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Defocusing Disasters? Climate Shocks and the Attention–Policy Translation Failure

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Abstract

Do climate disasters accelerate mitigation policy, or can they slow it down? We develop a political-economy model in which disasters simultaneously (i) raise the perceived returns to mitigation by increasing the salience of climate risk, amplified by diagnostic expectations, and (ii) tighten fiscal constraints by destroying output and triggering reconstruction. Contrary to the focusing events literature, we show that more extreme disasters are, under identifiable conditions, less likely to produce mitigation policy rather than more. The model delivers an attention-policy translation failure: sufficiently severe disasters can increase perceived climate risk and demand for climate action while reducing mitigation policy output in the near to medium run. In a dynamic extension, the mitigation shortfall can persist for a decade through capital dynamics even as beliefs revert. We empirically illustrate the mechanism using the 1990 Western European windstorm cluster as a natural experiment, where highly exposed countries show rising public concern alongside a relative slowdown in mitigation legislation over the subsequent decade, consistent with the model's defocusing channel.

JEL Codes: D72, D91, Q54, Q58

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1 Introduction

Over the coming decades, the world is set to experience more frequent and intense climate disasters (IPCC, 2022). Understanding how disasters shape incentives for climate action is central for the low-carbon transition, especially amid rising global costs from extreme weather events that are estimated at USD 280 billion in 2023, with annual average losses of USD 217 billion over 2014–2023 (Swiss Re Institute, 2024; Kahn, 2005). These losses are amplified by network effects that propagate shocks through global supply chains (Barrot and Sauvagnat, 2016). A central question for the political economy of climate policy is whether disasters act as a wake-up call that accelerates mitigation, or instead shift priorities and constrain resources in ways that slow it down. This paper argues that the answer depends on a distinction that the existing literature has not fully formalised: the difference between how disasters shift *public beliefs* and how they shift *policy output*. We call this gap the attention–policy translation failure, and we develop a political-economy model that explains when and why it arises.

Extreme events can function as focusing events (Birkland, 1998) that raise perceived climate risk and voter demand for mitigation. A natural microfoundation for this is the representativeness heuristic: a vivid flood, wildfire, or windstorm matches widely held mental models of climate change and is therefore treated as disproportionately diagnostic evidence about future hazards (Kahneman and Tversky, 1972; Tversky and Kahneman, 1974; Kahneman and Frederick, 2002; Kahneman, 2003). We capture this using diagnostic expectations (N. Gennaioli and Shleifer, 2010; Bordalo, N. Gennaioli, and Shleifer, 2018; Bordalo, N. Gennaioli, and Shleifer, 2022), which formalise the overweighting of salient recent events in belief formation. Yet increased public concern need not translate into mitigation legislation. Post-disaster periods are dominated by reconstruction and crisis management, which tighten fiscal constraints and raise the opportunity cost of mitigation precisely when it appears most urgent (Besley and Persson, 2009; Besley and Persson, 2011; Kunreuther, 2021; Demekas and Grippa, 2021). Consistent with this tension, recent work finds that disasters often have small or insignificant effects on mitigation policy output (Rowan, 2022; Wappenhans et al., 2024).

Our model formalises this tension. A disaster affects mitigation incentives through two opposing forces. The *signal channel*: disasters raise the perceived probability of future climate risk, amplified by diagnostic overweighting, increasing the perceived returns to mitigation and electoral demand for climate action. The *output channel*: disasters destroy output and capital and trigger reconstruction, tightening contemporaneous resource constraints and raising the marginal cost of mitigation. Theorem 1 decomposes the net effect of a disaster on optimal mitigation into these two forces and characterises when the output channel dominates. A linear-quadratic approximation yields a transparent sufficient condition: defocusing occurs when disaster severity and capital intensity are high relative to political patience, mitigation effectiveness, and belief diagnosticity. Crucially, this can occur even when disasters sharply increase perceived climate risk and public demand for action.

This yields a prediction that directly contradicts the standard focusing events framework (Birkland, 1998): the relationship between disaster severity and mitigation policy is the opposite of what is assumed. Moderate disasters may indeed function as wake-up calls, shifting both beliefs and policy in the same direction. But sufficiently extreme events, precisely those that generate the greatest public concern, are also those most likely to tighten fiscal constraints beyond the point where the salience channel can compensate. We formalise this inversion by showing that under reasonable conditions, more severe disasters make the defocusing channel dominate. This formalisation connects to a broader observation in Birkland (2006): that even within the focusing events framework, translation from awareness to policy is not guaranteed, and natural disasters in particular are less reliable drivers of policy learning than man-made events. Our model provides the micro-foundations for this observation by identifying the precise conditions under which the translation failure occurs, and by recovering the conditions under which the focusing events prediction holds. We extend the baseline to an infinite-horizon setting and show that the mitigation shortfall can persist for a decade through capital dynamics, even as beliefs revert toward their pre-disaster level.

We illustrate the mechanism empirically using the 1990 Western European windstorm cluster, in which storms such as Daria and Vivian generated historically unprecedented damage across parts of Western Europe (Koks and Haer, 2020). We compare the evolution of mitigation legislation in highly exposed countries to that in comparable neighbours using a difference-in-differences design. We emphasise that this exercise provides an empirical illustration rather than a definitive causal test of the model: it documents an overall pattern consistent with the model's defocusing channel, rather than estimating the full set of model parameters across contexts. Within these limits, the evidence is nevertheless informative. The empirical illustration is particularly well suited to the theoretical predictions, as the identification strategy isolates events that are by construction at the extreme end of the severity distribution, specifically years in which disaster frequency is several standard deviations above a country's historical mean. It is precisely these events, rare and severe enough to act as focusing events and shift public concern, that the theory predicts are most likely to trigger the defocusing channel. Highly exposed countries exhibit rising public concern about climate change alongside a relative slowdown in mitigation legislation over the subsequent decade, and experience measurably greater resource constraints, as proxied by damages to GDP. This combination, heightened salience without corresponding policy output, is precisely the pattern predicted by the model.

The paper contributes to three literatures. First, we contribute to the political economy of climate policy (Samuel Fankhauser, C. Gennaioli, and Collins, 2016; Sauquet, 2014; Carattini et al., 2023; de Silva and Tenreyro, 2021; Eskander and Sam Fankhauser, 2023; Galanis, Ricchiuti, and Tippet, 2025) by identifying a mechanism through which climate disasters can *reduce* mitigation output: reconstruction crowd-out raises the short-run opportunity cost of climate legislation even when perceived risks increase. Second, we contribute to the behavioural economics literature on overreaction to salient shocks (N. Gennaioli and Shleifer, 2010; Bordalo, N. Gennaioli, and Shleifer, 2018; Bordalo, N. Gennaioli, and Shleifer, 2022; Afrouzi et al., 2023) by showing how diagnostic belief updating can amplify perceived risk without guaranteeing policy progress. To our knowledge this is the first paper that links diagnostic expectations to climate disasters. Third, we contribute to the disaster economics literature (Healy and Malhotra, 2009; Cohen and Werker, 2008; Gasper and Reeves, 2011; Garrett and Sobel, 2003; Bakkensen and Ma, 2020; Hazlett and Mildenberger, 2020; Besley and Persson, 2009; Besley and Persson, 2011; Kahn, 2005; Barrot and Sauvagnat, 2016; Bodenstein and Scaramucci, 2025) by formalising the crowd-out of long-run policy by short-run reconstruction in a resource-constrained political environment.

The remainder of the paper is structured as follows. Section 2 presents stylised facts motivating the theory. Section 3 develops the model, first in a two-period framework that yields the core analytical results, then in a dynamic extension that characterises persistence, and finally in a robustness check under long-run risk preferences. Section 4 provides the empirical illustration. Section 5 concludes.

2 Stylized Facts and Motivation

The standard focusing events framework (Birkland, 1998) predicts that disasters, by raising salience, should accelerate mitigation policy, and that more severe disasters should do so more strongly. The evidence below challenges this prediction. We document a pattern in which the countries experiencing the largest shocks show the greatest increases in climate concern alongside the largest relative slowdowns in mitigation legislation, the opposite of what a salience-to-policy account would predict.

A useful way to motivate the mechanism in this paper is to distinguish shifts in *public demand* for climate action from changes in observable *mitigation policy* output. The literature points to a recurring pattern: extreme climate experiences can plausibly shift public demand, yet these shifts often do not translate into sustained mitigation policy production. This public demand–policy translation gap is the central motivation for the theoretical framework developed in the next section.

On the public demand side, a large literature suggests that salient climate experiences can move beliefs and political preferences. For Europe, exposure to climate extremes is associated with higher environmental concern and greater Green voting, with the strength of these effects moderated by economic conditions (e.g., regional income), consistent with the view that the economic environment shapes whether climate experiences translate into expressed support for climate action (Hoffmann et al., 2022). More broadly, Andre et al. (2024) document substantial (and often underestimated) support for climate action in globally representative data. Taken together, this evidence supports the premise that salient climate events can shift perceived risk and public demand, a force that corresponds to the *signal* channel in our theory.

A second set of findings, however, indicates that increased demand does not reliably translate into political supply. Using a large corpus of party communications across Europe, Wappenhans et al. (2024) show that, apart from short-lived responses by Green parties, mainstream parties do not increase attention to environmental issues following severe extreme weather events. This suggests a translation gap from public salience to agenda-setting and elite attention, especially relevant for mitigation, which typically requires sustained legislative effort, coalition management, and implementation capacity. More broadly, Otto et al. (2021) find that hazard frequency and severity are generally unassociated with improvements in disaster risk reduction policy across 85 countries once baseline policy levels and other covariates are accounted for. While disaster risk reduction is distinct from climate mitigation, this result reinforces the broader point that hazard exposure does not mechanically generate systematic policy progress. At the local level, when policy change occurs after extreme weather, it is typically oriented toward risk management and adaptation rather than mitigation; Giordono, Boudet, and Gard-Murray (2020) document scant evidence of mitigation-oriented policies proposed after events in a comparative analysis of 15 cases. Rowan (2022) also finds no statistically significant relationship between climate disasters and mitigation policy. Together, these findings are consistent with the possibility that post-disaster governance reallocates scarce policy effort toward urgent recovery and risk management tasks, crowding out mitigation even when perceived risks rise.

The descriptive patterns in our Western European sample align with this tension between salience and policy output. Western Europe was hit by a historically unprecedented concentration of extreme climate events in 1990, as discussed in detail in Section 4.1 below. Figure 1a, using data from Eurobarometer[1], shows that the share of people seriously concerned about global warming increased in all countries after the shock, and increased most in countries with the highest damages to GDP. For example, in Luxembourg the share of people seriously concerned about global warming increased on average by 30% between 1989 and 1991, while the 1990 extreme weather shock caused 3% of climate damages to Luxembourg's GDP. A line of best fit shows a positive and significant (at the 5% level) relationship between damages and heightened concern over global warming, consistent with the general finding in the literature that extreme weather shocks raise climate concern.

Yet this increase in concern was not associated with a corresponding increase in mitigation laws in the most affected countries. Figure 1b, using data from Climate Laws of the World, shows that the number of mitigation laws, while increasing across all countries, increased least in those with the highest damages to GDP. Luxembourg, which experienced the largest shock, was the only country that did not increase its mitigation laws over this period. A line of best fit shows a significant (at the 5% level) negative relationship between damages and the average number of mitigation laws, consistent with the idea that climate shocks constrain resources in ways that ultimately reduce mitigation output.

These motivating patterns suggest an organising framework with two opposing forces. Disasters may increase perceived climate risk and public demand for action (the *signal* channel), but at the same time they can tighten contemporaneous constraints and shift governmental priorities toward reconstruc-

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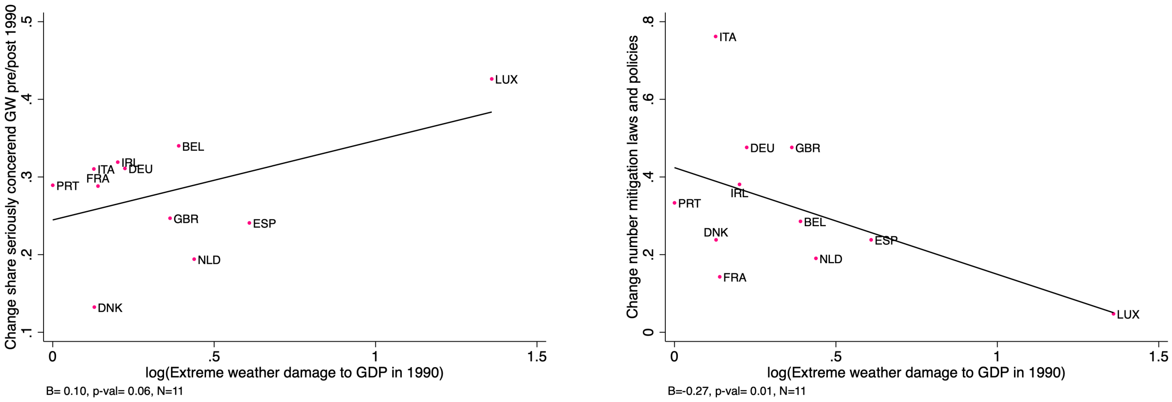
[1] See Appendix 5 for a detailed construction of this variable.

Figure 1: Changes in concern about global warming and mitigation laws vs damages to GDP from the 1990 shock



(a) Change in population share seriously concerned about global warming

(b) Change in annual frequency of mitigation laws implemented

Notes: In both panels, the x-axis shows log 1+damages to GDP from climate-related extreme weather events in 1990. We use logs given the potentially thick-tailed nature of climate shocks to GDP. Data are from EM-DAT. Panel (a) plots the change in the average share of people in each country who are seriously concerned about global warming from just before the shock (1989) to just after (1991), using Eurobarometer data. Panel (b) plots the change in the average annual frequency of mitigation laws implemented between the post-shock period (1991–2010) minus the pre-shock period (1980–1989), using data from Climate Laws of the World. Data are available only for a select number of countries.

tion and crisis governance (the *output* channel). The theoretical model in the next section formalises this trade-off and shows that sufficiently severe disasters can generate an attention–policy translation failure: perceived returns to mitigation rise, yet mitigation policy output falls when the output channel dominates.

3 Model

The model is developed in three steps, each building on the previous. We begin with a two-period framework that isolates the essential trade-off and yields sharp analytical results; this is where the core mechanism is established and where the attention–policy translation failure is formally characterised. We then embed the same mechanism in an infinite-horizon setting to show how the mitigation shortfall can persist over time through capital dynamics. Finally, we check whether the main result is sensitive to the choice of utility function by examining how it fares under long-run risk preferences. Readers primarily interested in the mechanism can focus on Section 3.1; the dynamic and robustness extensions in Sections 3.2 and 3.3 confirm that the core result is not an artefact of the two-period structure.

3.1 Two-Period Model

We begin with a tractable two-period model that captures the essential trade-off between *political demand* for mitigation (via disaster-induced salience) and *political supply* of mitigation (via contemporaneous resource costs). The simplicity yields closed-form solutions and clear comparative statics. We make several simplifying assumptions to tractably model the trade-off between salience and resource constraints after a disaster.

Belief Formation: Following Bordalo, N. Gennaioli, and Shleifer (2018) and Bordalo, N. Gennaioli, and Shleifer (2022), voters form *diagnostic expectations*, overweighting vivid recent events such as disasters. This captures the "availability heuristic" in risk perception (N. Gennaioli and Shleifer, 2010). We adopt diagnostic expectations because extreme natural disasters are particularly salient and memorable, making them more "diagnostic" or representative of future climate risk in the minds of individuals, even if statistically they may be rare. This over-weighting of recent, dramatic events is central to why disasters can sharply increase perceived climate risk.

Electoral Competition: The incumbent maximizes reelection probability via probabilistic voting, a standard approach in political economy (Lindbeck and Weibull, 1987; Dixit and Londregan, 1996; Besley and Persson, 2011).

Post-Disaster Constraints: Disasters destroy output and induce reconstruction needs, tightening fiscal constraints (Demekas and Grippa, 2021). Output losses may propagate through the economy (Barrot and Sauvagnat, 2016), amplifying the resource effect.

Environment

An incumbent government chooses policy in period $t = 0$ to maximize its probability of reelection. Elections are decided by probabilistic voting: a representative swing voter supports the incumbent if the voter's perceived utility under the incumbent weakly exceeds that under the challenger, up to an idiosyncratic ideology shock. As is standard, this implies that the incumbent's reelection probability is increasing in the swing voter's perceived expected utility from the incumbent's policy platform.

In period 0, a climate disaster may occur: $D_0 \in \{0, 1\}$ with $\Pr(D_0 = 1 \mid R_0) = p(R_0)$, with R_0 being the period 0 climate risk state, such that higher R_0 means a higher baseline probability of a disaster in period 0. After observing D_0, the incumbent chooses mitigation $m_0 \geq 0$ and reconstruction $r_0 \geq 0$. Period 1 involves no decisions, only stochastic consumption based on the realized disaster risk.

Production and Damage

Output in each period depends on capital K_t and disaster damages which, consistent with related literature (Nordhaus, 2018), reduce the output level:

$$Y_t = (A - \delta D_t)K_t, \quad \delta \in (0, 1). \tag{1}$$

The damage fraction δ captures disaster severity. Capital evolves as:

$$K_1 = (1 - d)K_0 + r_0 + \xi m_0, \tag{2}$$

where $d \in (0, 1)$ is depreciation and $\xi \in [0, 1]$ captures productive co-benefits of mitigation (e.g., green infrastructure that also enhances productivity).

Climate Risk Dynamics

Climate risk R_t follows:

$$R_1 = \rho R_0 - \alpha m_0 + \psi D_0 + \eta, \tag{3}$$

where $\rho \in (0,1)$ is persistence, $\alpha > 0$ is mitigation effectiveness, $\psi \geq 0$ captures how disasters increase future risk (e.g., through ecosystem damage), and $\eta \sim N(0, \sigma_\eta^2)$ is climate variability.

Resource Constraints

Consumption equals output net of investments:

$$C_0 = AK_0 - \delta D_0 K_0 - m_0 - r_0, \quad C_1 = AK_1 - \delta D_1 K_1, \tag{4}$$

where D_1 is stochastic with $\Pr(D_1 = 1 \mid R_1) = p(R_1)$.

Diagnostic Expectations

Following Bordalo, N. Gennaioli, and Shleifer (2018), voters form beliefs using diagnostic expectations with degree $\theta \geq 0$:

$$\hat{R}_1 \equiv \mathbb{E}_0^{DE}[R_1] = \rho R_0 - \alpha m_0 + \psi \mathbb{E}[D_0] + \theta \psi (D_0 - \mathbb{E}[D_0]). \tag{5}$$

The perceived disaster probability is $\hat{p}_1 = p(\hat{R}_1)$. When $\theta > 0$, disasters ($D_0 = 1$) lead to excessive pessimism: $\hat{R}_1 > \mathbb{E}_0^{RE}[R_1]$.

Electoral Competition and the Incumbent's Problem

Let the swing voter's perceived expected utility under the incumbent's policy be

$$U^{DE}(m_0, r_0; D_0) \equiv u(C_0) + \beta \mathbb{E}_0^{DE}[u(C_1)],$$

where beliefs $\mathbb{E}_0^{DE}$ are formed as above. Consider an election between the incumbent and a challenger offering an exogenous benchmark platform $(\tilde{m}_0, \tilde{r}_0)$ (e.g., the status quo). A voter i supports the incumbent if

$$U^{DE}(m_0, r_0; D_0) - U^{DE}(\tilde{m}_0, \tilde{r}_0; D_0) \geq \varepsilon_i,$$

where ε_i is an i.i.d. ideology/valence shock with strictly increasing CDF F. The incumbent's reelection probability is therefore

$$\Pr(\text{reelect}) = F\big(U^{DE}(m_0, r_0; D_0) - U^{DE}(\tilde{m}_0, \tilde{r}_0; D_0)\big).$$

Since F is strictly increasing and the challenger platform is exogenous, maximizing reelection probability is equivalent to maximizing the swing voter's perceived expected utility. Hence the incumbent chooses (m_0, r_0) to solve:

$$\max_{m_0 \geq 0,\, r_0 \geq 0} \left\{ u(C_0) + \beta \mathbb{E}_0^{DE}\left[u(C_1)\right] \right\},$$

subject to (1), (2), (3), (4), given (5). Throughout, the discount factor β admits a political interpretation: it governs how strongly electoral incentives load future outcomes relative to contemporaneous consumption costs.

Optimal Policy

The incumbent maximizes the swing voter's perceived expected utility $V(m_0, r_0) = u(C_0) + \beta E_0^{DE}[u(C_1)]$, subject to the constraints. Assume that the utility is CRRA with risk aversion parameter $\sigma > 0$ and $\neq 1$. The following theorem characterises the core trade-off in how a disaster affects optimal mitigation.

Theorem 1. *The effect of a disaster on optimal mitigation is:*

$$\frac{dm_0^*}{dD_0} = \frac{1}{\Delta}\left(\underbrace{\beta \alpha p'(\hat{R}_1)\theta\psi|\Delta u|}_{S} - \underbrace{\sigma \frac{u'(C_0)}{C_0}\delta K_0}_{O} + C \right),$$

where:

- $\Delta = V_{mm}V_{rr} - V_{mr}^2 > 0$ *(Hessian determinant, positive by concavity),*
- $S > 0$*: signal (salience) effect (increases mitigation via amplified perceived risk),*
- $O > 0$*: output (resource) effect (decreases mitigation via tightened contemporaneous resources),*

- $C = \frac{V_{mr}}{V_{rr}} \cdot O$: *cross-effect from optimal reconstruction adjustment (typically* $C < 0$*, reinforcing the output effect as mitigation and reconstruction compete for scarce resources),*
- $\Delta u = u(AK_1 - \delta K_1) - u(AK_1) < 0$*, so* $|\Delta u| > 0$.[2]

The theorem highlights the attention–policy translation failure: even as disasters raise the perceived marginal benefit of mitigation through diagnostic updating (the S channel), they can reduce mitigation effort if reconstruction needs and output losses dominate (the $-O+C$ channel), elevating the opportunity cost precisely when mitigation seems most urgent. This effect is more likely after severe disasters (high δ), in capital-intensive settings (high K_0), or under short political horizons (low β), while stronger mitigation effectiveness (α) or diagnosticity (θ) bolsters the signal channel. This reveals a tension that directly contradicts the standard focusing events prediction (Birkland, 1998): while a disaster raises perceived climate risk and generates demand for mitigation through the signal channel, greater disaster severity works in the opposite direction by amplifying the output effect. Moderate disasters may therefore function as wake-up calls, where the signal effect S dominates, while catastrophic disasters, precisely those that generate the greatest public concern and the loudest calls for action, are the ones most likely to see the output effect dominate and mitigation fall. This is the paper's sharpest prediction: the disasters that most alarm the public are, under these conditions, the least likely to produce the policy response that concern would seem to demand. This result also provides formal micro-foundations for the observation in Birkland (2006) that natural disasters are less reliable drivers of policy learning than man-made events: the parameters of the model identify the precise conditions under which translation from salience to policy fails. Specifically, the diagnostic expectations parameter θ captures the salience mechanism that Birkland (ibid.) identifies as necessary for policy change, the discount factor β captures political patience and horizon, and the fiscal constraint captures institutional capacity. The model shows that even when salience is high, the translation failure occurs when disaster severity and capital intensity are sufficiently large relative to these enabling conditions.

To obtain sharper intuition, we make a linear-quadratic approximation that yields closed-form policy rules and a transparent sign characterisation. Assume:

1. Quadratic utility: $u(C) = C - \frac{\gamma}{2}C^2$, $\gamma > 0$ small,

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[2] For proofs see Appendix F.

2. Linear risk probability: $p(R) = \underline{p} + \kappa R$, $\kappa > 0$,
3. No productive co-benefits: $\xi = 0$ (for tractability),
4. No climate variability: $\eta = 0$.

Proposition 1. *Under Assumptions 1–4, optimal mitigation is:*

$$m_0^* = \frac{\beta\alpha\kappa\delta K_1}{\beta\alpha^2\kappa\delta K_1 + \gamma} - \frac{\gamma\delta K_0}{\beta\alpha^2\kappa\delta K_1 + \gamma} D_0 + \frac{\beta\alpha\kappa\theta\psi(D_0 - \mathbb{E}[D_0])}{\beta\alpha^2\kappa\delta K_1 + \gamma},$$

and

$$\frac{dm_0^*}{dD_0} = \frac{\beta\alpha\kappa\theta\psi - \gamma\delta K_0}{\beta\alpha^2\kappa\delta K_1 + \gamma}.$$

Proposition 1 decomposes optimal mitigation into three terms. The first term is a baseline level of mitigation, increasing in the perceived returns to future risk reduction ($\beta\alpha\kappa$) and in the severity of potential damages (δK_1). The second term is negative and proportional to D_0: when a disaster occurs, the direct destruction of resources tightens the contemporaneous budget constraint and reduces optimal mitigation. The third term is positive and proportional to the diagnostic surprise ($D_0 - \mathbb{E}[D_0]$): when a disaster occurs unexpectedly, voters over-weight it as a signal of future climate risk, raising the perceived benefit of mitigation. The net effect is captured directly by $\frac{dm_0^*}{dD_0} = \frac{\beta\alpha\kappa\theta\psi - \gamma\delta K_0}{\beta\alpha^2\kappa\delta K_1 + \gamma}$, where the sign is determined by whether the salience term $\beta\alpha\kappa\theta\psi$ exceeds the resource term $\gamma\delta K_0$. The former captures political patience, mitigation effectiveness, and belief diagnosticity; the latter captures disaster severity and capital intensity. This provides a more intuitive characterisation of the conditions under which the defocusing mechanism operates, confirming the result from Theorem 1 in the linear-quadratic setting.

Cognitive Counterpart to Fiscal Constraints

The resource constraint in the model operates through fiscal constraints, but it also admits a natural cognitive interpretation that reinforces the same mechanism, and which we discuss informally. Bordalo, N. Gennaioli, Lanzani, et al. (2025) develop a theory of selective attention in which decision-makers categorise problems based on similarity to past experiences, allocating their attention budget to the features most salient in the activated category. A disaster shock plausibly triggers categorisation into a "crisis mode" schema, one in which immediate output losses, reconstruction needs, and emergency governance are the goal-relevant features, rather than a "planning mode" schema in which long-run climate risk is central. This categorical shift is self-reinforcing: the same salience mechanism that drives diagnostic overweighting of disaster risk (our signal channel) simultaneously cues a reconstruction-focused attentional frame, crowding out the legislative and administrative bandwidth required to produce mitigation policy.

This cognitive account complements rather than replaces our fiscal mechanism. Even in the absence of binding budget constraints, attentional crowd-out alone would generate a wedge between heightened perceived climate risk and mitigation policy output. The two channels are therefore mutually reinforcing: fiscal constraints limit the *resources* available for mitigation, while attentional crowd-out limits the *political will and administrative capacity* to deploy whatever resources remain. Together they widen the gap between the signal and output effects identified in Theorem 1, making the attention–policy translation failure more likely and more persistent than either mechanism would produce in isolation.

3.2 Dynamic Model

The two-period model establishes when a disaster reduces mitigation on impact. We now ask how long this effect lasts. To capture the persistence observed in the empirical illustration, we embed the same mechanism in an infinite-horizon setting. The key result is that even a one-time disaster can generate a mitigation shortfall lasting a decade, because the output channel propagates through capital dynamics long after beliefs have reverted.

Infinite-Horizon Model

Time is discrete, $t = 0, 1, 2, \ldots$. The incumbent solves:

$$\max_{\{m_t, r_t\}} \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t u(C_t) \right]$$

subject to:

$$C_t = AK_t - \delta D_t K_t - m_t - r_t \tag{6}$$

$$K_{t+1} = (1-d)K_t + r_t + \xi m_t \tag{7}$$

$$R_{t+1} = \rho R_t - \alpha m_t + \psi D_t + \eta_t \tag{8}$$

with $\eta_t \sim N(0, \sigma_\eta^2)$ i.i.d. The Bellman equation is:

$$V(K_t, R_t) = \max_{m_t, r_t} \left\{ u(C_t) + \beta \mathbb{E}_t^{DE} \left[V(K_{t+1}, R_{t+1}) \right] \right\}$$

where $\mathbb{E}_t^{DE}$ incorporates diagnostic expectations as before.

Steady State and Impulse Responses

We analyse the model's dynamics by linearizing around the non-disaster steady state. Let variables with asterisks denote steady-state values.

Lemma 1. *The non-stochastic steady state ($D_t = 0$ $\forall t$) satisfies:*

$$u'(C^*) = \beta V_K^* \tag{9}$$

$$V_K^* = \frac{u'(C^*)A}{1 - \beta(1-d)} \tag{10}$$

$$V_R^* = -\frac{\beta \delta K^* p'(R^*) u'(C^*) p(R^*)}{1 - \beta\rho}. \tag{11}$$

Now consider an unanticipated disaster at $t = 0$: $D_0 = 1$, $D_t = 0$ for $t \geq 1$. We linearize the system around the steady state and compute impulse responses.

Proposition 2. *The impulse response function for mitigation is:*

$$\frac{dm_t}{dD_0} = \sum_{s=0}^{\infty} \beta^s \left(\frac{\partial m_t}{\partial \hat{R}_{t+s}} \cdot \underbrace{\theta \psi \rho^s}_{\text{signal propagation}} - \frac{\partial m_t}{\partial C_{t+s}} \cdot \underbrace{\frac{\partial C_{t+s}}{\partial D_0}}_{\text{output propagation}} \right)$$

The cumulative effect over T periods is:

$$\sum_{t=0}^{T} \frac{dm_t}{dD_0} = \underbrace{\frac{\theta\psi}{1-\beta\rho} \sum_{t=0}^{T} \frac{\partial m_t}{\partial \hat{R}_t}}_{\textit{cumulative signal}} \underbrace{- \delta K_0 \sum_{t=0}^{T} \sum_{s=0}^{t} \frac{\partial m_t}{\partial C_s} \cdot M_{s,0}}_{\textit{cumulative output}}$$

where $M_{s,0}$ *is the output multiplier from period 0 to s.*

The proposition shows how both effects persist, but at different rates. The signal effect decays at rate ρ (risk persistence), so beliefs gradually return toward their pre-disaster level. The output effect persists through capital dynamics: the initial output loss reduces K_1, which reduces Y_1, creating a persistent income effect that continues to crowd out mitigation even after the salience of the original shock has faded. This asymmetry between the two channels is what generates the medium-run defocusing pattern observed in the empirical illustration.

3.3 Long-Run Risk Preferences and the Defocusing Channel

The disasters at the centre of this paper, severe events that destroy output and depress long-run growth prospects, are precisely the kind of shocks that feature prominently in the long-run risk literature: events that spike conditional volatility and shift expected consumption growth downward (Bansal and Yaron, 2004; Bansal, Kiku, and Yaron, 2016). This raises a natural question about whether the defocusing mechanism is strengthened or weakened when agents have preferences that are sensitive to this kind of persistent uncertainty. One might expect the signal channel to strengthen, since agents who fear long-run risk should respond more sharply to disaster-induced upward revisions in perceived climate risk, making mitigation more attractive. That the defocusing result survives and is amplified under these preferences is therefore informative: it suggests the output channel dominates even when the signal channel is given an additional boost, and that our CRRA baseline is conservative.

To assess this, we replace CRRA utility with Epstein-Zin recursive preferences, which separate risk aversion from the intertemporal elasticity of substitution and allow for a preference for early resolution of uncertainty (Bansal and Yaron, 2004; Bansal, Kiku, and Yaron, 2016). In our framework, disasters now affect utility through two additional routes beyond the baseline: they shift the long-run growth component x_t downward and spike conditional volatility σ_t^2, both of which enter the continuation value directly under Epstein-Zin. Diagnostic expectations operate as before, overweighting the disaster realisation in beliefs about future climate risk. Utility is recursive:

$$V_t = \left[(1-\delta) C_t^{\frac{1-\gamma}{\zeta}} + \delta \left(E_t[V_{t+1}^{1-\gamma}] \right)^{\frac{\zeta}{1-\gamma}} \right]^{\frac{\zeta}{1-\gamma}}, \tag{12}$$

where $\gamma > 1$ is risk aversion, $\psi > 1$ is IES (for early resolution preference), and $\zeta = \frac{1-\gamma}{1-1/\psi}$. We augment the endowment dynamics to include a persistent long-run growth component x_t and stochastic volatility σ_t^2, as in Bansal and Yaron (2004):

$$\begin{aligned} \Delta c_{t+1} &= \mu_c + x_t + \sigma_t \eta_{t+1}, \\ x_{t+1} &= \rho x_t + \varphi_e \sigma_t e_{t+1}, \\ \sigma_{t+1}^2 &= a\bar{\sigma}^2 + \nu(\sigma_t^2 - \bar{\sigma}^2) + \sigma_w w_{t+1}. \end{aligned} \tag{13}$$

Disasters shock x_t downward (reducing long-run growth prospects) and spike σ_t^2 (increasing uncertainty), while diagnostic expectations over-weight these in beliefs.

We calibrate preference parameters following Bansal and Yaron (ibid.), setting risk aversion $\gamma = 10$ and IES $\psi = 1.5$. These values are standard in the macro-finance literature and are chosen to match observed asset pricing moments rather than to fit our results; they therefore represent an external discipline on the calibration rather than free parameters. The long-run growth and volatility persistence parameters ($\rho = \nu = 0.98$) are likewise taken directly from that literature, with all remaining parameters held at their baseline values. The qualitative result is robust to moderate variation in γ and ψ around these benchmark values.

The key finding is that under Epstein-Zin preferences, the disaster severity threshold above which defocusing occurs is strictly lower than in the baseline. Intuitively, the volatility spike generated by a disaster raises the value of eliminating future uncertainty, which might be expected to increase mitigation effort. But it simultaneously raises the opportunity cost of any forward-looking investment, including mitigation, by increasing agents' aversion to the reconstruction-induced income uncertainty of the post-disaster period. When this second force dominates, Epstein-Zin preferences amplify the output channel relative to the signal channel, expanding the parameter region in which defocusing occurs. In a linearized version of the model, one can derive conditions under which disasters reduce mitigation when long-run risk persistence ρ is high, consistent with the calibrated values.

Taken together, the CRRA and Epstein-Zin results reinforce the paper's central finding rather than merely checking its robustness. The defocusing mechanism is not an artifact of a particular utility specification; it becomes stronger precisely in the environments where one might most expect salience to win out. The advanced economies that form our Western European sample are, if anything, the contexts where the attention–policy translation failure is most likely to operate, not least. The sharp analytical conditions in Theorem 1 and Proposition 1 are derived under the simpler CRRA specification for transparency, but the underlying economic logic carries through to richer attitudes toward intertemporal risk.

4 Empirical Illustration

This section provides an empirical illustration of the paper's mechanism. Our aim is to document a pattern consistent with the model's defocusing channel: large disaster shocks coincide with (i) a temporary slowdown in mitigation policy production and (ii) a tightening of economic resources. We are explicit about the limits of what follows. The difference-in-differences design we employ identifies a pattern in the data that is consistent with the theory, but it does not constitute a definitive causal test. A fully credible causal estimate would require either a larger number of comparable shock episodes across countries or direct measurement of the attention and capacity margins the model emphasises. The value of the exercise is to show that the negative mitigation prediction is not merely a theoretical possibility, and to establish the empirical regularity that motivates the theoretical framework.

4.1 Data and sample

We measure climate-related disasters using the Emergency Events Database (EM-DAT) and follow the IMF classification, defining climate-related disasters as droughts, extreme temperatures, floods, landslides, storms, and wildfires. We use annual country-level counts. EM-DAT records events that meet at least one of the following criteria: ten or more deaths, 100 or more affected/injured, a declared state of emergency, or a request for international assistance.

Domestic mitigation legislation is taken from the Climate Change Laws of the World database. Our baseline outcome focuses on mitigation-only laws (excluding laws primarily classified as adaptation or disaster response). We focus on this narrow definition in order to capture a relatively comparable measure of mitigation action. One concern with this indicator is that not all mitigation laws are equally effective at reducing emissions. Previous work has shown, however, that mitigation laws captured in this dataset do effectively reduce GHG emissions (de Silva and Tenreyro, 2021). Table 1 confirms this in a simple fixed effects model: implementing a mitigation law in a given period is significantly associated with a reduction in GHG emissions contemporaneously and in the following period.

Table 1: The impact of mitigation laws on total GHG emissions

	(1) GHG
Mitigation laws (t)	-10.361**
	(0.047)
Mitigation laws (t-1)	-9.461*
	(0.060)
Mitigation laws (t-2)	-9.915
	(0.153)
N	624

P-value in parentheses | * 0.10 **0.05 ***0.01 | Country and Year fixed effects are included

We use direct economic damages to GDP from extreme weather events to measure the extent to which disasters tightened resources. We use direct economic damages to GDP (%) rather than aggregate statistics (such as the fiscal balance or aggregate capital stock), as aggregate indicators will be shaped by broad macroeconomic factors beyond extreme weather events. Direct damages to GDP are drawn from EM-DAT and cover the same extreme weather events discussed above.

Our sample consists of Western European countries from 1980–2020.[3] We focus on this region because countries share broadly similar institutional and economic environments and because climate

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[3] We define Western Europe geographically to include Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom.

policy was politically salient over the period.[4]

4.2 Identifying an extreme disaster episode

Motivated by the model, we focus on unusually large disasters relative to a country's typical experience. Our baseline definition classifies an *extreme* year as one in which the annual count of climate-related disasters exceeds the country mean by four standard deviations. This threshold follows common definitions of extremes in the climate-statistics literature (Hansen, Sato, and Ruedy, 2012; Rahmstorf and Coumou, 2011).[5] Annual counts of climate-related disasters, rather than damages to GDP, are used to identify the exogenous shock, as damages to GDP from natural disasters are determined by endogenous factors, such as the history of adaptation and risk management investments. An abnormal number of extreme events hitting a country in a given year is, by contrast, highly exogenous and unpredictable. Importantly, this identification strategy isolates events that are by construction at the extreme end of the severity distribution, several standard deviations above a country's historical experience, and it is precisely these events that the model predicts are most likely to trigger the defocusing channel.

A notable result of this data-driven identification strategy is that almost all the shocks occur in 1990.[6] The year 1990 was particularly severe for climate-related disasters in Western Europe. Six major storms, including Daria, Herta, Judith, Ottilie, Vivian, and Wiebke, hit the continent in quick succession, causing historically high levels of damage.[7] These events represent a highly unusual concentration of extreme weather activity, with multiple countries experiencing disaster counts more than four standard deviations above their historical average. Figure **??** in the appendix presents the frequency of disasters and four standard deviation cutoff for all countries.

The treatment group consists of countries crossing the extreme threshold in 1990 (Finland, Netherlands, Luxembourg, and Denmark); the remaining Western European countries form the control group.

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[4] The IPCC was established in 1988, while *Time Magazine* put the endangered earth on their front cover at the beginning of 1989, indicating that it had partly seeped into the cultural consciousness.

[5] Appendix 5 considers alternative cutoffs and related definitions.

[6] The only exception is Spain in 2019, which we exclude as it falls at the end of the sample and its effects cannot be analysed.

[7] See Koks and Haer (2020), which uses OpenStreetMap data to confirm the exceptional nature of damages in 1990.

These shocks were concentrated within 35 days,[8] providing a natural experiment setting that is both temporally sharp and plausibly exogenous. As climate disasters of this magnitude are unpredictable and outside the scope of normal political planning, we treat the 1990 shock as an exogenous treatment affecting only the identified countries. Importantly, 1990 precedes major international climate agreements (e.g., the 1992 UNFCCC and 1997 Kyoto Protocol), making it a natural focal point for evaluating how extreme events may have influenced the domestic climate policy trajectory during a critical formative period.

4.3 Empirical model

Following the predictions of the theoretical model, we estimate the impact of an extreme disaster shock on two outcome variables.

First, we estimate the average treatment effect by comparing the cumulative number of mitigation laws passed in the treated countries to those in the control group of Western European countries that did not experience such an extreme shock.

Second, we estimate the impact of the 1990 shock on realised GDP damages, to assess whether the impact on mitigation policies is likely to be driven by the resource constraint mechanism suggested by the model. While it would also be useful to estimate a similar difference-in-differences with the measure of public concern over climate change, there are insufficient data to do so. Figure 1 above does, however, provide preliminary evidence that countries with the highest damages to GDP implemented fewer laws, consistent with the story of this paper.

Given the common shock year, we use a simple difference-in-differences specification to summarise the post-1990 divergence in mitigation policy output:

$$y_{it} = \beta\left(\mathit{Treated}_i \times \mathit{Post}_t\right) + \Gamma' X_{it} + \mu_i + \tau_t + \varepsilon_{it}, \tag{14}$$

where y_{it} is either (i) the cumulative number of mitigation policies since 1980 or (ii) the damages to GDP of extreme weather events since 1980, μ_i and τ_t are country and year fixed effects, and X_{it} includes standard covariates (fossil fuel rents, GDP per capita, population, democracy, and government ideology).

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[8] See Table A1 in the Appendix for details.

We report results over 1980–2000 to focus on medium-run responses around the episode; Appendix 5 considers alternative horizons and specifications.

4.4 Results

Figure 2 presents the change in the cumulative number of mitigation laws between the treated and control groups. The climate disaster shock occurs in 1990, indicated by the dark vertical line. The parallel trends assumption holds for the pre-treatment period, as both groups have the same flat trends. From 1990 onward, the control group begins to implement mitigation laws, while the treated group does not implement laws until 1997.[9] The parallel trends assumption implies that both groups would have followed the same trajectory had the treated group not suffered the disaster shock in 1990.

Table 2 columns 1 and 2 report the estimated post-1990 divergence in mitigation policy output between treated and control countries. Across specifications, the interaction term $\mathit{Treated}_i \times \mathit{Post}_t$ is negative, indicating a relative slowdown in mitigation policy production in the treated group following the 1990 disaster episode. Each treated country had on average 0.303 fewer mitigation laws than the control countries in the post-shock period from 1990 to 2000, significant at the 5% level. This effect is comparable in magnitude to the average number of mitigation laws per country in this period, which was 0.30 cumulative laws.

The negative association is robust to including standard covariates (column 2), although none of the covariates are individually significant. These patterns are consistent with the first aspect of the model's defocusing channel: even if disasters raise perceived risk (as shown in Figure 1a), the supply of mitigation policy can decline.

We next investigate whether this decline in mitigation laws was driven by a constraint on resources. Figure 3 shows the damages to GDP between the treated and control groups. We statistically find that the pre-treatment trends are parallel (we do not reject the null of parallel trends with Prob $>$ F $=$ 0.7481). In 1990, there is a clear upward shift in damages to GDP in the treated countries, without any significant change in the control group, which continues on its pre-treatment trend. Table 2 column 3 reports the estimated post-1990 divergence in damages to GDP. The interaction term is positive,

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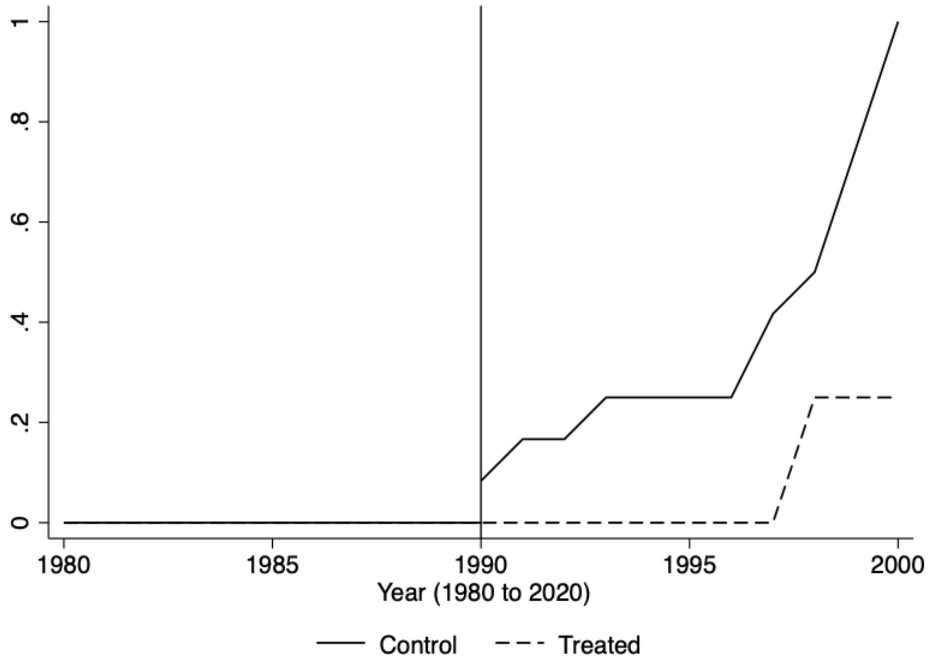
[9] The increase in mitigation laws for both groups in 1997 is driven by all countries signing the Kyoto Protocol.

Figure 2: Impact of climate disaster shock on cumulative no. mitigation laws



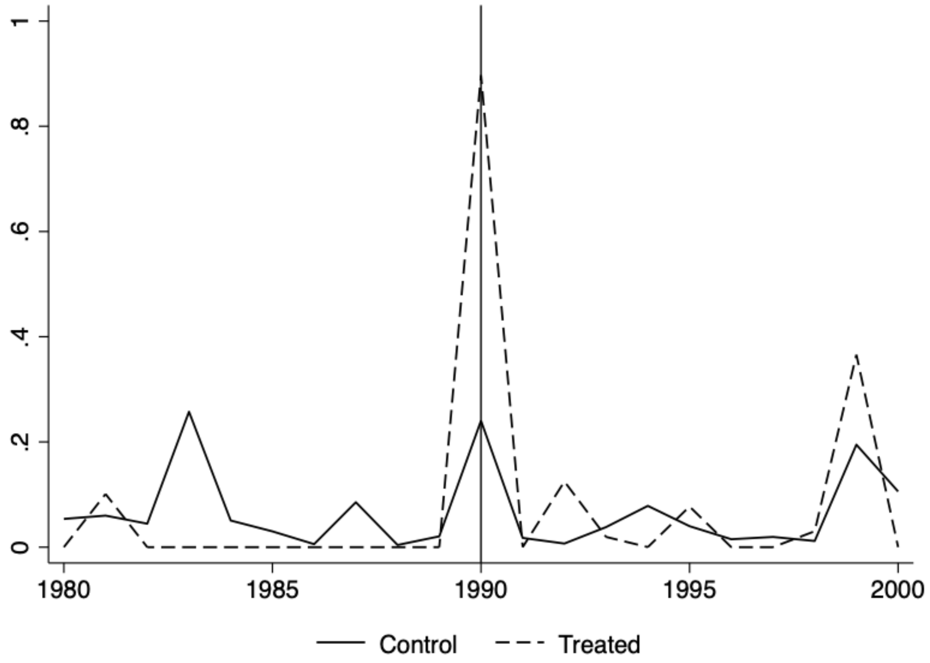
Note: 1990 is identified as the only year where the number of climate damages 4σ above the country mean. Treated group = Finland, Netherlands, Luxembourg and Denmark. Control group = Austria, Belgium, France, Germany, Ireland, Italy, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom.

Table 2: The impact of climate disaster shock on mitigation laws and damages to GDP

	(1) Laws	(2) Laws	(3) Damage/GDP
Interaction	-0.303**	-0.338**	0.119*
	(0.026)	(0.045)	(0.090)
Controls			
Fossil fuel rents/GDP		0.009	
		(0.693)	
Population		-0.000	
		(0.563)	
Left-right index		-0.028	
		(0.482)	
GDP per capita		-0.006	
		(0.540)	
Democracy index		-3.358	
		(0.439)	
N	336	315	336

P-value in parentheses | * 0.10 **0.05 ***0.01 | Country + Year fixed effects included

Figure 3: Impact of climate disaster shock on annual damages to GDP



Note: 1990 is identified as the only year where the number of climate damages 4σ above the country mean. Treated group = Finland, Netherlands, Luxembourg and Denmark. Control group = Austria, Belgium, France, Germany, Ireland, Italy, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom.

indicating a substantial increase in damages to GDP in the treated group. The treated group suffers 0.119% of GDP more in damages per year on average over 1990–2000 than the control group, significant at the 10% level. This is considerably larger than the average damages to GDP across all countries over 1990–2000, which was 0.08% of GDP per year.

This is consistent with the resource constraint channel of the model: countries that experience extreme weather events face tighter resource constraints, proxied here by greater damages to GDP. Taken together, the two results, fewer mitigation laws and greater resource constraints in treated countries, match the pattern the model predicts. They do not, however, rule out alternative explanations, and we interpret them as illustrative rather than as definitive causal evidence.

We conduct a series of further estimations to test the robustness of these results. These extra estimations vary (i) the definition of an extreme episode (alternative cutoffs), (ii) the time horizon, (iii) the outcome definition (laws versus laws and policies; cumulative versus annual counts), (iv) placebo treatment years and (v) the treatment group to check if outliers are driving the results. The qualitative finding, a relative post-episode slowdown in mitigation policy output, is broadly stable across these exercises. Appendix 5 summarises these results and findings.

5 Conclusion

Climate disasters are expected to become more frequent and severe over the coming decades. This paper develops a novel micro-founded framework to study how such shocks affect mitigation. We show that disasters can generate attention–policy translation failures: although disasters increase public attention to climate risk, this does not reliably translate into sustained mitigation policy. Indeed, and contrary to the predictions of the focusing events literature, our model shows that it is precisely the most extreme disasters, those that generate the greatest public alarm, that are most likely to crowd out the mitigation response entirely. As a result, even large shocks may fail to produce meaningful long-run reductions in climate risk, highlighting a key limitation of relying on disasters to spur policy action. The mechanism operates through two opposing forces. A disaster raises the perceived probability of future climate risk via diagnostic overweighting, generating electoral demand for mitigation. At the same time, it destroys contemporaneous resources and triggers reconstruction, raising the opportunity cost of mitigation precisely when it appears most needed. Theorem 1 decomposes these forces and characterises when the resource channel dominates. The linear-quadratic approximation in Proposition 1 shows that defocusing is more likely following extreme disasters with large damages relative to GDP, and under short political horizons. The dynamic extension shows the mitigation shortfall can persist for a decade even as beliefs revert, because the capital losses from the disaster continue to crowd out mitigation long after salience has faded.

The empirical illustration, using the 1990 Western European windstorm cluster, is consistent with this mechanism. Highly exposed Western European countries show greater public concern about climate change alongside a relative slowdown in mitigation legislation over the subsequent decade, and face measurably tighter resource constraints.

The analysis has two practical implications. First, institutions that pre-commit resources for post-disaster mitigation, such as pre-arranged disaster financing, automatic stabilisation mechanisms, or ring-fenced reconstruction budgets, can reduce the likelihood that mitigation is crowded out precisely when perceived risks are highest. Second, institutions that lengthen political horizons or strengthen commitment to future climate targets can shift the balance toward the signal channel, making it more likely that heightened salience translates into policy output. Crucially, these institutional safeguards matter most for the most extreme events: it is precisely the disasters severe enough to dominate headlines and maximise public concern that are also most likely, in the absence of pre-committed resources and long political horizons, to crowd out the mitigation response entirely. More broadly, the results underscore a general point: attention shocks are not sufficient for policy change. Translating disaster salience into mitigation legislation requires institutional capacity, not just public concern.

Several directions for future work follow naturally. On the theoretical side, the framework could be extended to allow for heterogeneous voter groups, partisan competition, and endogenous legislative capacity. On the empirical side, the most promising direction is to measure the attention and capacity margins directly, using parliamentary speech records, media text analysis, and budget composition data, to separately quantify the signal and resource channels the model identifies. A systematic cross-country analysis of disaster episodes with sufficient variation in institutional capacity would also help establish whether the defocusing effect we identify in Western Europe generalises more broadly.

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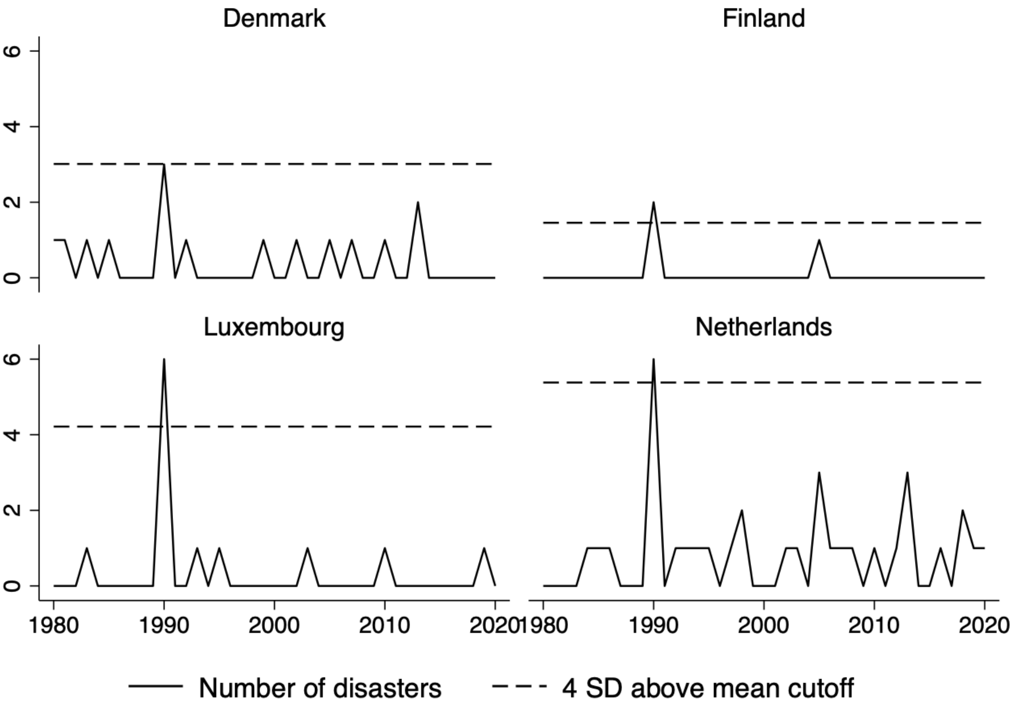
Appendix

A. The 1990 windstorm episode

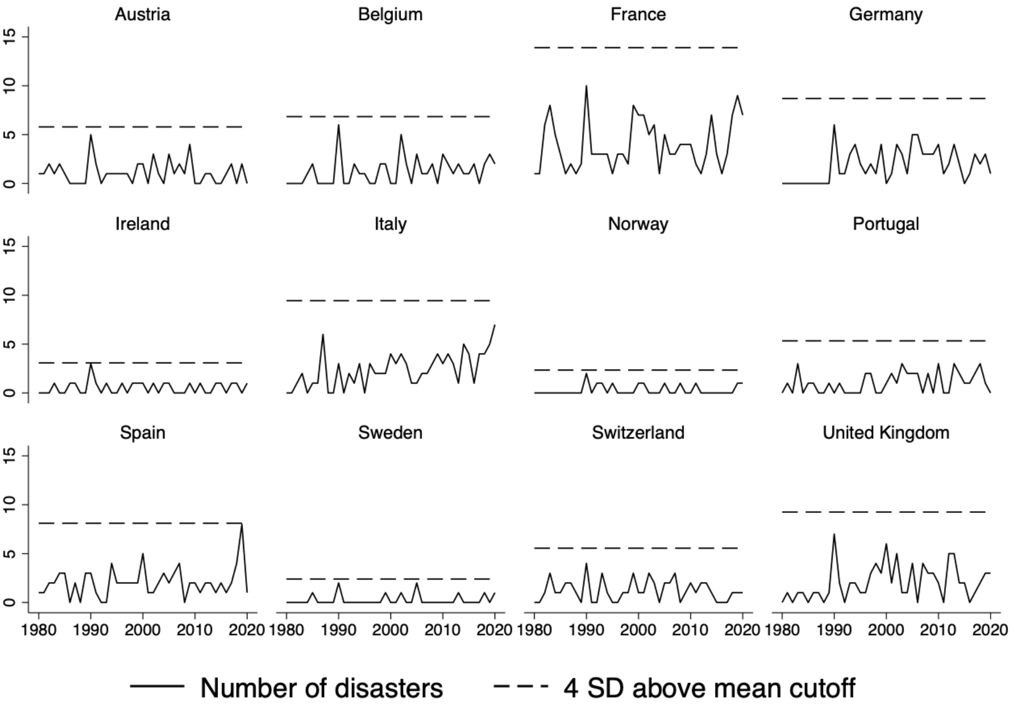
Table A1: Major European Windstorms in 1990

Storm Name	**Dates**	**Main Countries Affected**	**Notable Impacts**
Burns' Day Storm (Daria)	25–26 Jan 1990	UK, Netherlands, Denmark, Luxembourg, Germany	Winds up to 230 km/h; 97 fatalities across Europe; severe damage to infrastructure and forests; widespread power outages.
Herta	1–6 Feb 1990	UK, France, Germany, Belgium, Netherlands	Significant wind damage; insured losses estimated at \$1.5 billion (2012 USD); disruption to transport and utilities.
Judith	7–8 Feb 1990	Western Europe	Moderate storm with localized damage; limited widespread impact.
Nana	11–12 Feb 1990	Western Europe	Part of the 1990 storm sequence; caused minor structural and tree damage.
Ottilie	13–14 Feb 1990	Western Europe	Minor to moderate impacts; damage to roofs, trees, and power lines.
Polly	14–15 Feb 1990	Western Europe	Localized wind damage; part of prolonged storm activity in February.
Vivian	25–28 Feb 1990	Netherlands, Finland, Germany, Switzerland	Winds up to 268 km/h; 64 fatalities; extensive forest damage (esp. in Germany and Switzerland); transport disruptions.
Wiebke	28 Feb – 1 Mar 1990	Germany, Netherlands, France, Switzerland	Major forest destruction; severe economic damage; insured losses of \$1.4 billion (2012 USD); followed closely after Vivian.

Sources: EM-DAT; European Windstorm Database; ESWD.



(a) Treatment group



(b) Control group

Figure A1: Frequency of climate disasters (4σ cutoff)

B. Extreme-event definitions

Table A2: Periods where frequency of disasters is more than 4σ above country mean

Country	Date	No. Disaster	Mean No. Disaster	σ No. Disaster
Denmark	1990	3	.372093	.6554989
Finland	1990	2	.0697674	.337734
Luxembourg	1990	6	.3023256	.9644856
Netherlands	1990	6	.8604651	1.125069

Table A3: Periods where frequency of disasters is more than 5σ above country mean

Country	Date	No. Disaster	Mean No. Disaster	σ No. Disaster
Finland	1990	2	.0697674	.337734
Luxembourg	1990	6	.3023256	.9644856

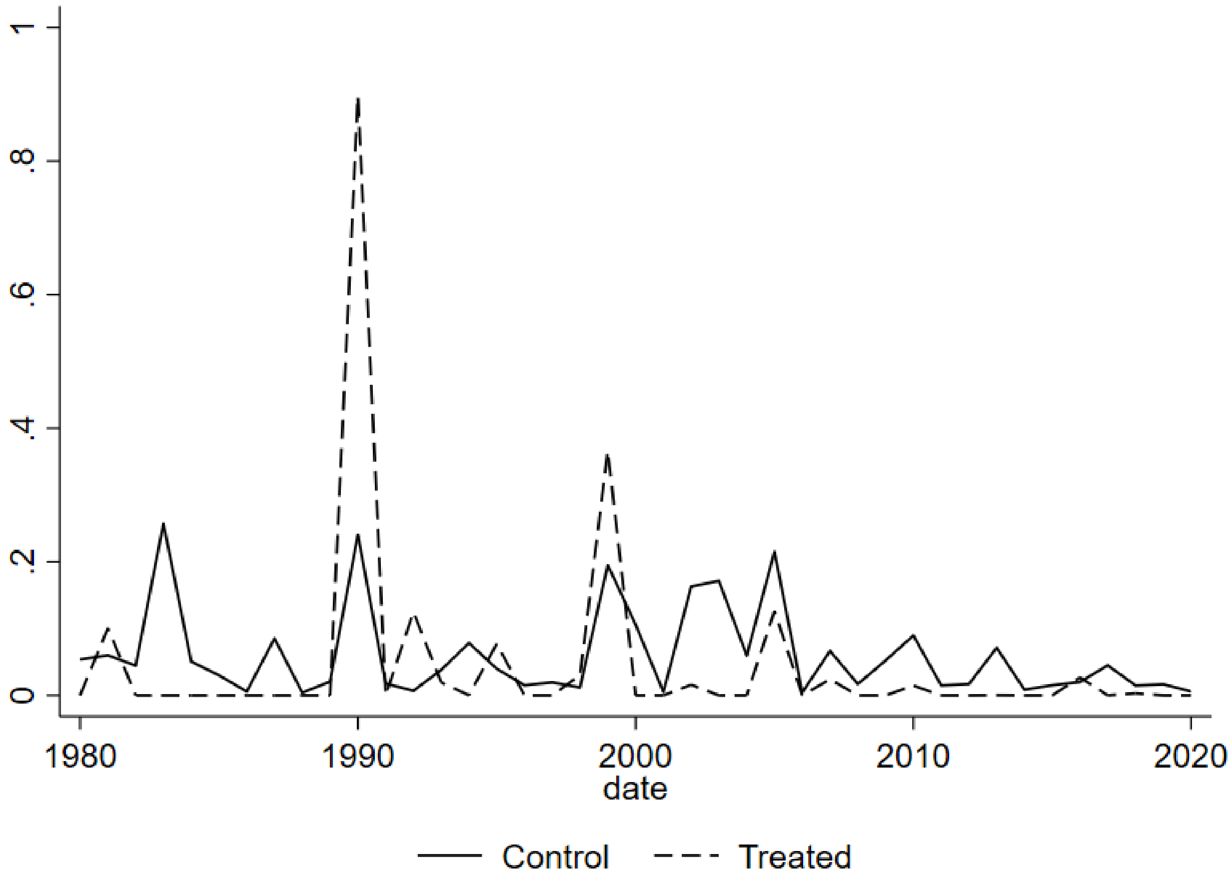
Table A4: Periods where frequency of disasters is more than 3σ above country mean

Country	Date	No. Disaster	Mean No. Disaster	σ No. Disaster
Sweden	1990	2	.255814	.5386502
Norway	1990	2	.3023256	.5133867
Austria	1990	5	1.116279	1.13828
Belgium	1990	6	1.255814	1.39886
Ireland	1990	3	.5348837	.6305265
Netherlands	1990	6	.8604651	1.125069
Denmark	1990	3	.372093	.6554989
Finland	1990	2	.0697674	.337734
Luxembourg	1990	6	.3023256	.9644856
Sweden	2005	2	.255814	.5386502
Spain	2019	8	2.069767	1.486372

C. Summary statistics and ancillary evidence

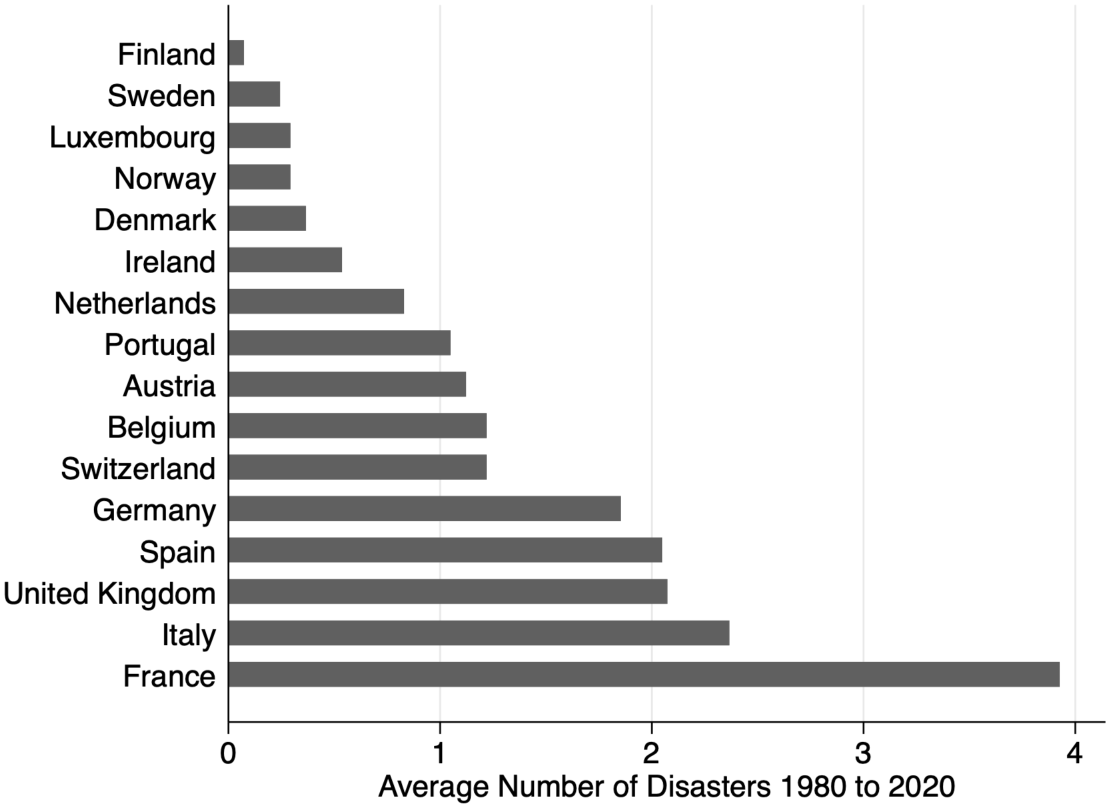
	Obs	Mean	σ	Min	Max
Annual frequency mitigation laws | Climate Laws Dataset	656	0.143	0.414	0.000	3.000
Annual climate damages to GDP % | EM-DAT	656	0.056	0.207	0.000	2.895
Annual frequency of climate related disasters | EM-DAT	656	1.220	1.629	0.000	10.000
Coal gas and oil rents % GDP | World Bank	654	0.613	1.800	0.000	12.248
Number of people (1000s) | World Bank	656	23933.321	25870.970	364.150	83160.871
Left-right index of chief minister (1=right, 2=centre, 3=left)	568	1.879	0.932	0.000	3.000
Democracy index (0–1) | Uni Gothenberg Var of Demo	656	0.877	0.024	0.797	0.924
GDP per capita constant 2015 USD (1000s) | World Bank	656	41.287	19.803	10.744	112.418
Annual GHG in CO2 equiv (million tonnes) | Our World in Data	656	244.979	283.422	8.651	1299.919
Share of people who believe GW is a serious concern | EM-DAT	71	0.591	0.151	0.296	0.866

Figure A2: Damages to GDP from Extreme Weather Events: Treatment and Control Group (% of GDP)



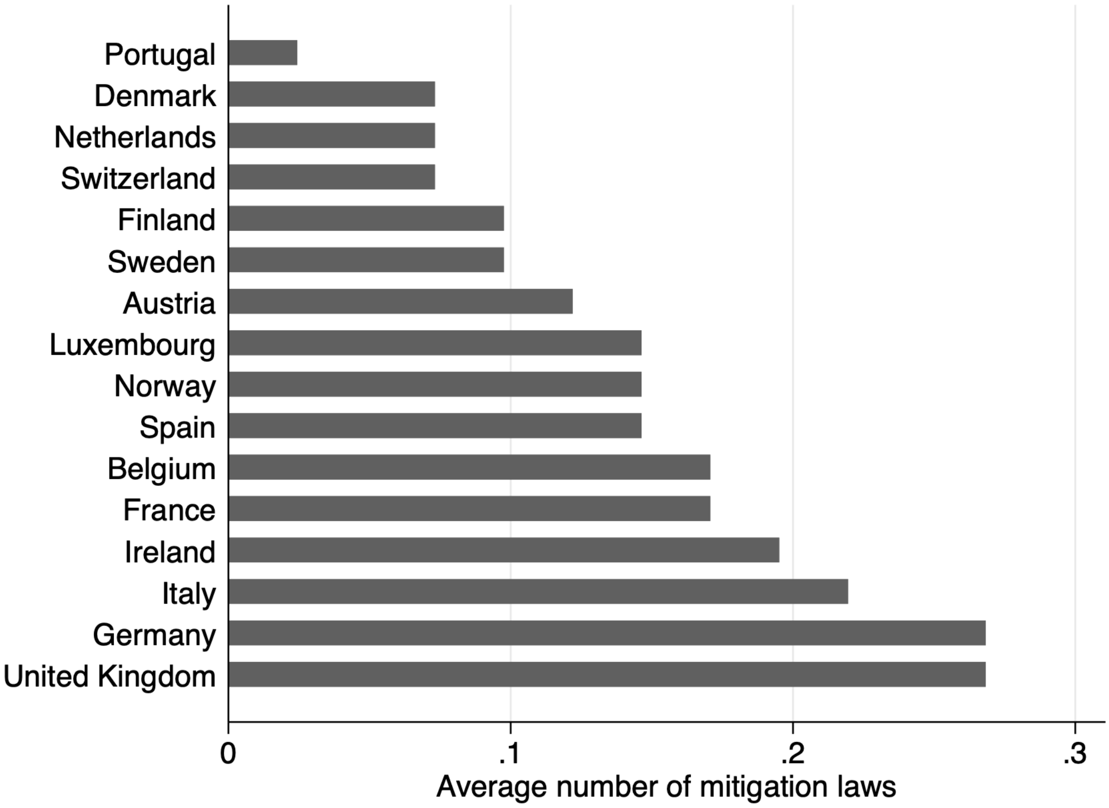
Note: 1990 is identified as the only year where the number of climate disasters exceeds 4σ above the country mean. Treated group = Finland, Netherlands, Luxembourg and Denmark. Control group = Austria, Belgium, France, Germany, Ireland, Italy, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom.

Figure A3: Average number of climate related disasters 1980-2020



Note: Data from EMDAT database. Climate related disasters are defined as drought, extreme temperature, flood, landslide, storm and wildfire.

Figure A4: Average number of mitigation laws per year 1980-2020



Note: Data from Climate Laws of the World. Mitigation laws are all laws that only refer to mitigation.

D. Robustness and placebo exercises

This section outlines the results for the robustness tests. We do not include control variables in the robustness test as they are insignificant.

The first robustness test in column 1 uses as the dependent variable the annual number of mitigation laws rather than the cumulative number of mitigation laws passed. The coefficient of the interaction term is still significant at the 5% level. After the 1990 shock, the treated countries have 0.068 less laws on average each year than the control group.

The second robustness test in column 2 changes the time frame to include a longer period going from 1980 to 2010, rather than our initial shorter period from 1980 to 2000[10]. As can be seen the coefficient on the interaction term remains significant at the 5% significant level.

The third robustness test changes the identification strategy. It identifies the extreme weather shock as years where there are more than 5σ above the country mean. Table A3 lists these shocks by country and year. Using the 5σ cutoff decreases the number of countries that experience a shock to just Finland and Luxembourg. Figure A5 below presents the plots of the treated and control group.

Table A5: Robustness: The impact of 1990 disaster shock on mitigation laws

	(1)	(2)	(3)	(4)	(5)	(6)
main						
Interaction	-0.068**	-0.893**	-0.338***	0.205		
	(0.032)	(0.011)	(0.003)	(0.228)		
No climate disaster lag 1					-0.006	-0.018
					(0.949)	(0.856)
No climate disaster lag 2					0.065	0.073
					(0.508)	(0.464)
No climate disaster lag 3					0.098	0.093
					(0.317)	(0.352)
No climate disaster lag 4					0.128	0.144
					(0.186)	(0.156)
No climate disaster lag 5					-0.238**	-0.266**
					(0.022)	(0.028)
N	336	496	336	315	576	576

P-value in parentheses | * 0.10 **0.05 ***0.01 | Country + Year fixed effects included

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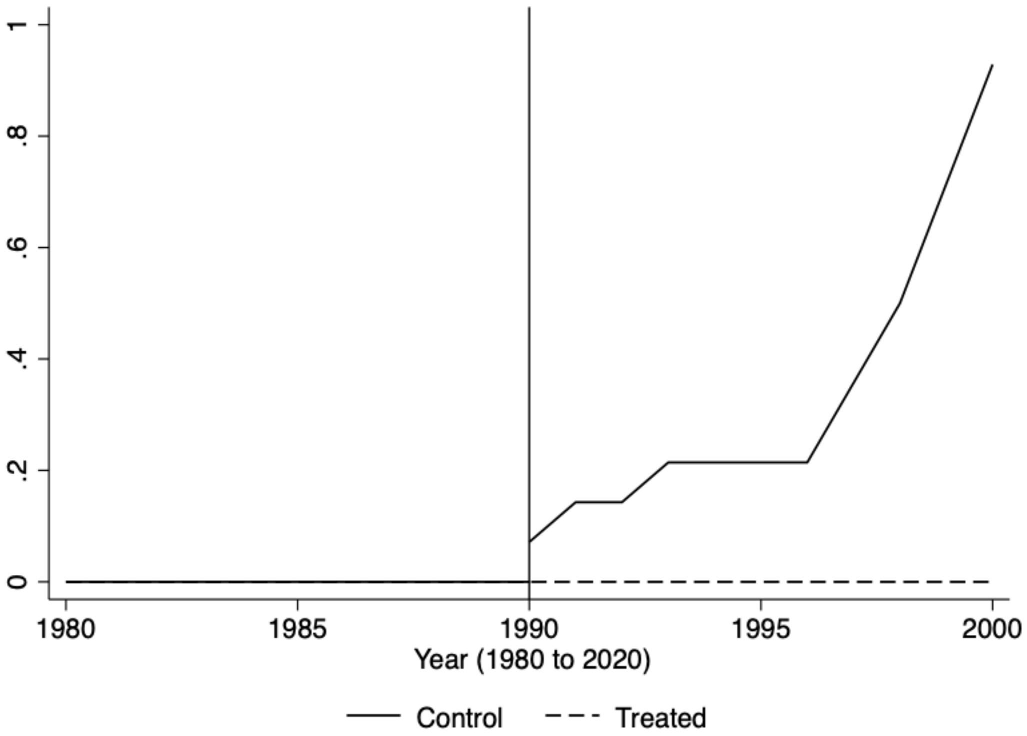
[10] The significance of the interaction term when extending the horizon beyond 2010 may not necessarily imply that the impact of the 1990 shock continues to grow or re-emerge over time. Rather, it could reflect the persistence of the initial post-shock divergence between treated and control countries, which remains visible in cumulative terms even after two decades. Alternatively, the result might simply stem from the increased statistical power associated with a longer panel.

Figure A5: Robustness: Impact of climate disaster shock on cumulative no. mitigation laws with 5σ cutoff



Note: Shock is identified as years where the number of climate damages 5σ above the country mean. Full list of shocks is in table A3 in the Appendix.

Columns 3 of table A5 presents the results. As can be seen, the coefficient is -0.338, almost the same as when the 4σ cutoff is used, and is significant at the 1% significant level.

The fourth robustness test changes the identification strategy so that the cutoff is 3σ above the mean. Table A4 lists these shocks by country and year.

Sweden is dropped from the sample as it experiences two shocks over the time period. All the other shocks also occur in 1990, however when defined in this way, the coefficient becomes insignificant. We interpret this results as suggesting that the shocks need to be sufficiently strong enough in order to have the impact on mitigation laws.

The fifth and sixth robustness test estimate a two-way fixed effects regression equation, given its use in the empirical literature (Rowan, 2022). Given that we are now estimating the impact of multiple shocks over many years, we change the dependent variable to the frequency (rather than the cumulative frequency) of laws. This is different to the diff in diff, where there is one shock and we want to understand its total cumulative effect. Given that the dependent variable is a count variable with many potential zeros, we two types of fixed effects regression, a Poisson fixed effects regression (column 4) and a zero-inflated negative binomial regression (column 5). We include 5 lags given the potential in the baseline for the shock to have an impact on laws into the future. Column 4 and 5 presents the results for laws and policies respectively. The fifth lag is significant and negative at 5% level for both estimations. All other lags are insignificant. Increasing the number of climate disasters a country experiences by 1, leads to a decline in the number of climate laws passed by -0.238/-0.266 after 5 years. The number of observations increases for this specification as we estimate this now over the whole period from 1980 to 2017, as we include all disasters and not just extreme shocks. While these effects are more muted, there is still some evidence that any shock can lead to a decline in the number of mitigation laws. This is to be expected given that not all these disasters will act as focusing events, particularly compared to the 1990 shock, and therefore the results are expected to be less significant. The fifth column estimates the fixed effects model and sixth column a zero inflated poission model, but the results are the same.

The seventh set of robustness checks presented in Table A6 estimates a placebo test by varying the start year of the treatment from 1990. Specifically, column 2 examines the effect of a placebo shock beginning in 1992 on the cumulative number of mitigation laws, column 3 considers the impact if the shock commenced in 1993, and so forth. The primary objective of this placebo test is to assess whether the observed impact of the 1990 shock genuinely drives the results. If the placebo tests (columns 2 to 7) yield statistically significant coefficients, it would imply that the 1990 shock may not be responsible for the observed differences between the treated and control groups. The dependent variable used in these tests is the cumulative number of laws and policies.

The coefficients become statistically insignificant after 1993, with the pattern of insignificance persisting through 1996. While the results suggest that 1990 is not the sole year exhibiting significance, they also indicate that the further the hypothetical shock deviates from 1990, the less significant the coefficients become. This finding underscores that the 1990 shock likely captures a genuine effect. To summarise, we find that unexpected climate disasters significantly reduce the number of climate mitigation laws implemented. This result is robust across several identification strategies and controls.

Table A6: Placebo test: impact of shock on cumulative laws and policy with different shock start dates (1990 to 1996)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Start treatment year	1990	1991	1992	1993	1994	1995	1996
Interaction	-0.606*	-0.619*	-0.611*	-0.615	-0.595	-0.586	-0.590
	(0.089)	(0.089)	(0.099)	(0.116)	(0.152)	(0.203)	(0.269)
N	336	336	336	336	336	336	336

P-value in parentheses | * 0.10 **0.05 ***0.01 | Country and Year fixed effects are included

The last set of robustness tests checks whether the results are being driven by a single country, particularly as the number of treated countries is four. To check this, we estimate the baseline regression, removing one country at a time in Table A7. The results remain significant in all specifications.

Table A7: Robustness: Leave-one-out test excluding one treated country at a time

	(1) Excl. NLD	(2) Excl. FIN	(3) Excl. DNK	(4) Excl. LUX
ATET				
interaction	-0.364***	-0.252*	-0.252*	-0.252*
	(0.002)	(0.069)	(0.069)	(0.069)
N	336	336	336	336

P-value in parentheses | * 0.10 **0.05 ***0.01 | Country and Year fixed effects are included

E. Data: Eurobarometer

To construct a variable on attitudes to climate change, used in Figure 1, we use survey data from Eurobarometer. There are some inconsistencies across waves regarding the exact question asked, the range of answers, and the countries surveyed. Before 1990, the question asked is: how concerned or worried are you about the possible atmosphere damages affecting the world's weather brought about by the gas (carbon dioxide) emitted from burning coal and oil products? The answers range from "a great deal" to "not at all". After 1990, the question changes to: can you tell me if the greenhouse effect (global warming) is a very serious problem, quite serious or not very serious? We combine these questions to understand how the share of people who regard global warming as either a very serious problem or who worry about it a great deal changed just before and after the 1990 shock. We therefore take the first answer to each question.

Regarding country coverage, we focus on the subset of countries present in all waves: BE, DE, DK, ES, FR, GB, GR, IE, IT, LU, NL, PT. This means we drop Finland from the treatment group and Austria, Norway and Switzerland from the control group.

F. Proofs

Theorem 1

Assuming interior solutions ($m_0, r_0 > 0$), the first-order conditions are:

$$u'(C_0) = \beta \left(\xi \cdot \frac{\partial E_0^{DE}[u(C_1)]}{\partial K_1} - \alpha \cdot \frac{\partial E_0^{DE}[u(C_1)]}{\partial \hat{R}_1} \right), \tag{15}$$

$$u'(C_0) = \beta \cdot \frac{\partial E_0^{DE}[u(C_1)]}{\partial K_1}, \tag{16}$$

where

$$\frac{\partial E_0^{DE}[u(C_1)]}{\partial K_1} = \hat{p}_1 u'(AK_1 - \delta K_1)(A - \delta) + (1 - \hat{p}_1) u'(AK_1) A, \tag{17}$$

$$\frac{\partial E_0^{DE}[u(C_1)]}{\partial \hat{R}_1} = p'(\hat{R}_1)[u(AK_1 - \delta K_1) - u(AK_1)]. \tag{18}$$

Total differentiation of the system (15) and (16) yields:

$$\begin{bmatrix} V_{mm} & V_{mr} \\ V_{mr} & V_{rr} \end{bmatrix} \begin{bmatrix} dm_0/dD_0 \\ dr_0/dD_0 \end{bmatrix} = \begin{bmatrix} \sigma u'(C_0)/C_0 \cdot \delta K_0 + \beta \alpha p'(\hat{R}_1)|\Delta u|\theta\psi \\ \sigma u'(C_0)/C_0 \cdot \delta K_0 \end{bmatrix}, \tag{19}$$

where we use $u''(C_0) = -\sigma u'(C_0)/C_0$ for CRRA utility. Solving by Cramer's rule gives the expression. The Hessian is negative definite at an interior maximum, ensuring $\Delta > 0$. ☐

Proposition 1

With quadratic utility and linear probability, the objective function becomes quadratic in m_0, r_0. Solving the linear FOCs yields the expression. The derivative follows directly. ☐

Lemma 1

At the steady state, the FOCs and envelope conditions simplify to these equations. Solving recursively yields the expressions. ☐

Proposition 2

Linearize the system: $\mathbf{A}\mathbf{x}_{t+1} = \mathbf{B}\mathbf{x}_t + \mathbf{C}D_t$, where $\mathbf{x}_t$ is the vector of deviations from steady state. The solution takes the form $\mathbf{x}_t = \mathbf{P}^t\mathbf{Q}$. The signal effect enters through $\theta\psi$ in $\mathbf{Q}$, propagating via ρ^s due to risk persistence. The output effect enters through $-\delta K_0$ in $\mathbf{Q}$, propagating via capital dynamics. $\square$