Democracy, Public Support, and Measurement Uncertainty

August 15, 2021

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: 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 di-

rectly 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). 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 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. 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 second analysis of Claassen (2020b). 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 preserve measurement uncertainty.

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 uncertainty, and ignoring that uncertainty in analyses can both attenuate or exaggerate coefficient estimates as well as bias standard errors (see, e.g., Blackwell, Honaker, and King 2017b, 318–19; 2017a, 360–61; 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" (Tanner 1993, 52; Treier and Jackman 2008, 215; Caughey and Warshaw 2018, A15–16). For additional detail on this technique, see the Supplementary Materials.

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).[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.

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, 128, Model 1) in the left panel and democratic support separated by regime type (Model 2) on the right. The uppermost set of results replicate the analysis of Claassen (2020a), including its exclusion of measurement uncertainty, and reproduce that article's findings. The middle results introduce a single change: the uncertainty in the measurement of public support is taken into account. The bottom results also incorporate uncertainty but additionally replace the estimates of democratic support with those based on the expanded dataset; this change works to increase the number of observations analyzed as well.

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 or controlling for corruption alter the conclusion (see the Supplementary Materials).

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 expose another risk for ignoring uncertainty: missestimation. As shown in Figure 1, besides the confidence intervals the (point) estimates also shift. Methodologically, the shifts indicate that the 900 regressions of public support on democracy do not yield consistent results, although the explanatory and control variables were drawn from the same distribution. In this sense, the coefficients produced simply by the means of the variable distributions are no more than a one-time guess of the true parameters and apparently not a robust one. More importantly, what this methodological difference leads to is a substantively opposite conclusion of the relationship between public opinions and institutional

democratization. Our replication results manifest the uncertainty ignorance with mounting risk.

```
{r coefName-AJPS} # index_coefName <- c( #     `Democracy\n (t-1)` =
"Democracy[t-1]", #     `Democracy\n (t-2)` = "Democracy[t-2]", #     `Support\n
(t-1)` = "Support[t-1]", #     `Support\n demo only\n (t-1)` = "Support[t-1](demo~only
#     `Support\n auto only\n (t-1)` = "Support[t-1](auto~only)", #     `Log
GDP\n per capita\n (t-1)` = "Log~GDP~per~capita[t-1]", #     `GDP per\n
capita growth\n (t-1)` = "GDP~per~capita~growth[t-1]", #     `Regional\n
democracy\n (t-1)` = "Regional~democracy[t-1]", #     `Percent\n Muslim\n
(t-1)` = "Percent~Muslim[t-1]", #     `Resource\n dependence\n (t-1)` =
"Resource~dependence[t-1]" # ) #
```

The importance for taking the measurement uncertainty into account 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, 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.

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

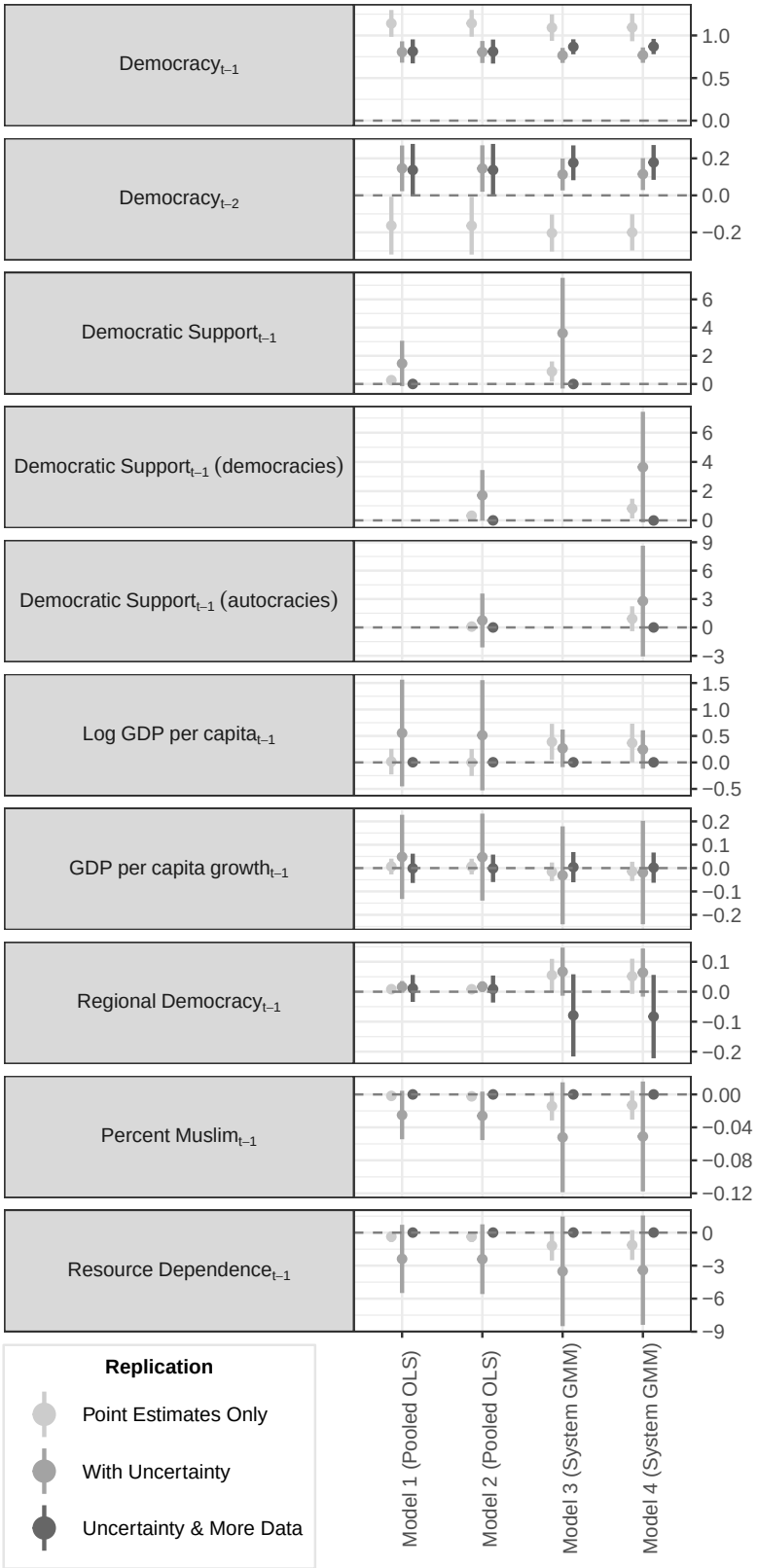

Figure 1: The Effect of Public Support on Democracy with Uncertainty

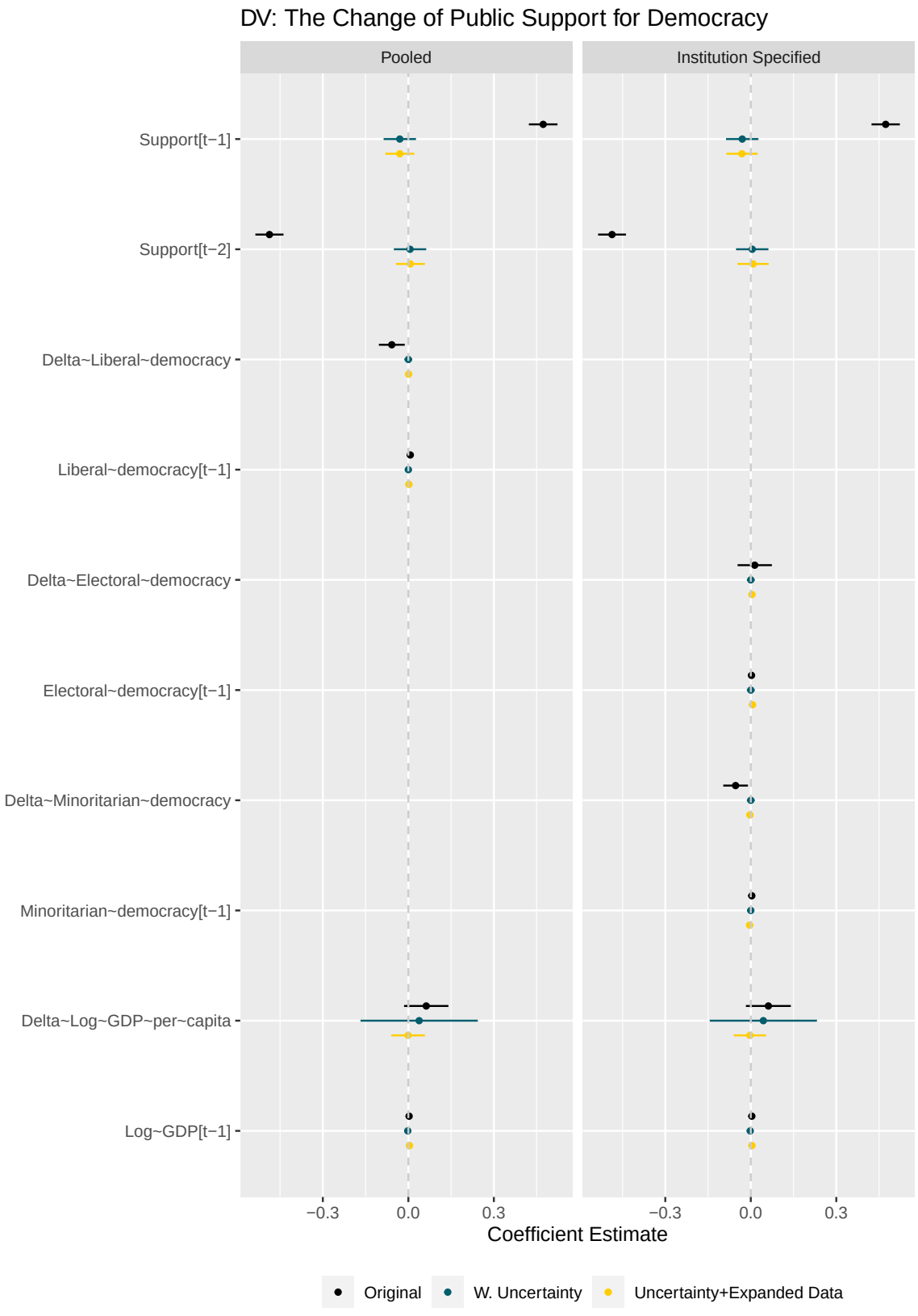

Figure 2: The Effect of Democracy on the Change of Public Support

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, 423) contends outspoken support for democracy is a "deceptive indicator of public's affinity to democracy" 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 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 decision making (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 pro-

fess 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 (2020b) 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.

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 thermostatic 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 public will rally to them—is not supported by the current evidence. Those who would defend democracy have no grounds to be complacent.

References

Bartels, Larry M. 2020. "Ethnic Antagonism Erodes Republicans' Commitment to Democracy." *Proceedings of the National Academy of Sciences* 117 (37): 22752–59.

Blackwell, Matthew, James Honaker, and Gary King. 2017a. "A Unified Approach to Measurement Error and Missing Data: Details and Extensions." *Sociological Methods & Research* 46 (3): 342–69.

———. 2017b. "A Unified Approach to Measurement Error and Missing Data: Overview and Applications." *Sociological Methods & Research* 46 (3): 303–41.

Brunkert, Lennart, Stefan Kruse, and Christian Welzel. 2019. "A Tale of Culture-Bound Regime Evolution: The Centennial Democratic Trend and Its Recent Reversal." *Democratization* 26 (3): 422–43.

Carey, John, Katherine Clayton, Gretchen Helmke, Brendan Nyhan, Mitchell Sanders, and Susan Stokes. 2020. "Who Will Defend Democracy? Evaluating Tradeoffs in Candidate Support Among Partisan Donors and Voters." *Journal of Elections, Public Opinion and Parties*, 1–16.

Caughey, Devin, Tom O'Grady, and Christopher Warshaw. 2019. "Policy Ideology in European Mass Publics, 1981–2016." *American Political Science Review* 113 (3): 674–93.

Caughey, Devin, and Christopher Warshaw. 2018. "Policy Preferences and Policy Change: Dynamic Responsiveness in the American States, 1936–2014." *American Political Science Review* 112 (2): 249–66.

Claassen, Christopher. 2019. "Estimating Smooth Country–Year Panels of Public Opinion." *Political Analysis* 27 (1): 1–20. https://doi.org/10.1017/pan.2018.32.

———. 2020a. "Does Public Support Help Democracy Survive?" *American Journal of Political Science* 64 (1): 118–34.

———. 2020b. "In the Mood for Democracy? Democratic Support as Thermostatic Opinion." *American Political Science Review* 114 (1): 1–18. https://doi.org/10.1017/S0003055419000558.

Coppedge, Michael, John Gerring, Carl Henrik Knutsen, Staffan I Lindberg, Svend-Erik Skaaning, Jan Teorell, David Altman, et al. 2018. "V-Dem [Country-Year/Country-Date] Dataset V8." *Varieties of Democracy (V-Dem) Project*.

Crabtree, Charles D., and Christopher J. Fariss. 2015. "Uncovering Patterns Among Latent Variables: Human Rights and de Facto Judicial Independence." *Research & Politics* 2 (3): 1–9.

Denemark, David, Todd Donovan, and Richard G. Niemi. 2016. "The Advanced Democracies: The Erosion of Traditional Democratic Citizenship." In *Growing up Democratic: Does It Make a Difference?*, edited by David Denemark, Robert Mattes, and Richard G. Niemi, 181–206. Boulder: Lynne Rienner.

Diamond, Larry. 2015. "Facing up to the Democratic Recession." *Journal of Democracy* 26 (1): 141–55.

Easton, David. 1965. *A Systems Analysis of Political Life*. New York: Wiley.

Fails, Matthew D., and Heather Nicole Pierce. 2010. "Changing Mass Attitudes and Democratic Deepening." *Political Research Quarterly* 63 (1): 174–87.

Foa, Roberto Stefan, and Yascha Mounk. 2017. "The Signs of Deconsolidation." *Journal of*

Democracy 28 (1): 5–15.

Gandhi, Jennifer, and Jane Lawrence Sumner. 2020. "Measuring the Consolidation of Power in Nondemocracies." *Journal of Politics* 82 (4): 1545–58. https://doi.org/10.1086/708683.

Graham, Matthew H., and Milan W. Svolik. 2020. "Democracy in America? Partisanship, Polarization, and the Robustness of Support for Democracy in the United States." *American Political Science Review* 114 (2): 392–409.

Grossman, Jonathan, and Ami Pedahzur. 2020. "Can We Do Better? Replication and Online Appendices in Political Science." *Perspectives on Politics*, 1–6.

Inglehart, Ronald, and Christian Welzel. 2005. *Modernization, Cultural Change, and Democracy*. Cambridge: Cambridge University Press.

Juhl, Sebastian. 2019. "Measurement Uncertainty in Spatial Models: A Bayesian Dynamic Measurement Model." *Political Analysis* 27 (3): 302–19.

Kastellec, Jonathan P., Jeffrey R. Lax, Michael Malecki, and Justin H. Phillips. 2015. "Polarizing the Electoral Connection: Partisan Representation in Supreme Court Confirmation Politics." *Journal of Politics* 77 (3): 787–804.

Kirsch, Helen, and Christian Welzel. 2019. "Democracy Misunderstood: Authoritarian Notions of Democracy Around the Globe." *Social Forces* 98 (1): 59–92.

Krieckhaus, Jonathan, Byunghwan Son, Nisha Mukherjee Bellinger, and Jason M. Wells. 2014. "Economic Inequality and Democratic Support." *Journal of Politics* 76 (1): 139–51.

Kruse, Stefan, Maria Ravlik, and Christian Welzel. 2019. "Democracy Confused: When People Mistake the Absence of Democracy for Its Presence." *Journal of Cross-Cultural Psychology* 50 (3): 315–35.

Levitsky, Steven, and Daniel Ziblatt. 2018. *How Democracies Die: What History Tells Us about Our Future*. London: Viking.

Linzer, Drew A., and Jeffrey K. Staton. 2015. "A Global Measure of Judicial Independence, 1948–2012." *Journal of Law and Courts* 3 (2): 223–56. https://doi.org/10.1086/682150.

Lipset, Seymour Martin. 1959. "Some Social Requisites of Democracy: Economic Development and Political Legitimacy." *American Political Science Review* 53 (1): 69–105.

Magalhães, Pedro C. 2014. "Government Effectiveness and Support for Democracy." *European Journal of Political Research* 53 (1): 77–97.

McCoy, Jennifer, Gábor Simonovits, and Levente Littvay. 2020. "Democratic Hypocrisy: Polarized Citizens Support Democracy-Eroding Behavior When Their Own Party Is in Power." PsyArXiv `https://psyarxiv.com/vrn85/`.

McGann, Anthony J. 2014. "Estimating the Political Center from Aggregate Data: An Item Response Theory Alternative to the Stimson Dyad Ratios Algorithm." *Political Analysis* 22 (1): 115–29.

O'Grady, Tom, and Tarik Abou-Chadi. 2019. "Not so Responsive After All: European Parties Do Not Respond to Public Opinion Shifts Across Multiple Issue Dimensions." *Research & Politics* 6 (4): 1–7.

Qi, Lingling, and Doh Chull Shin. 2011. "How Mass Political Attitudes Affect Democratization: Exploring the Facilitating Role Critical Democrats Play in the Process." *International Political Science Review* 32 (3): 245–62.

Schedler, Andreas, and Rodolfo Sarsfield. 2007. "Democrats with Adjectives: Linking Direct and Indirect Measures of Democratic Support." *European Journal of Political Research* 46 (5): 637–59.

Solis, Jonathan A., and Philip D. Waggoner. 2020. "Measuring Media Freedom: An Item Response Theory Analysis of Existing Indicators." *British Journal of Political Science* FirstView (June): 1–20. https://doi.org/10.1017/S0007123420000101.

Solt, Frederick. 2020a. "DCPO: Dynamic Comparative Public Opinion." Available at the Comprehensive R Archive Network (CRAN). `https://CRAN.R-project.org/package=DCPO`.

———. 2020b. "Modeling Dynamic Comparative Public Opinion." SocArXiv `10.31235/osf.io/d5n9p`.

Stegmueller, Daniel. 2011. "Apples and Oranges? The Problem of Equivalence in Comparative Research." *Political Analysis* 19 (4): 471–87.

Tanner, Martin Abba. 1993. *Tools for Statistical Inference: Methods for the Exploration of Posterior Distributions and Likelihood Functions*. 2nd ed. New York: Springer-Verlag. http://books.google.com?id=YR3vAAAAMAAJ.

Treier, Shawn, and Simon Jackman. 2008. "Democracy as a Latent Variable." *American Journal of Political Science* 52 (1): 201–17. https://doi.org/10.1111/j.1540-5907.2007.00308.x.

Wuttke, Alexander, Konstantin Gavras, and Harald Schoen. 2020a. "Have Europeans Grown Tired of Democracy? New Evidence from Eighteen Consolidated Democracies, 1981–2018." *British Journal of Political Science* FirstView: 1–13.

———. 2020b. "Leader of the Free World or Pioneer in Democracy's Decline? Examining the Democratic Deconsolidation Hypothesis on the Mass Level in East and West Germany." *Research & Politics* 7 (1): 1–10.

Wuttke, Alexander, Christian Schimpf, and Harald Schoen. 2020. "When the Whole Is Greater Than the Sum of Its Parts: On the Conceptualization and Measurement of Populist Attitudes and Other Multidimensional Constructs." *American Political Science Review* 114 (2): 356–74.

Online Supplementary Materials

Supplementary Appendix A: Data Recollection and 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 country-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.

Since many variables, dependent variables, key independent variables, and control variables in the original analysis are latent variables, which cannot be observed directly and are inherently contaminated by measurement errors. We include measurement errors in five variables, public support for democracy, liberal democracy index, electoral democracy index, liberal component index, and corruption perception index.

In respect of the key independent variable, public support for democracy, we preserve its posterior distribution from Model 5 using recollected and expanded data, separately.

For the three indices of democratic development, we take two strategies. Regarding original data and recollected data, we use three democratic indices from V-Dem Version 8 which covers 201 countries from 1789 to 2017 and is the version Claassen used in his analyses.

We use their posterior distribution provided by Coppedge et al. (2018). Regarding the expanded data used to replicate Claassen's analyses, we use the same three democratic indices but from V-Dem Version 10 because its year range from 1789 to 2019 is compatible with the expanded data. However, since V-Dem project has not released posterior distributions for indices in version 10, we simulated 900 data set for each democracy index using their standard error.

Finally, to account for measurement error in Corruption Perceptions Index, we simulated 900 draws from a distribution with the point estimate and standard error provided by CPI for the year from 2012 to 2018. However, CPI does not provide standard error for the years before 2012. To simulate "posterior distribution," we first estimated the standard error for the country-year index. For each country, we identified its maximum relative standard error (standard error/cpi index) during these years and then calculated the estimated country-year standard error by multiplying the country's maximum relative error and its year CPI index. We used this estimated standard error to simulate 900 draws for each country-year.

In the following section, we illustrate how we utilize these simulated distributions to take uncertainty into account in analysis models.

Appendix B: The Method of Composition

In analysis models, we have latent variables in both sides of equations, public suppport for democracy, democracy indices, and corruption index (The latter one is included in APSR analyses). Since measurement uncertainty associated with these latent variables can propagate into the inferences over coefficient parameters in models, we incorporate uncertainty by employing "Method of Composition" (Tanner 1993, p52), which has been applied in analyses with latent variables (Treier and Jackman 2008; Caughey and Warshaw 2018; Kastellec et al. 2015).

As Caughey and Warshaw (2018) 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 (P A-15). More explicitly, we wish to integrate 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 varibles with measurement errors conditional on data Z and a measurement model, w is other predictors without errors, Z is indicators for latent variables X, and y is the outcome variable. In this way, we incorportate 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 dentsity and the marginal density in the right side of the equation, we follow iterative Monte Carlo procdure described by Treier and Jackman (2008), at iteration t,

1. We sample θ^s from its posterior distribution $p(\theta|Z)$ and y from $p(y|Z)$.

2. For each analysis model, we run the model with y, θ, and w, and save the coefficient estimates β^s and variance-covariance matrix of β^s, V^s, both of which change due to the uncertainty in θ^s and y^s.

3. We sample $\tilde{\beta}^t$ from the multivariate normal density with mean vector βs and variance-covariace matrix V^s.

We incorporate uncertainty for five variables, public support for democracy, liberal democracy, electoral democracy, liberal component index, and 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 datesets independently and save the resulting estimates of coefficients and the matrix of variance-covariance for each run. We then draw one sample from the mulitivariate 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.

Appendix C: Secondary Models from Claassen (2020*a*, 2020*b*)

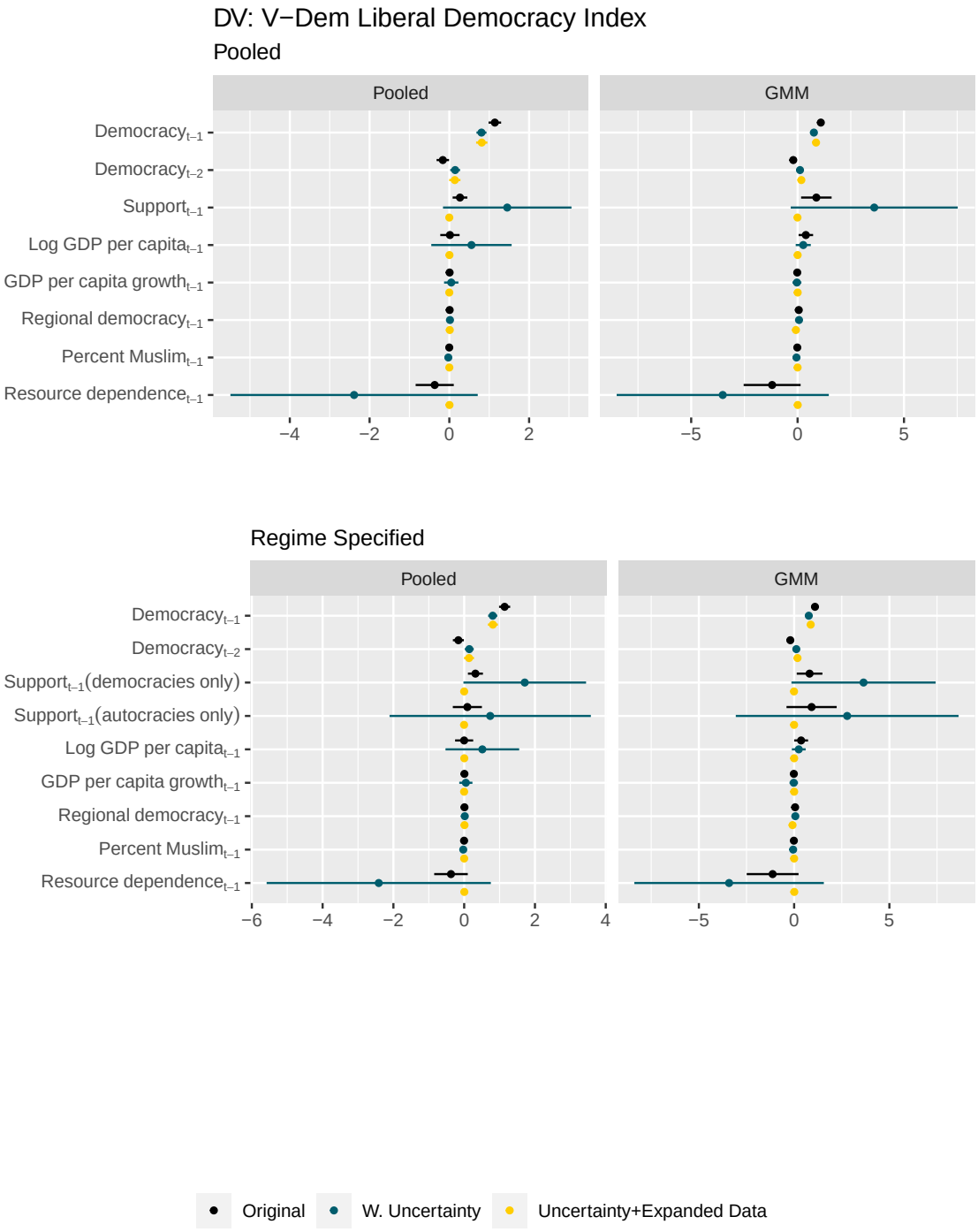

Figure A.1: The Effect of Public Support on Democracy

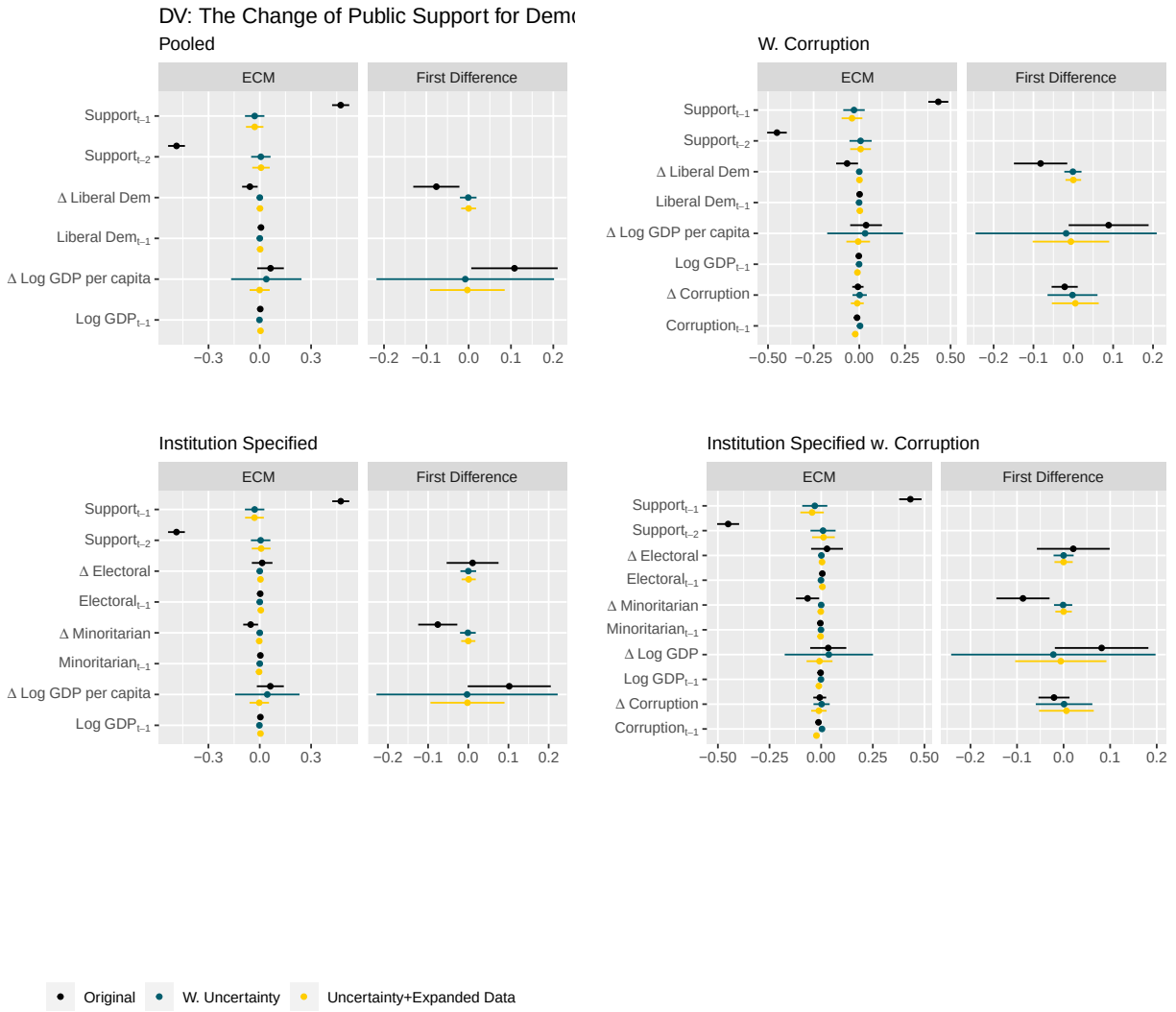

Figure A.2: The Effect of Democracy on the Change of Public Support

Figure A.1 and A.2 presents the results of using MOC to engage measurement error. The results are consistent as we gained from the MO method (cf. Figure 1 and 2).

Appendix D: DCPO Replication

As a further test of the classic arguments on democracy and public support, we apply the superior DCPO model to a bigger 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 the expanded data using the `DCPO` package for R (Solt 2020a). We use the estimated public support from DCPO model to replicate analyses by following the same steps. Then, we compare the DCPO results with two types of replication results from Model 5: estimation of original data and without uncertainty and estimation of expanded data and with uncertainty.

The comparison is presented in Appendix B. Still, even with the superior DCPO model and expanded data, there is no evidence to support that public support can sustain democratic development or public support responds thermostatically to changes in democracy.

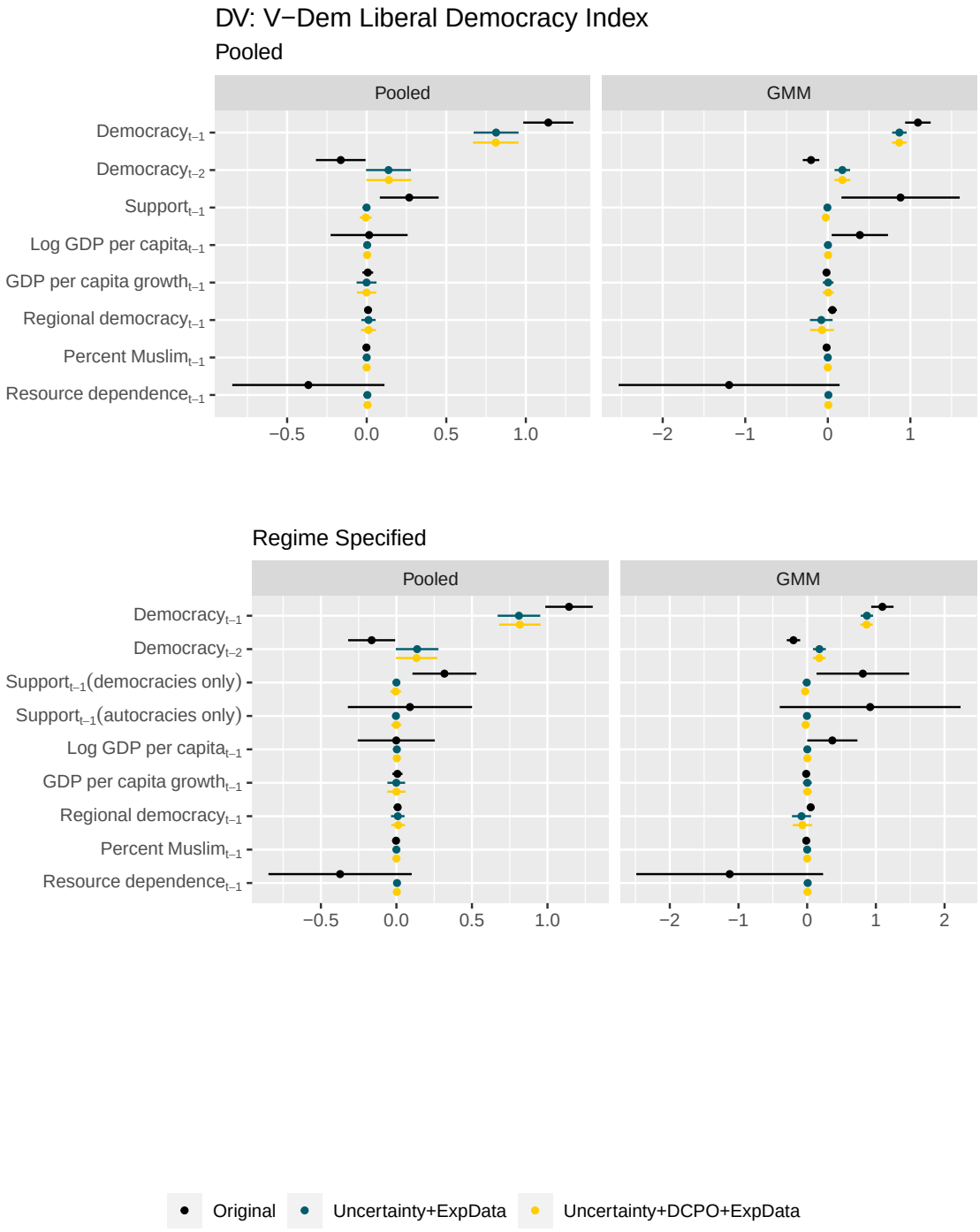

Figure A.3: The Effect of Public Support on Democracy

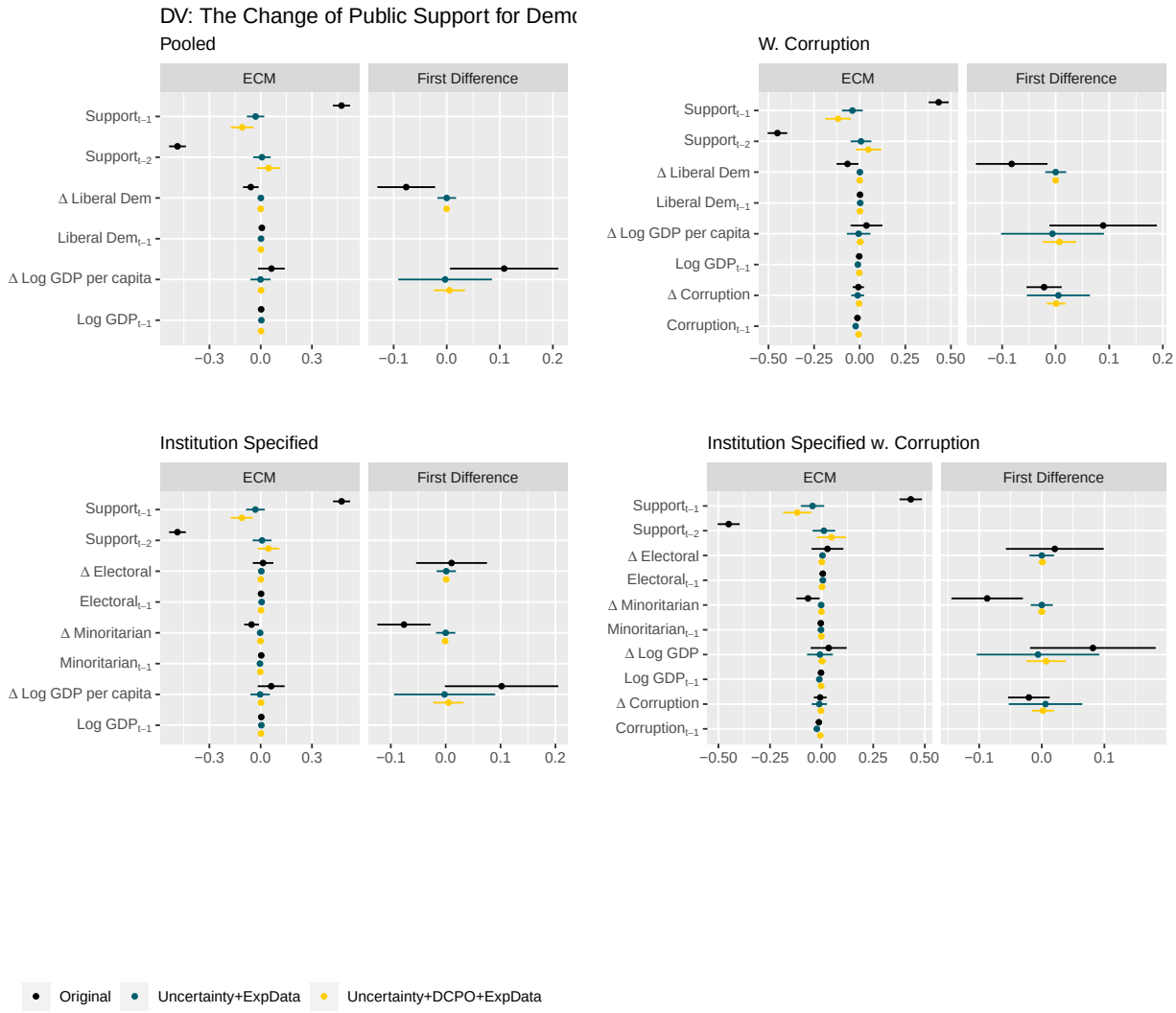

Figure A.4: The Effect of Democracy on the Change of Public Support