Democracy, Public Support, and Measurement Uncertainty

Abstract

Do democratic regimes depend on public support to avoid backsliding? Does public support, in turn, respond thermostatically to changes in democracy? Two prominent recent studies (Claassen 2020a, 2020b) reinvigorated the classic hypothesis on the positive relationship between public support for democracy and regime survival—and challenged its reciprocal counterpart—by using a latent variable approach to measure mass democratic support from cross-national survey data. But such approaches come with concomitant measurement uncertainty, and neither study incorporated this uncertainty into its analyses. In this letter, we correctly take measurement uncertainty in account and show that there is no support for the conclusion of either study. We then work to minimize the measurement uncertainty in public support by incorporating additional survey data. Even with this expanded evidentiary base, however, our analyses fail to yield evidence in support of either hypothesis, underscoring the necessity of accounting for measurement uncertainty. [144/150 words]

(Word count: 3888)

It has long been argued that democratic regimes and public support for them are mutually reinforcing: that high levels of public support ensure democracies remain strong, and that experience with democratic governance generates robust public support (see, e.g., Lipset 1959; Easton 1965). But the evidence for either part of this claim has been decidedly mixed. Countries with greater democratic support have been found to become stronger and more stable democracies (e.g., Inglehart and Welzel 2005, 251–54) and just the opposite (Fails and Pierce 2010, 182–83). Similarly, studies have alternately found that more experience with democracy yields more democratic support (e.g., Fails and Pierce 2010, 183; Wuttke, Gavras, and Schoen 2020b, 5–6) or instead that long-established democracies are suffering from democratic fatigue (e.g., Denemark, Donovan, and Niemi 2016; Foa and Mounk 2017).

One important reason for these mixed results is the difficulty in measuring democratic support over time and across many countries. Public support for democracy cannot be directly observed, and its incorrect measurement will limit inferences about the relationships between public opinion and institutional development. Further, the survey data available across countries and over time on support for democracy—or indeed most topics in public opinion—are sparse and incomparable, greatly hindering broadly comparative research. Recently, a few pioneering studies have sought to overcome the hurdle of sparse and incomparable data by developing latent variable measurement models of public opinion (see Caughey, O'Grady, and Warshaw 2019; Claassen 2019; Solt 2020b). A pair of prominent recent works took advantage of this latent variable approach to measure democratic support for over one hundred countries for up to nearly three decades and to then assess, respectively, its consequences for and roots in democratic change (Claassen 2020a, 2020b). The first of these works concluded, supporting the classic argument, that mass support had a positive impact on democratic change, especially the endurance of democracy (Claassen 2020a, 127–30). The second directly contradicted the classic argument, concluding that democratic change has a thermostatic effect on public support, that is, that rather than generating its own support, deepening democracy provokes a backlash and it is instead democratic backsliding that calls forth greater public support (Claassen 2020b, 46–50).

The models employed in these studies' analyses, though, do not account for uncertainty in their measurement of democratic support. Because they are unobserved, latent variables are inherently accompanied by measurement uncertainty. To leave this uncertainty unacknowledged is to make the implausible assumption that the latent variables are measured perfectly, an assumption which distorts both statistical and substantive inference (see, e.g., Crabtree and Fariss 2015; Juhl 2019).

In this letter, we reexamine the classic arguments about support for democracy and democratic change tested in these two pieces while correcting this oversight. In addition to incorporating the measurement uncertainty, we also sought to reduce it by expanding considerably the survey data drawn upon and re-estimating democratic support for 144 countries for up to 33 years between 1988 and 2020. Our analyses reveal that the significant relationships between public support and democratic change disappear once measurement uncertainty is taken into account, both in replications with the studies' original data and in our extension analyses that incorporate the additional data. That is, once measurement uncertainty is accounted for, there is no empirical support for either claim put forward in these two works: declining democratic support does not signal subsequent democratic backsliding, and changes in democracy do not spur a thermostatic response in democratic support.

There are several important implications of these null results. They point to a need for closer attention to the conditional aspects of the classic theory (see Lipset 1959, 86–89; Easton 1965, 119–20). On the one side, the effect of democracy on public support may depend not on its mere existence but on its effectiveness (see Magalhães 2014) and particularly with regard to redistribution (see Krieckhaus et al. 2014). On the other, the impact of public support on democracy may depend on the extent to which those who support democracy are also dissatisfied with the current regime's performance (see Qi and Shin 2011). Similarly, the results presented here are further evidence that the survey items commonly employed to measure democratic support are inadequate to the task. Because these questions contain no information on respondents' support for democracy relative to other values with which it may come into conflict, such as their partisanship (see, e.g., Carey et al. 2020; McCoy, Simonovits, and Littvay 2021)—or on whether respondents even understand the meaning of the democracy they are claiming to support (see, e.g., Kirsch and Welzel 2019; Wuttke, Schimpf, and Schoen 2020)—these questions appear to miss capturing, when public support is in fact needed, the true extent of the support among the public that democracy will actually find. Our results also reinforce arguments that relationships between democracy and public support unfold only over the long term (see, e.g., Welzel, Inglehart, and Kruse 2017) and that democratic change in the short-term is instead best understood as an elite-driven phenomenon (see, e.g., Levitsky and Ziblatt 2018; Haggard and Kaufman 2021).

We draw two conclusions, one methodological and one substantive. Many constructs in social science are latent variables, including but not limited to corruption, polarization, public attitudes, policy preference, social norms, and economic behaviors. As latent variable measurement models become more commonly used, it is absolutely necessary for researchers employing them to incorporate the associated uncertainty into analyses. The technique and codes used in this study can be handily applied to empirical studies with latent variables and address the uncertainty for models with only one or multiple latent variables on both sides of the models without any further change in modeling strategy. This letter contributes to the recent methodological development in measurement models by emphasizing the necessity of incorporating uncertainty. It highlights a necessary procedure and provides a practicable approach for examining theory generalization in comparative studies. And, at a time when democracy is seen as under threat around the world (e.g., Diamond 2015; IDEA 2021), taken together, Claassen (2020a, 2020b) send what is ultimately a reassuring message: the fate of democracy rests with us, the public, and when democratic institutions are undermined, we will swing to their support and constitute "an obstacle to democratic backsliding" (Claassen 2020b, 51). Both of these assertions may well be true, but the evidence we have, properly assessed, does not support them. There is no room for complacency.

Method

We proceed in three steps. First, we reproduce the original analyses of Claassen (2020a, 2020b), which included only the point estimates of the latent variable of democratic support and so exclude its measurement uncertainty. Second, we collect the original cross-national survey data, replicate the latent variable measure of democratic support used in the two articles, and conduct the articles' analyses again, this time maintaining the entire distribution of estimates of democratic support in each country-year.[1] As democracy is also a latent variable in these analyses, we include the uncertainty in its estimates as well, along with that for corruption in the models of Claassen (2020b). We also include the uncertainty for GDP and Resource Dependence variables by using multiple imputation. In the third step, we collect even more survey data—increasing these source data by one-third—and re-estimate the two articles' analyses once more, again maintaining the full distribution of estimates to

[1] Additional details on this data replication process are found in Supplementary Information Appendix A.

preserve measurement uncertainty.[2]

Incorporating Uncertainty

Although measurement uncertainty has not yet attracted attention in the field of comparative public opinion (see, in addition to the works examined here, O'Grady and Abou-Chadi 2019), latent variables are estimated with a quantifiable amount of measurement errors, and measurement errors can reverse the sign of estimation of coefficients (Bound, Brown, and Mathiowetz 2001, 3709; Saccenti, Hendriks, and Smilde 2020, 8), attenuate or exaggerate coefficient estimates as well as bias standard errors (see, e.g., Blackwell, Honaker, and King 2017, 318–19; Caughey and Warshaw 2018, 254). In light of this, recent studies measuring other latent variables have recommended incorporating their measurement uncertainty in analyses (see Solis and Waggoner 2020, 18; Gandhi and Sumner 2020, 1553), and research examining the consequences of public opinion in the United States has done so (see, e.g., Kastellec et al. 2015, 791–92; Caughey and Warshaw 2018, 254).

Therefore, after replicating the original analyses that use only the point estimates for public support and the other variables included in the model, we perform the analyses again only this time incorporating uncertainty in analysis models using our replication data. We conduct inferences from the distributive data via the technique known as the "method of composition" (MOC) (Tanner 1993, 52). MOC accounts for uncertainty from opinion estimates and analysis models through each modeling stage. In analysis stage, uncertainty is incorporated through simulation based on variance-covariance matrix of a given model, regardless of the structures or features of the given model. Therefore MOC can adapt any different types of models, including but not limited to different specifications for a Time-Series-Cross-Sectional approach for TSCS data (Caughey and Warshaw 2018, A15–16), a Cox proportional hazards model (Treier and Jackman 2008, 215), or individual level roll call

[2] We also attempted to make fuller use of the available survey data by employing the DCPO model (Solt 2020b), which unlike the (Claassen 2019) model does not dichotomize ordinal responses. The better fit of the DCPO model to the data on democratic support (see Solt 2020b, 10–12) and the additional information it incorporates, however, did not yield substantively different results; see Supplementary Information Appendix C.

voting model (Kastellec et al. 2015, 791).[3]

As an alternative way, a structural equation model(SEM) which incorporates measurement model and structural links between variables together can also account for bias caused by simultaneity between variables and measurement models. However, SEM is a method to test the match between the model and the data, subject to confirmation bias due to the existing of competing theories which we have in the theory on democracy and public opinion, omitted variables, linear causal relationship assumption, the sensitivity to the estimator choice when both endogenous and endogenous are contaminated by measurement errors (Umeh Edith and Ogu Ezenwa 2019), among others (Tomarken and Waller 2005).

In contrast, MOC is flexible to accommodate not only various models but also multiple layers of uncertainty in both opinion estimates and substantive models (Kastellec et al. 2015, 792) where the model and joint distribution of the error and all the variables in the model determine the bias introduced by measurement errors (Bound, Brown, and Mathiowetz 2001, 3708).

Adding More Data

To provide a further test of the classic arguments on democracy and public support, we generated estimates of democratic support using the same procedure as in Claassen (2020a, 2020b) on a bigger data set, assembling as much survey data on democratic support as possible. We employed 4905 national opinions on democracy from 1889 national surveys, representing a 32.0% and 37.3% increase respectively over the 1165 opinions and 1376 national surveys used in Claassen (2020a, 2020b).[4]

[3]For additional details on this technique, see Supplementary Information Appendix B.

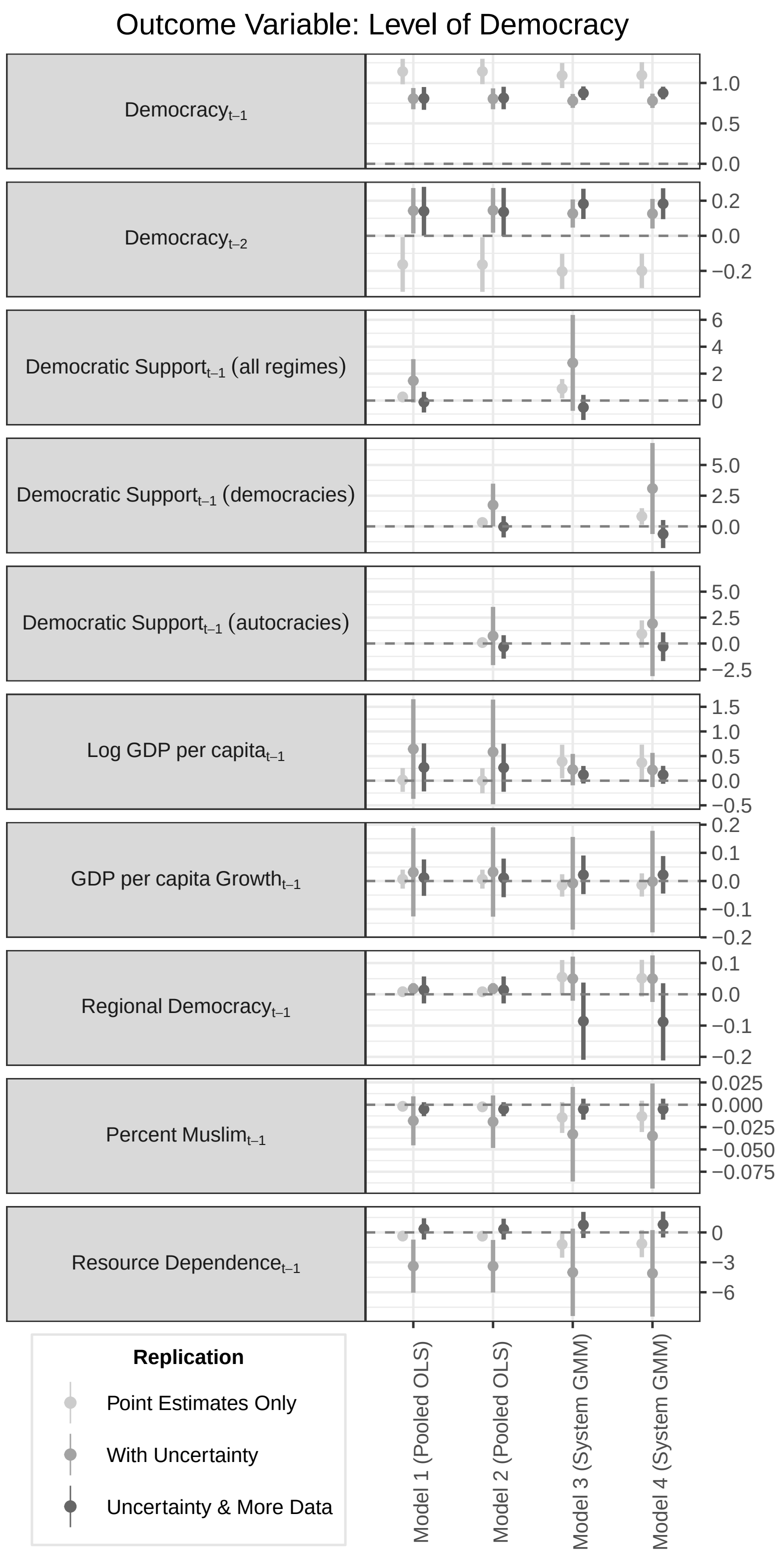
[4]These figures represent the survey data actually used in estimating public support for democracy; as in Claassen (2020a, 2020b), countries for which two separate years of survey data were not available were excluded.

Results

Figure 1 presents the reanalyses of the hypothesis that public support influences the level of democracy (Claassen 2020a, Table 1, 128). The lighter, lefthand set of results replicate the analysis of Claassen (2020a), including its exclusion of measurement uncertainty by using only the point estimates of public democratic support and the other variables measured with quantified error (democracy and corruption), and they reproduce that article's findings. The middle results introduce a single change: the uncertainty in the measurement of public support is taken into account. In all four models, the positive coefficients for democratic support are no longer statistically significant. The darker, righth and results also incorporate uncertainty but additionally replace the estimates of democratic support with those based on our expanded dataset; this change works to increase the number of observations analyzed as well. Although the confidence intervals shrink considerably, the coefficient estimates move much closer to zero; the hypothesis remains unsupported.

In Figure 2, we examine the thermostatic model of democratic support per Claassen (2020b, 47, Table 1, 49, Table 2). The negative coefficient estimates for change in liberal democracy in the lefthand set of results, which do not take uncertainty into account, imply that the immediate effect of a increase in the level of democracy is a decline in public support for democracy and of a decrease in democracy an expansion of support—that democratic support indeed does respond thermostatically to democracy. However, the middle results demonstrate that this thermostatic effect, too, does not hold after the measurement uncertainty is accounted for. And again, the righthand results reveal that the additional data of our extension do not provide support for the original conclusion.

In short, the conclusions of Claassen (2020a, 2020b) that democratic support has a positive effect on democracy and change in democracy a negative effect on change in support are not empirically supported once measurement uncertainty is taken into account, even when more data are used.



Replications of Claassen (2020a), Table 1, 128.

Figure 1: The Effect of Public Support on Democracy with Uncertainty

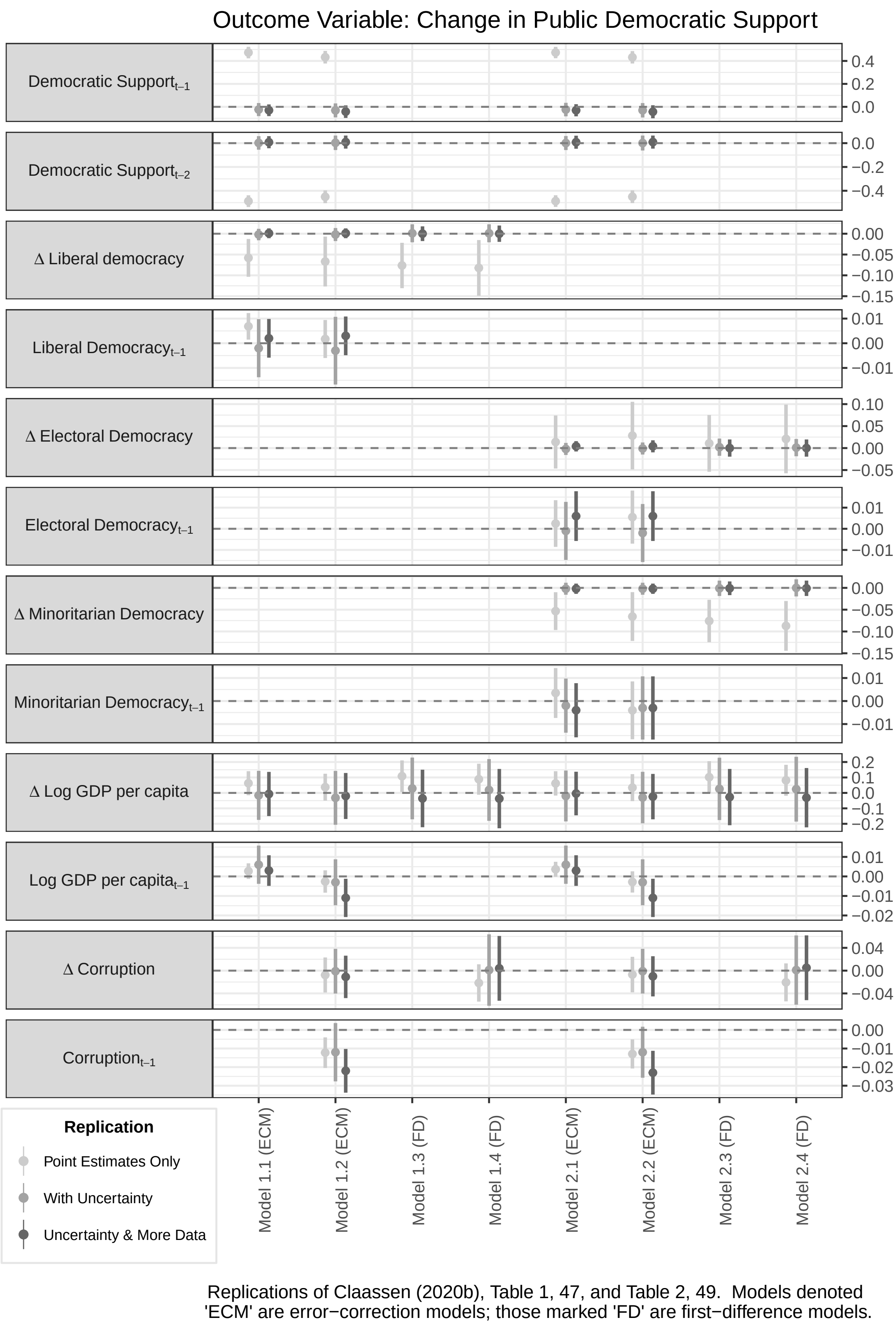


Figure 2: The Effect of Democracy on Change in Public Support with Uncertainty

Discussion

These null results have a number of important substantive implications. First, they underscore that it is crucial to recognize the conditional aspects of the classic theory regarding democracy and democratic support. With regard to how levels of democracy affect public support, even the early proponents of the classic argument did not contend that the mere existence of democratic institutions, no matter how consistently feckless and ineffective, would generate support among the public: instead, they maintained, public support would be gained through experience with government performance that was generally effective (Lipset 1959, 86–89; Easton 1965, 119–20). There is some empirical evidence for this, with government effectiveness positively related to public support among democracies and negatively related in non-democracies (Magalhães 2014). The finding of Krieckhaus et al. (2014) that income inequality is strongly negatively related to public support in democracies suggests that performance regarding redistribution is particularly important. On the reverse part of the classic argument, Qi and Shin (2011) suggests that democratic support alone cannot be expected to generate democratic change and oppose backsliding. Instead, that work contends, it is the combination of democratic support and dissatisfaction with current regime performance that generates demand for greater democracy. Whether these conditional relationships exist among the newly available latent-variable data on democracy and democratic support remain questions for future research.

Further, these null results recommend building recent and more refined conceptualizations of democratic support into our measures. In other words, the survey items employed by Claassen (2020a, 2020b)—which ask respondents to assess the desirability or appropriateness of democracy, to compare democracy to some undemocratic alternative, or to assess one of these alternatives—although often used by researchers, may not capture every aspect of democratic support necessary for it to play its hypothesized roles in the classic theory. One possibility is that only those who profess to prefer democracy to its alternatives *and also* value freedom of expression, freedom of association, and pluralism of opinion will take appropriate action when democracy is threatened (see, e.g., Schedler and Sarsfield 2007).

Another is that respondents' other values, such as their policy preferences or partisanship, may weigh more heavily than their support for democracy: there is growing evidence that, at least in the United States, there are many for whom these other considerations excuse substantial transgressions against democracy (see Carey et al. 2020; Graham and Svolik 2020; McCoy, Simonovits, and Littvay 2021). Yet another is that the answers to the above items reflect actual support for democracy only when respondents also either hold a robust understanding of what liberal democracy means or anchor their support in emancipative values of universal freedoms. If they do not, their positive responses to these items indicate support for autocracy instead (see, e.g., Brunkert, Kruse, and Welzel 2019; Kirsch and Welzel 2019; Wuttke, Gavras, and Schoen 2020a). Taking any or all of these into account requires considering the *combination* of attitudes: even the inclusion of additional questions in a unidimensional public opinion model such as that provided by Claassen (2019) will not be sufficient (see, e.g., Wuttke, Schimpf, and Schoen 2020).

Finally, by failing to provide evidence for a short-term relationship between democratic support and democracy, these null findings can be seen to lend additional support to other theories of regime change. There are compelling arguments that episodes of democratic transition (see, e.g., O'Donnell, Schmitter, and Whitehead 1986; Karl 1987) and backsliding (see, e.g., Levitsky and Ziblatt 2018; Haggard and Kaufman 2021) are best understood as products of elite decision making. With regard to the latter, critics have charged that these claims overlook the extent of demand for authoritarian rule among the public (see, e.g., Norris 2021). The null results reported here, by finding that year-to-year changes in democratic support bear little relationship to changes in democracy, highlight that levels of public support appear to relate to regime only over the long run (see also Welzel, Inglehart, and Kruse 2017), leaving elite decisions as a powerful explanation for when and how short-term developments unfold.

Conclusion

In this letter, we reexamined the findings from Claassen (2020a, 2020b), two articles that maintain that public support helps the survival of democracy and democratic development has a thermostatic effect on public support. We demonstrated the importance of incorporating measurement uncertainty in analyzing the relationship between public support and democracy. Taking uncertainty into account rendered both articles' conclusions without empirical support, even when we added a considerable quantity of additional data.

This points to the absolute necessity of incorporating measurement uncertainty into analyses that include latent variables. As the use of latent variables grows more common in political science, both researchers and readers should be aware that these variables' concomitant measurement uncertainty cannot be neglected. Since measurement uncertainty distorts both statistical and substantive inferences with unknown directions on the sign and size of coefficients (Bound, Brown, and Mathiowetz 2001; Blackwell, Honaker, and King 2017; Caughey and Warshaw 2018), it is not only a methodological concern but also has substantive implications (Juhl 2019).

The null results reached in this letter have several substantive implications. They highlight theoretical arguments that maintain that levels of democratic support undergird democracy only over the long term and so lend indirect support to other explanations for short-run changes in regime. They also draw attention to the conditional nature of the classic argument on democracy and democratic support as well as to challenges in measuring the concept of democratic support that remain unmet by existing time-series cross-sectional latent-variable models. Most importantly, the sanguine assessment that readers may draw from Claassen (2020a, 2020b)—that the fate of democracies depend on public support, and when eroded, their publics will rally to them—is not supported by the current evidence. Those who would defend democracy have no grounds to be complacent.

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Online Supplementary Information Appendix

A Replication Notes

Because the Dataverse replication files for Claassen (2020a) and Claassen (2020b) included only the point estimates of their variables, replicating those articles' analyses while incorporating the quantified uncertainty in their latent variables was not possible using only those files. Instead, it required re-collecting all of the data employed in those articles directly from their original sources, that is, in the terminology of Grossman and Pedahzur (2020), it required a primary replication rather than a secondary one. We describe this process for the latent variables here.

Democratic Support

First, for each item used in the two articles' measure of democratic support, we identified the original variable names and corresponding values in each survey dataset. We then used the `dcpo_setup` and `format_claassen` functions of the `DCPOtools` R package to automate the process of generating a dataset of survey marginals. These survey marginals were then used to generate estimates of democratic support in Stan using the `supdem.stan.mod5.stan` script from the Claassen (2020a) Dataverse materials. Draws from the posterior distribution quantify the uncertainty in the estimates.

Democracy

The democracy variables in the two articles are drawn from Version 8 of the V-Dem Dataset (Coppedge et al. 2018). This version of the dataset includes draws from the posterior distribution of the estimates to quantify their uncertainty. In our extension (the rightmost replication of each model in our Figures 1 and 2), we are able to extend the time series beyond the last year of Version 8, 2017, so we use the updated Version 10 instead. Version 10, however, does not include posterior draws of the estimates, but rather standard errors. For the purposes of incorporating this uncertainty into our analyses, we assumed a normal distribution around the point estimates.

Corruption

The corruption variable used in Claassen (2020b) is the Corruption Perceptions Index, which provides point estimates and standard errors for the years from 2012 to 2018. For country-years beyond that range, we estimated standard errors for by first identifying the country's maximum relative standard error (standard error/point estimate) during 2012-2018 and then multiplying this quantity by the country-year's point estimate. For the purposes of incorporating this uncertainty into our analyses, we again assumed a normal distribution around the point estimates.

In Appendix B, we illustrate how we employed these simulated distributions to take uncertainty into account in our analysis models.

A.1 Numeric Results for Figure 1 and Figure 2

During the replications of Claassen (2020a);Claassen (2020b), we found several miscoding across the original data. For example, in Claassen (2020b) that the author coded the option "Necesitamos un líder fuerte que no tenga que ser elegid" as "strong_lapop_2" for the question:

> Hay gente que dice que necesitamos un líder fuerte que no tenga que ser elegido a través del voto. AUT1 Otros dicen que aunque las cosas no funcionen, la democracia electoral, o sea el voto popular, es siempre lo mejor. ¿Qué piensa usted? [Leer alternativas]

But according to the description of the question, this ought to be "strong_amb_1." Another example involves a miscount of the midpoint of its three-point scale as a positive, democracy-supporting response, when the original work coded "evdemoc_asiab" in the Asian Barometer. In a separate ongoing research project, we will identify the main types of miscoding and evaluate the extent to which they affect on the inferences. In this work, we use the corrected data for the replications with uncertainty to ensure that the data quality would not distort the results.

Moreover, for the GMM models, the original publication presented the observation number based on the trimmed data, i.e., "2435", while the tabulating function in the replication file (line 86) uses the full used-observation number, "4735." We follow the replication file in the following tables.

Table A.1: The Effect of Public Support on Democracy (Original Results)

	Pooled	Pooled-Regime	GMM	GMM-Regime
(Intercept)	0.647	0.765		
	(0.947)	(0.998)		
Democracy (t-1)	1.141	1.142	1.091	1.095
	(0.080)	(0.080)	(0.079)	(0.083)
Democracy (t-2)	−0.163	−0.164	−0.203	−0.200
	(0.080)	(0.079)	(0.051)	(0.050)
Support (t-1)	0.267		0.881	
	(0.094)		(0.366)	
Support in Democracy		0.318		0.810
		(0.108)		(0.344)
Support in Autocracy		0.090		0.917
		(0.210)		(0.672)
Log GDP Per Capita (t-1)	0.015	−0.001	0.388	0.366
	(0.123)	(0.130)	(0.174)	(0.186)
GDP Per Capita Growth (t-1)	0.007	0.007	−0.016	−0.014
	(0.017)	(0.017)	(0.020)	(0.021)
Regional Democracy (t-1)	0.008	0.008	0.055	0.051
	(0.005)	(0.004)	(0.028)	(0.030)
Percent Muslim (t-1)	−0.002	−0.002	−0.014	−0.013
	(0.003)	(0.003)	(0.009)	(0.009)
Resource Dependence (t-1)	−0.367	−0.373	−1.196	−1.128
	(0.244)	(0.242)	(0.683)	(0.694)
N observations	2435	2435	4735	4735
N countries	135	135	135	135
N instruments			122	124

Table A.2: The Effect of Public Support on Democracy (With Uncertainty)

	Pooled	Pooled-Regime	GMM	GMM-Regime
Democracy (t-1)	0.806	0.804	0.778	0.779
	(0.067)	(0.066)	(0.044)	(0.045)
Democracy (t-2)	0.143	0.145	0.127	0.126
	(0.066)	(0.065)	(0.041)	(0.043)
Support (t-1)	1.468		2.799	
	(0.821)		(1.817)	
Support in Democracy		1.739		3.083
		(0.887)		(1.890)
Support in Autocracy		0.722		1.915
		(1.434)		(2.586)
Log GDP Per Capita (t-1)	0.643	0.584	0.225	0.218
	(0.516)	(0.542)	(0.163)	(0.177)
GDP Per Capita Growth (t-1)	0.031	0.032	−0.008	−0.002
	(0.080)	(0.081)	(0.084)	(0.092)
Regional Democracy (t-1)	0.018	0.018	0.050	0.050
	(0.009)	(0.009)	(0.036)	(0.038)
Percent Muslim (t-1)	−0.018	−0.019	−0.033	−0.035
	(0.014)	(0.015)	(0.027)	(0.030)
Resource Dependence (t-1)	−3.381	−3.389	−4.004	−4.104
	(1.357)	(1.344)	(2.235)	(2.213)
N observations	2430	2430	4726	4726
N countries	134	134	135	135
N instruments			122	122

Table A.3: The Effect of Public Support on Democracy (Uncertainty & More Data)

	Pooled	Pooled-Regime	GMM	GMM-Regime
Democracy (t-1)	0.809	0.814	0.873	0.876
	(0.072)	(0.071)	(0.043)	(0.040)
Democracy (t-2)	0.140	0.136	0.182	0.183
	(0.071)	(0.070)	(0.044)	(0.045)
Support (t-1)	−0.119		−0.510	
	(0.392)		(0.476)	
Support in Democracy		−0.032		−0.622
		(0.442)		(0.583)
Support in Autocracy		−0.333		−0.310
		(0.578)		(0.709)
Log GDP Per Capita (t-1)	0.270	0.263	0.121	0.119
	(0.249)	(0.249)	(0.091)	(0.093)
GDP Per Capita Growth (t-1)	0.012	0.011	0.022	0.022
	(0.033)	(0.035)	(0.035)	(0.034)
Regional Democracy (t-1)	0.014	0.014	−0.086	−0.088
	(0.022)	(0.022)	(0.063)	(0.063)
Percent Muslim (t-1)	−0.005	−0.005	−0.005	−0.005
	(0.004)	(0.004)	(0.006)	(0.006)
Resource Dependence (t-1)	0.350	0.328	0.749	0.791
	(0.544)	(0.534)	(0.669)	(0.663)
N observations	2792	2792	5443	5443
N countries	141	141	143	143
N instruments			130	130

Table A.4: The Effect of Democracy on Change in Public Support (Original)

	ECM	ECM-Regime	FD	FD-Regime	ECM Corrup	ECM Corrup-Regime	FD Corrup	FD Corrup-Regime
Democratic Mood (t-1)	0.473	0.473			0.433	0.432		
	(0.026)	(0.025)			(0.028)	(0.028)		
Democratic Mood (t-2)	−0.487	−0.487			−0.451	−0.450		
	(0.025)	(0.025)			(0.027)	(0.027)		
Liberal Democracy (Difference)	−0.058		−0.076		−0.067		−0.082	
	(0.023)		(0.028)		(0.031)		(0.034)	
Liberal Democracy (t-1)	0.007				0.002			
	(0.003)				(0.004)			
Electoral Democracy (Difference)		0.014		0.011		0.028		0.021
		(0.031)		(0.033)		(0.039)		(0.040)
Electoral Democracy (t-1)		0.002				0.006		
		(0.006)				(0.006)		
Minoritarian Democracy (Difference)		−0.053		−0.076		−0.066		−0.087
		(0.022)		(0.025)		(0.029)		(0.029)
Minoritarian Democracy (t-1)		0.003				−0.004		
		(0.006)				(0.006)		
Log GDP Per Capita (Difference)	0.063	0.062			0.037	0.034		
	(0.040)	(0.040)			(0.044)	(0.045)		
Log GDP per capita (Difference)			0.108	0.102			0.089	0.082
			(0.052)	(0.053)			(0.051)	(0.051)
Log GDP (t-1)	0.003	0.004			−0.003	−0.003		
	(0.002)	(0.002)			(0.003)	(0.003)		
Corruption (Difference)					−0.008	−0.007	−0.022	−0.021
					(0.016)	(0.016)	(0.017)	(0.017)
Corruption (t-1)					−0.012	−0.013		
					(0.004)	(0.004)		
N observations	2300	2300	2435	2435	1949	1949	2040	2040
N countries	135	135	135	135	135	135	135	135

Table A.5: The Effect of Democracy on Change in Public Support (With Uncertainty)

	ECM	ECM-Regime	FD	FD-Regime	ECM Corrup	ECM Corrup-Regime	FD Corrup	FD Corrup-Regime
Democratic Mood (t-1)	−0.024	−0.024			−0.031	−0.030		
	(0.029)	(0.030)			(0.031)	(0.032)		
Democratic Mood (t-2)	0.002	0.001			0.003	0.001		
	(0.029)	(0.030)			(0.031)	(0.032)		
Liberal Democracy (Difference)	−0.002		0.001		−0.002		0.001	
	(0.007)		(0.011)		(0.008)		(0.011)	
Liberal Democracy (t-1)	−0.002				−0.003			
	(0.006)				(0.007)			
Electoral Democracy (Difference)		−0.002		0.002		−0.001		0.001
		(0.007)		(0.010)		(0.007)		(0.010)
Electoral Democracy (t-1)		−0.001				−0.002		
		(0.007)				(0.007)		
Minoritarian Democracy (Difference)		−0.002		−0.001		−0.002		0.000
		(0.007)		(0.009)		(0.007)		(0.010)
Minoritarian Democracy (t-1)		−0.002				−0.003		
		(0.006)				(0.007)		
Log GDP Per Capita (Difference)	−0.016	−0.020			−0.032	−0.030		
	(0.081)	(0.084)			(0.089)	(0.085)		
Log GDP per capita (Difference)			0.029	0.026			0.019	0.024
			(0.102)	(0.103)			(0.102)	(0.107)
Log GDP (t-1)	0.006	0.006			−0.003	−0.003		
	(0.005)	(0.005)			(0.006)	(0.006)		
Corruption (Difference)					−0.001	−0.001	0.001	0.001
					(0.020)	(0.020)	(0.032)	(0.031)
Corruption (t-1)					−0.012	−0.012		
					(0.008)	(0.007)		
N observations	2296	2296	2430	2430	2076	2076	2167	2167
N countries	134	134	134	134	134	134	134	134

Table A.6: The Effect of Democracy on Change in Public Support (Uncertainty & More Data)

	ECM	ECM-Regime	FD	FD-Regime	ECM Corrup	ECM Corrup-Regime	FD Corrup	FD Corrup-Regime
Democratic Mood (t-1)	−0.030	−0.030			−0.042	−0.043		
	(0.026)	(0.027)			(0.028)	(0.029)		
Democratic Mood (t-2)	0.008	0.008			0.009	0.009		
	(0.026)	(0.028)			(0.028)	(0.028)		
Liberal Democracy (Difference)	0.001		0.000		0.001		0.000	
	(0.006)		(0.009)		(0.006)		(0.010)	
Liberal Democracy (t-1)	0.002				0.003			
	(0.004)				(0.004)			
Electoral Democracy (Difference)		0.004		0.000		0.004		0.000
		(0.006)		(0.010)		(0.007)		(0.010)
Electoral Democracy (t-1)		0.006				0.006		
		(0.006)				(0.006)		
Minoritarian Democracy (Difference)		−0.002		−0.001		−0.002		−0.001
		(0.006)		(0.008)		(0.006)		(0.009)
Minoritarian Democracy (t-1)		−0.004				−0.003		
		(0.006)				(0.007)		
Log GDP Per Capita (Difference)	−0.007	−0.004			−0.020	−0.024		
	(0.073)	(0.072)			(0.076)	(0.075)		
Log GDP per capita (Difference)			−0.036	−0.027			−0.037	−0.031
			(0.095)	(0.093)			(0.098)	(0.098)
Log GDP (t-1)	0.003	0.003			−0.011	−0.011		
	(0.004)	(0.004)			(0.005)	(0.005)		
Corruption (Difference)					−0.011	−0.010	0.004	0.005
					(0.019)	(0.018)	(0.029)	(0.029)
Corruption (t-1)					−0.022	−0.023		
					(0.006)	(0.006)		
N observations	2655	2655	2794	2794	2386	2386	2478	2478
N countries	141	141	141	141	139	139	139	139

B The Method of Composition

In our analysis models, we have latent variables in both sides of the equations: public democratic support, democracy, and corruption. Since measurement uncertainty associated with these latent variables can propagate into the inferences over coefficient parameters in models, we incorporate uncertainty by employing the "Method of Composition" (Tanner 1993, 52), which has often been applied in analyses with latent variables in political science (see, e.g., Treier and Jackman 2008; Caughey and Warshaw 2018; Kastellec et al. 2015).

As Caughey and Warshaw (2018, A–15) explained, the main idea of MOC is to estimate the marginal distribution of coefficient parameter vector β, integrating over the uncertainty in latent variables θ. More explicitly, MOC integrates the joint density of β and θ over the distribution of θ.

$$p(\beta, \theta | w, y, Z) = p(\beta | \theta, w, y) p(\theta | Z). \tag{1}$$

where θ is latent variables with measurement errors conditional on data Z and a measurement model, w is other predictors without errors, Z is indicators for latent variables θ, and y is the outcome variable. In this way, we incorporate uncertainty in measuring predictor θ, and uncertainty in the effects of latent variables θ and other variables w on outcome variable y (Treier and Jackman 2008, 215).

To sample from the conditional density and the marginal density in the right side of the equation, we follow iterative Monte Carlo procedure described by Treier and Jackman (2008), at iteration t,

1. We sample θ^t from its posterior distribution $p(\theta|Z)$.
2. For each analysis model, we run the model with θ^t, and w, and save the coefficient estimates β^t and variance-covariance matrix of $\hat{\beta}^t$, $\hat{V}^t$, both of which change due to the uncertainty in θ.
3. We sample $\tilde{\beta}^t$ from the multivariate normal density with mean vector βt and variance-

covariance matrix V^t.

In the step 3, the marginal distribution of a parameter vector β was estimated, integrating over $p(\theta|Z)$:

$$p(\beta|w, y) = \int_\theta p(\beta|\theta, w, y)p(\theta|Z)\, d\theta \tag{2}$$

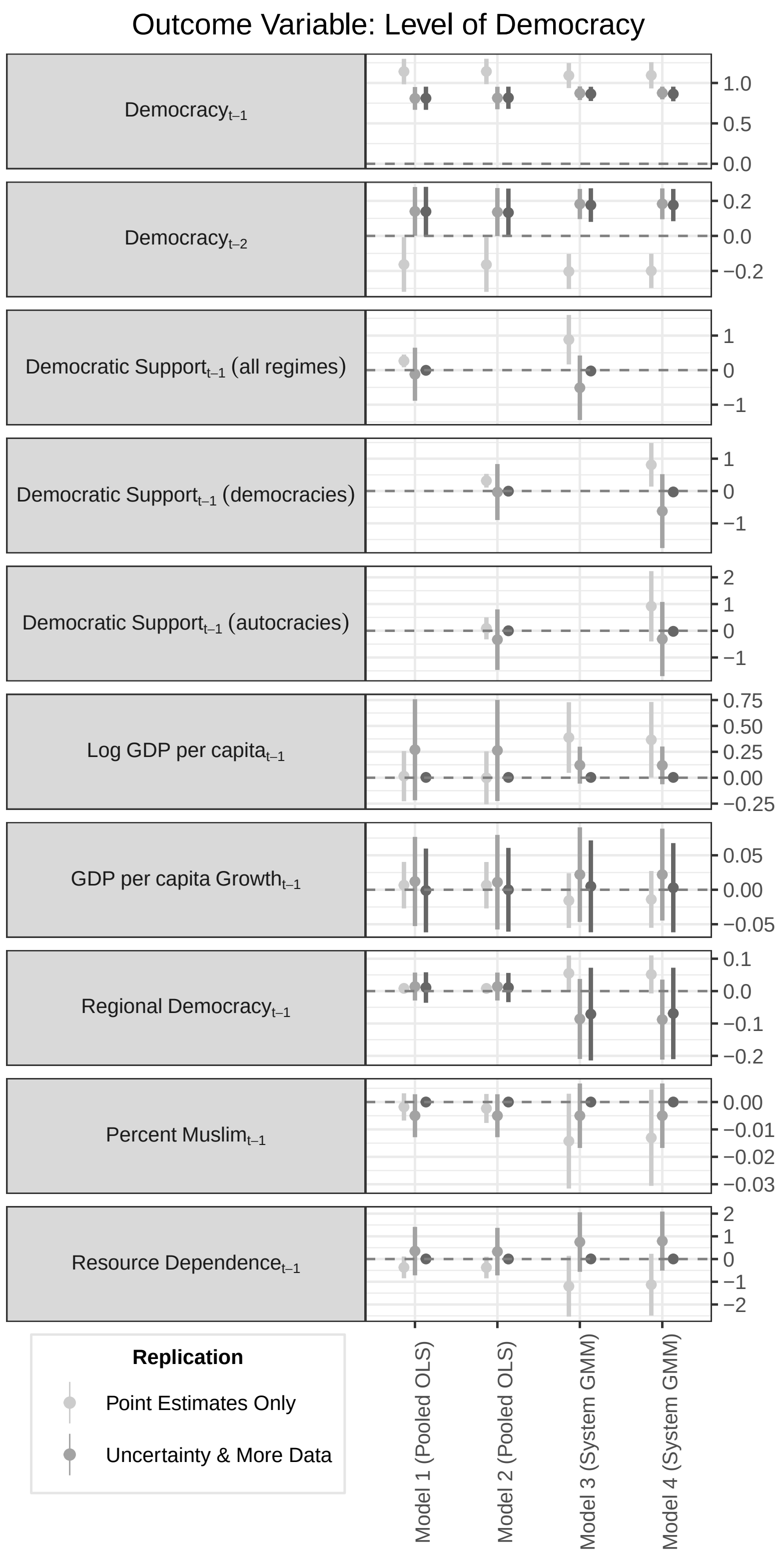
In our re-analyses, we incorporate uncertainty for five variables, public support for democracy, liberal democracy, electoral democracy, the liberal component index, and the corruption perceptions index. For each of these five latent variables, we take 900 draws from its posterior distribution. We duplicate the dataset of variables "without" measurement error 900 times, and assign them to each a different random draw from the distributions of variables with measurement error, which yields 900 dataset. In next step, we run each of analysis models with these 900 datasets independently and save the resulting estimates of coefficients and the matrix of variance-covariance for each run. We then draw one sample from the multivariate normal distribution with the mean vector of coefficient estimates and variance-covariance matrix produced from each run. This procedure finally yields 900 samples of estimated coefficients drawn from the joint density of β and θ. We calculate point estimates and standard error based on these 900 samples.

C DCPO Replication

To make fuller use of the available survey data, we also replicated the tests of the classic arguments on democracy and public support using the DCPO model put forward in Solt (2020b) on our expanded data set. The DCPO model has several advantages over the Claassen (2019) model used in Claassen (2020a, 2020b). First, while the Claassen (2019) model dichotomizes responses and so discards some information provided by 50 of the 52 survey items employed in Claassen (2020a, 2020b), the DCPO model makes use of all of the information available from these ordinal items (Solt 2020b, 5). Second, as the DCPO model includes both parameters for the dispersion of each survey item and for the standard deviation of aggregate public opinion in each country-year, it is a complete population-level item-response model and so, unlike the Claassen (2019) model, is explicitly derived from an individual-level model of survey responses (Solt 2020b, 3–4; see also McGann 2014). Third, to produce more sensible estimates of uncertainty for observations at the extremes of the scale (see Linzer and Staton 2015, 229), the DCPO model places bounds on its estimates of public opinion (Solt 2020b, 8). Further commending the DCPO model to us—and demonstrating that its advantages make a difference—the validation tests in Solt (2020b, 10–12) reveal that it fits survey data on democratic support better than the Claassen (2019) model does.

We employ the superior DCPO model to our expanded dataset using the `DCPO` package for R (Solt 2020a). We then use the estimated public support from the DCPO model to replicate all of the analyses presented in the text. Figures A.1 and Figures A.2 display these results as the righthand set of results, with the replication of the articles' original results based only on point estimates on the left and our extension with uncertainty and more data, but the articles' original, Claassen (2019), model in the middle for comparison.

Even with the advantages of the DCPO model, there is no evidence to support the conclusions of Claassen (2020a, 2020b) that public support sustains democratic regimes or public support responds thermostatically to changes in democracy.



Replications of Claassen (2020a), Table 1, 128, with DCPO.

Figure A.1: The Effect of Public Support on Democracy

Table A.7: The Effect of Public Support on Democracy (Uncertainty & DCPO)

	Pooled	Pooled-Regime	GMM	GMM-Regime
Democracy (t-1)	0.811	0.817	0.865	0.864
	(0.073)	(0.070)	(0.045)	(0.046)
Democracy (t-2)	0.139	0.133	0.176	0.176
	(0.072)	(0.070)	(0.049)	(0.047)
Support (t-1)	−0.006		−0.025	
	(0.019)		(0.024)	
Support in Democracy		−0.005		−0.029
		(0.018)		(0.025)
Support in Autocracy		−0.001		−0.022
		(0.017)		(0.024)
Log GDP Per Capita (t-1)	0.003	0.003	0.003	0.003
	(0.002)	(0.003)	(0.002)	(0.002)
GDP Per Capita Growth (t-1)	−0.001	0.000	0.005	0.003
	(0.031)	(0.031)	(0.034)	(0.033)
Regional Democracy (t-1)	0.011	0.011	−0.071	−0.069
	(0.024)	(0.023)	(0.073)	(0.072)
Percent Muslim (t-1)	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Resource Dependence (t-1)	0.005	0.003	0.006	0.005
	(0.006)	(0.005)	(0.006)	(0.006)
N observations	2792	2792	5443	5443
N countries	141	141	143	143
N instruments			130	130

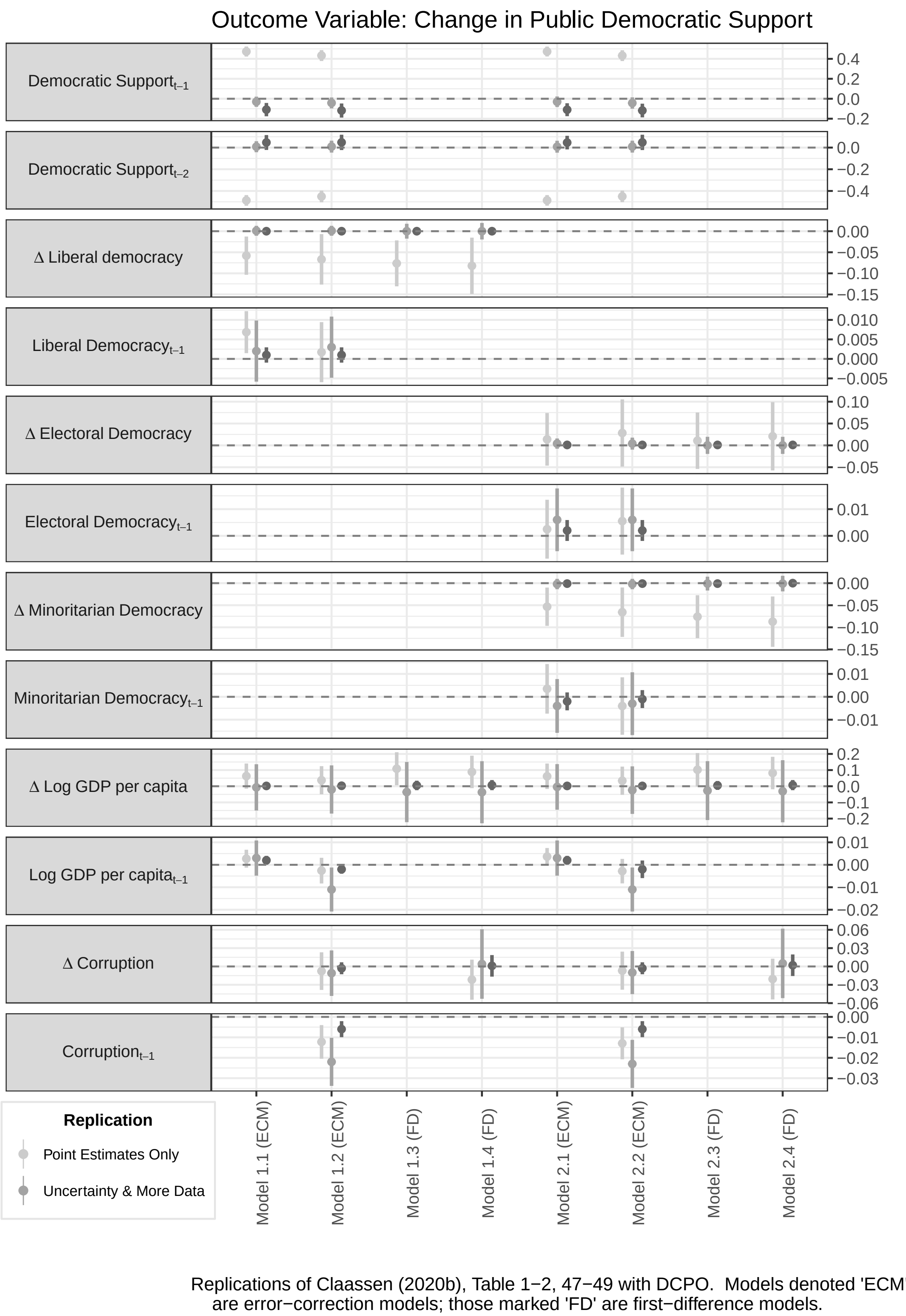


Figure A.2: The Effect of Democracy on the Change of Public Support

Table A.8: The Effect of Public Support on Democracy (Uncertainty & DCPO)

	ECM	ECM-Regime	FD	FD-Regime	ECM Corrup	ECM Corrup-Regime	FD Corrup	FD Corrup-Regime
Democratic Mood (t-1)	−0.109	−0.110			−0.118	−0.118		
	(0.034)	(0.033)			(0.036)	(0.035)		
Democratic Mood (t-2)	0.047	0.046			0.048	0.048		
	(0.035)	(0.032)			(0.036)	(0.036)		
Liberal Democracy (Difference)	0.000		0.000		0.000		0.000	
	(0.002)		(0.002)		(0.002)		(0.003)	
Liberal Democracy (t-1)	0.001				0.001			
	(0.001)				(0.001)			
Electoral Democracy (Difference)		0.001		0.001		0.001		0.001
		(0.002)		(0.003)		(0.002)		(0.003)
Electoral Democracy (t-1)		0.002				0.002		
		(0.002)				(0.002)		
Minoritarian Democracy (Difference)		−0.001		−0.001		−0.001		0.000
		(0.002)		(0.002)		(0.002)		(0.003)
Minoritarian Democracy (t-1)		−0.002				−0.001		
		(0.002)				(0.002)		
Log GDP Per Capita (Difference)	0.002	0.002			0.003	0.002		
	(0.009)	(0.009)			(0.010)	(0.010)		
Log GDP per capita (Difference)			0.005	0.005			0.007	0.007
			(0.015)	(0.014)			(0.016)	(0.016)
Log GDP (t-1)	0.002	0.002			−0.002	−0.002		
	(0.001)	(0.001)			(0.001)	(0.002)		
Corruption (Difference)					−0.003	−0.003	0.001	0.002
					(0.005)	(0.005)	(0.009)	(0.009)
Corruption (t-1)					−0.006	−0.006		
					(0.002)	(0.002)		
N observations	2655	2655	2794	2794	2386	2386	2478	2478
N countries	141	141	141	141	139	139	139	139

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