Democracy, Public Support, and Measurement Uncertainty*

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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 this 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 bringing additional survey data and a superior model of public opinion. Even with these improvements, however, our analyses fail to yield evidence in support of either hypothesis, underscoring the necessity of accounting for measurement uncertainty. [149/150 words]

(Word count: 3628)

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

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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 2020). 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). These works concluded, first and supporting the classic argument, that mass support had a positive impact on democratic change, especially the endurance of democracy (Claassen 2020a, 127–30), and, second and directly contrary to it, 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. Measurement error challenges statistical analyses, especially when it is correlated with an outcome variable which is the case of democratic support, but it is often ignored in the analysis (Blackwell, Honaker, and King 2017b, 2017a). 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 correcting and expanding survey data to including 144 countries for up to 33 years between 1988 and 2020 (based on 26% more questions and 33% more survey sources). 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 with expanded 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 many plausible explanations for these null results, both theoretical and methodological. From a theoretical perspective, 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). Similarly, 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; that is, that it is not democratic support that is important to democratic change, but rather unsatisfied democratic demand (see Qi and Shin 2011). Whether the public support has a pro-democratic or anti-authoritarian effect is also bounded by the emancipative value that, as a belief-anchored orientation, shapes the public's understanding of democracy (see Brunkert, Kruse, and Welzel 2019; Kirsch and Welzel 2019; Kruse, Ravlik, and Welzel 2019). Moreover, the cultural and historical attributes of the emancipative value decide that it cannot be shifted shortly by institutional changes. Of course, it could in fact be that democratic change does not actually depend on public opinion of any sort at all but instead is an elite-driven phenomenon (see, e.g., Levitsky and Ziblatt 2018).

Methodologically, one possible issue is that support for democracy is multidimensional, and the survey questions used to measure it simply do not capture all of the dimensions relevant to democratic change, such as commitments to political equality and freedom of expression (see Schedler and Sarsfield 2007; Wuttke, Schimpf, and Schoen 2020). Another is that the relationships among these survey items have varied substantially over time (see Wuttke, Gavras, and Schoen 2020a); this would violate the assumptions of the public opinion models used and would yield faulty estimates of democratic support. A third is that these survey questions do not ask respondents how they prioritize democracy relative to other values with which it may come into conflict, such as their partisanship, and so miss capturing the true extent of support democracy would find among the public when public support was actually needed (see Carey et al. 2020; Graham and Svolik 2020; McCoy, Simonovits, and Littvay 2020).

We draw two conclusions, one methodological and one substantive. As latent variable measurement models become more commonly used, it is absolutely necessary for researchers employing them to incorporate the associated uncertainty into analyses. And, at a time when democracy is seen as

under threat around the world (e.g., Diamond 2015), 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 provide support for them. There is no room for complacency.

1 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. As 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 preserve measurement uncertainty.

1.1 Data Recollection and Incorporating Uncertainty

Despite the great effort of collecting data and identifying differences, we could not entirely achieve a primary replication (see Grossman and Pedahzur 2020, 18) based on Claassen (2020a)'s Dataverse materials. Our replication data has differences in number of country-year surveys and in sample size. Specificially, we have five fewer observations, three of which are no longer available in originial survey data and two seem to have never existed, and one more survey item which was conflated in original data [see Online Supplementary Material].

Although measurement uncertainty has 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 uncertainty, and ignoring that uncertainty in analyses can bias coefficient estimates and standard errors. Especially when measurement error is correlated with the outcome variable, the resulting bias could either attenuate or

exaggerate the magnitude of the estimated effects (see, e.g., Blackwell, Honaker, and King 2017b, 360; 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).

Following this line, after replicating the original analyses with point estimates, we incorportate uncertainty in analysis models using our replication data. We take the distribution of the latent (explanatory) variable, the outcome variable, and control variables to account for the uncertainty. We take 900 draws from the posterior distribution of democratic support, outcome, and control variables with errors. We then duplicate each article's analysis 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. We estimate each analysis model repeatedly on its respective collection of the datasets, and then make inferences from the distribution of parameter estimates by accounting for both within model standard error and between model variance. This combine rule was set out in Rubin (1987), and has been employed in research of measurement errors (see, e.g., Schnakenberg and Fariss 2014; Crabtree and Fariss 2015) as well as incorporated in Blackwell, Honaker, and King (2017a)'s multiple overimputation (MO) to handle missing values and measurement uncertainty. We also employ one alternative technique known as "method of composition" (MOC) (Treier and Jackman 2008, 215) as a robustness check [see Online Supplementary Material D].

We also expanded Claassen's data pool assembling as much data on democratic support as possible from available opinion surveys around the world. The expansion ended with 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).[1]

[1] 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.

2 Results

Figure 1 presents the reanalyses of the hypothesis that public support influences the level of democracy, with democratic support pooled for all countries (Claassen 2020a, Model 1) in the left panel and separated by regime type (Model 2) on the right. The uppermost set of results replicate Claassen (2020a) without uncertainty. The middle results introduce the uncertainty in the measurement of public support and democratic indices into the model. And the lowermost set presents the results estimated with the expanded data with uncertainty.

In comparison to the original result, the positive coefficients for democratic support in both models accounting for the uncertainty are no longer statistically significant. This result is robust when using separated regime types in the explanatory variable. Nor do applying system GMM models and using MOC for uncertainty incorporation alters the conclusion (see Online Supplementary Material A, B, and D).

Adding more data is indeed helpful for increasing the certainty to the analytic estimates. The confidence intervals of the explanatory variable (and some control variables) are considerably narrower than the cases just bringing the uncertainty back—or even the original case when uncertainty was completely ignored. Nonetheless, the insignificance remains and is robust across different model specifications.

Moreover, the results also manfiest another risk of ignoring uncertainty: missestimation. As shown in Figure 1, besides the confidence intervals the (point) estimates also shift. Methodologically, these shifts indicates that the 900 regressions of public support on democracy do not yield consistent results although the support opinions were drawn from the same distribution. In this sense, the coefficient produced simply by the mean of the public support distribution is no more than a one-time guess of the true parameter and definitely not a robust one. What this methodological issue lead to, however, is a substantively different conclusion of the relationship between public opinions and institutional democratization in both direction and magnitude. The replication results illustrate the uncertainty ignorance with mounting risk.

The importance of accounting for the measurement uncertainty appear more evident when the relevant variable plays as the outcome variable. In Figure 2, we examine the thermostatic model of democratic support per Claassen (2020b, 47, Models 1.1 and 1.2). When the uncertainty is ignored,

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

the coefficient of Δliberal democracy (the uppermost set), the yearly changes of the institutional feature is negative inferring that the change in democratic mood decreases as change in democracy increases and vice versa. However, when the measurement uncertainty is properly accounted (the middle set), the point estimate shifts towards zero and the coefficient is no longer significant. More data (the lowermost set), again, only adjusts the confidence intervals but not direction nor significance.

3 Discussion

In short, the conclusions of Claassen (2020a, 2020b) that public 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.

There are theoretical explanations for the null results. With regard to how levels of democracy affect public support, we note that even the 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 support 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. Relatedly, 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. The effects of public support also have cultural-bound. Brunkert, Kruse, and Welzel (2019) contends outspoken support for democracy is a "deceptive indicator of public's affinity to democracy" [423] and finds public support has neither pro-democratic nor anti-authoritarian effect without controlling emancipative values. Empirical results show that the meaning of support for democracy is dependent on emancipation values and is reversed to its own negation in a society

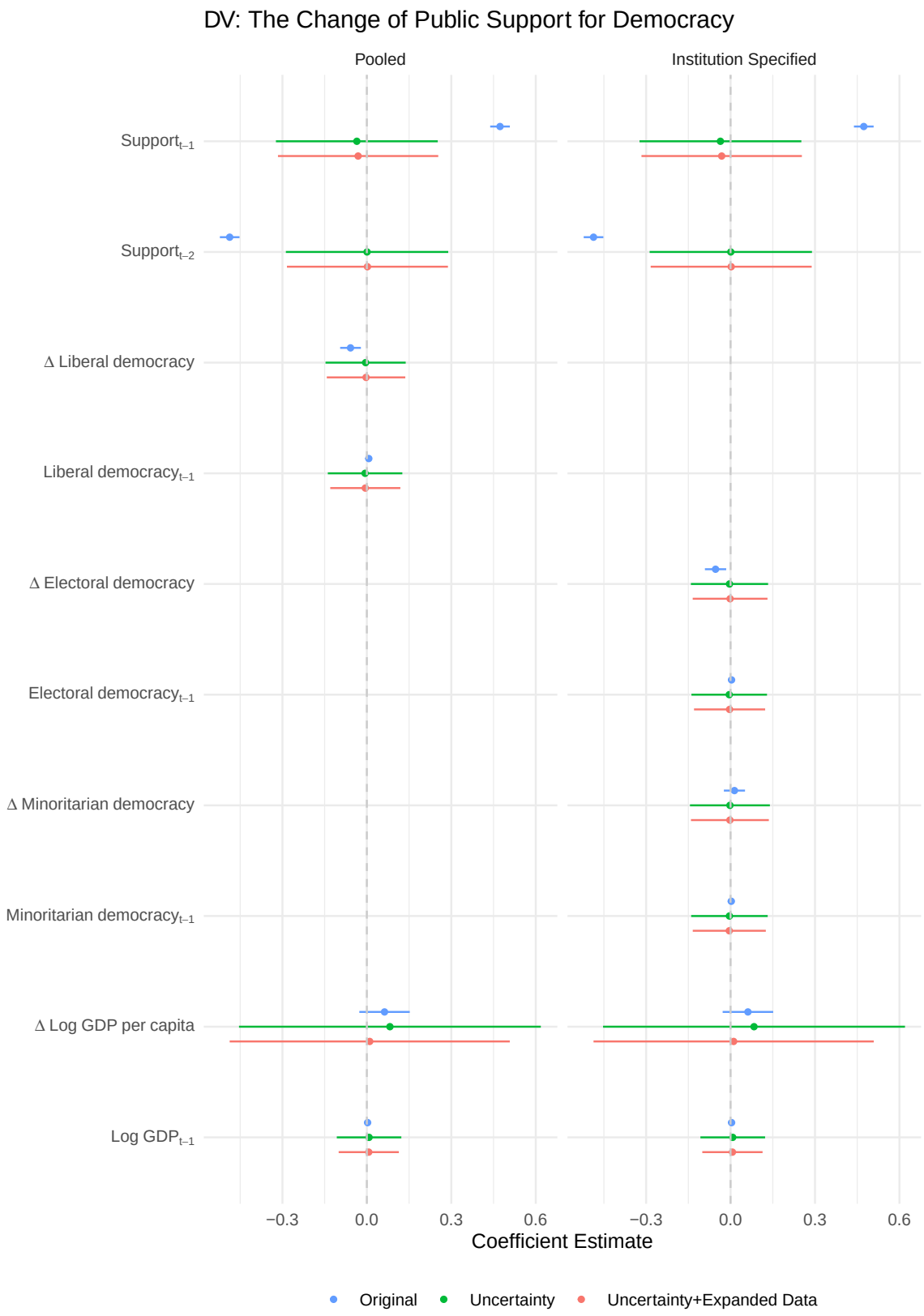

Figure 2: The Effect of Democracy on the Change of Public Support

with weak emancipative values (see, e.g., Kirsch and Welzel 2019, 83–85). And we must be open to the possibility that no theoretical elaboration, no respecification of these models will reveal relationships between public opinion and democracy. Democratic backsliding may simply be primarily a matter of elite decisionmaking (see, e.g., Levitsky and Ziblatt 2018).

There are several potential methodological explanations for these null results as well. One issue is that the survey items employed—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—may not capture every aspect of democratic support necessary for it to play its hypothesized roles in the classic theory. If 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, then this measure is inadequate to its purpose (see, e.g., Schedler and Sarsfield 2007). Moreover, given the multi-faceted nature of democratic attitudes, even the inclusion of such questions in unidimensional public opinion models such as those provided by Claassen (2019) or Solt (2020) are unlikely to be sufficient (see, e.g., Wuttke, Schimpf, and Schoen 2020). Another issue is that even if these survey questions do capture support for the generic concept of democracy, these measurement models might still be incapable of suitably capturing democratic support due to the variation in understanding the concept across countries or over time within countries (Wuttke, Gavras, and Schoen 2020a). Yet another is that this measure provides no assessment of the *relative* importance the public affords democracy. It provides no information on the extent to which other values, such as policy preferences or partisanship, weigh more heavily—and 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 Bartels 2020; Carey et al. 2020; Graham and Svolik 2020; McCoy, Simonovits, and Littvay 2020). Regardless, these explanations indicate that there remains much work to be done in the empirical study of public support and democracy.

4 Conclusion

In this letter, we reexamine the findings from Claassen (2020a, 2020b), two articles that maintain that public support helps the survival of democracy and democratic development has a thermo-

static effect on public support. We demonstrate 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 considerable more data.

This points to the absolute necessity of incorporating measurement uncertainty into analyses that include latent variables. Measurement issues have never had a prominent place in comparative political studies because they need more time to estimate models, but they ground the quality of data and the basis of analysis (Stegmueller 2011, 484). 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.

The null results reached in this letter could arise from several sources. There are theoretically grounded reasons of government effectiveness, democratic understanding, and generical-or-behavioral support to suspect that the relationships are in fact negligible. We also identified a number of potential shortcomings in the measurement of democratic support and ways in which the analysis models might be underspecified. All of these could and should be explored in future research. In any event, 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 Materials

A Numeric Results for Replicating Claassen 2020a

Table 1: Original

	Pooled	Pooled-Regime	GMM	GMM-Regime
(Intercept)	0.647	0.765		
	[-0.625, 1.919]	[-0.520, 2.050]		
Democracy[t-1]	1.141	1.142	1.091	1.095
	[1.102, 1.181]	[1.103, 1.182]	[1.090, 1.093]	[1.093, 1.096]
Democracy[t-2]	-0.163	-0.164	-0.203	-0.200
	[-0.203, -0.124]	[-0.203, -0.125]	[-0.205, -0.202]	[-0.201, -0.199]
Support[t-1]	0.267		0.881	
	[0.105, 0.430]		[0.871, 0.892]	
Support in Democracy		0.318		0.810
		[0.137, 0.499]		[0.800, 0.820]
Support in Autocracy		0.090		0.917
		[-0.233, 0.412]		[0.900, 0.933]
Log GDP Per Capita[t-1]	0.015	-0.001	0.388	0.366
	[-0.145, 0.175]	[-0.163, 0.161]	[0.383, 0.393]	[0.361, 0.371]
GDP Per Capita~growth[t-1]	0.007	0.007	-0.016	-0.014
	[-0.018, 0.031]	[-0.018, 0.031]	[-0.017, -0.015]	[-0.015, -0.013]
Regional Democracy[t-1]	0.008	0.008	0.055	0.051
	[-0.001, 0.018]	[-0.002, 0.018]	[0.054, 0.056]	[0.051, 0.052]
Percent Muslim[t-1]	-0.002	-0.002	-0.014	-0.013
	[-0.007, 0.003]	[-0.007, 0.003]	[-0.015, -0.014]	[-0.013, -0.013]
Resource Dependence[t-1]	-0.367	-0.373	-1.196	-1.128
	[-0.878, 0.144]	[-0.884, 0.138]	[-1.214, -1.178]	[-1.146, -1.111]
Num.Obs.	2435	2435	4735	4735
n.country	135.000	135.000	135.000	135.000

Table 2: W. Uncertainty

	Pooled	Pooled-Regime	GMM	GMM-Regime
Democracy[t-1]	0.805	0.805	0.761	0.764
	[0.315, 1.295]	[0.315, 1.295]	[0.387, 1.135]	[0.390, 1.137]
Democracy[t-2]	0.145	0.145	0.109	0.111
	[-0.339, 0.629]	[-0.339, 0.629]	[-0.261, 0.479]	[-0.258, 0.480]
Support[t-1]	1.753		4.134	
	[-0.085, 3.590]		[0.648, 7.621]	
Support in Democracy		1.953		4.158
		[-0.007, 3.912]		[0.671, 7.644]
Support in Autocracy		1.125		3.510
		[-1.615, 3.865]		[-1.316, 8.336]
Log GDP Per Capita[t-1]	0.502	0.466	0.264	0.250
	[-0.908, 1.911]	[-0.955, 1.888]	[-0.519, 1.048]	[-0.529, 1.029]
GDP Per Capita~growth[t-1]	0.044	0.044	-0.029	-0.025
	[-0.529, 0.618]	[-0.529, 0.617]	[-0.647, 0.589]	[-0.640, 0.591]
Regional Democracy[t-1]	0.018	0.017	0.073	0.069
	[-0.169, 0.204]	[-0.169, 0.204]	[-0.288, 0.434]	[-0.289, 0.428]
Percent Muslim[t-1]	-0.023	-0.024	-0.052	-0.051
	[-0.257, 0.211]	[-0.260, 0.212]	[-0.386, 0.283]	[-0.385, 0.284]
Resource Dependence[t-1]	-2.470	-2.480	-3.965	-3.877
	[-5.220, 0.279]	[-5.232, 0.272]	[-7.822, -0.108]	[-7.713, -0.040]
Num.Obs.	2423	2423	4711	4711
n.country	135.000	135.000	137.000	137.000

Table 3: W. Uncertainty and Expanded Data

	Pooled	Pooled-Regime	GMM	GMM-Regime
Democracy[t-1]	0.806	0.806	0.764	0.769
	[0.316, 1.295]	[0.316, 1.295]	[0.393, 1.136]	[0.397, 1.140]
Democracy[t-2]	0.145	0.145	0.111	0.115
	[-0.339, 0.629]	[-0.339, 0.629]	[-0.259, 0.481]	[-0.253, 0.483]
Support[t-1]	1.682		4.040	
	[-0.200, 3.563]		[0.430, 7.651]	
Support in Democracy		1.753		3.681
		[-0.258, 3.764]		[0.282, 7.081]
Support in Autocracy		1.467		4.096
		[-1.345, 4.278]		[-1.017, 9.210]
Log GDP Per Capita[t-1]	0.568	0.555	0.270	0.250
	[-0.852, 1.989]	[-0.882, 1.992]	[-0.517, 1.058]	[-0.536, 1.036]
GDP Per Capita~growth[t-1]	0.046	0.046	-0.023	-0.016
	[-0.527, 0.619]	[-0.527, 0.619]	[-0.637, 0.590]	[-0.626, 0.594]
Regional Democracy[t-1]	0.017	0.017	0.070	0.064
	[-0.169, 0.203]	[-0.169, 0.203]	[-0.288, 0.427]	[-0.291, 0.420]
Percent Muslim[t-1]	-0.023	-0.024	-0.050	-0.046
	[-0.257, 0.211]	[-0.260, 0.213]	[-0.381, 0.281]	[-0.371, 0.278]
Resource Dependence[t-1]	-2.470	-2.476	-3.744	-3.496
	[-5.208, 0.268]	[-5.218, 0.267]	[-7.518, 0.030]	[-7.213, 0.221]
Num.Obs.	2423	2423	4711	4711
n.country	135.000	135.000	145.000	145.000

B Numeric Results for Replicating Claassen 2020b

Table 4: Original

	ECM	ECM-Regime	FD	FD-Regime	ECM Corrup	ECM Corrup-Regime	FD Corrup	FD Corrup-Regime
(Intercept)	-0.033	-0.042*	-0.009**	-0.008**	0.018	0.020	-0.011**	-0.011**
	(0.019)	(0.019)	(0.004)	(0.004)	(0.028)	(0.026)	(0.004)	(0.003)
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	0.108*	0.102*	0.037	0.034	0.089+	0.082
	(0.040)	(0.040)	(0.052)	(0.053)	(0.044)	(0.045)	(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)		
Num.Obs.	2300	2300	2435	2435	1949	1949	2040	2040
n.country	135.000	135.000	135.000	135.000	135.000	135.000	135.000	135.000

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: W. Uncertainty

	ECM	ECM-Regime	FD	FD-Regime	ECM Corrup	ECM Corrup-Regime	FD Corrup	FD Corrup-Regime
Democratic Mood (t-1)	-0.036	-0.036			-0.047	-0.047		
	[-0.323, 0.252]	[-0.324, 0.251]			[-0.342, 0.249]	[-0.342, 0.248]		
Democratic Mood (t-2)	0.001	0.001			0.004	0.004		
	[-0.288, 0.289]	[-0.288, 0.289]			[-0.291, 0.299]	[-0.291, 0.299]		
Liberal Democracy (Difference)	-0.004		-0.001		-0.004		0.000	
	[-0.147, 0.138]		[-0.171, 0.169]		[-0.149, 0.141]		[-0.173, 0.172]	
Liberal Democracy (t-1)	-0.006				-0.006			
	[-0.139, 0.126]				[-0.144, 0.132]			
Electoral Democracy (Difference)		-0.002		0.000		-0.002		0.000
		[-0.144, 0.140]		[-0.168, 0.168]		[-0.146, 0.142]		[-0.170, 0.171]
Electoral Democracy (t-1)		-0.004				-0.004		
		[-0.140, 0.132]				[-0.144, 0.136]		
Minoritarian Democracy (Difference)		-0.004		-0.001		-0.003		-0.001
		[-0.141, 0.133]		[-0.164, 0.163]		[-0.142, 0.136]		[-0.166, 0.165]
Minoritarian Democracy (t-1)		-0.005				-0.004		
		[-0.139, 0.129]				[-0.143, 0.135]		
Log GDP per capita (Difference)	0.082	0.083	-0.007	-0.007	0.042	0.044	-0.019	-0.019
	[-0.454, 0.618]	[-0.453, 0.620]	[-0.568, 0.555]	[-0.568, 0.555]	[-0.507, 0.591]	[-0.505, 0.593]	[-0.588, 0.550]	[-0.588, 0.551]
Log GDP (t-1)	0.008	0.008			-0.003	-0.004		
	[-0.107, 0.122]	[-0.107, 0.123]			[-0.138, 0.131]	[-0.138, 0.131]		
Corruption (Difference)					-0.012	-0.012	0.002	0.002
					[-0.247, 0.222]	[-0.247, 0.222]	[-0.298, 0.303]	[-0.298, 0.303]
Corruption (t-1)					-0.018	-0.018		
					[-0.167, 0.130]	[-0.167, 0.130]		
Num.Obs.	2300	2300	2300	2300	2080	2080	2093	2093
n.country	135.000	135.000	135.000	135.000	135.000	135.000	135.000	135.000

Table 6: W. Uncertainty and Expanded Data

	ECM	ECM-Regime	FD	FD-Regime	ECM Corrup	ECM Corrup-Regime	FD Corrup	FD Corrup-Regime
Democratic Mood (t-1)	-0.031	-0.032			-0.040	-0.041		
	[-0.316, 0.254]	[-0.317, 0.253]			[-0.333, 0.253]	[-0.334, 0.252]		
Democratic Mood (t-2)	0.002	0.002			0.001	0.001		
	[-0.284, 0.288]	[-0.284, 0.288]			[-0.292, 0.294]	[-0.292, 0.294]		
Liberal Democracy (Difference)	-0.003		0.001		-0.003		0.001	
	[-0.142, 0.137]		[-0.162, 0.164]		[-0.144, 0.139]		[-0.164, 0.166]	
Liberal Democracy (t-1)	-0.006				-0.006			
	[-0.130, 0.119]				[-0.134, 0.122]			
Electoral Democracy (Difference)		-0.002		0.001		-0.003		0.001
		[-0.141, 0.136]		[-0.161, 0.163]		[-0.143, 0.138]		[-0.164, 0.165]
Electoral Democracy (t-1)		-0.005				-0.005		
		[-0.134, 0.125]				[-0.138, 0.128]		
Minoritarian Democracy (Difference)		-0.002		0.001		-0.001		0.001
		[-0.134, 0.131]		[-0.156, 0.157]		[-0.135, 0.133]		[-0.157, 0.159]
Minoritarian Democracy (t-1)		-0.004				-0.004		
		[-0.130, 0.123]				[-0.133, 0.126]		
Log GDP per capita (Difference)	0.010	0.011	-0.069	-0.070	-0.026	-0.025	-0.064	-0.064
	[-0.487, 0.508]	[-0.487, 0.509]	[-0.614, 0.475]	[-0.615, 0.475]	[-0.544, 0.492]	[-0.544, 0.494]	[-0.616, 0.489]	[-0.616, 0.488]
Log GDP (t-1)	0.007	0.007			-0.007	-0.007		
	[-0.100, 0.114]	[-0.100, 0.114]			[-0.131, 0.118]	[-0.131, 0.118]		
Corruption (Difference)					-0.012	-0.012	0.003	0.003
					[-0.236, 0.212]	[-0.236, 0.212]	[-0.281, 0.287]	[-0.281, 0.287]
Corruption (t-1)					-0.021	-0.021		
					[-0.161, 0.118]	[-0.160, 0.118]		
Num.Obs.	2300	2300	2300	2300	2080	2080	2093	2093
n.country	135.000	135.000	135.000	135.000	135.000	135.000	135.000	135.000

C Data Recollection and Control Uncertainty in Control Variables.

Due to revisions to the underlying datasets (and, possibly, transcription errors), we were not able to achieve a primary replication (Grossman and Pedahzur 2020) based on survey data summarized in Claassen (2020a) and Claassen (2020b)'s Dataverse files.

Specifically, we are not able to identify 5 cournty-year surveys, including South Sudan in Arab Barometer Wave 4, Dominican Republic in 2003 Latinobarometer, XXXX, and Spain in 2005 Latinobarometer. In addition, we still have different sample size and number of respondents answering supportively by following approaches of cleanning data and treatment of non-responses described in Claassen (2020a)'s supplementatry materials. Specifically, we used Claassen's year coding to recode 85 unmatching country-year observations and added one more item "strong leader 2" in Arabbarometer which has different response categories but was conflated into "strong leader 1."

V-Dem data was standardized in Claassen (2020b)'s analyses, but we did not figure out how the standardization was exactly performed. We standardized variables using Z-score, and the standardized values are different from Claassen's data.

We also include measurement errors in control variables, including three democratic indices and corruption index. We extracted the posterior distributions of democratic indices, including Liberal Democracy,polyarchy, and electoral democracy index, which are provided by (Coppedge et al. 2018). We drew 900 samples from the distribution of the Corruption Perception Index. Since Corruption Perception Index does not provide standard error before 2011, we imputed the missing standard error using the multiplication of a country's corruption index and the ratio of its available maximum standard error to its corresponding index.

D Replication with Alternative Methods Accounting for Uncertainty

To ensure the robustness of our analysis, we apply another method to account for uncertainty. The method we employ is "method of composition" (MOC). It is a common method for Monte Carlo integration, but can also be applied for addressing uncertainty (Treier and Jackman 2008). To

compare these two methods, let's denote `y` as a vector of the outcome variable Claassen (2020b). Let x (variables without subscript are used to denote vectors of observations, viz., $x = (x_1, \ldots\ldots, x_i)$) be a vector of the explanatory variable (e.g., mass support or institutional democracy) and θ be the parameter of interest.

Rubin's Rules (RR, the method used in the main article) take variables with measurement error as missing value, and combine the point estimates and standard errors into single values yet accounting for both within and between imputation variances (Rubin 1987).

Rubein's Rules is defined in the following formulas.

$$\bar{\theta}_m = \frac{1}{m}\sum_{i=1}^{m}\theta_i. \tag{1}$$

$$V_B = \frac{1}{m-1}\sum_{i=1}^{m}(\theta_i - \bar{\theta}_m)^2. \tag{2}$$

$$V_W = \frac{1}{m}\sum_{i=1}^{m}SE_i^2. \tag{3}$$

$$V_T = V_w + (1 + \frac{1}{m})\frac{V_B}{m}. \tag{4}$$

$\bar{\theta}_M$ is the pooled parameter estimate, m is the number of imputed datasets, V_B is between imputation variance, V_W within imputation variance, V_T is total variance.

The general formula for confidence interval (CI) is defined as:

$$\bar{\theta} \pm t_{df,1-\alpha/2} * \sqrt{V_T}. \tag{5}$$

df is calculated by using $df_{Adjusted}$ (Barnard and Rubin 1999) and the Fraction of Missing information, lambda, is derived from between and total variance Van Buuren (2018).

$$df_{Adjusted} = \frac{df_{Old} * df_{Observed}}{df_{Old} + df_{Observed}}. \tag{6}$$

$$df_{Old} = \frac{(n-k)+1}{(n-k)+3} * (n-k)(1-lambda). \tag{7}$$

$$df_{Observed} = \frac{(n-k)+1}{(n-k)+3} * (n-k)(1-lambda). \tag{8}$$

$$Lambda = \frac{V_B + \frac{V_B}{m}}{V_T} \tag{9}$$

One main idea behind RR is to account for both within imputation variance and sample variance which is due to the missing data (measurement error in our case).

MOC addresses the same issue from a slightly different angle. The method assumes that the explanatory and outcome variables are samples from their estimate functions, and their paired sample follows a joint density (Tanner 1993, 31). From the joint density, one can decomposite the likelihood of the explanatory variable and its parameter to a product of their own probabilities. When x is measured with errors w, the probability becomes conditional:

$$\mathcal{L}(\theta, x|y, w) = p(\theta|x, y)p(x|w). \tag{10}$$

Based on this decomposition, one can estimate the marginal density for & &:

$$\mathcal{L}(\theta|y, x) \propto \int_{\chi} p(\theta|y, x)p(x|w)dx. \tag{11}$$

Again, the gained parameter density can be combined into single values. A common way to do so is using the mean of *theta* as the point estimate, and the variance from the density as the standard error.

Figure 3 and 4 presents the results of using MOC to engage measurement error. The results are

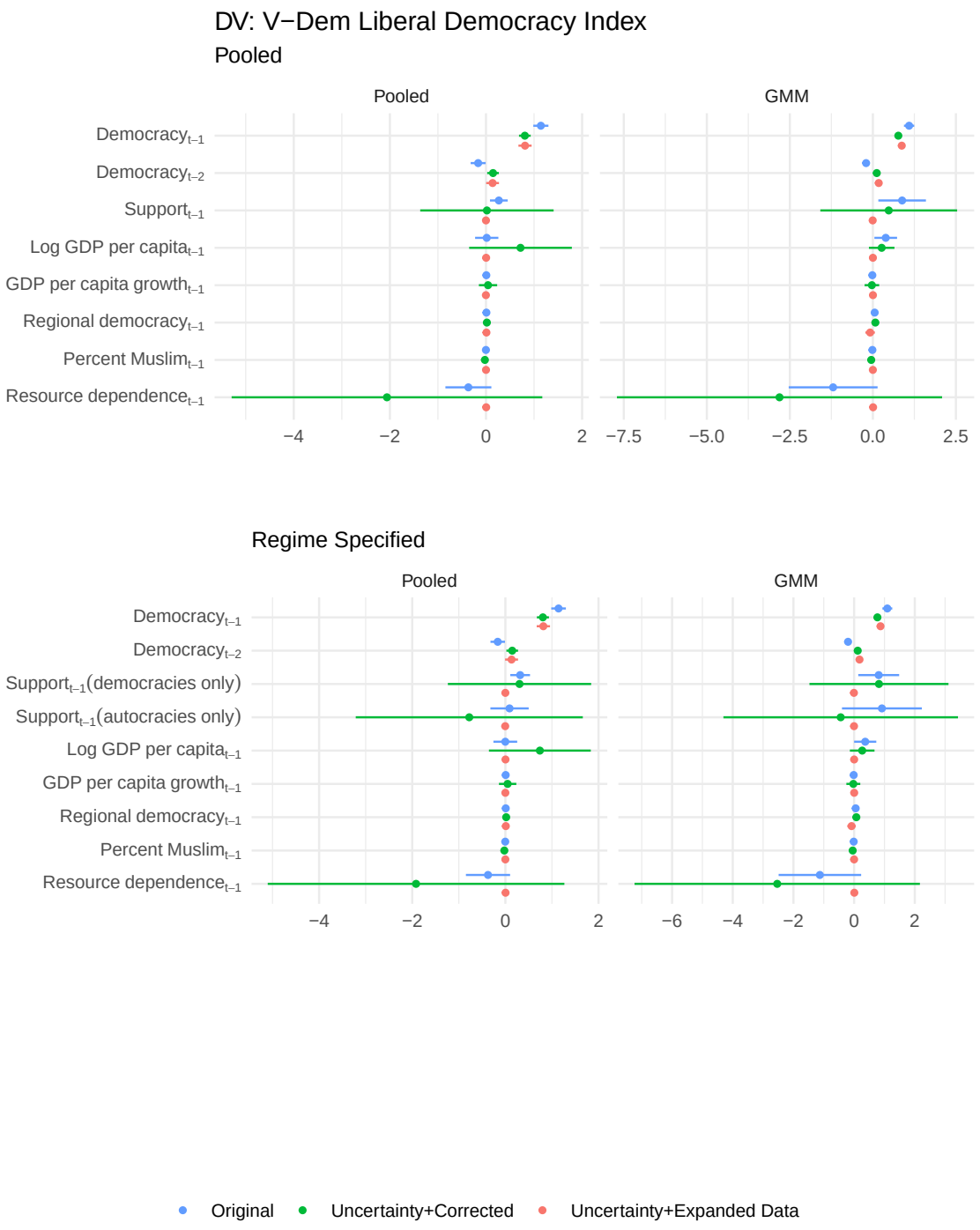

Figure 3: The Effect of Public Support on Democracy

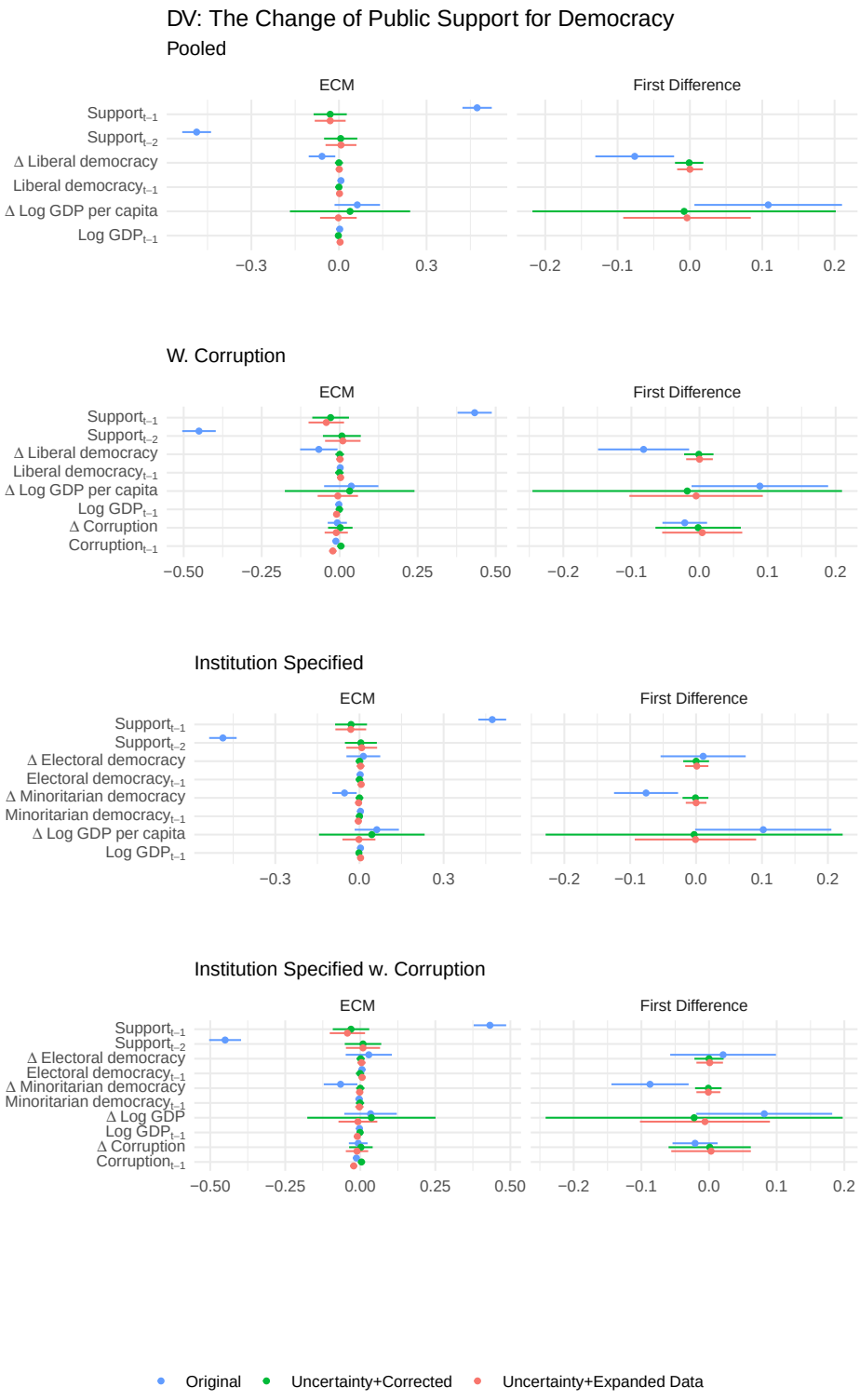

Figure 4: The Effect of Democracy on the Change of Public Support

consistent as we gained from the MO method (cf. Figure 1 and 2).