Online Appendix

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1 Robustness Tests

TABLE A1. Logit: Election Years

	Dependent variable: Erosion		
Gini	0.077***	0.078**	0.079**
	(0.019)	(0.024)	(0.028)
Logged GDP per capita		−0.001	−0.485
		(0.228)	(0.284)
Year			0.152***
			(0.036)
Constant	−5.035***	−5.107	−305.673***
	(0.859)	(2.841)	(71.898)
Observations	560	558	558
Note:	$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$		

Note: Replication of Table 1, using only years in which national elections were held.

TABLE A2. Rare Events Logit

	Dependent variable:		
	Erosion		
	(1)	(2)	(3)
Gini	0.067***	0.066***	0.070***
	(0.009)	(0.010)	(0.011)
Logged GDP per capita		−0.014	−0.529***
		(0.106)	(0.113)
Year			0.179***
			(0.017)
Constant	−4.928	−4.768	−360.023
	(0.371)	(1.267)	(33.792)
Observations	1,922	1,901	1,901

$^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Note: Logistic regression with Firth's correction and conventional standard errors, applied to the full set of cases analyzed in Table 1.

TABLE A3. Rare Events Logit: Election Years

	Dependent variable: Erosion		
	(1)	(2)	(3)
Gini	0.077***	0.077***	0.077***
	(0.016)	(0.019)	(0.021)
Logged GDP per capita		−0.007	−0.481*
		(0.188)	(0.202)
Year			0.149***
			(0.027)
Constant	−5.015	−5.011	−299.523
	(0.641)	(2.262)	(54.612)
Observations	560	558	558

$^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Note: Logistic regression with Firth's correction and conventional standard errors, applied only to country-years in which a national election was held (as in Table A1).

TABLE A4. Haggard and Kaufman Recode

	Dependent variable: Erosion		
	(1)	(2)	(3)
Gini	0.063**	0.069**	0.071*
	(0.019)	(0.023)	(0.028)
Log(GDPpc)		0.135	−0.357
		(0.246)	(0.278)
Year			0.166***
			(0.039)
Constant	−4.902***	−6.453*	−335.952***
	(0.872)	(2.995)	(78.244)
Observations	1922	1901	1901

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Note: Replication of Table 1 after re-coding the dependent variable to match Haggard and Kaufman's list of eroders (they do not include India, the Philippines, or Senegal among their cases of erosion).

1.1 Alternate Measures of Inequality

To test whether our results are sensitive to a particular measure of inequality, we re-ran our main models using eleven different measures of inequality. First, we consider alternative sources of Gini data: the World Income Inequality Database (WIID), the World Bank World Development Indicators (WDI), and the World Inequality Database (WID). We also use data from WID on income and wealth distributions. We consider the share of income earned by the top 1%, the top 10%, and the bottom 50% of the income distribution.[1] And we consider the share of wealth controlled by the top 1%, top 10%, and bottom 50%, by wealth.

Figure A1 summarizes the main results for the bivariate model and the model that includes year and GDP per capita, using the alternative sources of gini data. (For the wealth and income shares estimates, see Figure 3 in the main text.) Tables A5–A7 provide the full results for all three models (bivariate, gini + GDP, and gini + GDP + year) with each inequality measure (both the alternative gini sources and the income and wealth shares).

We retain significant effects in the expected direction in bivariate models for every measure of inequality. When we add controls for logged GDP per capita, inequality remains statistically significant in most models, with two exceptions. In the World Bank and WID post-fisc gini models, inequality is not significant. Note that each of these models substantially cuts the sample size - the World Bank model by 45% and the WID model by 27%. Using the World Bank data, we lose all observations for Venezuela, Turkey, and many Caribbean countries. We also lose more than 80% of all observed years for many African countries, including Botswana, Benin, Senegal, South Africa, and Zambia (as well as many other non-eroding countries). Using the WID data, we again lose all observations for many Caribbean countries, and we lose more than 80% of all observed years for Turkey, Botswana, Benin, South Africa, Ukraine, the Philippines, India, Senegal, and the Dominican Republic (as well as many other non-eroding countries). Although we prefer post-fisc gini, as it more closely reflects experiences of inequality, WID data on pre-fisc gini has far fewer missing cases. Thus, we ran our models again using WID data on pre-fisc gini. And in these models, gini is once again a significant predictor of erosion.

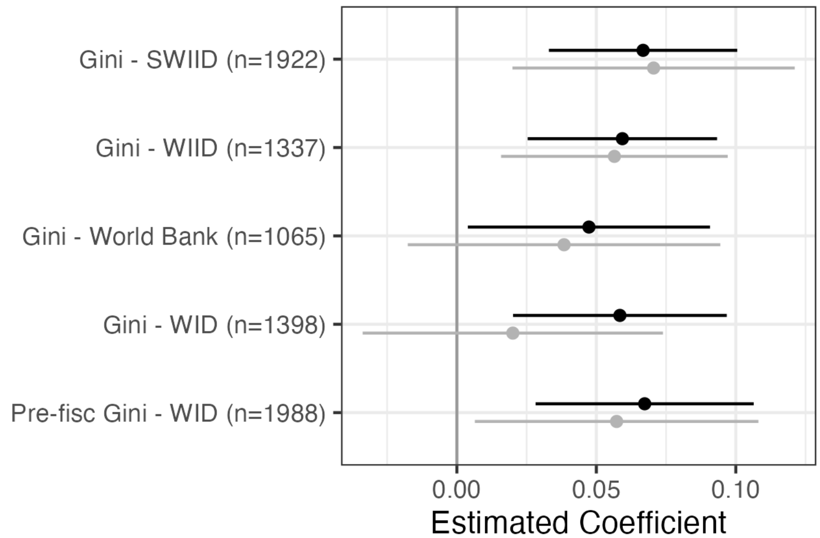
All measures of income and wealth shares remain significant in all models (bivariate, gini + GDP, gini + GDP + year), except for the bottom 50% income share, which loses significance in the model with year and logged GDP per capita ($p = 0.051$).

GDP per capita is insignificant in most models that control for only inequality and GDP. It attains significance in the World Bank and post-fisc WID models (with the smaller sample size cases discussed above). It also attains significance alongside inequality in the version using the bottom 50% wealth share. When we add a control for year, GDP is significant in each model. The overall pattern is similar to what we observe in our main models: GDP is usually not significant without a control for year; once we control for year, GDP either attains significance or comes very close to it.

Comparing the predictiveness of various measures of wealth and income shares, we see slight improvements when shifting from income to wealth inequality and when moving up to

[1]Note that income shares are pre-tax, as post-tax income shares were not available.

FIGURE A1. Robustness to Alternative Measures of Inequality



Note: Coefficients presented with 95% confidence intervals. Black points indicate coefficients from a bivariate model (Model 1 in Table 1). Gray points indicate coefficients from a model controlling for economic development and year (Model 3 in Table 1). See Tables A5 and A7 for full model results.

concentrations among the smallest elite groups. Recall that Model 3 from Table 1 yielded an AUC of 80%. We find the same predictiveness in a model that uses bottom 50% income shares in place of Gini. In models that deploying the top one percent or the top 10% income shares, or those that deploy bottom 50% or top 10% wealth shares, the AUC increases slightly to 81%. And measuring inequality via top 1% wealth shares yields another marginal increase in predictiveness, to 82%. Finally, noting that the top 10% shares include the top 1%, we conduct additional analyses where we decompose the top 10% into the top 1% and the next 9% (see Table A8). When we control for shares of both the top 1% and the next 9%, only the top 1% retains significance.

TABLE A5. Alternative Inequality Measures (Bivariate)

	Dependent variable: Erosion				
	Inequality Measure				
	Gini WIID	Gini World Bank	Gini WID	Pre-fisc Gini WID	Top 1% Income WID
Inequality	0.059***	0.047*	0.058**	0.067***	12.231***
	(0.017)	(0.022)	(0.020)	(0.020)	(3.107)
Constant	−4.482***	−4.064***	−5.127***	−6.028***	−4.123***
	(0.774)	(0.942)	(1.019)	(1.211)	(0.588)
Observations	1337	1065	1398	1988	1988

	Inequality Measure				
	Top 10% Income WID	Bottom 50% Income WID	Top 1% Wealth WID	Top 10% Wealth WID	Bottom 50% Wealth WID
Inequality	6.855***	−12.201**	7.262***	7.132***	−15.661**
	(1.915)	(3.972)	(1.688)	(1.681)	(5.729)
Constant	−5.314***	−0.415	−4.394***	−6.726***	−1.639***
	(0.957)	(0.579)	(0.615)	(1.156)	(0.264)
Observations	1988	1988	1975	1975	1975

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

TABLE A6. Alternative Inequality Measures (with GDP)

	Gini WIID	Gini World Bank	Gini WID	Pre-fisc Gini WID	Top 1% Income WID
	Dependent variable: Erosion				
	Inequality Measure				
Inequality	0.046^{*}	0.010	0.034	0.059^{**}	10.608^{**}
	(0.018)	(0.021)	(0.020)	(0.022)	(3.275)
Log(GDPpc)	−0.328	-0.770^{***}	-0.850^{**}	−0.223	−0.278
	(0.210)	(0.226)	(0.311)	(0.208)	(0.206)
Constant	−0.818	4.807	4.184	−3.437	−1.258
	(2.308)	(2.520)	(3.295)	(2.676)	(2.182)
Observations	1333	1063	1396	1978	1978

	Top 10% Income WID	Bottom 50% Income WID	Top 1% Wealth WID	Top 10% Wealth WID	Bottom 50% Wealth WID
	Inequality Measure				
Inequality	6.077^{**}	-10.324^{*}	6.332^{***}	6.122^{***}	-14.398^{*}
	(2.124)	(4.217)	(1.896)	(1.855)	(5.669)
Log(GDPpc)	−0.211	−0.244	−0.279	−0.303	-0.426^{*}
	(0.215)	(0.201)	(0.217)	(0.209)	(0.189)
Constant	−2.985	1.598	−1.491	−3.238	2.320
	(2.605)	(1.752)	(2.366)	(2.662)	(1.782)
Observations	1978	1978	1965	1965	1965

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

TABLE A7. Alternative Inequality Measures (with GDP and Year)

	Dependent variable: Erosion				
	Inequality Measure				
	Gini WIID	Gini World Bank	Gini WID	Pre-fisc Gini WID	Top 1% Income WID
Inequality	0.056**	0.038	0.020	0.057*	10.202**
	(0.021)	(0.029)	(0.027)	(0.026)	(3.854)
Year	0.155***	0.197***	0.134***	0.144***	0.144***
	(0.035)	(0.038)	(0.036)	(0.028)	(0.029)
Log(GDPpc)	−0.842**	−1.208***	−1.229**	−0.576*	−0.632*
	(0.264)	(0.303)	(0.418)	(0.267)	(0.268)
Constant	−308.317***	−387.677***	−260.155***	−288.944***	−288.050***
	(70.112)	(76.866)	(68.888)	(53.984)	(57.429)
Observations	1333	1063	1396	1978	1978

	Inequality Measure				
	Top 10% Income WID	Bottom 50% Income WID	Top 1% Wealth WID	Top 10% Wealth WID	Bottom 50% Wealth WID
Inequality	5.890*	−10.086	6.248**	6.227**	−15.570*
	(2.460)	(5.178)	(2.183)	(2.145)	(6.462)
Year	0.144***	0.144***	0.148***	0.149***	0.150***
	(0.028)	(0.027)	(0.030)	(0.030)	(0.030)
Log(GDPpc)	−0.562*	−0.597*	−0.639*	−0.651*	−0.764**
	(0.273)	(0.262)	(0.282)	(0.276)	(0.260)
Constant	−288.279***	−284.158***	−294.837***	−298.820***	−295.465***
	(54.474)	(54.048)	(58.278)	(58.410)	(58.594)
Observations	1978	1978	1965	1965	1965

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

TABLE A8. Top 1% and Next 9% Shares

	Dependent variable: Erosion			
Wealth Top 1%	6.887^{***}		5.851^{**}	
	(1.677)		(2.119)	
Wealth Next 9%	-6.533		-6.386	
	(7.428)		(12.036)	
Income Top 1%		8.306^{*}		$7.552^{\dagger}$
		(3.695)		(4.439)
Income Next 9%		5.464		3.974
		(3.763)		(4.912)
Logged GDP per capita			-0.645^{*}	-0.583^{*}
			(0.278)	(0.291)
Year			0.147^{***}	0.145^{***}
			(0.030)	(0.029)
Constant	-2.110	-5.126^{***}	-291.261^{***}	-289.922^{***}
	(2.566)	(1.046)	(59.557)	(55.494)
Observations	1975	1975	1965	1965

Note: $^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

TABLE A9. Logit: Region Fixed Effects

	Dependent variable: Erosion		
Gini	0.130*	0.132*	0.185*
	(0.057)	(0.054)	(0.073)
Logged GDP per capita		−0.106	−1.156**
		(0.225)	(0.437)
Year			0.227***
			(0.059)
Europe/Central Asia	1.148	1.312	2.497
	(1.130)	(1.131)	(1.443)
LatAm/Caribbean	−0.338	−0.354	−0.026
	(1.273)	(1.241)	(1.219)
MENA	−13.085***	−12.911***	−12.221***
	(1.267)	(1.296)	(1.654)
North America	0.683	0.921	2.622
	(1.077)	(1.120)	(1.550)
South Asia	0.706	0.630	−0.500
	(1.074)	(1.065)	(1.151)
Sub-Saharan Africa	−0.774	−0.813	−1.610
	(1.397)	(1.345)	(1.423)
Constant	−7.729**	−6.900*	−454.796***
	(2.366)	(3.194)	(116.918)
Observations	1922	1901	1901
Note:			$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Note: Replication of Table 1 with the addition of region fixed effects (regions defined according to the WDI seven world regions). East Asia & Pacific is the reference category for region.

TABLE A10. Logit: All Controls

	Dependent variable:
	Erosion
Gini	0.145*
	(0.060)
Logged GDP per capita	−0.357
	(0.608)
Year	0.144*
	(0.068)
Bureaucratic Quality	−3.414
	(2.171)
Age of Democracy	−0.004
	(0.018)
Political Polarization	1.151***
	(0.324)
Europe/Central Asia	−0.343
	(1.280)
LatAm/Caribbean	−2.058
	(1.331)
MENA	−15.190***
	(1.573)
North America	0.977
	(3.353)
South Asia	−1.376
	(1.873)
Sub-Saharan Africa	−2.056
	(1.981)
Constant	−290.907*
	(134.519)
Observations	1340
Note:	$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Note: This table presents the full results, including the coefficients on world-region dummy variables, for the model summarized in Figure 4.

TABLE A11. Logit: Alternative Demonstration Estimates

	Dependent variable: Erosion	
Gini	0.071^{**}	0.070^{**}
	(0.025)	(0.026)
Logged GDP per capita	-0.485	-0.507
	(0.264)	(0.273)
Cumulative Prior Erosion Years	0.017^{***}	
	(0.004)	
Constant	-1.688	-16.859
	(2.951)	(3.015)
Observations	1901	1901
Year Fixed Effects	No	Yes

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

1.2 Age of Democracy

TABLE A12. Logit: Age of Democracy

	Dependent variable: Erosion		
Gini	0.061**	0.064**	0.069**
	(0.021)	(0.021)	(0.025)
Logged GDP per capita		0.101	−0.403
		(0.278)	(0.307)
Year			0.183***
			(0.040)
Age of Democracy	−0.004	−0.006	−0.009
	(0.006)	(0.008)	(0.010)
Constant	−4.536***	−5.535*	−369.024***
	(1.074)	(2.823)	(79.061)
Observations	1920	1899	1899
Note:	$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$		

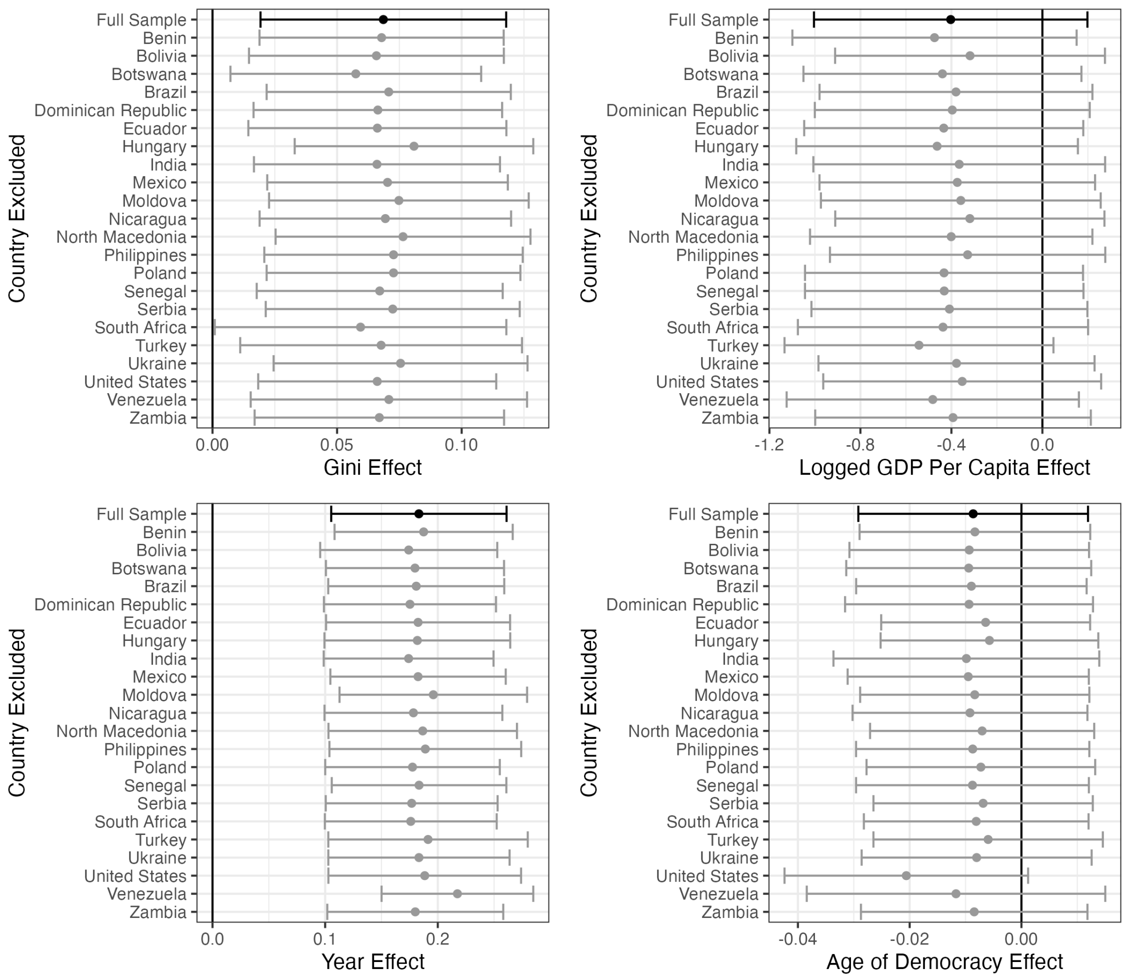
Note: Replicating the models from Table 1 with an additional control for age of democracy. (Note that age of democracy is not strongly correlated with year — the correlation coefficient is only 0.17). See also Figure A2 for further testing of age of democracy.

It's possible that the United States might be driving the lack of an effect for age of democracy: the U.S., one of our eroding observations, is nearly 50 years older than the next-oldest democracy in the dataset. Considering the role that outliers might play in the model estimate, we also conducted sensitivity analyses where we remove each eroder, one by one, and re-estimate Model 3 from Table A12. The coefficient plot in Figure A2 presents the coefficients for each of these regressions, with 95% confidence intervals. At the top of the plot, we present the estimate from the model using the full sample (the model reported in the table). Comparing each country-exclusion result to the main result, we note two important facts. Age of democracy never attains significance, though it does come closer in the model excluding the United States. And each of our other predictors are substantively unchanged across the models. Gini remains a positive, significant predictor of erosion in every estimate; and the magnitude of the effect is never statistically distinguishable from the estimate in the main model — allaying concerns that a particular country might be driving or exaggerating the inequality effect too. Year of observation remains significant, and GDP per capita does not attain significance in any of these models.

1.3 State Capacity

In all three models reported in Table A13, state capacity has a statistically significant negative coefficient — meaning that democracies with greater state capacity are less likely to erode. Inequality and year of observation also maintain significance in these models. GDP

FIGURE A2. Outliers Test



Note: Tests for outliers by removing each erosion case from the dataset and re-running Model 3 from Table A12. Results reported with 95% confidence intervals. The estimate from the main model (not excluding any countries) is presented in black.

per capita — which was significant in Model 3 of Table 1 (our main analyses) loses significance in the presence of the state capacity control.

As state capacity and GDP are highly correlated, it is difficult to say which is doing the work. But the findings of these models, along with the other models presented throughout the paper, are consistent with the general argument that economic development helps to insulate against erosion (even if highly developed countries remain vulnerable to eroding when they are unequal).

TABLE A13. Logit: State Capacity

	Dependent variable: Erosion		
	(1)	(2)	(3)
Gini	0.045*	0.054**	0.060*
	(0.022)	(0.020)	(0.026)
Logged GDP per capita		0.259	−0.377
		(0.406)	(0.467)
Year			0.165***
			(0.047)
Bureaucratic Quality	−3.768***	−4.121**	−3.420*
	(1.028)	(1.476)	(1.563)
Constant	−1.497	−4.096	−331.177***
	(1.246)	(3.529)	(92.402)
Observations	1357	1354	1354
Note:	$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$		

1.4 Polarization

Table A14 presents the results of models that incorporate polarization as a predictor of erosion. We measure polarization with two V-dem variables. V-dem's *political polarization* variable (v2cacamps) is a measure of affective polarization. We also compare to V-dem's measure for *societal polarization* (v2smpolsoc).

Using either measure of polarization, both polarization and inequality are significant predictors of erosion. And both polarization and inequality add predictiveness to the model that is not achieved using the other variable alone. Knowing the level of (political) polarization and the year yields a model predictiveness (AUC) of 83%. Adding Gini to the model increases the predictiveness to 88%. We observe a similar increase in models that do not control for year: polarization alone yields an AUC of 0.80; polarization and Gini yield an AUC of 0.85. Using the alternative societal polarization variable, the AUC for polarization + year is 0.84, and adding Gini yields an AUC of 0.89.

Our analyses also reveal a connection between inequality and partisan polarization. In our cross-national data, income inequality is a strong predictor of polarization. Figure A3 illustrates the relationship. Each point indicates the Gini coefficient and level of polarization corresponding to a given country in a given year. (The vertical line marks the median Gini coefficient in the sample.) We use V-Dem's *political polarization* variable, a measure of affective polarization. These points are overlaid with a LOESS trend line. Moving from low-inequality contexts to those with moderate or high inequality, we observe a sharp increase in levels of polarization, one that plateaus at very high levels of inequality.

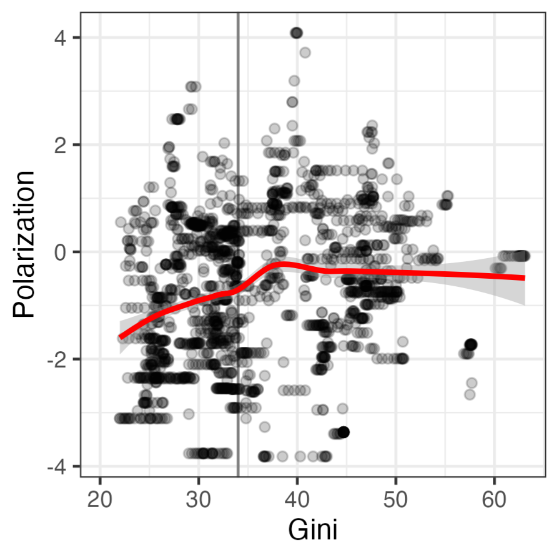
Our data similarly suggest a heightened risk of erosion in countries with high levels of partisan polarization. Figure A4 shows trends in polarization over the last 25 years in democracies that did and did not erode. Countries that would go on to erode were more

TABLE A14. Logit: Polarization Models

	Dependent variable: Erosion				
Political Polarization	1.003***	0.910***	1.067***		
	(0.232)	(0.227)	(0.287)		
Societal Polarization				1.189***	1.227***
				(0.255)	(0.299)
Year		0.086***	0.114***	0.030	0.067
		(0.023)	(0.035)	(0.033)	(0.043)
Gini			0.102***		0.100***
			(0.025)		(0.029)
Constant	−2.152***	−174.076***	−236.164***	−62.360	−142.083
	(0.278)	(46.245)	(71.540)	(65.893)	(87.971)
Observations	1983	1983	1761	1435	1435
Note:			$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$		

Note: For both polarization variables, we code the variable such that higher values correspond to higher levels of polarization. (In their original format in the V-dem dataset, lower values correspond to higher polarization.)

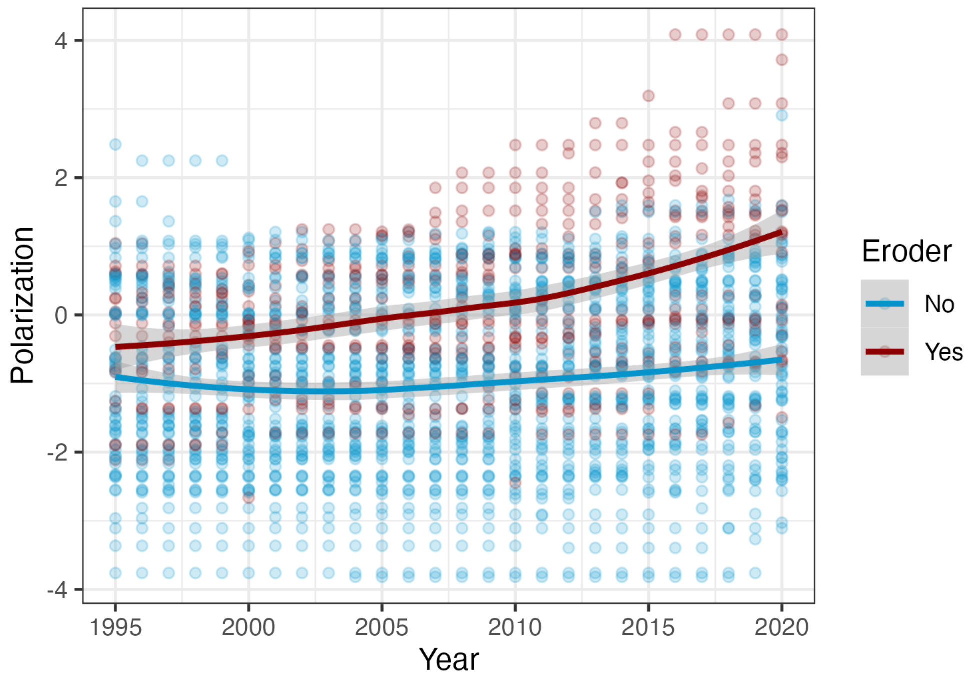
FIGURE A3. Inequality and Polarization



Note: Inequality (post-fisc Gini) and polarization (V-Dem) for every country-year in our dataset. The vertical line marks the median gini coefficient in the sample (36.8). Points are overlaid with a LOESS estimate (red).

polarized than non-eroders in the 1990's. And over time this gap widened as democracies that were eroding — or that would go on to erode in the future — grew increasingly polarized. Among non-eroding countries, polarization has remained relatively flat over time.

FIGURE A4. Polarization and Democratic Erosion



Note: Each point reflects one country-year in our dataset. "Eroders" are countries that eroded at any point between 1995 and 2020. All other countries included remained democracies from 1995 to 2020. We estimate LOESS trend lines of polarization (V-Dem's *political polarization* variable) for eroders and non-eroders.

Lastly, we test for interaction effects between polarization and inequality. Table A15 presents the results from three models. The first includes only inequality, polarization, and the interaction between the two. Model 2 adds controls for year of observation and GDP per capita. Model 3 adds additional controls for age of democracy, bureaucratic quality, and world region. Across all three models, the interaction is never significant. Gini remains a significant positive predictor of erosion in all three models. Polarization retains significance at $p < 0.05$ in the first two models. In Model 3, with the full set of controls, polarization does not reach significance at the $p < 0.05$ level; but it is borderline, with $p < 0.1$.

1.5 Country Fixed Effects and Trends during Erosion

Table A16 replicates our main analyses with the addition of country fixed effects. Beginning with our main model, Model 3, inequality and year maintain significance (with larger estimated coefficients, compared to our main analyses) and logged GDP per capita attains significance. Looking at Models 1 and 2, however, the presence of country fixed effects reverses key coefficients. In Model 1, inequality maintains significance but in the opposite direction — higher inequality is associated with lower erosion odds. In Model 2, the inequality coefficient returns to a positive estimate but is statistically insignificant. Meanwhile,

TABLE A15. Logit: Polarization and Inequality Interaction

	Dependent variable: Erosion		
	(1)	(2)	(3)
Gini	0.093^{***}	0.095^{**}	0.167^{*}
	(0.025)	(0.031)	(0.070)
Polarization	2.701^{*}	2.537^{*}	$3.441^{\dagger}$
	(1.184)	(1.272)	(1.929)
Inequality X Polarization	-0.037	-0.037	-0.057
	(0.027)	(0.030)	(0.043)
Logged GDP per capita		$-0.515^{\dagger}$	-0.522
		(0.290)	(0.639)
Year		0.137^{***}	0.158^{*}
		(0.042)	(0.077)
Bureaucratic Quality			$-3.854^{\dagger}$
			(2.295)
Age of Democracy			-0.008
			(0.020)
Constant	-6.074^{***}	-276.808^{***}	-317.493^{*}
	(1.283)	(82.631)	(153.023)
Observations	1761	1756	1340
Region FE?	No	No	Yes

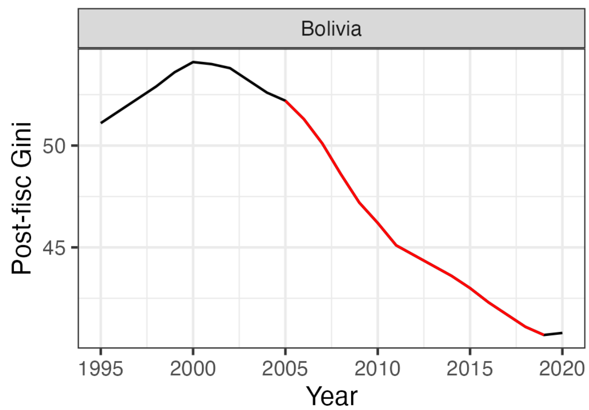
Note: $^{\dagger}p < 0.1$;$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

logged GDP per capita attains significance with a positive coefficient (again, reversed from other models, indicating that wealthier countries are more likely to erode).

This is, we argue, a problem of misspecification from omitting year in these two models. We know that erosion has grown more common over time in recent years. As more countries erode, aspiring autocrats have more opportunities to learn from the successes of other eroders; they witness the very public ways in which other leaders attempt to erode their democracies and can imitate their most successful tactics. When we exclude year of observation from the models, we fail to account for this dynamic, and the time dynamic is then captured by the Gini and GDP coefficients. Average logged GDP per capita increases over time in our data; hence, without a control for the year of observation, this pair of time trends — increasing GDP and increasing erosion — yields a positive coefficient on GDP per capita. But once we control for year, the estimated effect flips. Acknowledging that most countries in our sample have grown wealthier over time, it is the countries with lower growth rates that were more likely to erode.

For inequality, the story is slightly more complicated. Inequality is not steadily decreasing around the world (this would be the analogous explanation to the GDP per capita results). Instead, the key factor here is how inequality changes after a country begins to erode. Recall that our model predicts whether a country is eroding in any given year; it does not just predict the first year in which a country erodes, but every subsequent year as well. Whereas inequality steadily increased for many years leading up to the wave of erosion, once countries begin to erode, inequality often started to abate. Perhaps the starkest example of this dynamic is Bolivia. Inequality in Bolivia peaked in 2000, with a Gini of 54.1. After abating slightly over the next four years, to the still-high 52.6, Bolivia began to erode in 2005. From 2005 to 2019, Bolivia's Gini plummeted to 40.7 — averaging a decline of 0.82 per year (see Figure A5).

FIGURE A5. Inequality Trend during Erosion in Bolivia

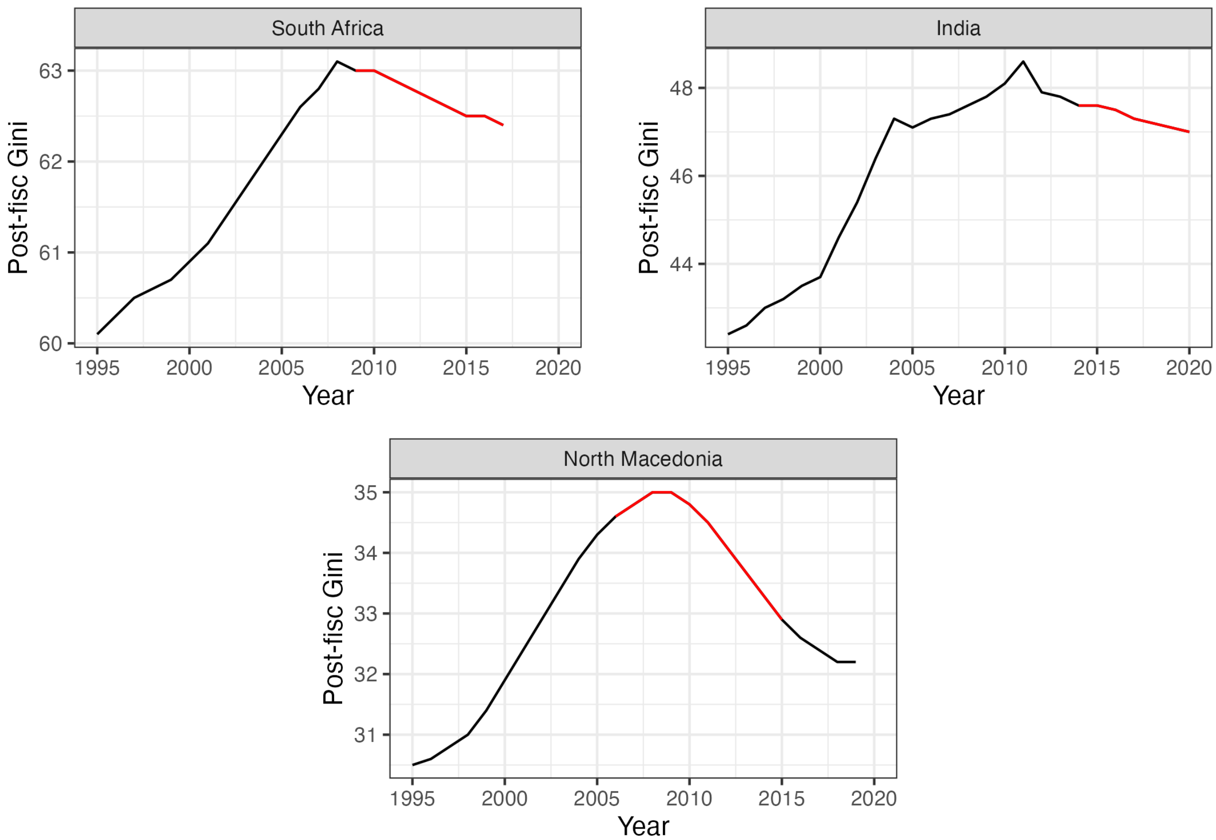


Note: Red line indicates years of erosion; black indicates years in which Bolivia was not eroding.

Bolivia's declining Gini in the 2000s is a familiar pattern for Latin America, one for which social scientists offer several explanations. But in Bolivia, the trend toward greater income equality accelerated after the election of Evo Morales, who was both a champion of poor and indigenous Bolivians and a president who was willing to trample on democratic institutions. Hicks et al. (2018: 28) note that, in Bolivia, rapid economic growth in the early 2000s was associated with a "narrowing in inequalities across ethnic populations," but "this development is far more pronounced in the post-Morales election period."

But we also see declines, if less steep, in other regions — from India to South Africa to North Macedonia, each of whose inequality trends are illustrated in Figure A6. North Macedonia's Gini had risen almost four points over the ten-year period preceding erosion. It continued to rise (a bit more slowly) for the first few years of erosion, plateauing at a high of 35 in its third and fourth years of erosion (2008 and 2009). It then began to drop, reaching 32.9 by its final year of erosion (2015). From 1995 to 2008, inequality in South Africa steadily climbed from a Gini of 60.1 to 63.1. But upon eroding, its Gini began to fall steadily, if less sharply — returning to 62.4 by the end of its erosion period in 2017. In India, inequality peaked in 2011, three years before Modi was elected Prime Minister and began eroding Indian democracy. Under Modi, inequality continued to decline from 47.6 in 2014 to 47.0 in 2020.

FIGURE A6. Inequality Trends during Erosion



Note: Red line indicates years of erosion; black indicates years in which the country was not eroding.

Not every country experienced a decline in inequality when eroding. In Botswana, inequality held remarkably steady, dropping only 0.2 points over seven years. In the United States and Hungary, inequality increased slightly — with Gini growing by 0.4–0.5 points during each country's spell of erosion (a period of four years in the US, ten years in Hungary).

But in no country do we observe a sharp increase in inequality during a period of erosion. And once we account for country fixed effects to focus on changes over time within countries, this becomes especially relevant to the statistical models we estimate.

Adding year-of-observation to Model 1 yields a Gini coefficient that is again positively and significantly associated with erosion (Model 4 in Table A16). Hence, when properly specified to include year of observation, the coefficients on our key economic variables are once again consistent with the other models reported throughout the paper and appendix, with erosion more common in unequal countries and (often) less common in wealthier countries (but GDP per capita is, as noted in the paper, much more sensitive to model specification throughout).

In sum, it is notable that our main findings hold in the presence of country fixed effects. This indicates that our main model is not just capturing some fixed country-level charac-

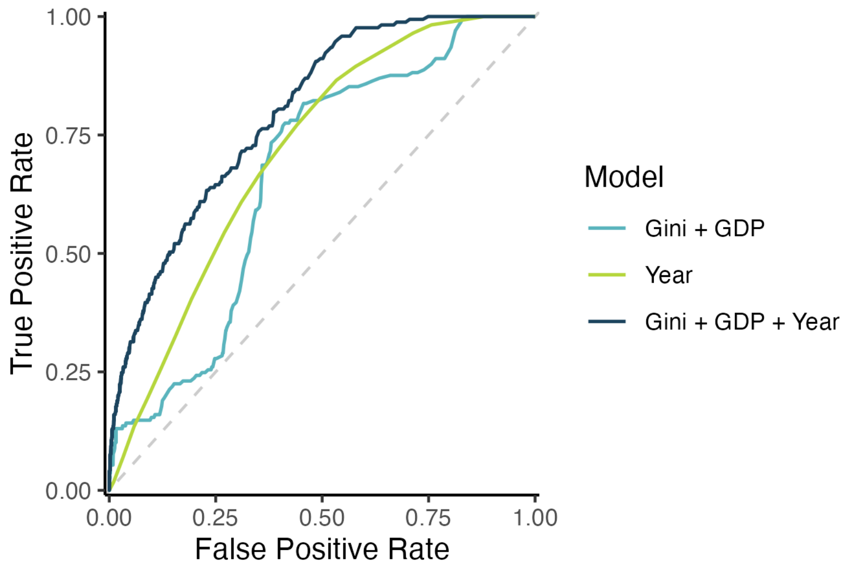
TABLE A16. Logit: Country Fixed Effects

	Dependent variable:			
	Erosion			
	(1)	(2)	(3)	(4)
Gini	-0.277^{***}	0.128	0.263^{**}	0.313^{**}
	(0.058)	(0.089)	(0.100)	(0.101)
Logged GDP per capita		5.229^{***}	-8.026^{***}	
		(0.704)	(2.010)	
Year			0.757^{***}	0.356^{***}
			(0.118)	(0.043)
Constant	−12.949	−77.695	−1,475.980	−748.280
	(7,308.013)	(5,405.610)	(4,934.798)	(6,707.887)
Observations	1,922	1,901	1,901	1,922
Country FE	Yes	Yes	Yes	Yes
Note:				$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

teristic that happens to covary with inequality; after we incorporate country fixed effects and control for year of observation to capture the over-time snowballing (or demonstration) effects, inequality still matters. That said, political dynamics don't react instantaneously to slow-moving changes in inequality. (And in often-close elections, the question of whether a country elects an aspiring autocrat in any given year often turns on chance events.) Our model is thus best-suited to telling us about which countries are vulnerable and about the periods of time in which they are most vulnerable, as opposed to giving precise annual predictions about the change in likelihood from, say, 2010 to 2011.

2 Model Predictions

FIGURE A7. ROC Curves



Note: The dashed $x = y$ line indicates an AUC of 0.5 (achieved by random guessing).

Figure A7 illustrates the predictiveness of three models: Models 2 and 3 from table 1, and a model controlling only for year. We calculate the AUC (area under the ROC curve) for each model. In the pure economic model (Gini + GDP), the AUC is 0.663. (A model controlling only for Gini yields an AUC of 0.662; controlling only for GDP yields an AUC of 0.629). The year-only model has an AUC of 0.696. And the complete model (controlling for Gini, GDP, and year) has an AUC of 0.797.

The predictiveness of the year-only model illustrates the extent to which erosion has been a wave. The AUC is calculated by selecting two country-years at random — one for which $y = 1$ (eroding) and one for which $y = 0$ (not eroding). We then apply the logit model to calculate the odds of erosion for each case. If the model assigns a higher probability of erosion to the case that is actually eroding, it is a success. We then calculate the proportion of random pairs that are successfully predicted.

If we randomly select two country-years, and one comes from 1998 and the other from 2018, it is fairly easy to guess which is eroding without any information about the countries selected. But if we happen to select one case from 2016 and another from 2019, the task of guessing which is eroding becomes much more difficult. This is where the additional economic information comes into play. If the 2016 case is a highly unequal country and the 2019 case is a very equal country, chances are the economically unequal 2016 case is eroding, not the economically equal 2019 case. If we only know the year, we will guess correctly about seven out of ten times. If we only know some basic facts about a country's economic status, but not the year, we'll get it right about two-thirds of the time. But with three simple pieces of data — the year, GDP per capita, and Gini — we get it right 80% of the time.