Constellations of fragility:

an empirical typology of states

Supplementary file

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This is a supplementary file (online appendix) to the article *Constellations of fragility: an empirical typology of states* published in *Studies in Comparative International Development*. It provides additional details on the data used, model selection and results, as well as access to replication files.

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Contents

1 Data

1.1 Sources

Table A1 lists all indicators used and their sources.[1] To determine our universe of cases, we employ the list of independent states as defined by the CShapes package (Weidmann, Kuse, & Gleditsch 2010).

Table A1: Indicator sources

Dimension and indicator	Source name	Reference
Violence control:		
- Battle deaths	Uppsala Conflict Data Program (UCDP)	Gleditsch, Wallensteen, Eriksson, Sollenberg, and Strand (2002), Themnér and Wallensteen (2011)
- Homicides	United Nations Office on Drugs and Crime (UNODC)	UNODC (2013)
- Monopoly of violence	Bertelsmann Transformation Index (BTI)	BTI (2016b)
Implementation capacity:		
- Basic administration	BTI	BTI (2016b)
- Child mortality	UN Inter-agency Group for Child Mortality Estimation (IGME)	IGME (2014)
- Primary enrollment	UNESCO Institute for Statistics (UIS) and UNICEF	UISUNESCO (2015)
- Water access	World Health Organization (WHO) and UNICEF	WHOUNICEF (2012)
Empirical legitimacy:		
- Asylums granted	United Nations High Commissioner for Refugees (UNHCR)	UNHCR (2015)
- Press freedom	Freedom of the Press	Freedom House (2014)
- Human rights	Human rights protection scores	Fariss (2014)

Table A2 provides information on the properties of the raw data before transformation. This includes data beyond the time period considered in the clustering exercise, as information from 1999 to 2015 is used to interpolate missing observations. The BTI variables are our only ordinal indicators, with 1 representing the lowest and 10 representing the highest performance. Since they come in ten levels that appear to be approximately equally spaced (BTI 2016a: 12), we treat them as interval scores. As the collection of expert assessments ends early in the year preceding the nominal BTI issue year and is calibrated and updated during that year (BTI 2016a: 7), we lag all BTI data by one year.

[1] Some indicators were not obtained directly from the sources, but via the World Development Indicators (The World Bank 2015).

1.2 Missing data

Our indicators exhibit varying levels of coverage and missingness. The most problematic variables in this regard are those from the BTI, being collected only for about 125 countries and only every other year starting in 2005 (i.e., with the 2006 publication). Moreover, after a recent revision of provider to the methodology, *homicides* has very few reliable data points for most African countries before 2012 (UNODC 2013: 109-114). The coverage of the latent human rights scores (Fariss 2014) currently ends in 2015. We thus restrict our period of investigation to 2005–2015. Within this period, we can keep all countries in our sample by imputing the remaining missing data based on conservative assumptions. Data from 1999 to 2015 are used for imputation where available.

As their sources claim global coverage, we assume *battle deaths* and *asylums granted* to be zero where not otherwise reported, thus removing all missing observations in years covered by the source. We assume *monopoly of violence* and *basic administration* to have the highest score for all OECD countries not covered by the BTI. This may not be valid in all cases, but our minimum approach for aggregating the dimension scores (explained below) removes most upward bias. The remaining missing observations between existing ones are interpolated linearly. For some indicators, we extrapolate both beyond the first and the last observation, using the score of the closest available observation – a more conservative estimate than linear extrapolation. We extrapolate only those indicators that are known to change slowly over time, and we extrapolate more years for those known to be most stable (see table 1 in the main text). Note that we maintain a temporal coverage from 1999 to 2015 during the interpolation step to reduce our reliance on extrapolation. If we abstained from extrapolating, the low availability of some data – particularly homicide – would severely reduce our sample. This procedure results in 1,885 observations for our eight year period, or 172 countries per year (save the Republic of Macedonia in 2005).

We imputed missing observations for variable x linearly:

$$x_{im} = x_{il} + (m-l)\frac{n-l}{x_{in}-x_{il}},$$

Table A2: Summary statistics (raw data) and assignment of dimensions, 1999-2015

Dimension	Indicator	N	Mean	Std. dev.	Min.	Max.
Violence control:	Battle deaths per 100,000 inh.	2927	0.15	1.99	0.00	73.69
	Homicides per 100,000 inh.	1862	8.13	12.53	0.00	108.60
	BTI monopoly of violence	893	7.83	2.23	1.00	10.00
Implementation capacity:	BTI basic administration	893	7.14	2.37	1.00	10.00
	Child mortality per 1,000 births	2919	45.90	47.46	2.20	239.00
	Primary school enrollment rate	1968	0.90	0.14	0.26	1.00
	Access to improved water source rate	2864	0.85	0.17	0.23	1.00
Empirical legitimacy:	Asylums granted per 100,000 inh.	2757	1.03	4.67	0.00	100.94
	FH freedom of the press	2926	49.39	24.06	0.00	100.00
	Human rights protection score	2927	0.45	1.29	-2.73	4.71

where i is the country indicator, m the year of the missing observation, l the year of the last available observation, and n the year of the next available observation.

For some variables (see table 1 in the main article), we extrapolated missing observations that do not have preceding or following observations. Formally, the extrapolation set

$$x_{im} = \begin{cases} x_l & if\ n = \varnothing \,\&\, e \geq m - l \\ x_n & if\ n = \varnothing \,\&\, e \leq m - n \end{cases},$$

where e is the extent of extrapolation as indicated in table 1 in the main article. Note that we maintain a temporal coverage from 1999 to 2015 during the interpolation step to reduce our reliance on extrapolation.

As an alternative to linear interpolation, we also experimented with multiple imputation with the Amelia package (Honaker & King 2010). We did not achieve satisfactory levels of face validity, however. Large and unexplained leaps occurred within country series despite the inclusion of country fixed effects. The simple imputation technique we opt for has the additional advantage that it keeps our index more transparent for non-experts.

1.3 Discarded indicators

We reviewed a large number of data sources to find the most suitable indicators for measuring our three state functions. Most were discarded due to concerns over validity, reliability, coverage, and technical suitability. In this section, we provide two examples and explain in detail why they were not included.

Table A3: Countries affected by including ICRG bureaucracy quality as additional indicator in the implementation capacity dimensions

Country	Impl. capacity	Impl. cap. incl. ICRG BQ	Difference
North Korea	0.57	0.00	0.57
Romania	0.73	0.25	0.48
Russia	0.70	0.25	0.45
Ukraine	0.70	0.25	0.45
Belarus	0.70	0.28	0.42
Armenia	0.65	0.25	0.40
Moldova	0.62	0.25	0.37
Cuba	0.83	0.50	0.33
Nicaragua	0.57	0.25	0.32
Paraguay	0.57	0.25	0.32
Serbia	0.81	0.50	0.31
Estonia	0.93	0.62	0.30
Italy	0.92	0.62	0.29
Togo	0.29	0.00	0.29
Bahrain	0.77	0.50	0.27
Bulgaria	0.76	0.50	0.26
Venezuela	0.50	0.25	0.25
Cote d Ivoire	0.25	0.00	0.25
Qatar	0.75	0.50	0.25
Kuwait	0.74	0.50	0.24

The first example is the International Country Risk Guide's (ICRG) *bureaucracy quality* indicator (Political Risk Services 2012). Due to the scarcity of indicators measuring the strength of public administration across countries, this is a frequently used indicator in the study of state capacity. However, the codebook notes that 'high points are given to countries where the bureaucracy has the strength and expertise to govern without drastic changes in policy or interruptions in government services. In these low-risk countries, the bureaucracy tends to be somewhat autonomous from political pressure and to have an established mechanism for recruitment and training' (Political Risk Services 2012: 7). The indicator thus puts more emphasis on autonomy than on capacity – while we are primarily interested in the latter. Table A3 shows the effect of including ICRG as additional indicator in the implementation capacity dimension. The first data column shows implementation capacity scores as used in the main text; the second column, capacity scores calculated from the original variables plus ICRG bureaucracy quality; and the third column, the difference between the two scores. Results are sorted by the third column in descending order. Due to our 'weakest link' aggregation procedure (explained in the main text and in detail below),

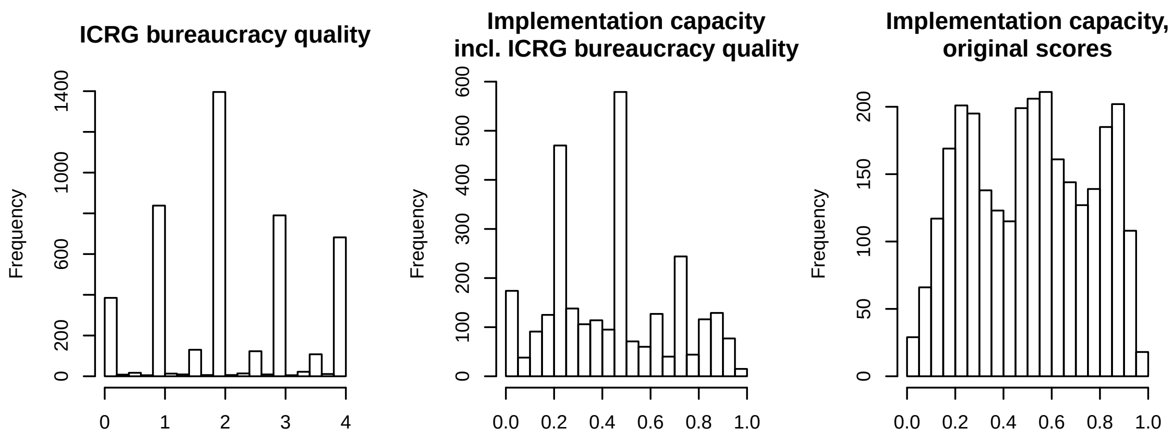

Figure A1: Histograms of ICRG bureaucracy quality and implementation capacity

adding an additional indicator can only decrease scores for countries, but never increase them. Mostly countries with socialist systems or traditions and closed autocratic regimes are considered as less capable – including states, such as Russia and Qatar that are difficult to envision in the vicinity of typical countries with poor implementation capacity. They are obviously downgraded for a lack of autonomy from political actors, as intended by the ICRG, but not for a lack of capacity. This is a validity concern for our application.

A second concern relates to the technical suitability of the indicator with our methodological approach. The indicator has a categorical measurement level, i.e., countries are assigned scores of either 0, 1, 2, 3, or 4 (although a few observations may take scores in-between these levels due to imputation). Figure A1 panel 1 shows the distribution of ICRG bureaucracy quality in its original scale for our sample. Panel 2 shows the distribution of the implementation capacity dimension if ICRG bureaucracy quality was added as fifth indicator. And panel 3 shows the distribution of our original implementation capacity dimension as presented in the main text. The former two clearly show the categorical nature of ICRG bureaucracy quality: five peaks appear in the distribution. With our current model specification, these 'unnatural' peaks would mislead our cluster-finding algorithm and force thresholds onto our distribution that are artifacts of the ICRG scaling, but not of the latent groupings we want to uncover. One could modify the aggregation method to accommodate both categorical and continuous indicators, but given the validity concerns we do not find

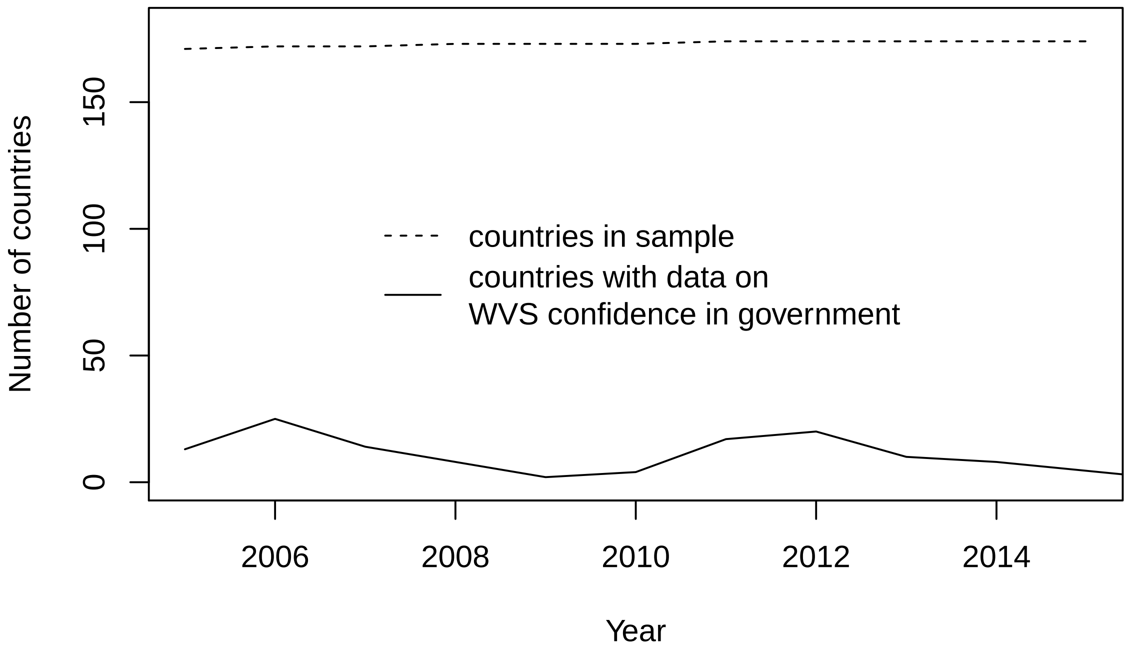

Figure A2: Country-year coverage of WVS confidence in government

that the added value of including ICRG is worth increasing technical complexity further. Finally, the ICRG is a proprietary data source, which would prevent us from providing a fully replicable data archive.

The second example indicator that we dismissed is *confidence in government* as measured by the World Values Survey (WVS) (Inglehart et al. 2014). As we discuss in the main text, particularly in autocratic settings attempts to assess from population surveys if a state enjoys empirical legitimacy face validity issues. Here we provide an additional, empirical argument on why using WVS data is not feasible for our approach: there is not enough data. Figure A2 shows the number of countries in our sample in each year from 2005 to 2015, and the number of countries for which WVS confidence in government is available. The year with the best coverage is 2006 with 25 countries; in 2008 and 2015, there is not one observation available. Over the whole period, the indicator is available for only 79 of our 171 countries. For 44 of these countries, confidence in government was assessed in only one single year; for the 35 remaining countries, it was asked in two years. This amounts to a missingness rate of more than 95%, whereas the highest missingness rate in the indicators employed in the main text is 69% for the BTI indicators. These, however, are available every other year, which makes it rather safe to interpolate, and missing for most OECD countries, for which our alternative indicators are readily available. The next worst missingness rate in our set of indicators is 32% for primary education. Given these contrasts in coverage, and the potential correlation of availability and validity bias, we opted to discard WVS data.

1.4 Transformation of indicators

The following equations specify the transformation of the indicators described in the main article. First, we truncate the raw scores x^R:

$$x_q^{'} = \begin{cases} min_q & if\ x_q^R < min_q \\ x_q^R & if\ min_q \leq x_q^R \geq max_q \\ max_q & if\ x_q^R > max_q \end{cases},$$

where q identifies the indicator, min_q the lower cutoff and max_q the upper cutoff.

After truncation, all variables are normalized to adhere to a zero-to-one scale by setting

$$x_q^{''} = \frac{x_q' - min(x_q')}{max(x_q') - min(x_q')}.$$

Some variables are heavily skewed. We assume marginally decreasing effects for these variables and thus take their logarithms:

$$f(x_{qij}^{''}) = \frac{log_{10}(100 * x_{qij}'' + 1)}{log_{10}(100 + 1)}.$$

Some variables need to be inverted in order to adhere to a worst-to-best scale:

$$g(x_{qij}^{''}) = -x_{qij}^{*} + 1.$$

Figure A3: Raw to transformed data: the example *homicides*

We obtain the final indicator scores x_q^* by applying logarithm and inversion as indicated in table 1 in the main article:

$$x_{qij}^* = \begin{cases} x_{qij}^{''} & if \text{ LOGGED} = 0 \text{ \& INVERTED} = 0 \\ f(x_{qij}^{''}) & if \text{ LOGGED} = 1 \text{ \& INVERTED} = 0 \\ g(x_{qij}^{''}) & if \text{ LOGGED} = 0 \text{ \& INVERTED} = 1 \\ g(f(x_{qij}^{''}) & if \text{ LOGGED} = 1 \text{ \& INVERTED} = 1 \end{cases}$$

Figure A3 provides an example of a transformed indicator. It shows how raw homicide rates (per 100,000 inhabitants, on the x-axis) for all country-years in our sample project onto our transformed scores (on the y-axis). A transformed score of .5 is reached at about 8 homicides per 100,000 inhabitants. This happens to be equivalent to the sample mean, which was not a goal of the transformation, but it seems plausible. More importantly, the figure shows the non-linear relationship introduced by logging the scores: At very high levels, additional homicides contribute less to reducing the transformed homicides scores (and thus the violence control score) than at low levels. The difference between 80 and 90 homicides per 100,000 is treated as negligible, whereas the difference between 0 and 10 is massive. Note that there is no theoretical guide as to what level of homicide is 'acceptable' for a society, nor does our model imply that there is a clear threshold somewhere on this curve. Calibrated jointly with the other violence-control indicators, we pose that the non-linear transformation adequately represents the decreasing marginal impact of additional homicides, and that both extremes and midpoint are sensibly adjusted to sample extremes and midpoint.

1.5 Dimension scores

The dimension scores are then produced with the 'weakest-link approach' described in the main article. To describe the procedure more formally, let set

$$S_m = \left\{x^*_{m1}, \cdots, x^*_{mn}\right\},$$

where m is the fragility dimension and $\left\{x^*_{m1}, \cdots, x^*_{mn}\right\}$ are the transformed indicators that constitute the dimension. Then, the scores d for dimension m,

$$d_m = \begin{cases} min(S_m) & if\ |S_m| \geq 2 \\ \varnothing & if\ |S_m| < 2 \end{cases}.$$

Figure A4 presents the histograms of the resulting dimension variables as well as their correlations and bivariate scatterplots. The strong correlations of the dimension scores do not come as a surprise, since states that perform well in one dimension also tend to perform well in the other two. But this is not a deterministic relationship, and, as our clustering results show, pairs of states (and consequently fragility constellations) that exhibit rather opposing performances exist across all dimensions. States that obtain the highest possible scores near 1 in any one dimension, however, tend to have similarly high scores in the other dimensions. This observation is in line with theories of socio-economic development that

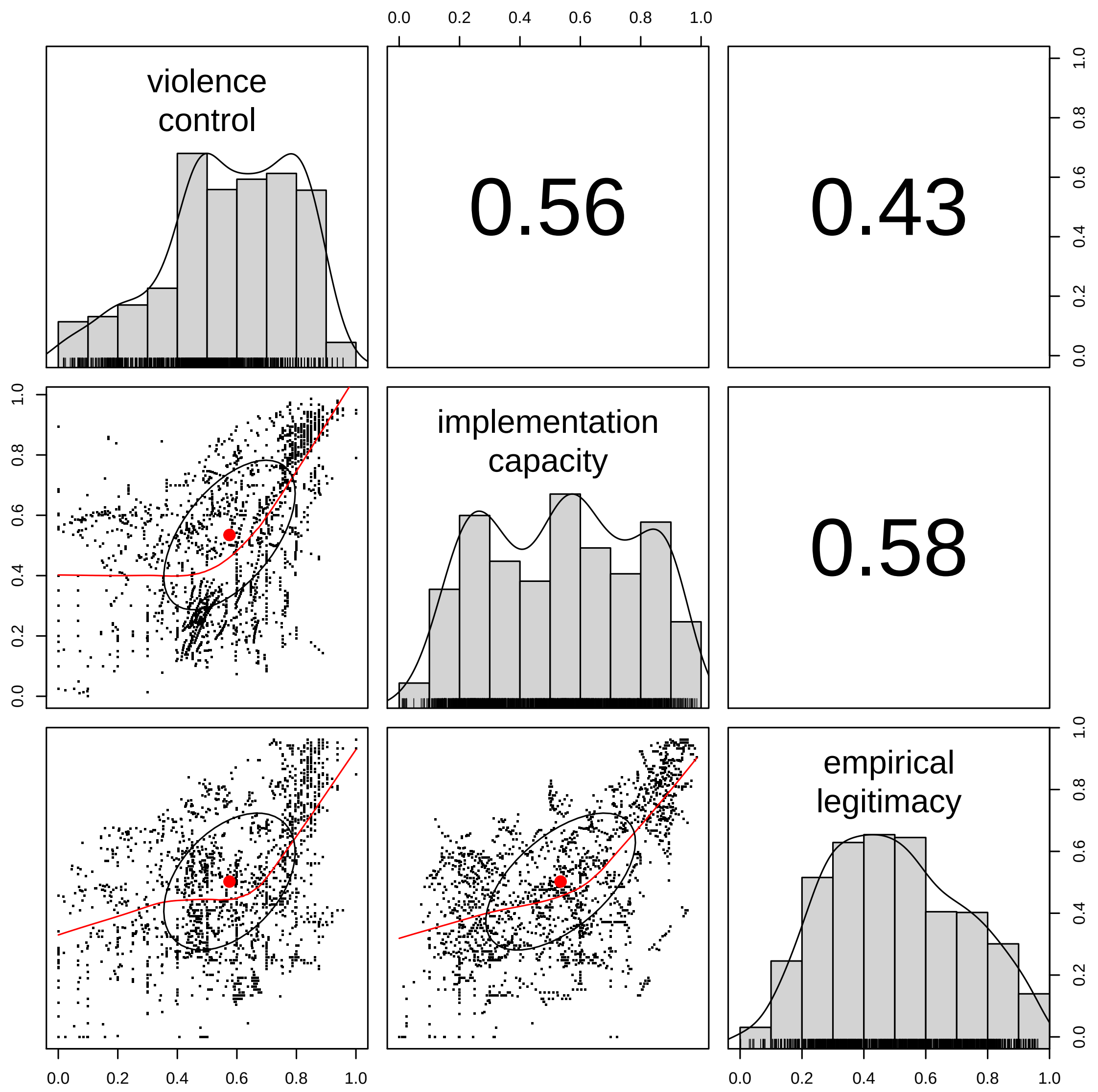

Figure A4: Densities and scatterplots of the dimension scores

conclude that high levels of prosperity and liberty can only be achieved simultaneously (Acemoglu & Robinson 2012; North, Wallis, & Weingast 2009).

Figure A5 shows how the average dimension scores have changed over the period under investigation. Violence control and empirical legitimacy do not exhibit strong time trends. Implementation capacity, however, shows a positive trend significant at the .99 level of .007 additional implementation capacity points per year on the 0 to 1 scale. At this speed, a country at 0 implementation capacity would reach perfect implementation capacity within a bit more than 140 years, which does not seem completely inconceivable.

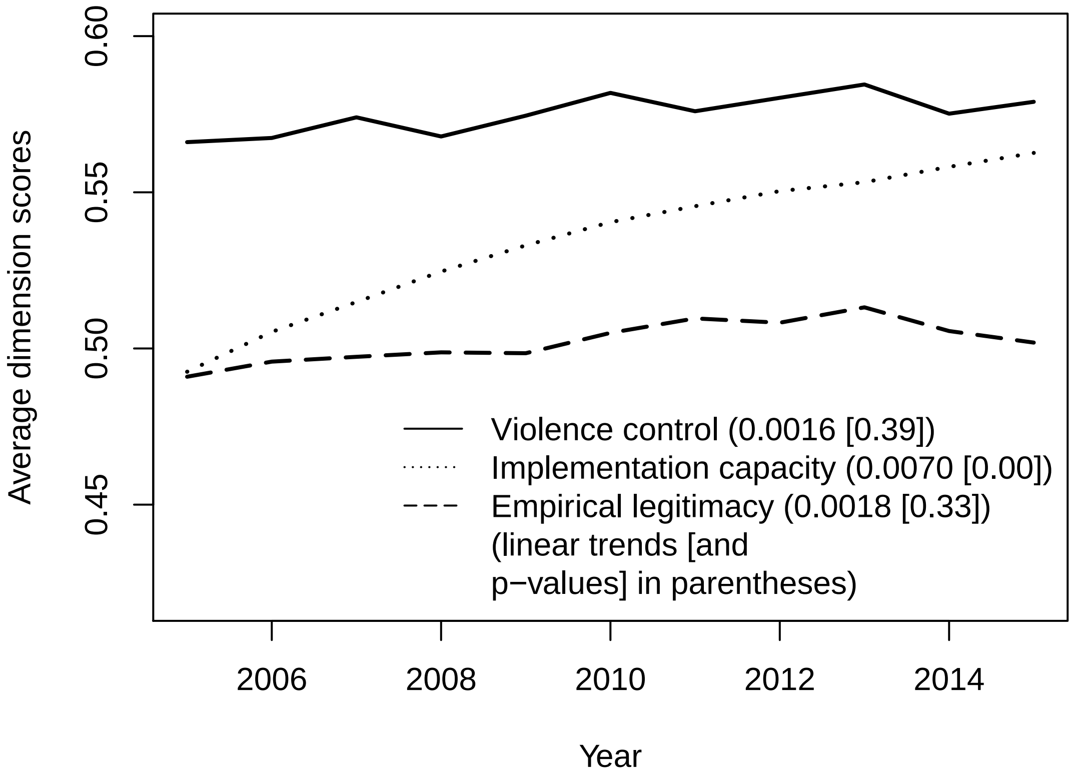

Figure A5: Time trends in the dimension scores

2 Model selection

This section gives additional information on the model selection procedure described in the main article. The estimation of model parameters and goodness-of-fit measures other than the Calinski-Harabasz (CH) index was implemented with the *mclust* package version 5 in R (Fraley & Raftery 2002; Scrucca, Fop, Murphy, & Raftery 2016).

2.1 Model specifications

In the main text, we discuss only finite mixture model specification with spherical distributions. Here, we consider two more potential specifications to determine the shapes Σ of our fragility constellations. The most flexible specification that we allow reads $\Sigma_{EEE} = \lambda DAD^T$, where λ is a scalar and determines the volume of the tri-axial ellipsoids representing the clouds of data points that constitute the groups. The orthogonal matrix of eigenvectors D determines the orientation of the ellipsoids in our data space relative to the three axes. The elements of the diagonal matrix A are proportional to the eigenvalues of Σ; A determines the shape of the ellipsoids, i.e. the extension across the three dimensions. As λ, D and A do not vary between groups, all groups are of equal volume, equal orientation and equal shape – thus the label 'EEE' (Scrucca et al. 2016: : 292). A more restrictive specification $\Sigma_{EEI} = \lambda A$. The removal of D fixes the orientation of the ellipsoids to be parallel to the axes of our data space. Finally, $\Sigma_{EII} = \lambda I$, where I is the identity matrix, restricts the multivariate normal distributions that constitute the ellipsoids to have identical spread in all directions, resulting – in our three-dimensional application – in spherical group properties, which is the model presented in the main text.

These specifications have one property in common: They force all group shapes to be equal. Restricting groups to equal shapes means that the three dimensions cover equal ranges in a particular dimension. This prevents that groups spread widely over particular dimensions and that individual countries with rare score combinations are identified as separate groups.

2.2 Model selection via integrated complete-data likelihood criterion

The standard goodness-of-fit measure for finite mixture model clustering is the Bayesian Information Criterion (BIC). The BIC, however, has been criticized for overestimating the number of components, as noted by Baudry, Raftery, Celeux, Lo, and Gottardo (2010). They suggest combining mixture components with the purpose of avoiding overfitting. Instead of adopting such an increasingly complex multi-step procedure, we instead opt for the integrated complete-data likelihood criterion (ICL) that takes cluster overlap into consideration in a single-step procedure. Scrucca et al. (2016: : 297) suggest the ICL in response to the critique that the BIC helps identify the number of necessary components rather than the number of groups. If components overlap, we would prefer not to interpret them as substantively different groups.

Figure A6 shows the suggested number of groups over the range of 3 to 12 groups[2] when using the ICL. Penalizing overlapping components, local maxima occur at 5 and 8 for EEE, less clearly at 7 for EEI, and at 6 and 10 for EII. Figure A7 shows the ICL scores for a dataset of 1,866 observations that excludes outliers. Outliers are defined as the 99th percentile of observations on the Mahalanobis distance (McLachlan 1999). Removing only this one percent of observations changes the picture: Now both EEI and EEE also have a local maximum at 6 (and also 9). The first local maximum of EII moves to 5. Removing the five instead of one percent of outliers confirms this preference for six groups in the EEI and EEE specifications. In sum, the six-cluster solution seems preferable. If we aim at employing the full dataset for the estimation, it is the EII specification which is most suitable to recovering this configuration.

[2]One and two components showed worse fit and were omitted for better distinction of differences between higher-order models.

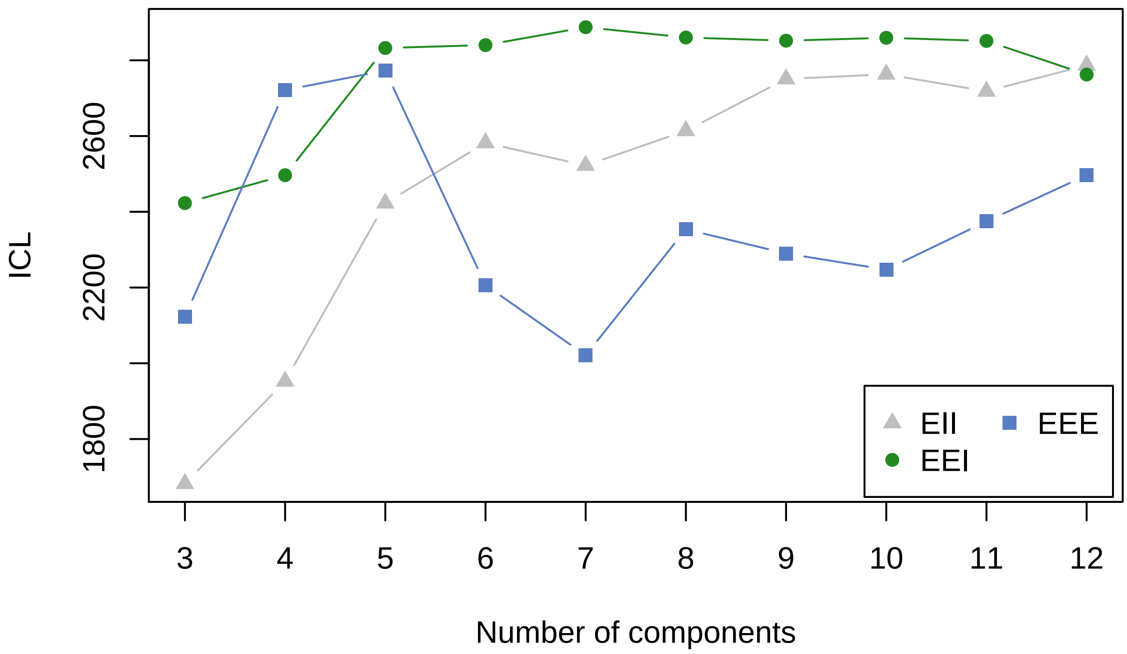

Figure A6: Integrated complete-data likelihood criterion (ICL)

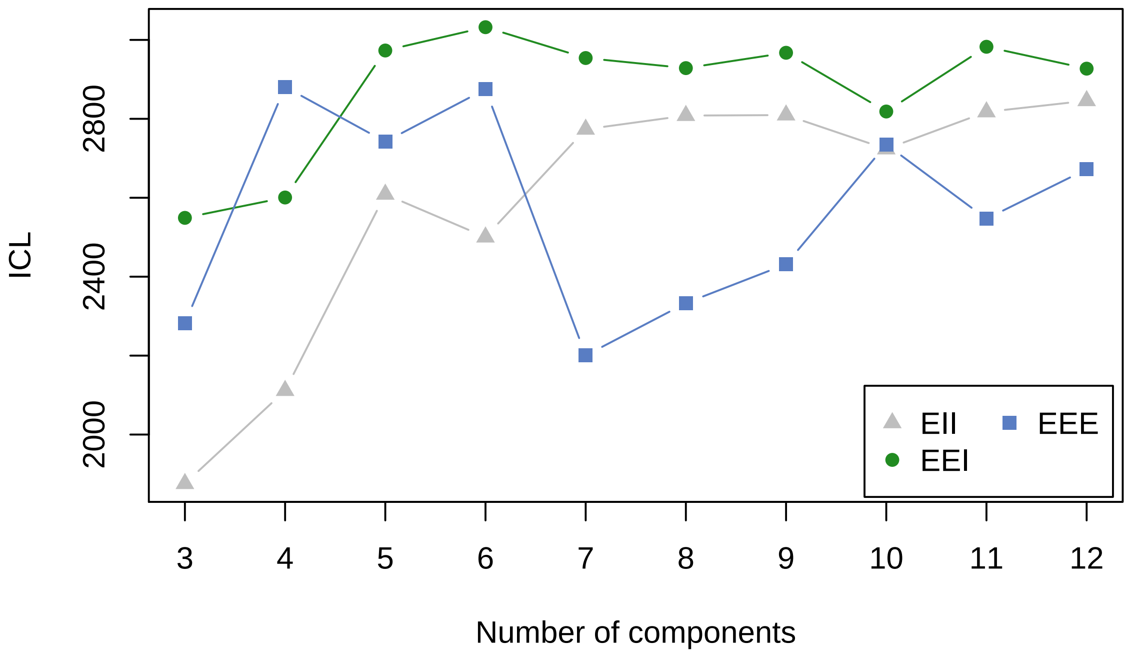

Figure A7: ICL excluding one percent of outliers

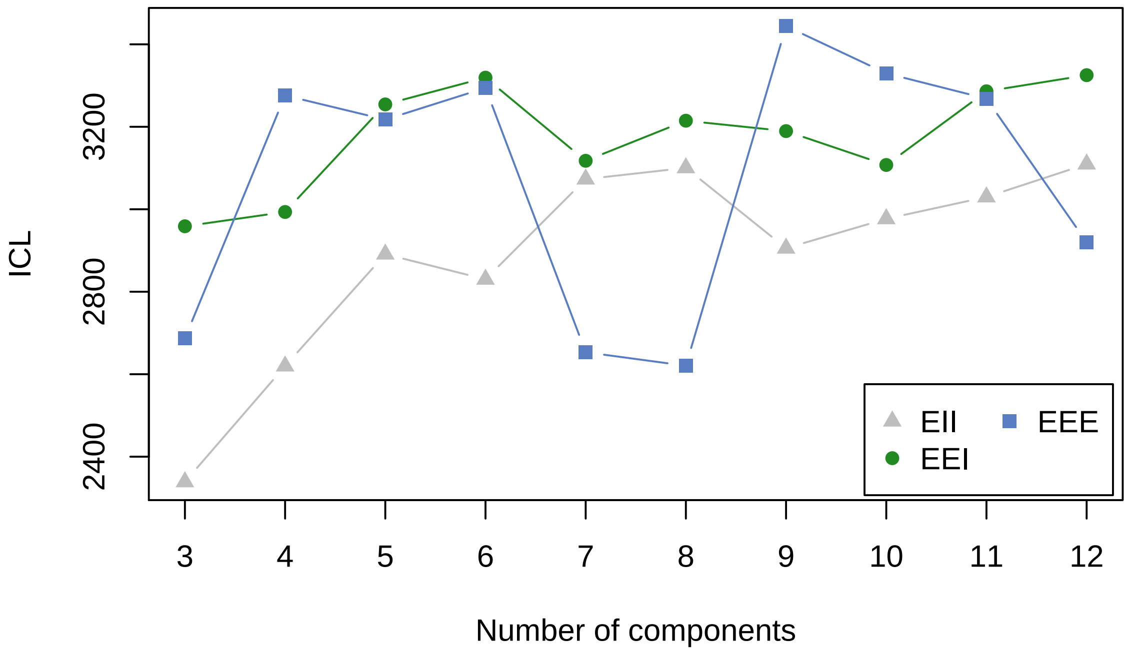

Figure A8: ICL excluding five percent of outliers

2.3 Model selection for other clustering methods

It is also informative to assess the number of clusters suggested by alternative clustering methods. This decreases model-dependence and may increase our trust that we found latent classes that carry some empirical meaning. Grimmer and King (2011) conduct such an exercise on a larger scale, with hundreds of clustering methods. But since their R package has not been made available, we restrict our validation to one model out of each of the most common branches: mixture models, k-means clustering and hierarchical clustering. Replicating the Grimmer and King approach would go beyond the scope of this application.

2.3.1 K-means

K-means clustering (Hartigan & Wong 1979) can be considered a restricted specification of finite mixture model clustering (see Vermunt 2011). It assigns observations to the cluster with the nearest mean, then re-calculates cluster means until convergence is reached. It is thus similar to the EII specification, which forces the data into spherical multivariate normal distributions. This method is not model-based and thus does not provide a likelihood for assessing model fit. The Calinski-Harabasz (CH) index (Calinski & Harabasz 1974), defined as the 'ratio of the between-cluster variance [...] to the total within-cluster variance' (Zumel & Mount 2014: 187), can help identify the best fitting number of components. A higher CH-index indicates a better fit. Similar to the BIC employed above, the CH-index does not explicitly penalize overlap.

Figure A9 shows the CH-index for k-means clustering applied to our data. The maximum is at two groups, which is contrary to the finding from the ICL assessment of the mixture model results. The maximum is followed by a scree at three groups, and then the index descends monotonously at a lesser slope. The same picture emerges when using the dataset that excludes the most extreme outliers (figure A10). As three groups is insufficient for our purpose, we treat that the result of the k-means clustering as inconclusive within our range of interest. At the same time, the k-means approach does not produce evidence that would strongly contradict our preferred model.

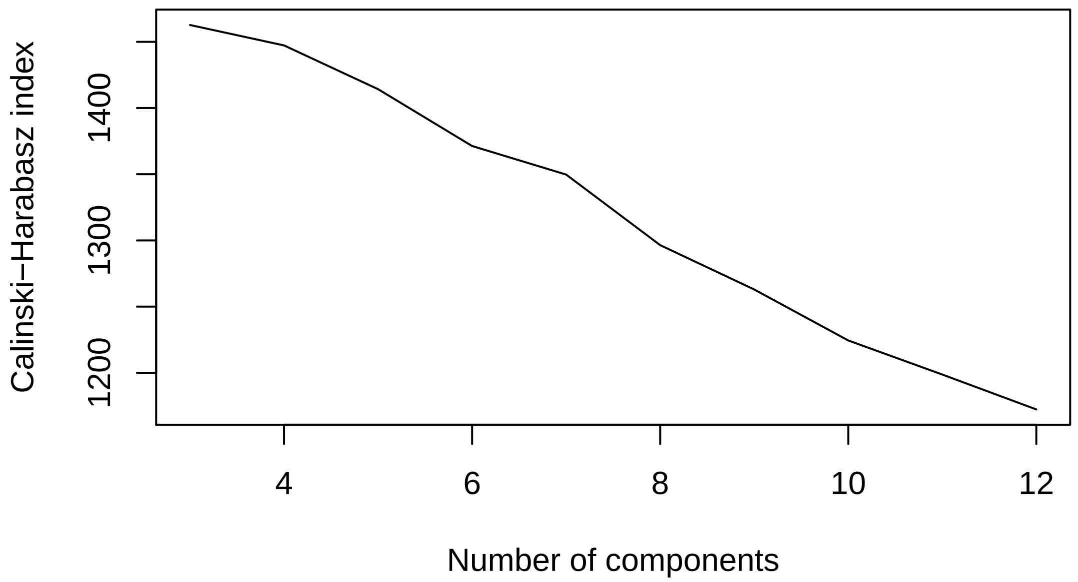

Figure A9: Selecting the number of components for the k-means clustering result

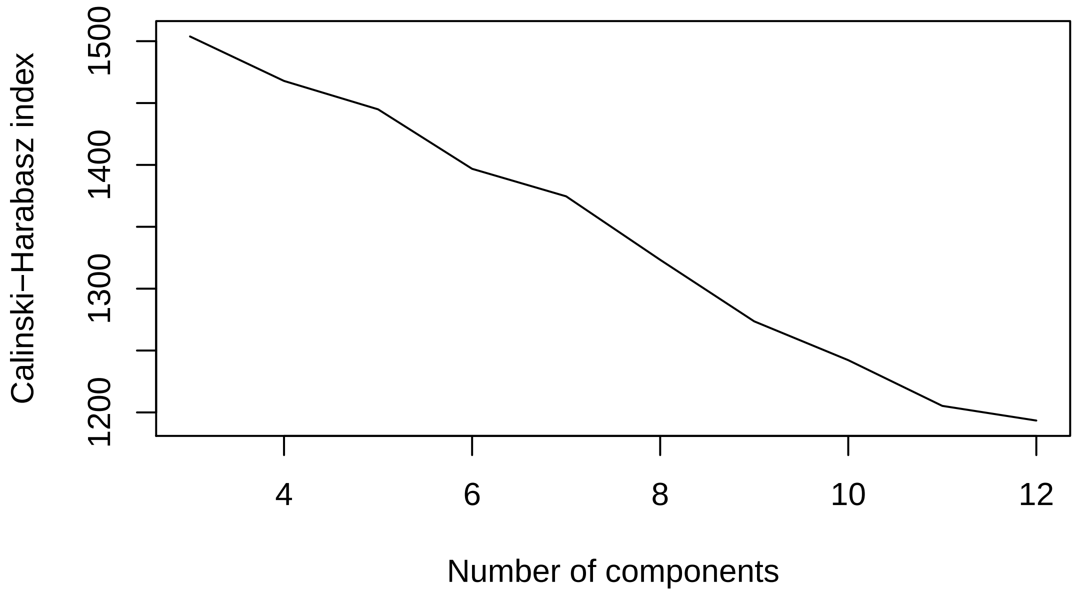

Figure A10: Selecting the number of components for the k-means clustering result, excluding outliers

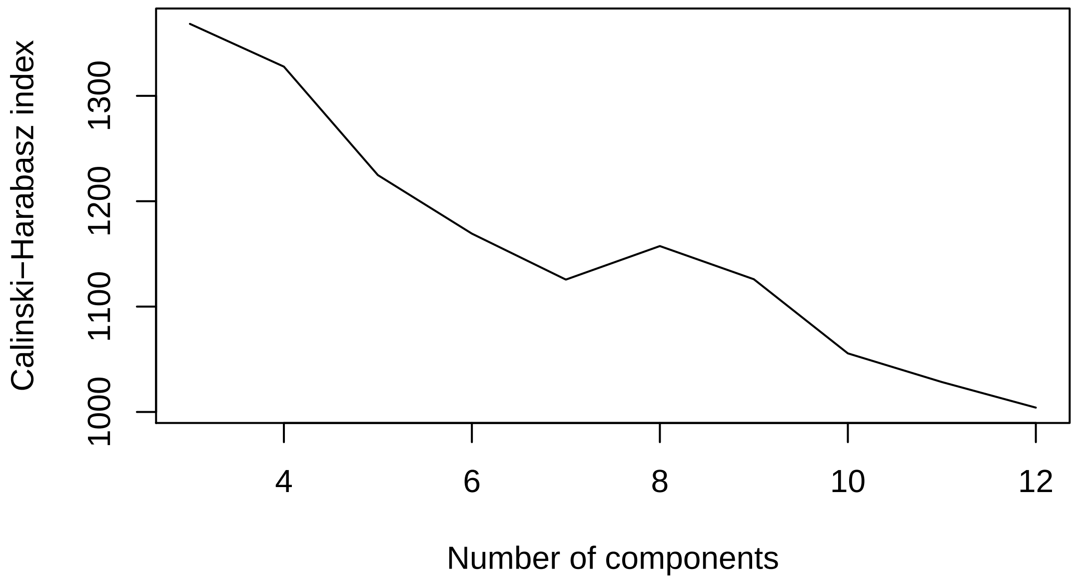

Figure A11: Selecting the number of components for the hierarchical clustering result

2.3.2 Hierarchical clustering

An alternative to k-means clustering, hierarchical clustering, starts with each observation in its own cluster, and then combines observations by minimizing the variance within these clusters (Murtagh & Legendre 2014; Ward 1963). Here, the CH-index produces a local maximum for eight groups (see figure A11). Considering the dataset that excludes one percent of outliers, this local maximum disappears. There is a hint of a scree, however, at the six-group mark. This is again not strong evidence for a six-cluster solution, or that any cluster-structure underlies the data. But we consider the mixture model approach more suitable due to the advantages discussed above and thus trust in the specification employing six spherical groups.

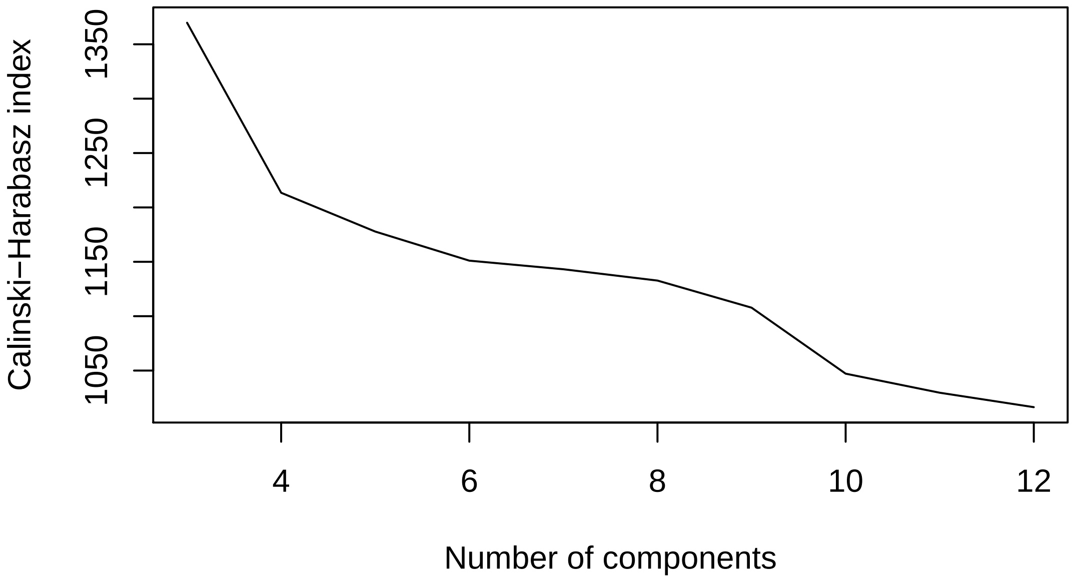

Figure A12: Selecting the number of components for the hierarchical clustering result, excluding outliers

3 Comparison with alternative solutions

3.1 Comparison with alternative finite mixture model solutions

We now compare our favored clustering solution with alternative solutions from mixture models and other clustering techniques. As shown in figure A6, using the full sample, EEE-5 and EEI-7 constitute alternative local maxima (albeit these choices do not receive additional support when removing outliers, as the six-cluster solution does). Tables A4 and A5 show how the classifications generated by these specifications compare to the classifications of our favored EEI-6 specification. The order of the alternative clusters (columns) was aligned to correspond as closely as possible to the reference clustering.

In the EEE-5 solution, countries from groups A and C are mostly placed in one joint group (column 1 in table A4). The remaining groups B, D, E, and F are recovered at rates between 69 and 98 percent. In total, considering the joining of groups A and C, 88 of all country years are classified as in our preferred solution.

The EEI-7 solution splits group D evenly into two (columns 4 and 5 in table A5). All other countries assigned to one group in our original solution again end up mostly in the same group in the new solution, at rates between 81 and 96 percent. Overall, 91 percent of all country years are classified as in our preferred solution. In general, the alternative solutions thus do not provide different, but rather less or more nuanced solutions that do not fundamentally contradict our preferred solution.

Table A4: Comparison of EII-6 (rows) and EEE-5 (columns) clusters

	1	2	3	4	5
A	0.88	0.07	0.00	0.04	0.00
B	0.00	0.69	0.01	0.30	0.00
C	0.94	0.00	0.04	0.02	0.00
D	0.09	0.00	0.89	0.01	0.01
E	0.00	0.02	0.03	0.73	0.22
F	0.00	0.00	0.02	0.00	0.98

Row percentages

Table A5: Comparison of EII-6 (rows) and EEI-7 (columns) clusters

	1	2	3	4	5	6	7
A	0.82	0.02	0.16	0.00	0.00	0.00	0.00
B	0.08	0.87	0.01	0.00	0.01	0.04	0.00
C	0.01	0.00	0.90	0.09	0.00	0.00	0.00
D	0.00	0.01	0.00	0.46	0.49	0.03	0.02
E	0.00	0.03	0.08	0.00	0.07	0.81	0.01
F	0.00	0.00	0.00	0.00	0.04	0.00	0.96

Row percentages

3.2 Comparison with k-means clustering

Table A6 shows how the six cluster k-means classification compares to the EII-6 classification, in row percentages. The order of the former is aligned to the latter. A total of 87 percent of all observations are classified in the same clusters, with overlaps of 72 to 100 percent (as can be seen on the diagonal of the table). The main difference between the solutions is that 27 percent of all semi-functional states (E) are classified with low-control states (B) instead (column 2).

Table A6: Comparison of EII-6 (rows) and k-means clustering (columns) results

	6	1	3	2	4	5
A	1.00	0.00	0.00	0.00	0.00	0.00
B	0.02	0.98	0.00	0.00	0.00	0.00
C	0.11	0.03	0.85	0.01	0.00	0.00
D	0.00	0.02	0.00	0.91	0.08	0.00
E	0.00	0.27	0.02	0.00	0.72	0.00
F	0.00	0.00	0.00	0.01	0.10	0.89

Row percentages

3.3 Comparison with hierarchical clustering

Table A7 shows the overlap of the EII-6 result with the result of a hierarchical clustering specification with six groups. A total of 87 percent of all observations are classified in the same clusters, with overlaps of 36 to 99 percent. The largest shifts are caused by originally semi-functional (E) countries being classified by the hierarchical solution as either low-control (B) or low-legitimacy (D) countries; and by about half of all low-capacity (C) states being classified as dysfunctional (A) states. Overall, the relatively large coincidence with alternative clustering solutions again strengthens our belief that we are picking up relevant latent classes that exist independently of our preferred model specification.

Table A7: Comparison of EII-6 (rows) and hierarchical clustering (columns) groups

	4	3	5	1	6	2
A	0.99	0.01	0.00	0.00	0.00	0.00
B	0.01	0.99	0.00	0.00	0.00	0.00
C	0.47	0.02	0.44	0.07	0.00	0.00
D	0.00	0.03	0.00	0.97	0.00	0.00
E	0.00	0.32	0.01	0.31	0.36	0.00
F	0.00	0.00	0.00	0.08	0.09	0.83

Row percentages

4 Results

The following pages provide details about the results of the EII-6 clustering result. This includes cluster properties, regional and temporal distributions of the fragility constellations, and classifications of individual countries.

4.1 Group properties

Table A8 shows the group means of the bootstrapped standard errors (1,000 samples).

Table A8: Group parameters with bootstrapped standard deviations

Group	Probability	CV mean	CV SD	IC mean	IC SD	EL mean	EL SD
A: Dysfunctional	0.052	0.19	0.030	0.18	0.013	0.19	0.016
B: Low-control	0.102	0.22	0.017	0.54	0.013	0.46	0.022
C: Low-capacity	0.303	0.53	0.007	0.28	0.005	0.41	0.010
D: Low-legitimacy	0.203	0.69	0.008	0.62	0.010	0.35	0.010
E: Semi-functional	0.121	0.53	0.031	0.58	0.023	0.65	0.012
F: Well-functioning	0.219	0.81	0.006	0.86	0.005	0.79	0.007

CV = violence control; IC = implementation capacity; EL = empirical legitimacy; SD = standard deviation.

Table A9 shows the number of countries that were assigned to each group over the years. Table A10 shows the share of countries that each group covers within a year. Figure A13 provides a graphical representation on how the relative shares of the groups have developed during the period under investigation.

Table A9: Number of countries per group per year

Group	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Δ
A: Dysfunctional	11	8	7	9	6	7	9	8	9	10	10	-9
B: Low-control	17	19	17	20	21	18	20	17	16	17	14	-18
C: Low-capacity	57	57	56	51	54	51	49	49	49	46	48	-16
D: Low-legitimacy	32	32	34	34	34	35	34	39	37	36	37	16
E: Semi-functional	21	21	23	21	20	20	20	20	21	23	23	10
F: Well-functioning	32	34	34	36	36	40	40	39	40	40	40	25
Countries	171	171	171	171	171	172	172	172	172	172	8	

Δ: percentage change 2005 to 2015

Table A10: Percentage of countries per group over years

Group	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
A: Dysfunctional	0.06	0.05	0.04	0.05	0.04	0.04	0.05	0.05	0.05	0.06	0.06
B: Low-control	0.10	0.11	0.10	0.12	0.12	0.11	0.12	0.10	0.09	0.10	0.08
C: Low-capacity	0.34	0.33	0.33	0.30	0.32	0.30	0.28	0.28	0.28	0.27	0.28
D: Low-legitimacy	0.19	0.19	0.20	0.20	0.20	0.20	0.20	0.23	0.22	0.21	0.22
E: Semi-functional	0.12	0.12	0.13	0.12	0.12	0.12	0.12	0.12	0.12	0.13	0.13
F: Well-functioning	0.19	0.20	0.20	0.21	0.21	0.23	0.23	0.23	0.23	0.23	0.23

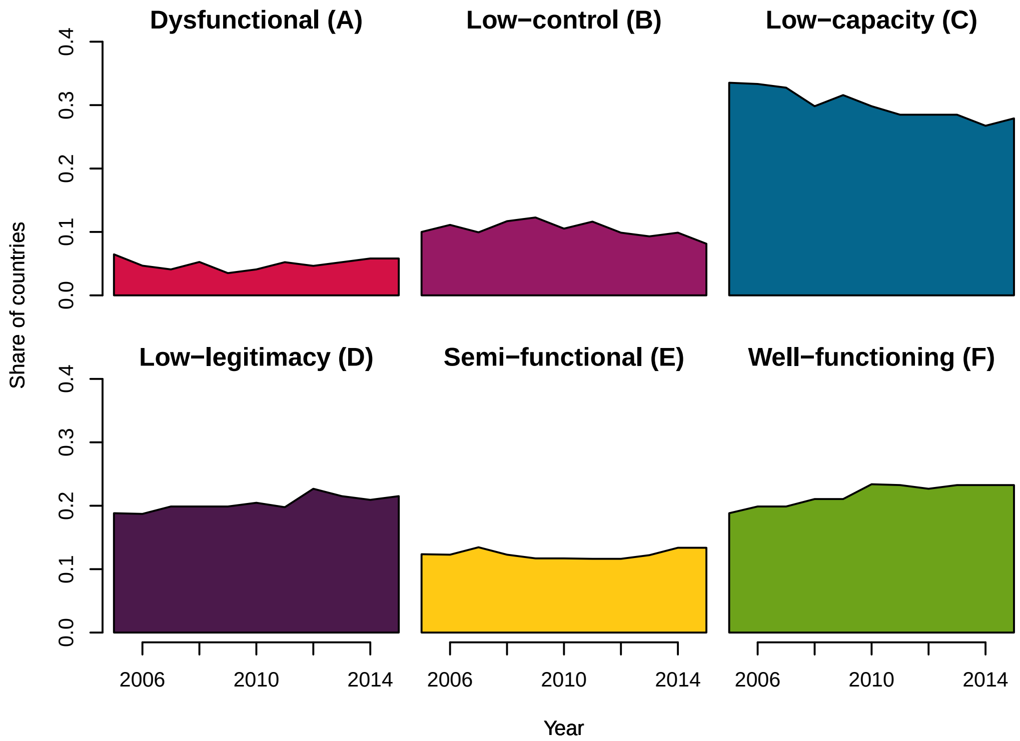

Figure A13: Proportions of fragility constellations over time

Tables A11, A12 and A12 show how groups are distributed over world regions, both in frequencies and in percentages.

Table A11: Fragility constellations by region, number of country years

	A dysfunctional	B low-control	C low-capacity	D low-legitimacy	E semi-functional	F well-functioning
East Asia & Pacific	0	0	62	81	39	49
Europe & Central Asia	0	12	39	115	32	329
Latin America & Caribbean	3	144	16	16	107	11
Middle East & North Africa	18	14	22	148	7	11
North America	0	0	0	2	9	11
South Asia	15	4	47	22	0	0
Sub-Saharan Africa	58	22	381	0	39	0

Table A12: Fragility constellations by region, region percentages

	A dysfunctional	B low-control	C low-capacity	D low-legitimacy	E semi-functional	F well-functioning
East Asia & Pacific	0	0	0.27	0.35	0.17	0.21
Europe & Central Asia	0	0.02	0.07	0.22	0.06	0.62
Latin America & Caribbean	0.01	0.48	0.05	0.05	0.36	0.04
Middle East & North Africa	0.08	0.06	0.1	0.67	0.03	0.05
North America	0	0	0	0.09	0.41	0.5
South Asia	0.17	0.05	0.53	0.25	0	0
Sub-Saharan Africa	0.12	0.04	0.76	0	0.08	0

Table A13: Fragility constellations by region, group percentages

	A dysfunctional	B low-control	C low-capacity	D low-legitimacy	E semi-functional	F well-functioning
East Asia & Pacific	0	0	0.11	0.21	0.17	0.12
Europe & Central Asia	0	0.06	0.07	0.3	0.14	0.8
Latin America & Caribbean	0.03	0.73	0.03	0.04	0.46	0.03
Middle East & North Africa	0.19	0.07	0.04	0.39	0.03	0.03
North America	0	0	0	0.01	0.04	0.03
South Asia	0.16	0.02	0.08	0.06	0	0
Sub-Saharan Africa	0.62	0.11	0.67	0	0.17	0

4.2 Country classifications

Tables A14, A15 and A16 list all countries with their classifications and the range of scores that each country covers between 2005 and 2015. Country years with a classification probability below .9 are listed in parentheses.

Note that some countries change their territory within our observation period, e.g., Sudan in 2012 when South Sudan becomes an independent country. The inclusion and extent of countries considered in this study is derived from the `CShapes` package (Weidmann et al. 2010).

Table A14: Country classifications and dimension ranges, 2005–2015

Country	’05	’06	’07	’08	’09	’10	’11	’12	’13	’14	’15	Viol. ctrl.	Impl. cap.	Emp. legit.
Afghanistan	A	->	->	->	->	->	->	->	->	->	A	0.00-0.20	0.10-0.30	0.22-0.29
Albania	D	->	->	(D)	->	->	->	->	D	->	D	0.57-0.73	0.57-0.65	0.27-0.52
Algeria	(D)	->	(C)	(D)	(C)	(D)	->	->	->	->	(D)	0.55-0.70	0.47-0.53	0.33-0.49
Angola	C	->	->	->	->	->	->	->	->	->	C	0.43-0.47	0.13-0.27	0.36-0.44
Argentina	E	(E)	E	(E)	->	->	->	->	->	->	(E)	0.52-0.54	0.62-0.69	0.55-0.60
Armenia	D	->	->	->	->	->	->	->	->	->	D	0.67-0.75	0.54-0.65	0.23-0.45
Australia	F	->	->	->	->	->	->	->	->	->	F	0.80-0.84	0.83-0.90	0.78-0.84
Austria	F	->	->	->	->	->	->	->	->	->	F	0.85-0.90	0.85-0.91	0.73-0.84
Azerbaijan	C	(C)	->	->	->	(D)	->	->	->	->	(C)	0.50-0.70	0.38-0.48	0.20-0.35
Bahamas	E	(E)	->	->	(B)	->	->	->	->	->	(B)	0.20-0.37	0.62-0.70	0.64-0.73
Bahrain	D	->	->	->	->	->	->	->	->	->	D	0.60-0.92	0.71-0.77	0.22-0.37
Bangladesh	C	(C)	->	->	C	(C)	->	->	->	->	(C)	0.60-0.70	0.32-0.45	0.29-0.35
Barbados	E	->	->	->	->	->	->	->	->	->	E	0.41-0.53	0.63-0.67	0.63-0.74
Belarus	D	->	->	->	->	->	->	->	->	->	D	0.49-0.66	0.60-0.80	0.16-0.21
Belgium	F	->	->	->	->	->	->	->	->	->	F	0.74-0.77	0.85-0.89	0.81-0.91
Belize	(B)	->	->	B	->	->	->	->	(B)	->	(B)	0.08-0.24	0.57-0.63	0.60-0.68
Benin	C	->	->	->	->	->	->	->	->	->	C	0.53-0.56	0.19-0.24	0.58-0.66
Bhutan	(C)	->	->	(D)	(C)	->	->	(D)	->	->	(D)	0.64-0.75	0.35-0.47	0.04-0.50
Bolivia	(C)	->	->	->	(E)	(C)	->	->	(E)	->	(E)	0.42-0.55	0.34-0.44	0.58-0.64
Bosnia-Herz.	D	->	->	(F)	->	->	->	->	->	->	(F)	0.75-0.80	0.70-0.80	0.34-0.60
Botswana	(C)	->	(E)	->	->	->	->	->	->	->	(E)	0.37-0.45	0.31-0.42	0.62-0.71
Brazil	B	->	->	->	->	->	->	->	->	->	B	0.25-0.30	0.52-0.63	0.31-0.36
Bulgaria	(E)	->	->	(F)	->	->	->	->	F	->	F	0.71-0.79	0.66-0.76	0.59-0.70
Burkina Faso	C	->	->	->	->	->	->	->	->	->	C	0.60-0.89	0.14-0.26	0.52-0.59
Burundi	(A)	C	->	->	->	->	->	->	->	->	C	0.35-0.63	0.19-0.30	0.16-0.36
Cambodia	C	->	(C)	->	->	->	(D)	->	->	->	(D)	0.66-0.76	0.33-0.48	0.39-0.45
Cameroon	C	->	->	->	->	->	->	->	->	(C)	C	0.32-0.69	0.17-0.28	0.40-0.43
Canada	F	->	->	->	->	->	->	->	->	->	F	0.74-0.80	0.81-0.85	0.79-0.88
Cape Verde	E	->	->	->	->	->	->	->	->	->	E	0.41-0.56	0.51-0.56	0.73-0.78
Central Afr. Rep.	A	->	->	->	->	(A)	->	A	->	->	A	0.10-0.30	0.10-0.16	0.00-0.35
Chad	C	A	(C)	A	C	->	->	->	->	->	C	0.11-0.48	0.12-0.18	0.30-0.35
Chile	(F)	->	->	->	->	->	->	->	->	->	(F)	0.65-0.71	0.73-0.75	0.66-0.79
China	D	->	->	->	->	->	->	->	->	->	D	0.78-0.88	0.54-0.70	0.22-0.26
Colombia	(A)	(B)	B	->	->	->	->	->	->	->	B	0.18-0.26	0.40-0.60	0.19-0.38
Comoros	C	->	->	->	->	->	->	->	->	->	C	0.47-0.51	0.24-0.30	0.51-0.60
Congo	C	->	->	->	->	->	->	->	->	->	C	0.44-0.46	0.26-0.36	0.30-0.54
Congo DR	A	->	->	(A)	->	->	->	A	->	->	(A)	0.20-0.30	0.10-0.20	0.17-0.24
Costa Rica	E	->	->	->	->	->	->	->	->	->	E	0.43-0.51	0.71-0.74	0.71-0.80
Cote d Ivoire	A	->	(A)	->	(C)	(A)	->	C	->	->	C	0.20-0.43	0.18-0.25	0.28-0.47
Croatia	F	->	->	->	->	->	->	->	->	->	F	0.78-0.86	0.79-0.86	0.65-0.70
Cuba	D	->	->	->	->	->	->	->	->	->	D	0.56-0.61	0.79-0.83	0.13-0.19
Cyprus	F	->	->	->	->	->	->	->	->	->	F	0.75-0.88	0.85-0.95	0.69-0.74
Czech Rep.	F	->	->	->	->	->	->	->	->	->	F	0.81-0.88	0.87-0.93	0.74-0.88
Denmark	F	->	->	->	->	->	->	->	->	->	F	0.81-0.90	0.86-0.88	0.89-0.95
Djibouti	C	->	->	(C)	C	->	->	->	->	->	C	0.33-0.53	0.10-0.32	0.33-0.39
Dominican Rep.	B	(B)	->	->	->	->	B	(B)	->	->	(B)	0.26-0.35	0.45-0.48	0.38-0.52
East Timor	C	->	->	(C)	->	->	->	->	->	(E)	(C)	0.56-0.68	0.28-0.38	0.56-0.68
Ecuador	(B)	->	->	->	->	->	->	->	(E)	(D)	(D)	0.34-0.50	0.50-0.56	0.42-0.55
Egypt	D	->	->	->	->	->	(D)	->	D	->	(D)	0.60-0.88	0.45-0.54	0.30-0.39
El Salvador	B	->	->	->	->	->	->	->	->	->	B	0.00-0.17	0.53-0.62	0.27-0.57
Equ. Guinea	C	->	->	->	->	->	->	->	->	->	C	0.66-0.67	0.18-0.25	0.18-0.21
Eritrea	(C)	->	->	(A)	->	->	->	C	->	->	C	0.48-0.52	0.12-0.32	0.00-0.15
Estonia	(E)	(F)	->	->	F	->	->	(D)	F	->	F	0.50-0.68	0.78-0.93	0.51-0.90
Ethiopia	C	->	->	->	->	->	->	->	->	->	C	0.47-0.51	0.12-0.34	0.26-0.32
Fiji	(E)	->	->	E	(D)	->	->	->	->	->	(E)	0.65-0.71	0.54-0.55	0.50-0.67
Finland	F	->	->	->	->	->	->	->	->	->	F	0.71-0.78	0.90-0.97	0.94-0.96
France	F	->	->	->	->	->	->	->	->	->	F	0.78-0.82	0.86-0.89	0.69-0.80
Gabon	C	->	->	->	->	->	->	->	->	->	C	0.44-0.48	0.30-0.38	0.37-0.41
Gambia	C	->	->	->	->	->	->	->	->	->	(C)	0.46-0.48	0.24-0.32	0.03-0.35
Georgia	(C)	(E)	->	B	(B)	(E)	->	->	->	->	(E)	0.06-0.52	0.40-0.60	0.27-0.56

Arrows indicate that there was no change in the fragility constellation. Group label in parentheses when uncertainty >.1.

Table A15: Country classifications (cont.)

Country	’05	’06	’07	’08	’09	’10	’11	’12	’13	’14	’15	Viol. ctrl.	Impl. cap.	Emp. legit.
Germany	F	->	->	->	->	->	->	->	->	->	F	0.83-0.86	0.86-0.89	0.82-0.90
Ghana	C	->	->	->	->	->	->	->	(C)	->	(C)	0.75-0.77	0.27-0.34	0.47-0.59
Greece	F	->	->	->	->	->	->	->	->	->	F	0.78-0.86	0.86-0.90	0.56-0.66
Guatemala	B	->	->	->	->	->	->	->	->	->	B	0.15-0.23	0.42-0.50	0.45-0.50
Guinea	C	->	->	->	->	->	->	->	->	->	C	0.46-0.49	0.18-0.25	0.35-0.46
Guinea-Bissau	C	->	->	->	->	->	->	->	->	->	C	0.44-0.48	0.16-0.26	0.41-0.60
Guyana	(B)	->	(E)	(B)	(E)	->	->	->	->	->	(E)	0.31-0.37	0.42-0.47	0.53-0.67
Haiti	(A)	(C)	C	->	->	(C)	(A)	(C)	->	->	C	0.20-0.50	0.08-0.20	0.35-0.57
Honduras	B	->	->	->	->	->	->	->	->	->	B	0.00-0.15	0.50-0.58	0.40-0.49
Hungary	F	->	->	->	->	->	->	->	->	->	F	0.76-0.82	0.77-0.84	0.67-0.74
Iceland	F	->	->	->	->	->	->	->	->	->	F	0.84-1.00	0.93-0.99	0.90-0.96
India	C	->	->	->	->	(C)	->	->	->	->	(C)	0.65-0.67	0.30-0.41	0.25-0.37
Indonesia	(C)	->	(D)	->	->	->	->	->	->	D	D	0.60-0.80	0.42-0.51	0.30-0.48
Iran	(D)	->	D	->	->	->	->	->	->	->	D	0.58-0.63	0.53-0.60	0.17-0.25
Iraq	A	->	->	->	->	(A)	(B)	->	(A)	A	A	0.00-0.10	0.10-0.40	0.11-0.30
Ireland	F	->	->	->	->	->	->	->	->	->	F	0.76-0.89	0.84-0.90	0.83-0.90
Israel	D	B	(B)	B	->	D	->	->	->	B	D	0.00-0.80	0.83-0.90	0.28-0.36
Italy	F	->	->	->	->	->	->	->	->	->	F	0.83-0.86	0.87-0.92	0.65-0.73
Jamaica	B	->	->	->	->	->	->	->	->	->	B	0.08-0.19	0.58-0.63	0.42-0.49
Japan	F	->	->	->	->	->	->	->	->	->	F	0.90-0.94	0.90-0.95	0.80-0.85
Jordan	D	->	->	->	->	->	->	->	->	->	D	0.70-0.80	0.54-0.60	0.40-0.47
Kazakhstan	(C)	->	->	->	(D)	->	->	D	->	->	D	0.43-0.60	0.48-0.67	0.24-0.33
Kenya	C	->	->	->	->	->	->	->	->	->	C	0.50-0.55	0.28-0.38	0.34-0.44
Kuwait	(D)	->	->	->	->	->	->	D	->	->	(D)	0.73-0.80	0.68-0.74	0.49-0.53
Kyrgyz Rep.	(C)	->	->	->	->	(B)	(C)	(D)	->	->	(D)	0.32-0.65	0.44-0.50	0.35-0.44
Laos	C	->	->	->	->	->	->	->	->	->	C	0.47-0.53	0.24-0.33	0.23-0.28
Latvia	(E)	->	->	->	->	(F)	->	->	F	->	F	0.57-0.67	0.71-0.85	0.71-0.76
Lebanon	(B)	B	(E)	->	->	->	->	(B)	->	->	(E)	0.07-0.50	0.50-0.60	0.48-0.52
Lesotho	(B)	->	->	->	->	->	->	->	->	->	(B)	0.14-0.19	0.21-0.24	0.58-0.65
Liberia	C	->	->	->	->	->	->	->	->	->	C	0.50-0.69	0.07-0.18	0.32-0.51
Libya	D	->	->	->	->	->	B	(D)	C	(A)	A	0.00-0.68	0.10-0.62	0.13-0.31
Lithuania	E	(E)	->	->	->	(F)	->	->	->	->	(F)	0.44-0.57	0.74-0.85	0.77-0.84
Luxembourg	F	->	->	->	->	->	->	->	->	->	F	0.75-1.00	0.91-0.94	0.92-0.94
Macedonia	(E)	->	(D)	(F)	->	->	(D)	->	->	D	D	0.70-0.83	0.65-0.71	0.46-0.62
Madagascar	C	->	->	->	->	->	->	->	->	->	C	0.61-0.80	0.17-0.31	0.42-0.59
Malawi	C	->	->	->	->	->	->	->	->	(C)	(C)	0.55-0.78	0.21-0.35	0.48-0.62
Malaysia	D	->	->	->	->	->	->	->	->	->	D	0.72-0.75	0.76-0.76	0.40-0.45
Maldives	D	->	->	(D)	->	->	->	->	->	->	(D)	0.69-0.85	0.55-0.74	0.38-0.57
Mali	C	->	->	->	->	->	->	->	(C)	C	C	0.30-0.44	0.12-0.21	0.37-0.70
Malta	F	->	->	->	->	->	->	->	->	->	F	0.69-1.00	0.79-0.79	0.83-0.86
Mauritania	C	->	->	->	->	->	->	->	->	->	C	0.42-0.46	0.22-0.27	0.36-0.59
Mauritius	(E)	->	->	->	->	->	->	->	->	->	(E)	0.68-0.71	0.62-0.65	0.67-0.70
Mexico	(D)	->	->	(B)	->	B	->	->	->	(B)	(B)	0.29-0.51	0.57-0.64	0.33-0.41
Moldova	(B)	(D)	->	->	->	(E)	->	->	->	->	(E)	0.30-0.63	0.50-0.62	0.41-0.54
Mongolia	(E)	->	->	->	->	->	->	E	->	(E)	(E)	0.37-0.53	0.42-0.49	0.55-0.65
Montenegro		(F)	->	(D)	->	F	->	(F)	F	->	F	0.64-0.78	0.72-0.88	0.55-0.71
Morocco	(D)	->	->	->	->	->	D	->	->	->	D	0.77-0.80	0.43-0.51	0.40-0.47
Mozambique	C	->	->	->	->	->	->	->	->	->	C	0.59-0.66	0.17-0.30	0.49-0.53
Myanmar	(C)	->	C	(C)	->	->	->	->	->	C	C	0.40-0.50	0.20-0.30	0.12-0.27
Namibia	(C)	->	->	(E)	->	->	->	->	->	->	(E)	0.34-0.40	0.31-0.39	0.63-0.72
Nepal	(A)	(C)	->	C	(C)	->	->	->	->	->	(C)	0.30-0.60	0.34-0.40	0.17-0.53
Netherlands	F	->	->	->	->	->	->	->	->	->	F	0.83-0.89	0.84-0.89	0.91-0.95
New Zealand	F	->	->	->	->	->	->	->	->	->	F	0.79-0.85	0.80-0.83	0.86-0.92
Nicaragua	(E)	->	->	->	->	->	->	->	->	->	(E)	0.39-0.43	0.48-0.57	0.53-0.63
Niger	C	->	->	->	->	->	->	->	->	->	C	0.50-0.61	0.12-0.25	0.40-0.57
Nigeria	(C)	C	->	->	->	->	->	->	(C)	->	(C)	0.40-0.45	0.14-0.22	0.25-0.29
North Korea	(D)	->	->	->	->	->	->	D	->	->	D	0.59-0.62	0.47-0.57	0.10-0.13
Norway	F	->	->	->	->	->	->	->	->	->	F	0.73-0.90	0.89-0.95	0.94-0.96
Oman	D	->	->	->	->	->	->	->	->	->	D	0.83-0.88	0.67-0.70	0.37-0.38
Pakistan	C	->	->	->	(C)	->	(A)	->	->	(C)	C	0.30-0.50	0.23-0.28	0.23-0.30

Arrows indicate that there was no change in the fragility constellation. Group label in parentheses when uncertainty >.1.

Table A16: Country classifications (cont.)

Country	’05	’06	’07	’08	’09	’10	’11	’12	’13	’14	’15	Viol. ctrl.	Impl. cap.	Emp. legit.
Panama	E	->	(E)	->	(B)	->	->	(E)	(B)	(E)	E	0.29-0.44	0.55-0.61	0.57-0.64
Papua N. G.	C	->	->	->	->	->	->	->	->	->	C	0.45-0.50	0.10-0.14	0.52-0.61
Paraguay	(B)	->	->	->	->	(E)	->	->	->	->	(E)	0.33-0.48	0.50-0.57	0.47-0.50
Peru	(E)	->	->	->	->	->	->	->	->	->	E	0.43-0.58	0.51-0.62	0.53-0.62
Philippines	(C)	->	->	->	->	->	->	->	->	->	(C)	0.46-0.55	0.46-0.51	0.25-0.34
Poland	F	->	->	->	->	->	->	->	->	->	F	0.80-0.88	0.77-0.85	0.74-0.80
Portugal	F	->	->	->	->	->	->	->	->	->	F	0.76-0.85	0.86-0.91	0.70-0.79
Qatar	(D)	->	->	->	->	->	->	->	->	->	(D)	0.50-0.60	0.71-0.75	0.39-0.47
Romania	(D)	->	->	->	->	(F)	->	->	->	->	F	0.73-0.79	0.60-0.73	0.55-0.68
Russia	(B)	->	->	->	->	->	->	(D)	->	->	(D)	0.36-0.44	0.60-0.72	0.26-0.29
Rwanda	C	->	->	->	->	->	->	(C)	->	->	(C)	0.59-0.64	0.21-0.43	0.24-0.30
Saudi Arabia	D	->	->	->	->	->	->	->	->	->	D	0.70-0.80	0.60-0.66	0.23-0.30
Senegal	C	->	->	->	->	->	->	(C)	->	->	(C)	0.47-0.52	0.25-0.39	0.50-0.60
Serbia	D	->	->	->	->	->	->	(D)	->	->	(D)	0.75-0.83	0.74-0.81	0.21-0.51
Sierra Leone	C	->	->	->	->	->	->	->	->	->	C	0.67-0.75	0.08-0.20	0.49-0.58
Singapore	(D)	->	->	->	->	->	(F)	->	->	->	(F)	0.89-0.96	0.94-0.95	0.39-0.42
Slovakia	F	->	->	->	->	->	->	->	->	->	F	0.75-0.85	0.76-0.82	0.74-0.80
Slovenia	F	->	->	->	->	->	->	->	->	->	F	0.82-0.90	0.88-0.97	0.81-0.86
Solomon Isl.	E	->	->	->	->	->	->	->	->	->	E	0.57-0.64	0.50-0.52	0.74-0.79
Somalia	A	->	->	->	->	->	->	->	->	->	A	0.00-0.10	0.00-0.10	0.00-0.12
South Africa	(B)	->	->	->	->	->	->	->	->	B	B	0.18-0.23	0.30-0.41	0.41-0.45
South Korea	F	->	->	->	->	->	->	->	->	->	F	0.85-0.88	0.83-0.91	0.70-0.75
South Sudan							(C)	->	A	->	A	0.07-0.40	0.01-0.15	0.16-0.28
Spain	F	->	->	->	->	->	->	->	->	->	F	0.82-0.88	0.86-0.92	0.62-0.78
Sri Lanka	(C)	B	->	->	->	D	->	->	->	->	D	0.00-0.69	0.50-0.70	0.22-0.43
Sudan	A	->	->	(A)	(C)	->	(A)	->	->	->	(A)	0.30-0.40	0.20-0.30	0.07-0.15
Surinam	(E)	E	->	->	->	->	->	->	->	->	E	0.45-0.68	0.50-0.57	0.67-0.77
Swaziland	C	->	->	(C)	->	->	C	->	->	->	C	0.33-0.50	0.19-0.31	0.27-0.32
Sweden	F	->	->	->	->	->	->	->	->	->	F	0.82-0.88	0.91-0.94	0.89-0.94
Switzerland	F	->	->	->	->	->	->	->	->	->	F	0.84-0.90	0.85-0.88	0.74-0.90
Syria	D	->	->	->	->	->	B	(A)	A	->	A	0.00-0.73	0.10-0.60	0.00-0.26
Tajikistan	C	->	->	(C)	->	C	(C)	->	->	(D)	(D)	0.40-0.80	0.30-0.41	0.26-0.32
Tanzania	C	->	->	->	->	->	->	->	->	->	C	0.48-0.53	0.25-0.35	0.50-0.57
Thailand	(D)	->	D	->	->	->	->	->	(D)	D	D	0.52-0.66	0.60-0.67	0.31-0.44
Togo	C	->	->	->	->	->	->	->	->	->	C	0.44-0.48	0.23-0.29	0.30-0.48
Trinidad&Tob.	B	(B)	B	->	->	->	(B)	->	->	->	(B)	0.16-0.26	0.53-0.59	0.58-0.66
Tunisia	D	->	->	->	->	->	(D)	->	->	(E)	(D)	0.68-0.72	0.55-0.65	0.24-0.58
Turkey	(D)	->	->	->	->	->	->	->	D	->	D	0.59-0.62	0.51-0.66	0.36-0.43
Turkmenistan	C	->	->	->	->	->	(C)	->	->	->	(C)	0.60-0.62	0.31-0.37	0.13-0.14
Uganda	(C)	C	->	->	->	->	->	->	->	->	(C)	0.40-0.48	0.20-0.36	0.26-0.50
Ukraine	(E)	->	(D)	->	->	->	->	->	D	B	D	0.16-0.62	0.60-0.72	0.00-0.52
UAE	D	->	->	->	->	->	->	->	->	->	D	0.86-0.89	0.70-0.77	0.30-0.43
UK	F	->	->	->	->	->	->	->	->	->	F	0.79-0.85	0.82-0.87	0.63-0.85
Uruguay	E	->	(E)	->	->	->	->	->	->	->	(E)	0.49-0.57	0.64-0.73	0.76-0.82
USA	(D)	->	(E)	->	->	->	->	->	->	->	(E)	0.57-0.62	0.76-0.80	0.50-0.60
Uzbekistan	(C)	->	(D)	->	->	->	->	->	D	->	D	0.65-0.68	0.39-0.52	0.14-0.19
Vanuatu	(E)	->	->	->	->	->	->	->	->	->	(E)	0.71-0.74	0.50-0.51	0.77-0.83
Venezuela	B	->	->	->	->	->	->	->	->	->	B	0.08-0.19	0.50-0.61	0.28-0.36
Vietnam	D	->	->	->	->	->	->	->	->	->	D	0.79-0.82	0.53-0.56	0.23-0.31
Yemen	C	->	->	->	->	->	(C)	(A)	C	(A)	A	0.00-0.62	0.30-0.35	0.25-0.32
Zambia	C	->	->	->	->	->	->	->	->	->	C	0.53-0.58	0.22-0.33	0.43-0.48
Zimbabwe	C	->	->	->	->	->	->	->	->	->	C	0.45-0.59	0.24-0.35	0.19-0.38

Arrows indicate that there was no change in the fragility constellation. Group label in parentheses when uncertainty >.1.

4.3 World maps

Figures A14 to A19 show maps with country classifications for the years 2005, 2007, 2009, 2011, 2013 and 2015.

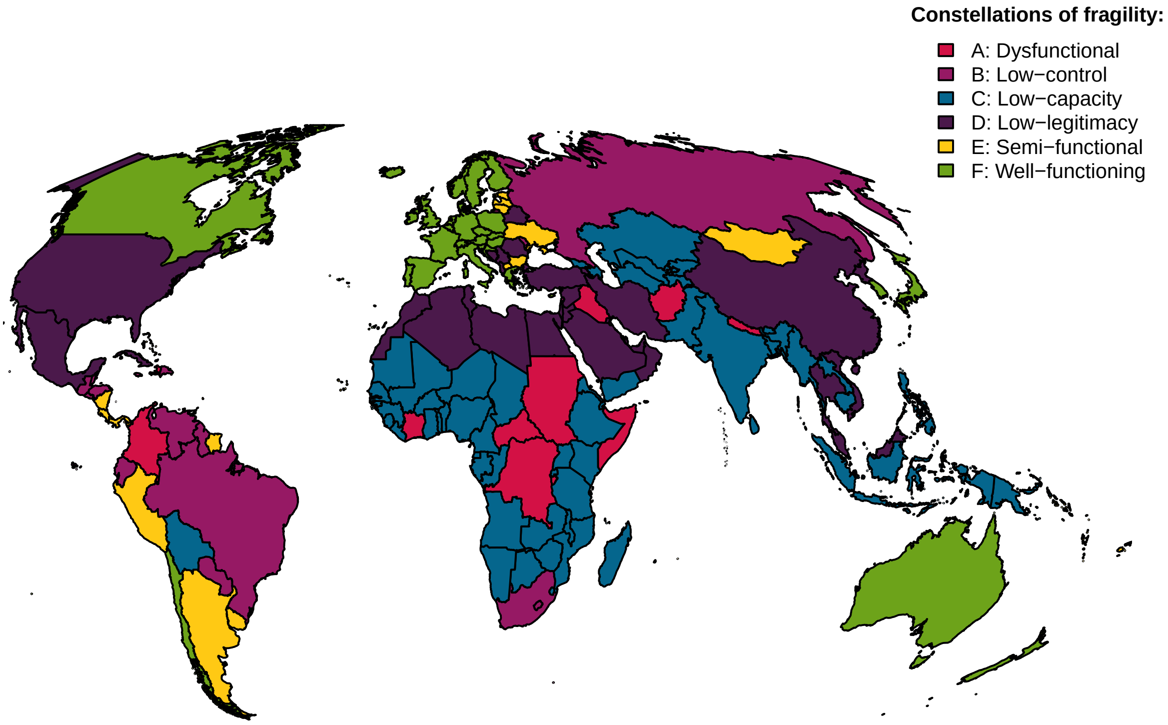

Figure A14: World map of fragility constellations, 2005

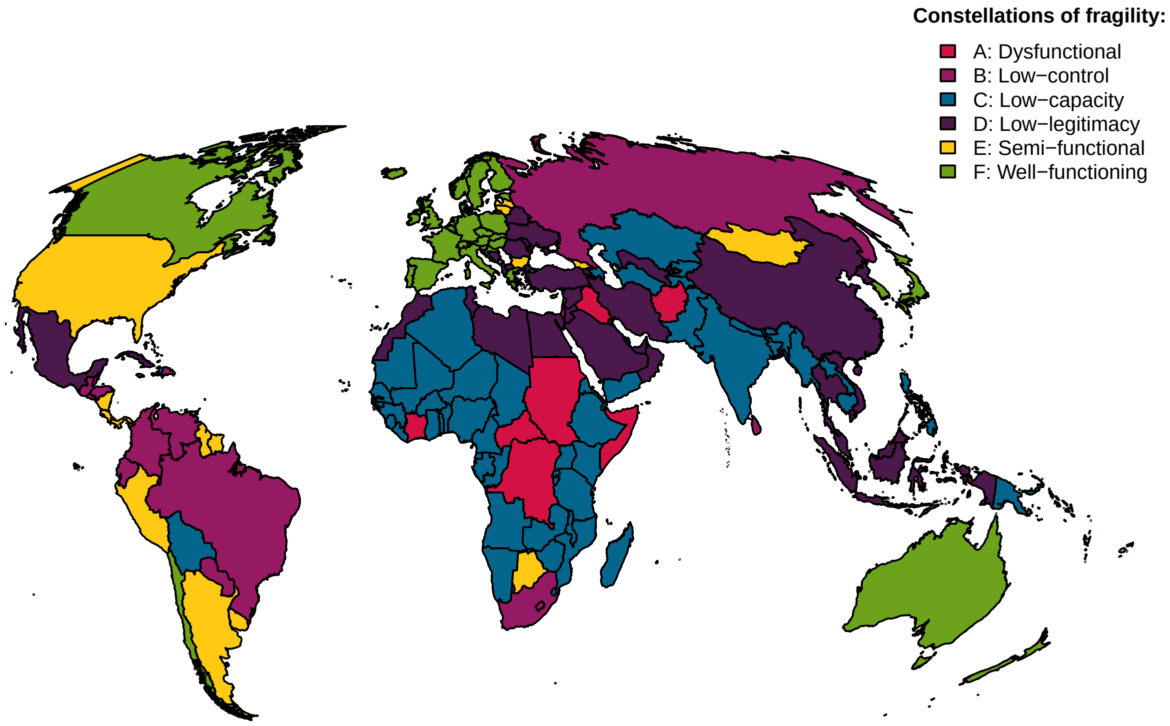

Figure A15: World map of fragility constellations, 2007

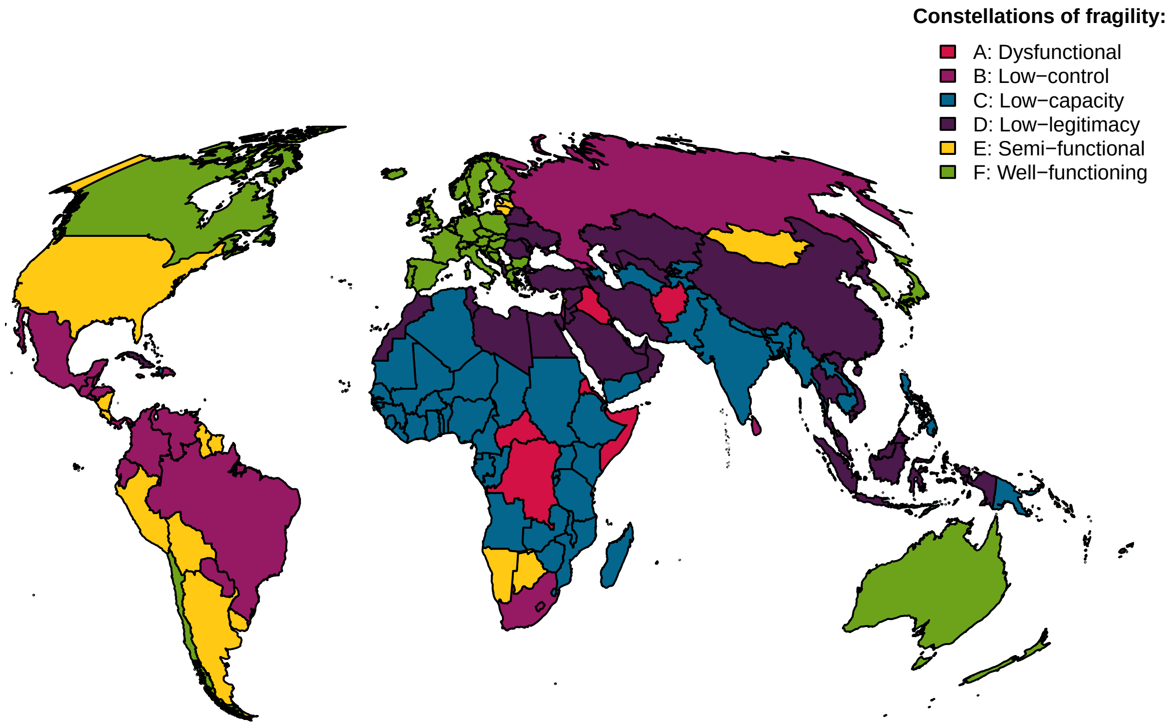

Figure A16: World map of fragility constellations, 2009

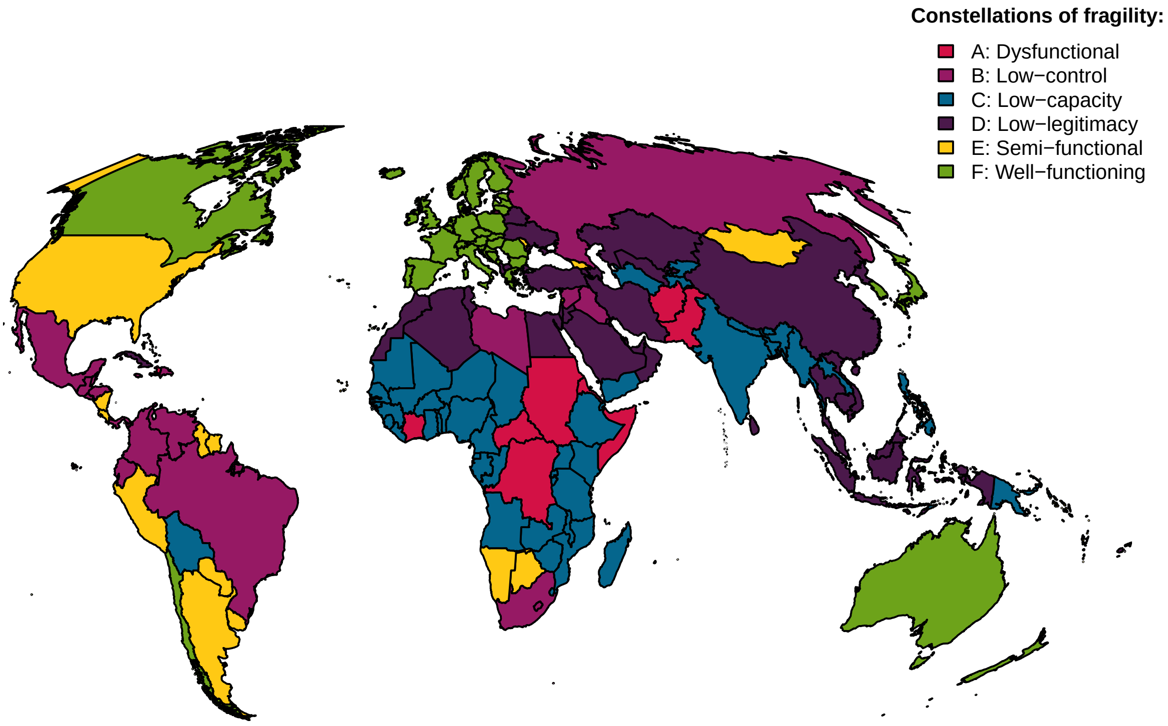

Figure A17: World map of fragility constellations, 2011

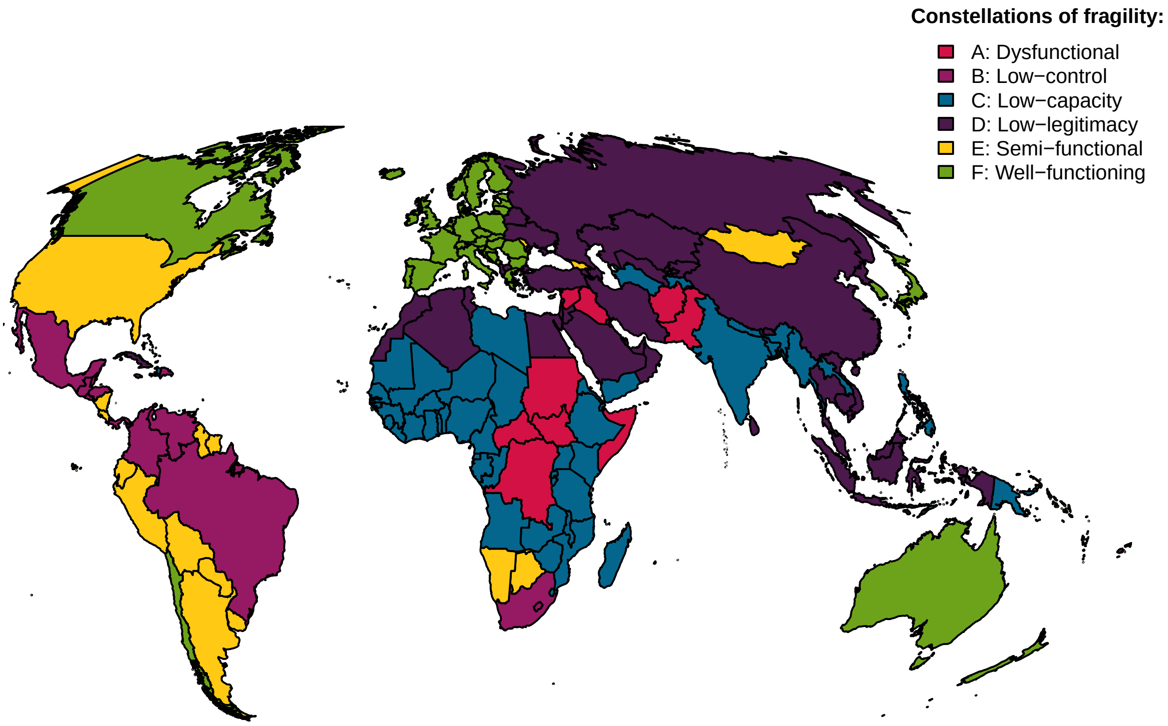

Figure A18: World map of fragility constellations, 2013

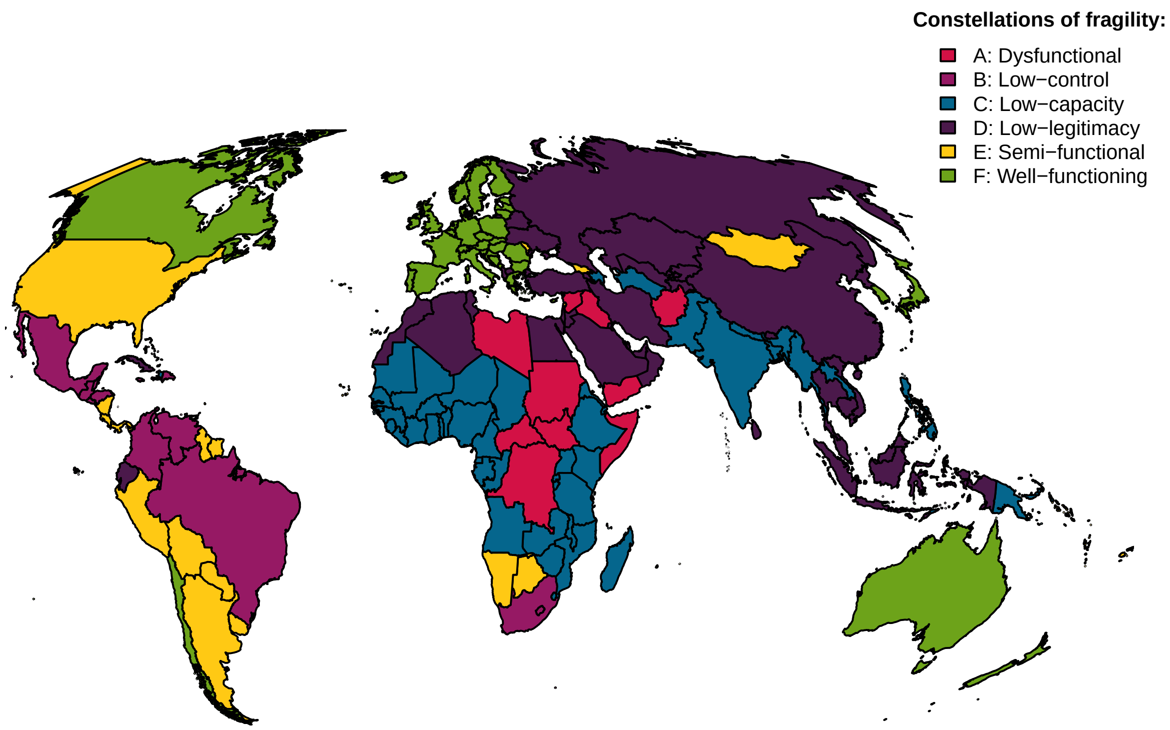

Figure A19: World map of fragility constellations, 2015

4.4 Transitions

Table A17 provides information on the number of transitions that have taken place from any group to any other. Table A18 lists the specific transition countries and the years when the transitions were completed. The information on transitions is combined with the group properties in figures A20 to A22. The strength of the arrows indicates the number of directed transitions taking place between two groups. Two dimensions are represented on the plot axes, the third is represented in the size of the bubble around the group letter.

Table A17: Number of transitions between groups, 2005-2015

	A	B	C	D	E	F
A: Dysfunctional		2	12			
B: Low-control	2		1	7	9	
C: Low-capacity	11	2		11	6	
D: Low-legitimacy		6	5		4	6
E: Semi-functional		6	2	5		4
F: Well-functioning				3		

Read row to column; 1,885 country years in sample.

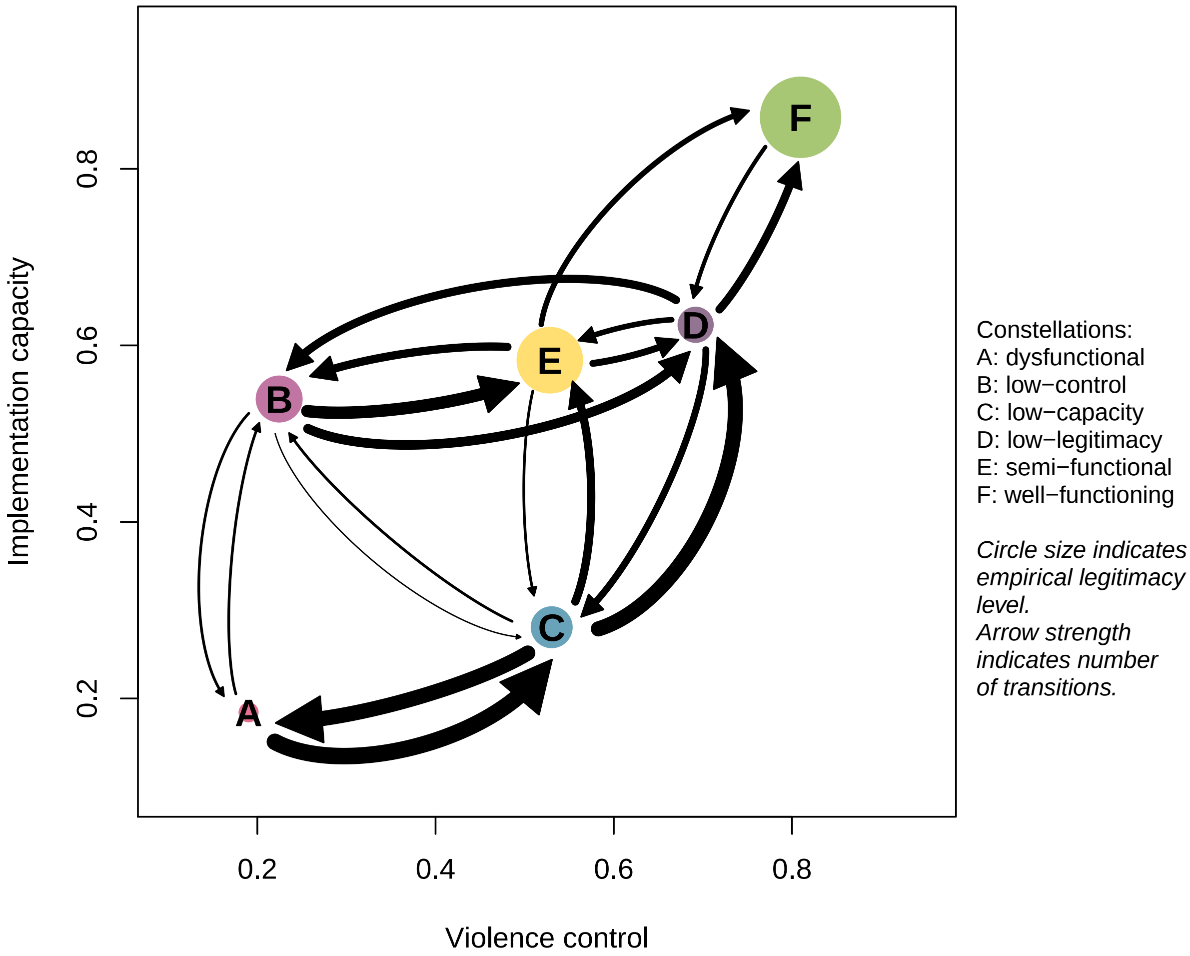

Figure A20: Transitions between constellations; violence control and implementation capacity perspective; 2005-2015

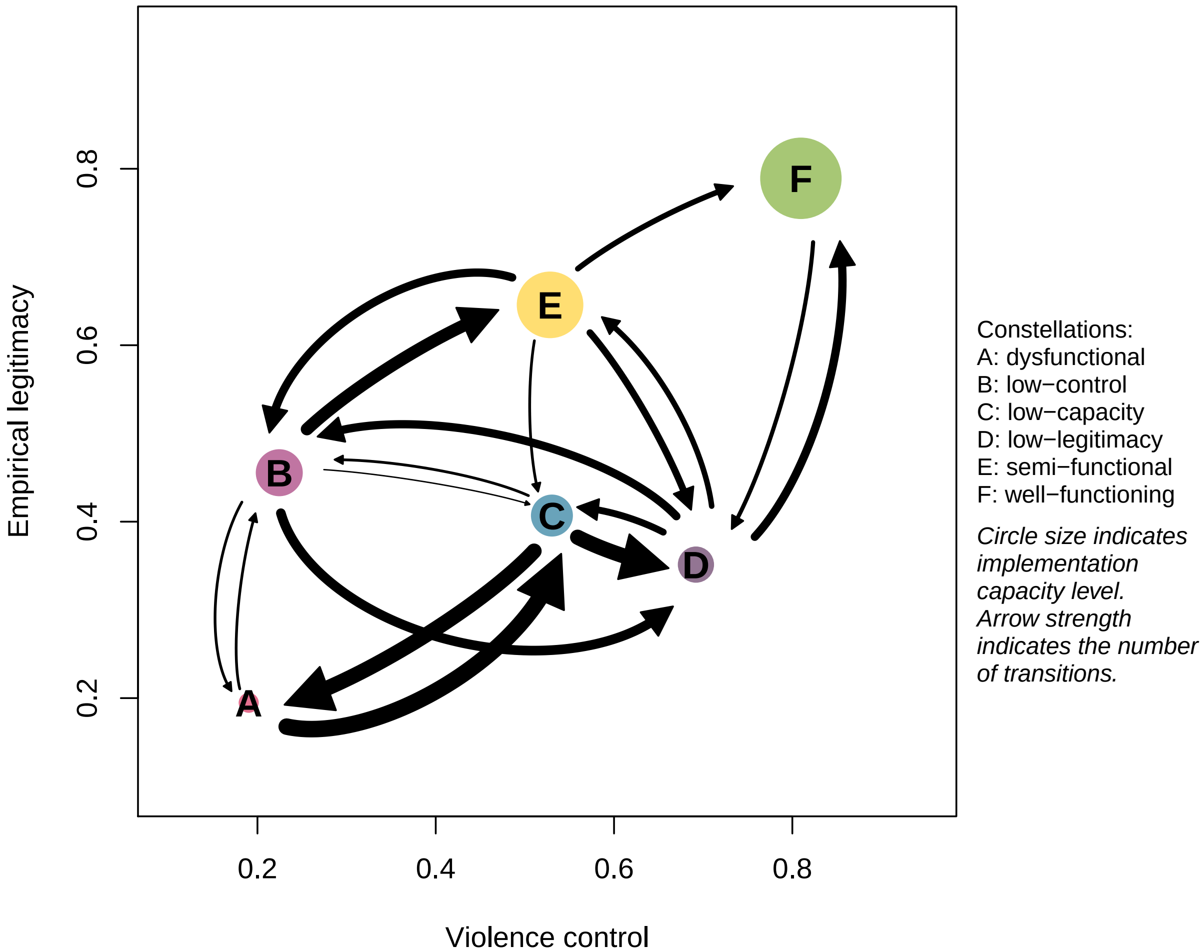

Figure A21: Transitions between constellations; violence control and empirical legitimacy perspective; 2005-2015

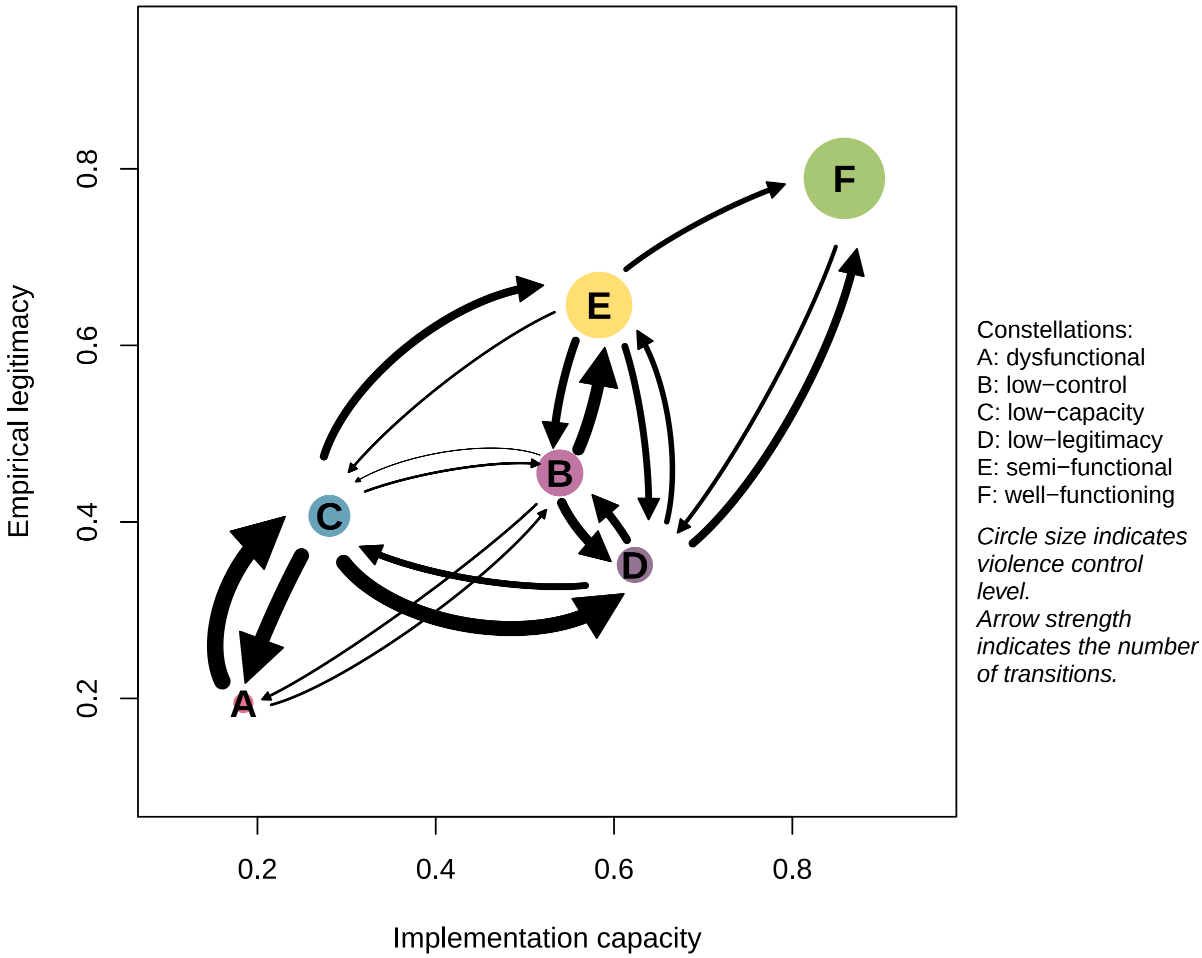

Figure A22: Transitions between constellations; implementation capacity and empirical legitimacy perspective; 2005-2015

Table A18: All country transitions, 2005-2015

	A: dysfunctional	B: low-control	C: low-capacity	D: low-legitimacy	E: semi-functional	F: well-functioning
A	→	Colombia 2006, Iraq 2011	Haiti 2006, Burundi 2006, Nepal 2006, Chad 2007, Cote d Ivoire 2009, Chad 2009, Sudan 2009, Haiti 2012, Cote d Ivoire 2012, Eritrea 2012, Yemen 2013, Pakistan 2014			
B	Syria 2012, Iraq 2013	⟷	Kyrgyz Republic 2011	Moldova 2006, Israel 2010, Sri Lanka 2010, Russia 2012, Libya 2012, Ukraine 2015, Israel 2015	Guyana 2007, Lebanon 2007, Guyana 2009, Paraguay 2010, Georgia 2010, Panama 2012, Ecuador 2013, Panama 2014, Lebanon 2015	
C	Chad 2006, Chad 2008, Eritrea 2008, Cote d Ivoire 2010, Haiti 2011, Sudan 2011, Pakistan 2011, Yemen 2012, South Sudan 2013, Libya 2014, Yemen 2014	Sri Lanka 2006, Kyrgyz Republic 2010	⟷	Uzbekistan 2007, Indonesia 2007, Algeria 2008, Bhutan 2008, Kazakhstan 2009, Azerbaijan 2010, Algeria 2010, Cambodia 2011, Kyrgyz Republic 2012, Bhutan 2012, Tajikistan 2014	Georgia 2006, Botswana 2007, Namibia 2008, Bolivia 2009, Bolivia 2013, East Timor 2014	
D		Israel 2006, Mexico 2008, Libya 2011, Syria 2011, Ukraine 2014, Israel 2014	Algeria 2007, Algeria 2009, Bhutan 2009, Libya 2013, Azerbaijan 2015	⟷	USA 2007, Moldova 2010, Tunisia 2014, Fiji 2015	Macedonia 2008, Bosnia-Herzegovina 2008, Montenegro 2010, Romania 2010, Singapore 2011, Estonia 2013
E		Guyana 2008, Georgia 2008, Bahamas 2009, Panama 2009, Lebanon 2012, Panama 2013	Bolivia 2010, East Timor 2015	Macedonia 2007, Ukraine 2007, Fiji 2009, Ecuador 2014, Tunisia 2015	⟷	Estonia 2006, Bulgaria 2008, Latvia 2010, Lithuania 2010
F				Montenegro 2008, Macedonia 2011, Estonia 2012		←

Read row to column.

4.5 Dataset

The dataset and replication files can be downloaded from http://statefragility.info/.

For countries with dimension scores available beyond our period of investigation, we provide ex-post classifications for the years 1999-2004 in this dataset.

5 Statistical software employed

All calculations have been performed using the statistical environment R (R Core Team 2019), save some data management with Stata (StataCorp 2013). Within R, we employed the packages `Mclust` (Fraley & Raftery 2002; Fraley, Raftery, Murphy, & Scrucca 2012), `cshapes` (Weidmann et al. 2010), `diagram` (Soetaert 2017), `dplyr`(Wickham, François, Henry, & Müller 2019), `foreach` (Calaway, Revolution Analytics, & Weston 2014), `fpc` (Hennig 2015), `lattice` (Sarkar 2008), `psych` (Revelle 2015), `RColorBrewer` (Neuwirth 2011), `xtable` (Dahl 2014), and some of their dependencies.

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