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Global Governance under Populism: The Challenge of Information Suppression

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Abstract

Populists' ideological opposition to global governance is well recognized, yet whether and how these actors systematically undermine international organizations (IOs) remains unclear. We argue that a key means by which populists warp global governance is by distorting scientific information, which is necessary for global responses to many public health and environmental issues. Populists are motivated to withhold or misreport scientific information due to their anti-elite, pro-state sovereignty views. Using new data on the source and quality of information provided to IOs, we find that populist leaders are significantly less likely to provide scientific information to these organizations than other types of leaders. When they do offer such data, it is less accurate than the information supplied by other sources. Our findings suggest that populism may stymie international institutions' ability to govern in areas of pressing international concern.

Keywords: populism, global governance, transparency, information, science

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Online Appendices

A Summary Statistics

Country	Spell Start	Spell End
Argentina	1990	1999
Argentina	2003	2015
Bolivia	2006	2018
Brazil	1990	1992
Bulgaria	2009	2018
Ecuador	1997	1997
Ecuador	2007	2017
Greece	1993	1995
Greece	2015	2018
Hungary	2010	2018
India	2014	2018
Indonesia	2014	2018
Israel	1996	1999
Israel	2009	2018
Italy	1994	1995
Italy	2001	2011
Italy	2018	2018
Japan	2001	2006
Mexico	2018	2018
Peru	1990	2000
Philippines	1998	2001
Philippines	2016	2018
Poland	2005	2007
Poland	2015	2018
Slovakia	1990	1998
Slovakia	2006	2018
South Africa	2009	2018
South Korea	2003	2008
Thailand	2001	2006
Turkey	2003	2018
United States	2017	2018
Venezuela	1999	2018

Table A4: Populist spells 1990–2018 (Funke, Schularick, and Trebesch 2022).

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Scientific missingness	7,656	0.617	0.157	0.187	0.508	0.683	1.000
Non-scientific missingness	7,656	0.555	0.195	0.138	0.414	0.660	1.000
Scientific missigness (raw)	7,656	0.610	0.204	0.127	0.436	0.745	1.000
Scientific missingness (estimated)	7,656	0.557	0.155	0.137	0.470	0.581	1.000
Populism	7,656	0.045	0.206	0	0	0	1
Polity2	4,614	3.039	6.632	-10.000	-3.000	9.000	10.000
Right-wing	2,593	0.368	0.482	0.000	0.000	1.000	1.000
GDP per capita	6,830	12,406.880	19,057.410	161.834	1,379.505	13,943.140	191,586.600
IMF program	7,656	0.184	0.387	0	0	0	1

Table A5: Summary statistics for main regression models. Note that no transformations (e.g., standardization, natural log) have been applied to these variables.

Category	Subcategory	Quantity	Example Indicator
Environment	Emissions	26	CO2 emissions from liquid fuel consumption (kt)
	Land	26	Arable land (% of land area)
	Water	20	Marine protected areas (% of territorial waters)
	Energy	30	Energy use (kg of oil equivalent per capita)
Health	Disease	18	Incidence of malaria (per 1,000 pop at risk)
	Mortality	39	Mortality rate, adult, male (per 1,000 male adults)
	Nutrition	28	Low-birthweight babies (% of births)
	Hygiene	12	People using safely managed sanitation services (% of pop)
	Access to care	34	Antiretroviral therapy coverage (% people with HIV)
	Sex & reproduction	19	Fertility rate, total (births per woman)

Table A6: Categories of Scientific WDI Variables. We include 252 variables in total in our calculation of missingness in reporting across scientific measures.

B Coding Procedures

To identify the source of WDI variables, we first examined the metadata for each variable under consideration. If the data was provided by a non-governmental organization, another IO, or an academic source, we next combed through that source's website for additional information about the original source of the data in question. We then placed each variable into one of two categories. The first, which should be most affected by populism, is raw state-provided data. This category consists of variables that are of state-reported origin, including data either provided directly by states to the World Bank or data provided by states to a non-governmental entity that is subsequently relayed to the World Bank. The second, which should not be impacted by populism, includes data that is either independently collected or estimated/imputed by non-governmental organizations, academics, or IOs. Around half of the WDI variables fall into each category.

C Bayesian Item Response (IRT) Model

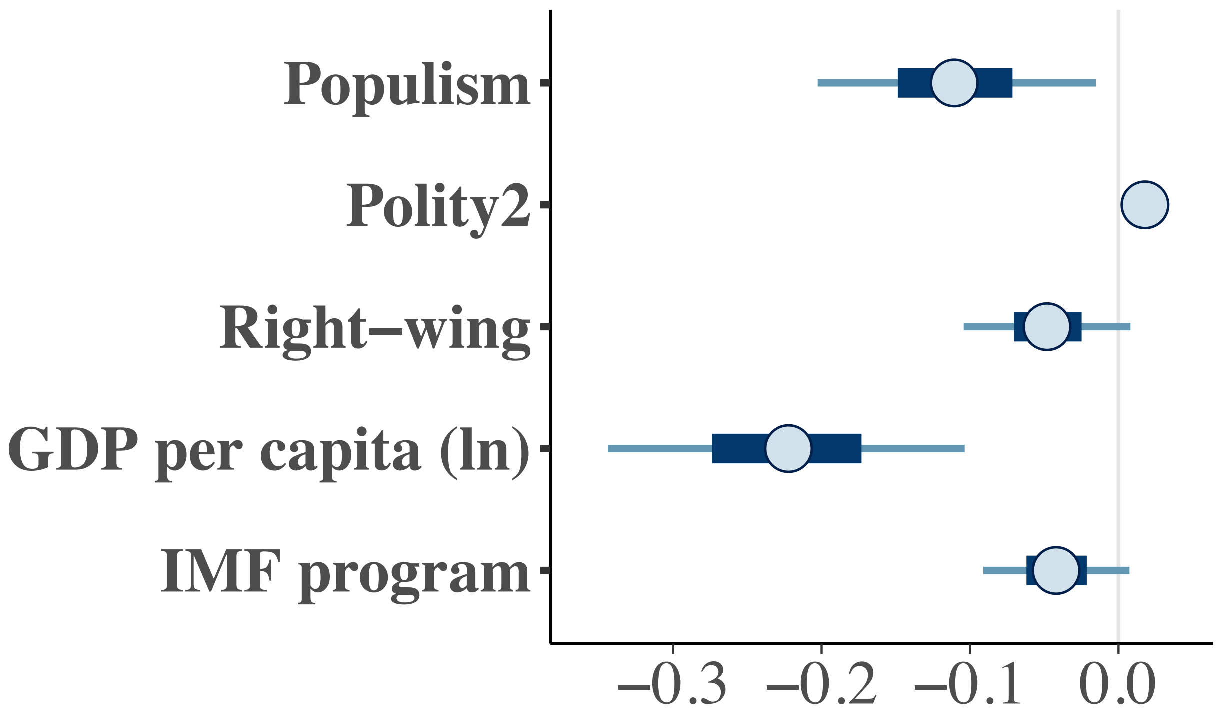

Figure C4: Posterior distributions from Markov Chain Monte Carlo for Gaussian Linear Regression with plotted means, 50% confidence boxes, and 90% confidence intervals. The result for populism remains robust (p = 0.05). We run the model with 1,000 burnin iterations and 1,000 MCMC iterations. The dependent variable is latent scientific transparency (i.e., higher values indicate *greater* transparency), which we construct utilizing the replication materials from Hollyer et al (2014) on our WDI sample of raw state-provided scientific WDI variables. MCMC allows us to address two key concerns with our primary analysis by accounting for potential variation in the importance and difficulty of disclosure across variables. Model also includes Blair Institute coding of populism and our complete cohort of control variables as well as country and year fixed effects.

D Weighted Missingness

	Missingness of Scientific Variables		
	All	Raw	Estimated
	(1)	(2)	(3)
Populism	0.045***	0.059**	0.017
	(0.014)	(0.026)	(0.011)
Polity2	-0.006^{***}	-0.007^{**}	-0.004^{**}
	(0.002)	(0.004)	(0.002)
Right-wing	0.007	0.007	0.006
	(0.006)	(0.013)	(0.005)
GDP per capita (ln)	-0.006	-0.012	-0.006
	(0.026)	(0.075)	(0.052)
IMF program	-0.007	-0.018	-0.005
	(0.007)	(0.014)	(0.007)
Observations	4,026	4,026	4,026
Note:			*p$<$0.1; **p$<$0.05; ***p$<$0.01

Table D7: Regressions of the weighted proportion of scientific WDI indicators missing in a given year on the populism indicator. This model weights each WDI variable incorporated into the dependent variable by the average missingness found for that variable in a given year across all countries (i.e., the dependent variable is a weighted average of missingness). Highly reported variables are weighted more than less reported variables, to account for the greater notability of not reporting a highly reported variable. It therefore incorporates a time-variant measure of difficulty in reporting a given variable. All models include country and year fixed effects and standard errors clustered by country. Independent variables are lagged by one year.

E Populist Entry, Exit, and Stickiness

	Missingness of Scientific Variables			
	Two Years Pre/Post **Entry**		Two Years Pre/Post **Exit**	
	All	Raw	All	Raw
	(1)	(2)	(3)	(4)
Populism	0.341**	0.318*	−0.294	−0.141
	(0.149)	(0.164)	(0.190)	(0.185)
Observations	56	56	33	33
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table E8: Regressions of the proportion of scientific WDI indicators missing in a given year on the populism indicator. These models compare missingness two years prior to and two years post populist entry into office (models 1–2), as well as missingness two years prior to and two year post populist *exit* from office (models 3–4). We opt for the two-year buffer in order to compare missingness independent of general dynamics associated with government transitions. Models include country fixed effects. We omit year fixed effects because there are not many observations in any given year in this sample, and we are interested in variation within a country over time. This setup helps to allay concerns that slower-moving background or omitted variables are driving our results.

	Missingness of Scientific Variables		
	All	Raw	Estimated
	(1)	(2)	(3)
Populism ($t-3$)	0.041	0.035	0.020
	(0.053)	(0.036)	(0.078)
Polity2 ($t-3$)	−0.007**	−0.006***	−0.002
	(0.003)	(0.002)	(0.004)
Right-wing (ln, $t-3$)	−0.008	−0.008	−0.004
	(0.013)	(0.010)	(0.019)
GDP per capita (ln, $t-3$)	0.041	−0.003	0.054
	(0.044)	(0.048)	(0.055)
IMF program ($t-3$)	−0.007	0.006	−0.012
	(0.014)	(0.012)	(0.018)
Observations	2,124	2,124	2,124
Note:		*p<0.1; **p<0.05; ***p<0.01	

Table E9: Regressions of the proportion of scientific WDI indicators missing in a given year on a three-year lagged populism indicator limited to countries that did not have a populist in power in the prior year. Includes country and year fixed effects. These results show that the suppressive effects of populism on scientific information provision to IOs do not seem to linger after a populist exits office.

F Drop Outliers

	Missingness of Scientific Variables		
	All	Raw	Estimated
	(1)	(2)	(3)
Populism	0.067**	0.044**	0.058*
	(0.031)	(0.020)	(0.035)
Polity2	−0.010***	−0.002	−0.010***
	(0.003)	(0.002)	(0.004)
Right-wing	0.008	0.001	0.014
	(0.010)	(0.008)	(0.015)
GDP per capita (ln)	−0.004	0.0001	−0.034
	(0.048)	(0.041)	(0.056)
IMF program	0.032**	0.020**	0.038**
	(0.014)	(0.009)	(0.017)
Observations	2,251	2,250	2,254
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table F10: Regressions of the proportion of scientific WDI indicators missing in a given year on the populism indicator. Includes country and year fixed effects. Outliers are classified as observations with the outcome measure more than two standard deviations from the mean.

	Missingness of Scientific Variables
Populism	0.255**
	(0.114)
Polity2	0.001
	(0.023)
Right-wing	0.102
	(0.119)
GDP per capita (ln)	−0.051
	(0.365)
IMF program	−0.052
	(0.136)
Fossil fuel (% energy consumption)	0.023*
	(0.012)
Value added by agriculture, forestry, and fishing (% GDP)	0.031
	(0.032)
Observations	741
Note:	*p<0.1; **p<0.05; ***p<0.01

Table F11: Regressions of the absolute difference (ln) between the total emissions estimate provided by Annex I Parties to the UNFCCC in a given year and the total emissions figure estimated by EDGAR (as reported in the WDI) in that same year on populism. All models include country and year fixed effects and standard errors clustered by country. Independent variables are lagged by one year. Outliers are classified as observations with the outcome measure more than two standard deviations from the mean.

G Non-Scientific Indicators

	Missingness of Non-Scientific Variables		
	(1)	(2)	(3)
Populism	0.043	0.016	-0.001
	(0.027)	(0.025)	(0.025)
Polity2		-0.010^{***}	-0.007^{***}
		(0.003)	(0.002)
Right-wing			0.041^{***}
			(0.014)
GDP per capita (ln)			-0.078
			(0.061)
IMF program			-0.028^{**}
			(0.013)
Observations	7,656	4,614	4,026
Note:			*p$<$0.1; **p$<$0.05; ***p$<$0.01

Table G12: Regressions of the proportion of non-scientific WDI indicators missing in a given year (standardized) on populism. All models include country and year fixed effects and standard errors clustered by country. Independent variables are lagged by one year.

H Drop United States

	Missingness of Scientific Variables		
	All	Raw	Estimated
	(1)	(2)	(3)
Populism	0.068^{**}	0.044^{**}	0.061^{*}
	(0.031)	(0.020)	(0.036)
Polity2	-0.010^{***}	-0.003	-0.010^{***}
	(0.003)	(0.002)	(0.003)
Right-wing	0.009	0.002	0.016
	(0.010)	(0.008)	(0.016)
GDP per capita (ln)	-0.005	-0.0003	-0.007
	(0.049)	(0.042)	(0.062)
IMF program	0.033^{**}	0.020^{**}	0.038^{**}
	(0.014)	(0.010)	(0.017)
Observations	2,250	2,250	2,250
Note:			*p$<$0.1; **p$<$0.05; ***p$<$0.01

Table H13: Regressions of the proportion of scientific WDI indicators missing in a given year on the populism indicator. Includes country and year fixed effects. The U.S. is dropped to ensure that former US president Donald Trump is not driving the results.

	Missingness of Scientific Variables
Populism	0.231*
	(0.116)
Polity2	0.011
	(0.023)
Right-wing	0.129
	(0.142)
GDP per capita (ln)	-0.196
	(0.395)
IMF program	-0.053
	(0.131)
Fossil fuel (% energy consumption)	0.033*
	(0.016)
Value added by agriculture, forestry, and fishing (% GDP)	0.022
	(0.032)
Observations	774
Note:	*p<0.1; **p<0.05; ***p<0.01

Table H14: Regressions of the absolute difference (ln) between the total emissions estimate provided by Annex I Parties to the UNFCCC in a given year and the total emissions figure estimated by EDGAR (as reported in the WDI) in that same year on populism. All models include country and year fixed effects and standard errors clustered by country. Independent variables are lagged by one year. The U.S. is dropped to ensure that former US president Donald Trump is not driving the results.

I Drop Most Recent Years

	Dependent variable:		
	Scientific missingness (all)	Scientific missingness (raw)	Scientific missingness (estimated)
	(1)	(2)	(3)
Populism	0.067^{**}	0.031^{*}	0.063^{*}
	(0.028)	(0.017)	(0.035)
Polity2	-0.009^{***}	-0.002	-0.011^{***}
	(0.003)	(0.002)	(0.004)
Right-wing	0.010	0.004	0.014
	(0.010)	(0.008)	(0.017)
GDP per capita (ln)	-0.010	-0.010	-0.015
	(0.052)	(0.046)	(0.064)
IMF program	0.032^{**}	0.015^{*}	0.040^{**}
	(0.015)	(0.009)	(0.018)
Observations	2,203	2,203	2,203
Note:			*p<0.1; **p<0.05; ***p<0.01

Table I15: Regressions of the proportion of scientific WDI indicators missing in a given year on the populism indicator. Includes country and year fixed effects. Post-2015 years are dropped from the data because there is often a lag of a few years in reporting of some indicators.

	Dependent variable:
	Emissions data gap (ln)
Populism	0.307^{**}
	(0.134)
Polity2	0.012
	(0.025)
Right-wing	0.116
	(0.138)
GDP per capita (ln)	-0.160
	(0.375)
IMF program	-0.031
	(0.125)
Fossil fuel (% energy consumption)	0.033^{**}
	(0.016)
Value added by agriculture, forestry, and fishing (% GDP)	0.031
	(0.032)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table I16: Regressions of the absolute difference (ln) between the total emissions estimate provided by Annex I Parties to the UNFCCC in a given year and the total emissions figure estimated by EDGAR (as reported in the WDI) in that same year on populism. All models include country and year fixed effects and standard errors clustered by country. Independent variables are lagged by one year. Post-2015 years are dropped from the data because there is often a lag of a few years in reporting of some indicators.

J Alternate Populism Measure

This section utilizes populism data from the Blair Institute for Global Change. This dataset analyzes the contents of thousands of academic articles published in 66 leading political science, sociology, and regional studies journals to code whether a given country's leader is a populist. The Institute "identified all articles published in these journals on the subject of populism, as well as political leaders linked with populism; then vetted each potential case study, consulting with country and regional experts." They define populists as leaders who share two core ideologies: (1) elites or "outsiders" threaten the interests of the "true people," and (2) populists stand for the "true people."

	Dependent variable:	
	Scientific missingness	
	(1)	(2)
Populism	0.047^{**}	0.060^{**}
	(0.019)	(0.027)
Polity2	-0.012^{***}	-0.010^{***}
	(0.002)	(0.003)
Right-wing		0.008
		(0.010)
GDP per capita (ln)		-0.004
		(0.049)
IMF program		0.033^{**}
		(0.014)
Observations	4,614	2,277
Adjusted R^2	0.928	0.866
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table J17: Regressions of the proportion of scientific WDI indicators missing in a given year (standardized) on populism. All models include country and year fixed effects and standard errors clustered by country. Independent variables are lagged by one year. Estimated via OLS.

	Dependent variable:
	Emissions data gap (ln)
Populism	0.307^{**}
	(0.134)
Polity2	0.012
	(0.025)
Right-wing	0.116
	(0.138)
GDP per capita (ln)	-0.160
	(0.375)
IMF program	-0.031
	(0.125)
Fossil fuel (% energy consumption)	0.033^{**}
	(0.016)
Value added by agriculture, forestry, and fishing (% GDP)	0.031
	(0.032)
Observations	790
Adjusted R^2	0.845
Note:	*p<0.1; **p<0.05; ***p<0.01

Table J18: Regressions of the absolute difference (ln) between the total emissions estimate provided by Annex I Parties to the UNFCCC in a given year and the total emissions figure estimated by EDGAR (as reported in the WDI) in that same year on populism. All models include country and year fixed effects and standard errors clustered by country. Independent variables are lagged by one year. Estimated via OLS.

K Additional Covariates

	Missingness of Scientific Variables		
	All	Raw	Estimated
	(1)	(2)	(3)
Populism	0.075*	0.060**	0.036
	(0.044)	(0.028)	(0.079)
Polity2	−0.021***	0.002	−0.029***
	(0.006)	(0.005)	(0.007)
Right-wing	−0.004	−0.026	0.003
	(0.027)	(0.020)	(0.041)
GDP per capita (ln)	0.066	0.057	0.003
	(0.067)	(0.066)	(0.112)
IMF program	0.065***	0.016	0.076**
	(0.024)	(0.014)	(0.029)
Fossil fuel (% energy consumption)	0.0004	0.0005	0.002
	(0.002)	(0.001)	(0.004)
Value added by agriculture, forestry, and fishing (% GDP)	0.001	−0.001	0.003
	(0.004)	(0.003)	(0.006)
Net ODA and official assistance received	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)
GDP growth (year-over-year, %)	−0.004	0.002	−0.005
	(0.003)	(0.002)	(0.005)
Unemployment rate	−0.010***	−0.002	−0.012**
	(0.003)	(0.002)	(0.005)
Economic crisis	−0.006	0.002	−0.016
	(0.012)	(0.005)	(0.018)
Observations	651	651	651
Note:			*p<0.1; **p<0.05; ***p<0.01

Table K19: Regressions of the proportion of scientific WDI indicators missing in a given year on the populism indicator. Includes country and year fixed effects.

	Missingness of Scientific Variables		
	All	Raw	Estimated
	(1)	(2)	(3)
Populism spell length	0.014**	0.008*	0.012*
	(0.005)	(0.004)	(0.007)
Polity2	−0.017***	0.003	−0.024***
	(0.006)	(0.005)	(0.007)
Right-wing	−0.010	−0.028	−0.005
	(0.027)	(0.020)	(0.042)
GDP per capita (ln)	0.066	0.055	0.006
	(0.066)	(0.066)	(0.112)
IMF program	0.061***	0.013	0.075**
	(0.022)	(0.014)	(0.028)
Fossil fuel (% energy consumption)	0.001	0.001	0.002
	(0.002)	(0.001)	(0.004)
Value added by agriculture, forestry, and fishing (% GDP)	0.001	−0.001	0.003
	(0.005)	(0.002)	(0.006)
Net ODA and official assistance received	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)
GDP growth (year-over-year, %)	−0.004	0.002	−0.005
	(0.003)	(0.002)	(0.005)
Unemployment rate	−0.009***	−0.002	−0.012**
	(0.003)	(0.002)	(0.005)
Economic crisis	−0.004	0.003	−0.015
	(0.011)	(0.005)	(0.017)
Observations	651	651	651
Note:			*p<0.1; **p<0.05; ***p<0.01

Table K20: Regressions of the proportion of scientific WDI indicators missing in a given year on the length of a given populist "spell" (uninterrupted period of populist governance of country). Includes country and year fixed effects.

L Nationalism

	Missingness of Scientific Variables		
	All	Raw	Estimated
	(1)	(2)	(3)
Populism	0.077^{**}	0.052^{**}	0.068^{*}
	(0.030)	(0.020)	(0.035)
Polity2	-0.012^{***}	-0.005^{***}	-0.012^{***}
	(0.003)	(0.002)	(0.003)
Right-wing	0.008	0.003	0.013
	(0.010)	(0.008)	(0.017)
GDP per capita (ln)	-0.005	0.0004	-0.008
	(0.047)	(0.040)	(0.061)
IMF program	0.031^{**}	0.017^{*}	0.037^{**}
	(0.014)	(0.010)	(0.017)
Nationalism	-0.042	-0.037^{*}	-0.036
	(0.028)	(0.021)	(0.034)
Observations	2,275	2,275	2,275
Note:			*p$<$0.1; **p$<$0.05; ***p$<$0.01

Table L21: Regressions of the proportion of scientific WDI indicators missing in a given year on the populism indicator. Includes country and year fixed effects. The nationalism measure comes from V-DEM and captures the extent to which the government promotes a nationalist ideology.

M Conditionality

	Missingness of Scientific Variables		
	All	Raw	Estimated
	(1)	(2)	(3)
Populism	0.060^{**}	0.038^{*}	0.055
	(0.030)	(0.021)	(0.035)
Polity2	-0.009^{***}	-0.002	-0.010^{***}
	(0.003)	(0.002)	(0.003)
Right-wing	0.006	0.001	0.011
	(0.010)	(0.008)	(0.016)
GDP per capita (ln)	-0.00004	0.004	-0.005
	(0.046)	(0.041)	(0.060)
IMF program	0.031^{**}	0.018^{*}	0.038^{**}
	(0.014)	(0.010)	(0.017)
conditions	-0.003^{*}	-0.003^{**}	-0.002
	(0.002)	(0.001)	(0.002)
Observations	2,277	2,277	2,277
Note:			*p$<$0.1; **p$<$0.05; ***p$<$0.01

Table M22: Regressions of the proportion of scientific WDI indicators missing in a given year on the populism indicator. Includes country and year fixed effects. The conditionality measure is a country-year aggregate count of the number of prior actions mandated by Development Policy Financing programs from the World Bank. Data comes from Clark and Dolan (2021).

N Interaction Models

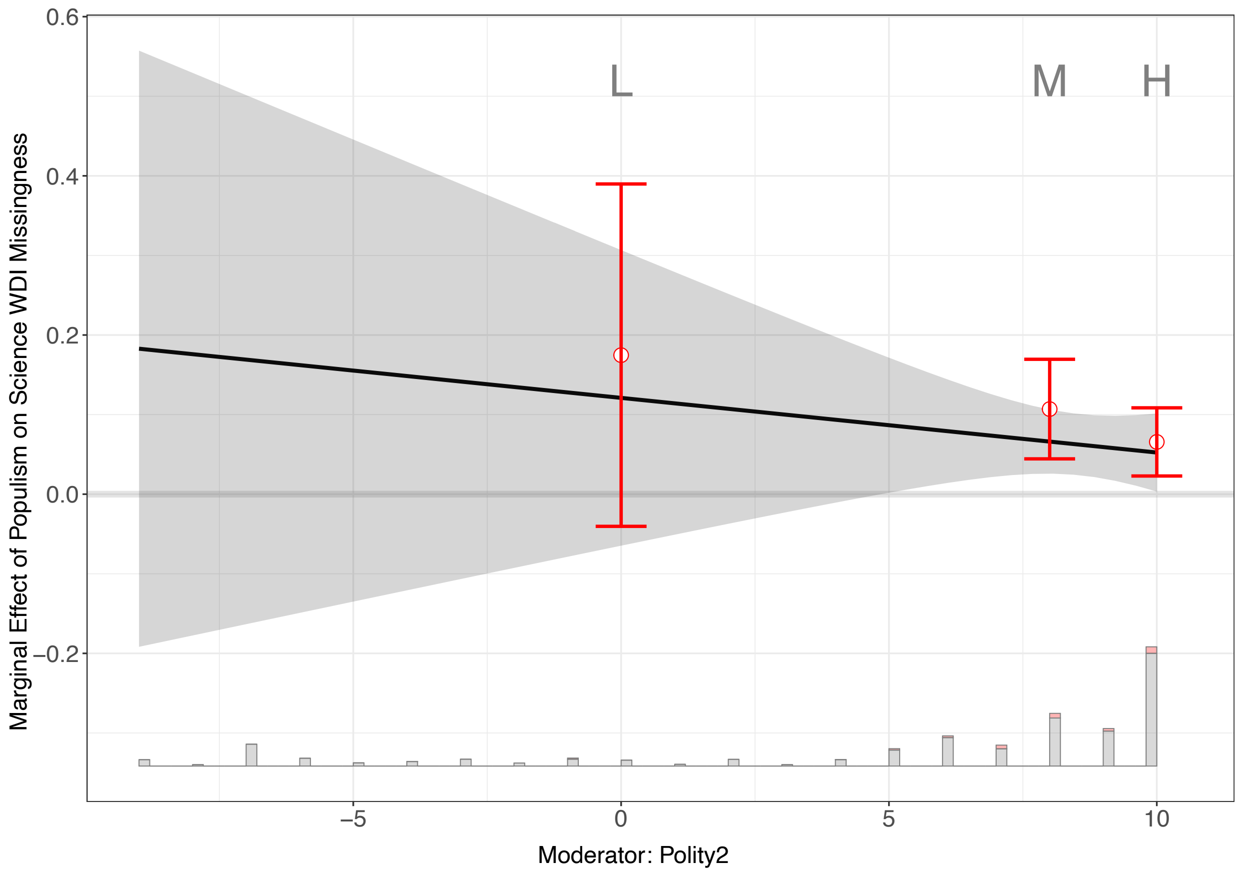

Figure N5: Populism × Polity2 Interaction Plot. The dependent variable is standardized missingness in scientific WDI variables. The interaction independent variables are the populism measure from Funke, Schularick, and Trebesch (2022) and Polity2 democracy scores. All covariates from main regressions are included in the underlying model. We utilize the binning estimator and `interflex` package from Hainmueller et al. (2019) to ensure common support in the moderator. The red confidence intervals represent the results with the binning approach, while the grey background illustrates the results with a linear interaction approach. **NB:** Populism has a positive relationship with information suppression for all Polity2 bins (terciles), as Table N5 shows.

	Lowest tercile	Middle tercile	Highest tercile
Coefficient	0.175	0.107	0.066
Standard error	0.110	0.032	0.022
95% CI	(−0.040, 0.390)	(0.044, 0.170)	(0.023, 0.108)
Moderator (Polity2) range	[−9, 6]	(6, 9]	(9, 10]

Table N23: Populism × Polity2 Interaction Table. This table shows the results of binned estimations with robust standard errors clustered by country.

O GHG Data Gap and WDI Non-Reporting

P Discussion of Ethical and Human Subjects Principles

The human subjects research included in this paper complies the with Principles and Guidance for Human Subjects Research outlined by the APSA and was deemed exempt by the Institutional Review Board at the appropriate univer-

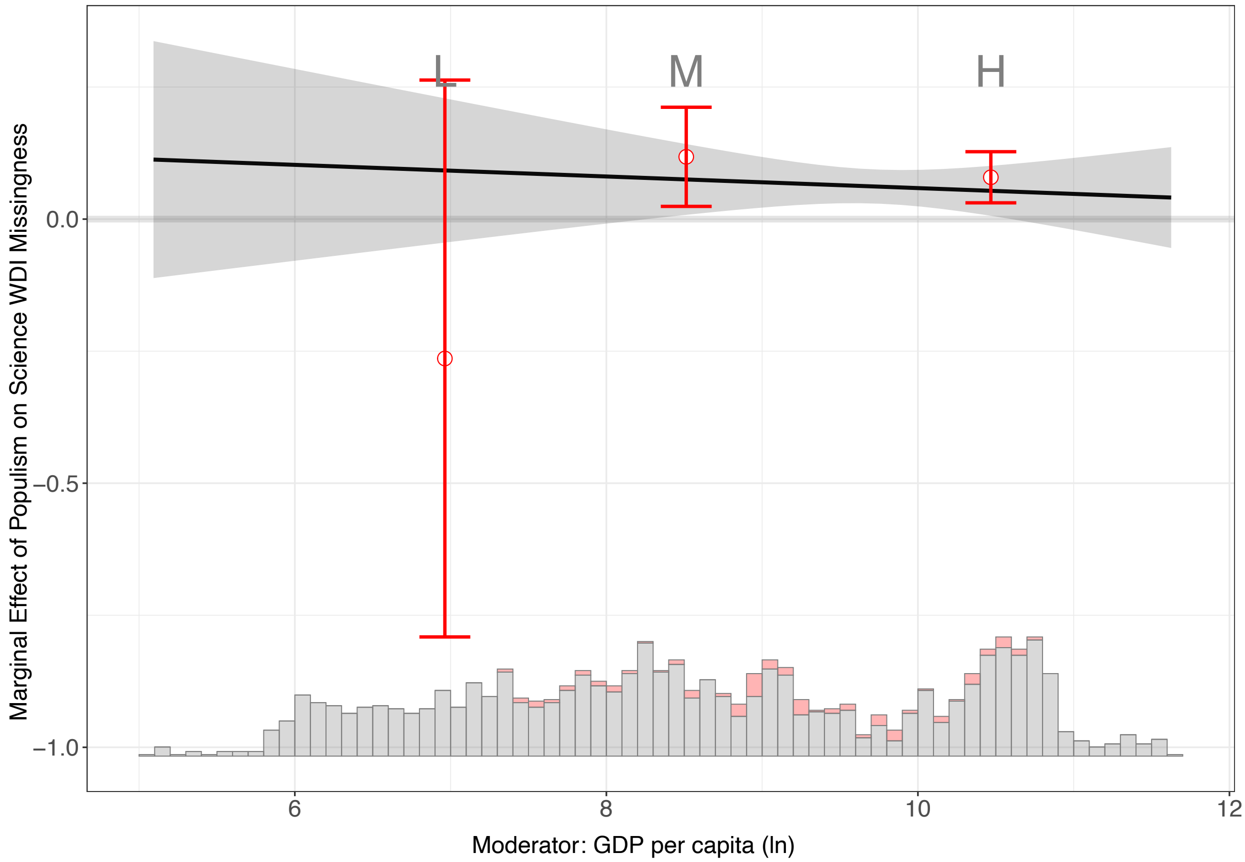

Figure N6: Populism × GDPPC Interaction Plot. The dependent variable is standardized missingness in scientific WDI variables. The interaction independent variables are the populism measure from the Funke, Schularick, and Trebesch (2022) and per capita GDP from the WDI. All covariates from main regressions are included in the underlying model. We utilize the binning estimator and `interflex` package from Hainmueller et al. (2019) to ensure common support in the moderator. The red confidence intervals represent the results with the binning approach, while the grey background illustrates the results with a linear interaction approach.

sities. We interviewed only high-ranking current officials from international organizations who were acting in their official capacity. We asked only about their professional work in their IOs. All interviewees consented to the inclusion of the specific quotes that appear in the paper with appropriate anonymization.

With regard to Principal 10 on the impact of the research on the political processes, we do not believe there is any reason to believe that our studies would have had an impact on political processes such as elections or policy creation. Subjects were only asked descriptive questions about how they collect and use data.

	Lowest tercile	Middle tercile	Highest tercile
Coefficient	−0.264	0.118	0.079
Standard error	0.269	0.048	0.025
95% CI	(−0.791, 0.263)	(0.024, 0.212)	(0.031, 0.128)
Moderator (GDPPC) range	[5.09, 7.85]	(7.85, 9.34]	(9.34, 11.6]

Table N24: Populism × GDPPC Interaction Table. This table shows the results of binned estimations with robust standard errors clustered by country.

	Dependent variable:			
	GHG data gap (standardized)			
	(1)	(2)	(3)	(4)
WDI missingness	0.314**	0.269*	0.261	0.089
	(0.119)	(0.141)	(0.194)	(0.204)
Populism	0.136**	0.145*	0.135**	0.150**
	(0.062)	(0.072)	(0.062)	(0.070)
Polity2		0.005		0.005
		(0.013)		(0.014)
Right-wing		0.036		0.037
		(0.073)		(0.072)
GDP per capita (ln)		−0.082		−0.076
		(0.255)		(0.253)
IMF		−0.052		−0.049
		(0.081)		(0.080)
WDI missingness × populism	0.006	0.028	−0.001	0.025
	(0.070)	(0.083)	(0.075)	(0.083)
Observations	936	847	936	847
Adjusted R^2	0.866	0.846	0.864	0.844
Note:				*p<0.1; **p<0.05; ***p<0.01

Table O25: Regressions of the absolute difference between the total emissions estimate provided by Annex I Parties to the UNFCCC in a given year and the total emissions figure estimaed by EDGAR in that same year (standardized) on the standardized rate of missingness in WDI scientific variables by country-year. Country and year fixed effects included; standard errors clustered by country parenthesized.

Q Illustrative Example: The U.S. under Trump

To trace our mechanism and supplement our main results, we include an illustrative example in which we investigate the effects of the election of Donald Trump – a prototypical populist – on scientific information distortion. We selected this case both due to the geopolitical importance of the U.S. and data availability.

Our theory expects that the Trump administration would lead efforts or threats to stymie the flow of accurate scientific information from the U.S. to IOs. We discuss these suppression dynamics further and provide some descriptive statistics of what kinds of information were silenced or distorted in Appendix 2.2. In general, we find that suppression events were primarily related to information in the areas of public health and climate change — two scientific areas of particular interest to development IOs as they pursue their sustainable development mandates. Moreover, the Trump administration often justified the withholding of such information using populist rhetoric, such as anti-elite statements.[43] This implies that the administration's choice to stop providing this information is at least partly attributable to populism, though we acknowledge that other factors may also have contributed to it.

Consider several examples that show that the Trump administration restricted information in these domains. First, the Trump administration forbade scientists to share information with international bodies or otherwise constrained their work. For example, when a U.S. scientist co-authored a report for the UN Intergovernmental Panel on Climate Change – which prepares climate reports for leaders around the world – he received a cease-and-desist letter. He "viewed the letter as an attempt to deter him from speaking out."[44] Similarly, in April 2020, a research chemist from the U.S. Geological Survey was told not to disclose his affiliation to the government when publishing research on climate change, and an August 2018 survey of scientists from the DOI found that over one-quarter were silenced in some way under Trump.[45] Many such scientists were also dismissed. For instance, the U.S. Navy's climate change task force was shut down in August 2019, and several EPA panels and advisory boards were disbanded in 2018 and 2019.[46]

A second method the Trump administration used to restrict information to IOs was to cut funding for information-gathering activities. One example is the United Nations' REDD+ program, which encourages countries to reduce deforestation. Compliance with this program was monitored

[43]See, e.g. accusations that scientific agencies such as the FDA and CDC have 'deep state motives.' Diamond, Dan. "Trump Officials Interfered with CDC Reports on Covid-19." *Politico* September 11, 2020. Also see McGinley, Laurie, Carolyn Y. Johnson, and Josh Dawsey. "Trump Without Evidence Accuses 'deep State' at FDA of Slow-Walking Coronavirus Vaccines and Treatments." *The Washington Post.* September 16, 2020.

[44]Plumer, Brad and Coral Davenport. "Science Under Attack: How Trump is Sidelining Researchers and Their Work." *The New York Times.* December 28, 2019.

[45]See `https://climate.law.columbia.edu/Silencing-Science-Tracker`.

[46]See `https://climate.law.columbia.edu/Silencing-Science-Tracker`.

by NASA's Carbon Monitoring System; however, the Trump administration canceled this system. As a result, the UN could no longer obtain critical information that it needed to run the program.[47] Similarly, the Intergovernmental Panel on Climate Change (IPCC), an IO that produces scientific assessments of climate change's impact, relies exclusively on information provided by scientists and peer-reviewed studies. The U.S. "has some of the best climate data in the world, and they are essential to the production of the IPCC." As a result of cuts to funding, however, "the quality of such assessments could suffer from a reduction in available data."[48] More generally, many bodies that conduct scientific research or create information that might be shared with IOs faced cuts.[49]

A third way that the U.S. curtailed information was to inject bias into domestically gathered information that was then shared with IOs, or that led IOs to doubt the quality of the information provided by the United States more generally. For example, the White House ordered changes to the CDC's coronavirus guidelines in May 2020 based on political considerations.[50]

Finally, we provide an additional description of Trump's efforts to do so that is relevant to IOs' operations. In particular, we explore such events over the period 2017-2019 using data from the Silencing Science Tracker.[51] This database systematically documents the Trump administration's "attempts to restrict or prohibit scientific research, education or discussion, or the publication or use of scientific information, since the November 2016 election."[52] Suppression events are primarily related to information in the areas of public health and climate change — two areas of particular interest to development IOs as they pursue their sustainable development mandates.

Figure Q7 shows the number of suppression events undertaken by the U.S. government over the period 2017-2019, while Figure Q8 places these suppression events into categories corresponding to the type of suppression. These plots show that the Trump administration has engaged in system-

[47]Bassett, Luke, Kristina Costa, and Lia Cattaneo. "Burning the Data: Attacks on Climate and Energy Data and Research." *Center for American Progress*. June 13, 2018.

[48]Bassett, Luke, Kristina Costa, and Lia Cattaneo. "Burning the Data: Attacks on Climate and Energy Data and Research." *Center for American Progress*. June 13, 2018. Indeed, two U.S. federal data sets proved pivotal to its 2014 conclusions, and the DOE's carbon emissions data is a key source for its determinations regarding precipitation patterns (Ibid).

[49]For instance, the Trump administration's proposed 2020 budget would have cut funding to the EPA by 30 percent; NIH by 12 percent; NSF by 9 percent; and USDA by 15 percent. See `https://climate.law.columbia.edu/Silencing-Science-Tracker`. While these cuts were merely proposed, IOs may worry that such threats will be acted upon, and seek to share information preemptively.

[50]See `https://climate.law.columbia.edu/Silencing-Science-Tracker`.

[51]See `https://climate.law.columbia.edu/Silencing-Science-Tracker`.

[52]Ibid.

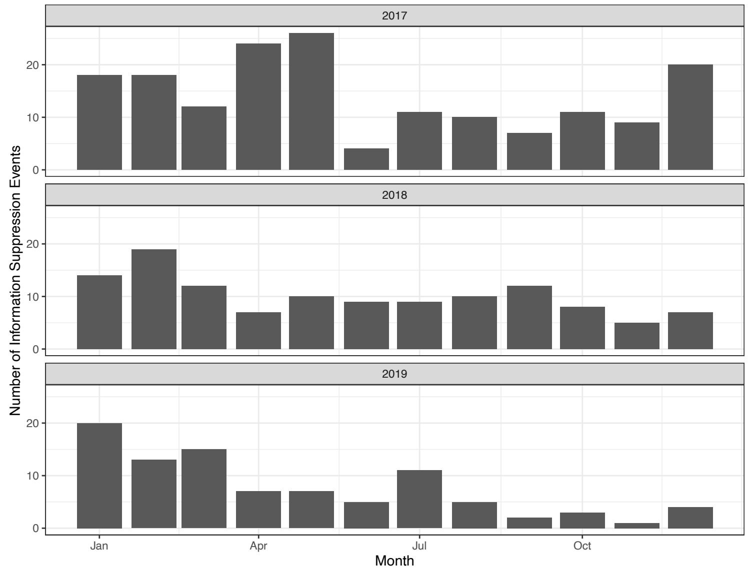

Figure Q7: U.S. Information Suppression 2017-2019. The vertical line denotes 2016. Data comes from Silencing Science Tracker `https://climate.law.columbia.edu/Silencing-Science-Tracker`.

atic and prolonged efforts to undermine the provision and publication of scientific information.

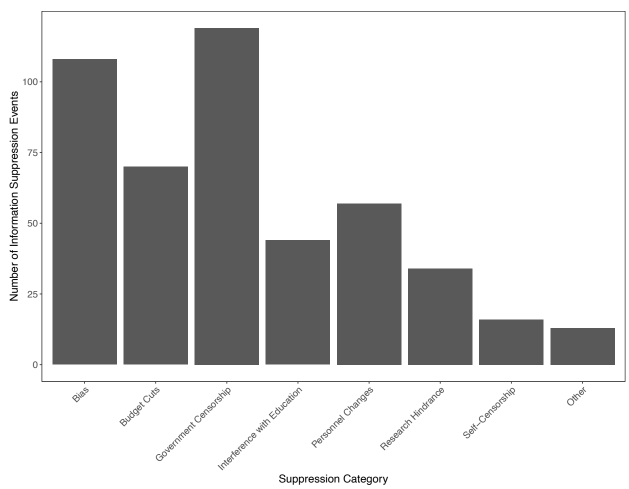

Figure Q8: U.S. Information Suppression Events by Category 2017-2019. The vertical line denotes 2016. Data comes from Silencing Science Tracker `https://climate.law.columbia.edu/Silencing-Science-Tracker`.

Several of these categories are relevant to IOs' data collection efforts. Specifically, the "Bias" category represents attempts to inject misinformation or political bias into scientific reports and government studies. Next, "Budget Cuts" comprise efforts to defund bodies that conduct scientific research or create information that might be shared with IOs. "Personnel Changes" represents the dismissal of scientists or the gutting of agencies like the EPA. "Research Hindrance" is perhaps most relevant to this paper, as it involves government intervention to block the publication of reports or transmission of information. "Self-Censorship" includes instances where government researchers avoid inquiry into certain topics for fear of government censorship or suppression.

In sum, descriptive evidence tracking information suppression by the Trump administration and information sharing by U.S.-led development IOs offers support for our theoretical contentions. Shortly after President Trump assumed office in January 2017, his administration began gutting scientific agencies, injecting bias into scientific government data and publications, and restricting the transmission of scientific information to IOs.