Supplementary Online Appendix

Democracy Manifest or Democracy Latent?

A Unified Framework for Identifying Regime Types and Transitions

Omer Faruk Orsun

Muhammet A. Bas

Contents

A Construction of UNITAS 1

B Properties of UNITAS 6

C Monte Carlo Simulations 16

D Comparison of Regime Indicators with UNITAS 24

E Predictive Checks and Comparative Performance Analysis 25

F Regime Types, Regime Transitions, and Civil War 29

A Construction of UNITAS

Let $i = 1, \ldots, N$ index countries and $t = 1, \ldots, T_i$ index time periods, where T_i denotes the number of observations for country i. For a given country i, with the assumption of three latent regime categories in our illustrative example, UNITAS employs a Hidden Markov Model that captures a latent process $\mathrm{d_i} = (d_{i1}, ..., d_{iT_i})$, with $d_{it} \in \{A, S, D\}$ denoting Autocracy (A), Semi-democracy (S), and Democracy (D). The latent variable d is assumed to follow a first-order Markov process, meaning that the future values of the latent regime type for a country are independent of its past regime values given the current regime type of the country. The parameters of the Markov chain are (i) initial probabilities of the three regime types, a_1, and (ii) transition probabilities, or the probability of a change from regime r to regime s, a_{rs}. The measurement part of HMM uses information from a finite set of $K \geq 1$ different regime indicators, labeled as *manifest variables*, to estimate the latent regime type. It assumes that the probability of observing a particular pattern of regime scores in K manifest variables, $\mathrm{Y_{it}}$, is conditional on the value of the latent variable, d_{it}. We formally define these conditional probabilities as *emission probabilities*:[1]

$$\mathrm{P}(\mathrm{Y_{it}}|d_{it}) = \prod_{k=1}^{K} P(Y_{it}^{k}|d_{it}) \tag{A.1}$$

which quantify the likelihood of having a specific configuration of observable regime scores given each latent regime type. Each component $P(Y_{it}^{k} = c|d_{it} = s)$ follows a categorical distribution, where $c \in \{1, 2, ..., C_k\}$ represents the possible categories for indicator k, which ranges from 2 (e.g., PACL) to 21 (e.g., Polity IV) in our application. To estimate these parameters, the HMM approach specifies the log-likelihood function

$$\log \mathcal{L}(\mathrm{M}) = \sum_{i=1}^{N} \log P(\mathrm{Y}_{i,1:T_i} \mid \mathrm{M}) \tag{A.2}$$

where $\mathrm{Y}_{it} = (Y_{it}^{1}, \ldots, Y_{it}^{K})$ is the vector of all K regime indicators for country i at time t, and $\mathrm{M} = \{a_1, \mathrm{A}, \mathrm{B}\}$ contains the initial state probabilities a_1, transition probabilities A, and emission probabilities B. We employ the Baum-Welch algorithm (Baum 1972), a special case of the expectation-maximization (EM) algorithm as an optimization step. To avoid local maxima, we use 100 random initializations of the algorithm, followed by global and local optimization steps to ensure convergence to the global maximum likelihood estimates.

Given these parameters of the HMM, the joint probability that regime type d is s in period t for country i, and the sequence of all current and previous observations in manifest datasets up to time

[1] Similar to other latent variable approaches in the literature (e.g., Treier and Jackman 2008; Pemstein, Meserve and Melton 2010), our measure assumes conditional independence of manifest indicators given the latent regime type. When indicators have residual correlation given regime type, this assumption is violated and can lead to overconfident posterior probabilities and uncertainty estimates. Applied researchers who prioritize well-calibrated uncertainty estimates should adopt a selective approach using manifest indicators from different sources that they are confident will be conditionally independent given the latent regime type. For methodologists, this caveat presents opportunities for future extensions that explicitly model conditional dependence among manifest variables.

t, $\mathrm{Y_{i,1:t}}$, is given as follows:

$$P(d_{it} = s, \mathrm{Y_{i,1:t}}) = a_{it}(s) = \sum_{r=1}^{m} a_{i,t-1}(r) a_{rs} P(\mathrm{Y}_{it}|s) \tag{A.3}$$

where $a_{i,t-1}(r)$ is the probability of regime type r in period $t-1$ for country i, a_{rs} is the probability of transition from regime r to regime s[2] and $P(\mathrm{Y}_{it}|s)$ is the probability of observed pattern of the manifest variables for country i at time t given the regime type s as defined above.

Our first quantity of interest is the conditional probability of latent regime type j at time t for a given country i, given all current and past realized regime scores in the observed manifest datasets for that country, which produces our (probabilistic) guess of that country's regime type in that year:

$$P(d_{it} = s|\mathrm{Y_{i,1:t}}) = \tau_{it}(s) = \frac{a_{it}(s)}{a_{it}(A) + a_{it}(S) + a_{it}(D)} \tag{A.4}$$

Our second quantity of interest is the probability of regime transition from r in $t-1$ to s in t for country i, $\tau_{it}(r, s)$. We calculate it as the joint probability of observing regime type r in $t-1$ and regime type s in t for country i, given all current and past realized regime scores in the observed manifest datasets for that country, as follows:

$$P(d_{it} = s, d_{i,t-1} = r|\mathrm{Y_{i,1:t}}) = \tau_{it}(r, s) = \frac{a_{i,t-1}(r) a_{rs} P(\mathrm{Y}_{it}|s)}{\sum_{r=1}^{m}\sum_{s=1}^{m} a_{i,t-1}(r) a_{rs} P(\mathrm{Y}_{it}|s)} \tag{A.5}$$

Using equation A.5, probability of democratization ($\tau_{it}(\mathrm{D}\Delta)$), autocratization ($\tau_{it}(\mathrm{A}\Delta)$), stability ($\tau_{it}(\mathrm{ST})$) given the previous and current observations and the model are

$$\begin{aligned}
\tau_{it}(\mathrm{A}\Delta) &= \tau_{it}(D, S) + \tau_{it}(D, A) + \tau_{it}(S, A) \\
\tau_{it}(\mathrm{D}\Delta) &= \tau_{it}(A, S) + \tau_{it}(A, D) + \tau_{it}(S, D) \\
\tau_{it}(\mathrm{ST}) &= \tau_{it}(A, A) + \tau_{it}(D, D) + \tau_{it}(S, S)
\end{aligned} \tag{A.6}$$

In other words, democratization and autocratization refer to the sum of the probabilities of transition from less democratic to more democratic regime categories, and the sum of probabilities of transition from more democratic to less democratic types, respectively.[3] One can easily expand our

[2] In our empirical application, our approach assumes a single, time-homogeneous transition matrix during the time period from 1800 to 2017 (n=23,787 country-years). This assumption facilitates reliable estimation of rare transition types such as shifts from democracy to autocracy (n=6), or autocracy to democracy (n=8). If transition dynamics vary significantly across different historical eras, the time-homogeneous estimates may understate transition probabilities during volatile periods and overstate them during stable periods. This potential misspecification primarily affects cases where manifest indicators provide ambiguous evidence for a given regime type. When indicators clearly agree on regime type, emission probabilities dominate and this potential misspecification has limited influence on posterior classifications. Given that regime transitions are rare, modeling a more dynamic, time-varying transition matrix is not feasible in our case because most year-specific matrices would be undefined, or driven by a single case. For this reason, we leave the extension that allows for time-varying transition matrices for future research.

[3] In empirical analysis, one can adopt different operationalizations of regime transition using our approach as we show in Figure 3 following Mansfield and Snyder (2002): incomplete democratization, i.e., transitions from autocracy to semi-democracy, complete democratization, i.e., transitions from either autocracy or semi-democracy to democracy.

formulation to estimate the probability of transitions taking place over varying time periods, as we detail below. For example, one can estimate the probability of observing a three-year sequence of regime categories rsq given all current and past observations in the manifest datasets as follows:

$$\tau_{it}(r,s,q) = \frac{a_{i,t-2}(r)a_{rs}P(\mathrm{Y}_{i,t-1}|s)a_{sq}P(\mathrm{Y}_{it}|q)}{\sum_{q=1}^{m}\sum_{s=1}^{m}\sum_{r=1}^{m} a_{i,t-2}(r)a_{rs}P(\mathrm{Y}_{i,t-1}|s)a_{sq}P(\mathrm{Y}_{it}|q)} \tag{A.7}$$

To summarize, we generate three types of HMM-based quantities of interest: (I) $\tau_{it}(r)$ in equation A.4, the latent regime type in year t for country i as the probability of type r following the first t observations in the regime datasets; (II) $\tau_{it}(r,s)$ in equation A.5, two-year regime type as the probability of a regime change from r to s in year t for country i; and (III) n-year regime type as the probability of a specific regime sequence in a given n-year time window $\tau_{it}(r,s,...)$ (as in $\tau_{it}(r,s,q)$ in A.7 above.) As described below, we then use $\tau_{it}(r)$ and $\tau_{it}(r,s)$ in multiple imputation in order to incorporate measurement uncertainty into statistical inferences on regime types and transitions (Rubin 1987).

Steps for Multiple Imputation

1. Generate m multinomially distributed random number vectors based on[4]
   - $\tau_{it}(A)$, $\tau_{it}(D)$, and $\tau_{it}(S)$ for the imputation of regime types: democracy, semi-democracy, autocracy,
   - $\tau_{it}(A,A), ..., \tau_{it}(D,D)$ for the imputation of each type of two-year regime types,
   - $\tau_{it}(\mathrm{D}\Delta)$, $\tau_{it}(\mathrm{A}\Delta)$, and $\tau_{it}(\mathrm{ST})$ for the imputation of democratization, autocratization, and stability, based on two-year regime type information.
   - $\tau_{it}(A,A,A,...), ..., \tau_{it}(D,D,D,...)$ for the imputation of the n-year regime types,
2. Extract the quantities of interest q_l, e.g., proportion, regression coefficient, predicted probability, using each random vector,
3. Calculate the point estimates by taking the average of m separate estimates

$$\bar{q} = \frac{1}{m}\sum_{l=1}^{m} q_l \tag{A.8}$$

4. Calculate the pooled standard errors:

$$SE(q) = \left[\frac{1}{m}\sum_{l=1}^{m} SE(q_l)^2 + (1+\frac{1}{m})\sum_{l=1}^{m}\frac{(q_l-\bar{q})^2}{m-1}\right]^{\frac{1}{2}} \tag{A.9}$$

[4]Our current multiple imputation approach draws each country-year's regime type independently from its marginal distribution. Alternatively, one can reconstruct historical regime sequences consistent with the estimated transition dynamics using forward filtering backward sampling, which samples states backward in time using the transition matrix and the emission probabilities. We leave this refinement as a direction for future research.

Derivation of Regime Probabilities:

One-Year Regime Probability:

For notational simplicity, we omit the country index i in the following derivations.[5] We start by deriving the one-year regime type probability $p(d_t|\mathrm{Y}_{1:t})$. We first express the joint probability of the regime type at time t and the observations up to time t as a sum over the possible regime types at time $t-1$:

$$p(d_t, \mathrm{Y}_{1:t}) = \sum_{d_{t-1}=1}^{m} p(d_t, d_{t-1}, \mathrm{Y}_{1:t}) \tag{A.10}$$

We then expand this sum as:

$$p(d_t, \mathrm{Y}_{1:t}) = \sum_{d_{t-1}=1}^{m} p(\mathrm{Y}_t|d_t, d_{t-1}, \mathrm{Y}_{1:t-1}) p(d_t|d_{t-1}, \mathrm{Y}_{1:t-1}) p(d_{t-1}, \mathrm{Y}_{1:t-1}) \tag{A.11}$$

We make two conditional independence assumptions to simplify this equation:

- Y_t is conditionally independent of d_{t-1} and $\mathrm{Y}_{1:t-1}$ given d_t
- d_t is conditionally independent of $\mathrm{Y}_{1:t-1}$ given d_{t-1}

This allows us to simplify the equation to:

$$p(d_t, \mathrm{Y}_{1:t}) = \sum_{d_{t-1}=1}^{m} p(\mathrm{Y}_t|d_t) p(d_t|d_{t-1}) p(d_{t-1}, \mathrm{Y}_{1:t-1}) \tag{A.12}$$

Given that $p(\mathrm{Y}_{1:t}) = \sum_{d_t=1}^{m} p(d_t, \mathrm{Y}_{1:t})$, we can write:

$$p(\mathrm{Y}_{1:t}) = \sum_{d_t=1}^{m} \sum_{d_{t-1}=1}^{m} p(\mathrm{Y}_t|d_t) p(d_t|d_{t-1}) p(d_{t-1}, \mathrm{Y}_{1:t-1}) \tag{A.13}$$

Therefore, the one-year regime type probability is:

$$p(d_t|\mathrm{Y}_{1:t}) = \frac{\sum_{d_{t-1}=1}^{m} p(\mathrm{Y}_t|d_t) p(d_t|d_{t-1}) p(d_{t-1}, \mathrm{Y}_{1:t-1})}{\sum_{d_t=1}^{m} \sum_{d_{t-1}=1}^{m} p(\mathrm{Y}_t|d_t) p(d_t|d_{t-1}) p(d_{t-1}, \mathrm{Y}_{1:t-1})} \tag{A.14}$$

Two-Year Regime Probability:

Next, we derive the two-year regime type probability $p(d_t, d_{t-1}|\mathrm{Y}_{1:t})$. The joint probability of observing a certain regime type in year $t-1$ and another in year t is $p(d_t, d_{t-1}, \mathrm{Y}_{1:t})$:

$$p(d_t, d_{t-1}, \mathrm{Y}_{1:t}) = p(\mathrm{Y}_t|d_t, d_{t-1}, \mathrm{Y}_{1:t-1}) p(d_t|d_{t-1}, \mathrm{Y}_{1:t-1}) p(d_{t-1}, \mathrm{Y}_{1:t-1}) \tag{A.15}$$

We again use the same two conditional independence assumptions to simplify this equation:

[5] These derivations extend the forward algorithm (Rabiner 1989) to joint probabilities of regime sequences.

- Y_t is conditionally independent of d_{t-1} and $\mathrm{Y}_{1:t-1}$ given d_t
- d_t is conditionally independent of $\mathrm{Y}_{1:t-1}$ given d_{t-1}

This simplifies the equation to:

$$p(d_t, d_{t-1}, \mathrm{Y}_{1:t}) = p(\mathrm{Y}_t|d_t)p(d_t|d_{t-1})p(d_{t-1}, \mathrm{Y}_{1:t-1}) \tag{A.16}$$

And the total probability of the observations up to time t is:

$$p(\mathrm{Y}_{1:t}) = \sum_{d_t=1}^{m} \sum_{d_{t-1}=1}^{m} p(d_t, d_{t-1}, \mathrm{Y}_{1:t}) \tag{A.17}$$

Therefore, the two-year regime type probability is:

$$p(d_t, d_{t-1}|\mathrm{Y}_{1:t}) = \frac{p(\mathrm{Y}_t|d_t)p(d_t|d_{t-1})p(d_{t-1}, \mathrm{Y}_{1:t-1})}{\sum_{d_t=1}^{m} \sum_{d_{t-1}=1}^{m} p(\mathrm{Y}_t|d_t)p(d_t|d_{t-1})p(d_{t-1}, \mathrm{Y}_{1:t-1})} \tag{A.18}$$

Three-Year Regime Probability:

Finally, we derive the three-year regime type probability $p(d_t, d_{t-1}, d_{t-2}|\mathrm{Y}_{1:t})$. The joint probability of observing certain regime types in years $t-2$, $t-1$, and t is:

$$\begin{aligned} p(d_t, d_{t-1}, d_{t-2}, \mathrm{Y}_{1:t}) = p(\mathrm{Y}_t|d_t, d_{t-1}, \mathrm{Y}_{t-1}, d_{t-2}, \mathrm{Y}_{1:t-2})p(d_t|d_{t-1}, \mathrm{Y}_{t-1}, d_{t-2}, \mathrm{Y}_{1:t-2}) \\ p(\mathrm{Y}_{t-1}|d_{t-1}, d_{t-2}, \mathrm{Y}_{1:t-2})p(d_{t-1}|d_{t-2}, \mathrm{Y}_{1:t-2})p(d_{t-2}, \mathrm{Y}_{1:t-2}) \end{aligned} \tag{A.19}$$

We use similar conditional independence assumptions to simplify this equation:

- Y_t is conditionally independent of d_{t-1}, $\mathrm{Y}_{1:t-1}$, d_{t-2}, and $\mathrm{Y}_{1:t-2}$ given d_t
- d_t is conditionally independent of $\mathrm{Y}_{1:t-1}$ given d_{t-1}

This simplifies the equation to:

$$p(d_t, d_{t-1}, d_{t-2}, \mathrm{Y}_{1:t}) = p(\mathrm{Y}_t|d_t)p(d_t|d_{t-1})p(\mathrm{Y}_{t-1}|d_{t-1})p(d_{t-1}|d_{t-2})p(d_{t-2}, \mathrm{Y}_{1:t-2}) \tag{A.20}$$

The total probability of the observations up to time t is:

$$p(\mathrm{Y}_{1:t}) = \sum_{d_t=1}^{m} \sum_{d_{t-1}=1}^{m} \sum_{d_{t-2}=1}^{m} p(d_t, d_{t-1}, d_{t-2}, \mathrm{Y}_{1:t}) \tag{A.21}$$

Therefore, the three-year regime type probability is:

$$p(d_t, d_{t-1}, d_{t-2}|\mathrm{Y}_{1:t}) = \frac{p(\mathrm{Y}_t|d_t)p(d_t|d_{t-1})p(\mathrm{Y}_{t-1}|d_{t-1})p(d_{t-1}|d_{t-2})p(d_{t-2}, \mathrm{Y}_{1:t-2})}{\sum_{d_t=1}^{m} \sum_{d_{t-1}=1}^{m} \sum_{d_{t-2}=1}^{m} p(\mathrm{Y}_t|d_t)p(d_t|d_{t-1})p(\mathrm{Y}_{t-1}|d_{t-1})p(d_{t-1}|d_{t-2})p(d_{t-2}, \mathrm{Y}_{1:t-2})} \tag{A.22}$$

B Properties of UNITAS

1. Combines Information from Imperfect Regime Indicators

UNITAS is designed to accommodate multiple regime indicators as input. Unlike simple additive (Polity IV, Freedom House) or multiplicative (Munck, Vanhannen) aggregation methods that may miss important variations in the underlying regime characteristics by simply summing or multiplying underlying subcomponent values — a limitation highlighted by Gleditsch and Ward (1997) and Treier and Jackman (2008), our model can capture more fine-grained associations between the values of the manifest variables and the latent regime categories.[6] By assuming a hidden categorical regime type, our approach groups together similar observations based on the values of their regime indicators and iteratively assigns probabilities for the mutually exclusive regime categories. This process maps each value in a given manifest regime indicator to the underlying hidden regime type via emission probabilities and estimates the probability of various institutional, behavioral, opinion-based characteristics co-occurring in democracies, semi-democracies, or autocracies.[7] In doing so, we treat manifest regime indicators as imperfect signals of a given true underlying regime type and evaluate whether a given trait is more likely to be observed in a typical autocracy such as Libya or Iran, a democracy such as Norway or Australia, or a semi-democracy such as Thailand or Russia. For instance, rather than automatically associating high participation with democracy, our approach evaluates whether high participation is common only among democracies or if it is also observed in semi-democracies or autocracies. Indeed, coercion in some authoritarian regimes can lead to higher voter turnout than in democracies as a tactic often employed for authoritarian stability (Martinez i Coma and Morgenbesser 2020). Thus, instead of just relying solely on single measures like Vanhanen (2014)'s measurement of participation as an indicator of democracy, our approach synthesizes information from multiple imperfect indicators by empirically verifying the relationship between each individual variable and different regime types via emission probabilities.[8]

How well do the empirical patterns in the estimated emission probabilities align with the theoretical expectations? To assess this, we calculate the probability of a regime type given a certain value of a manifest variable via the Bayes rule. When regime type has three categories, theoretically, the probability of democracy (autocracy) should increase with the manifestation of more (less) democratic attributes in a given regime indicator, while the probability of semi-democracy should exhibit an inverse u-shaped curve around the intermediate values, at least for indicators with more than two values. Figure A1 shows how the estimated probabilities from our model actually map to the values of each manifest regime indicator, suggesting variation across manifest variables in terms of how closely they follow the theoretical benchmark.[9] For example, Liberal Democracy Index (Libdem VDEM) shows a relationship that is more in line with this ideal measurement scenario. Despite

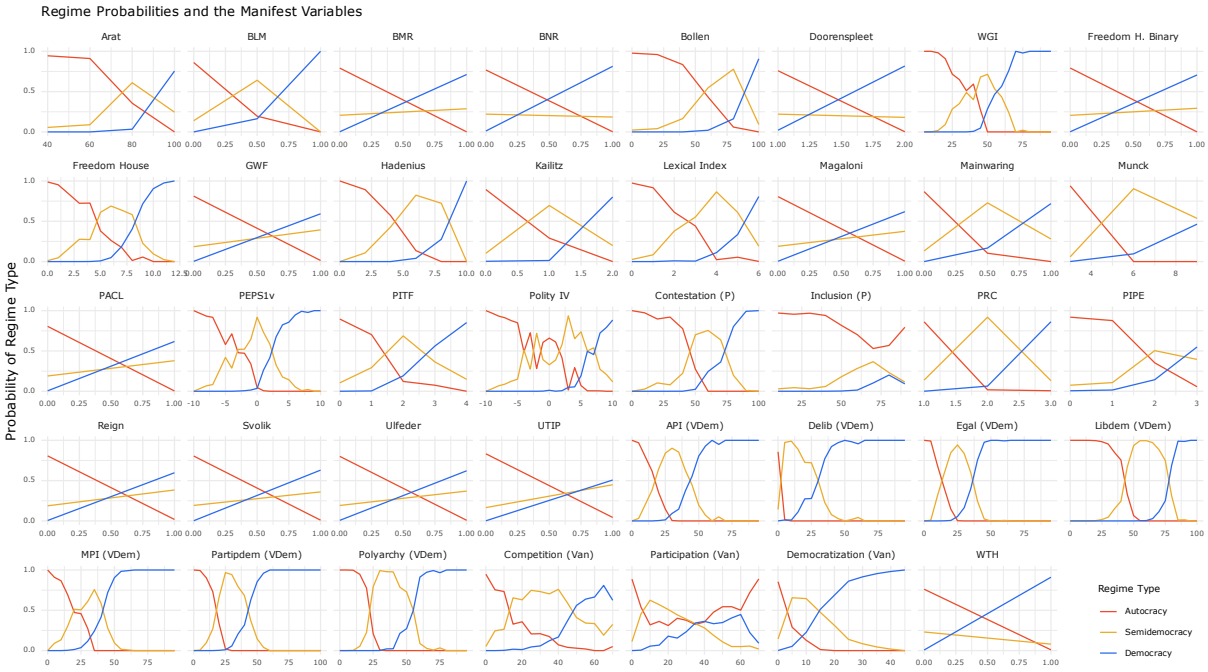
[6] We analyze the level of alignment between our measure and the manifest regime indicators in Appendix D. The results indicate a high level of agreement with many existing regime indicators.

[7] The estimated emission probabilities are presented in Appendix Figure A8.

[8] Furthermore, related to the recent debate in the literature on the objective versus subjective measurement of political regimes (e.g., Little and Meng 2024; Knutsen et al. 2024), our method can use information from both types of measurement approaches in the literature to recover hidden regime types.

[9] These probabilities are based on equation A.4 with the assumption of t=1 with the estimated initial probabilities of $q_1(D)$ =0.09, $q_1(S)$ =0.22, $q_1(A)$ =0.69.

Figure A1: Regime Type Probabilities and the Manifest Variables



some deviations from this expected theoretical relationship, such as participation (Vanhanen 2014) as discussed above (and Polity IV as discussed below), manifest variables typically reflect the expected patterns, supporting the validity of our HMM-based aggregation in capturing various regime types.

To illustrate how our approach accommodates diverse regime traits, consider an important debate in the literature on the implications of alternation of power for different regime types. The relationship between alternation of power and the classification of political regimes has long been a subject of debate in regime type measurement (e.g., Cheibub, Gandhi and Vreeland (2010) vs. Svolik (2012); Boix, Miller and Rosato (2012)). This debate focuses on whether the presence or absence of leader turnover can or should serve as an indicator of regime type. If we were to limit our focus on key PACL features (Cheibub, Gandhi and Vreeland 2010), we would consider multiparty elections and turnover as defining traits of regime types. In a non-democratic regime, we would typically observe a single party, if any, dominating the political system. The elections, if any, are not competitive and the absence of true competition precludes any meaningful alternation of power. However, in a democratization process, multiparty elections might be introduced. Over time, the regime may allow meaningful competition that leads to an actual change of incumbent. This change indicates a shift toward democracy in PACL's framework, while its absence continues to signify an autocratic regime.[10] Other scholars (e.g., Svolik 2012; Boix, Miller and Rosato 2012), however, do not see the turnover as a sufficient condition for democracy or for autocracy classification.

By including PACL as a manifest variable along with other indicators, our model can unpack this relationship and assess whether absence of turnover might occur in democracies as a result

[10] Alternatively, Bas and Stone (2025) build on PACL's minimalistic conceptualization and estimates the probability of democracy in a structural model.

of satisfaction with a successful incumbent or whether it is sign of authoritarian continuity due to restricted competition or flawed elections. The emission probabilities from our model based on PACL data show that none of the autocratic regimes exhibit turnover via competitive elections (with probability 1), aligning with theoretical expectations, and a large portion of semi-democracies (75 percent) also do not show turnover. We also find that a small fraction of democracies (5 percent) do not exhibit turnover. As a result, while a strong sign, our approach suggests that the absence of turnover is not a sufficient condition to classify a regime as an autocracy. Given that we include other manifest indicators, our model does not immediately default to an authoritarian regime if a polity exhibits multiparty elections but lacks alternation of power as determined by PACL. Instead, it draws information from other datasets that examine these periods without turnover by focusing on outside observers' evaluations of the integrity of elections (e.g., Svolik 2012) as well as the absence of coups, foreign interventions, incumbents' power abuses, or reports of fraud (e.g., Boix, Miller and Rosato 2012), among other factors such citizens' perceptions of their actual influence in electing their government (Kaufmann and Kraay 2017), media freedom, civil liberties (e.g., Freedom House, VDem's Liberal Democracy Index), strength of civil society organizations (e.g., VDEM's Participatory Democracy Index). On the flip side, the mere presence of turnover, while significant, is not a sufficient condition for democracy either, as it can still be observed in semi-democratic settings where the overall electoral process is manipulated in favor of the incumbents (Levitsky and Way 2010). This is reflected in the emission probabilities from our model: while 95 percent of democracies experience turnover, a non-negligible 25 percent of semi-democracies also have this trait.

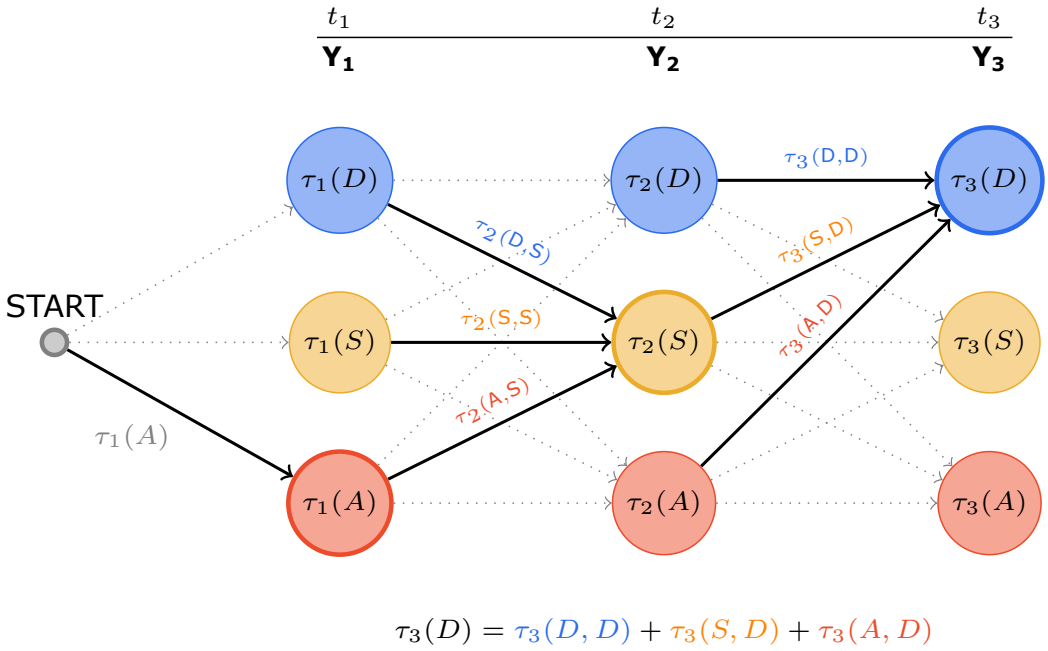
2. Jointly Estimates Regime Types and Transitions

Our approach models regime transitions in a probabilistic framework by assuming a first-order Markov chain with initial probabilities of and transition among regime types. The estimated initial probabilities of the Markov process are 0.69 for autocracy, 0.22 for semi-democracy, and 0.09 for democracy. The transition probabilities, presented in Table A1, indicate that the regime type in a given year is highly dependent on the previous year's regime type and different regimes exhibit different levels of stickiness, with semi-democracies exhibiting the lowest levels of stability and democracies the highest. Moreover, transitions from democracy to autocracy and vice versa are low-probability events.[11] In practice, to detect a regime transition with high probability, our approach requires strong evidence such as a high level of agreement among observable features in the regime indicators.

To illustrate how our approach unifies the measurement of regime types and transitions, consider a three-year period for country g, as illustrated in Figure A2. Suppose that we are interested in calculating the probability of g being democratic at the last period, t_3. This probability is calculated recursively as the sum of (1) $\tau_3(D, D)$, the probability of democracy in t_3 and t_2, (2) $\tau_3(S, D)$, the probability of democracy in t_3 and semi-democracy in t_2, and (3) $\tau_3(A, D)$, the probability of democracy in t_3 and autocracy in t_2. Each of these three constituent probabilities can further be unpacked: for instance, $\tau_3(S, D)$ is based on (1) the probability of observing manifest regime scores Y_3 given that the latent regime type is a democracy in t_3 (emission probability), (2) the probability

[11] On this point, our results are consistent with previous findings in the literature (e.g., Epstein et al. 2006).

Figure A2: Trellis Diagram of Regime Type and Transition



Notes: The blue, yellow, and red colors, respectively, indicate democracy, semi-democracy, autocracy. The figure illustrates a scenario where autocracy, semi-democracy, and democracy each have the highest probabilities in periods t_1, t_2, and t_3, respectively. The continuous arrows trace the paths contributing to these probabilities, while dashed arrows trace alternative paths with lower probabilities. The figure emphasizes that the probability distribution over regime types in a given time period t_3 depends on the probability distribution in t_2, and therefore, t_1, which are based on the observed variables Y_3, Y_2, Y_1 as well as the initial and transition probabilities. $\tau_3(i,j)$ is the joint probability of observing i in t_2 and j in t_3. The probability of democracy in t_3, $\tau_3(D)$, is calculated as the sum of observing democracy in t_3 and autocracy, semi-democracy, and democracy in t_2 as $\tau_3(A,D) + \tau_3(S,D) + \tau_3(D,D)$.

of semi-democracy in t_2 and (3) the unconditional transition probability from semi-democracy to democracy. Similarly, the probability of semi-democracy in t_2 depends on the probability of observing Y_2 given that the latent regime is a semi-democracy in t_2, and so on. As a result, the identification and the probability distribution of regime assignments in a sequence recursively depend on the emission probabilities associated with the current and previous values of the manifest variables, and the initial and transition probabilities from the first-order Markov process. After calculating the probability distribution over possible regime types, country-years can either be hard-assigned deterministically to the regime type with the highest estimated conditional probability (modal assignment), or soft-assigned probabilistically and incorporated into empirical analyses using multiple imputation.

3. Detects Gradual or Abrupt Transitions

Our approach effectively captures both abrupt changes that are often triggered by major events, as well as gradual, multi-year changes driven by subtle changes in the domestic political system. More

Table A1: Transition Probabilities

State in t \ State in $t+1$	A	S	D
A	0.976	0.023	0.001
S	0.030	0.942	0.028
D	0.001	0.011	0.988

specifically, we use the conditional probabilities, $\tau_t(i)$, to locate the most likely point at which a country moves from one regime type to another. As a result, our approach does not require an assumption of a time window: for instance, a change in regime type can be recorded when the modal assignment of the conditional probabilities change, which does not require focusing on a specific time window. The speed of this change in the conditional probabilities determines whether a country is experiencing a gradual multi-year or abrupt transition from one regime type to another. As a result, even if the underlying variables with continuous conceptualization do not exhibit a year-to-year change large enough to qualify as, e.g., an abrupt democratic transition, they can gradually feed into the conditional probabilities of democracy to finally make it higher relative to the two other probabilities, the point at which the regime is identified to experience democratization in a hard-assignment framework.[12] Similarly, if the regime exhibits multi-year gradual backsliding, the manifest variables gradually feed into the probabilities of the more autocratic types to eventually record an autocratic transition.

Most manifest democracy indicators generally identify important notable events such as free or fraudulent elections, or military coups as the time for a regime change. However, political changes initiated by these characteristic events generally take time to qualify as a transition, and not all notable events qualify as "a moment of regime change" (Lueders and Lust 2018). To capture regime transitions, our approach goes beyond these significant events and additionally considers underlying shifts in institutional (e.g., shifts in suffrage, introduction of multiparty elections, civilian rule), behavioral (e.g., peaceful alternation of power, coups, abuses of state power by incumbents), and opinion- and perception-based characteristics (e.g., changes in outside observers' evaluations of electoral integrity, citizens' perceptions of electoral impact). Furthermore, regime transitions are inherently rare events and this rarity is illustrated in our transition matrix in Table A1, where a transition from semi-democracy to autocracy in a given year has a mere probability of 0.03, while a shift from democracy to autocracy is even less likely, occurring with a probability of 0.001. Proportional to this rarity, our approach requires strong and consistent signs of a new regime type to emerge before registering an abrupt regime transition. In practical terms, this means that after a significant event, such as a coup in a semi-democracy, our approach does not automatically switch a country's status to autocratic. It also focuses on shifts in institutional traits, such as erosion of checks and balances, behavioral factors such as ongoing suppression of political opposition, and opinion-based characteristics such as public's perception of the erosion of their influence, and how persistent these shifts are to identify regime changes. Only when these overall patterns become clear and persistent

[12] In a soft-assignment framework, the full probability distribution is utilized without imposing cut-offs through multiple imputation.

does our approach record a transition to an autocratic regime.[13] This way, brief transient authoritarian or democratic reversals are not immediately coded as full-fledged regime transitions.[14]

Figure A3a illustrates these points by analyzing the evolution of the political system in Thailand from 1980 to 2000. The politics in Thailand before the 1980s were mainly characterized by the dominance of the bureaucratic and military elite, who lost their supremacy around mid-1980s. The earliest signs of democratization came in 1988 with the rise of Chatichai Choonhavan, who assumed the office of prime minister based on constitutional provisions, with no reliance on the military (Neher 1996). During this period of gradual democratization, Thailand experienced two notable events: (1) a short-lived coup d'état in 1991, and (2) a return to civilian rule in 1992, which was followed by constitutional reforms and the September 1992 elections. Both events led to only moderate changes in the regime type and regime transition probabilities in the given years. Although the agreement among manifest variables on an autocratic regime coding substantively increased in 1991, the coup did not last long enough to alter the entire political scene to record a full-fledged autocratic transition: the probability of semi-democracy fell from 1.00 to 0.74 and autocratic transtition probability increased from 0 to 0.26. Following the Black May uprisings against the military rule, the return to civilian rule in 1992 increased the probability of regime continuation in semi-democracy from 0.740 to 0.991. The 1992 elections, while crucial in eventually moving Thailand from a military to civilian rule, did not immediately mark a democratic transition. Only five years after the coup, with the continuation of civilian rule and the routinization of democratic transfer of power, as evidenced by the July 1995 elections, did the transition from semi-democracy to democracy take place with a democratization probability of 0.987 in 1996 according to our measure.[15]

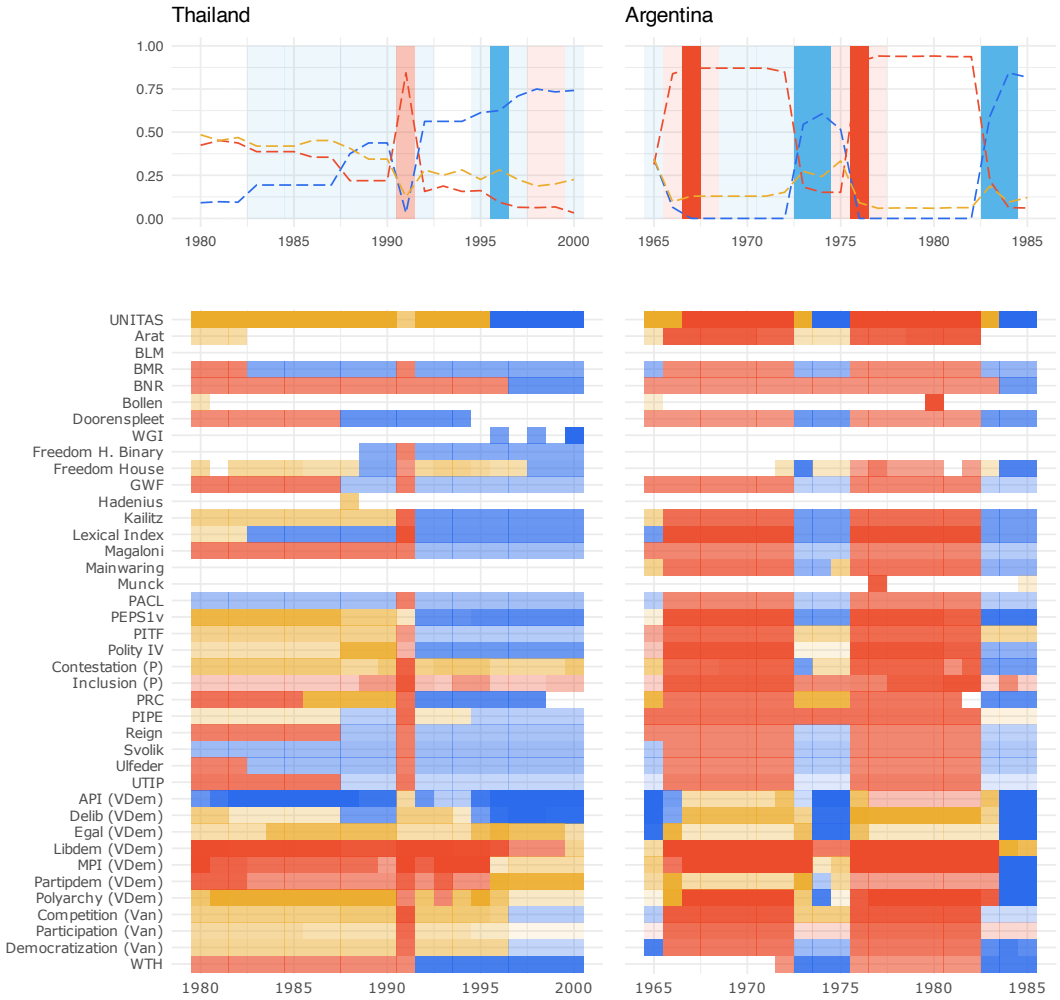
Next, Figure A3b shows the evolution of Argentina's political system between 1965 and 1985. Similar to Thailand, the politics in Argentina was also characterized by the dominance of the military in politics. In 1966, a military coup overthrew president Arturo Illia. The new military rule continued until the 1973 elections. Another military coup replaced civilian rule in 1976 and started the period of Dirty War, which led to large-scale human rights violations and the disappearance of around thirty-thousand opponents. The defeat in the Falklands War in 1982 led to the demise of military rule and eventually the return to civilian rule with the 1983 elections (Tedesco 2013). Our measure during this period identifies (1) one episode of autocratization (S-A) in 1967 resulting from the coup in 1966, (2) a subsequent episode of a two-year democratic transition (A-S-D) due to a return to civilian rule in 1973–1975, (3) an abrupt transition from democracy to autocracy in 1976, and (4) a final episode of two-year democratization (A-S-D) starting in 1983. These two autocratization episodes in Argentina contrast with the 1991 coup in Thailand, which did not

[13] Technically speaking, for a coup to lead to an autocratic transition, either emission probabilities should indicate substantial agreement of regime change in favor of a more autocratic type or we should observe a multi-year change in the political scene following the coup.

[14] However, a lack of transition in the modal assignment does not necessarily mean an absence of change in the underlying regime probabilities. Indeed, these probabilities dynamically respond to the evidence drawn through the emission probabilities. As a result, we would observe an increase in the conditional probability of autocracy and a corresponding decrease for democracy and semi-democracy. These slow adjustments can lead to multi-year gradual changes and potentially set the stage for a future regime transition from democracy or semi-democracy to autocracy.

[15] Only two other regime measures indicate a democratic transition in 1996 and the remaining 29 indicators all agree on the absence of a regime type change. Our measure captures a democratic transition in that year, mainly due to the gradually increasing evidence for democracy based on an overall consistent trend in the manifest regime scores used in the analysis.

Figure A3: Regime Characteristics and Transitions in Thailand and Argentina



Notes: The blue, yellow, and red lines, respectively, indicate the agreement among manifest variables on a given regime type. For example, 48.5 percent of the manifest indicators agree on a semi-democracy assignment, 42.4 on autocracy and the 9.1 percent on democracy in 1980 for Thailand. These values are based on modal assignments presented in Figure A1. The light blue and red vertical bars on the top figures show UNITAS democratic transition and autocratic transitions, respectively, with darker shades indicating higher certainty, while the white spaces represent periods of stability where the transition probability is zero. The below figures show UNITAS regime assignments and the manifest indicators' regime assignments (based on modal assignment) throughout the period, with darker shades representing the certainty estimated by our model. White spaces in below figures indicate periods with missing data.

translate into a regime type change according to our measure but indicated a semi-democracy with uncertainty. As Figure A3b shows, the 1966 and 1976 coups in Argentina, unlike the 1991 coup in Thailand, exhibited a clear and persistent autocratization pattern in a vast majority of regime characteristics. Therefore, the changes in Thailand and Argentina imply autocratization with differing levels of uncertainty and our approach distinguishes these transitions by quantifying the associated uncertainties.

4. Captures Long-term Temporal Dynamics

One can go beyond two-year regime transitions and estimate the probability of sequences of different lengths such as $SSSS$ or $SAASD$ based on the parameters of the Hidden Markov Model. For example, if a researcher's theory focuses on the implications of a failed democratization, it is straightforward to calculate the probability of sequences such as $SDDA$ (e.g., Argentina during 1976 coup following a democratization process) or $ASDSA$ using our n-year regime type measure. Such flexibility allows researchers to test the implications of different historical trajectories and to account for the stickiness of transitions, such as whether changes towards democratization continue to consolidate following an initial democratization event or not. Moreover, some scholars analyzing the relationship between violence and regime type suggest that semi-democracies are at higher risk for violence, without distinguishing different long term processes through which a country can become a semi-democracy (e.g., Hegre et al. 2001). For example, the sequences of $SSSSS$, $ASSSS$, $DSSSS$, $SSDSS$ all imply a semi-democracy in their last period, but they are based on different historical trajectories that may be associated with different risks of conflict. As we show in our empirical application in Appendix F, our framework allows applied researchers to estimate the probabilities of such sequences to distinguish substantively different implications for conflict behavior.

5. Captures Measurement Uncertainty

Regime indicators contain varying levels of measurement error and pose inferential challenges for empirical research.[16] Consider, for instance the Polity IV index. As shown in Figure A1, the modal latent regime type changes four times when we change Polity IV from -5 and +2, indicating a significant departure from anticipated patterns, potentially resulting from problems in the index's aggregation methods (Gleditsch and Ward 1997; Treier and Jackman 2008) and its handling of missing data (Plümper and Neumayer 2010). These inconsistencies and measurement error are not unique to Polity IV, but likely present in other regime indicators. Traditional approaches that rely on a single measure fail to account for this inherent measurement error, which can lead to bias and unwarranted precision in empirical applications.

Our approach addresses these challenges by incorporating information from multiple regime indicators, including global long-term projects (e.g., Polity IV, Freedom House, V-Dem) as well as regionally focused datasets that claim higher measurement accuracy (e.g., Mainwaring, Brinks and Pérez-Liñán (2001); Bowman, Lehoucq and Mahoney (2005) focus on Latin America only).

[16] For an analysis of the effects of regime uncertainty on interstate crisis behavior, see Bas and Orsun (2021).

Rather than excluding imperfect measures from the measurement process or assigning them uniform weights, our method dynamically adjusts the influence of each indicator based on its estimated association with the underlying latent regime type using emission probabilities. This way, UNITAS weighs more reliable indicators more heavily in calculating the hidden regime type probabilities. If a particular indicator contains uncorrelated noise or is irrelevant for a given latent regime type, the model will effectively downweight its influence in the regime probability calculations.[17] In other words, our approach incorporates information from imperfect indicators within an estimation framework, extracts the regime information, and accounts for the uncorrelated measurement error.[18] As our Monte Carlo simulations show, this approach allows us to leverage the information contained in each regime indicator and mitigate the impact of their individual limitations.

Finally, we incorporate measurement uncertainty into inferences through multiple imputation (Boeschoten, Filipponi and Varriale 2020), which generates multiple datasets, reflecting the uncertainty in the data and avoids unwarranted certainty on regime type and transition assignments in empirical analyses. Our approach produces a fully rectangular dataset of regime types and regime transitions along with their appropriate uncertainty estimates, avoiding unnecessary loss of observations in empirical analyses due to missingness in underlying individual democracy datasets. Our approach addresses missingness in two different contexts. In the first stage, when indicator k is missing at time t for country i, we gain no information from that indicator for that observation regarding the latent regime type. Instead of dropping that observation, the model infers regime type from (1) all other non-missing indicators and (2) temporal dynamics given the Markov structure. Because all indicators share the same underlying latent state, the absence of one indicator is compensated by available information in the observed values of other variables. This multi-indicator framework can also help alleviate non-ignorable missingness, missingness related to underlying regime characteristics, e.g., Polity during interregnum years (Plümper and Neumayer 2010), by pooling information across multiple sources like Freedom House, V-Dem, or PACL.[19] Second, after obtaining the parameter estimates, if one would like to incorporate the resulting regime categories to specific empirical analyses, we propose multiple imputation to appropriately reflect measurement uncertainty. This process involves simulating m complete regime type datasets based on the probability distribution

[17] This is because we model the probability of each hidden regime type based on the previous hidden regime type and the current values of the manifest democracy measures. If a democracy measure is irrelevant for a hidden regime type, the model effectively ignores it.

[18] Our application incorporates information from multiple regime indicators, some of which are themselves aggregate measures constructed from multiple underlying indicators or complex coding rules. While our application accounts for the variability across different aggregate measures and quantifies such uncertainty, it does not quantify measurement uncertainty stemming from within measure aggregation processes. That being said, our framework is flexible enough to incorporate within-measure uncertainty as well (e.g., in Polity) if the underlying component indicators are fed into the model as separate manifest variables, such as estimating regime types and transitions based on Polity component indicators analogous to Treier and Jackman (2008). Secondly, as our Monte Carlo analyses show, our approach can work under varying levels of measurement error across individual indicators when estimating the latent categories of regime type.

[19] While missingness across all regime indicators never occurs in our data, near-complete missingness in regime indicators can rarely affect some micro-states, non-sovereign territories, or countries in the post-conflict periods. As an extreme example, East Germany from 1945-1948 has only 2-3 indicators available out of 39, and our approach classifies it as an autocracy with probabilities ranging from 0.88 to 0.99 during this period. Even in this extreme case, while the agreement among available indicators increases our confidence (PRC, BMR, and PITF all code East Germany as an autocracy), higher uncertainty due to missingness is appropriately reflected in the estimated probabilities.

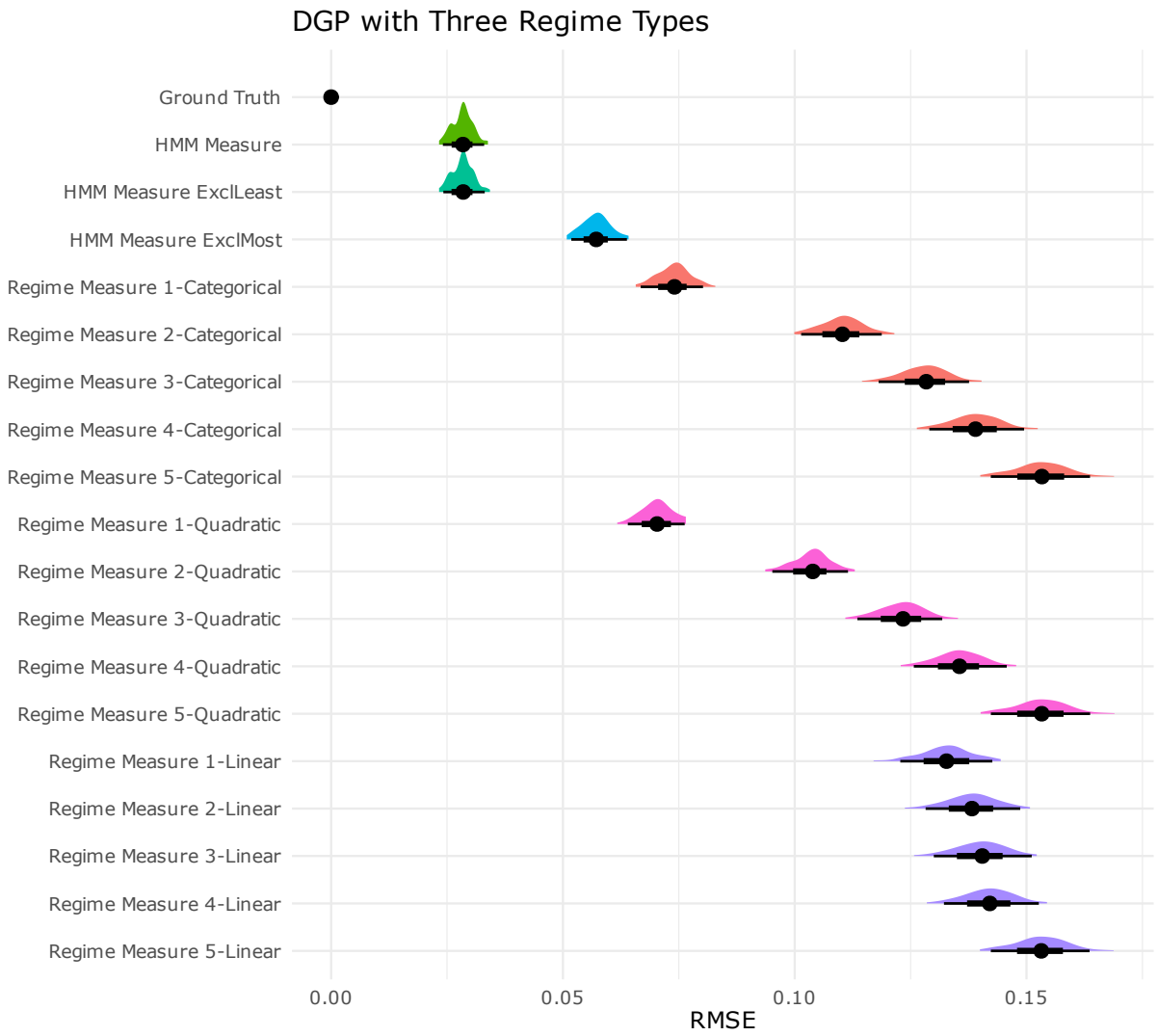
over different regime categories that the HMM produced. The researcher then runs the analyses in each dataset, and combines the estimates across the simulated datasets to capture uncertainty. Given regime transitions are rare events (as shown in Table A1) and these events need to be well-represented across the imputed datasets, in our application we set m to a value of 100 rather than standard practice ($m = 5$) to avoid underrepresenting these rare events.

C Monte Carlo Simulations

In this section, we evaluate the performance of the UNITAS framework (our HMM-based approach) and address the following questions: First, given the varying quality and precision of existing measures, does combining them introduce bias in our inference? Some measures are clearly noisier than others, while some could be completely irrelevant. Why not just use the most precise, sophisticated measure available? What are the consequences of failing to include such informative measure in recovering true regime type or including a highly noisy measure? How is the performance of our approach affected when individual measures exhibit different levels of measurement error. Second, applying a Hidden Markov Model means we have to make assumptions about the number of regime types; if our assumption is incorrect, could this create problems for our inference or would it be safer to use a single well-known measure in that case? To answer these questions, we conduct a Monte Carlo analysis to compare various approaches. In this analysis, we assume that regime type is a latent, categorical construct with a limited number of distinct categories. To match our empirical application in the paper, we will assume that regime type affects the probability of conflict in a given observation. To match most of the existing literature, we will consider two, three, or four regime categories in the data generating process, but our results are generalizable. For space considerations, we will assume that there exist five different observable measures for regime type, as imperfect manifestations of the underlying unobservable categorical variable. Similar to real-world data, these measures will show varying levels of noise in them, ranging from almost perfectly capturing the underlying construct to pure noise. This variation in the quality of these measures could be interpreted as individual measures capturing different dimensions of the underlying multiple dimensional concept, or just simple variation in measurement accuracy or error. We then fit various HMM specifications that match, overestimate, or underestimate the number of latent measure categories, that use all measures available, or subsets of them, and compare the resulting measure to individual measures in estimating various regression models of the relationship between regime type and conflict. To analyze the implications of using traditional regime measures with different functional forms in these conflict analyses later, we design our data generating process with specific configurations: In our DGP with three regime types, we assume that each manifest variable takes on six values to examine the effect of assuming quadratic, categorical (based on cut-offs) and linear functional forms. For the DGP with two regime types, we assume four values for comparability to evaluate the consequences of categorical and linear functional form assumptions. For the DGP with four regime types, we assume four values to ensure a one-to-one mapping between the manifest variable values and the regime types without assuming cut-offs.

Five key findings emerge from our Monte Carlo analysis. First, predicted probabilities of conflict from our unified approach are closer to the ground truth compared to any individual regime measure, including the most precise ones. When using all five measures, our approach produces a median RMSE of 0.028 (95% CI: 0.025-0.032), substantially outperforming the best individual measure which has a median RMSE of 0.073 (95% CI: 0.069-0.080). This represents a 61.6 percent reduction in prediction error. Second, strikingly, the HMM specification that only uses noisier regime measures still outperforms traditional models based on the most informative regime measure in linear, quadratic or categorical specifications (median RMSE for categorical specification is 0.057 with 95%CI: 0.052-0.062). Third, our approach is robust to measurement noise. The predic-

Figure A4: Monte Carlo Simulation Results



Notes: This figure presents distribution of the root mean squared error (RMSE) for predicted probabilities of conflict across various model specifications in our Monte Carlo simulations. In these analyses, we assume that the data generating process (DGP) includes three regime categories with different levels of conflict propensity, from highest to lowest as follows: semi-democracy, autocracy, and democracy. The models include both conventional approaches using individual regime measures with different functional forms (linear, quadratic, and categorical) and HMM specifications. The regime measures, labeled from Regime Measure 1 to Regime Measure 5, vary in informativeness, with Regime Measure 1 being the most precise, and Regime Measure 5 being the noisiest. *HMM Measure ExclMost* is our HMM measure excluding the most informative measure (Regime Measure 1), while *HMM Measure ExclLeast* excludes the least informative measure (Regime Measure 5).

tive performance of our unified approach does not seem to be harmed by incorporating the noisiest of the measures considered, as excluding it in an alternative HMM specification produces virtually identical performance (RMSE: 0.028, 95% CI: 0.024-0.032). Fourth, our approach is robust to misspecification of the number of latent regime categories. As shown in Appendix Table A4, when there are two latent regime categories and we instead fit a specification that assumes three, the predictive performance is practically identical to the correctly specified HMM (with median RMSE: 0.014). The misspecified HMM still outperforms all the individual regime measures including the most informative one. Underestimating the regime categories leads to similar conclusions. Fitting an HMM with three categories while in fact there were four in the data generating process still leads to a slightly lower RMSE than the best individual measure (0.107 vs. 0.112), though with overlapping confidence intervals (misspecified HMM: 0.098-0.123; best individual measure: 0.107-0.117). Finally, our simulations reveal important limitations of conventional approaches that rely on individual manifest variables and functional form assumptions. We find that the common practice of using arbitrary cut-offs to categorize ordinal/continuous measures or assuming specific functional forms introduces significant bias in empirical applications. We detail our evaluation approach and present the full results below, with main findings summarized in Figure A4.

Data Generating Process for the Measurement Model

We generate a panel data with 100 countries and 100 time periods, resulting 10,000 observations in each Data Generating Process (DGP) specification. We focus on scenarios where DGP assumes two, three, and four regime types, each generating ground truth and five manifest variables with varying informativeness based on the specified initial, transition, emission probabilities. To verify informativeness of manifest variables, we calculate overall Kullback–Leibler divergence (KLD) for each DGP specification as follows:

$$D_{KL}(P \parallel Q) = \frac{1}{n} \sum_{i=1}^{n} \sum_{t=1}^{T} P(\text{Regime Type}{=}t \mid x_i) \log \left(\frac{P(\text{Regime Type}{=}t \mid x_i)}{Q(\text{Regime Type}{=}t \mid x_i)} \right) \tag{C.1}$$

where $P(\text{Regime Type}{=}t \mid x_i)$ is the probability of Regime Type t given value x_i in a given emission probability matrix, and $Q(\text{Regime Type}{=}t \mid x_i)$ is the probability of Regime Type t given value x_i in the non-informative emission probability matrix, where all values are uniformly distributed. To compute the overall KL divergence, we average the divergences across all values x_i. Informativeness of each manifest variable within each number of regime type specification increases with the KL Divergence values. For each DGP (two, three, and four regime types), we created five manifest variables with varying levels of informativeness. We present the initial, transition, and emission probability matrices in Table A2.

Hidden Markov Model Specifications

We analyze the robustness of our approach to misspecification in both the variable selection and the assumed number regime types. We fit various HMM specifications that match, overestimate, or underestimate the number of latent measure categories, that use all measures available, or subsets of

Table A2: Initial Probabilities, Transition Probabilities, and Emission Probability Matrices E_k for $k = 1$ to 5 Across Different DGPs

Component	DGP with Two Regime Types	DGP with Three Regime Types	DGP with Four Regime Types
Init. Pr.	$\begin{pmatrix}0.5 & 0.5\end{pmatrix}$	$\begin{pmatrix}0.33 & 0.33 & 0.34\end{pmatrix}$	$\begin{pmatrix}0.25 & 0.25 & 0.25 & 0.25\end{pmatrix}$
Trans. Pr.	$\begin{pmatrix}0.95 & 0.05\\ 0.06 & 0.94\end{pmatrix}$	$\begin{pmatrix}0.95 & 0.04 & 0.01\\ 0.05 & 0.90 & 0.05\\ 0.01 & 0.04 & 0.95\end{pmatrix}$	$\begin{pmatrix}0.76 & 0.08 & 0.08 & 0.08\\ 0.08 & 0.76 & 0.08 & 0.08\\ 0.08 & 0.08 & 0.76 & 0.08\\ 0.08 & 0.08 & 0.08 & 0.76\end{pmatrix}$
E_1	$\begin{pmatrix}0.90 & 0.05 & 0.03 & 0.02\\ 0.02 & 0.03 & 0.05 & 0.90\end{pmatrix}$	$\begin{pmatrix}0.90 & 0.05 & 0.04 & 0.01 & 0.00 & 0.00\\ 0.01 & 0.04 & 0.45 & 0.45 & 0.04 & 0.01\\ 0.00 & 0.00 & 0.01 & 0.04 & 0.05 & 0.90\end{pmatrix}$	$\begin{pmatrix}0.90 & 0.05 & 0.03 & 0.02\\ 0.04 & 0.90 & 0.04 & 0.02\\ 0.02 & 0.04 & 0.90 & 0.04\\ 0.02 & 0.03 & 0.05 & 0.90\end{pmatrix}$
E_2	$\begin{pmatrix}0.80 & 0.10 & 0.06 & 0.04\\ 0.04 & 0.06 & 0.10 & 0.80\end{pmatrix}$	$\begin{pmatrix}0.75 & 0.10 & 0.06 & 0.04 & 0.03 & 0.02\\ 0.025 & 0.10 & 0.375 & 0.375 & 0.10 & 0.025\\ 0.02 & 0.03 & 0.04 & 0.06 & 0.10 & 0.75\end{pmatrix}$	$\begin{pmatrix}0.80 & 0.10 & 0.06 & 0.04\\ 0.10 & 0.80 & 0.10 & 0.05\\ 0.05 & 0.10 & 0.80 & 0.10\\ 0.04 & 0.06 & 0.10 & 0.80\end{pmatrix}$
E_3	$\begin{pmatrix}0.60 & 0.25 & 0.10 & 0.05\\ 0.05 & 0.10 & 0.25 & 0.60\end{pmatrix}$	$\begin{pmatrix}0.60 & 0.20 & 0.10 & 0.05 & 0.03 & 0.02\\ 0.05 & 0.15 & 0.30 & 0.30 & 0.15 & 0.05\\ 0.02 & 0.03 & 0.05 & 0.10 & 0.20 & 0.60\end{pmatrix}$	$\begin{pmatrix}0.60 & 0.25 & 0.10 & 0.05\\ 0.15 & 0.60 & 0.15 & 0.10\\ 0.10 & 0.15 & 0.60 & 0.15\\ 0.05 & 0.10 & 0.25 & 0.60\end{pmatrix}$
E_4	$\begin{pmatrix}0.50 & 0.30 & 0.13 & 0.07\\ 0.07 & 0.13 & 0.30 & 0.50\end{pmatrix}$	$\begin{pmatrix}0.45 & 0.30 & 0.15 & 0.05 & 0.03 & 0.02\\ 0.075 & 0.20 & 0.225 & 0.225 & 0.20 & 0.075\\ 0.02 & 0.03 & 0.05 & 0.15 & 0.30 & 0.45\end{pmatrix}$	$\begin{pmatrix}0.50 & 0.30 & 0.13 & 0.07\\ 0.20 & 0.50 & 0.20 & 0.10\\ 0.10 & 0.20 & 0.50 & 0.10\\ 0.07 & 0.13 & 0.30 & 0.50\end{pmatrix}$
E_5	$\begin{pmatrix}0.25 & 0.25 & 0.25 & 0.25\\ 0.25 & 0.25 & 0.25 & 0.25\end{pmatrix}$	$\begin{pmatrix}0.167 & 0.167 & 0.167 & 0.167 & 0.167 & 0.167\\ 0.167 & 0.167 & 0.167 & 0.167 & 0.167 & 0.167\\ 0.167 & 0.167 & 0.167 & 0.167 & 0.167 & 0.167\end{pmatrix}$	$\begin{pmatrix}0.25 & 0.25 & 0.25 & 0.25\\ 0.25 & 0.25 & 0.25 & 0.25\\ 0.25 & 0.25 & 0.25 & 0.25\\ 0.25 & 0.25 & 0.25 & 0.25\end{pmatrix}$

KL Divergence scores for the emission probabilities E_k from $k = 1$ (most informative) to 5 (non-informative) are as follows: two-regime case: 0.31, 0.27, 0.26, 0.20, 0.00; three-regime case: 0.72, 0.46, 0.38, 0.31, 0.00; four-regime case: 0.96, 0.63, 0.32, 0.22, 0.00.

them. To test the consequences of

- including an irrelevant variable in the measurement model, we exclude the non-informative manifest variable generated by E_5.
- failing to include an important variable in the measurement model, we exclude the most informative manifest variable generated by E_1.
- overestimating the number of latent regime types, we assume three regime types in fitting HMM when DGP has in fact two types.
- underestimating the number of latent regime types, we assume three regime types in fitting HMM when DGP has in fact four types.

Simulation Results

In our Monte Carlo analyses, we generate 100 simulated datasets for each specification presented in Table A3. To evaluate the performance of each specification relative to the ground truth, we calculate

Table A3: Analysis Models by DGP Regime Types

DGP	Model Specifications
Two Regime Types	
	· Ground Truth: $y_2^* = \alpha + \beta_1 D_{GT} + \varepsilon$ $C_2 = 1$ if $\Phi(y_2^*) > 0.5,$ and 0 otherwise
	· HMM (Correct): $C_2 = a + b_1 D_H + u$
	· HMM (Assumes More (3) Regime Types): $C_2 = a + b_1 A_H + b_2 D_H + \varepsilon$
	· Regime Measure Categorical: $C_2 = a + b_1 D_{Cat} + u$ (Cut-offs: (1,2) for A, (3,4) for D)
	· Regime Measure Linear: $C_2 = a + b_1$Measure $+ u$
Three Regime Types	
	· Ground Truth: $y_3^* = \alpha + \beta_1 A_{GT} + \beta_2 D_{GT} + \varepsilon$ $C_3 = 1$ if $\Phi(y_3^*) > 0.5,$ and 0 otherwise
	· HMM (Correct): $C_3 = a + b_1 A_H + b_2 D_H + u$
	· HMM (Excludes Non-informative): $C_3 = a + b_1 A_{H1} + b_2 D_{H1} + u$
	· HMM (Excludes Most Informative): $C_3 = a + b_1 A_{H2} + b_2 D_{H2} + u$
	· Regime Measure Categorical: $C_3 = a + b_1 A_{Cat} + b_2 D_{Cat} + u$ (Cut-offs: (1,2) for A, (3,4) for S, (5,6) for D)
	· Regime Measure Quadratic: $C_3 = a + b_1$Measure $+ b_2$Measure$^2 + u$
	· Regime Measure Linear: $C_3 = a + b_1$Measure $+ u$
Four Regime Types	
	· Ground Truth: $y_4^* = \alpha + \beta_1 A_{GT} + \beta_2 D_{GT} + \beta_3 S_{1,GT} + \varepsilon$ $C_4 = 1$ if $\Phi(y_4^*) > 0.5,$ and 0 otherwise
	· HMM (Correct): $C_4 = a + b_1 A_H + b_2 D_H + b_3 S_{1H} + u$
	· HMM (Assumes Fewer (3) Regime Types): $C_4 = a + b_1 A_H + b_2 D_H + u$
	· Regime Measure Categorical: $C_4 = a + b_1 A_{Cat} + b_2 D_{Cat} + b_3 S_{1Cat} + u$ (No cut-offs used)
$\alpha = 0.5, \beta_1 = -0.5, \beta_2 = -1, \beta_3 = 0.75, \varepsilon \sim N(0,1)$	

Table A4: Monte Carlo RMSE Results from 100 Simulations

Measure	Specification	2.5%	Median	97.5%
Specification: DGP has 3 Regime Types				
Ground Truth		0	0	0
HMM	Correct Specification	0.024	0.028	0.033
HMM	Excluding Non-informative	0.024	0.028	0.033
HMM	Excluding Most Informative	0.052	0.057	0.064
Regime Measure 1	Categorical	0.067	0.074	0.080
Regime Measure 2	Categorical	0.101	0.110	0.119
Regime Measure 3	Categorical	0.118	0.128	0.138
Regime Measure 4	Categorical	0.129	0.139	0.149
Regime Measure 5	Categorical	0.142	0.153	0.164
Regime Measure 1	Quadratic	0.064	0.070	0.076
Regime Measure 2	Quadratic	0.095	0.104	0.111
Regime Measure 3	Quadratic	0.114	0.123	0.132
Regime Measure 4	Quadratic	0.126	0.136	0.146
Regime Measure 5	Quadratic	0.142	0.153	0.164
Regime Measure 1	Linear	0.123	0.133	0.143
Regime Measure 2	Linear	0.128	0.138	0.149
Regime Measure 3	Linear	0.130	0.140	0.151
Regime Measure 4	Linear	0.132	0.142	0.153
Regime Measure 5	Linear	0.142	0.153	0.164
Specification: DGP has 2 Regime Types				
Ground Truth		0	0	0
HMM	Correct Specification	0.012	0.014	0.016
HMM	Estimates More (3) Regime Types	0.012	0.014	0.018
Regime Measure 1	Categorical	0.037	0.041	0.046
Regime Measure 2	Categorical	0.052	0.057	0.062
Regime Measure 3	Categorical	0.062	0.067	0.074
Regime Measure 4	Categorical	0.070	0.076	0.083
Regime Measure 5	Categorical	0.087	0.094	0.103
Regime Measure 1	Linear	0.034	0.037	0.041
Regime Measure 2	Linear	0.048	0.052	0.057
Regime Measure 3	Linear	0.060	0.065	0.072
Regime Measure 4	Linear	0.068	0.074	0.081
Regime Measure 5	Linear	0.087	0.095	0.103
Specification: DGP has 4 Regime Types				
Ground Truth		0	0	0
HMM	Correct Specification	0.074	0.080	0.086
HMM	Estimates Fewer (3) Regime Types	0.098	0.107	0.122
Regime Measure 1	Categorical	0.107	0.113	0.118
Regime Measure 2	Categorical	0.151	0.158	0.163
Regime Measure 3	Categorical	0.193	0.200	0.207
Regime Measure 4	Categorical	0.197	0.204	0.212
Regime Measure 5	Categorical	0.211	0.219	0.227

the Root Mean Squared Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{100}\sum_{m=1}^{100}(\text{P}(\text{Conflict}|\text{Ground Truth})_m - \text{P}(\text{Conflict}|\text{Spec})_m)^2} \tag{C.2}$$

where m denotes each simulated dataset. Table A4 presents the median RMSE along with the 2.5th and 97.5th percentiles of the RMSE distribution across the 100 simulated datasets for each specification.

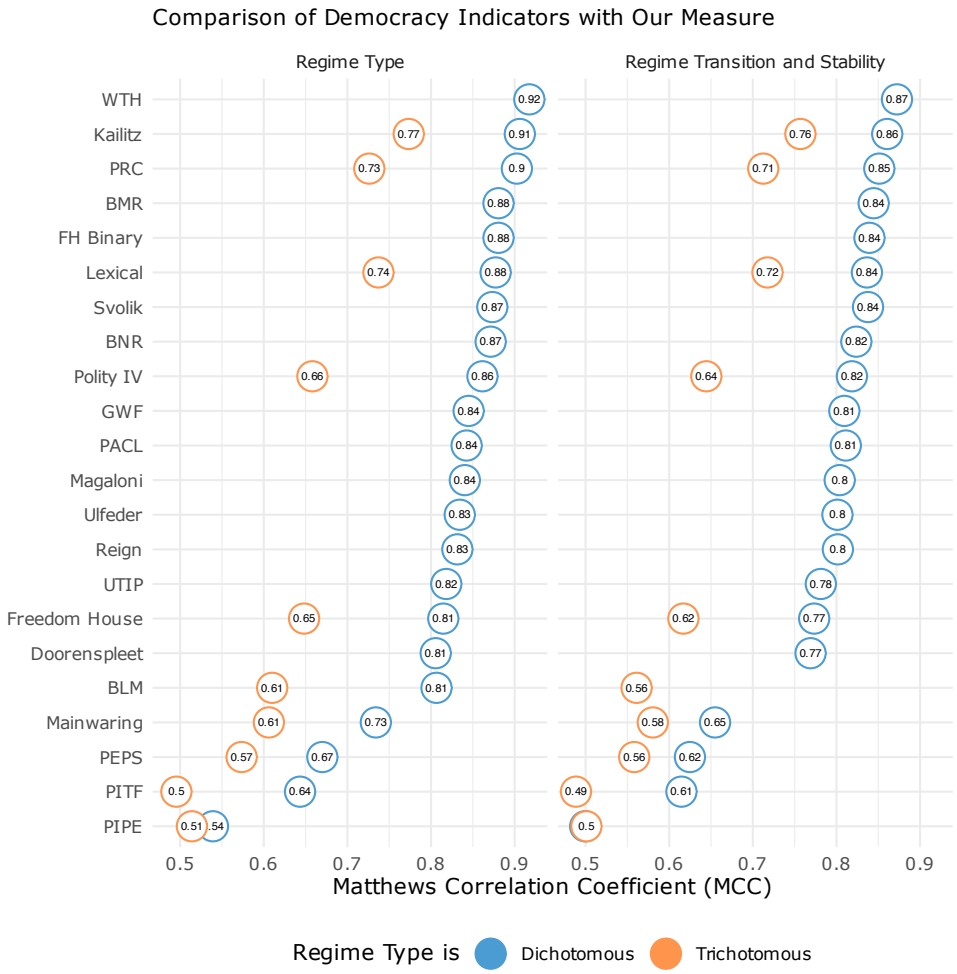
Given the application in our paper assumes three latent regime types, we first focus on specifications where DGP has three regime types and then analyze potential misspecifications. We find that the predictions from the correct *HMM* specification are significantly closer to the ground truth compared to even the most precise manifest variable, *Regime Measure 1-Categorical*, that was used to construct our *HMM* measure along with *Regime Measure 2-5-Categorical*. Specifically, the median RMSE for our *HMM* measure is 0.028 (95%CI: 0.024 and 0.033), while *Regime Measure 1-Categorical* has a median RMSE of 0.074 (95%CI: 0.067 and 0.080). This indicates that our *HMM* measure significantly outperforms the underlying manifest variables that were used to construct it and recover true regime types with higher accuracy than the most precise regime measure, *Regime Measure 1*. Furthermore, these results still hold when we fail to include the most informative indicator in building our *HMM* measure. As shown by *HMM Excluding Most Informative*, this specification still has a lower median RMSE of 0.057 (95%CI: 0.052 and 0.064) than individual *Regime Measure 1-Categorical*. Moreover, including or excluding an uninformative indicator in the measurement model has no noticeable effect on the performance of our HMM measure as shown by the almost overlapping RMSE distributions of our *HMM* measure and *HMM Excluding Non-Informative*.

What are the consequences of overestimating or underestimating the number of regime types in a measurement model on our inferences? If the DGP has two regime types and we assume three types in building our HMM measure, the median and the distribution of the RMSE remain nearly unchanged (median RMSE is 0.014 with 95%CI of 0.012 and 0.018) compared to the scenario where the HMM model has the correct number of regime types (median RMSE is 0.014 with the 95%CI of 0.012-0.016). If the DGP has four types and we estimate three types, the RMSE is higher compared to the case where we correctly estimate four regimes. However, the median RMSE (median RMSE is 0.107 with 95%CI of 0.098-0.122) in this case is still slightly lower than the one produced by the single measure with the highest precision (median RMSE is 0.113 with 95%CI: 0.107-0.118).

These findings together indicate that in recovering true regime types, UNITAS achieves higher accuracy than any single manifest variable, including the most precise one. This result is robust to various misspecifications.

Having established the accuracy of our UNITAS measure, we now turn to the limitations of conventional approaches that rely on manifest variables and functional form assumptions. If semi-democracies are assumed to be more conflict-prone as in our DGP with three regime types, what are the consequences of using (1) cut-offs to identify different regime categories, using (2) a quadratic functional form, and (3) linear functional form on a given manifest regime measure? We find that quadratic specifications have slightly lower RMSE compared to their categorical counterparts, which use cut-offs (1,2 for autocracies, 3,4 for semi-democracies, 5,6 for democracies) as shown in Table A3. This indicates that using cut-offs can be problematic because of its inability to capture the vari-

Figure A5: Comparison of Other Regime Indicators with UNITAS



ability implied by DGP in the regime categories. Linear specification has the highest RMSE as it cannot capture the non-linear relationship implied by the DGP. However, if DGP has two regime types (democracy and autocracy) and autocracies are assumed to be more conflictual as in our DGP with two regime types, linear specification outperforms the specification with cut-offs (1,2 for autocracies, 3,4 for democracies). This indicates that even when the underlying measure DGP is assumed to be dichotomous, using cut-offs remains problematic.

D Comparison of Regime Indicators with UNITAS

Our Monte Carlo simulations indicate significant advantages of our measurement approach compared to conventional approaches. To contextualize our measure with other democracy indicators, we use Matthew's correlation coefficient (MCC) between our measure and each manifest indicator and compare our measure with other democracy indices. MCC returns a value between -1 (perfect disagreement) and +1 (perfect agreement) and handles both dichotomous and multi-class regime type and transition variables. Figure A5 plots the average MCC between each categorical regime measure and our measure based on 100 imputations. Orange circles represent MCCs with trichotomous measures (democracy, semi-democracy, autocracy), while blue circles indicate MCC with dichotomous measures (democracy, non-democracy), including those that are originally dichotomous as well as dichotomized versions of trichotomous measures.

We observe high MCC values, predominantly exceeding 0.81 for regime type measurement and 0.80 for regime transition and stability measurement. However, we observe relatively lower agreement with Mainwaring, PEPS, PITF and PIPE datasets, which we attribute to their significant deviation from other measures in the dataset.[20] The average MCC for dichotomous indicators, such as WTH, Kailitz, PRC, and BMR, consistently hit high levels of 0.80 and above. Unsurprisingly, dissecting non-democracies into semi-democracies and autocracies, as shown with orange circles, slightly lowers the MCC values.

[20] For instance, these specific measures demonstrate the lowest agreement with the rest of the existing measures in the figure, with average MCC scores at 0.66 for Mainwaring, 0.61 for PEPS, 0.59 for PITF, and 0.51 for PIPE.

E Predictive Checks and Comparative Performance Analysis

In this section, as a further validity check, we benchmark UNITAS against two continuous latent variable models from the literature: Reuning, Kenwick and Fariss (2019) and Pemstein, Meserve and Melton (2010). First, we replicate the estimates reported in Reuning, Kenwick and Fariss (2019) for both the UDS and the Robust-UDS, using the 10 regime indicators in their original dataset. Then, we fit our model on this same dataset. We compare each model's performance (1) in predicting observed manifest variable values and (2) and predicting the year-to-year changes in each regime indicator. We present our results in Table A5.

While there is some variation across predicting specific regime indicators, on average, all three latent variable measures produce predictions that are highly correlated with regime indicators' observed values, with individual correlations ranging around .9. Based on this metric, the 3-class UNITAS approach seems highly comparable to the two continuous latent measures, with the average correlation with 10 regime measures being only slightly lower (median difference of .025 in correlation scale) than the UDS, and higher than the Robust Dynamic UDS (median difference of .005 in correlation scale). We also find that UNITAS fares better than both approaches in terms of predicting indicator changes, due to its Markov structure: while correlations between expected and observed indicator changes are more moderate in magnitude for all three approaches, UNITAS outperforms either continuous variable approach, with a .123 median difference advantage over UDS and a .085 median difference over Robust Dynamic UDS in correlations.

A further comparison of UNITAS with the UDS based on 39 regime indicators reinforces these findings (Tables A6 and A7). In terms of the correlation between the observed and the expected values of the regime indicators, UDS and UNITAS were highly comparable, with both UNITAS and UDS achieving high correlation levels, and the median correlation difference between the two models across indicators slightly favoring UDS (.008 correlation difference), as shown in Table A6. When we look at the correlation between the expected versus observed changes in the regime indicators, UNITAS again fared slightly better, with the median correlation difference across indicators being .068 in favor of the HMM, as shown in Table A7.[21]

As we described above, this performance was despite the small number of latent regime classes we assumed for UNITAS for theoretical reasons. If one were to use UNITAS with 10 categories instead of 3, for instance, this leads to significantly better correlations between the observed and expected regime scores than the UDS, the median correlation difference this time being .134 in favor of UNITAS when predicting changes in regime indicators, and .016 again in favor of UNITAS for correlations between expected vs observed values of the indicators.[22] Together, these results provide empirical evidence for the construct validity of our unified measurement approach.

[21] As a practical consideration, the HMM approach was computationally less demanding than the alternatives considered, though this is partly due to different estimation frameworks (MLE vs. Bayesian MCMC). For instance, the HMM completed the 39-variable analysis in 25.4 minutes on standard hardware (MacBook Pro M4 24GB RAM), while the same hardware was not sufficient to run the model for the UDS. The UDS took close to 6 days on more powerful, specialized cloud computing (AWS ml.r5.4xlarge, 16 vCPUs, 128GB RAM).

[22] Despite this advantage, however, we do not recommend using UNITAS with higher categories unless it is theoretically justified. In our specific application, for instance, there is no obvious way to determine ex-ante what these 10 distinct regime categories would be in studying the effect of regime transitions on civil conflict. For this reason, we implemented the theoretically grounded 3-class analysis in the paper.

Table A5: Comparative Performance of UNITAS, UDS, and Robust-UDS Models

Panel A: Predicting Indicator Levels					
	Correlations			Differences	
Indicator	UNITAS	UDS	R.UDS	UNITAS−UDS	UNITAS−R.UDS
Polity	0.930	0.942	0.902	−0.012	+0.028
Freedom House	0.925	0.939	0.927	−0.015	−0.003
PRC	0.917	0.937	0.901	−0.020	+0.016
Hadenius	0.908	0.972	0.918	−0.064	−0.009
Bollen	0.887	0.940	0.871	−0.053	+0.016
PACL	0.884	0.904	0.872	−0.020	+0.013
Vanhanen	0.877	0.908	0.891	−0.030	−0.014
Polyarchy	0.876	0.961	0.915	−0.085	−0.039
Arat	0.874	0.881	0.839	−0.007	+0.036
BLM	0.840	0.940	0.846	−0.100	−0.006
Median	0.886	0.939	0.896	−0.025	+0.005
Panel B: Predicting Indicator Changes					
	Correlations			Differences	
Indicator	UNITAS	UDS	R.UDS	UNITAS−UDS	UNITAS−R.UDS
PACL	0.643	0.425	0.484	+0.218	+0.158
Polity	0.631	0.431	0.713	+0.200	−0.082
Arat	0.591	0.391	0.404	+0.200	+0.188
BLM	0.527	0.461	0.272	+0.066	+0.255
Freedom House	0.512	0.389	0.520	+0.123	−0.008
PRC	0.408	0.398	0.323	+0.009	+0.085
Vanhanen	0.400	0.287	0.340	+0.113	+0.060
Median	0.527	0.398	0.404	+0.123	+0.085

Note: Panel A shows correlations between expected values and observed values of manifest indicators. Panel B shows correlations between year-to-year changes in the expected values and observed values in these indicators. Values are median correlations for UNITAS, UDS, and Robust-UDS, as well as differences of UDS and Robust-UDS from HMM, respectively.

Table A6: Performance of UNITAS and UDS on Our Manifest Variables: Predicting Levels

Predicting Indicator Levels					
	Correlations			Differences	
Indicator	UNITAS-3	UNITAS-10	UDS	UNITAS-3−UDS	UNITAS-10−UDS
Polyarchy (VDem)	0.936	0.988	0.999	-0.063	-0.011
WTH	0.920	0.907	0.902	0.018	0.005
Hadenius	0.918	0.928	0.928	-0.010	0.0003
Partipdem (VDem)	0.916	0.977	0.982	-0.066	-0.005
PRC	0.908	0.924	0.911	-0.003	0.013
Freedom House	0.899	0.931	0.918	-0.019	0.013
Kailitz	0.898	0.904	0.893	0.005	0.010
Delib (VDem)	0.898	0.957	0.981	-0.083	-0.024
MPI (VDem)	0.897	0.971	0.997	-0.099	-0.026
Lexical Index	0.896	0.926	0.905	-0.009	0.020
BMR	0.895	0.921	0.888	0.008	0.033
Svolik	0.894	0.931	0.894	-0.0004	0.037
Freedom H. Binary	0.891	0.917	0.871	0.020	0.047
API (VDem)	0.888	0.905	0.997	-0.109	-0.092
PEPS1v	0.887	0.946	0.906	-0.019	0.040
Bollen	0.885	0.912	0.889	-0.004	0.023
Contestation (P)	0.884	0.913	0.881	0.003	0.032
Libdem (VDem)	0.876	0.895	0.982	-0.105	-0.087
BNR	0.876	0.892	0.876	0.0003	0.016
GWF	0.874	0.915	0.869	0.004	0.045
Egal (VDem)	0.872	0.961	0.969	-0.097	-0.008
Polity IV	0.871	0.927	0.874	-0.003	0.053
Competition (Van)	0.866	0.873	0.845	0.022	0.028
PACL	0.866	0.896	0.855	0.011	0.041
Magaloni	0.865	0.900	0.853	0.012	0.047
UTIP	0.865	0.890	0.878	-0.013	0.012
Arat	0.860	0.877	0.863	-0.004	0.013
Ulfeder	0.858	0.917	0.866	-0.008	0.050
Reign	0.856	0.895	0.857	-0.0004	0.038
PITF	0.855	0.917	0.858	-0.003	0.059
BLM	0.848	0.912	0.910	-0.062	0.002
WGI	0.846	0.925	0.923	-0.077	0.001
Democratization (Van)	0.838	0.907	0.899	-0.061	0.008
Mainwaring	0.832	0.887	0.876	-0.044	0.011
Doorenspleet	0.811	0.857	0.846	-0.035	0.012
Munck	0.760	0.776	0.739	0.020	0.037
PIPE	0.693	0.728	0.697	-0.004	0.031
Participation (Van)	0.631	0.776	0.691	-0.061	0.085
Inclusion (P)	0.478	0.664	0.560	-0.082	0.104
Median	0.874	0.912	0.888	-0.008	0.016

Note: The table shows median correlations between the expected values and observed values in these indicators.

Table A7: Performance of UNITAS and UDS on Our Manifest Variables: Predicting Changes

Predicting Indicator Changes					
	Correlations			Differences	
Indicator	UNITAS-3	UNITAS-10	UDS	UNITAS-3−UDS	UNITAS-10−UDS
Polyarchy (VDem)	0.545	0.738	0.917	-0.372	-0.179
API (VDem)	0.519	0.628	0.868	-0.349	-0.240
MPI (VDem)	0.506	0.720	0.904	-0.399	-0.185
Partipdem (VDem)	0.499	0.690	0.787	-0.288	-0.097
Delib (VDem)	0.489	0.670	0.775	-0.286	-0.105
Egal (VDem)	0.480	0.683	0.773	-0.293	-0.090
Contestation (P)	0.474	0.611	0.327	0.147	0.285
Kailitz	0.468	0.510	0.403	0.065	0.107
Lexical Index	0.467	0.555	0.354	0.113	0.202
BMR	0.455	0.582	0.337	0.118	0.245
Freedom House	0.454	0.518	0.360	0.095	0.159
Magaloni	0.448	0.613	0.379	0.069	0.235
PEPS1v	0.446	0.676	0.348	0.098	0.328
BNR	0.443	0.449	0.349	0.095	0.100
Libdem (VDem)	0.442	0.543	0.787	-0.345	-0.244
Svolik	0.439	0.655	0.393	0.046	0.263
Arat	0.425	0.530	0.351	0.074	0.179
PACL	0.424	0.622	0.382	0.042	0.240
Freedom H. Binary	0.423	0.524	0.353	0.070	0.172
Polity IV	0.404	0.665	0.297	0.107	0.368
Competition (Van)	0.402	0.473	0.267	0.136	0.206
Mainwaring	0.398	0.588	0.454	-0.056	0.134
Ulfeder	0.394	0.657	0.361	0.033	0.296
WTH	0.394	0.349	0.278	0.115	0.071
UTIP	0.386	0.470	0.318	0.068	0.151
Inclusion (P)	0.376	0.301	0.305	0.070	-0.004
Doorenspleet	0.368	0.392	0.274	0.094	0.119
Reign	0.363	0.619	0.313	0.050	0.306
PITF	0.353	0.630	0.238	0.116	0.392
PRC	0.352	0.460	0.280	0.072	0.180
GWF	0.347	0.626	0.319	0.028	0.307
Democratization (Van)	0.296	0.338	0.208	0.088	0.130
PIPE	0.295	0.277	0.208	0.086	0.069
Munck	0.230	0.301	0.383	-0.153	-0.082
WGI	0.207	0.282	0.221	-0.014	0.061
Participation (Van)	0.188	0.130	0.188	0.0002	-0.058
BLM	0.146	0.284	0.353	-0.207	-0.069
Median	0.423	0.555	0.351	0.068	0.134

Note: The table shows median correlations between year-to-year changes in the expected values and observed values in these indicators.

F Regime Types, Regime Transitions, and Civil War

Long-term Transition Dynamics and Civil War

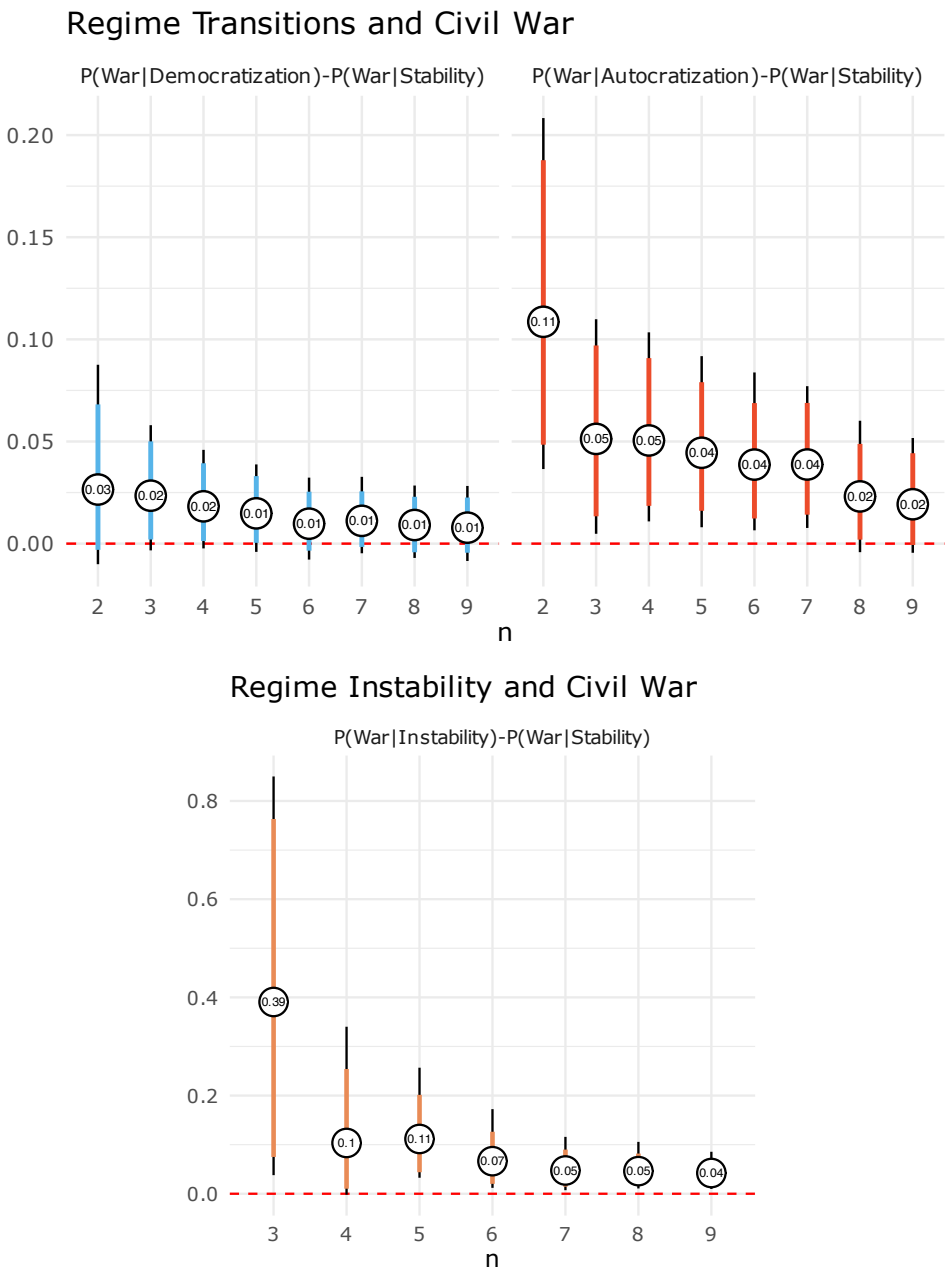
To illustrate the versatility of UNITAS, we also analyze how the association between regime transitions and conflict onset changes when the transition is sustained, or when instances of instability are spread over a period of time. More specifically, we focus on scenarios where a regime experiences a monotonic sustained transition. In the context of democratization, this captures a sequence of regime shifts that either maintains or advances towards a more democratic type. For instance, a sequence represented by $P(ASD)$ signifies a sustained transition observed over a duration of 3 years (*n*=3). Similarly, the sequence $P(AASSS)$ illustrates another example of a sustained transition, this time spanning over a 5-year period (*n*=5). We calculate these individual probabilities and then sum the probability of weakly monotonic transitions for each *n*. For example, when *n*=3, our sustained democratization variable captures the sum of the probabilities of observing monotonic regime type sequences in the previous three years as $P(A, A, S) + P(A, A, D) + P(A, S, S) + P(A, S, D) + P(A, D, D) + P(S, S, D) + P(S, D, D)$. In contrast, instances of instability are denoted by non-monotonic changes in the regime type, such as failed democratization (e.g., $P(SDS)$) or autocratization (e.g., $P(SAS)$), as well as non-monotonic democratization (e.g., $P(SAD)$) or autocratization (e.g., $P(SDA)$). We estimate the following equation when n is higher than 2:

$$War_{it} = a + \beta_1 DT_{it} + \beta_2 AT_{it} + \beta_3 SD_{it} + \beta_4 SSD_{it} + \beta_5 SA_{it} + \lambda x_{it} + \varepsilon \qquad \text{(F.1)}$$

where DT_{it} and AT_{it}, SD_{it}, SSD_{it}, and SA_{it} respectively indicate democratic transition, autocratic transition, stable democracy, stable semi-democracy, and stable autocracy. The reference category, instability, records the non-monotonic changes in the regime type. We vary *n* from 2 to 9 and analyze how different temporal spans of sustained transitions and instabilities are associated with conflict.[23] Figure A6 presents the associations of sustained democratization (first panel), sustained autocratization (second panel), and instability (third panel) over a duration of n-years with the probability of civil war onset. More specifically, the x-axis indicates the duration of sustained democratization, denoted by n, which ranges from 2 to 9 years. The y-axis indicates difference in the probability of civil war between the specific regime transition scenario (sustained democratization, sustained autocratization, or instability) and a stable regime maintained over the same n-year period. The figure shows that the associations of both democratic and autocratic transitions with conflict decrease as *n* increases. As the duration of a sustained autocratic transition increases, the risk of a civil war decreases over time and eventually disappears by the eighth year (p>0.05). A similar pattern is observed for sustained democratization, however, the effect is insignificant (p>0.05) across all *n* durations. These findings indicate that the danger of civil conflict peaks in the first year following an autocratic transition ($n = 2$) and the risk dissipates once the transition becomes increasingly entrenched ($n = 9$). Figure A6, third panel indicates that the first year of regime instability ($n = 3$) is associated with a 0.39 higher probability of civil war than a stable regime (with 95 percent confidence intervals of 0.07 and 0.76). As the duration for non-monotonicity increases, while the probability of civil war decreases, the association with conflict remains significant. This also means that abrupt

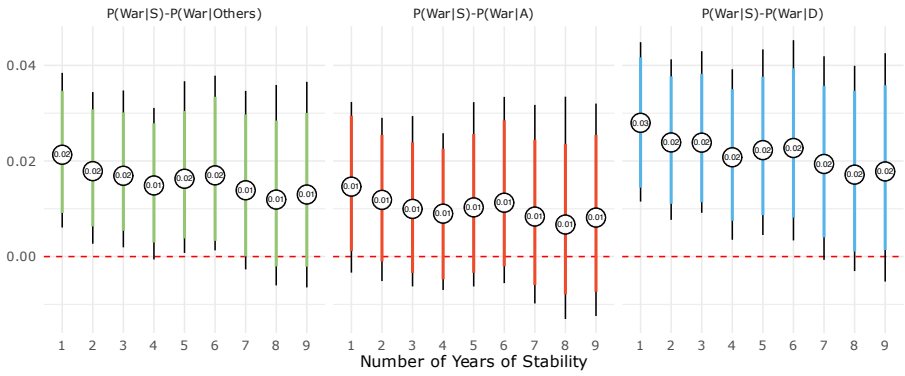
[23] When n is 9, our method constructs an extensive array of $3^9 = 19683$ unique probabilistic sequences for each observation.

Figure A6: Regime Transitions and Civil War



Notes: The figure plots the association of sustained democratization (first panel), sustained autocratization (second panel), instability (third panel) over a duration of n-years with the probability of civil war onset. The x-axis shows the duration of specific regime transition type, denoted by n. The y-axis indicates difference in the probability of civil war between the specific regime transition scenarios (sustained democratization, sustained autocratization, or instability) and a stable regime maintained over the same n-year period. The thick intervals represent 95 percent confidence intervals, while the thin intervals correspond to 99-percent confidence intervals.

Figure A7: Is Murder in the Middle: Accounting for Regime Stability



Notes: The figures plot the difference between the probability of war under semi-democracy and (i) either autocracy or democracy (first panel), (ii) autocracy (second panel), and (ii) democracy (third panel). The thick intervals represent 95 percent confidence intervals, while the thin intervals correspond to 99 percent confidence intervals.

reversals in transitions are highly risky and this risk decreases as these non-monotonic changes become more entrenched over time.

Conflictual Semi-democracies: Is There "Murder in the Middle?"

As a second application of our UNITAS measure, we evaluate the relationship between regime type and civil war onset. While there is a vast literature on this topic, here we mainly focus on evaluating a specific result: previous research in the literature that suggests that semi-democracies are more prone to civil war than autocracies and democracies (e.g., Hegre et al. 2001; Regan and Bell 2010; Jones and Lupu 2018). Unlike existing approaches that conflate the effect of regime type, regime transitions, and regime stability, our measurement approach allows us to isolate the effect of regime type by producing estimates for the probabilities of temporal sequences of any given length. As an example, consider the following historical regime trajectories: SSSSS, ASSSS, DSSSS, SSDSS. Given that all these trajectories are semi-democracies in year t, a static analysis will treat them equally in linking to conflict behavior. However, the first sequence is a stable semi-democracy, the second one is a democratic transition, the third is an autocratic transition, and the last one is a failed democratic transition, and it is possible that they are associated with civil war onset at different risk levels if stability and the dynamics of transitions are also relevant for conflict. By explicitly differentiating these historical trajectories, our approach isolates the effect of regime type from regime transition and stability and tests whether semi-democracies (e.g, SSSSS) are indeed more war-prone than other regime types (e.g, DDDDD or AAAAA) as they reach a stable state.

Figure A7 presents our results. In each case, time spent in a given regime type is defined over a duration of n years, with n ranging between 1 and 9.[24] For example, when n equals 3, a semi-

[24]Given that we do not have a priori theoretical expectation, we vary this duration to examine its association with

democracy would refer to a semi-democratic regime that has maintained the semi-democracy status without undergoing any transitions over the span of the current year and the two preceding years (SSS). We find that shorter sequences tend to conflate recent transition effects with regime type effects. More specifically, we find a higher conflict propensity of semi-democracies (SS) compared to other regime types (AA or DD) in short sequences and this diminishes when we examine longer regime trajectories (SSSSSSS vs. AAAAAAA or DDDDDDD). As the first panel in Figure A7 shows, the conflict propensities of semi democracies become indistinguishable from those of other regime types by the seventh year of stability. This indicates that higher conflict risk of semi-democracies is likely due to recent regime changes or failed regime transitions. Further unpacking these results in the first panel, the comparison of the risk between semi-democracies and autocracies is not significant, except during the first year of the regime. This indicates that semi-democracies and autocracies have similar conflict risk once the immediate effect of recent transitions dissipates. In comparison to stable democracies, however, increased risk of conflict remains significant at the .05 level during all considered periods of stability even after controlling for recent regime transitions and instability, indicating that the lack of significance with respect to autocracies is not an artifact due to the low power of the test. Considered together, these findings qualify the existing results in literature that are established through static models. Our findings show that the apparent association between semi-democracies and conflict is not inherently due to the regime type. Rather, it results from conflating the effect of regime type with regime transitions and regime instability.

civil war across regime types.

Table A8: Summary Statistics of Democracy Indicators

Measurement Project	Citation	N	Mean	St.D.	Min	Max
Arat	Arat (1991)	3,873	73.4	20.4	40	100
Bollen	Bollen (2001)	510	56.2	33.8	0	100
BLM	Bowman, Lehoucq and Mahoney (2005)	505	0.5	0.7	0	2
BMR	Boix, Miller and Rosato (2012)	16,759	0.3	0.5	0	1
BNR	Bernhard, Nordstrom and Reenock (2001)	10,318	0.3	0.5	0	1
Doorenspleet	Doorenspleet (2000)	12,807	1.2	0.4	1	2
Freedom H. Binary	Freedom House (2018)	5,320	0.6	0.5	0	1
Freedom House	Freedom House (2018)	8,189	6.6	4.1	0	12
GWF	Geddes, Wright and Frantz (2014)	9,349	0.4	0.5	0	1
Hadenius	Hadenius (1992)	129	4.6	3.7	0	10
Kailitz	Kailitz (2013)	9,605	1.0	0.9	0	2
Lexical Index	Skaaning, Gerring and Bartusevicius (2015)	17,827	2.9	2.3	0	6
Magaloni	Magaloni, Chu and Min (2013)	10,257	0.4	0.5	0	1
Mainwaring	Mainwaring, Brinks and Pérez-Liñán (2001)	2,156	0.7	0.8	0	2
Munck	Munck (2009)	342	8.2	1.8	3	9
PACL	Cheibub, Gandhi and Vreeland (2010)	9,115	0.4	0.5	0	1
PEPS1v	Moon et al. (2006)	14,089	-2.9	5.7	-10	10
PIPE	Przeworski (2013)	16,808	1.6	0.9	0	3
PITF	Goldstone et al. (2010)	16,248	1.4	1.5	0	4
Polity IV	Marshall, Gurr and Jaggers (2015)	16,981	-0.6	7.1	-10	10
Contestation (P)	Coppedge, Alvarez and Maldonado (2008)	7,533	51.9	25.5	0	100
Inclusion (P)	Coppedge, Alvarez and Maldonado (2008)	7,533	68.0	17.4	10	90
PRC	Reich (2002)	10,786	1.6	0.8	1	3
Reign	Bell (2016)	12,397	0.5	0.5	0	1
Svolik	Svolik (2012)	8,535	0.4	0.5	0	1
Ulfeder	Ulfelder (2012)	10,859	0.3	0.5	0	1
UTIP	Hsu (2008)	6,110	0.5	0.5	0	1
Polyarchy (VDem)	Coppedge et al. (2017)	21,273	30.1	28.6	0	95
Libdem (VDem)	Coppedge et al. (2017)	20,522	25.9	26.4	0	100
Delib (VDem)	Coppedge et al. (2017)	17,168	26.1	28.1	0	95
Partipdem (VDem)	Coppedge et al. (2017)	17,119	22.5	24.3	0	95
Egal (VDem)	Coppedge et al. (2017)	16,987	26.3	26.5	0	95
API (VDem)	Coppedge et al. (2017)	21,273	43.6	31.5	0	100
MPI (VDem)	Coppedge et al. (2017)	21,273	15.8	28.3	0	95
Competition (Van)	Vanhanen (2014)	15,731	25.2	25.2	0	70
Democratization (Van)	Vanhanen (2014)	15,731	8.4	11.8	0	45
Participation (Van)	Vanhanen (2014)	15,731	21.1	22.0	0	70
WGI	Kaufmann and Kraay (2017)	3,553	55.4	24.4	5	95
WTH	Wahman, Teorell and Hadenius (2013)	7,428	0.4	0.5	0	1

Note: Marquez (2017) provides a single merged file to access these datasets.

Table A9: Transformation Rules for Manifest Indicators

Indicator	Original Scale	HMM Categories	Discretization Rule
Dichotomous and Trichotomous Indicators			
BMR, BNR, Doorenspleet, GWF PACL, Reign, Svolik, Ulfelder, FH Electoral	0 and 1	2	None
BLM, Kailitz, Mainwaring, PRC UTIP, WTH	1 to 3	3	None
Low-Resolution Ordinal (3-7 categories)			
Munck	0 to 100	3	Discretized
PIPE	1 to 4	4	None
PITF	0 to 5	5	None
Arat	29 to 109	4	Discretized
Bollen, Hadenius	0 to 100	6	Discretized
Lexical Index	1 to 7	7	None
Medium-Resolution Ordinal (10-15 categories)			
Vanhanen Democratization	0 to 49	10	Discretized
Polyarchy Contestation	-2.06 to 1.90	11	Normalized & discretized
Polyarchy Inclusion	-3.95 to 1.85	11	Normalized & discretized
Freedom House	0 to 12	13	None
Vanhanen Competition	0 to 70	15	Discretized
Vanhanen Participation	0 to 71	15	Discretized
High-Resolution Ordinal (19-21 categories)			
WGI Democracy	-2.31 to 1.80	19	Normalized & discretized
V-Dem indices (7 measures)	0-1	20	Normalized & discretized
PEPS	-10 to +10	21	Rounded to integer
Polity2	-10 to +10	21	None

Notes: To uncover non-linear patterns in the emission probabilities, we preserve the variation in each manifest indicator, only applying minimal discrete transformations in some cases: binary measures (e.g., BMR, PACL, Svolik) remain binary and integer-valued measures (e.g., Lexical, Polity IV, PITF, Freedom House) retain their original scales. Continuous indicators (e.g., V-Dem, Polyarchy, WGI) are discretized at regular increments (5-, 10-, 20-point intervals on 0-100 normalized scales). This dicretization approach balances the need of preserving variation with ensuring adequate observation per category to reliably estimate the emission probabilities (probabilities of observing each category conditional on the latent regime type). This process yields manifest indicators with 2 to 21 different categories, maintains substantial variation from the original measure, and allows our model to capture non-linear relationships between indicator values and regime types as shown in Figure A1.

Figure A8: Emission Probabilities

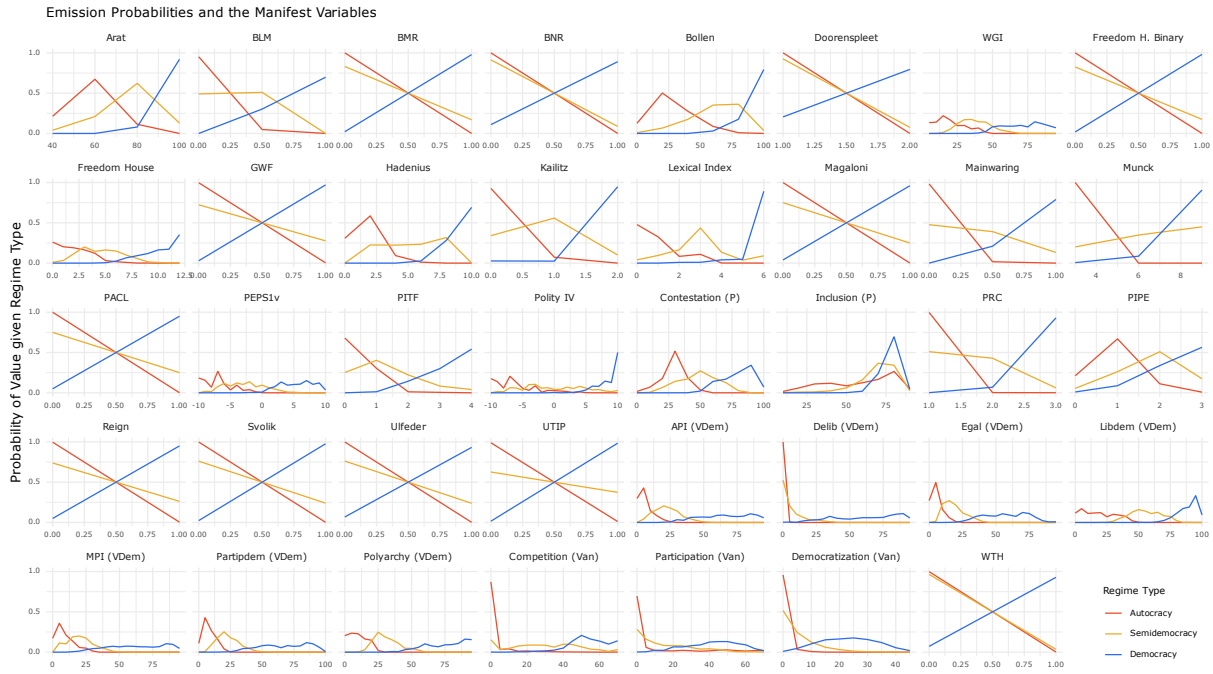
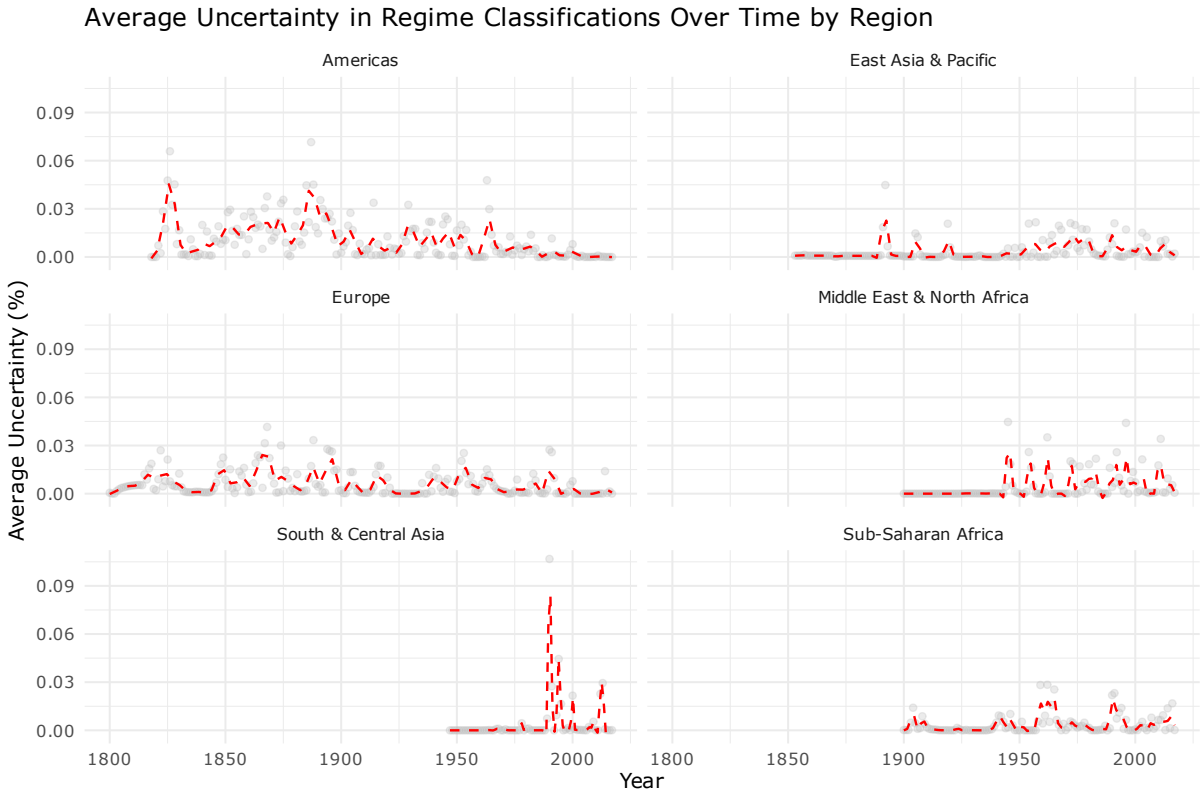


Figure A9: Uncertainty in UNITAS Regime Classifications Across Time and Space



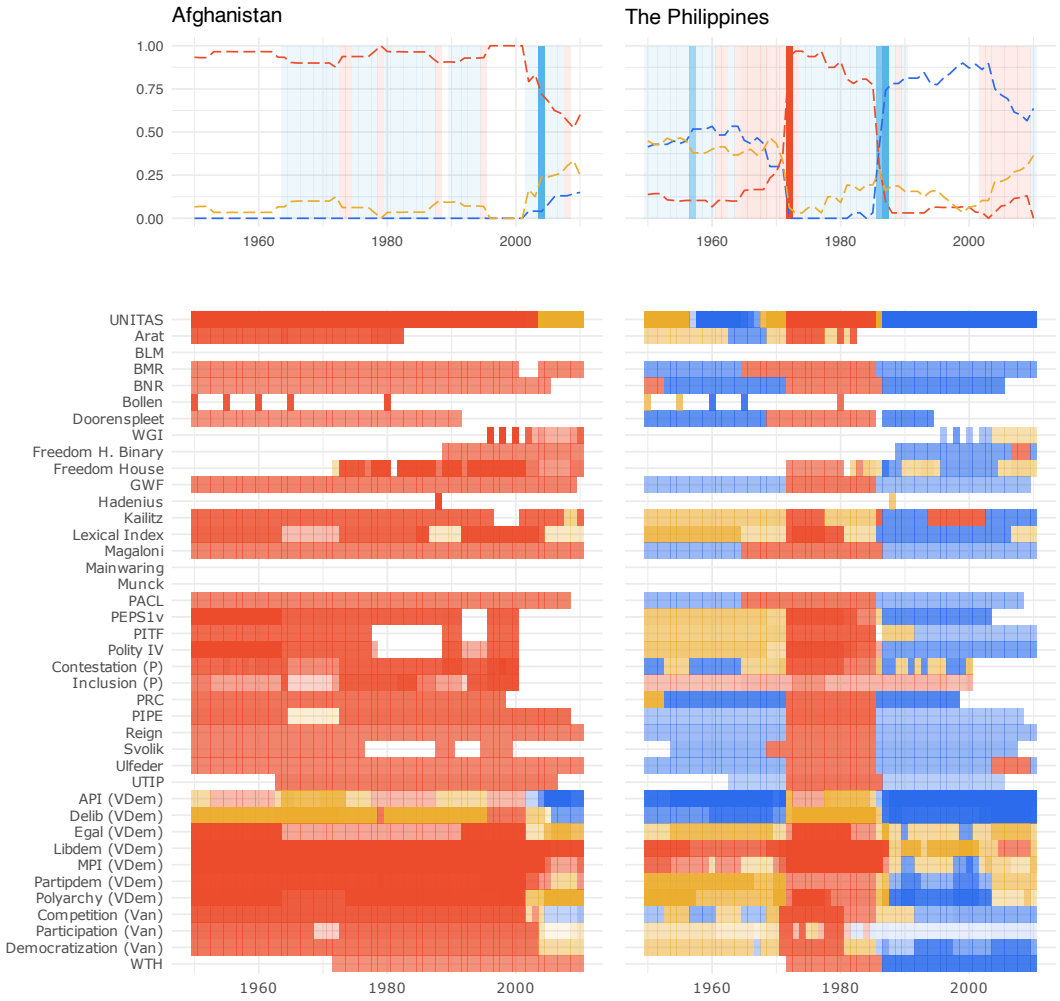
Notes: The figure shows average uncertainty in regime classifications by region from 1800 to 2017. Uncertainty is calculated as $1 - \max(\tau_t(A), \tau_t(S), \tau_t(D))$. Gray points represent individual region-year average values, while the dashed red line shows the smoothed regional average over time. The figure only includes region-years that have at least 5 observations to avoid small sample noise and maintain comparability across regions. A closer examination of uncertain cases reveals that they cluster systematically around important periods of political transformation. Uncertainty vary across regions and historical periods: Latin American independence period (1820s-1830s) generates high uncertainty scores (e.g., Great Colombia 0.44 in 1828, United Provinces of Central America 0.47 in 1826, Brazil 0.20 in 1826). African decolonization produces similar patterns (e.g., Sierra Leone 0.48 in 1962, Central African Republic 0.49 in 1959). A spike occurs during post-Soviet transitions in 1990, when former republics' regime classifications exhibit high uncertainty (e.g., Kazakhstan 0.45, Turkmenistan 0.45) as these countries emerged from the Soviet rule. Revolutionary periods also generate high uncertainty, particularly Europe's 1848 "Spring of Nations" (e.g., Spain 0.49, Switzerland 0.32). The Middle East and North Africa maintain elevated uncertainty throughout the post World War II era (e.g., Egypt 0.46 in 1983, Lebanon 0.42 in 1972), with states continuing to oscillate between regime classifications decades after independence.

Figure A10: Continuous UDS Measures and Threshold Sensitivity



Notes: The figure plots the effect of autocratization and democratization compared to stability, shown with 95-percent (thick) and 99-percent (thin) credible intervals for UDS (Pemstein, Meserve and Melton 2010) and Robust-UDS (Reuning, Kenwick and Fariss 2019). Given that these are continuous scores, we implemented four different approaches to assess the consequences of cut-off and magnitudes of change choices: (1.1) tercile categorization (Categorize-Transition), (1.2) mean±1 standard deviation categorization (±1SD Categorize-Transition), (2.1) 10% change (Continuous-10% Change), and (2.2) 1 standard deviation change (Continuous-1SD Change) over the continuous score.

Figure A11: Regime Characteristics and Transitions in Afghanistan and the Philippines



Notes: The blue, yellow, and red lines, respectively, indicate the agreement among manifest variables on a given regime type. The light blue and red vertical bars on the top figures show UNITAS democratic and autocratic transitions, respectively, with darker shades indicating higher certainty, while the white spaces represent periods of stability where the transition probability is zero. The below figures show UNITAS regime assignments and the manifest indicators' regime assignments (based on modal assignment) throughout the period, with darker shades representing the certainty estimated by our model. White spaces in below figures indicate periods with missing data.

Bibliography

Arat, Zehra F. 1991. *Democracy and Human Rights in Developing Countries*. Boulder: Lynne Rienner Publishers.

Bas, Muhammet A. and Omer Faruk Orsun. 2021. "Regime Uncertainty and Interstate Conflict." *International Studies Quarterly* 65(3):838–851.

Bas, Muhammet A and Randall W. Stone. 2025. "Probabilistic Democracy." *International Studies Quarterly* 69(4):sqafo67.

Baum, Leonard E. 1972. "An Inequality and Associated Maximization Technique in Statistical Estimation for Probabilistic Functions of Markov Processes." *Inequalities* 3(1):1–8.

Bell, Curtis. 2016. "The Rulers, Elections, and Irregular Governance Dataset (REIGN).".
URL: *http://oefresearch.org/datasets/reign*

Bernhard, Michael, Timothy Nordstrom and Christopher Reenock. 2001. "Economic Performance, Institutional Intermediation, and Democratic Survival." *Journal of Politics* 63(3):775–803.

Boeschoten, Laura, Danila Filipponi and Roberta Varriale. 2020. "Combining Multiple Imputation and Hidden Markov Modeling to Obtain Consistent Estimates of Employment Status." *Journal of Survey Statistics and Methodology* 9(3):549–573.

Boix, Carles, Michael Miller and Sebastian Rosato. 2012. "A Complete Dataset of Political Regimes, 1800-2007." *Comparative Political Studies* 46(12):1523–1554.

Bollen, Kenneth A. 2001. "Cross-National Indicators of Liberal Democracy, 1950-1990.".

Bowman, Kirk, Fabrice Lehoucq and James Mahoney. 2005. "Measuring Political Democracy: Case Expertise, Data Adequacy, and Central America." *Comparative Political Studies* 38(8):939–970.

Cheibub, Jose, Jennifer Gandhi and James Vreeland. 2010. "Democracy and Dictatorship Revisited." *Public Choice* 143(1):67–101.

Coppedge, Michael, Angel Alvarez and Claudia Maldonado. 2008. "Two Persistent Dimensions of Democracy: Contestation and Inclusiveness." *The Journal of Politics* 70(03):632–647.

Coppedge, Michael, John Gerring, Staffan I. Lindberg, Svend-Erik Skaaning and Jan Teorell et al. 2017. "V-Dem [Country-Year/Country-Date] Dataset, version 8.".

Doorenspleet, Renske. 2000. "Reassessing the Three Waves of Democratization." *World Politics* 52(03):384–406.

Epstein, David L., Robert Bates, Jack Goldstone, Ida Kristensen and Sharyn O'Halloran. 2006. "Democratic Transitions." *American Journal of Political Science* 50(3):551–569.

Freedom House. 2018. "Freedom in the World 2018: Democracy in Crisis.".
URL: *https://freedomhouse.org/sites/default/files/FH_FITW_Report_2018_Final_SinglePage.pdf*

Geddes, Barbara, Joseph Wright and Erica Frantz. 2014. "Autocratic Breakdown and Regime Transitions: A New Data Set." *Perspectives on Politics* 12(1):313–331.

Gleditsch, Kristian S. and Michael D. Ward. 1997. "Double Take: A Reexamination of Democracy and Autocracy in Modern Polities." *Journal of Conflict Resolution* 41(3):361–383.

Goldstone, Jack, Robert Bates, David Epstein, Ted Gurr, Michael Lustik, Monty Marshall, Jay Ulfelder and Mark Woodward. 2010. "A Global Model for Forecasting Political Instability." *American Journal of Political Science* 54(1):190–208.

Hadenius, Axel. 1992. *Democracy and Development*. New York: Cambridge University Press.

Hegre, Havard, Tanja Ellingsen, Scott Gates and Nils Petter Gleditsch. 2001. "Toward a Democratic Civil Peace? Democracy, Political change, and Civil war, 1816-1992." *American Political Science Review* 95(1):33–48.

Hsu, Sara. 2008. "The Effect of Political Regimes on Inequality, 1963-2002." *UTIP Working Paper* (53).

Jones, Zachary M. and Yonatan Lupu. 2018. "Is There More Violence in the Middle?" *American Journal of Political Science* 62(3):652–667.

Kailitz, Steffen. 2013. "Classifying Political Regimes Revisited: Legitimation and Durability." *Democratization* 20(1):39–60.

Kaufmann, Daniel and Aart Kraay. 2017. "Worldwide Governance Indicators.".
URL: *http://www.govindicators.org*

Knutsen, Carl Henrik, Kyle L. Marquardt, Brigitte Seim, Michael Coppedge, Amanda B. Edgell, Juraj Medzihorsky, Daniel Pemstein, Jan Teorell, John Gerring and Staffan I. Lindberg. 2024. "Conceptual and Measurement Issues in Assessing Democratic Backsliding." *PS: Political Science and Politics* p. 1–16.

Levitsky, Steven and Lucan A. Way. 2010. *Competitive Authoritarianism: Hybrid Regimes after the Cold War*. Problems of International Politics Cambridge University Press.

Little, Andrew T. and Anne Meng. 2024. "Measuring Democratic Backsliding." *PS: Political Science and Politics* p. 1–13.

Lueders, Hans and Ellen Lust. 2018. "Multiple Measurements, Elusive Agreement, and Unstable Outcomes in the Study of Regime Change." *The Journal of Politics* 80(2):736–741.

Magaloni, Beatriz, Jonathan Chu and Eric Min. 2013. "Autocracies of the World, 1950-2012 (Version 1.0).".
URL: *http://cddrl.fsi.stanford.edu/research/autocracies_of_the_world_dataset*

Mainwaring, Scott, Daniel Brinks and Aníbal Pérez-Liñán. 2001. "Classifying Political Regimes in Latin America." *Studies in Comparative International Development* 36(1):37–65.

Mansfield, Edward D. and Jack Snyder. 2002. "Incomplete Democratization and the Outbreak of Military Disputes." *International Studies Quarterly* 46(4):529–549.

Marquez, Xavier. 2017. "democracyData: A Package for Accessing and Manipulating Existing Measures of Democracy.".
URL: *http://github.com/xmarquez/democracyData*

Marshall, Monty G., Ted Robert Gurr and Keith Jaggers. 2015. *Polity IV Project: Political Regime Characteristics and Transitions, 1800-2015. Dataset Users' Manual.*

Martinez i Coma, Ferran and Lee Morgenbesser. 2020. "Election Turnout in Authoritarian Regimes." *Electoral Studies* 68:102222.

Moon, Bruce E., Jennifer Harvey Birdsall, Sylvia Ciesluk, Lauren M. Garlett, Joshua J. Hermias, Elizabeth Mendenhall, Patrick D. Schmid and Wai Hong Wong. 2006. "Voting Counts: Participation in the Measurement of Democracy." *Studies in Comparative International Development* 41(2):3–32.

Munck, Gerardo. 2009. *Measuring Democracy: A Bridge between Scholarship and Politics*. Baltimore: The Johns Hopkins University Press.

Neher, Clark D. 1996. "The Transition to Democracy in Thailand." *Asian Perspective* 20(2):301–321. Publisher: Lynne Rienner Publishers.

Pemstein, Daniel, Stephen A. Meserve and James Melton. 2010. "Democratic Compromise: A Latent Variable Analysis of Ten Measures of Regime Type." *Political Analysis* 18(4):426–449.

Plümper, Thomas and Eric Neumayer. 2010. "The Level of Democracy during Interregnum Periods: Recoding the Polity2 Score." *Political Analysis* 18(2):206–226.

Przeworski, Adam. 2013. "Political Institutions and Political Events (PIPE) Data Set.".
URL: *https://sites.google.com/a/nyu.edu/adam-przeworski/home/data*

Rabiner, Lawrence R. 1989. "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition." *Proceedings of the IEEE* 77(2):257–286.

Regan, Patrick M. and Sam R. Bell. 2010. "Changing Lanes or Stuck in the Middle: Why Are Anocracies More Prone to Civil Wars?" *Political Research Quarterly* 63(4):747–759.

Reich, G. 2002. "Categorizing Political Regimes: New Data for Old Problems." *Democratization* 9(4):1–24.

Reuning, Kevin, Michael R. Kenwick and Christopher J. Fariss. 2019. "Exploring the Dynamics of Latent Variable Models." *Political Analysis* 27(4):503–517.

Rubin, Donald B. 1987. *Multiple Imputation for Nonresponse in Surveys*. Vol. 81 John Wiley & Sons.

Skaaning, Svend-Erik, John Gerring and Henrikas Bartusevicius. 2015. "A Lexical Index of Electoral Democracy." *Comparative Political Studies* 48(12):1491–1525.

Svolik, Milan. 2012. *The Politics of Authoritarian Rule*. Cambridge: Cambridge University Press.

Tedesco, Laura. 2013. *Democracy in Argentina: Hope and Disillusion*. Routledge.

Treier, Shawn and Simon Jackman. 2008. "Democracy as a Latent Variable." *American Journal of Political Science* 52(1):201–217.

Ulfelder, Jay. 2012. "Democracy/Autocracy Data Set.".
URL: *http://hdl.handle.net/1902.1/18836*

Vanhanen, Tatu. 2014. "Measures of Democracy 1810-2012.".
URL: *http://www.fsd.uta.fi/english/data/catalogue/FSD1289/meF1289e.html*

Wahman, Michael, Jan Teorell and Axel Hadenius. 2013. "Authoritarian Regime Types Revisited: Updated Data in Comparative Perspective." *Contemporary Politics* 19(1):19–34.
URL: *https://sites.google.com/site/authoritarianregimedataset/data*