The Democracy-Support Nexus Revisited: Accounting for Measurement Error and Simultaneous Effects

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Abstract

Recent research has demonstrated several connections between the presence and vitality of a democratic system and public support toward that system: firstly, that public support helps to sustain democracy, and secondly, that changes in democracy prompt an immediate and opposite thermostatic reaction in public opinion. We revisit these links (and others) in the democracy-support nexus, using Bayesian MCMC methods to include measurement uncertainty in democracy, public mood towards democracy, and satisfaction with democracy, and to simultaneously estimate the links between these three variables. Substantively, we find similar results to existing research, both in terms of the supportive effect of mood on democracy and the thermostatic effect of democratic change on mood. However we also show that the method by which measurement uncertainty is included matters at least as much as whether such uncertainty is included at all.

Keywords: democracy, support for democracy, satisfaction with democracy, measurement error, latent variables, Bayesian statistics

Words: 4,150

1. Introduction

Democracy is closely linked with public support. In one sense, this follows from the nature of the democratic process: free elections, for example, demand that candidates compete for public support. Yet there exist other links – less obvious but no less significant – between the presence of a democratic system and public support for the system itself. For example, political scientists have long believed that stable democracy requires the support of the public (e.g., Lipset 1959) and that such support is created by public socialization into a democratic system (e.g., Rose, Mishler, and Haerpfer 1998).

Recent work has provided empirical evidence for these two connections between democracy and public support, while also casting doubt on two more. Claassen (2020*a*) shows that democratic institutions and processes are indeed buoyed by public support for democracy, but also finds that public satisfaction with the way democracy works has no similar salutatory effect. And, examining the reverse effects, from democratic institutions to opinions, Claassen (2020*b*) identifies a thermostatic effect, where changes in democracy provoke opposite public reactions. But he finds little evidence for the presumed socialization effect whereby democratic systems inculcate democratic support gradually over the long run.

Yet two concerns might be raised with this research into the democracy-support nexus. Firstly, existing analyses have not accounted for the uncertainty that accrues from measuring abstract concepts such as democratic support using noisy and sparse survey data. A two-step approach has been used, with support (and indeed, democracy) being measured in the first step, and the point estimates (but not the accompanying uncertainty) carried forward to a second step where links between democracy and support are estimated. As has long been known (e.g., Stefanski 2000), omitting measurement uncertainty may result in biased estimates of the associations between two or more variables.

The second problem is that the various links in the democracy-support nexus have been studied piecemeal, with either democracy or public support acting as the dependent variable in different analyses. The presence of multiple, reciprocal effects between two or more variables might distort or confound any analyses that focus only on one variable at a time (see, e.g., Reuveny and Li 2003).

This paper tackles both concerns. We combine measurement models of democracy, support for democracy (or mood), and satisfaction with democracy with dynamic structural models that allow for various linkages between these concepts to play out over time. By simultaneously estimating these linkages, we improve on existing analyses of the democracy-support nexus that relied on piecemeal analyses. And by measuring each concept and modeling its determinants and consequences in a single step, we improve on previous two-step analyses that ignore measurement uncertainty. Moreover, by modeling the interplay between democracy, mood, and satisfaction, we advance beyond analyses which have focused on two of these three concepts. Finally, we extend the range of existing analyses to focus on 144 countries and time-series which stretch back from 2020 to 1973 in some cases.

We compare the estimates obtained for five approaches to analyzing the democracy-support nexus. The first is a baseline approach which ignores measurement error and models democracy, mood, and satisfaction using separate equations (e.g., Claassen 2020*a*;*b*). We then model the three variables as an interlinked set of endogenous variables. We then include measurement error, in two ways: first, using a simple, but limited, two-step operation, "the method of composition" (Tanner 1996); and second, using a more computationally intensive but more powerful single-step method in which measurement and structural parameters are estimated simultaneously.

We find that the method by which measurement uncertainty is included matters a great deal – at least as much as whether such uncertainty is included at all. We show also that decisions regarding which variables are to have measurement uncertainty modeled and included are also consequential. The results from our most comprehensive model, which includes measurement uncertainty for democracy, mood, and satisfaction, largely replicate the findings of earlier research. Specifically, we find, like Claassen (2020*b*), that democracy exhibits a negative, thermostatic effect on public support, even when measurement error and reciprocal effects between democracy, mood, and satisfaction are accommodated. And like Claassen (2020*a*), we show a positive effect of mood on democracy, which, although small, accumulates over time.

In sum, this analysis of the democracy-support nexus confirms a number of linkages between the presence and vitality of democracy and public attitudes to the democratic system. It further demonstrates the utility and viability of modeling political and social systems as systems of interlinked simultaneous models, in which measurement uncertainty can naturally be included. Finally, this paper shows that analysts should more carefully select and motivate the method by which measurement uncertainty is to be modeled and included.

2. Methods

Our methodological approach advances beyond existing work in five stages. First, in contrast to the unidimensional dynamic latent variable model introduced by Claassen (2019), we employ a multidimensional latent variable model that allows for common shocks to affect multiple distinct opinion series. Second, in a departure from the separate analyses of mood and democracy in previous work, we employ our opinion estimates in a simultaneous equation model. Although still a two-step approach like those used in existing research, this SEM allows for such features as reciprocal links between variables and correlated residuals. Third, we then use a two-step method for incorporating measurement error, the "method of composition" (Tanner 1996). This involves taking a number of draws from the posterior distributions of our estimates of interest, rather than only the point estimates, and using these in a set of separate regression models. Fourth, we adopt a more powerful one-step approach to the problem of including measurement error: in the same likelihood function we include measurement models of the latent opinion variables of mood and satisfaction as well as structural models. Finally, we add a measurement model for democracy using publicly available point estimates and standard errors.

2.1. A two-dimensional dynamic measurement model

Our first innovation is to develop a two-dimensional version of the dynamic Bayesian latent variable model proposed by Claassen (2019). This allows for two correlated opinion series to be estimated, and is applied here to estimate democratic support and satisfaction jointly. The benefit of this simultaneous estimation is that information on common shocks is shared between the two opinion estimates, to the extent that they are correlated, thereby improving estimates.

Claassen's model uses a beta-binomial link function between observed, nationally-aggregated survey responses y_{ikt} for each country i, year t, and survey questions k, and the probabilities of offering a supportive response π_{ikt}. These probabilities are modeled as a function of the latent country-year opinion estimates of interest θ_{it}, item slopes γ_k, item bias parameters λ_k and item-country bias parameters δ_{ik}. The latent estimates are furthermore modeled as evolving over time via a random walk process:

$$y_{ikt} \sim \text{Beta-Binomial}(s_{ikt},\ \pi_{ikt},\ \phi) \tag{1}$$

$$\pi_{ikt} = \text{logit}^{-1}(\delta_{ik} + \lambda_k + \gamma_k \theta_{it}) \tag{2}$$

$$\theta_{it} \sim \text{N}(\theta_{i,t-1},\ \sigma^2_{\theta}) \tag{3}$$

We extend this single-variable latent variable model to multivariate scenarios by generalizing the final step (3). The dynamic evolution of multiple opinion series is modeled using a multivariate normal distribution, allowing correlations between the errors of each opinion series. With two latent opinions toward democracy that are of interest, satisfaction $y^{(s)}_{ikt}$ and democratic mood $y^{(m)}_{ikt}$, the dynamic component of our measurement model can be described as follows:

$$\begin{pmatrix} \theta^{(s)}_{it} \\ \theta^{(m)}_{it} \end{pmatrix} \sim \text{MVN}\left[\begin{pmatrix} \theta^{(s)}_{i,t-1} \\ \theta^{(m)}_{i,t-1} \end{pmatrix}, \begin{pmatrix} \sigma^2_{\theta^{(s)}} & \rho_{\theta}\sigma_{\theta^{(m)}}\sigma_{\theta^{(s)}} \\ \rho_{\theta}\sigma_{\theta^{(s)}}\sigma_{\theta^{(m)}} & \sigma^2_{\theta^{(m)}} \end{pmatrix}\right] \tag{4}$$

2.2. Modeling simultaneous structural effects

We then extract the point estimates for the two opinion series, $\hat{\theta}_{it}^{(s)}$ and $\hat{\theta}_{it}^{(m)}$. Retaining the two-step methods used previously, we discard uncertainty in these estimates, but now model them as a set of simultaneous equations. These SEMs include direct effects between mood and satisfaction as well as correlated errors. We treat democracy as a endogenous variable with a set of structural links with mood, satisfaction and other covariates (equation 8). The democracy model residuals are treated as uncorrelated with those from the mood and satisfaction models (9). Instead we allow democracy to exert both immediate and lagged effects on mood and satisfaction (e.g., Claassen 2020*b*):

$$\hat{\theta}_{it}^{(s)} = \mu^{(s)} + \zeta_1^{(s)}\theta_{it-1}^{(s)} + \zeta_2^{(s)}\theta_{it-2}^{(s)} + \delta_1^{(s)}\theta_{it-1}^{(m)} + \delta_2^{(s)}d_{it-1}^{obs} + \delta_3^{(s)}\Delta d_{it}^{obs}X_{it-1}\mathrm{B}^{(s)} + \epsilon_{it}^{(s)} \tag{5}$$

$$\hat{\theta}_{it}^{(m)} = \mu^{(m)} + \zeta_1^{(m)}\theta_{it-1}^{(m)} + \zeta_2^{(m)}\theta_{it-2}^{(m)} + \delta_1^{(m)}\theta_{it-1}^{(s)} + \delta_2^{(m)}d_{it-1}^{obs} + \delta_3^{(m)}\Delta d_{it}^{obs} + X_{it-1}\mathrm{B}^{(m)} + \epsilon_{it}^{(m)} \tag{6}$$

$$\begin{pmatrix} \epsilon_{it}^{(s)} \\ \epsilon_{it}^{(m)} \end{pmatrix} \sim \mathrm{MVN}\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{(s)}^2 & \rho^{(m,s)}\sigma_{(m)}\sigma_{(s)} \\ \rho^{(m,s)}\sigma_{(s)}\sigma_{(m)} & \sigma_{(m)}^2 \end{pmatrix}\right] \tag{7}$$

$$d_{it}^{obs} = \mu^{(d)} + \zeta_1^{(d)}d_{it-1}^{obs} + \zeta_2^{(d)}d_{it-2}^{obs} + \delta_1^{(d)}\theta_{it-1}^{(s)} + \delta_2^{(d)}\theta_{it-1}^{(m)} + X_{it-1}\mathrm{B}^{(d)} + \epsilon_{it}^{(d)} \tag{8}$$

$$\epsilon_{it}^{(d)} \sim \mathrm{N}(0, \sigma_{(d)}^2) \tag{9}$$

As described above, we allow three links between democracy, and each of mood and satisfaction, to be estimated: the lagged effects of mood and satisfaction on subsequent democracy ($\delta_1^{(d)}$ and $\delta_1^{(s)}$); the lagged effect of democracy on subsequent mood and subsequent satisfaction ($\delta_2^{(m)}$ and $\delta_2^{(m)}$); and the immediate effect of change in democracy on mood and satisfaction ($\delta_3^{(m)}$ and $\delta_1^{(m)}$). We also permit three links between mood and satisfaction to be estimated: the correlation between mood and satisfaction residuals $\rho^{(m,s)}$, as well as the direct effect of mood on satisfaction $\delta_1^{(s)}$ and the direct effect of satisfaction on mood $\delta_1^{(m)}$.

2.3. A two-step approach to incorporating measurement uncertainty

Several studies employ a two-step approach to including measurement uncertainty referred to as the "method of composition" (e.g., Tanner 1996; Treier and Jackman 2008). In a situation with a country and year-varying latent variable θ_{it}, the analyst takes a number of draws p from the posterior distribution of their latent estimates $\tilde{\theta}_{pit}$. These draws, rather than than a single set of point estimates, are then employed in subsequent analyses. We illustrate with the following model of democratic mood, which incorporates draws from the posterior distributions of mood and satisfaction (but retaining only the point estimates for democracy):

$$\tilde{\theta}^{(m)}_{pit} = \mu^{(m)} + \zeta^{(m)}_1 \tilde{\theta}^{(m)}_{pit-1} + \zeta^{(m)}_2 \tilde{\theta}^{(m)}_{pit-2} + \delta^{(m)}_1 \tilde{\theta}^{(s)}_{pit-1} + \delta^{(m)}_2 d^{obs}_{it-1} + \delta^{(m)}_3 \Delta d^{obs}_{it} + X_{it-1}\mathrm{B}^{(m)} + \epsilon^{(m)}_{it} \tag{10}$$

Such a model is fit p times, once for each posterior draw of mood and satisfaction. Parameter uncertainty is including by simulating, e.g., 10 draws from the j parameter by p draw matrix of coefficient estimates B and the p-length array of j by j by variance-covariance matrices Σ. Point estimates and confidence intervals can be extracted from the resulting $100 \times 10 = 1000$ draws of estimates for each parameter.

2.4. A one-step approach to incorporating measurement uncertainty

An alternative approach to including measurement uncertainty is to incorporate both the measurement and structural models in a single likelihood function, i.e, to measure latent variables and estimate downstream structural links simultaneously. We present such a one-step measurement and structural model below. It effectively integrates the structural models of mood and satisfaction described above (equations 5 through 7) as expectations into the multivariate dynamic component of the measurement model (equation 4):

$$\begin{pmatrix} \theta_{it}^{(s)} \\ \theta_{it}^{(m)} \end{pmatrix} \sim \text{MVN}\left[\begin{pmatrix} \eta_{it}^{(s)} \\ \eta_{it}^{(m)} \end{pmatrix}, \begin{pmatrix} \sigma^2_{\theta^{(s)}} & \rho_\theta \sigma_{\theta^{(m)}} \sigma_{\theta^{(s)}} \\ \rho_\theta \sigma_{\theta^{(s)}} \sigma_{\theta^{(m)}} & \sigma^2_{\theta^{(m)}} \end{pmatrix}\right] \tag{11}$$

$$\eta_{it}^{(s)} = \mu^{(s)} + \zeta_1^{(s)} \theta_{it-1}^{(s)} + \zeta_2^{(s)} \theta_{it-2}^{(s)} + \delta_1^{(s)} \theta_{it-1}^{(m)} + \delta_2^{(s)} d_{it-1}^{obs} + \delta_3^{(s)} \Delta d_{it}^{obs} X_{it-1} \mathrm{B}^{(s)} \tag{12}$$

$$\eta_{it}^{(m)} = \mu^{(m)} + \zeta_1^{(m)} \theta_{it-1}^{(m)} + \zeta_2^{(m)} \theta_{it-2}^{(m)} + \delta_1^{(m)} \theta_{it-1}^{(s)} + \delta_2^{(m)} d_{it-1}^{obs} + \delta_3^{(m)} \Delta d_{it}^{obs} + X_{it-1} \mathrm{B}^{(m)} \tag{13}$$

This one-step approach allows links between variables, whether observed or measured, to be estimated while accommodating measurement error. It follows a similar logic to the method of structural equation modeling (e.g., Skrondal and Rabe-Hesketh 2004). Yet it can also be understood as a means of using auxiliary variables to improve estimates of latent variables, as, e.g., Blackwell, Honaker, and King (2017) propose in their method of "multiple overimputation." By admitting structural links between covariates into the model, we likely improve the quality of measurement.[1] And by admitting measurement models into the structural models, we improve the validity of parameter estimates. We therefore view this method as superior to the two-step "method of composition."

2.5. Modeling uncertainty in the measurement of democracy

Out final innovation is to include a measurement model for democracy within our one-step approach. Although V-Dem uses a rich set of annual indicators to measure democracy and other governance indices, there still exists uncertainty around these point estimates. We use the country-year point estimates of V-Dem's liberal democracy scale d_{it}^{obs} as well as the corresponding country-year standard deviations d_{it}^{sd}. The following simple measurement model allows measurement error in

[1]The two-step method of composition assumes that the latent estimates θ depend only on the observed indicators of this construct z and not on the covariates X which are linked with θ in the subsequent structural model, i.e., the assumption is $p(\theta \mid z) = p(\theta \mid z, X)$. The one step method described here makes no such assumption.

latent democracy $\theta_{it}^{(d)}$ to be passed on to a structural model of democracy:

$$d_{it}^{obs} \sim N(\theta_{it}^{(d)}, d_{it}^{sd}) \tag{14}$$

$$\theta_{it}^{(d)} \sim N(\eta_{it}^{(d)}, \sigma_{(d)}^{2}) \tag{15}$$

$$\eta_{it}^{(d)} = \mu^{(d)} + \zeta_1^{(d)}\theta_{it-1}^{(d)} + \zeta_2^{(d)}\theta_{it-2}^{(d)} + \delta_1^{(d)}\theta_{it-1}^{(s)} + \delta_2^{(d)}\theta_{it-1}^{(m)} + X_{it-1}\mathrm{B}^{(d)} \tag{16}$$

2.6. Data

Survey measures of support for democracy versus autocracy are used to measure democratic mood, with survey measures of satisfaction with democracy being used for the corresponding construct. We extend Claassen's (2019; 2020*a*) dataset of mood and satisfaction measures, which originally ranged from 1988 to 2017. This is extended forward in time to 2020 for both mood and satisfaction, and backwards in time to 1973 for satisfaction.[2]

We use the Liberal Democracy Index from the Varieties of Democracy (V-Dem) project to measure democracy; both the point estimates and standard deviations of this scale are used as described in the above section. Other covariates included in our structural models are: (1) regional democracy, in both lagged levels and first differences, measured using V-Dem's liberal democracy index aggregated to United Nations regions; (2) corruption, in lagged levels, measured using V-Dem's political corruption index; and (3) logged GDP per capita, in lagged levels and first differences (we treat the latter as a measure of economic growth). We do not model measurement error in these covariates.

2.7. Empirical Strategy

We adopt five approaches to analyzing the interplay between democracy, democratic mood and satisfaction with democracy (see Table 1). The first corresponds to the approach used in previous work on the democracy-support nexus (Claassen 2020*a*;*b*): it ignores measurement uncertainty

[2] See the supplementary materials for further details.

Table 1. Research Design

	Measurement model	Measurement uncertainty	Correlated errors in structural model	Estimation method
1.	Univariate	Omitted	None	MCMC (both steps)
2.	Multivariate	Omitted	Mood & satisfaction	MCMC (both steps)
3.	Multivariate	Included for mood & satisfaction using 2-step method	Mood & satisfaction	MCMC (step 1); GLS (step 2)
4.	Multivariate	Included for mood & satisfaction using 1-step method	Mood & satisfaction	MCMC
5.	Multivariate	Included for mood, satisfaction & democracy using 1-step method	Mood & satisfaction	MCMC

The five approaches we take to analyzing the links in the democracy-support nexus. These either ignore or include measurement uncertainty and either treat mood and satisfaction residuals as orthogonal or correlated.

and analyzes each variable separately. Point estimates of mood and satisfaction are saved and used in a second simultaneous equation model, described by equations 5 through 7. The second utilizes the new multivariate latent variable model, which allows for correlated errors between satisfaction and mood. The uncertainty of measurement is again ignored, with the point estimates of mood and satisfaction saved and used in second step. The third approach also takes two steps but includes measurement uncertainty in the second by modeling 100 draws of the posterior distributions of mood and satisfaction, i.e., the method of composition described in section 2.3 above. The fourth approach integrates measurement and structural links, estimating these in a single step. However it only models measurement uncertainty for mood and satisfaction. The final model, the most powerful, additionally includes measurement uncertainty for liberal democracy.

2.8. Estimation

We use Bayesian Markov Chain Monte Carlo methods to estimate most of our models. Specifically, we use Stan software (Carpenter et al. 2017), which employs a combination of Hamiltonian Monte Carlo and the No-U-Turn Sampler (NUTS) that is particularly useful for the complex models presented here. The one exception is the third approach (Table 1), which uses the method of composition. Here, the second step SEMs are fit using generalized least squares, as employed by the systemfit library for R (Henningsen and Hamann 2007).

3. Analysis

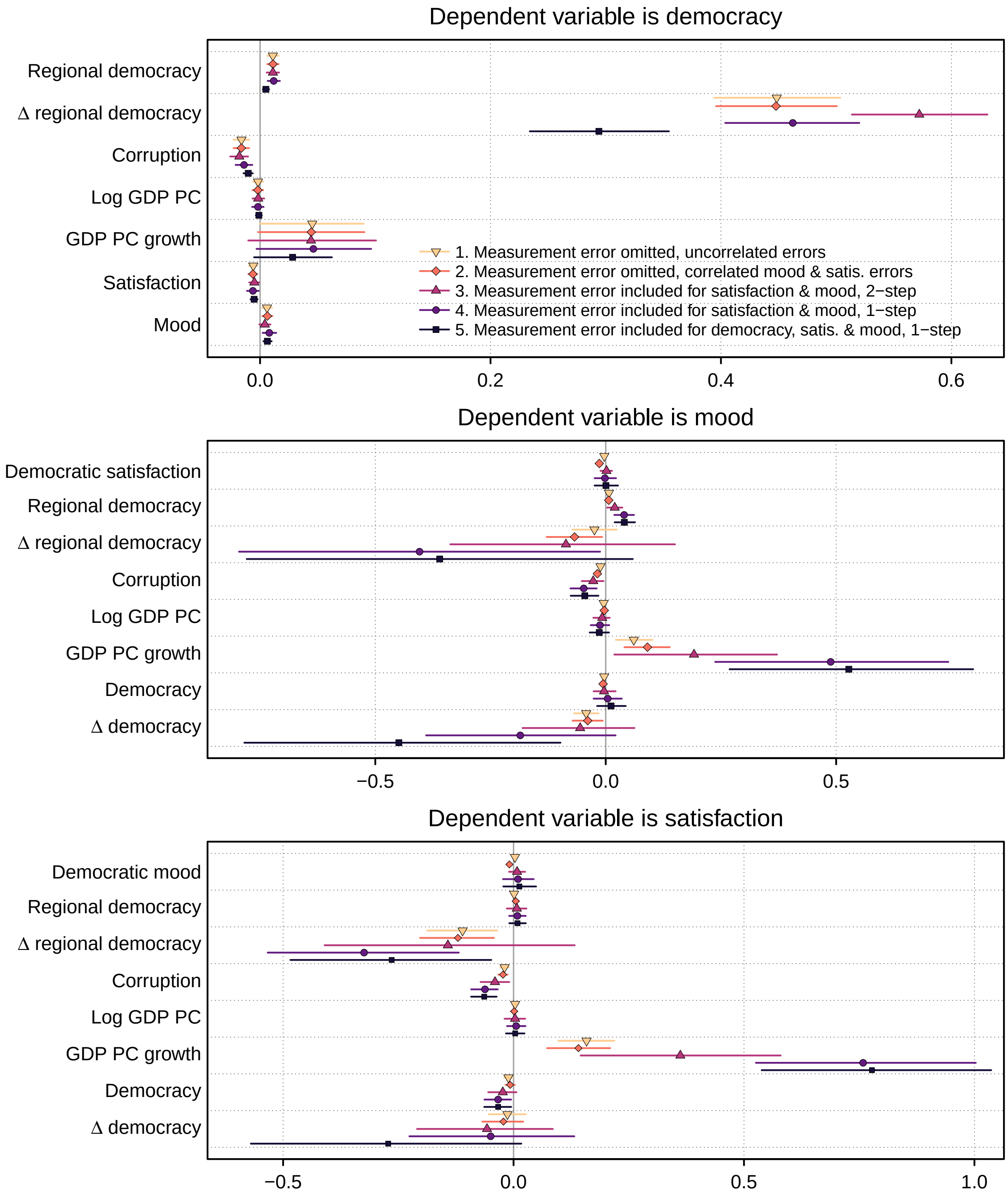
Our analysis proceeds in two parts. We first examine the direct effects of various covariates on mood, satisfaction and democracy (i.e., B), as well as direct effects on these variables on each other (i.e., δ). Since these are short run effects and we have dynamic models, we then examine the long run effects of changes in mood on democracy and satisfaction, as well as changes in democracy on mood and satisfaction.

3.1. Short run effects

The short run effects are shown in Figure 1 (we have omitted the lags and intercepts for clarity of presentation). Beginning with our first endogenous variable, democracy (top plot), one can see that the effects are largely consistent across the five modeling approaches, regardless whether we exclude measurement error (yellow triangles and orange diamonds), include it via the two-step method (pink triangles), or include it via the one-step models (violet circles and navy squares). This is likely a product of the low levels of measurement uncertainty in the V-Dem Liberal Democracy Index, which, in turn, is the result of the large number of annual indicators used in the measurement of that Index. Examining the structural links between democracy and our measures of system support, we see that mood exhibits a consistently positive short run effect on subsequent democracy, very much in line with the results originally reported by Claassen (2020*a*). Note that this link between lagged mood and subsequent democracy is not distinguishable from zero under the third approach, but is greater than zero (at the 95% level) in the other four approaches. We return to this particular link in the next sub-section, when we consider long run effects.

Turning to the results for mood as an endogenous variable (middle plot), we see somewhat different effects across the five modeling approaches, reflecting the greater degree of uncertainty in the measurement of mood. In particular, there is considerable variation across the five approaches in the estimated thermostatic effect of democracy (i.e., Δ democracy), one of the key links in the democracy-support nexus. While the five estimates all show the negative thermostatic effect

Figure 1. Direct, short-run effects of covariates on democracy, democratic mood and satisfaction



Estimated effects of covariates (in rows) on each endogenous variable (panels) in the model. Points show the mean of the posterior distribution for each parameter; horizontal bars, the 95% uncertainty intervals. Markov-Chain Monte Carlo methods are used for all approaches (details in online supplementary materials) except the third, which is estimated using GLS. Each model includes two lags of the endogenous variable and an intercept, which are not shown here.

identified by Claassen (2020*b*), the magnitude of the effect increases to the extent that measurement uncertainty is included. The uncertainty of the estimates increase too. Nevertheless, in the model including measurement error for democracy, mood, and satisfaction, this thermostatic effect is clearly distinguishable from zero, supporting the results of Claassen (2020*b*).

It is also evident that the lagged level of democracy lacks much of impact on mood. Although the small positive effects seen in the fourth and fifth models would accumulate over time in our dynamic setup, both these uncertainty intervals include zero. As such, in the long run, it is no clear whether democracy has a positive effect on mood, or, rather, no effect at all. This is consistent with the findings of Claassen (2020*b*).

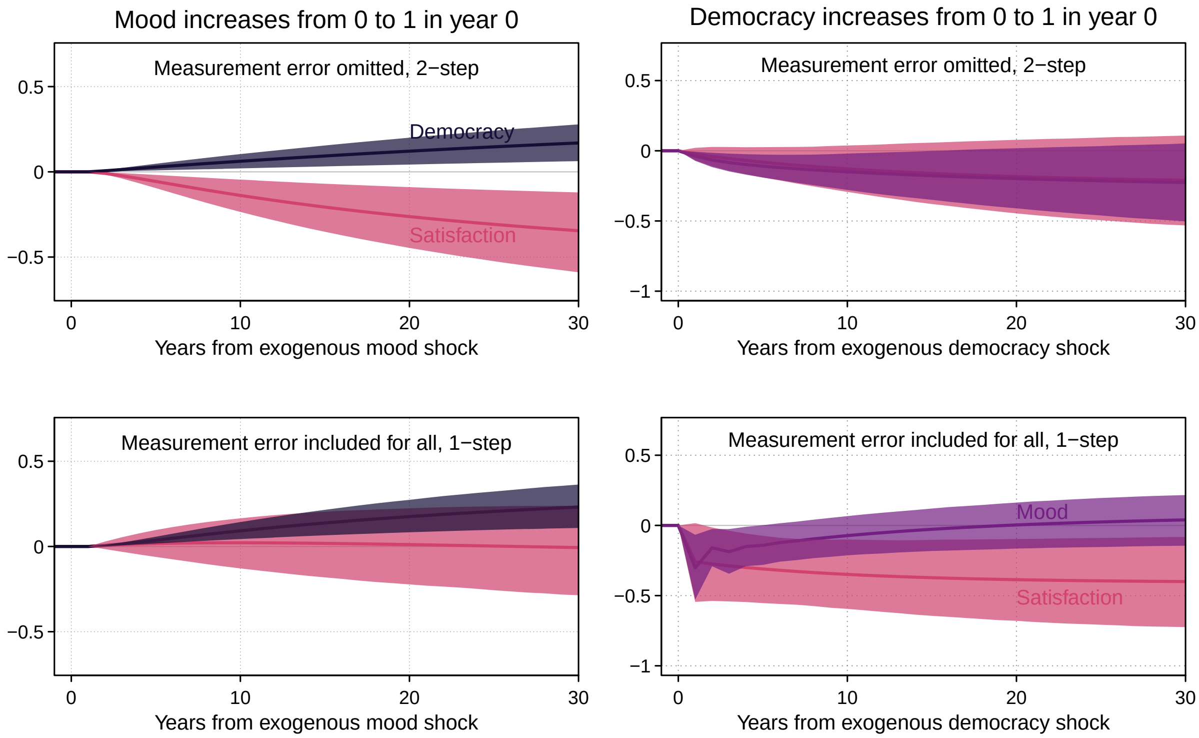
As mentioned, our dynamic models allow the short-run effects of lagged covariates to build up over time to the extent that there are positive effects of lagged endogenous variables. Moreover, since our modeling framework allows for reciprocal effects, structural effects can spill over from one model onto another. To examine the net impact of both features, i.e., long run dynamics and reciprocal effects, we turn to simulated dynamic effects. The estimation of such effects naturally fits within the one-step approach, particularly when estimated using MCMC methods, because the simulation draws of MCMC algorithms allow measurement and model uncertainty to propagate to any simulated quantities.[3]

3.2. Long run effects

These long run effects are presented in Figure 2. Simulations from only two of the five approaches are presented for brevity: the simple two-step method that omits measurement uncertainty (the second approach in Table 1) and the most powerful one-step approach that includes measurement uncertainty for mood, satisfaction, and democracy (the fifth approach in Table 1). The plots on the left show the simulated long-run effects, on democracy and satisfaction, of a one standard deviation increase in mood, while the plots on the right show the long-run effects, on mood and satisfaction,

[3]Note that these simulations are within-sample, counterfactual analyses and are not forecasts. Uncertainty in structural parameters, e.g., B is retained, but not residual uncertainty, e.g., $\sigma^2_{(m)}$.

Figure 2. Long run effects of changes in mood and democracy



Simulated long run effects of a one standard deviation increase in mood (left) and democracy (right). These effects were generated as part of the Markov-Chain Monte-Carlo process for each model using the fitted parameter estimates of each MCMC draw. Being a within-sample analysis of a counterfactual, rather than a forecast, uncertainty in direct effects (δ and B) and lags ζ, but not error variances ($\sigma^{(s)}$) are included.

of a one standard deviation increase in democracy.

The simulated effects of an increase in mood on democracy (left) illustrate how the small short run effects shown in Figure 1 accumulate over time. The long run effects are similar whether measurement error in mood and democracy is included (bottom plot) or whether it is excluded. These results again suggest that mood creates positive pressure on democratic change, as argued by Claassen (2020*a*).

The long run effects of change in democracy (right plots) are somewhat more complex. Not only are there short run effects of lagged democracy at play, but also immediate effects of democratic change, as per the mood and satisfaction models specified earlier. While the effect of lagged democracy accumulates slowly over time, the effect of change in democracy should make an immediate impact before dissipating. Here we see the long run effects vary somewhat when measurement error is excluded (top) or included (bottom). The former shows a gradual, but largely permanent decline in mood following the increase in democracy. The latter, in contrast, shows a long run effect consistent with that reported by Claassen (2020*b*): an increase in democracy triggering a more dramatic decline in mood, but one that is reversed relatively quickly, within a decade or two.

4. Conclusion

This paper returns to the democracy-support nexus, with both methodological and substantive objectives. We advance beyond existing work on this topic by incorporating satisfaction with democracy into the nexus, modeling links between mood, democracy, and satisfaction simultaneously, including correlated errors in the measurement of latent mood and satisfaction, and testing two methods of including measurement uncertainty.

Methodologically we show (as have others before) that omitting versus including measurement error matters. Yet we find also that the method of including measurement error matters at least as much, as does the variables for which measurement error is included. In addition to the two-step approach to including measurement error (i.e., the method of composition), we demonstrate a one-step method where variables are measured and structural links estimated in a single step. By including measurement uncertainty, this offers an improvement over two-step methods which omit uncertainty. It also offers an improvement over two-step methods of including uncertainty because the incorporation of auxiliary variables helps improve the quality of latent estimates.

Substantively, we find – when accommodating measurement uncertainty and allowing for correlated errors between mood and satisfaction – that changes in democracy do provoke a thermostatic reaction in which democratic mood immediately falls. As we show in our dynamic simulations, however, this reaction is temporary, and is entirely reversed within a decade. We also show that mood exerts a positive influence on subsequent levels of democracy. Although small in the short run, an increase in mood produces pressure for democratization that accumulates steadily over the decades.

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