of military burden: military expenditure as a proportion of SDP ($2 per day subsistence threshold), as a proportion of SDP ($3 per day subsistence threshold), and as a proportion of GDP.

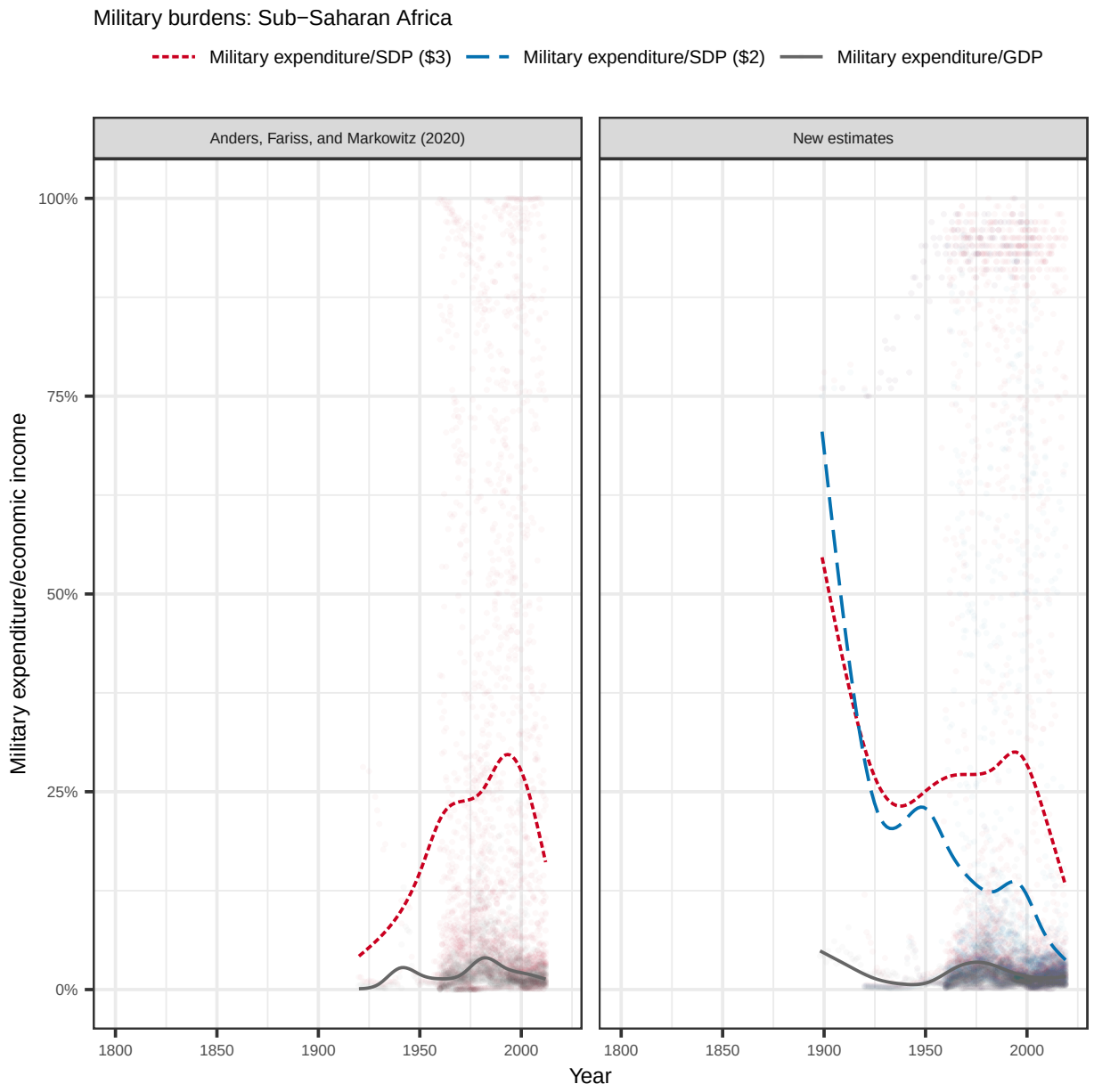

Figure 112: Change in military burdens over time in Sub-Saharan Africa: comparison of new estimates with those from Anders et al. Lines represent the smoothed average over all countries in the region for three indicators of military burden: military expenditure as a proportion of SDP ($2 per day subsistence threshold), as a proportion of SDP ($3 per day subsistence threshold), and as a proportion of GDP.

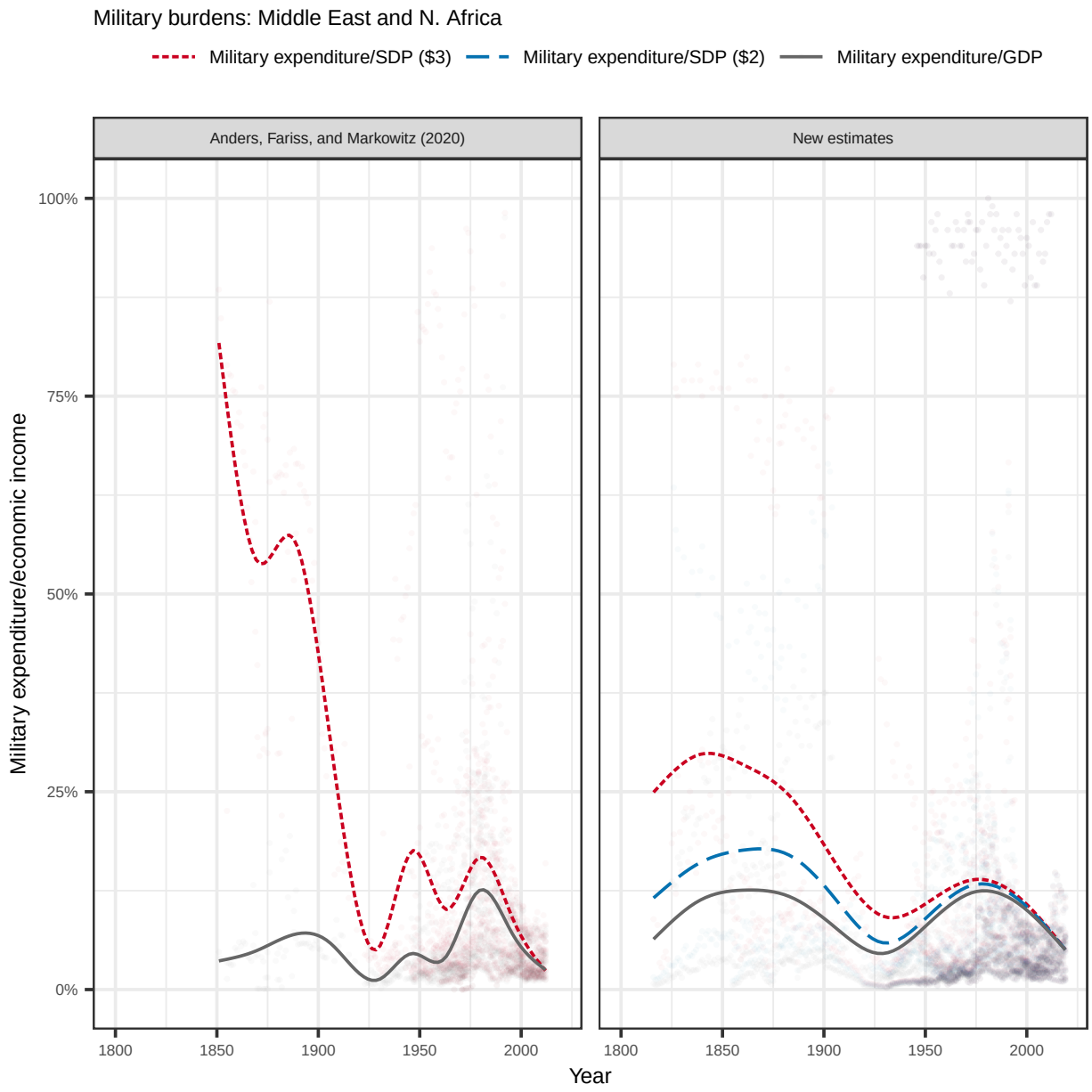

Figure 113: Change in military burdens over time in the Middle East and North Africa: comparison of new estimates with those from Anders et al. Lines represent the smoothed average over all countries in the region for three indicators of military burden: military expenditure as a proportion of SDP ($2 per day subsistence threshold), as a proportion of SDP ($3 per day subsistence threshold), and as a proportion of GDP.

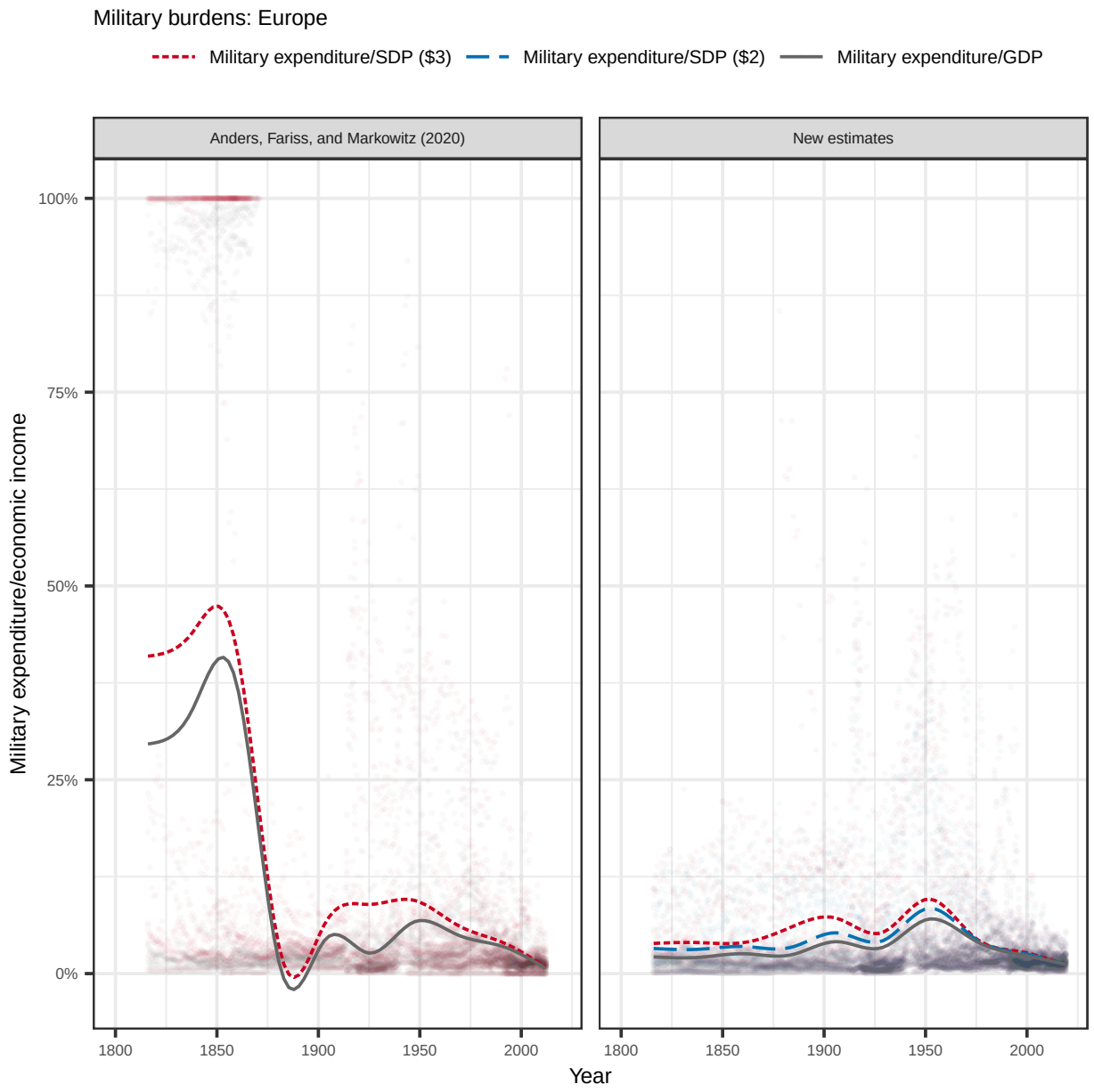

Figure 114: Change in military burdens over time in Europe (including Russia): comparison of new estimates with those from Anders et al. Lines represent the smoothed average over all countries in the region for three indicators of military burden: military expenditure as a proportion of SDP ($2 per day subsistence threshold), as a proportion of SDP ($3 per day subsistence threshold), and as a proportion of GDP.

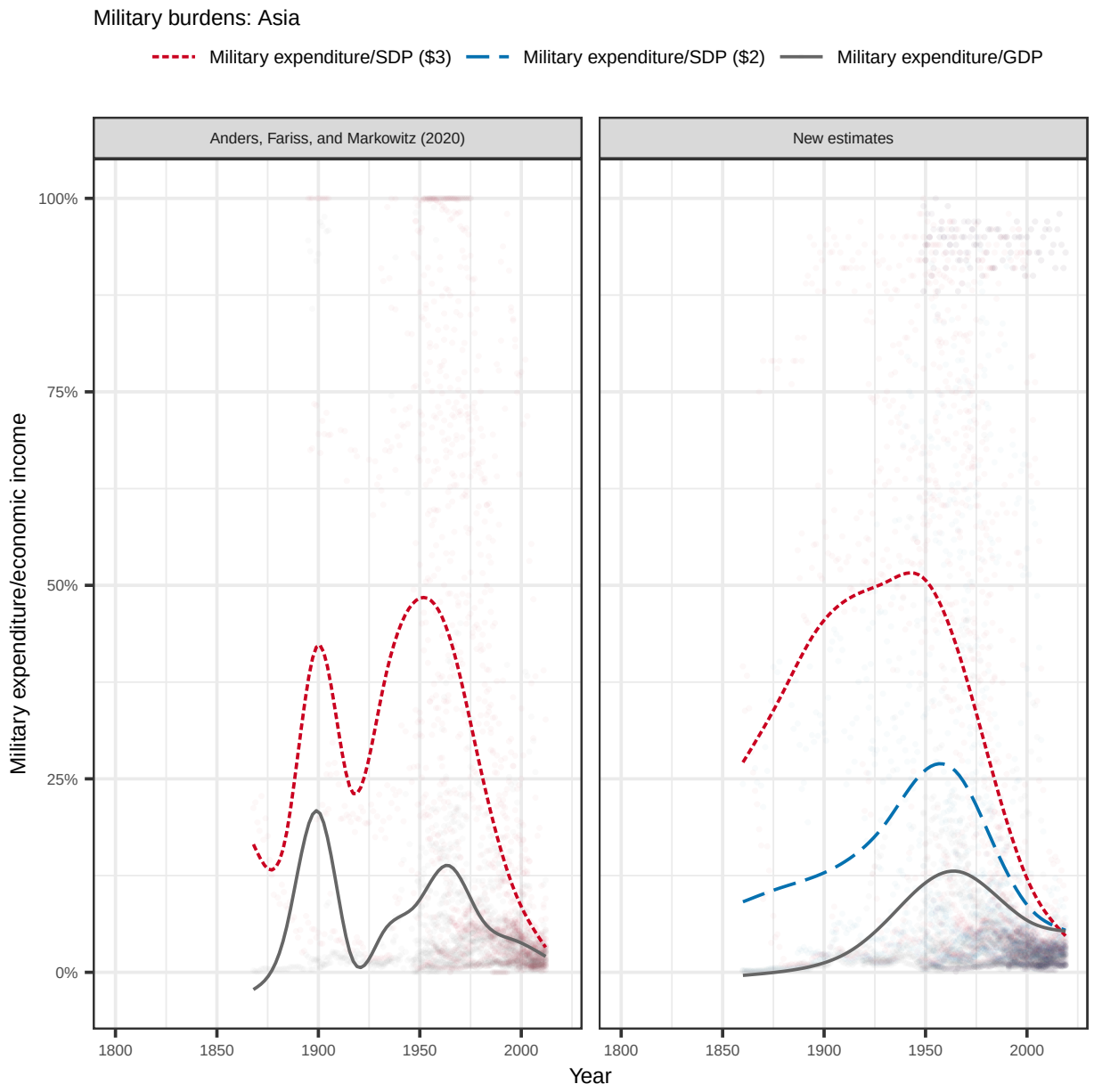

Figure 115: Change in military burdens over time in Asia: comparison of new estimates with those from Anders et al. Lines represent the smoothed average over all countries in the region for three indicators of military burden: military expenditure as a proportion of SDP ($2 per day subsistence threshold), as a proportion of SDP ($3 per day subsistence threshold), and as a proportion of GDP.

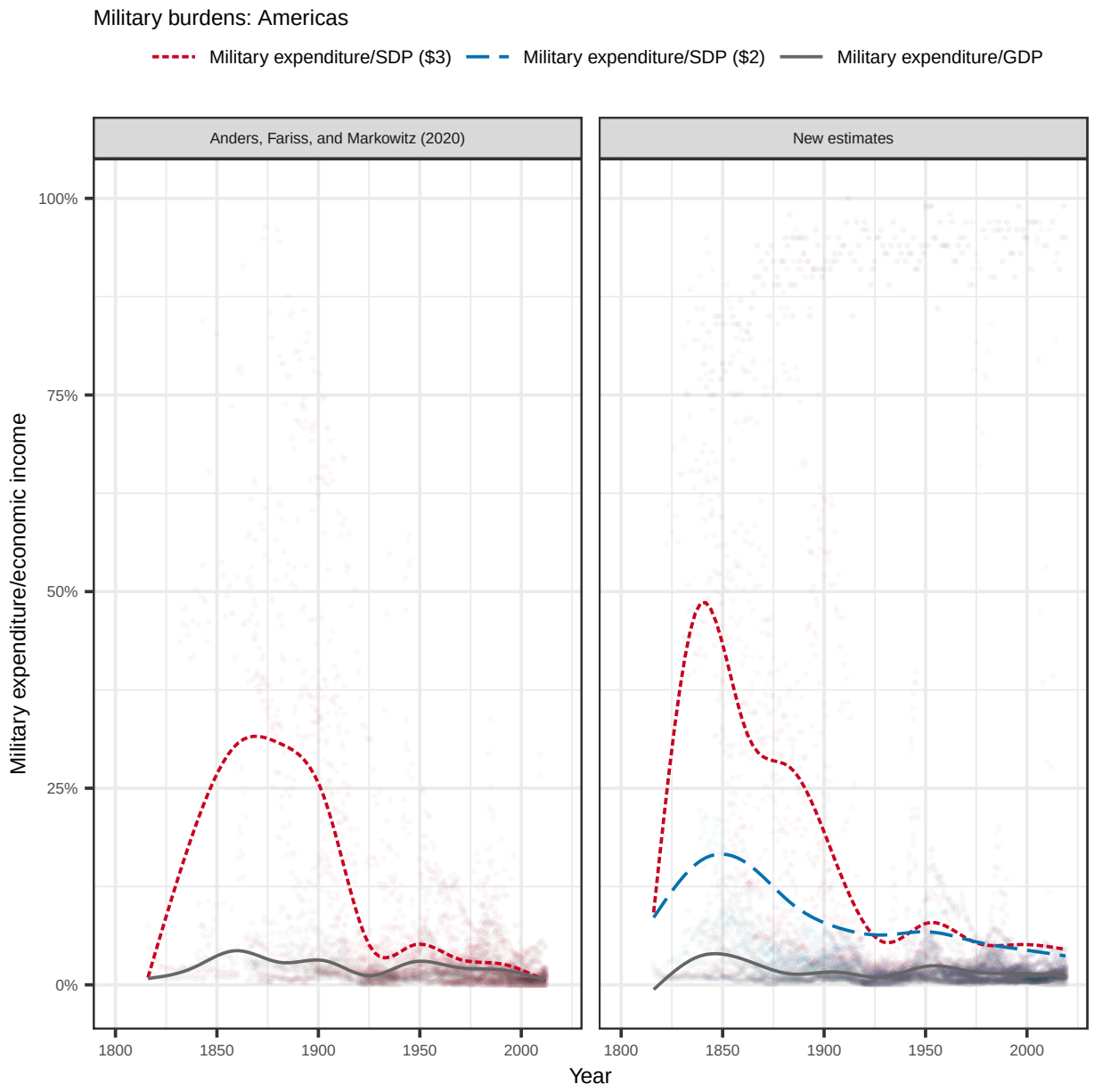

Figure 116: Change in military burdens over time in the Americas (including the US and Canada): comparison of new estimates with those from Anders et al. Lines represent the smoothed average over all countries in the region for three indicators of military burden: military expenditure as a proportion of SDP ($2 per day subsistence threshold), as a proportion of SDP ($3 per day subsistence threshold), and as a proportion of GDP.

12 Historic Arming Sources

The most useful citations include: Australia, Parliament (1914); Becker (1963); Belgium, Ministasre des Finances (1889); Belgium, Chambre des Representants (1840); Bogart (1919); Bornstein (1959); Carrias (1960); Chalmin (1957); Clode (1869); Clowes (1897); Curtiss (1965); DeGaulle (1945); Dernberger (1975); Dupuy (1970); Erickson (1962); Ermarth (1964); The Europa Yearbook (1960); Foot (1961); France (1838); France, Institut National de la Statistique et des Etudes Economiques (1845); France, MinistÃšre des Finances (1823); Fujiwara (1961); Genealogisch historisch statistischer Almanach Fur das Jahr (1824); Genealogischer und Statistischer Almanach fur Zeitungsleser (1859); Gerlach (n.d.); Germany (1862); Gittings (1967); Godaire (1962); Great Britain, Board of Trade, Statistical Department (1874); Great Britain, Central Statistical Office (1840); Guichi (1922); Hislam (1908); Howard (1961); International Institute for Strategic Studies (1959, 1962); Italy, Direzione Generale della Statistica (1878); Japan, Office of the Prime Minister, Bureau of Statistics (1960); Khromov (1950); Klein (1959); La Gorce (1963); League of Nations (1926); Lee (1977); Liu (1956); Labell (1874); Loftus (1968); Malchus (1830); Monteilhet (1932); Naikoko (1967); New York Times (1947); Ogawa (1923); Powell (1955); Prussia, Statistisches Landesamt (1851); Quetelet (1829); Romanones (1924); Romero (1898); RÃŒstow (1867); Schneider and Hoeber (1976); Sellers (1966); Sivard (1979); Stockholm International Peace Research Institute (1969); Taylor and Jodice (1983); United Nations, Department of International Economic and Social Affairs, Statistical Office (1948); United Nations, Office of the Secretary General (1962); United States, Arms Control and Disarmament Agency (1964); United States, Office of Naval Intelligence (1911); United States, War Department, Military Commission to Europe (1861); Upton (1878); Wanty (1957); Whiting (1966).

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