Timing Matters: Analyzing Climate Policies and Adaptive Resilience

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Appendix A Change Point Analysis

To identify significant shifts in the nature of climate laws over time, we execute a change point analysis using the Grantham Institute's Climate Change Laws of the World Data, which is presented in Figure A.1 (Grantham Research Institute on Climate Change and the Environment, 2023).

The change point analysis fitted a piecewise constant model to the climate laws data, identifying statistically meaningful points where the mean of aggregated percent change in climate law features changed significantly. These features included the category of laws (legislative, executive, UNFCCC, domestic), document type (constitutional, framework, decree, policy), and response type (mitigation, adaptation, loss and damage, disaster risk management). The analysis identified three statistically meaningful change points at 1998, 2008, and 2016, providing three distinct eras. However, given the extremely limited variation in climate adaptation measures Pre-1998, we collapse the first two periods for our main analysis, resulting in three periods: Pre-2006 (where the first meaningful changepoint occurs), 2007-2015, and 2016 onward.

The mean squared error for change point detection is specified as:

$$\text{MSE}(k) = \sum (y_i - \mu_i)^2 \tag{A.1}$$

where $\text{MSE}(k)$ represents the mean squared error for a model with k change points, y_i is the observed value at time i, and $\hat{y}_i$ is the predicted value for time i based on the piecewise constant model.

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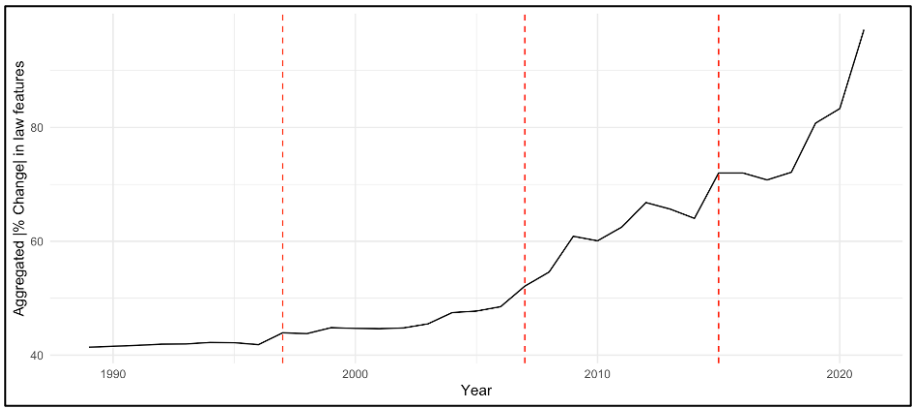

Figure A.1: Empirical Change Points in the Nature of Climate Adaptation Laws. This figure shows changes in climate adaptation laws over time from the Grantham Institute's database, including document types, categories, sectors, and hazards, highlighting key legislative shifts.

Appendix B Development, Laws, and Countries

Below, Table A.1 summarizes the number of laws, unique countries involved, and the percentage of countries in the Global North over various time periods that are meaningful to this analysis.

Table A.1: Number of Laws, Unique Countries, and Percentage of Countries in the Global North by Time Window

Time Window	Number of Laws	Unique Countries	Percentage of OECD Countries
Up to 2006	576 laws	158 countries	27.22%
2007-2015	1872 laws	198 countries	18.69%
2016 onwards	4259 laws	201 countries	18.41%

Appendix C Trends in Category, Response, and Document Types Across Eras

Below, Table A.2 details the categories, responses, and types of documents associated with climate policies across our eras of interest.

Table A.2: Category, Response, and Document Types

	Executive	**Legislative**	**UNFCCC**	**Domestic**
Category (%)				
Up to 2006	32.81	67.01	0.17	99.83
2007-2015	58.44	36.49	5.07	94.93
2016 onwards	42.78	12.63	44.59	55.41
	Adaptation	**Mitigation**	**Loss & Damage**	**Disaster Risk Management**
Response (%)				
Up to 2006	31.25	78.82	1.04	15.28
2007-2015	41.68	70.57	1.76	11.86
2016 onwards	25.91	45.62	1.27	6.25
	Act	**Policy**	**Law**	**Plan**
Document Types (%)				
Up to 2006	15.28	9.20	46.53	4.51
2007-2015	5.72	10.37	24.97	10.05
2016 onwards	4.04	3.90	4.98	12.36

Appendix D Trends in Global Climate Commitments

Below, Table A.3 outlines significant global climate commitments made through international agreements, highlighting key legal milestones over the years.

Table A.3: Global Climate Commitments

Year	**Name of Commitment/Agreement**
Up to 2006	1992: United Nations Framework Convention on Climate Change
	1997: Kyoto Protocol (COP3)
	2001: Bonn Agreement
	2005: Montreal Action Plan
2007-2015	2007: Bali Road Map (COP13)
	2009: Copenhagen Accord (COP15)
	2010: Cancun Agreements (COP16)
	2011: Durban Platform (COP17)
	2012: Doha Amendment (COP18)
	2013: International Warsaw Mechanism (COP19)
	2015: Paris Agreement
2016 onwards	2016: Kigali Amendment to the Montreal Protocol
	2018: Katowice Rulebook
	2021: Glasgow Climate Pact

Appendix E Random Forest Variable Importance

To investigate the most important variables influencing adaptive capacity, we employed a Random Forest (RF) model. Equation A.2 for the RF model can be expressed as follows:

$$\text{Capacity} = f \left(\begin{array}{l} \text{Adaptation Laws}, \\ \text{Rule of Law}, \\ \text{Federalism}, \\ \text{Global North}, \\ \text{GDP}, \\ \text{GDP Growth}, \\ \text{Imports}, \\ \text{Services}, \\ \text{Environmental Spending}, \\ \text{Populism}, \\ \text{Adaptation Aid}, \\ \text{Paris Sign.}, \\ \text{Paris Rat.}, \\ \text{Kyoto Sign.}, \\ \text{Kyoto Rat.}, \\ \text{NDC Submitted}, \\ \text{Disaster Count}, \\ \text{Financial Recession} \end{array} \right) \tag{A.2}$$

where *Capacity* represents the adaptive capacity score lagged by one period, while the other variables denote the predictors included in the analysis. This formulation allows us to assess how each variable contributes to the overall capacity in the context of climate adaptation. The results of the variable importance analysis are illustrated in Figure A.2, which shows the significance of the top ten most important variables in predicting adaptive capacity.

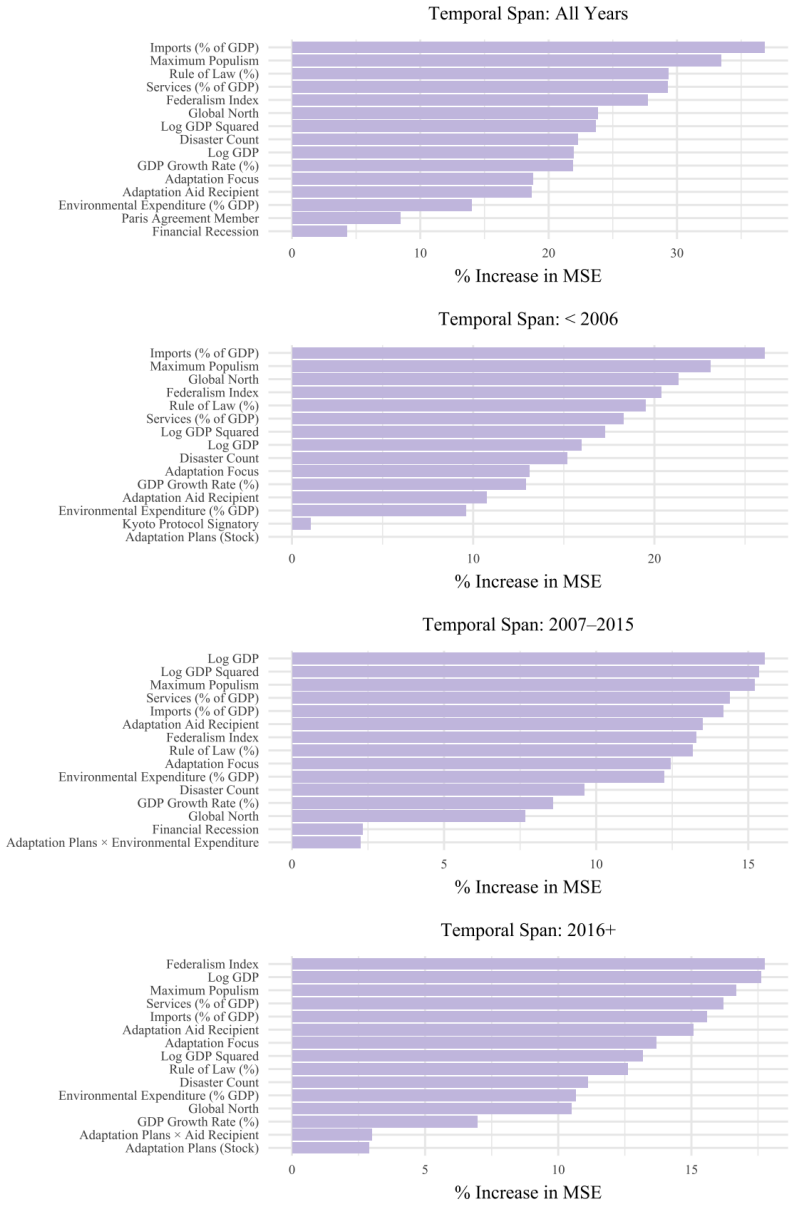

Figure A.2: Random Forest Variable Importance. The variable importance plot displays the significance of various factors influencing adaptive capacity. Each bar represents the percentage increase in mean squared error (%IncMSE) when the respective variable is permuted, highlighting how each contributes to the model's predictive accuracy.

The variable importance analysis supports the robustness of our variable selection across different temporal specifications. Variables selected for the full temporal span model constitute 89.3% of cumulative variable importance (mean decrease in Gini) in the random forest model. In the Pre-2006 model, selected variables account for 84.7% of cumulative variable importance (mean decrease in Gini) in the random forest model; in 2007–2015, 85.05%; and in post-2016, 82.8%.

Table A.4: Random Forest Variable Importance by Time Period

Time Period	Cumulative Importance (%)
Full temporal span	89.3
Pre-2006	84.7
2007–2015	85.1
Post-2016	82.8

The consistently high cumulative importance across all time periods, as shown in Table A.4, demonstrates that our selected variables capture the key drivers of adaptive capacity regardless of the temporal framework. This temporal stability strengthens confidence in our model specification and variable selection approach.

Appendix F Model Specification Selection

We examined five alternative panel data specifications to ensure robust findings for our analysis of adaptive capacity determinants. All models use the baseline specification shown in equation A.3, which includes ten explanatory variables covering governance, economics, and climate factors. The data is the full (all years) panel, with the dependent variable being the t - 1 adaptive capacity lag.

$$\begin{aligned}\text{lag1_capacity}_{i,t} = \alpha &+ \beta_1 \text{adaptation_law_stock}_{i,t} + \beta_2 \text{imports_pGDP}_{i,t} \\ &+ \beta_3 \text{max_populism}_{i,t} + \beta_4 \text{ROL_perc}_{i,t} \\ &+ \beta_5 \text{percent_gdp_services}_{i,t} + \beta_6 \text{auton}_{i,t} \\ &+ \beta_7 \text{disaster_count}_{i,t} + \beta_8 \ln(\text{gdp})_{i,t} \\ &+ \beta_9 \text{gdpgrowth_per}_{i,t} + \beta_{10} \text{adaptationaid_recipient}_{i,t} + \epsilon_{i,t}\end{aligned} \tag{A.3}$$

The tested models range from simple pooled OLS (equation A.8) to two-way fixed effects (equation A.4) that control for both country and time heterogeneity. We also evaluated country-only fixed effects (equation A.5), time-only fixed effects (equation A.6), and random effects (equation A.7) specifications.

Two-Way Fixed Effects:

$$y_{i,t} = \alpha + \mathbf{X}_{i,t}\boldsymbol{\beta} + \mu_i + \lambda_t + \epsilon_{i,t} \tag{A.4}$$

Country Fixed Effects Only:

$$y_{i,t} = \alpha + \mathbf{X}_{i,t}\boldsymbol{\beta} + \mu_i + \epsilon_{i,t} \tag{A.5}$$

Time Fixed Effects Only:

$$y_{i,t} = \alpha + \mathbf{X}_{i,t}\boldsymbol{\beta} + \lambda_t + \epsilon_{i,t} \tag{A.6}$$

Random Effects:

$$y_{i,t} = \alpha + \mathbf{X}_{i,t}\boldsymbol{\beta} + u_i + \epsilon_{i,t} \tag{A.7}$$

Pooled OLS:

$$y_{i,t} = \alpha + \mathbf{X}_{i,t}\boldsymbol{\beta} + \epsilon_{i,t} \tag{A.8}$$

Table A.5 presents the comparison results. The time fixed effects model demonstrates superior performance with an R^2 of 67.67% and six significant variables out of ten, substantially outperforming the two-way fixed effects model which suffers from overfitting (R^2 = 0.99% but adjusted R^2 = -1.35%). The Hausman test results strongly favor fixed effects over random effects specifications, with test statistics of $\chi^2 = 1,365.45$ and $\chi^2 = 211.65$ (both $p < 0.001$) as shown in equation A.9.

Hausman Test Statistic:

$$H = (\hat{\boldsymbol{\beta}}_{\text{FE}} - \hat{\boldsymbol{\beta}}_{\text{RE}})'[\text{Var}(\hat{\boldsymbol{\beta}}_{\text{FE}}) - \text{Var}(\hat{\boldsymbol{\beta}}_{\text{RE}})]^{-1}(\hat{\boldsymbol{\beta}}_{\text{FE}} - \hat{\boldsymbol{\beta}}_{\text{RE}}) \tag{A.9}$$

Table A.5: Alternative Model Specifications Comparison

Model	R^2 (%)	Adj. R^2 (%)
Two-way FE	0.99	-1.35
Country FE	15.76	14.32
Time FE	**67.67**	**67.44**
Random Effects	15.96	15.87
Pooled OLS	66.55	66.52

We selected the time fixed effects model as our preferred specification because it captures global trends while maintaining strong explanatory power and avoiding the overfitting issues present in the two-way fixed effects approach. This specification is theoretically appropriate for modeling adaptive capacity, which varies primarily due to global development patterns rather than country-specific fixed characteristics.

Appendix G Diagnostic Testing

Comprehensive diagnostic testing confirms the robustness of our selected model while identifying several econometric challenges that require correction. Table

A.6 shows the model achieves strong fit statistics with 9,828 observations across 156 countries over 63 time periods.

Table A.6: Time Fixed Effects Model Fit Statistics

Statistic	Value
R-squared	67.67%
Adjusted R-squared	67.44%
F-statistic	2,042.2
Observations	9,828
Countries	156
Time periods	63
Average obs. per country	63.0

Residual analysis reveals non-normal distribution patterns, with the Jarque-Bera test statistic of 84.16 ($p < 0.001$) and Shapiro-Wilk W-statistic of 0.9954 ($p < 0.001$) both rejecting normality as calculated in equation A.10. While concerning, non-normality is common in large panel datasets and does not invalidate our inference when using robust standard errors.

Jarque-Bera Test:

$$JB = \frac{n}{6}\left[S^2 + \frac{(K-3)^2}{4}\right] \tag{A.10}$$

Heteroscedasticity testing using the Breusch-Pagan test (equation A.11) yields a test statistic of 597.28 ($p < 0.001$), clearly indicating non-constant variance. Serial correlation tests reveal autocorrelation in both AR(1) and AR(2) specifications, with test statistics of 7,379.25 and 7,897.98 respectively (both $p < 0.001$) using the Breusch-Godfrey procedure shown in equation A.12.

Breusch-Pagan Test:

$$LM = nR^2_{\text{aux}} \sim \chi^2_k \tag{A.11}$$

Breusch-Godfrey Test:

$$LM = (n-p)R^2_{\text{aux}} \sim \chi^2_p \tag{A.12}$$

Multicollinearity analysis using variance inflation factors (equation A.13) shows no problematic correlations, with all VIF values below 5 as detailed in Table A.7. The highest VIF of 1.85 for adaptation law stock indicates low multicollinearity concerns.

Variance Inflation Factor:

$$VIF_j = \frac{1}{1 - R^2_j} \tag{A.13}$$

Table A.7: Variance Inflation Factors

Variable	VIF	Status
Adaptation Law Stock	1.85	Low
Imports as GDP (%)	1.04	Low
Populism	1.06	Low
Rule of Law Percentile	1.69	Low
Services as GDP (%)	1.46	Low
Federalism	1.08	Low
Disaster Count	1.35	Low
GDP (PPP, log)	1.42	Low
GDP Growth (%)	1.02	Low
Adaptation Aid Received	1.72	Low

To address the heteroscedasticity and serial correlation issues, we implement cluster-robust standard errors using the Arellano (2003) method (equation 12). Table A.8 demonstrates that cluster-robust standard errors are substantially larger than conventional standard errors, with an average ratio of 4.62, confirming the necessity of robust inference for valid hypothesis testing.

Cluster-Robust Standard Errors:

$$\hat{\mathbf{V}}_{\text{cluster}} = (\mathbf{X}'\mathbf{X})^{-1} \sum_{i=1}^{N} \mathbf{X}_i' \hat{\mathbf{u}}_i \hat{\mathbf{u}}_i' \mathbf{X}_i (\mathbf{X}'\mathbf{X})^{-1} \tag{A.14}$$

Table A.8: Standard vs. Cluster-Robust Standard Errors Comparison

Variable	Standard SE	Cluster-Robust SE	Ratio
Adaptation Law Stock	0.000256	0.001071	4.18
Imports as GDP (%)	0.000493	0.001369	2.78
Populism	0.004385	0.030135	6.87
Rule of Law Percentile	0.000057	0.000362	6.34
Services as GDP (%)	0.000107	0.000510	4.78
Federalism	0.002775	0.018253	6.58
Disaster Count	0.000175	0.000632	3.61
GDP (PPP, log)	0.000644	0.003851	5.98
GDP Growth (%)	0.000190	0.000347	1.82
Adaptation Aid Received	0.000239	0.000788	3.29

Appendix H Causal Inference

We employ the Dumitrescu and Hurlin (2012) panel Granger causality test to examine whether adaptation laws causally precede changes in adaptive capacity. This test addresses the important question of whether observed correlations reflect genuine causal relationships or merely spurious associations.

The test uses the standardized statistic shown in equation A.15, which aggregates individual country-level Wald statistics to test the null hypothesis that adaptation laws do not Granger-cause adaptive capacity for any country in the panel.

Dumitrescu-Hurlin Test Statistic:

$$\tilde{Z}_{N,T} = \sqrt{\frac{N}{2K}} \left(\bar{W}_{N,T} - K \right) \xrightarrow{d} N(0,1) \tag{A.15}$$

Table A.9 presents the panel Granger causality test results. The standardized test statistic of $\tilde{Z} = 37.915$ with $p < 0.001$ provides strong evidence that adaptation laws Granger-cause adaptive capacity across countries. This finding supports the interpretation that legal frameworks for climate adaptation represent genuine policy interventions rather than mere correlates of adaptive capacity.

Table A.9: Panel Granger Causality Test Results

Test	Statistic	p-value
Null Hypothesis	Adaptation laws don't Granger-cause adaptive capacity	
Alternative Hypothesis	Adaptation laws Granger-cause adaptive capacity	
Dumitrescu-Hurlin Z	37.915	< 0.001
Decision	**Reject Null Hypothesis**	
Conclusion	**Strong evidence of Granger causality**	

The Granger causality evidence, combined with our comprehensive diagnostic testing, strengthens confidence in the causal interpretation of our main findings. The temporal precedence of adaptation laws over capacity improvements, coupled with the robust statistical relationship after controlling for multiple confounders, provides compelling evidence for policy effectiveness.

Appendix I Trends in Laws and Capacity

Figure A.3 shows trends in adaptation law stock and average capacity When we compare the two graphs, we might conclude that adaptation laws do not correlate with adaptive capaci. However, when we use change point analysis and segmented regression methodology, we uncover new patterns that indicate some junctures at which adaptation policies lead to their intended outcomes. More specifically, we found the years between 1999 and 2006 to be the golden age of adaptation laws, a time when these laws had more positive impact on adaptive capacity across the world. By contrast, adaptation laws seem to negatively correlate with adaptive capacity in post-2016 years.

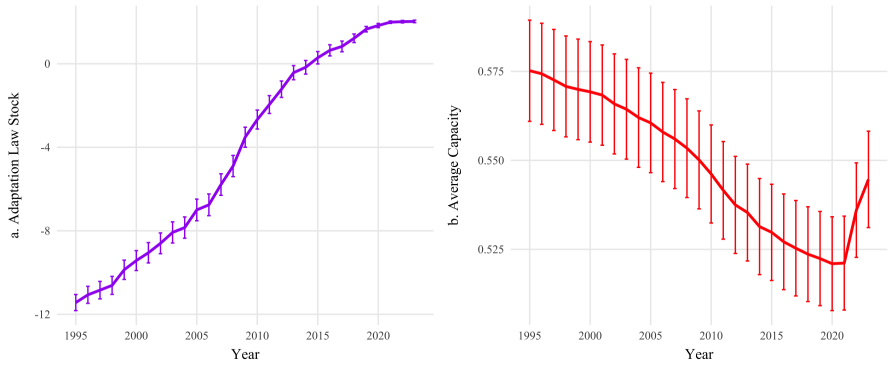

Figure A.3: Trends in Adaptation Law Stock and Average Capacity. This figure shows trends in climate adaptation laws and capacity scores over time based on the Grantham Institute's database and ND-GAIN respectively.

Appendix J Populism Trends

The rise of populism and its objectives during this period, possibly influencing the efficacy of policy measures and, and as we can see in Figure A.4, populism has been on the rise, particularly in recent years

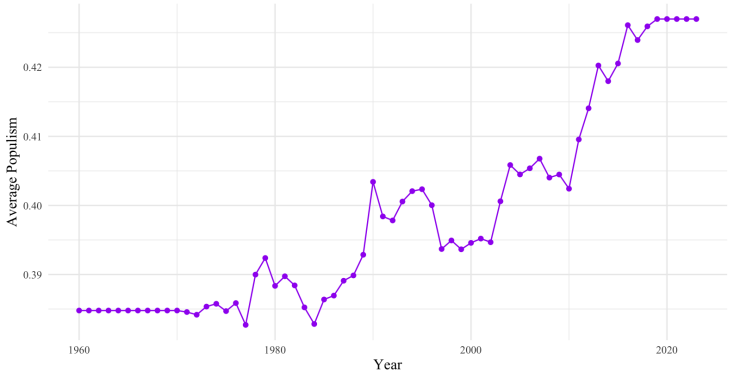

Figure A.4: Average Levels of Populism Over Time (1960-2023). Data comes from the `vdemdata` package in R and uses the VPARTY data, in particular, the average of the `v2xpa_popul` variable (Institute, 2023).

Data in Table A.10 shows the corresponding table and comes from the `vdemdata` package in R and uses the VPARTY data, in particular, the average of the `v2xpa_popul` variable, which captures the "extent to which representatives

of the party use populist rhetoric" (Institute, 2023).

Table A.10: Average Levels of Populism Over Time (1960-2023)

Year	Average Populism
1960	0.38
1961	0.38
1962	0.38
1963	0.38
1964	0.38
1965	0.38
1966	0.38
1967	0.38
1968	0.38
1969	0.38
1970	0.38
1971	0.38
1972	0.38
1973	0.39
1974	0.39
1975	0.38
1976	0.39
1977	0.38
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1979	0.39
1980	0.39
1981	0.39
1982	0.39
1983	0.39
1984	0.38
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2004	0.41
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2007	0.41
2008	0.40
2009	0.40
2010	0.40
2011	0.41
2012	0.41
2013	0.42
2014	0.42
2015	0.42
2016	0.43
2017	0.42
2018	0.43
2019	0.43
2020	0.43
2021	0.43
2022	0.43
2023	0.43

Appendix K Climate Trends

There has been a significant increase in climate events during this time period (see Figure A.5), likely contributing to heightened awareness and, in some cases, an increase in climate-related laws.

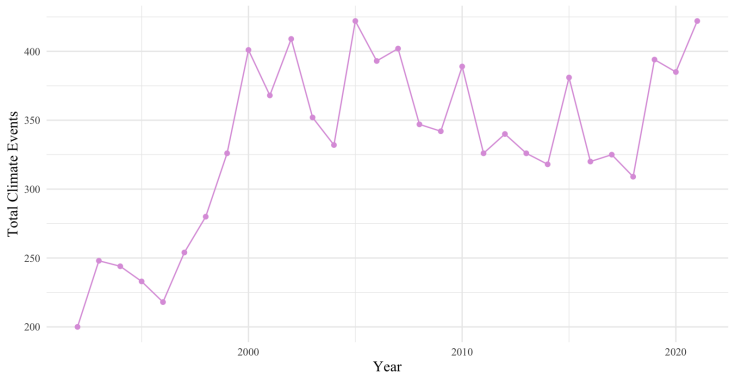

Figure A.5: Total Climate Events Over Time (1992-2021). Data comes from the Emergency Events Database (EM-DAT) (EM-DAT, 2024).

Data in Table A.11 comes from the Emergency Events Database (EM-DAT) (EM-DAT, 2024).

Table A.11: Total Climate Events Over Time (1992-2021)

year	total_climate_events
1992	200
1993	248
1994	244
1995	233
1996	218
1997	254
1998	280
1999	326
2000	401
2001	368
2002	409
s 2003	352
2004	332
2005	422
2006	393
2007	402
2008	347
2009	342
2010	389
2011	326
2012	340
2013	326
2014	318
2015	381
2016	320
2017	325
2018	309
2019	394
2020	385
2021	422

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