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Extreme weather events and firms' eco-innovation: the role of psychological distance

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ABSTRACT

How does exposure to extreme weather events influence firms' eco-innovation? Drawing on Construal Level Theory, we argue that extreme weather events collapse psychological distance, transforming abstract climate change into concrete operational reality through two pathways (direct managerial cognition and indirect shifts in regional environmental concern). Using causal mediation analysis with 8,366 Spanish firms (2008–2016), we decompose the association of extreme weather episodes with eco-innovation into direct and indirect pathways, finding that the direct pathway predominates over the indirect. This relationship is strongest among small, lower-rigidity firms. Their reaction to heat waves and dry spells is nearly twice the aggregate estimate, whereas medium and large firms show null responses. Sectoral heterogeneity reinforces this pattern; services respond through the indirect pathway, while agriculture and manufacturing respond through direct operational necessity. These findings indicate that low organisational rigidity, not mere physical exposure, shapes whether extreme weather events are associated with eco-innovation.

KEYWORDS

Eco-innovation; extreme weather events; construal level theory; SMEs; organisational rigidity

JEL CLASSIFICATION

O31; Q54; Q55

1. Introduction

Extreme weather events are intensifying worldwide and have become one of the primary channels through which climate change disrupts firm operations (De Marchi 2026; Hoegh-Guldberg et al. 2019). Droughts, floods, wildfires, heat and cold waves damage infrastructure, disrupt supply chains, and challenge established business models (Gasbarro, Iraldo, and Daddi 2017; Lamperti et al. 2020; Li and Flammer 2025; Pankratz and Schiller 2024). Yet while traditionally viewed as threats, such disruptions can also stimulate eco-innovation, the introduction of new products, processes, and organisational methods that reduce environmental impact (Carrillo-Hermosilla, Del González, and Könnölä 2009; Rennings 2000), as firms seek solutions to maintain operations under climate stress (Benischke et al. 2025; Horbach and Rammer 2025; Ponce Oliva et al. 2022).

However, empirical evidence on the relationship between extreme weather events and eco-innovation is divided. One strand of literature argues that climate disasters reduce innovation by destroying capital and increasing financial constraints (Agostino and Rondinella 2025; Le et al. 2024; Wen et al. 2023). Conversely, other studies find that climate shocks stimulate eco-innovation by heightening risk awareness (Horbach and Rammer 2025; Miao and Popp 2014). These mixed findings suggest that physical exposure alone does not explain organisational responses; rather, we must understand how exposure to extreme weather events shapes perceptions of climate change (McDonald, Chai, and Newell 2015). Moreover, the reliance on patent-based measures (Miao and Popp 2014; Wen et al. 2023) fails to capture eco-innovation among the majority of firms that innovate without patenting.

Drawing on Construal Level Theory (CLT) (Liberman and Trope 2008; Trope and Liberman 2010), we argue that extreme weather events stimulate eco-innovation by collapsing psychological distance to climate risk through two pathways. Through the direct pathway, managers who experience extreme weather firsthand shift from abstract to concrete construals, reframing climate change from a desirability question

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to a feasibility challenge that demands technological solutions (Benischke et al. 2025; Bleda and Pinkse 2025; Wiesenfeld et al. 2017). Through the indirect pathway, regional exposure collapses distance for the broader population, reshaping consumer preferences and intensifying institutional pressures that push firms towards environmentally oriented innovation (Demski et al. 2017; Hoffmann et al. 2022; Konisky, Hughes, and Kaylor 2016). In addition, the intensity of both pathways depends on two boundary conditions. First, organisational rigidity, namely the inertial pressures that intensify with firm size and constrain structural adaptation to environmental change (Hannan and Freeman 1984). Building on this logic, we argue that lower rigidity allows smaller firms to convert local climate signals into organisational action more readily. Second, sectoral heterogeneity; agriculture, manufacturing, and services differ in their exposure profiles and stakeholder structures, which should channel the climate-to-innovation link through distinct pathways.

Combining satellite-based climate data with a survey-based eco-innovation measure for 8,366 Spanish firms, this study makes three contributions. First, rather than treating the net effect of exposure as the end point, we apply CLT to decompose the total effect of extreme weather events on firms' eco-innovation into two distinct causal pathways integrated under a single cognitive mechanism, the collapse of psychological distance (Berrone et al. 2013; Daddi et al. 2020; Miao and Popp 2014). Second, we introduce organisational rigidity as a boundary condition of CLT, resolving a paradox in the eco-innovation literature. Although larger firms are typically expected to eco-innovate more strongly under climate risk given their superior financial slack (Horbach and Rammer 2025), we argue that small firms' lower organisational rigidity, flatter structures, and shorter decision chains may make them more responsive to local climate signals (Leonard-Barton 1992; Vossen 1998) and explain why SMEs can respond more strongly than incumbents (Alam et al. 2022; Lin et al. 2019). Finally, we apply causal mediation analysis to disentangle each pathway (Imai, Keele, and Yamamoto 2010). This design overcomes three limitations of prior work, including self-reported affectedness that conflates exposure with perception (Horbach and Rammer 2025), narrow patent-based outcomes that miss non-patenting eco-innovation (Agostino and Rondinella 2025; Le et al. 2024; Wen et al. 2023), and single-channel specifications that cannot distinguish managerial from societal effects (Miao and Popp 2014).

Section 2 reviews the literature and develops our hypotheses. Section 3 describes the empirical strategy. Section 4 presents the results, and Section 5 discusses the results and concludes.

2. Literature review, theoretical framework and hypotheses

2.1. Extreme weather events and eco-innovation: a literature review

Extreme weather events are among the most tangible manifestations of climate change and have become a growing concern for innovation and management scholars (Benischke et al. 2025; Li and Flammer 2025; Perotti, Tsoligkas, and Wang 2026). Yet the conflicting evidence on whether such events inhibit or stimulate eco-innovation reflects an unresolved question about the pathways through which exposure operates and the firms for which it matters (Tisch and Galbreath 2018).

Studies using objective measures of physical damage document negative effects grounded in the logic of resource constraints. At country level, Wen et al. (2023) find that extreme weather events reduce green patent applications, suggesting a crowding-out effect where companies redirect resources from research towards immediate recovery. Lamperti et al. (2020) corroborate this through agent-based modelling, showing that climate damages constrain productive investment. Enterpriselevel studies using objective exposure data confirm this pattern. Le et al. (2024) show that natural disasters reduce U.S. companies' patent quantity and quality, while Agostino and Rondinella (2025) find that exposure to extreme climate events reduces green innovation propensity in Italy, and Chen et al. (2021) document similar effects across a panel of 49 countries. Underlying these patterns is a 'threat rigidity' response, where material adversity forces resource conservation rather than the exploratory behaviour required for innovation (Staw, Sandelands, and Dutton 1981).

Conversely, studies focusing on risk perception and institutional pressure document positive effects. Miao and Popp (2014) find that countries experiencing more severe natural disasters produce more risk-mitigating patents, though without identifying the cognitive mechanism behind this response. Notably, studies measuring perceived rather than objective impact often find stronger innovation responses. Horbach and Rammer (2025) find a robust positive association between self-reported climate affectedness and eco-innovation among German companies, though treating this link as a direct association without decomposing its pathways. Furthermore, these events appear to intensify stakeholder pressures that stimulate innovation among organisations seeking legitimacy (Berrone et al. 2013; Daddi et al. 2020). Critically, these market and regulatory forces stem from the same perceptual shift. When extreme weather events sharpen consumers' and policymakers' perception of climate risk (Hoffmann et al. 2022), they amplify the demand pull and regulatory pull long emphasised in the eco-innovation literature (Horbach, Rammer, and Rennings 2012; Rennings 2000), raising market demand for greener products (Mainieri et al. 1997) and tightening the environmental regulation that pulls firms towards eco-innovation (Porter and Linde 1995). These findings suggest that when the signal is interpreted as a warning rather than a financial blow, it triggers proactive eco-innovation.

These conflicting findings can be reconciled by distinguishing between organisational *sensitivity* and *exposure* (Linnenluecke, Griffiths, and Winn 2012). Sensitivity refers to material disruption; high sensitivity implies asset damage and resource diversion that interrupts the adaptation cycle (Gasbarro, Iraldo, and Daddi 2017). Exposure, by contrast, refers to the experience of the event without necessarily suffering material losses. This distinction explains why Dessaint and Matray (2017) find that managers of companies located near, but not within, disaster zones exhibit heightened risk perception despite unchanged objective probability. Similarly, Di Giuli et al. (2025) demonstrate that exposure to abnormally hot temperatures persistently shifts fund managers' voting and divestment decisions. These findings align with Weber (2006), who argues that experience-based risk perception generates stronger affective reactions than description-based information, explaining why direct exposure triggers behavioural change where statistical evidence does not. At the firm level, Gasbarro and Pinkse (2016) confirm that it is not objective exposure but managers' interpretation of climate events that determines the type and intensity of organisational response.

Finally, what divides this literature is not whether extreme weather matters but how it matters. The effect runs through interpretation rather than physical damage, yet no study formalises that cognitive process, decomposes its pathways, or explains why firms facing the same signal respond differently. Construal Level Theory provides the missing mechanism.

2.2. Construal level theory and psychological distance

Construal Level Theory (CLT) provides the theoretical framework to explain why objective exposure alone fails to predict organisational responses to extreme weather events. CLT posits that human cognition fundamentally depends on *psychological distance*, the subjective sense of remoteness from direct experience (Liberman and Trope 2008; Trope and Liberman 2010). Distant events trigger *high-level construals*, abstract and decontextualised mental representations that focus on 'desirability' and overarching goals. Conversely, psychologically proximate events trigger *low-level construals*, concrete and detailed representations that prioritise 'feasibility' and immediate, actionable steps (Wiesenfeld et al. 2017). This distinction matters for eco-innovation. When climate change remains psychologically distant, managers frame it through high-level construals focused on desirability, an abstract concern that can always be postponed (Brügger et al. 2015; Soderberg et al. 2015). This creates a systematic attitude-behaviour gap between acknowledging climate change and acting on it (Whitmarsh 2009).

Psychological distance operates across four interlinked dimensions, namely *temporal* (now vs. future), *spatial* (here vs. there), *social* (self/in-group vs. other/out-group), and *hypothetical* (certain vs. uncertain) (Trope and Liberman 2010). Crucially, these dimensions are not independent but cognitively associated; reducing distance in one dimension tends to automatically collapse the others. For instance, an event perceived as occurring 'now' is automatically processed as more probable and spatially closer. This interdependence implies that risk perceptions are constructed holistically rather than dimension by dimension. When a threat remains distant across all dimensions, it fails to trigger the cognitive engagement necessary for action. However, when an external shock forces a collapse in just one dimension, it can trigger a systemic shift in risk assessment across all dimensions, transforming a theoretical possibility into a concrete reality that demands immediate response (Trope and Liberman 2010). For organisational responses to climate change, *social distance* is particularly consequential. When affected parties are perceived as 'others' rather than 'us', the urgency to act diminishes regardless of spatial proximity (Spence, Poortinga, and Pidgeon 2012).

Climate change has historically suffered from extreme psychological distance across all four dimensions, perceived as a problem for future generations, affecting foreign lands, happening to other people, and remaining fundamentally uncertain (Spence, Poortinga, and Pidgeon 2012). This multidimensional distance fosters a 'spatial optimism bias' where actors acknowledge global threats but systematically downplay local risks, maintaining abstract mental models that encourage inertia over action (Brügger 2020; Keller et al. 2022). Extreme weather events disrupt this cognitive equilibrium at two levels. At the individual level, when managers witness heat episodes disrupting operations or floods threatening facilities firsthand, the phenomenon is cognitively reframed as no longer hypothetical or distant, but occurring *here, now*, and to *us* (Akerlof et al. 2013; Bergquist, Nilsson, and Schultz 2019; Zaval et al. 2014). At the societal level, regional populations experiencing extreme weather similarly undergo this cognitive shift, translating into heightened environmental concern and changing expectations towards local businesses (Demski et al. 2017; Hoffmann et al. 2022). This dual collapse of psychological distance, both managerial and societal, provides the foundation for two complementary pathways to eco-innovation.

Through this theoretical lens, the impact of extreme weather on eco-innovation is not merely a reaction to physical damage, but a result of the collapse of psychological distance operating through two complementary channels, a *direct pathway* through managerial cognition and an *indirect pathway* through societal pressure. The following section develops hypotheses for both pathways.

2.3. Hypothesis development

2.3.1. Direct pathway: managerial cognition

The *direct pathway* operates by collapsing decision-makers' psychological distance to climate change. Traditional management literature assumes organisations manage climate risks through formal assessments and rational calculation (Linnenluecke, Griffiths, and Winn 2013). However, these analytical frameworks often maintain high psychological distance, framing climate change as distant (Spence, Poortinga, and Pidgeon 2012). Consequently, when assessments indicate manageable risks, managers perceive the threat as abstract, resulting in inaction. Direct experience with extreme weather events disrupts this cognitive detachment. A heat episode disrupting operations or a flood threatening facilities instantaneously closes all four dimensions of distance, rendering the abstract threat temporally immediate, spatially proximate, and relevant (Akerlof et al. 2013). Lived experience overrides abstract data, triggering critical *sensemaking* processes whereby the event transforms from a statistic into a salient threat requiring immediate interpretation (Tisch and Galbreath 2018). Unlike gradual environmental shifts that permit procrastination, extreme events force cognition from high-level abstraction to low-level concreteness, compressing development timelines and prioritising immediate solutions (Wiesenfeld et al. 2017).

The translation from cognitive shift to eco-innovation decision operates through a feasibility reframing. Once psychological distance collapses, managers shift from asking *whether* to address climate change (a desirability question that invites inaction) to *how* to maintain operations under the new conditions (a feasibility question that demands immediate technological solutions) (Trope and Liberman 2010). This cognitive shift channels responses towards eco-innovation rather than alternative strategies such as relocation, divestment, or insurance. Concrete cases from the Mediterranean water-scarcity context illustrate this mechanism. The Valencia-based firm Jeanologia developed laser and ozone-based denim finishing that reduces water consumption from 100 litres to just one litre per garment (European Circular Economy Stakeholder Platform 2019). Similarly, olive producers in semiarid Spain adopted precision deficit irrigation to reduce water use per hectare while maintaining yields (Arbizu-Milagro et al. 2023). In both cases, the response was not a mere operational adjustment (rescheduling production shifts) or standard capital expenditure (purchasing conventional equipment), but a novel product, process, or organisational solution with measurable environmental benefit, the defining feature of eco-innovation (Carrillo-Hermosilla, Del González, and Könnölä 2009; Horbach 2008).

Empirical evidence aligns with this mechanism across contexts. At the country level, Miao and Popp (2014) find that countries facing recurrent disasters exhibit accelerated patenting for risk-mitigating technologies. Sector-specific studies document similar patterns. Among German manufacturing and service firms, Horbach and Rammer (2025) document robust positive associations between perceived climate affectedness and eco-innovation. In energy, Gasbarro, Rizzi, and Frey (2016) show that companies facing water scarcity induced by climate change adopt innovative measures that trigger new technological trajectories. In agriculture, Tisch and Galbreath (2018) find that dairy farmers confronting extreme weather develop anticipatory adaptation strategies through sensemaking processes embedded in local social networks. These patterns are consistent with direct experience transforming abstract risk into concrete, action-oriented cognition. Thus, we hypothesise:

Hypothesis (H1). *Extreme weather events increase firms' propensity to eco-innovate.*

2.3.2. Indirect pathway: regional environmental concern

The *indirect pathway* operates through the reduction of psychological distance at the societal level. Unlike the direct pathway, which affects decision-makers personally, this mechanism functions through shifts in public attitudes that reshape the institutional environment (Birkland 1998). When communities experience heat episodes, floods, or droughts, these act as focusing events that dissolve the abstraction of climate change for the broader population. The shared experience diminishes psychological distance across all dimensions, transforming climate change from a distant political debate into a tangible local reality that demands a collective response (Spence et al. 2011).

Empirical research confirms that this societal shift generates a dual pressure on companies. First, individuals with personal experience of extreme weather express significantly higher environmental concern (Hoffmann et al. 2022). Even short-term temperature anomalies increase public concern about climate change (Sisco and Weber 2022). This creates *demand-pull* as consumers shift preferences towards environmentally friendly goods (Horbach, Rammer, and Rennings 2012; Kesidou and Demirel 2012). Second, heightened public concern translates into political demand for stricter environmental regulations (Konisky, Hughes, and Kaylor 2016), which in turn direct technological change towards cleaner technologies (Calel and Dechezleprêtre 2016).

This dual pressure translates into corporate behaviour through institutional channels (Daddi et al. 2020). Regional environmental concern signals both shifting market preferences and impending regulatory tightening, pushing organisations to eco-innovate to capture emerging demand (Dangelico and Pujari 2010) and maintain legitimacy in an evolving socio-political landscape (Berrone et al. 2013). Thus, we hypothesise:

Hypothesis (H2). *Regional environmental concern mediates the relationship between extreme weather events and firms' eco-innovation.*

2.3.3. The moderating role of organisational rigidity

While extreme weather events collapse psychological distance for all decision-makers, the *intensity* of this cognitive shift varies with organisational context. Prior climate change adaptation literature, grounded in the Resource-Based View (RBV), assumes that large corporations are better positioned to eco-innovate due to superior financial slack and sophisticated risk management capabilities (Andries and Stephan 2019). However, this perspective overlooks a countervailing force, namely organisational rigidity. Structural inertia and reproducible routines can buffer organisational adjustment to environmental threats and discontinuous change (Hannan and Freeman 1984) and reinforce established patterns of response (Gilbert 2005). We propose that this slower adjustment weakens the translation of climate exposure into eco-innovation. Although the physical dimensions of a heat episode are objective, the reduction of *social distance* is subjective. In high-rigidity hierarchies, proximity is mediated by reporting layers and global aggregation; under lower rigidity, it remains direct and immediate (Delmas and Toffel 2008; Trope and Liberman 2010). This asymmetry is consistent with the attention-based view of the firm (Ocasio 1997). We propose that lower-rigidity organisations have fewer hierarchical filtering structures capable of attenuating novel environmental signals before they reach decision-makers.

Organisational rigidity reflects the extent to which hierarchical layers, bureaucracy, and entrenched routines slow organisational adjustment (Leonard-Barton 1992; Vossen 1998). Extending these arguments to climate risk, we propose that lower rigidity allows signals generated by operational disruptions to reach decision-makers more directly (Dekker and Hasso 2016). Under CLT, this proximity preserves a concrete construal and increases attention to immediate action (Trope and Liberman 2010). We propose that the same logic applies to the indirect pathway. Under lower rigidity, shifts in regional environmental concern and regulatory pressure reach decision-makers with less hierarchical filtering.

This mechanism qualifies the RBV emphasis on resource availability. Under the attention-based view, resources are mobilised only after a signal captures managerial attention (Ocasio 1997), so attention, not endowment, is the binding constraint on responding to climate exposure. We propose that low organisational rigidity confers an attentional advantage that can offset resource constraints, whereas high rigidity dampens urgency even under identical exposure. This logic aligns with evidence that flexibility and speed drive SME responsiveness, while bureaucracy and coordination costs slow larger firms (Alam et al. 2022; Lin et al. 2019). Thus, we hypothesise:

Hypothesis (H3). *The positive association between extreme weather exposure and eco-innovation is stronger among firms with lower organisational rigidity.*

3. Empirical strategy

3.1. Causal identification strategy

Measuring how extreme weather events influence eco-innovation requires an identification strategy that translates the cognitive mechanisms of CLT into testable causal pathways. Establishing causality in observational settings is inherently challenging due to potential endogeneity and confounding factors (Hünermund and Louw 2025). To address this, Figure 1 illustrates our identification strategy based on Directed Acyclic Graphs (DAGs). The treatment variable (X) represents regional extreme weather events, whose stochastic occurrence provides exogenous variation in firms' *exposure* to climate-related disruptions. Critically, our strategy exploits regional exposure rather than enterprisespecific sensitivity. Since extreme weather events occur independently of firm characteristics, this approach offers a quasi-experimental setting that mitigates standard endogeneity concerns, capturing the cognitive signal of climate risk without the confounding noise of material asset damage (Dessaint and Matray 2017).

The model decomposes the total effect into two distinct causal pathways corresponding to our theoretical framework. The *direct pathway* ($X \rightarrow Y$; Hypothesis 1) identifies the Natural Direct Effect (NDE), representing the collapse of psychological distance at the managerial level. Here, the shock of direct experience transforms the abstract threat of climate change into an immediate operational reality, stimulating eco-innovation independent of societal shifts (Akerlof et al. 2013). Simultaneously, the *indirect pathway* ($X \rightarrow M \rightarrow Y$; Hypothesis 2) identifies the Natural Indirect Effect (NIE) mediated by regional environmental concern (M). In this channel, extreme events function as 'focusing events' that shift public sentiment, generating a dual pressure of demand-pull and regulatory-push (Birkland 1998; Calel and Dechezleprêtre 2016; Kesidou and Demirel 2012). This structure allows us to isolate the mechanism of managerial cognitive reorientation from the broader institutional pressures exerted by the community (Imai, Keele, and Yamamoto 2010).

To identify these effects, we condition on a vector of regional controls (R) while deliberately excluding firm-level characteristics from the causal model. Regional controls are intended to support the sequential

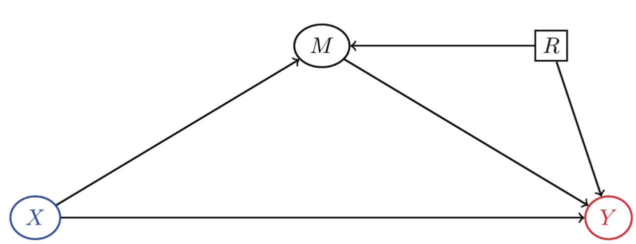

Figure 1. Identification strategy. *Notes.* X=Extreme weather events (treatment); M=Regional environmental concern (mediator); Y= Eco-innovation (outcome); R=Regional covariates. The model decomposes the total effect into two pathways: the Average Direct Effect (ADE; $X \rightarrow Y$), capturing effects not mediated through regional environmental concern and interpreted as consistent with managerial responses to direct climate exposure, and the Average Causal Mediation Effect (ACME; $X \rightarrow M \rightarrow Y$), capturing the demand and regulatory pressures that arise from shifting regional concern. Conditioning on R is intended to make the sequential ignorability assumption more plausible, but cannot guarantee it.

ignorability assumption required for mediation analysis by blocking the confounding path $M \leftarrow R \rightarrow Y$ (Imai, Keele, and Yamamoto 2010). Following Hünermund and Louw (2025), we distinguish between pre-treatment covariates and potential colliders. We include sector fixed effects to account for time-invariant industrial heterogeneity. However, we exclude dynamic firm-level variables (e.g. current R&D intensity, profits) from the causal model, as they may be outcomes of the climate shock itself. Conditioning on these post-treatment variables would introduce collider bias (Vanderweele and Vansteelandt 2009). Identification of the two pathways relies on distinct assumptions. For the direct pathway ($X \rightarrow Y$), the exogeneity of the weather shock makes it unlikely that the treatment-outcome relationship is confounded by firm-level characteristics. For the mediated pathway ($X \rightarrow M \rightarrow Y$), identification of the $M \rightarrow Y$ link requires the additional assumption of no mediator-outcome confounding (sequential ignorability). We address this through the regional controls and fixed effects, which absorb systematic variation in environmental concern, combined with the region-level definition of the mediator itself. Because M is measured at the NUTS-2 level rather than at the firm level, it is less susceptible to firm-specific confounders that might jointly determine both a company's perception of local environmental concern and its eco-innovation decisions. Moreover, environmental regulation in Spain is predominantly centralised at the national and EU level, with limited autonomous-community variation in climate-specific policy during 2008–2016, which reduces the scope for time-varying regional policy confounding.

This approach addresses potential threats to identification arising from endogeneity. In observational studies, estimates are often confounded by unobserved organisational heterogeneity or reverse causality. However, our design mitigates these concerns through the assumed exogeneity of the treatment. First, *reverse causality* is implausible; while companies may influence long-term climate trajectories, they cannot influence the occurrence of specific, localised extreme weather events in the short run ($Y \nrightarrow X$) (Dell, Jones, and Olken 2014). Second, regarding *omitted variable bias*, the stochastic nature of extreme weather provides a quasi-natural experiment. Unlike strategic decisions (e.g. M&A or R&D investments), exposure to a heat episode or flood is assumed uncorrelated with unobserved enterprise characteristics such as managerial quality or culture (Dessaint and Matray 2017). Finally, we address *selection bias* related to location. While organisations may choose locations based on long-term climate patterns (sorting), they cannot predict or select into specific deviations from the mean in a given year. By exploiting these exogenous shocks rather than long-term averages, we estimate the cognitive response to the event separately from the baseline characteristics of the company's location (Pankratz and Schiller 2024).

Finally, to test Hypothesis 3, we stratify the analysis by firm size rather than including interaction terms. As developed in Section 2.3.3, we use firm size as an imperfect proxy for organisational rigidity (Hannan and Freeman 1984, 158–163); see also Lin et al. (2019). Large corporations, insulated by hierarchical layers, may experience attenuated cognitive urgency even when exposed to the same objective events (Delmas and Toffel 2008). Stratified estimation provides a flexible test of this heterogeneity, allowing the coefficients of both the direct and indirect pathways to vary freely across subsamples. This approach detects whether the 'cognitive buffer' of large organisations attenuates the translation of shock into eco-innovation, contrasting with the greater permeability of smaller enterprises.

3.2. Data

To test our model, we constructed a dataset merging enterprise-level microdata with objectively measured climate indicators and regional attitudinal metrics. While regional factors shape eco-innovation trajectories (Hansmeier and Losacker 2024), most company-level studies neglect the spatial dimension (Barbieri et al. 2023). By using external physical and social shocks, rather than self-reported climate affectedness, which suffers from recall bias (Horbach and Rammer 2025), we examine the theorised mechanisms linking climate experiences to eco-innovation.

Our firm-level data come from PITEC, the Spanish contribution to the Community Innovation Survey (CIS), comprising 8,366 firms and 52,455 observations spanning 2008–2016. PITEC employs stratified random sampling by firm size and NACE sector with an 87% response rate (Acebo, Miguel-Dávila, and Nieto 2021; Marzucchi and Montresor 2017). Since 2008, PITEC includes variables related to eco-innovation objectives in each survey series following the Oslo Manual; its reliability for eco-innovation research is well established (Horbach 2008; Kesidou and Demirel 2012).

Extreme climate events are captured through multiple objective data sources (Hoffmann et al. 2022; Pankratz and Schiller 2024; Peisker 2023). Temperature data come from the ERA5 reanalysis product (ECMWF), aggregated to NUTS-2 regional means. For hydrological events, we employ the Standardised Precipitation-Evapotranspiration Index (SPEI). Beyond gradual anomalies, we incorporate sudden disaster events, flood exposure from the Dartmouth Flood Observatory and wildfire exposure from NASA's FIRMS (Peisker 2023). These disaster variables are particularly relevant as 'focusing events' that may reduce psychological distance to climate change (Birkland 1998; Spence et al. 2011).

Environmental concern is measured using Standard Eurobarometer surveys, aggregated to NUTS-2 level (Hoffmann et al. 2022; Konisky, Hughes, and Kaylor 2016; Peisker 2023). While some studies operationalise regional environmental attitudes through voting for green parties (Lelli, Rentocchini, and Montresor 2025), this measure may be influenced by political dynamics and is only observable in election years. In contrast, the Eurobarometer provides a continuous indicator of regional environmental sentiment. This provides a direct operationalisation of the indirect pathway through shifting public attitudes (Akerlof et al. 2013). Finally, we integrate regional socio-economic controls from the European Commission to support sequential ignorability (Imai, Keele, and Yamamoto 2010; Lelli, Rentocchini, and Montresor 2025).

3.3. Variables

Table 1 presents descriptive statistics for all variables across the full sample and by firm size. The correlation matrix is presented in the Online Supplement (Table S1).

Our dependent variable is firm-level eco-innovation. We utilise a PITEC question that asks respondents, on a four-point scale, to what degree the firm has introduced any innovation pursuing an environmental objective. Following prior PITEC research (Acebo, Miguel-Dávila, and Nieto 2021), we code this as a binary indicator equal to one if the firm responds 'medium' or 'strong', and zero otherwise. Since PITEC surveys both innovative and non-innovative firms and the eco-innovation question is asked to all respondents, firms not reporting eco-innovation represent genuine non-adopters rather than missing data. Across the full sample ($N = 8{,}366$ firms), this indicator has a mean of 0.397 (SD = 0.489), rising with firm size. Small firms ($N = 4{,}895$) report eco-innovations in 32.1% of cases, medium firms ($N = 3{,}167$) in 44.6%, and large firms ($N = 1{,}563$) in 54.6%. Because its binary structure captures reported engagement but not the quality or complexity of the underlying eco-innovation (Acebo, Miguel-Dávila, and Nieto 2021; De Marchi 2012; Marzucchi and Montresor 2017), our measure reflects the propensity to eco-innovate rather than its depth, a limitation we revisit in the discussion.

For temperature variables (heat episodes and cold episodes), we use the 10% cut-off variants supplied in the replication data of Hoffmann et al. (2022), calculated against the 1971–2000 local monthly distributions. Heat episodes are periods of at least three consecutive days above the 90th percentile and cold episodes are periods of at least three consecutive days below the 10th percentile, aggregated annually. Spanish regions

Table 1. Descriptive statistics.

	Full Sample				Split Sample (Means)		
Variable	Mean	S.D.	Min	Max	Small	Medium	Large
Eco-innovation	0.397	0.489	0.000	1.000	0.321	0.446	0.546
Environmental Concern$_{,t-3}$	0.018	0.025	0.000	0.188	0.019	0.017	0.017
Heat episodes$_{,t-3}$	7.170	2.707	1.972	15.556	7.021	7.384	7.278
Cold episodes$_{,t-3}$	4.047	1.220	0.583	5.972	4.080	4.025	3.952
Dry Spells$_{t-3}$	1.311	0.373	0.450	2.443	1.296	1.325	1.341
Wet Spells$_{,t-3}$	0.524	0.264	0.025	1.258	0.523	0.519	0.533
Flood Fraction$_{,t-3}$	0.015	0.030	0.000	0.167	0.015	0.014	0.020
Burn Fraction$_{,t-3}$	0.000	0.000	0.000	0.001	0.000	0.000	0.000
GDP per capita $_{,t-3}$	3.316	0.193	2.851	3.586	3.313	3.310	3.336
Pop. share with second edu$_{t-3}$	0.575	0.073	0.397	0.680	0.574	0.571	0.585
Irrigated agricultural area$_{,t-3}$	0.149	0.104	0.004	0.373	0.149	0.155	0.137
Urban region$_{,t-3}$	0.790	0.408	0.000	1.000	0.781	0.789	0.814
Pop. share under 35 years$_{t-3}$	0.309	0.023	0.249	0.355	0.308	0.309	0.312
N firms	8,366				4,895	3,167	1,563

Notes: Firm size is measured at $t-3$. Because firms may move across size categories during the panel, the size-specific firm counts are not mutually exclusive and therefore do not sum to the full-sample total.

average 7.170 heat episodes (SD = 2.707) and 4.047 cold episodes (SD = 1.220) annually. For hydrological extremes (wet spells and dry spells), we use the three-month Standardised Precipitation – Evapotranspiration Index (SPEI3) from the same replication data, aggregated annually. Wet spells average 0.524 (SD = 0.264) while dry spells average 1.311 (SD = 0.373). We also include sudden disaster measures, including flood fraction, defined as the percentage of regional territory affected by floods annually (mean = 0.015, SD = 0.030), and burn fraction, measuring the percentage of territory affected by wildfires. This regional variation provides the identifying variation exploited in our empirical strategy. Heat episodes, for instance, range from approximately 2 to 16 annually across Spanish NUTS-2 regions. The limited variability in climate exposure across firm-size categories implies that these exogenous shocks are distributed fairly evenly among small, medium, and large enterprises.

Environmental concern is measured using the unweighted variable from the replication data of Hoffmann et al. (2022). It captures the regional share of Eurobarometer respondents naming environmental, climate, or energy issues among the two most important problems facing their country. The released monthly regional variable requires no individual-level recoding. We aggregate it to annual NUTS-2 means. This measure has an overall mean of 0.018 (SD = 0.025) and varies only marginally by firm size. Prior research documents an association between extreme weather events and heightened concern (Hoffmann et al. 2022), which may foster pro-environmental behaviours and shift consumer demand towards eco-friendly goods, thereby creating market incentives for firms to eco-innovate (Konisky, Hughes, and Kaylor 2016).

Because PITEC does not measure organisational rigidity directly, we use workforce size as a theorymotivated proxy because smaller firms tend to have fewer hierarchical layers, less bureaucracy, and shorter decision chains (Vossen 1998). We classify firms according to employment headcount relative to the year of the exogenous shock. Following European Commission Recommendation 2003/361/EC (European Commission, 2003), we define firms as small (≤49), medium (50–249), or large (≥250). These boundaries align with the size classes used in prior CIS-based eco-innovation research (Horbach and Rammer 2025; Kesidou and Demirel 2012). In addition, controlling for industry is vital because sectoral differences (such as distinct technological opportunities, regulatory environments, and competitive pressures) can affect a firm's propensity to eco-innovate; omitting these fixed effects would bias our estimates. Accordingly, we include dummy variables based on NACE Rev. 2 to absorb unobserved industry heterogeneity (Alam et al. 2022; Horbach and Rammer 2025).

Finally, to account for regional heterogeneity in eco-innovation and environmental concern, we include the following controls at the NUTS-2 level, following Hoffmann et al. (2022) and Lelli, Rentocchini, and Montresor (2025). Population (in millions) proxies overall market size, capturing potential demand for green technologies. Education is measured as the share of adults with upper-secondary education (mean = 0.575, SD = 0.073), reflecting regional human capital availability. We further control for GDP per capita in log (mean = 3.316, SD = 0.193), proportion of irrigated agricultural land (mean = 0.149, SD = 0.104), an urbanisation dummy (mean = 0.790, SD = 0.408), and share of residents under 35 years (mean = 0.309, SD = 0.023). Variance inflation factors (VIF) for all variables remain well below the conventional threshold of 10 (mean VIF ranges from 2.74 to 3.02 across specifications, maximum = 6.06 for education share), indicating that multicollinearity does not compromise the regression estimates.

3.4. Estimation strategy

Given the causal structure established in Section 3.1, we now describe the statistical implementation. Our outcome variable (eco-innovation) is binary and our mediator (environmental concern) is continuous. As Bammens and Hünermund (2020) note, standard linear mediation methods (e.g. Baron and Kenny) are inappropriate here because nonlinearity violates the assumption that coefficients can be simply multiplied. While structural equation modelling (SEM) can accommodate nonlinear specifications, it does not provide an explicit framework for assessing sensitivity to unmeasured confounding, nor does it define mediation effects as counterfactual quantities with a clear causal interpretation (Imai, Keele, and Yamamoto 2010). To address these limitations, we adopt the potential outcomes framework developed by Imai, Keele, and Yamamoto (2010), which defines the ACME and ADE as counterfactual quantities, makes its identifying assumptions explicit through the sequential ignorability condition, and provides a built-in sensitivity analysis for potential violations. This framework is particularly well-suited to our setting because the decision to eco-innovate is inherently binary while the climate stimuli are continuous and regionally varying, creating a mixed structure in which the marginal effect of environmental concern on eco-innovation probability is nonlinear. Moreover, the framework provides a clean decomposition of the direct cognitive effect of weather exposure on managers from the indirect effect operating through societal environmental concern, which is essential for testing whether the relative importance of these pathways differs by firm size.

The mediator model estimates environmental concern as a function of extreme weather exposure.

$$M_{r,t} = \alpha + b_1 X_{r,t} + \gamma' R_{r,t} + \tau t + \delta_r + \varepsilon_{r,t} \tag{1}$$

where $M_{r,t}$ denotes environmental concern in region r at time t, $X_{r,t}$ represents the extreme weather exposure, and $\mathrm{R}_{r,t}$ is a vector of time-varying regional controls (GDP per capita, population demographics, education, and land use). We include year fixed effects (τ_t) to capture macroeconomic shocks, region fixed effects (δ_r), and $\varepsilon_{r,t}$ is the error term.

The outcome model estimates the probability of firm-level eco-innovation using a probit specification.

$$\Pr\left(Y_{i,t} = 1\right) = \Phi\left(\alpha + \beta_2 X_{r,t-3} + \beta_3 M_{r,t-3} + \gamma' R_{r,t-3} + \tau_t + \delta_r + \lambda_k\right) \tag{2}$$

where $Y_{i,t}$ is a binary indicator for eco-innovation by firm i in period t, and $\Phi(\cdot)$ denotes the standard normal cumulative distribution function. We include year fixed effects (τ_t), region fixed effects (δ_r), and industry fixed effects (λ_k) to control for temporal shocks, regional heterogeneity, and sectoral opportunities. Crucially, we measure treatment (X) and mediator (M) at t −3. Since the PITEC survey records innovations 'during the period t −2 to t', both treatment and mediator measured at t −3 strictly precede the outcome window. As detailed in Section 3.3, we estimate separate models for different extreme weather events to isolate specific triggers.

We note that this specification embeds a two-way fixed effects (TWFE) structure. Region fixed effects (δ_r) absorb all time-invariant regional characteristics, year fixed effects (τ_t) capture common temporal shocks, and identification comes from within-region deviations in extreme weather exposure net of common time trends under a continuous-treatment fixed-effects specification. We adopt causal mediation rather than a standard reduced-form DiD because our theoretical contribution requires decomposing the total effect into the direct managerial pathway (ADE) and the indirect societal pathway through environmental concern (ACME), a decomposition that a reduced-form specification cannot provide.

The nonlinear mediation analysis decomposes the total effect into two distinct components (Pearl 2012). The Average Causal Mediation Effect (ACME), corresponding to Pearl's Natural Indirect Effect (NIE), captures the indirect societal pathway (X → M → Y), while the Average Direct Effect (ADE), corresponding to Pearl's Natural Direct Effect (NDE), isolates the managerial pathway (X → Y) (Imai, Keele, and Yamamoto 2010). Effects are computed for a shift from the minimum to maximum observed values of each treatment variable, capturing the full range of climate exposure variation in the sample.

As Bammens and Hünermund (2020) emphasise, causal identification relies on the assumption of *sequential ignorability*. This requires that (1) the treatment is effectively random conditional on pretreatment covariates, and (2) the mediator is independent of the outcome conditional on the treatment and controls. Our strategy is designed to make these conditions more plausible rather than to guarantee them. The exogeneity of extreme weather supports the first condition, and our regional and sector controls aim to block the major confounding paths. Sequential ignorability cannot be tested directly and may still be violated by unobserved regional or firm-level factors, so we report the sensitivity analysis of Imai, Keele, and Yamamoto (2010) in the Online Supplement and interpret the ACME estimates as conditional on these assumptions. Finally, to test Hypothesis 3, we stratify the estimation by firm size (Small, Medium, Large), allowing the ACME and ADE to vary freely across subsamples to detect systematic heterogeneity in the response.

4. Results

4.1. Causal mediation analysis

Table 2 reports the causal mediation decomposition for the full sample. For testing our hypotheses, we analyse how different types of extreme weather events relate to eco-innovation, distinguishing between the direct pathway (ADE) and the indirect pathway through environmental concern (ACME).

The results show that heat episodes and dry spells are significantly and positively linked to eco-innovation, supporting Hypothesis 1. For heat episodes, the Total Effect is 0.098 and significant, indicating that a shift from minimum to maximum observed exposure (approximately 2 to 16 episodes annually) is associated with an approximately ten-percentage-point higher predicted probability of eco-innovation, a 25% relative difference from the baseline rate of 39.7%. The decomposition indicates that the direct pathway predominates (ADE = 0.067), while the indirect effect through environmental concern is positive but not significant (ACME = 0.031). This result indicates that the managerial cognition pathway predominates over shifts in societal pressure, consistent with evidence that firm-level climate change affectedness is associated with eco-innovation (Horbach and Rammer 2025). In practical terms, the ADE of 0.067 corresponds to approximately two-thirds of the total effect, with predicted eco-innovation probability 6.7 percentage points higher even if regional environmental concern remained unchanged.

Dry spells show a similar pattern, with a significant Total Effect (0.038) concentrated almost exclusively in the direct pathway (ADE = 0.039). The indirect effect is negligible and not significant. This finding aligns with Miao and Popp (2014), who document that natural disasters spur innovation through necessity-driven adaptation (see also Alam et al. 2022; Gasbarro, Rizzi, and Frey 2016). In contrast, cold episodes, wet spells, flood fraction, and burn fraction show no significant effects on eco-innovation. Neither the Total Effects nor the individual pathway components reach statistical significance for these climate variables.

4.2. Heterogeneity by organisational rigidity

The aggregate findings provide support for Hypothesis 1 but leave Hypothesis 2 unconfirmed at the full-sample level. This absence of significant mediation may result from heterogeneous effects across levels of organisational rigidity. As developed in Section 2.3.3, firm size serves as a proxy for organisational rigidity. Table 3 reports the mediation decomposition stratified by firm size, examining whether the climate – eco-innovation relationship varies in the direction predicted by Hypothesis 3.

Small firms are treated as lower-rigidity firms because their flat organisational structures and short decision chains make them highly permeable to local climate signals. Heat and dry-spell estimates are largest for small firms, a pattern consistent with Hypothesis 3. For heat episodes, the Total Effect is 0.177 and highly significant, nearly double the aggregate estimate. Both pathways contribute significantly, with the direct effect (ADE = 0.098) and the indirect effect through environmental concern (ACME = 0.080) both reaching statistical significance. The mediated share accounts for approximately 45% of the total impact, providing support for Hypothesis 2 within this subsample. Given the baseline eco-innovation rate of 32.1%

Table 2. Mediation analysis.

	Heat	Cold	Wet	Dry	Flood	Burn
Effect	Episodes	Episodes	Spells	Spells	Fraction	Fraction
ACME (Indirect)	0.031	−0.001	−0.001	−0.001	−0.000	0.000
	[−0.014, 0.076]	[−0.004, 0.001]	[−0.005, 0.003]	[−0.016, 0.014]	[−0.002, 0.002]	[−0.015, 0.015]
ADE (Direct)	0.067*	0.001	−0.010	0.039**	0.012	0.013
	[−0.001, 0.135]	[−0.045, 0.046]	[−0.044, 0.025]	[0.003, 0.075]	[−0.017, 0.041]	[−0.023, 0.049]
Total Effect	0.098***	−0.001	−0.011	0.038**	0.012	0.013
	[0.033, 0.163]	[−0.046, 0.045]	[−0.045, 0.024]	[0.002, 0.074]	[−0.017, 0.040]	[−0.022, 0.049]

Notes: N. obs. = 52,455. Nonlinear causal mediation analysis with probit outcome model and OLS mediator model. ACME = Average Causal Mediation Effect, corresponding to Pearl's Natural Indirect Effect (societal pathway: $X \rightarrow M \rightarrow Y$); ADE = Average Direct Effect, corresponding to Pearl's Natural Direct Effect (managerial pathway: $X \rightarrow Y$); Total Effect = ACME + ADE. Treatment (X) and mediator (M) measured at $t-3$ so both precede the outcome window. Effects represent the change in eco-innovation probability for a shift from minimum to maximum observed exposure. 95% confidence intervals (in brackets) constructed via nonparametric bootstrap with 1,000 replications. Heat/cold episodes: count of ≥ 3 consecutive days above 90th/below 10th percentile of regional monthly temperature (ERA5). Dry/wet spells: Standardised Precipitation-Evapotranspiration Index (SPEI-3). Flood fraction: share of regional area affected by flooding events (Dartmouth Flood Observatory). Burn fraction: share of regional area burned by wildfires (NASA FIRMS). All models include year, region (NUTS-2), and industry fixed effects, plus regional controls (GDP per capita, education, urbanisation, irrigation, age structure). ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table 3. Mediation analysis by firm size.

Effect	Heat Episodes	Cold Episodes	Wet Spells	Dry Spells	Flood Fraction	Burn Fraction
Panel A: Small Firms						
ACME (Indirect)	0.080**	−0.001	−0.001	0.019	0.000	−0.008
	[0.007, 0.153]	[−0.004, 0.002]	[−0.003, 0.002]	[−0.007, 0.044]	[−0.006, 0.007]	[−0.031, 0.016]
ADE (Direct)	0.098**	0.022	−0.053**	0.054**	0.017	0.036
	[0.007, 0.188]	[−0.034, 0.079]	[−0.096, −0.009]	[0.004, 0.103]	[−0.024, 0.057]	[−0.015, 0.087]
Total Effect	0.177***	0.021	−0.053**	0.072***	0.017	0.028
	[0.087, 0.267]	[−0.035, 0.077]	[−0.097, −0.010]	[0.021, 0.124]	[−0.024, 0.057]	[−0.022, 0.078]
Panel B: Medium Firms						
ACME (Indirect)	−0.028	−0.003	0.000	−0.013	−0.000	0.001
	[−0.103, 0.047]	[−0.010, 0.003]	[−0.004, 0.004]	[−0.041, 0.015]	[−0.003, 0.002]	[−0.022, 0.024]
ADE (Direct)	0.046	−0.034	0.055	0.003	−0.005	−0.012
	[−0.069, 0.162]	[−0.121, 0.052]	[−0.012, 0.122]	[−0.063, 0.069]	[−0.060, 0.050]	[−0.077, 0.053]
Total Effect	0.018	−0.038	0.055	−0.010	−0.005	−0.010
	[−0.091, 0.128]	[−0.122, 0.047]	[−0.012, 0.122]	[−0.074, 0.055]	[−0.060, 0.050]	[−0.075, 0.054]
Panel C: Large Firms						
ACME (Indirect)	0.005	0.000	0.004	−0.014	−0.000	0.004
	[−0.076, 0.087]	[−0.003, 0.003]	[−0.028, 0.035]	[−0.031, 0.003]	[−0.007, 0.006]	[−0.009, 0.017]
ADE (Direct)	−0.028	−0.007	0.007	0.026	0.024	−0.058
	[−0.189, 0.134]	[−0.114, 0.100]	[−0.086, 0.101]	[−0.063, 0.115]	[−0.041, 0.089]	[−0.151, 0.036]
Total Effect	−0.022	−0.007	0.011	0.012	0.023	−0.054
	[−0.179, 0.135]	[−0.114, 0.101]	[−0.072, 0.094]	[−0.077, 0.101]	[−0.041, 0.087]	[−0.146, 0.038]

Notes. Nonlinear causal mediation analysis with probit outcome model and OLS mediator model. ACME = Average Causal Mediation Effect, corresponding to Pearl's Natural Indirect Effect (societal pathway: $X \rightarrow M \rightarrow Y$); ADE = Average Direct Effect, corresponding to Pearl's Natural Direct Effect (managerial pathway: $X \rightarrow Y$); Total Effect = ACME + ADE. Treatment (X) and mediator (M) measured at $t - 3$ so both precede the outcome window. Effects represent the change in eco-innovation probability for a shift from minimum to maximum observed exposure. 95% confidence intervals (in brackets) constructed via nonparametric bootstrap with 1,000 replications. N. obs.: Small firms = 26,953; Medium firms = 16,449; Large firms = 8,483. Small firms: <50 employees; Medium firms: 50–249 employees; Large firms: ≥250 employees. All models include year, region (NUTS-2), and industry fixed effects, plus regional controls (GDP per capita, education, urbanisation, irrigation, age structure). ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

among small firms, the ADE of 0.098 implies that moving from the least to the most heat-exposed region is associated with a 9.8-percentage-point higher predicted eco-innovation probability through the direct pathway. The ACME of 0.080 captures an independent channel; the shift in regional environmental concern associated with heat exposure corresponds to an additional 8-percentage-point difference in predicted eco-innovation probability, underscoring the role of societal climate sensitivity as a transmission channel for low-rigidity enterprises. This pattern is consistent with the greater speed of structural adjustment associated with smaller organisations (Hannan and Freeman 1984). Dry spells also exhibit a significant Total Effect (0.072) operating predominantly through the direct pathway (ADE = 0.054). However, unlike heat episodes, the indirect pathway through environmental concern does not reach statistical significance for dry spells, indicating that support for Hypothesis 2 among small firms is specific to heat episodes. This direct-pathway dominance aligns with Alam et al. (2022), who find that climate change exposure is associated with innovation investment among resource-constrained SMEs, and with Horbach and Rammer (2025), who report that perceived extreme-weather affectedness is positively associated with eco-innovation. An unexpected result emerges for wet spells, where the Total Effect is negative and significant (−0.053), driven entirely by a negative direct effect. This suggests that excessive precipitation is negatively associated with innovation, potentially reflecting a 'threat rigidity' response (Staw, Sandelands, and Dutton 1981), consistent with evidence that natural disasters suppress corporate innovation (Le et al. 2024).

In contrast, medium-sized and large enterprises exhibit higher organisational rigidity and show no significant effects across any climate variable. For medium-sized companies, neither Total Effects nor individual pathway components reach statistical significance. This null pattern may reflect their intermediate position, as medium-sized organisations have begun developing hierarchical layers that attenuate direct cognitive responses, yet lack the formalised environmental management systems of large corporations (Delmas and Toffel 2008). Large enterprises display an identical pattern, with Total Effects, ADEs, and ACMEs statistically indistinguishable from zero across all climate variables. This result differs from resource-based predictions that financial slack and capabilities should facilitate adaptation (Andries and Stephan 2019). This pattern is consistent with hierarchical insulation and geographically dispersed operations buffering these organisations from local climate signals and limiting the collapse of psychological distance associated with eco-innovation responses.

4.3. Sectoral analysis

The preceding analysis indicates that low organisational rigidity amplifies the collapse of psychological distance, with small firms exhibiting the strongest eco-innovation responses. However, the intensity of this cognitive shift may also depend on sectoral characteristics that determine companies' physical exposure and operational vulnerability to climate hazards (Linnenluecke, Griffiths, and Winn 2013). Following the exposure – sensitivity distinction developed in Section 2.1, sectors with high physical dependence on weather conditions (e.g. agriculture) should experience the collapse of psychological distance primarily through the direct managerial pathway, whereas sectors with lower physical exposure but higher consumer visibility (e.g. services) should respond predominantly through the indirect societal pathway. Table 4 presents the mediation analysis disaggregated by sector, namely agriculture, manufacturing, and services.

Agriculture exhibits the most direct exposure to climate variability, with production systems fundamentally dependent on weather conditions. Consistent with this inherent vulnerability, dry spells show a marginally significant Total Effect of 0.236, concentrated entirely in the direct pathway (ADE = 0.243). This effect magnitude, substantially larger than the full-sample estimate, reflects the sector's immediate operational dependence on precipitation patterns. The absence of significant mediation (ACME = −0.007, not significant) suggests that agricultural enterprises respond to water scarcity through direct operational necessity rather than institutional pressures, consistent with Miao and Popp (2014), who find that droughts spur innovation through necessity-driven adaptation, and Alam et al. (2022), who document that climate exposure is associated with innovation among resource-constrained SMEs. The wide confidence intervals reflect the limited sample size, yet the pattern aligns with the CLT framework. For agricultural decision-makers, drought transforms abstract climate risk into immediate crop failure, collapsing psychological distance across all dimensions simultaneously (Wiesenfeld et al. 2017).

Manufacturing exhibits a marginally significant Total Effect for heat episodes (0.077), though the decomposition does not reveal a clearly dominant pathway; neither the direct effect (ADE = 0.035) nor the indirect effect (ACME = 0.042) reaches statistical significance individually, and both are similar in magnitude. This pattern reflects manufacturing's broad vulnerability to thermal stress; equipment malfunction, worker productivity losses, and supply chain disruptions (Dell, Jones, and Olken 2014; Pankratz

Table 4. Mediation analysis by sector.

Effect	Heat Episodes	Cold Episodes	Wet Spells	Dry Spells	Flood Fraction	Burn Fraction
Panel A: Agriculture						
ACME (Indirect)	0.055	0.019	0.028	−0.007	0.021	−0.011
	[−0.086, 0.196]	[−0.027, 0.065]	[−0.056, 0.111]	[−0.160, 0.145]	[−0.038, 0.080]	[−0.077, 0.054]
ADE (Direct)	0.151	0.050	0.112	0.243*	−0.160	0.042
	[−0.245, 0.546]	[−0.243, 0.343]	[−0.125, 0.350]	[−0.024, 0.510]	[−0.421, 0.100]	[−0.231, 0.315]
Total Effect	0.206	0.069	0.140	0.236*	−0.139	0.031
	[−0.184, 0.596]	[−0.208, 0.347]	[−0.091, 0.371]	[−0.026, 0.498]	[−0.387, 0.108]	[−0.218, 0.280]
Panel B: Manufacturing						
ACME (Indirect)	0.042	−0.001	−0.001	−0.000	−0.003	−0.008
	[−0.027, 0.112]	[−0.007, 0.005]	[−0.009, 0.006]	[−0.030, 0.029]	[−0.009, 0.003]	[−0.030, 0.015]
ADE (Direct)	0.035	0.003	−0.058**	0.037	0.036	0.047*
	[−0.058, 0.128]	[−0.063, 0.068]	[−0.106, −0.011]	[−0.013, 0.088]	[−0.008, 0.080]	[−0.001, 0.095]
Total Effect	0.077*	0.001	−0.060**	0.037	0.033	0.040
	[−0.009, 0.164]	[−0.062, 0.065]	[−0.107, −0.012]	[−0.012, 0.086]	[−0.010, 0.076]	[−0.009, 0.088]
Panel C: Services						
ACME (Indirect)	0.063**	0.001	−0.013	0.005	−0.000	0.012
	[0.004, 0.122]	[−0.002, 0.004]	[−0.034, 0.008]	[−0.005, 0.014]	[−0.002, 0.001]	[−0.008, 0.032]
ADE (Direct)	0.012	−0.033	0.039	−0.012	0.012	0.002
	[−0.092, 0.116]	[−0.098, 0.033]	[−0.015, 0.094]	[−0.068, 0.043]	[−0.029, 0.053]	[−0.055, 0.060]
Total Effect	0.075	−0.032	0.027	−0.007	0.012	0.014
	[−0.032, 0.181]	[−0.097, 0.034]	[−0.023, 0.076]	[−0.064, 0.050]	[−0.029, 0.053]	[−0.044, 0.073]

Notes: Nonlinear causal mediation analysis with probit outcome model and OLS mediator model. ACME = Average Causal Mediation Effect, corresponding to Pearl's Natural Indirect Effect (societal pathway: $X \rightarrow M \rightarrow Y$); ADE = Average Direct Effect, corresponding to Pearl's Natural Direct Effect (managerial pathway: $X \rightarrow Y$); Total Effect = ACME + ADE. Treatment (X) and mediator (M) measured at $t-3$ so both precede the outcome window. Effects represent the change in eco-innovation probability for a shift from minimum to maximum observed exposure. 95% confidence intervals (in brackets) constructed via nonparametric bootstrap with 1,000 replications. N. obs.: Agriculture = 872; Manufacturing = 31,429; Services = 18,709. Sectors defined by NACE Rev. 2: Agriculture (01–03), Manufacturing (10–33), Services (45–99). All models include year, region (NUTS-2), and industry fixed effects, plus regional controls (GDP per capita, education, urbanisation, irrigation, age structure). ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

and Schiller 2024) activate both managerial cognition and societal pressure without a single dominant mechanism. An unexpected finding emerges for wet spells, which show a significant negative effect (Total Effect = −0.060), driven by the direct pathway (ADE = −0.058). This result suggests that excessive precipitation is consistent with 'threat rigidity' responses (Staw, Sandelands, and Dutton 1981), whereby rather than stimulating adaptive innovation, flooding disruptions may force manufacturers to redirect resources towards immediate recovery, crowding out R&D investment or new product development (Agostino and Rondinella 2025; Le et al. 2024). Burn fraction shows a marginally significant direct effect (ADE = 0.047), potentially reflecting eco-innovation responses to supply chain vulnerabilities from regional wildfires that disrupt input availability and logistics networks.

Services display a qualitatively distinct pattern that provides additional support for Hypothesis 2. Heat episodes show a significant indirect effect (ACME = 0.063) while the direct effect is negligible and not significant (ADE = 0.012). Although the total effect does not reach statistical significance, the key finding is that the indirect pathway is significant while the direct pathway is not, with the estimated association concentrated in societal environmental concern rather than direct managerial cognition. This contrasts with agriculture and manufacturing, where direct pathways predominate. The theoretical explanation lies in the sector's distinct characteristics. Service organisations face lower physical exposure to climate hazards than agriculture or manufacturing, as their operations are less dependent on weather-sensitive infrastructure or outdoor conditions (Linnenluecke, Griffiths, and Winn 2013). Consequently, our evidence is consistent with the collapse of psychological distance for service-sector managers operating primarily through the societal channel (shifting consumer preferences and intensifying institutional pressures) rather than through direct operational disruption (Cainelli and Mazzanti 2013). This finding suggests that the relative importance of direct versus indirect pathways depends not only on organisational rigidity but also on sectoral vulnerability profiles.

4.4. Robustness analysis

We assess robustness through two approaches (detailed results in Online Supplement). First, we incorporate firm-level precision covariates (prior eco-innovation, firm age, R&D subsidies, cooperation, R&D intensity, firm size, and tertiary-educated employees), all measured at $t-3$ to preserve temporal ordering (Horbach and Rammer 2025). Adding these covariates shifts the decomposition rather than leaving it unchanged. In the baseline full-sample specification the indirect effect is positive but non-significant, whereas in the augmented model the ACME for heat episodes becomes significant (0.035), the direct effect is no longer significant, and the total effect also loses significance. Thus, neither the precise pathway allocation nor the total-effect inference is invariant to the covariate set. The mediated societal pathway remains detectable in the augmented specification, but the robustness results should not be read as reproducing the baseline decomposition. Stratified analyses reaffirm that small firms show substantial responses while medium and large firms exhibit null effects (Online Supplement, Tables S2–S3).

Second, we implement sensitivity analysis following Imai, Keele, and Yamamoto (2010) to assess how robust our estimates are to potential unmeasured confounding. The sensitivity parameter ρ represents residual correlation between mediator and outcome model errors. Results show that departures from the no-confounding assumption ($\rho = 0$) attenuate estimated effects and qualify our main findings (Online Supplement, Figures S1–S2). Third, an event study analysis (Online Supplement, Table S4) supports the absence of differential pre-trends and the dynamic pattern predicted by our theoretical framework.

5. Discussion and conclusions

This study applies Construal Level Theory to explain how extreme weather events influence firms' eco-innovation through the collapse of psychological distance. As developed in Section 2.2, CLT posits that psychologically distant events trigger high-level construals focused on abstract 'desirability', while proximate events trigger low-level construals focused on concrete 'feasibility' (Trope and Liberman 2010; Wiesenfeld et al. 2017). Climate change has historically suffered from extreme psychological distance across temporal, spatial, social, and hypothetical dimensions (Brügger 2020; Keller et al. 2022; Spence, Poortinga, and Pidgeon 2012), creating the attitude-behaviour gap that delays adaptation. We argued that extreme weather events disrupt this cognitive equilibrium by collapsing managerial-level distance and societal-level distance. Our causal mediation analysis provides evidence consistent with this theoretical framework while revealing important boundary conditions. Our results support Hypothesis 1; heat episodes and dry spells are positively and significantly associated with eco-innovation. The estimated direct effect accounts for approximately two-thirds of the heat-episode effect and nearly all of the dry-spell effect. The positive heat and drought results are consistent with broader evidence linking perceived extreme-weather affectedness to firm eco-innovation (Horbach and Rammer 2025) and disaster exposure to risk-mitigating invention (Miao and Popp 2014), but are not, on their own, the distinctive contribution of this study. Our contribution lies in decomposing the total relationship into a direct managerial pathway and an indirect societal pathway, and in showing how the relative weight of these pathways varies across firm size and sector.

First, our mediation analysis reveals only partial support for Hypothesis 2. As theorised in Section 2.3.2, the indirect pathway operates through 'focusing events' that collapse societal-level psychological distance, generating demand-pull from shifting consumer preferences and regulatory-push from heightened public concern (Birkland 1998; Hoffmann et al. 2022; Konisky, Hughes, and Kaylor 2016).

Recent evidence confirms that local temperature anomalies increase climate policy support (Sisco and Weber 2022), and that regional environmental concern is shaped by local climate conditions and socio-economic context (Peisker 2023). However, environmental concern mediates a significant portion of the climate-eco-innovation relationship only in two cases, small enterprises exposed to heat episodes (45% mediation) and the services sector. In services, the indirect pathway is significant while neither the direct pathway nor the total effect reaches significance; societal pressure transmits through the indirect channel but does not produce a reliably detectable overall effect. This partial support clarifies why the indirect pathway appears weak in aggregate samples. The translation of societal pressure into organisational action requires organisational permeability. The dual pressure of demand-pull and regulatory-push (Calel and Dechezleprêtre 2016; Kesidou and Demirel 2012; Losacker et al. 2023) reaches decision-makers only when organisational boundaries are sufficiently permeable to transmit external signals (Daddi et al. 2020; Yoon et al. 2024). For agriculture and manufacturing, direct operational disruption dominates because climate events update risk perceptions and drive adaptive innovation (Horbach and Rammer 2025; Miao and Popp 2014); for services, where physical exposure is lower but consumer visibility higher, institutional legitimacy concerns drive eco-innovation (Berrone et al. 2013; Cainelli and Mazzanti 2013; Suchman 1995).

Second, our analysis of organisational rigidity challenges standard Resource-Based View assumptions. Contrary to the emphasis on how large corporations manage climate risks through strategic repositioning and supply-chain reorganisation (Gasbarro, Iraldo, and Daddi 2017; Pankratz and Schiller 2024), we find that small enterprises show the strongest association between climate exposure and eco-innovation. This size-differentiated pattern is consistent with smaller organisations initiating structural change more readily (Hannan and Freeman 1984). We interpret this greater responsiveness as amplifying the collapse of psychological distance. In small companies, owner-managers experience climate events directly, maintaining low-level construals focused on concrete, proximate concerns (Park, Baer, and Nickerson 2025). Their flat structures may transmit external signals to decision-makers with less hierarchical filtering, so both direct experience and societal pressure can reach those who decide on innovation. This size-differentiated response aligns with recent evidence that SME eco-innovation is shaped by motives and organisational characteristics alongside resource endowments (Andries and Stephan 2019). Large corporations, despite greater resources, exhibit null effects, a pattern consistent with corporate departments and reporting structures mediating external pressures before they reach decision-makers (Delmas and Toffel 2008), maintaining hierarchical insulation even when spatially exposed. Our null results for medium-sized companies reveal an intermediate position. They have developed sufficient hierarchy to attenuate direct cognitive responses, yet lack the formalised environmental management systems of large corporations. This pattern aligns with Lin et al. (2019), who find that the marginal association between green innovation strategy and accounting-based financial performance weakens as firm size increases, and suggests that organisational structure conditions climate responsiveness beyond what resource endowments alone would predict.

Third, our results provide nuanced support for the 'necessity is the mother of invention' hypothesis (Miao and Popp 2014), revealing a critical boundary condition based on event type. Heat episodes and dry spells are significantly associated with eco-innovation via the direct managerial pathway, consistent with Horbach and Rammer (2025) who find that climate change affectedness positively links to eco-innovations. However, wet spells and floods show null or negative effects. Although Agostino and Rondinella (2025) find that climate extreme events hinder green innovation in Italian manufacturing through resource constraints, their mechanism extends to other high-sensitivity events. Climate shocks causing material damage lead firms to divert resources from innovation towards recovery. This bifurcation reconciles the conflicting literature reviewed in Section 2.1. Following Linnenluecke, Griffiths, and Winn (2012) and Dell, Jones, and Olken (2014), we interpret this through the exposure-sensitivity distinction. Heat and drought represent high exposure events that collapse psychological distance without destroying capital stock, shifting cognition towards low-level construals that prioritise feasible technological solutions (Wiesenfeld et al. 2017). Wet spells, however, show significant negative effects among small firms and manufacturing, consistent with the 'threat rigidity' response (Le et al. 2024; Staw, Sandelands, and Dutton 1981). As cumulative stressors, prolonged precipitation diverts resources from R&D towards immediate recovery, crowding out innovation (Lamperti et al. 2020; Wen et al. 2023; Zhao, Zheng, and Fu 2022). Floods, by contrast, show null effects across all subsamples, suggesting that sudden catastrophic events may be too disruptive and too transient to register as a sustained cognitive signal for innovation in either direction. Thus, the collapse of psychological distance is associated with eco-innovation only when the event is construed as an operational challenge demanding technological adaptation, not when it overwhelms organisational capacity (wet spells) or dissipates before reframing managerial cognition (floods).

In conclusion, our study explains why resource-constrained small enterprises might eco-innovate more than resource-rich incumbents (Parrilli, Balavac-Orlic, and Radicic 2025). We provide evidence that eco-innovation is not solely a function of ability (resources) but of cognitive urgency (psychological distance). This dichotomy echoes the distinction between the material advantages of large firms, namely scale and resources, and the behavioural advantages of small firms, namely flexibility and short decision chains (Lin et al. 2019). Small companies and stressors like heat waves or drought maximise this urgency by minimising hierarchical insulation and maintaining low-level construals, whereas large hierarchies create cognitive buffering and cumulative stressors like wet spells trigger threat rigidity. These findings point to organisational rigidity and event type as important boundary conditions for CLT in organisational contexts, advancing our understanding of how organisations adapt to climate change (Benischke et al. 2025).

5.1. Practical implications

Our findings carry implications for managers and policymakers engaged in climate adaptation. For managers, the strong direct estimates for heat episodes and dry spells suggest that climate disruptions should be reconceptualised not merely as threats but as catalysts for innovations that enhance both resilience and environmental performance (Benischke et al. 2025). The varying impacts of different climate extremes indicate that firms should develop climate risk profiles distinguishing between event types associated with adaptive innovation versus sudden disasters that require different response strategies focused on recovery rather than exploration (Linnenluecke, Griffiths, and Winn 2013; Pankratz and Schiller 2024).

For policymakers, our size-contingent patterns suggest differentiated approaches rather than uniform climate adaptation policies. Small enterprises demonstrate the strongest eco-innovation responses, yet face resource constraints that may limit their capacity to sustain innovations over the long run. Policy interventions should therefore combine immediate support with mechanisms for continuity, including simplified access to green technology financing with extended repayment terms, and technical assistance programmes that build internal capabilities rather than create dependency (Alam et al. 2022; Andries and Stephan 2019). Critically, knowledge-sharing networks connecting small, low-rigidity firms facing similar climate challenges can offset size disadvantages by enabling small companies to pool resources, share adaptation knowledge, and achieve collective resilience that individual enterprises cannot attain alone (Kotlar, Muñoz-Bullón, and Sanchez-Bueno 2025; Parrilli, Balavac-Orlic, and Radicic 2025). Medium-sized companies exhibit an 'eco-innovation gap' reflecting their intermediate position, with sufficient hierarchy to attenuate cognitive responses to climate signals, yet insufficient formalisation to respond through institutionalised channels (Delmas and Toffel 2008; Lin et al. 2019). Interventions should help these organisations develop environmental management capabilities without imposing bureaucratic burdens, perhaps through sector-specific guidance and peer-learning programmes. Large corporations require policies that reduce hierarchical insulation and counteract managerial myopia in climate strategy (Li and Flammer 2025), for instance by mandating climate risk disclosure at operational rather than aggregate levels, thereby reconnecting decision-makers with local climate realities.

Beyond firm-level interventions, our findings highlight the importance of systemic approaches. Because the indirect pathway through environmental concern shows only limited mediation, awareness campaigns and voluntary certification schemes alone may yield less robust eco-innovation outcomes than anticipated (Daddi et al. 2020). More effective may be policies addressing operational vulnerabilities through regional resilience planning, integrating climate adaptation into infrastructure development, strengthening supply chain redundancy in climate-sensitive sectors, and fostering cross-industry networks that enable collective responses to shared climate risks (Parrilli, Balavac-Orlic, and Radicic 2025). Our sectoral analysis reinforces this point, as agricultural support should emphasise immediate operational resilience through water-efficient technologies and drought-resistant inputs (Alam et al. 2022; Miao and Popp 2014), while service-sector initiatives might leverage consumer awareness to amplify the indirect pathway through environmental concern (Cainelli and Mazzanti 2013; Yoon et al. 2024). Because the direct pathway dominates in aggregate, institutional approaches remain valuable but function best as complements to direct adaptation incentives (Benischke et al. 2025).

5.2. Limitations and future research

While our study advances understanding of theorised mechanisms linking climate events to eco-innovation, several limitations warrant acknowledgement.

First, our reliance on Spanish data (PITEC) potentially limits generalisability, though Spain's internal climatic diversity (from Atlantic to Mediterranean to semi-arid regions) provides substantial within-country variation while holding institutional and regulatory frameworks constant (Marzucchi and Montresor 2017). In countries with stronger environmental institutions (e.g. Scandinavian countries), the indirect pathway through environmental concern may play a more prominent role, whereas in contexts with higher physical vulnerability but weaker institutional frameworks, the direct managerial pathway may dominate (Hoffmann et al. 2022). Whether organisational rigidity operates similarly in other contexts requires empirical testing. We also do not measure organisational rigidity directly. Firm size is an imperfect proxy that also captures resources, formalisation, and age, and the hierarchical-filtering mechanism we propose is theorised rather than directly tested. Future work using direct measures of organisational structure and managerial attention could disentangle these. The 2008–2016 time frame predates the post-2018 global climate mobilisation (Mede and Schroeder 2024), allowing us to isolate local climate-innovation links free from confounding global green policies, though future cross-national comparative studies using the harmonised CIS should examine whether findings replicate in more recent periods and different institutional settings (Parrilli, Balavac-Orlic, and Radicic 2025).

Second, our sensitivity analysis indicates bounded robustness of the mediated pathway to potential unobserved confounding. However, our use of objective climate data (ERA5, SPEI, satellite imagery) rather than self-reported affectedness supports the identification strategy (Dessaint and Matray 2017; Li and Flammer 2025). Since the Eurobarometer mediator is aggregated at NUTS-2, classical measurement error attenuates ACME estimates, making our significant indirect effects for small firms attenuated estimates. Our design captures eco-innovation associated with experienced climate events but cannot assess proactive adaptation driven by anticipated future risks; longitudinal studies could explore feedback loops between innovation outcomes and institutional dynamics (Benischke et al. 2025).

Third, our reliance on self-reported eco-innovation measures introduces potential measurement limitations. While self-reported measures cannot completely rule out symbolic responses or greenwashing (Berrone et al. 2013), our robustness controls for prior eco-innovation mitigate strategic reporting concerns. Moreover, SMEs may implement informal environmental improvements without formally reporting them as 'eco-innovation,' potentially underestimating their true adaptive responses (Jenkins 2006). A further limitation concerns the heterogeneity that our binary outcome conceals. Following prior PITEC research, we collapse 'medium' and 'strong' environmental-objective responses into a single indicator (Acebo, Miguel-Dávila, and Nieto 2021). This captures the propensity to report eco-innovation, but not its type, intensity, or novelty. Prior research distinguishes the decision to undertake environmental innovation from the amount invested (Kesidou and Demirel 2012), product and process innovations with different environmental impacts (Horbach, Rammer, and Rennings 2012), and incremental, radical, and system-level changes (Carrillo-Hermosilla, Del González, and Könnölä 2009). Our measure cannot distinguish these dimensions. Thus, a positive effect of climate exposure may partly reflect incremental responses rather than radical technological change, and the size- and sector-differentiated patterns could partly reflect differences in the type of eco-innovation undertaken. Future research should examine these dimensions separately.

Fourth, while firm size stratification reveals important heterogeneity, factors like ownership structure, corporate governance, and collaborative networks may also moderate the climate-innovation relationship (Sharafizad, Redmond, and Parker 2022). Our findings may be subject to survival bias, which our design cannot eliminate. Furthermore, our study captures eco-innovation propensity but cannot assess whether small firms sustain these innovations long-term or scale them beyond localised contexts (Kotlar, Muñoz-Bullón, and Sanchez-Bueno 2025). Additionally, our firm size classification relies solely on employment headcount, which may introduce minor imprecision for firms near the classification thresholds. Future research employing objective measures, longitudinal tracking of firm survival, and qualitative case studies could validate whether eco-innovations translate into lasting improvements diffusing through supply chains.

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