NETWORK
LISER

Discussion Paper Series

IZA DP No. 18553

April 2026

Gone with the Wind? Climate Shocks, Insurance Demand and Well-Being

Alpaslan Akay
University of Gothenburg,
Bahçesehir University and IZA@LISER

Olivier B. Bargain
University of Bordeaux, IUF and
IZA@LISER

Béka Lomidze
University of Bordeaux

Peter Martinsson
University of Gothenburg

IZA@LISER NETWORK
ISSN: 2365-9793

IZA DP No. 18553 April 2026

Gone with the Wind? Climate Shocks, Insurance Demand and Well-Being[1]

Abstract

We study the medium-run effects of a major climate shock on insurance demand and subjective well-being. Exploiting quasi-random exposure to storm Gudrun (Sweden, 2005) and conditioning on satellite-based forest and terrain characteristics, we treat realized damages as conditionally exogenous. Three years after the event, affected forest owners exhibit a persistent increase in insurance take-up alongside significant welfare losses. These losses are economically meaningful and consistent with important non-pecuniary and psychological costs, including landscape damage and heightened insecurity. Insurance provides only limited welfare buffering, operating partly as reassurance rather than full compensation. Overall, the results highlight the limits of climate insurance as a stand-alone adaptation tool.

JEL classification

G22, G54, Q54

Keywords

natural disasters, insurance take-up, subjective well-being, Gudrun

Corresponding author

Olivier B. Bargain

olivier.bargain@u-bordeaux.fr

[1] The authors are grateful to participants at the EEA conference and seminars at Göteborg University, Lund University, Bordeaux University, the Italian Economic Association summer school in Prato, for their helpful comments and suggestions. Usual disclaimers apply. This research has received financial support from the French State, through the Investments for the Future Program IdEx Université de Bordeaux / GPR HOPE.

1. Introduction

Extreme weather events are becoming more frequent and severe, exposing households and asset owners to rising climate-related risks.[2] Climate insurance, defined as coverage against losses from extreme weather events, has emerged as a key risk-management tool alongside preventive measures and state-supported interventions. By enabling consumption smoothing and faster recovery after shocks, insurance can reduce welfare losses and mitigate feelings of insecurity in anticipation of potential disasters. Yet the economic and psychological mechanisms underlying insurance demand are not well understood. This gap is particularly salient given that insurance uptake remains persistently low, even among populations facing high risk (Kunreuther 1984; Kraehnert et al., 2021).[3]

Understanding what triggers insurance demand is central to effective climate-risk management and policy design and has motivated a growing behavioral literature (Kunreuther & Pauly, 2005; Corcos et al., 2020; Wagner, 2022a, 2022b). Insurance behavior often changes following disasters, yet the underlying mechanisms remain unclear. Direct exposure may heighten perceived risk of recurrence through the availability heuristic (Tversky & Kahneman, 1973), thereby encouraging insurance purchase (Gallagher, 2014; Atreya et al., 2015; Pitthan & De Witte, 2021). Conversely, demand may decline if individuals exhibit a gambler's fallacy, believing that extreme events become less likely after having occurred (Yin et al., 2016). In parallel, a distinct literature documents substantial declines in subjective well-being (SWB) following natural disasters (e.g., Luechinger & Raschky, 2009), reflecting partial adaptation processes as well as non-pecuniary losses and heightened feelings of insecurity. These adaptations and emotional channels likely matter for climate insurance, yet are typically studied in isolation.

This paper bridges this gap by providing evidence on how exposure to an extreme weather event jointly affects insurance take-up and SWB. We study storm Gudrun (Erwin), one of the most severe windstorms ever recorded in Europe. Striking Sweden in January 2005, Gudrun was the most devastating storm in the country's history, causing unprecedented damage to forests and infrastructure. We exploit the quasi-random spatial variation in exposure to the storm among forest owners to estimate its middle-run impact on insurance behavior and well-being. Our analysis relies on an original survey of forest owners conducted three years after the event, which provides detailed information on pre-storm insurance histories, realized damages, and ex post SWB. The empirical design leverages the largely exogenous path and

[2] Since 2000, natural disasters have generated average annual damages of approximately USD 143 billion, according to the Centre for Research on the Epidemiology of Disasters (CRED, 2024). Both the frequency and severity of extreme weather events are expected to increase as climate change intensifies, further amplifying economic and social losses (Lee et al., 2023).

[3] In high-income countries, insurance covers only about 20% of total disaster-related losses, with substantially lower coverage elsewhere (ECB, 2023).

local wind intensity of the storm, which generated sharp spatial variation in exposure. Because realized damages reflect both storm intensity and local forest characteristics that may influence pre-storm insurance decisions, we match survey data with satellite-based measures of forest characteristics (including tree height, species composition, and micro-geography). Conditional on these observables, variation in storm-related damages can be treated as quasi-random. We support this identifying assumption with balance tests showing that, once forest characteristics are accounted for, damage variation is uncorrelated with forest owners' characteristics, including their pre-disaster insurance propensity.

Our results can be summarized as follows. Using detailed individual insurance histories, we first document forest owners' behavioral responses to past storms over an extended period, showing that Gudrun stands out as the most destructive event and the one that triggered the strongest increase in insurance demand. Focusing on Gudrun, we find persistent effects: three years after the event, affected forest owners exhibit higher insurance take-up, which is systematically associated with lower SWB. Welfare impacts are less pronounced among owners who were insured prior to the storm, underscoring the role of insurance in enhancing resilience. Heterogeneity analyses provide non-causal insights into the mechanisms underlying these effects. Our findings are consistent with non-adaptation, reflecting persistent economic losses or foregone opportunities not fully captured by income measures; with lasting emotional costs related to landscape degradation and lost amenities, particularly when forests are part of a family heritage; and with heightened feelings of insecurity linked to expectations of future destructive events. These mechanisms have partly distinct implications for insurance demand, which we explore through a set of informal tests. Overall, the results suggest that these channels coexist and jointly shape post-disaster insurance behavior and well-being.

This paper makes several contributions. *First*, it provides micro-level evidence on the medium-run effects of climate shocks on insurance behavior. As summarized in **Table A1**, much of the existing literature relies on experiments or perceived-risk measures (lower panels), which capture short-term responses. However, longer horizons are particularly relevant for tail events, given the typically long intervals between events, during which behavioral responses may evolve as availability bias fades (Atreya et al., 2015; Gallagher, 2014), memories weaken (Meyer, 2012), or repeated shocks trigger gambler's-fallacy-type beliefs. Evidence based on natural experiments often documents effects that dissipate over time, but is heavily concentrated in the US, frequently in the context of the National Flood Insurance Program, and often relies on aggregate data (county- or municipal-level observations). By contrast, we provide micro-level, medium-run evidence from a non-US institutional setting following a major climate shock.

Second, we contribute to the literature on natural disasters and SWB. As reviewed in **Table A2**, existing studies largely focus on short-run impacts. For high-income countries, the main exceptions are Luechinger and Raschky (2009), who adopt a longer-run perspective but find that flood-related well-being losses fade within two years, and Sekulova and van den Bergh (2016), who document persistence over six years. Other natural-experiment studies in rich-country settings typically rely on short horizons, rarely exceeding 18 months. In contrast, we provide medium-run evidence from a rich-country context, documenting the persistence of well-being losses and highlighting non-monetary mechanisms, including landscape degradation and heightened feelings of insecurity.

Third, this paper bridges the behavioral insurance and SWB literatures, which remain only loosely connected. Existing work shows that insurance can buffer well-being losses after natural disasters—such as floods in the US and Europe (Luechinger & Raschky, 2009), earthquakes in China (Wang & Wang, 2023), and cyclones in Australia (Nguyen & Mitrou, 2024)—but typically treats well-being outcomes and insurance take-up in isolation (e.g. Nguyen & Mitrou, 2024 versus 2025). Other studies document ex ante psychic gains from insurance through enhanced financial and health security, including the "peace of mind" associated with crop insurance (Tafere et al., 2019) or emotional correlates.[4] We contribute by providing micro-level causal evidence on how extreme weather events jointly shape insurance behavior and psychological welfare.

Fourth, we extend the literature beyond households to asset owners. To our knowledge, no study explicitly examines the SWB of firm or asset owners following a climate shock. Existing work focuses mainly on property-owning households (e.g. Hudson et al., 2019) or on asset-loss channels without linking them to well-being (e.g. Wang & Wang, 2023). Evidence on insurance demand by firms or asset owners is also limited, with contributions that are primarily theoretical (e.g. Gollier, 2017) or empirical studies set in different contexts, such as terrorism risk (Michel-Kerjan et al., 2015) or the adoption of weather-index insurance in low-income settings (Hill et al., 2013). Studying forest owners is particularly relevant given long production cycles and often irreversible or long-lasting damages, which make insurance a central mechanism for climate adaptation.

The paper is structured as follows. Section 2 provides background on storm Gudrun and the institutional setting of the insurance system. Section 3 describes the data, empirical strategy, and balance checks used to address potential confounding factors. Section 4 presents the main

[4] Foudi et al. (2017) show that direct experience with flooding triggers emotional responses, alters risk perception, and increases the likelihood of adopting preventive measures, including insurance. Leiserowitz (2006), who emphasizes the importance of affect and mental imagery in shaping climate-related policy preferences and behavioral responses. Czajkowski et al. (2017) show that perceptions of safety and risk awareness significantly influence insurance take-up. Kunreuther and Pauly (2018) further argue that emotions—such as fear, anxiety, and regret—play a central role in the dynamic decision-making process under rare but catastrophic risk, typically resulting in surges in insurance demand after disasters and lapses in coverage as emotional salience diminishes.

results, robustness analyses, and heterogeneity exercises exploring potential explanatory channels. Section 5 concludes.

2. Background: Past Storms, Gudrun and the Swedish Insurance System

2.1 Past Storms and Gudrun

Sweden has been affected by multiple major storms over the past century, with impacts largely concentrated in the Southern region (*Svealand* and *Götaland*). **Figure 1** illustrates the extent of damage caused by the most significant storms since World War II.[5] The maps reveal that damage intensity varies considerably across southern provinces, depending on the specific storm. For instance, central provinces were most severely affected during Gudrun, in contrast to the pattern observed in 1999. This spatial variability is important for causal identification, as it underscores the unpredictability of storm impacts—not only in timing but also in geographic exposure.

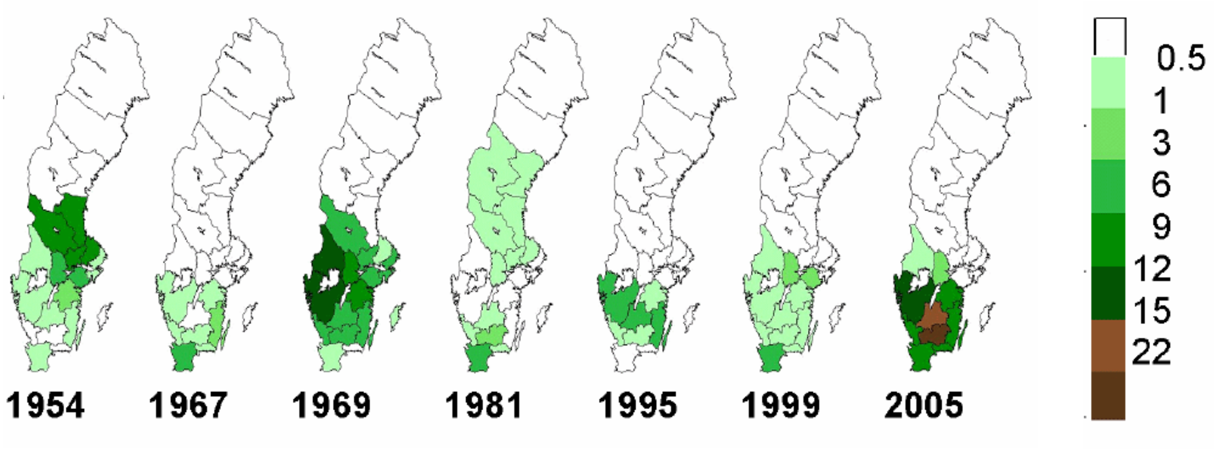
Gudrun is widely recognized as the most severe storm ever to hit Sweden. Its impact was estimated to be three times that of the second-strongest storm, which occurred on Christmas Eve in 1902 (not shown here, as our focus is limited to the past half-century). Gudrun made landfall in Sweden on January 8, 2005, and the event was largely unexpected (Ingemarsson et al., 2006). According to reports, the warning issued by the Swedish Meteorological and Hydrological Institute went largely unnoticed by the public (Klasson, 2005). The consequences were severe: 14 people lost their lives, approximately 250 million trees were windthrown—equivalent to 75 million cubic meters of timber (i.e. entire year of Sweden's national timber harvest—and over 30,000 km of power lines were destroyed, causing power outages that affected 730,000 customers.

Following the storm, only a small portion of the fallen timber could be sold, making the damage particularly acute. The economic loss for forest owners is estimated at €1.9–2.4 billion, a figure that primarily reflects direct revenue losses, as most windthrown timber could not be marketed under normal conditions and was instead sold at depressed salvage prices. This estimate thus provides a close approximation of the short-term loss of profit for forest owners. Compensation from private insurance amounted to approximately €275 million, arising from around 50,000 insurance claims. In addition, the state provided an estimated €145 million in support, comprising €82 million disbursed between 2005 and 2008 through a designated storm-relief fund, and €63 million in targeted subsidies for wood storage and reforestation. In total, only about 17%–22% of the damage was compensated by insurance and state support.

[5] These maps are adapted from Nilsson (2008) and depict the location and intensity of forest damage at the provincial level. The author compiled long-term storm damage series from regional forestry reports, complemented by case analyses based on high-resolution regional climate models for recent events, including Anatol (1999) and Gudrun (2005).

These figures highlight both the economic vulnerability of forest-dependent households and the limited capacity of existing insurance and public support mechanisms to absorb the financial impact of large-scale climate-related disasters.

Figure 1: Major Storms since World War II and Damaged Timber (M. of m m³)



Source: Maps adapted from Nilsson (2008), showing regional hurricane damage measured in millions of cubic meters of lost timber. Note: Northern regions are more mountainous, while timber-producing forests are primarily located in the South (*Svealand* and *Götaland*). The maps illustrate that the intensity of destruction is not systematically concentrated in the same southern regions and varies substantially across storm events.

Beyond immediate economic losses, storm Gudrun generated long-term challenges related to forest regrowth, imposing lasting burdens on affected owners (Nilsson, 2008; Seidl & Blennow, 2012). Large areas of damaged forest required costly clearing and replanting, often borne by owners, while the storm disproportionately affected mature, high-value spruce stands, disrupting age structures and reducing future income potential.[6] Beyond these economic impacts, Gudrun caused extensive damage to culturally and emotionally significant landscapes that cannot be fully restored through replanting alone (see **Figure A1**). While timber values may recover over time, losses in ecosystem services and emotional attachment persist, particularly in a country where forestry plays a central economic, social, and cultural role (Andersson et al., 2018). Qualitative evidence indicates that, consistently, forest owners reported lasting psychological distress following the storm (Grimby et al., 2018). Together, these delayed and non-pecuniary losses highlight the limits of standard insurance coverage and underscore the long-term consequences for well-being of extreme climate events.

[6] While 1.1 million hectares of forest were affected by Gudrun (i.e. about 16% of the 6.8 million hectares of productive forestland in southern Sweden), replanting occurred on a smaller subset of around 200,000 hectares. With a reforestation costs estimated at SEK 8,000–15,000 per ha.

2.2 The Swedish Climate Insurance System and Pre-Event Demand

In Sweden, private forest insurance has historically been provided mainly by companies represented within the Insurance Federation of Sweden, with the mutual insurer group *Länsförsäkringar* accounting for 90% of the national insurance market. Storm coverage was not offered as a standalone product but rather as a supplementary add-on to forest fire insurance, which constituted the default form of protection. Losses from exceptional, large-scale events were instead expected to be partially addressed through government intervention.[7] This institutional configuration contributed to low pre-Gudrun insurance uptake in the forestry sector, estimated at around 40% according to official sources (SOU, 2007).

Several additional factors likely reinforced this limited demand. Both forest owners and insurers systematically underestimated storm risk, as the last comparable major windthrow occurred in 1969 (as documented hereafter). Thus, catastrophe risk modeling was underdeveloped, and storm insurance premia were not fully actuarial—often perceived as high relative to expected benefits (Blennow, 2013). Moreover, limited communication regarding available preventive measures and risk-reducing forest management practices likely weakened both risk awareness and incentives to purchase coverage.

These factors produced a hybrid insurance regime in which private markets covered "normal" and more frequent risks (notably fire), while extreme events were implicitly socialized. This arrangement reduced incentives for comprehensive storm insurance and entrenched underinsurance at the time of Gudrun. While our data do not allow us to disentangle all demand-side mechanisms in this early period, it can be used to focus on the role of Gudrun itself in driving subsequent changes in insurance take-up.

2.3 Insurance Demand in a Historical Perspective

As described in the next section, our data also enables us to situate storm Gudrun in a historical context. We observe the first insurance date for forest owners who were insured *before* Gudrun and remained insured, as well as for those who entered the insurance system after Gudrun. **Figure A2** juxtaposes the resulting annual number of new insurance take-ups (blue bars, right axis) with forest damage from major storms (orange bars, left axis) drawn from official statistics (Bengtsson & Nilsson, 2007). New take-ups rise sharply in the two years following major storms, most notably after 1969, 1980–81, 1999, and especially Gudrun in 2005. We define major storm years as those with timber losses exceeding 5 million cubic meters, corresponding to the top 25% of years with positive losses (see also **Figure 1**). These patterns are consistent with a salience-driven response, whereby recent disaster experience heightens perceived risk,

[7] The expectation of government support in case of disaster is often referred to as "charity hazard", whereby anticipated public relief discourages private insurance uptake (Browne and Hoyt, 2000; Zahran et al, 2009; Atreya et al, 2015; Grislain-Letrémy, 2018; Kousky et al, 2018; Andor et al, 2020; Osberghaus et al, 2023).

consistent with increased attention, belief updating, and the availability heuristic (Browne & Hoyt, 2000; Atreya et al., 2015; Kousky et al., 2018).

At the same time, the smoothed series for non-storm years reveals a gradual upward trend in insurance adoption that is not driven by major storms, consistent with longer-run increases in risk awareness and structural changes in the Swedish forestry and insurance context. Occasional spikes unrelated to domestic storm damage coincide with the salience of large external events, such as Storm Vivian and Storm Wiebke in Central Europe. Note that owners who insured earlier but later dropped coverage are not shown in **Figure A2**, which therefore captures new take-ups only in the pre-Gudrun period and cannot document potential post-spike declines in insurance holding. These owners are nevertheless included in subsequent analyses of the full sample, which relies on observed insurance status immediately before Gudrun and post-event entry.

3. Empirical Approach

3.1 Data Survey and Satellite Data.

Survey. We rely on a tailored household survey conducted among 769 forest owners in southern Sweden, three years after storm Gudrun. While the sample is relatively modest, the survey is rich in content. It provided detailed information on socio-demographic characteristics (age, gender, and education of household heads) and individual preferences (notably risk aversion), and ownership characteristics (property size and productive area, financial dependence on forestry, ownership history). The survey further records insurance coverage (our first outcome), including the date of insurance purchase, insurance status prior to Gudrun, and insurance status three years after the storm.

It also provides SWB information (our second outcome), measured primarily through life satisfaction using a 4-point Likert scale ranging from unsatisfied to satisfied. Life satisfaction aggregates multiple life dimensions, is strongly correlated with other measures of subjective well-being, and is closely associated with objective indicators of a good life, which explains its widespread use in the literature (Kahneman & Krueger, 2006; Clark and Senik, 2011; Senik, 2015; Clark, 2018). These data are complemented by a set of treatment variables (described below) and by owners' perceptions of future climate-related risks, providing a strong basis for analyzing both behavioral and psychological responses to extreme weather events. From the initial sample, we exclude observations with missing information, including property size and county code (1.4%), SWB (1.4%), insurance information prior to the storm (1.7%), or insurance information after the storm (1.5%). The final analytical sample consists of 722 observations.

Satellite Data. We combine the survey data with geospatial information from the Forest Map dataset published by the Swedish University of Agricultural Sciences (SLU, 2015). This dataset integrates field-based observations from the Swedish National Forest Inventory (NFI) with satellite-derived remote-sensing data, notably *Landsat* imagery, using high-resolution mapping at a 25 m × 25 m grid. It provides spatially detailed, nationwide information on forest characteristics, including tree species composition, biomass, timber volume, and stand age, for the year 2000. We spatially match these data to the survey observations to impute pre-Gudrun local average forest characteristics for each forest owner.

Alternative Treatment Variables. Throughout the paper, we distinguish between *exposure*, defined as geographic or meteorological proximity to the storm, and *being affected (or hit)*, which refers to realized impacts. While exposure is assumed to be random, effective damage may depend on forest characteristics, which also influence ex ante insurance take-up. The survey includes several complementary measures of storm damage, primarily at the individual level: a binary indicator of whether forest owners report having been affected by Gudrun ($T1$); the area of fallen trees in hectares ($T2$); timber volume losses in m^3 ($T3$); financial impact on a 0–5 Likert scale ($T4$). These are supplemented with an administrative indicator of damage intensity at the municipality level ($T5$). **Table A3** reports statistics and documents strong internal consistency across these measures. To carry out comparisons, we binarize $T2$-$T5$ by defining dummies equal to one when reported losses/damages are strictly positive. Across binary measures, between 36% and 48% of respondents report being affected by Gudrun (column 3). As expected, the subjective binary measure yields the highest prevalence, potentially overstating perceived impact relative to objectively measured damage. Nevertheless, conditional on reporting being affected, average losses in terms of damaged area, timber volume, and financial impact are more than twice the unconditional means (column 4), indicating substantial realized damage. Strong correlations are also observed between the subjective indicator and the binarized damage measures, ranging from 0.76 to 0.88 (column 5).

Descriptive statistics. Sample statistics are reported in **Table A4** for the main outcomes—insurance holding and life satisfaction—as well as for the set of control variables. We distinguish between owners who report being hit and not hit by Gudrun using the binary subjective measure and report differences in means. While a more formal balance analysis is presented below, these descriptive statistics already suggest that owners reporting being hit were more likely to hold insurance prior to the storm, indicating ex-ante selection into insurance. This selection is plausibly driven by forest characteristics: satellite data show that, before Gudrun, affected owners were more often located in areas with taller stands, a higher prevalence of shallow-rooted Norway spruce—both of which increase vulnerability to windthrow (Ingemarsson et al., 2006; Klasson, 2005; Grimby, 2005)—and more elevated terrain. Controlling for these characteristics is therefore crucial in the empirical analysis, as realized damage, although arising from largely random storm paths, was correlated with forest attributes that shaped pre-storm insurance decisions. In contrast, the lower part of **Table**

A4 shows that socio-demographic characteristics are broadly balanced across groups, suggesting that differences in outcomes primarily reflect variation in exposure and forest characteristics rather than systematic differences in owner profiles.

Notice that owners reporting being hit by Gudrun were even more likely to be insured after the storm than before, relative to other owners. This is consistent with a storm-induced increase in insurance take-up: insurance coverage increased by 44% among affected owners (from 41% to 59%), compared with +21% among others (from 28% to 34%). The raw difference-in-difference yields an increase of 12 percentage points, hence a +42% effect of Gudrun on insurance take-up relative to the pre-event control group (28%). Finally, we observe significantly lower SWB among the affected group three years after Gudrun. In what follows, we investigate to what extent these differences reflect persistence effects of the "storm of the century" or some selection effects.

3.2 Empirical Model

Overview. A large literature examines the effects of natural disasters on a wide range of outcomes, including insurance demand (see **Table A1**), subjective well-being (see **Table A2**), and other dimensions such as health (Deryugina et al., 2018) and risk preferences (e.g., Hanaoka et al., 2018). A recurring challenge in this literature is that while natural shocks may be random in time, they are often not random in space or in damage intensity, reflecting heterogeneity in exposed populations and their capacity to take preventive actions. For earthquakes, volcanic activity, and floods, spatial exposure depends in part on households' location choices relative to risk zones (e.g., Grignoux & Menéndez, 2016). For floods, storms, and hurricanes, realized damage further varies with individual characteristics and protective capacity, including financial resources (Kousky, 2010; Bin & Landry, 2013; Gallagher, 2014; Boustan et al., 2020; Berlemann, 2016).

Identification. In our setting, Gudrun's trajectory overlaps only partially with those of past major storms (cf. **Figure 1**). While southern Sweden is generally more exposed to windstorms, the counties affected by Gudrun were scattered across different localities within the South, resulting in damage to forests that had not previously been repeatedly exposed (Klasson, 2005). **Panel A** of **Figure A3** illustrates the geographical dispersion of storm damage, measured as the share of hectares with fallen trees ($T2$). Damage is concentrated in the southern part of southern Sweden (*Götaland*), corresponding to the storm's core path, as reflected in the spatial distribution of high wind-speed intensity in **panel C**.

Importantly, pre-Gudrun insurance take-up is much more spatially dispersed, as shown in **panel B**, and only weakly correlated with Gudrun's damage intensity (correlation = 0.13 using $T2$, with similar values for alternative damage measures). This suggests that *exposure* to Gudrun was largely orthogonal to prior insurance coverage, and supports treating spatial exposure to the storm as quasi-random. This holds even at a finer scale: within affected counties, damage intensity varied substantially due to local topography and microclimatic conditions (e.g., sheltering behind ridges, wind acceleration effects), generating rich cross-sectional variation for identification.

At the forest-owner level, however, *realized impacts* were not fully random, as damage severity depended on forest characteristics and terrain. In particular, elevated terrain and forests with taller stands and a higher prevalence of storm-sensitive, shallow-rooted Norway spruce were more vulnerable to windthrow (Andersson and Keskitalo, 2016; Andersson et al., 2018). Areas with higher shares of spruce trees are depicted in **panel D** of **Figure A3**. Within *Götaland*, we find a correlation of 0.30 between hectares of fallen tree and spruce density (0.20 when using volume of lost timber to measure damage). Forest characteristics may have also influenced pre-storm preventive behavior, including insurance decisions, particularly as older and taller stands are more valuable. This selection bias appears limited in magnitude: a regression of pre-Gudrun insurance take-up on pre-storm forest and terrain characteristics yields an R^2 of only 0.01. Nevertheless, we explicitly control for these characteristics in the empirical analysis.

Empirical Model: Insurance Demand. To estimate the impact of Gudrun on insurance demand, we model post-storm insurance coverage conditional on pre-storm insurance status:

$$Ins_{i,post} = \alpha_{1c} + \beta_1 T_{ji} + \rho\, Ins_{i,pre} + X_i'\gamma_1 + F_i'\delta_1 + \varepsilon_{1i} \qquad (1)$$

where $Ins_{i,pre}$ and $Ins_{i,post}$ are binary indicators for insurance coverage before and after Gudrun, T_{ji} denotes alternative binary measures of being hit by the storm ($j = 1, \ldots, 5$), as previously defined, α_{1c} are county fixed effects, X_i includes socio-demographic characteristics, risk aversion, income, and property size, and F_i captures pre-storm forest and terrain characteristics (stand age/height, spruce share, elevation). This specification is equivalent to a basic two-period difference-in-differences estimator under standard assumptions. It is also more efficient than first-differencing insurance purchase when baseline outcomes are predictive of follow-up outcomes (McKenzie, 2012).[8] Because insurance is the outcome of interest, conditioning on $Ins_{i,pre}$ does not constitute a "bad control" here; rather, it exploits baseline outcome information to account for pre-storm differences, over and above controlling for pre-storm forest characteristics and owner attributes. Alternatively, we can estimate insurance take-up among forest owners who were uninsured prior to Gudrun. Focusing on

[8] Efficiency gains simply come from the fact that pre-storm insurance is a strong predictor of post-storm coverage and absorbs substantial variation, improving the precision of β_1. This specification also avoids the restrictive assumption of unit persistence implicit in change-score models. With a binary insurance outcome and a three-year interval between surveys, persistence is high but not mechanical.

this subsample allows us to isolate entry into insurance and avoids mechanically combining entry and exit decisions. Specifically, we estimate:

$$Takeup_{i,post} = \alpha'_{1c} + \beta'_1 T_{ji} + X'_i \gamma'_1 + F'_i \delta'_1 + \varepsilon'_{1i} \qquad (1')$$

where $Takeup_{i,post} = 1$ if an owner uninsured before Gudrun purchased insurance afterwards.

Empirical Model: Subjective Well-Being. We estimate the impact of Gudrun on SWB using:

$$SWB_{i,post} = \alpha_{2c} + \beta_2 T_{ji} + X'_i \gamma_2 + F'_i \delta_2 + \varepsilon_{2i} \qquad (2)$$

where $SWB_{i,post}$ denotes post-Gudrun life satisfaction measured three years after Gudrun, T_{ji} captures alternative binary measures of being hit by Gudrun, α_{2c} are county fixed effects, X_i includes individual characteristics as before, and F_i pre-storm forest and terrain characteristics. Under the assumption that exposure to Gudrun is conditionally random given F_i and location fixed effects, β_2 captures the *total effect* of being hit by Gudrun on post-event SWB. Importantly, this effect is net of any insurance protection and other coping mechanisms, as we do not condition on insurance status in this baseline specification.

To examine whether pre-existing insurance coverage mitigates the welfare impact of the storm, we then allow the effect of being hit to vary by pre-Gudrun insurance status:

$$\begin{aligned} SWB_{i,post} = {} & \alpha'_{2c} + \beta'_2 (T_{ji} \times NotIns_{i,pre}) + \rho'_2 \, (T_{ji} \times Ins_{i,pre}) \\ & + \lambda'_2 \, Ins_{i,pre} + X'_i \gamma'_2 + F'_i \delta'_2 + \varepsilon'_{2i} \end{aligned} \qquad (2')$$

where $Ins_{i,pre}$ indicates pre-Gudrun insurance coverage. This pre-event status may play two roles in our specification. It first captures baseline heterogeneity between insured and uninsured owners (λ'_2). Through its interaction with being hit, insurance may also exert a buffering effect following the storm, by providing financial compensation and facilitating faster recovery.[9]

Despite the ordinal nature of the dependent variable (a four-point Likert scale), we estimate these models using linear regressions, which have been shown to yield results comparable to ordered latent-response models in practice (Ferrer-i-Carbonell & Frijters, 2004). As in the insurance demand models, standard errors are clustered at the municipality level.

[9] This interaction specification allows us to test for insurance buffering using only pre-treatment information, thereby avoiding conditioning on post-storm insurance decisions, which would be endogenous responses to the shock.

Table 1: Balance Checks

Treatment:	My forest was affected		Some acres were affected		Some volume of timber was lost		Financially affected	
Specification:	Raw correlation	Controlling for forest charact. & county FE	Raw correlation	Controlling for forest charact. & county FE	Raw correlation	Controlling for forest charact. & county FE	Raw correlation	Controllin g for forest charact. & county FE
Male	0.040	-0.016	0.048	0.025	0.114 ***	0.153 *	0.036	0.011
	(0.030)	(0.062)	(0.031)	(0.052)	(0.030)	(0.085)	(0.031)	(0.026)
Age	0.423	1.981	-0.811	-1.159	0.352	1.316	-0.048	-0.044
	(0.918)	(1.841)	(0.938)	(1.498)	(0.931)	(1.934)	(0.957)	(1.721)
Low education	0.086 **	0.086	0.064 *	0.033	0.094 ***	0.091	0.093 **	0.084
	(0.036)	(0.075)	(0.037)	(0.074)	(0.036)	(0.073)	(0.037)	(0.068)
Risk aversion	0.028	0.143	-0.068	-0.175	-0.069	-0.150	-0.036	-0.014
	(0.165)	(0.532)	(0.168)	(0.454)	(0.167)	(0.458)	(0.171)	(0.373)
Income	-1.526	-2.503	-0.333	0.294	-0.287	0.196	-1.781	-2.428
	(1.252)	(1.637)	(1.282)	(1.476)	(1.273)	(2.048)	(1.306)	(1.625)
Pre-Gudrun insurance	0.126 ***	0.017	0.123 ***	0.011	0.124 ***	0.017	0.133 ***	0.054
	(0.035)	(0.099)	(0.036)	(0.082)	(0.036)	(0.051)	(0.037)	(0.084)

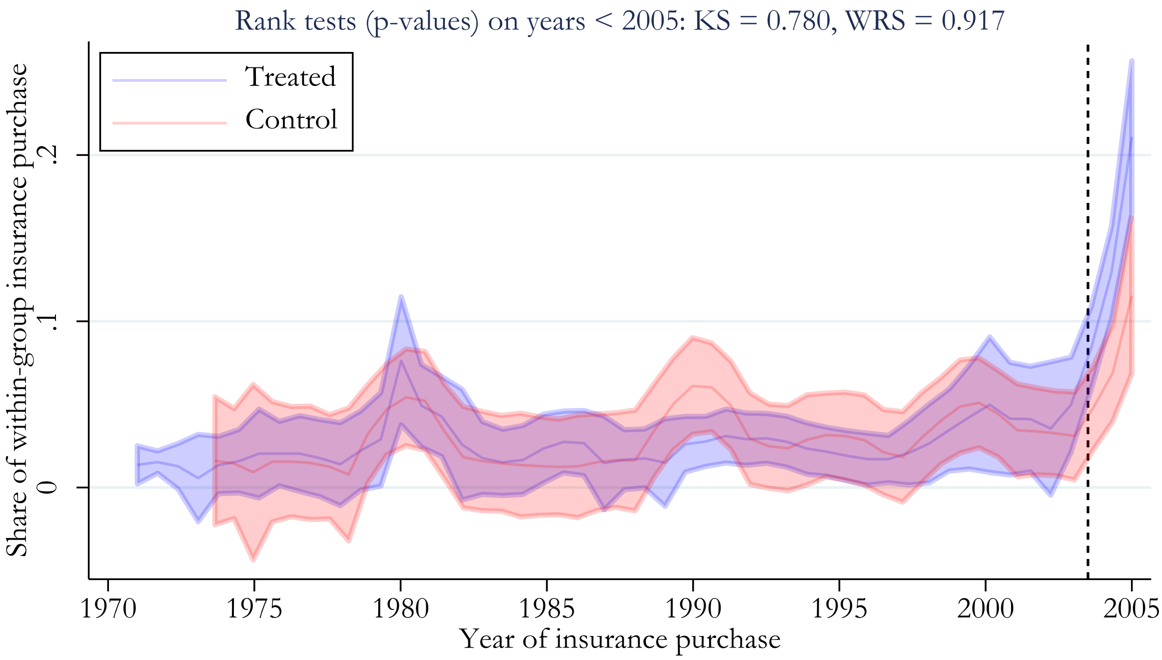
Note: the table represents balance checks. Each figure is the result of regressing in turn each binary shock variable on each of the characteristics (male, age, etc.), (1) without controls, (2) controlling for local mean forest & terrain characteristics (% spruce, tree age and height, elevation) and county dummies. Risk aversion question: "In general, are you a person who is prepared to take risks or do you try to avoid them?" (Very willing 1 to very unwilling 10). Standard errors in parentheses are clustered at county level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Number of observations: 722.

3.3 Balance Tests

In **Table 1**, we report balance checks obtained by regressing each binary shock measure on owner characteristics one at a time, under three specifications: without controls, controlling for local forest and terrain characteristics, and additionally including county fixed effects. Focusing on the main variable of interest, i.e. pre-Gudrun insurance take-up, we find that owners who were hit by the storm were significantly more likely to be insured prior to Gudrun in raw specifications, consistent with higher underlying risk exposure and forest value. However, this difference disappears once we control for pre-storm forest characteristics and terrain (stand age and height, spruce share, and elevation) as well as county fixed effects. This pattern holds consistently across all alternative damage measures (subjective impact, damaged area, lost timber volume, and financial impact). Overall, these results indicate that pre-storm selection into insurance was driven by observable forest characteristics rather than differential exposure to Gudrun per se. Accordingly, we include a rich set of forest characteristics in all subsequent estimations.

The other variables included in the balance checks are characteristics that are not expected to change over time, or that evolve mechanically, such as age. A potential exception is risk aversion, which prior studies have shown may be altered by shocks (e.g., Boutin et al., 2023) and natural disasters (e.g., Cameron & Shah, 2015; Hanaoka et al., 2018). In our data, however, we do not observe any systematic difference in reported risk preferences between owners hit and not hit by Gudrun, regardless of the shock measure used. More generally, once forest characteristics are accounted for, the treatment and control groups appear well balanced across observable characteristics under all alternative shock definitions, with only isolated and non-systematic exceptions.

Figure 2: Pre- and Post-Gudrun Insurance Adoption Timing, by Treatment Status



The figure shows the distribution of insurance purchase dates prior to Gudrun, by treatment status, conditional on being observed; it does not represent insurance holding over time. Densities are smoothed using local polynomial regression with confidence intervals. Because purchase dates are ordinal and directly comparable across groups, we assess distributional similarity using rank-based tests. Reported p-values correspond to the nonparametric Kolmogorov–Smirnov (KS) test (max gap between the distributions' CDFs) and the Wilcoxon rank-sum (WRS) test (equality of central tendency). Given high p-values, we do not reject similarity of pre-shock distribution.

Pre-event Comparison of Insurance Adoption Timing. A slightly different verification pertains to the difference-in-difference interpretation of (1). In that case, the usual practice consists of checking parallel trends, i.e. similar behavioral change between hit and not-hit owners. While the outcome does not allow this type of check, we can nonetheless verify that the timing of take-up is similar. **Figure 2** shows that the distribution of insurance purchase dates prior to Gudrun, conditional on being observed, is statistically indistinguishable between future treated and control owners. This is confirmed by rank-based tests applied to years prior to 2005, with high p-values for both the Kolmogorov–Smirnov test (KS = 0.780) and the Wilcoxon rank-sum test (WRS = 0.917), indicating that we cannot reject equality of the pre-shock distributions.[10] These results support the absence of differential pre-trends in insurance adoption timing groups. By contrast, a clear divergence in insurance adoption emerges after Gudrun, consistent with a shock-induced increase in take-up among affected owners.

Pre-Gudrun Correlates of Insurance Take-up. In **Table A5**, we report linear probability models estimating the correlates of holding forest insurance prior to Gudrun. As expected, more risk-averse owners exhibit a higher propensity to insure (column 1). Insurance coverage is also strongly associated with information and awareness (column 2): owners reporting greater knowledge of storm insurance are substantially more likely to be insured (Kunreuther and Pauly 2004; Kunreuther et al, 2001; Chivers and Flores, 2002), while those with lower education levels are significantly less likely to hold coverage (Atreya et al., 2015). Economic exposure to forestry and budget constraints matter as well (column 3): owners whose income depends more heavily on forest activities, as well as those with higher overall income, are more likely to be insured (Browne & Hoyt, 2000; Kriesel & Landry, 2004). By contrast, perceived premium costs do not play a significant role in our data, although evidence on this margin is mixed in the literature.[11] Finally, consistent with the balance checks, being hit by Gudrun is not correlated with pre-storm insurance coverage once forest and terrain characteristics and county fixed effects are included (column 4).

4. Results

4.1 Gudrun and Insurance Demand

Post-Gudrun Insurance Outcomes. We now turn to our main results, beginning with the impact of being hit by Gudrun on insurance demand. **Table 2** reports linear probability model estimates of post-Gudrun insurance outcomes. As expected, pre-storm insurance status is a very strong predictor of post-storm coverage (column i), reflecting substantial persistence in insurance behavior; auxiliary regressions indicate that past insurance status alone explains about 57% of the variance in post-Gudrun insurance coverage. Column (ii) then introduces the treatment indicator within the specification of model (1), conditioning on pre-Gudrun insurance status. Being hit by Gudrun—measured using the subjective damage indicator—is associated with a statistically and economically significant increase in insurance coverage: coverage rises by 10.1 percentage points (from 0.340 to 0.441), corresponding to a 29.7% increase relative to the pre-Gudrun insurance rate (lower panel). Column (iii) restricts the sample to owners uninsured before Gudrun, corresponding to model (1′). In this case, being

[10] This figure does not capture level differences in insurance holding prior to the storm, as it conditions on observed first purchase dates and excludes owners who insured earlier but subsequently dropped coverage. As a result, pre-storm selection into insurance driven by forest characteristics may exist in levels—as documented in **Table A4**—without implying differences in adoption timing, which is the dimension depicted here.
[11] For the NFIP in the US, demand is reduced by price in Browne & Hoyt (2000) but inelastic in Kriesel & Landry (2004) and Landry and Jahan-Parvar (2011).

hit by the storm increases the probability of insurance take-up by around 14 percentage points, which translates into an increase of 9.3 percentage points at the population level and a 27.5% relative effect, closely in line with the estimates of model (1).

Table 2: Estimates of Post-Gudrun Insurance Coverage and Take-Up

Dep. Variable:	Post-Gudrun Coverage		Post-Gudrun Take-up
Post-Gudrun	(i)	(ii)	(iii)
Male	-0.035**	-0.037**	-0.036
	(0.016)	(0.016)	(0.028)
Age	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.002)
Risk averse	0.013**	0.012**	0.015**
	(0.005)	(0.004)	(0.006)
Low education	-0.003	-0.004	0.006
	(0.028)	(0.027)	(0.031)
Economic dep. on forest	0.022*	0.020*	0.029
	(0.011)	(0.011)	(0.017)
Income	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Perception of premium cost	0.013	0.017	0.004
	(0.125)	(0.123)	(0.166)
Pre-Gudrun insurance purchase	0.768***	0.764***	
	(0.030)	(0.030)	
Hit by Gudrun ("My forest was affected")		0.101***	0.143**
		(0.029)	(0.053)
County FE	YES	YES	YES
Forest & terrain characteristics	YES	YES	YES
# obs.	708	708	463
R2	0.630	0.634	0.169
Hit by Gudrun, relative to pre-Gudrun coverage (and rescaled in column iii):			
My forest was affected		29.7%***	27.5%**
Some acres affected		31.5%***	25.6%***
Some m3 of timber lost		19.1%**	15.4%*
Financially affected		26.2%**	23.5%*

Note: the table reports the results of a linear probability model of holding a storm insurance post-Gudrun on individual characteristics (as specified), forest & terrain characteristics (% spruce, tree age, height, elevation), and county fixed effects. Standard error in parentheses are clustered at county level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Relative effects are estimates of being hit by Gudrun relative to pre-Gudrun coverage rate (34%), rescaled to total population size in column (iii).

Sensitivity Analysis. Overall, these results indicate that experiencing direct storm damage substantially increased insurance adoption beyond pre-existing differences in forest characteristics and owner profiles. The lower panel of **Table 2** corroborates this conclusion through robustness checks using alternative, more objective measures of storm exposure based on affected area, timber volume loss, and reported financial impact. Across all specifications, the estimated effect of being hit on post-Gudrun insurance take-up remains positive and statistically significant. Although effect sizes vary somewhat across measures (ranging from approximately 19% to 30%), the qualitative pattern is remarkably stable, indicating a robust increase in insurance demand following storm-related losses. In **Table A6**, we present additional sensitivity checks, implementing a propensity score (PS) reweighting to balance observable characteristics between forest owners hit and not hit by Gudrun. The PS is estimated using pre-storm covariates X_i and F_i. Observations are then reweighted by $w_i = 1/\hat{p}_i$ for treated owners ($H_i = 1$) and $w_i = 1/(1 - \hat{p}_i)$ for controls ($H_i = 0$), so that the reweighted samples are comparable in terms of observables. The results are broadly in line with the baseline estimates and confirm that Gudrun triggered an increase in insurance demand that persists three years after the shock.

Discussion. This result partly contrasts with the relatively mixed evidence observed in the literature on post-disaster insurance dynamics (see **Table A1**). Most studies document a relatively rapid attenuation of insurance demand following natural disasters—typically within two to four years (Michel-Kerjan et al., 2012; Atreya et al., 2015; Dumm et al., 2017; Kousky, 2017). Other contributions do not identify post-disaster fading, largely because they consider short time horizons (Dumm et al., 2020). Only a limited number of studies, exploiting longer time frames, point to a slower decay in insurance demand (Atreya et al., 2013; Gallagher, 2014; Kamiya & Yanase, 2019). Our results contribute to the limited evidence on prolonged post-disaster effects, suggesting several underlying mechanisms that account for persistence. First, it may reflect the exceptional magnitude of the shock. Incomplete adaptation is more likely when a highly salient and severe disaster induces durable availability effects and belief updating, an interpretation consistent with that of Atreya et al. (2013). A second, non-exclusive explanation lies in the presence of long-lasting non-pecuniary effects, such as affective losses associated with landscape destruction, as well as heightened insecurity or fear of recurrence. While these emotional and psychological channels are not directly observable in insurance data, they can be partially captured by SWB outcomes, which we examine explicitly in what follows.

Additional Tests using Heterogeneous Treatments. Before turning to SWB estimations, we exploit heterogeneous treatment definitions to probe specific behavioral dimensions, using the estimates reported in **Table A7**. We first examine *experience bias*, namely the idea that personally living through a disaster is not equivalent to observing its effects on others. Prior work shows that individuals tend to discount others' experiences relative to their own (Krawczyk et al., 2017). Consistent with this pattern, **panel (a)** reveals no significant effect on insurance take-up when exposure is defined through relatives', neighbors', or friends' forests being damaged by Gudrun, underscoring the primacy of direct personal exposure.

Next, the literature debates whether repeated exposure to shocks dampens behavioral responses through learning and adaptation or, alternatively, reinforces salience and precautionary behavior. For example, Yin et al. (2016) document heightened availability effects after an initial typhoon, followed by declining insurance coverage after repeated events, consistent with a gambler's fallacy mechanism. We assess the direction of such cumulative effects by interacting Gudrun's exposure with indicators of storm experience over the preceding ten years. The results in **panel (b)** show little evidence of either attenuation or amplification, suggesting that Gudrun's impact is not simply a function of accumulated disaster experience but instead reflects the distinct salience of this event.

By contrast, interacting treatment with the perceived likelihood of another Gudrun-type storm occurring in the near future yields a clearer pattern (see **panel c**): our baseline effects are concentrated among individuals who expect recurrence. This finding is consistent with a mechanism operating through subjective beliefs and perceived risk, rather than through objective exposure or damage intensity alone.

4.2 Gudrun and Subjective Well-being

Subjective well-being (SWB) measures have been extensively used to value intangible goods and non-market impacts (e.g., van Praag and Baarsma, 2005), particularly in environmental valuation.[12] A more specific strand of the literature applies SWB approaches to climate-related disasters (see **Table A2**). These studies typically focus on homeowners exposed to flood risk or actual flood damage, documenting substantial welfare losses following extreme events.[13]

Despite this growing body of evidence, two important gaps remain. First, most studies rely on geographic exposure (living in an affected area) rather than direct exposure, i.e. being personally hit by the disaster. Second, due to limited temporal depth and data constraints, relatively little is known about the medium- to long-term welfare impacts of natural disasters and about how insurance and reinsurance arrangements shape post-disaster well-being (Berlemann and Eurich, 2022). Our study addresses these gaps by focusing on individuals who were directly affected by a major forest storm and by jointly analyzing insurance behavior and SWB outcomes several years after the event.

---

[12] A large literature documents the effects of air quality, temperature, and pollution on life satisfaction and mental health (Welsch, 2006; Smyth et al., 2008; Levinson, 2012; Ferreira et al., 2013; Li et al., 2020), as well as more broadly the influence of climatic, environmental, and urban conditions on quality of life (Rehdanz and Maddison, 2005; Moro et al., 2008; Maddison and Rehdanz, 2011). Reviews and methodological discussions are provided by Ferreira and Moro (2010) and Welsch and Ferreira (2013).

[13] See for instance: Luechinger and Raschky (2009) in Europe; Van Ootegem and Verhofstadt (2016) in Belgian Flanders; Sekulova and Van den Bergh (2016) in Bulgaria; von Möllendorff and Hirschfeld (2016) in Germany. Some work examines environmental disasters affecting natural assets, such as forest fires (Kountouris and Remoundou, 2011, for Mediterranean forests) or nuclear catastrophes with long-lasting impacts on forestry (Berger, 2010, on Chernobyl in Germany).

Baseline Estimates. In **Table 3**, we report linear regressions of life satisfaction measured three years after Gudrun on alternative indicators of being affected. As specified in model (2), we control for individual characteristics, pre-storm forest and terrain characteristics, and county fixed effects. The estimated coefficients on standard covariates of life satisfaction are fully consistent with the SWB literature (e.g., Senik, 2006), including, in particular, a concave age profile and a positive association with income. Across specifications, being hit by Gudrun is associated with a statistically significant reduction in life satisfaction for most objective measures of damage. The subjective measure ("my forest was affected") yields a negative but less precisely estimated coefficient, consistent with greater measurement noise in self-reported exposure.

Table 3: Estimates of Subjective Well-Being, Three Years Post-Gudrun

Dep: Life satisfaction	Treatment			
	My forest was affected	Some acres affected	Some m3 of timber lost	Financially affected
	(1)	(2)	(3)	(4)
Male	-0.045	-0.047	-0.027	-0.044
	(0.064)	(0.065)	(0.062)	(0.066)
Age	-0.033*	-0.033*	-0.032*	-0.033*
	(0.016)	(0.017)	(0.016)	(0.016)
Age squared /10	0.025	0.025	0.024	0.024
	(0.014)	(0.015)	(0.014)	(0.014)
Risk averse	-0.027	-0.028*	-0.027	-0.027*
	(0.015)	(0.015)	(0.015)	(0.015)
Low education	-0.237**	-0.233**	-0.232**	-0.233**
	(0.096)	(0.095)	(0.097)	(0.095)
Income	0.011***	0.011***	0.012***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Treatment	**-0.109**	**-0.096****	**-0.148***	**-0.140****
	(0.090)	**(0.038)**	**(0.076)**	**(0.064)**
County FE	YES	YES	YES	YES
Forest & terrain charact.	YES	YES	YES	YES
# obs.	713	713	713	713
R2	0.207	0.207	0.210	0.210
Relative effect (relative to owners not hit by Gudrun):	-3.8%	-3.4%	-5.2%	-4.9%

Note: the table represents the results of a linear regression of life satisfaction three years after storm Gudrun on treatment, individual characteristics (as specified), forest & terrain characteristics (% spruce, tree age, height, elevation), and county fixed effects. Treatment captures whether the forest owner had damages, using alternative damage measure as specified. Standard error in parentheses are clustered at county level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

The estimated treatment effect ranges from −0.10 to −0.15 points on the 4-point scale. Using the income coefficient, we express this effect in terms of a compensating income variation. Across specifications, the implied welfare loss corresponds to 37–53% of average monthly income in Sweden in 2005. This magnitude is economically meaningful, especially given that the outcome is measured three years after the shock and thus reflects persistent welfare effects rather than short-run transitory losses.

Heterogeneous Effects: Mechanisms. These findings are consistent with our insurance-demand results, which document sustained insurance take-up three years after the event. We have outlined several economic and psychological mechanisms that could account for these patterns. *First*, the shock entailed the destruction of income-generating natural capital ("green capital"), losses that might not be fully captured by our observed income measure. *Second*, the insurance was not only characterized by low coverage but may have been imperfect in practice, among insured owners, as discussed before. *Third*, the magnitude of the event may have triggered psychological responses that are reflected in our welfare outcomes and contribute to incomplete adaptation.[14] In particular, persistent non-pecuniary costs may have arisen from prolonged recovery efforts, irreversible landscape degradation, and heightened perceived insecurity.[15] While the cross-sectional nature of the data precludes sharp causal identification of these mechanisms, we provide a circumstantial case for specific welfare-loss channels by exploiting non-causal heterogeneity analysis in treatment effects, as reported in **Table A8**. In **Panel (a)**, evidence in favor of a perceived insecurity channel emerges from the interaction with future risk perceptions: only individuals who believe that climate change poses a high risk to their forest experience a statistically significant decline in well-being, with differences significant for most treatment measures. In **Panel (b)**, we examine heterogeneity with respect to forest heritage. The estimated adverse effects increase with the length of ownership within the family, consistent with stronger emotional attachment and heightened landscape grief. While longer ownership is also correlated with older and more valuable stands, a purely economic interpretation would predict larger storm impacts among owners with high—rather than low—financial dependence on forest income, which is not supported by the data. Finally, **Panel (c)** exploits residential proximity to forests as a proxy for emotional salience. Significant declines in life satisfaction are entirely concentrated among owners

[14] The SWB literature points to heterogeneous adaptation to shocks, depending on the type of event, its severity, and individual characteristics (Oswald and Powdthavee 2008; Graham and Oswald, 2010).

[15] Non-financial losses may be due to the emotional ties individuals have to the forest. A literature shows how a landscape is valued through the cultural affective links owners have with their property (Berger, 2010; Berlemann & Eurich, 2022; Croitoru, 2007), the role of environmental amenities (Brereton et al, 2008; Ferreira & Moro, 2010), including scenic amenity (Ambrey & Fleming, 2011; Kopmann & Rehdanz, 2013) and biodiversity (Ambrey & Fleming, 2013). Few studies show that the persistence of past shock us exacerbated by fear and the perception about future shocks (Sekulova & Van Den Bergh, 2016, and Fluhrer & Kraenhert, 2022, on climate shocks and Danzer & Danzer, 2016, on Chernobyl).

residing on the property, whereas no statistically significant effects are observed for off-site owners; differences are significant across all treatment measures.

Heterogeneous Effects: Links with Insurance. In **Table A9**, we explore heterogeneity in the welfare effects of Gudrun with a particular focus on insurance. **Panel (a)** reports the baseline estimates (from **Table 3**), included primarily as a reference point for comparison. These baseline coefficients capture the total *net* effect of exposure to Gudrun, incorporating any buffering arising from insurance coverage or other coping responses. The model of **Panel (b)** additionally controls for pre-Gudrun insurance status (cf. equation 2). In principle, one would expect larger treatment effects once the cushioning effect of insurance is partialled out through the coverage indicator. The estimates move in this direction, but very marginally. The coefficient capturing heterogeneity between owners insured prior to Gudrun and those uninsured is positive and statistically significant, consistent with the former exhibiting lower baseline anxiety, greater forward planning and risk awareness, and more frequent adoption of complementary preventive strategies. **Panel (c)** reports the interaction with pre-Gudrun insurance (cf. equation 2′). Owners insured prior to Gudrun experience slightly smaller negative effects, suggesting a modest mitigating role of insurance; however, the difference relative to uninsured owners is not statistically significant. These results point to a limited protective effect of climate insurance on SWB, which is consistent both with the limited scope of the insurance system prior to Gudrun (cf. Section 2.2) and with the fact that important non-pecuniary costs, such as landscape damage, are not insurable. Finally, in a purely descriptive manner, **Panel (d)** shows a stronger correlation between SWB and the absence of insurance coverage *post*-Gudrun, suggesting that, at the time of the survey, insurance may have primarily operated as a source of reassurance. This interpretation aligns with the heterogeneous welfare effects discussed above, and notably the role of climate anxiety and risk perception.

5. Conclusions

This paper studies the medium-run consequences of a major climate shock for insurance behavior and subjective well-being. Exploiting quasi-random exposure to storm Gudrun (2005) and conditioning on detailed satellite-based measures of pre-event local forest and terrain characteristics, we treat realized storm damage as conditionally exogenous. This identification strategy allows us to jointly analyze post-disaster insurance demand and welfare outcomes among Swedish forest owners three years after the "storm of the century".

Our results document two main findings. First, exposure to Gudrun led to a large and persistent increase in insurance take-up, still clearly visible three years after the storm. This persistence contrasts with much of the existing literature, which often finds that post-disaster insurance responses fade relatively quickly, and underscores the lasting behavioral impact of highly salient, extreme events. Second, the storm generated significant medium-run welfare losses among affected forest owners. These losses are economically meaningful and persist well beyond the immediate aftermath of the shock. Heterogeneity analyses suggest that these welfare impacts may be driven to some extent by non-pecuniary and psychological costs. In particular, landscape destruction, emotional attachment to forests, and heightened feelings of insecurity appear central to explaining incomplete adaptation. Insurance plays only a limited mitigating role in this respect. While owners insured prior to Gudrun experience slightly smaller welfare losses, the buffering effect is modest. By contrast, post-event insurance coverage appears to function partly as reassurance, consistent with a role for insurance in alleviating perceived insecurity rather than fully compensating realized losses.

Several limitations qualify these conclusions. Although the cross-sectional design three years after the event does not undermine identification of the treatment effect, it constrains our ability to causally isolate the underlying mechanisms. Subjective well-being, risk perceptions, and expectations are only observed post-shock, limiting inference on belief updating. Moreover, insurance coverage is observed without detailed contract characteristics, preventing a precise assessment of how coverage depth, deductibles, or claims experience shape welfare outcomes. These limitations point to promising avenues for future research. Panel data tracking individuals before and after climate shocks would allow a direct analysis of belief updating, adaptation dynamics, and their interaction with insurance demand. Richer information on insurance contract design would also help assess how alternative insurance arrangements could better buffer welfare losses.

From a policy perspective, our findings suggest that climate insurance, while important, is not sufficient to fully offset the welfare consequences of extreme climate events. Persistent non-pecuniary and psychological losses call for broader adaptation strategies that go beyond financial compensation, combining ex post measures (such as landscape restoration, environmental recovery, and support for affected owners) with ex ante interventions aimed at reducing vulnerability before shocks occur. In this respect, clear communication on preventive forest management practices—i.e., diversifying species away from spruce, promoting uneven-aged stands, and adapting harvesting methods—may help limit both economic and non-pecuniary losses. Consistent with Wagner (2022a), such preventive measures should be designed to complement, rather than crowd out, insurance coverage.

References

Ambrey, C. L. and C. M. Fleming (2011). Valuing scenic amenity using life satisfaction data. Ecological Economics 72, 106–115.

Ambrey, C. L. and C. M. Fleming (2014). Valuing ecosystem diversity in south east Queensland: A life satisfaction approach. Social indicators research 115(1), 45–65.

Andersson, E., E. C. H. Keskitalo, and S. Bergstén (2018). In the eye of the storm: adaptation logics of forest owners in management and planning in Swedish areas. Scandinavian Journal of Forest Research 33(8), 800–808.

Andersson, L. F. and E. C. H. Keskitalo (2016). Insurance models and climate risk assessments in a historical context. Financial History Review 23(2), 219–243.

Andor, M. A., D. Osberghaus, and M. Simora (2020). Natural disasters and governmental aid: Is there a charity hazard? Ecological Economics 169, 106534.

Atreya, A., S. Ferreira, and W. Kriesel (2013). Forgetting the flood? an analysis of the flood risk discount over time. Land economics 89(4), 577–596.

Atreya, A., S. Ferreira, and E. Michel-Kerjan (2015). What drives households to buy flood insurance? new evidence from Georgia. Ecological Economics 117, 153–161.

Baetschmann, G., K. E. Staub, and R. Winkelmann (2015). Consistent estimation of the fixed effects ordered logit model. Journal of the Royal Statistical Society, Series A 178(3), 685–703.

Bengtsson, L., & Nilsson, C. (2007). Extreme value modelling of storm damage in Swedish forests. Natural Hazards and Earth System Sciences, 7(4), 515–521

Berger, E. M. (2010). The Chernobyl disaster, concern about the environment, and life satisfaction. Kyklos 63(1), 1–8.

Berlemann, M. (2016). Does hurricane risk affect individual well-being? empirical evidence on the indirect effects of natural disasters. Ecological Economics 124, 99–113.

Berlemann, M. and M. Eurich (2022). Natural disasters and self-reported well-being: a review of the literature. Handbook on the Economics of Disasters, 230–251.

Bin, O. and C. E. Landry (2013). Changes in implicit flood risk premiums: Empirical evidence from the housing market. Journal of Environmental Economics and Management 65(3), 361–376.

Boustan, L. P., M. E. Kahn, P. W. Rhode, and M. L. Yanguas (2020). The effect of natural disasters on economic activity in us counties: A century of data. Journal of Urban Economics 118, 103257.

Boutin, D., Petifour, L., & Megzari, H. (2023). Permanent instability of preferences after COVID-19 crisis: A natural experiment from urban Burkina Faso, IZA discussion paper 16075.

Brereton, F., J. P. Clinch, and S. Ferreira (2008). Happiness, geography and the environment. Ecological economics 65(2), 386–396.

Browne, M. J. and R. E. Hoyt (2000). The demand for flood insurance: empirical evidence. Journal of risk and uncertainty 20, 291–306.

Cameron, L. and M. Shah (2015). Risk-taking behavior in the wake of natural disasters. Journal of human resources 50(2), 484–515

Chivers, J. and N. E. Flores (2002). Market failure in information: the national flood insurance program. Land Economics 78(4), 515–521.

Clark, A. E. (2018). Four decades of the economics of happiness: Where next? Journal of Economic Literature, 56(2), 245–269

Clark, A. E. and C. Senik (2011). Is happiness different from flourishing? Cross-country evidence from the ESS. Revue d'Economie Politique 121(1), 17–34.

Cliche, L. (2000). Corporate demand for insurance: The case of environmental risk. The Geneva Papers on Risk and Insurance – Issues and Practice, 25(4), 541–558.

Corcos, A., C. Montmarquette, and F. Pannequin (2020). How the demand for insurance became behavioral. Journal of Economic Behavior & Organization 180, 590–595.

CRED (2024). EM-DAT: The International Disaster Database. Centre for Research on the Epidemiology of Disasters, Université catholique de Louvain, https://www.emdat.be

Croitoru, L. (2007). Valuing the non-timber forest products in the mediterranean region. Ecological Economics 63(4), 768–775.

Czajkowski, J., H. Kunreuther, E. Michel-Kerjan, H. de Moel, W. J. Botzen, and R. Sitkin (2017). The effects of information provision on flood insurance demand: Evidence from a randomized experiment in Poland. Risk Analysis 37(3), 557–570.

Danzer, A. M. and N. Danzer (2016). The long-run consequences of Chernobyl: Evidence on subjective well-being, mental health and welfare. Journal of Public Economics 135, 47–60.

Dumm, R. E., D. L. Eckles, C. Nyce, and J. Volkman-Wise (2017). Demand for windstorm insurance coverage and the representative heuristic. The Geneva Risk and Insurance Review 42, 117–139.

Dumm, R. E., D. L. Eckles, C. Nyce, and J. Volkman-Wise (2020). The representative heuristic and catastrophe-related risk behaviors. Journal of Risk and Uncertainty 60, 157–185.

ECB (2023). The climate insurance protection gap. European Central Bank, Climate Change Centre. https://www.ecb.europa.eu/ecb/climate/climate/html/index.en.html

Ferreira, S., A. Akay, F. Brereton, J. Cuñado, P. Martinsson, M. Moro, and T. F. Ningal (2013). Life satisfaction and air quality in Europe. Ecological economics 88, 1–10.

Ferreira, S. and M. Moro (2010). On the use of subjective well-being data for environmental valuation. Environmental and Resource Economics 46, 249–273.

Ferrer-i Carbonell, A. and P. Frijters (2004). How important is methodology for the estimates of the determinants of happiness? Economic Journal 114(497), 641–659.

Fluhrer, S. and K. Kraehnert (2022). Sitting in the same boat: Subjective well-being and social comparison after an extreme weather event. Ecological Economics 195, 107388.

Foudi, S., N. Osés-Eraso, and I. Tamayo (2017). Integrated spatial flood risk assessment: The role of flood experience in risk perception and preventive behavior. Risk Analysis 37(10), 1962–1981.

Gallagher, J. (2014). Learning about an infrequent event: Evidence from flood insurance take-up in the United States. American Economic Journal: Applied Economics, 206–233.

Gignoux, J. and M. Menéndez (2016). Benefit in the wake of disaster: Long-run effects of earthquakes on welfare in rural Indonesia. Journal of Development Economics 118, 26–44.

Gollier, C. (2007). The determinants of the demand for insurance: A theoretical analysis. Toulouse School of Economics (IDEI Working Paper No. 471).

Graham, L. and A. J. Oswald (2010). Hedonic capital, adaptation and resilience. Journal of Economic Behavior & Organization 76(2), 372–384.

Grimby (2005). Sadness and grief among forest owners the year after Gudrun: results from a survey on emotional reactions. Technical report (in Swedish), Swedish Forest Agency.

Grislain-Letrémy, C. (2018). Natural disasters: exposure and underinsurance. Annals of Economics and Statistics/Annales d'Économie et de Statistique (129), 53–83.

Hanaoka, C., H. Shigeoka, and Y. Watanabe (2018). Do risk preferences change? Evidence from the great East Japan earthquake. American Economic Journal: Applied Economics 10(2), 298–330.

Hill, R.V., Hoddinott, J. and N. Kumar (2013). Adoption of weather-index insurance: learning from willingness to pay among a panel of households in rural Ethiopia. Agricultural Economics, 44 (4-5). 385-398.

Hoyt, R. E., & Khang, H. (2000). On the demand for corporate property insurance. Journal of Risk and Insurance, 67(1), 91–107.

Ingemarsson, F., J. Malmhäll, B. Merkell, S. Basic, and S. Svensson (2006). How did the storm Gudrun affect individual forest owners? Survey evidence. Technical report (in Swedish), Swedish Forest Agency.

Kahneman, D., & Krueger, A. B. (2006). Developments in the measurement of subjective well-being. Journal of Economic Perspectives, 20(1), 3–24.

Kamiya, S. and N. Yanase (2019). Learning from extreme catastrophes. Journal of Risk and Uncertainty 59, 85–124.

Klasson, A. (2005). Ten foresters' experiences of storm Gudrun. The Norwegian Forestry Agency.

Kopmann, A. and K. Rehdanz (2013). A human well-being approach for assessing the value of natural land areas. Ecological Economics 93, 20–33.

Kousky, C. (2010). Learning from extreme events: Risk perceptions after the flood. Land Economics 86(3), 395–422.

Kousky, C. (2017). Disasters as learning experiences or disasters as policy opportunities? examining flood insurance purchases after hurricanes. Risk analysis 37(3), 517–530.

Kousky, C., E.O. Michel-Kerjan, and P. A. Raschky (2018). Does federal disaster assistance crowd out flood insurance? Journal of Environmental Economics and Management, 87, 150-164

Kraehnert, K., D. Osberghaus, C. Hott, L. T. Habtemariam, F. Wätzold, L. P. Hecker, and S. Fluhrer (2021). Insurance against extreme weather events: An overview. Review of Economics 72(2), 71–95.

Krawczyk, M.W., S. T. Trautmann, and G. van de Kuilen (2017). Catastrophic risk: social influences on insurance decisions. Theory and Decision 82, 309–326.

Kriesel, W. and C. Landry (2004). Participation in the national flood insurance program: An empirical analysis for coastal properties. Journal of Risk and Insurance 71(3), 405–420.

Kunreuther, H. (1984). Causes of underinsurance against natural disasters. Geneva Papers on Risk and Insurance, 206–220.

Kunreuther, H., N. Novemsky, and D. Kahneman (2001). Making low probabilities useful. Journal of risk and uncertainty 23, 103–120.

Kunreuther, H. and M. V. Pauly (2004). Neglecting disaster: Why don't people insure against large losses? Journal of Risk and Uncertainty 28, 5–21.

Kunreuther H. and Pauly M. (2005). Insurance decision-making and market behavior. Foundations and Trends in Microeconomics, n° 1, pp. 63-127.

Kunreuther, H. and M. V. Pauly (2018). Dynamic insurance decision-making for rare events: The role of emotions. Geneva Papers on Risk and Insurance-Issues and Practice 43, 335–355.

Landry, C. E. and M. R. Jahan-Parvar (2011). Flood insurance coverage in the coastal zone. Journal of Risk and Insurance 78(2), 361–388.

Lee, H., Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P., Trisos, C., Romero, J., Aldunce, P., Barrett, K., et al. (2023). Climate Change 2023: Synthesis Report. Summary for

Policymakers. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC, Geneva, Switzerland.

Leiserowitz, A. (2006). Climate change risk perception and policy preferences: The role of affect, imagery, and values. Climatic Change 77(1), 45–72.

Levinson, A. (2012). Valuing public goods using happiness data: The case of air quality. Journal of Public Economics 96(9-10), 869–880.

Li, M., S. Ferreira, and T. A. Smith (2020). Temperature and self-reported mental health in the United States. PloS one 15(3), e0230316.

Luechinger, S. and P. A. Raschky (2009). Valuing flood disasters using the life satisfaction approach. Journal of Public Economics 93(3-4), 620–633.

Maddison, D. and K. Rehdanz (2011). The impact of climate on life satisfaction. Ecological Economics 70(12), 2437–2445.

Meyer, R. J. (2012). Failing to learn from experience about catastrophes: The case of hurricane preparedness. Journal of Risk and Uncertainty 45, 25–50.

Michel-Kerjan E, and C. Kousky (2010). Come rain or shine: Evidence on flood insurance purchases in Florida. Journal of Risk and Insurance,77(2):369–397

Michel-Kerjan, E., Lemoyne de Forges, S., & Kunreuther, H. (2012). Policy tenure under the U.S. National Flood Insurance Program. Risk Analysis., 32(4), 644–658

Michel-Kerjan, E., Raschky, P. and Kunreuther, H. (2015), Corporate Demand for Insurance: New Evidence From the U.S. Terrorism and Property Markets. Journal Risk and Insurance, 82: 505-530.

Moro, M., F. Brereton, S. Ferreira, and J. P. Clinch (2008). Ranking quality of life using subjective well-being data. Ecological Economics 65(3), 448–460.

Nilsson, C. (2008). Windstorms in Sweden: variations and impacts. Lund University.

Nguyen, H.T., & Mitrou, F. (2024). Delving into the eye of the cyclone to quantify the cascading impacts of natural disasters on life satisfaction, Global Labor Organization (GLO), Discussion Paper No. 1446

Nguyen, H.T., & Mitrou, F. (2025). Natural disasters and the demand for health insurance. Journal of Environmental Economics and Management, 130, 103108

Osberghaus, D., M. Achtnicht, and N. Alimov (2023). The demand for public flood protection under a compulsory private flood insurance scheme. Land Economics 99(3), 380–396.

Oswald, A. J. and N. Powdthavee (2008). Does happiness adapt? a longitudinal study of disability with implications for economists and judges. Journal of Public Economics 92(5-6), 1061–1077.

Pitthan, F. and K. DeWitte (2021). Puzzles of insurance demand and its biases: A survey on the role of behavioural biases and financial literacy on insurance demand. Journal of Behavioral and Experimental Finance 30, 100471.

Rehdanz, K. and D. Maddison (2005). Climate and happiness. Ecological Economics 52(1), 111–125.

Seidl, R. and K. Blennow (2012). Pervasive growth reduction in Norway spruce forests following wind disturbance. PLoS ONE 7(3), e33301.

Sekulova, F. and J. C. Van den Bergh (2016). Floods and happiness: Empirical evidence from Bulgaria. Ecological Economics 126, 51–57.

Senik, C. (2015). Income distribution and subjective well-being: A survey. Journal of Economic Surveys, 29(3), 424–450

SLU (2015). Swedish University of Agricultural Sciences forest map: Nationwide data on forest conditions in Sweden. https://www.slu.se/en/Collaborative-Centres-and-Projects/the-swedish-national-forest-inventory/forest-statistics/forest-map/

Smyth, R., V. Mishra, and X. Qian (2008). The environment and well-being in urban China. Ecological Economics 68(1-2), 547–555.

SOU (2007). Sweden facing climate change – threats and opportunities. Technical report, Swedish Commission on Climate and Vulnerability, Statens Offentliga Utredningar (Swedish Government Official Reports).

Tafere, K., C. B. Barrett, and E. Lentz (2019). Insuring well-being? buyer's remorse and peace of mind effects from insurance. American Journal of Agricultural Economics 101(3), 627–650.

Tversky, A. and D. Kahneman (1973). Availability: A heuristic for judging frequency and probability. Cognitive psychology 5(2), 207–232.

Van Ootegem, L. and E. Verhofstadt (2016). Well-being, life satisfaction and capabilities of flood disaster victims. Environmental Impact Assessment Review 57, 134–138.

Van Praag, B. and A. Ferrer-i Carbonell (2007). Happiness quantified: A satisfaction calculus approach. OUP Oxford.

Van Praag, B. M. and B. E. Baarsma (2005). Using happiness surveys to value intangibles: The case of airport noise. Economic Journal 115(500), 224–246.

von Möllendorff, C. and J. Hirschfeld (2016). Measuring impacts of extreme weather events using the life satisfaction approach. Ecological Economics 121, 108–116.

Wagner, K. R. (2022a). Designing insurance for climate change. Nature Climate Change, 12(12), 1070-1072.

Wagner, K. R. (2022b). Adaptation and adverse selection in markets for natural disaster insurance. American Economic Journal: Economic Policy, 14(3), 380-421.

Welsch, H. (2006). Environment and happiness: Valuation of air pollution using life satisfaction data. Ecological Economics 58(4), 801–813.

Welsch, H., & Ferreira, S. (2014). Environment, well-being, and experienced preference. Journal of Environmental Economics and Management, 68(2), 181–196

Yin, H., J. Chen, H. Kunreuther, and E. Michel-Kerjan (2016). Availability heuristic and gambler's fallacy over time in a natural disaster insurance choice setting. Available at SSRN 2798371.

Zahran, S., S. Weiler, S. D. Brody, M. K. Lindell, and W. E. Highfield (2009). Modeling national flood insurance policy holding at the county scale in florida, 1999–2005. Ecological Economics 68(10), 2627–2636.

APPENDIX

Table A1: Brief Review on the Impact of Climate Shocks & Risks on Insurance Take-up

	Outcome type	Treatment (experiencing extreme weather event)	Country	Units	Time horizon	Effect fades away	Notes
Actual shocks							
This study	Insurance demand	Hurricane	Sweden	**Individual**	**3 years**	no	
Dumm et al. (2020)	Insurance demand	Hurricane	US	**Individual**	**3 years**	no, effects over 1-3 years (may have laster longer)	
Michel-Kerjan et al. (2012)	Insurance demand	Flood	US	**Individual**	**9 years**	within 2-4 years	
Atreya et al. (2013)	Insurance demand	Flood	US	**Individual**	**10 years**	within 4-9 years	
Michel-Kerjan & Kousky (2010)	Insurance demand	Hurricane/flood	US	Individual	<2 years	n.a.	
Gallagher (2014)	Insurance demand	Flood	US	County	16 years	within 9 years	
Kousky (2017)	Insurance demand	Hurricane/flood	US	County	9 years	within 3 years	Aid conditional on purchasing insurance
Dumm et al. (2017)	Insurance demand	Hurricane	US	County	4 years	within 2-4 years	
Kamiya & Yanase (2019)	Insurance demand	Earthquake	Japan	Municipality	4 years	no, effects over 4 years (may have lasted longer)	
Browne & Hoyt (2000)	Insurance demand	Flood	US	State	1 year	n.a.	Aid conditional on purchasing insurance
Atreya et al. (2015)	Insurance type	Flood	US	County	32 years	within 3 years	

	Outcome	Treatment (others)	Country	Units	Other results
Other treatments: perceptions					
Wagner (2022)	Insurance demand	Perceived flood severity	US	Individual	Decrease with adaptation or protective measures
Kriesel & Landry (2004)	Insurance demand	Perceived flood risk	US	Individual	Decrease with adaptation, protect. measures or long intervals btw events
Petrolia et al. (2013)	Insurance demand	Perceived flood risk	US	Individual	Decrease with adaptation, protect. measures or long intervals btw events
Experiments					
Kunreuther & Pauly (2018)	Insurance demand	Virtual: hurricane	US	Individual	
Osberghaus & Reif (2021)	Insurance demand	Virtual event	Germany	Individual	
Yin et al. (2016)	Insurance demand	Virtual: typhoon	China	Individual	Decline when repeated shocks, consistent with Gambler's fallacy
Cai & Song (2017)	Insurance demand	Virtual: natural hazards	China	Individual	
Kunreuther & Michel-Kerjan (2015)	Insurance type	Virtual: Hurricane	US	Individual	
Meyer (2012)	Protective measures	Virtual: Hurricane	US	Individual	Forgetting effect

Note: in the upper panel ("actual shocks"), studies are presented in lexicographic order starting with *Outcome type* (focusing first on "insurance demand", which includes insurance takeup or coverage measures), then with *Units* (focusing first on "individual" data), and finally on the *Time horizon*, which is the maximum time range surveyed in each paper following the event under study. The most comparable studies to ours are indicated in bold, namely those focusing on insurance takeup, using **individual data** and with a **middle/long-run time horizons**.

Additional references cited in Table A1:

Cai, J., & Song, C. (2017). Do disaster experience and knowledge affect insurance take-up decisions? Journal of Development Economics, 124, 83–94.

Kountouris, Y. and K. Remoundou (2011). Valuing the welfare cost of forest fires: a life satisfaction approach. Kyklos 64(4), 556–578.

Kunreuther, H. and Michel-Kerjan, E. (2015). Demand for fixed-price multi-year contracts: experimental evidence from insurance decisions. J. Risk Uncertain. 51(2), 171–194.

Osberghaus, D. and C. Reif (2021). How do different compensation schemes and loss experience affect insurance decisions? Experimental evidence from two independent and heterogeneous samples, Ecological Economics, 187, 107087.

Petrolia, D.R., Landry, C.E., Coble, K.E., 2013. Risk preferences, risk perceptions, and flood insurance. Land Econ. 89 (2), 227–245.

Table A2: Brief Review on the Impact of Climate Shocks On Subjective Well-Being

	Main outcome	Treatment	Country	Significant short-term effect (i.e. within a year)	Time horizon	The effect fades away within this time range ?
Extreme weather events (rich countries)						
This study	**Life satisfaction**	Hurricane / storm	Sweden	n.a	**3 years**	No
Luechinger & Raschky (2009)	**Life satisfaction**	Flood	Germany	Yes	**20 years**	After 1 or 2 years
Sekulova & Van Den Bergh (2016)	**Life satisfaction**	Flood	Bulgaria	Yes	**6 years**	No
von Mollendroff & Hirschfeld (2016)	**Life satisfaction**	Hurricane / storm	Germany	Yes	1.5 years	No
Hudson et al. (2019)	Life satisfaction	Flood	France	Yes	1 year	No
Ahmadiani & Ferreira (2021)	Life satisfaction	Extreme events	US	Yes	1 year	After 6-8 months
Kountouris & Remoundou (2011)	Life satisfaction	Fires	4 EU countries	Yes	7 months	No
Carroll et al. (2009)	Life satisfaction	Drought	Australia	Yes	3 months	No
Kimball et al (2006)	Happiness	Hurricane / storm	US	Yes	2 months	After 2-3 weeks
Extreme weather events (poorer countries)						
Tu Le (2020)	Life satisfaction	Flood	Thaïland/Vietnam	Yes	5 years	No
Stein & Weisser (2022)	Better off than past year	Flood	Thaïland/Vietnam	Yes	1 year	No
Fluhrer & Kraehnert (2021)	Life satisfaction	Extreme events	Mongolia	>0 effect of experiencing events 2-3 years before		
Lohmann et al. (2019)	Life satisfaction	Drought	Bougainville & Papua N.Guinea	>0 effect of experiencing events in past 5 years		
Human disaster						
Danzer & Danzer (2016)	Life satisfaction	Chernobyl	Ukraine	n.a	21 years	No
Berger (2010)	Life satisfaction	Chernobyl	Germany	No effect	4 months	n.a
Welsch & Biermann (2014)	Life satisfaction	Fukushima	Switzerland	Yes	6 months	No
Rehdanz et al. (2015)	Happiness	Fukushima	Japan	Yes	1 year	No

Note: in the upper panel, studies are presented in lexicographic order starting with *Main outcome* (focusing first on "Life satisfaction") , then with the *Time horizon* , which is the maximum time range surveyed in each paper following the event under study. The most comparable studies to ours are indicated in bold, namely those focusing on middle/long term (>1 year). Note we do not classify according to the type of climate shock ("Treatment"), but heterogeneous effects are sometimes reported depending on the shock. For instance, von Mollendroff & Hirschfeld (2016) find an effect only for storms; Lohmann et al(2019) find a more pronounced negative effect for droughts.

Additional references cited in Table A2:

Ahmadiani, M., and S. Ferreira (2021). Well-Being Effects of Extreme Weather Events in the US. Resource and Energy Economics 64: 101213.

Carroll, N., P. Frijters, and M. A. Shields. 2009. "Quantifying the Costs of Drought: New Evidence from Life Satisfaction Data." Journal of Population Economics 22(2): 445–61.

Hudson, P., Botzen, W. J. W., Poussin, J., & Aerts, J. C. J. H. (2019). Impacts of flooding and flood preparedness on subjective well-being: A monetisation of the tangible and intangible impacts. Journal of Happiness Studies, 20(2), 665-682.

Kimball, M.S., H. G. Levy, F. Ohtake, & Y. Tsutsui (2006). Unhappiness after hurricane Katrina.

Le, T. T. N. (2020). Floods and household welfare: Evidence from Southeast Asia. Economics of Disasters and Climate Change, 4(1), 145–170.

Lohmann, P., A. Pondorfer, and K. Rehdanz (2019). Natural Hazards and Well-Being in a Small-Scale Island Society. Ecological Economics 159: 344–53.

Rehdanz, K., Welsch, H., Narita, D., & Okubo, T. (2015). Well-being effects of a major natural disaster: The case of Fukushima. Journal of Economic Behavior & Organization, 116, 500-517.

Stein, W., & Weisser, R. (2022). Direct shock experience vs. tangential shock exposure: Indirect effects of flood shocks on well-being and preferences. World Bank Economic Review, 36(4), 909–933.

von Möllendorff, C., & J. Hirschfeld (2016). Measuring Impacts of Extreme Weather Events Using the Life Satisfaction Approach. Ecological Economics 121: 108–116.

Wang, F., & Wang, S. (2023). Well-being effects of natural disasters: Evidence from China's Wenchuan earthquake. Journal of Happiness Studies, 24(4), 1187–1210.

Welsch, H., & P. Biermann (2014). Fukushima and the Preference for Nuclear Power in Europe: Evidence from Subjective Well-Being Data. Ecological Economics 108: 171–79.

Table A3: Alternative Treatment Variables

Treatment question / variable	Continuous		Binarized		
	Mean	Mean if "my forest was affected"=1	Mean	Mean if "my forest was affected"=1	Correlation with "my forest was affected"
	(1)	(2)	(3)	(4)	(5)
T1 : My forest was affected			0.48	1.00	
			(0.50)	(0.00)	
T2 : # of acres of fallen trees	3.58	7.53	0.39	0.83	0.84
	(10.89)	(14.84)	(0.49)	(0.38)	
T3 : # of cubic meters lost	0.43	0.91	0.41	0.86	0.88
	(1.60)	(2.23)	(0.49)	(0.34)	
T4 : Perception of financial impact (0-5 scale)	0.80	1.69	0.36	0.75	0.78
	(1.30)	(1.44)	(0.48)	(0.43)	
T5 : Intensity of damage at municipality level (0-5 scale)	1.46	2.63	0.47	0.87	0.76
	(1.55)	(1.29)	(0.50)	(0.33)	

Source: statistics elaborated by the authors using the survey on forest owners (T1 to T4) and administrative data on municipality-level damage intensity (T5). Original variables are continuous/discrete (except the first one on "my forest affected", which is binary); binarized version is equal to 1 if original variable strictly positive. Standard deviations in parenthesis.

Table A4: Descriptive Statistics

		All	Hit (a)	Not hit (a)	Diff. (b)
		(1)	(2)	(3)	(2)-(3)
Insurance holding	Pre-Gudrun: hold an insurance	0.34	0.41	0.28	0.13 ***
		(0.47)	(0.49)	(0.45)	(0.04)
	Post-Gudrun: hold an insurance	0.46	0.59	0.34	0.25 ***
		(0.50)	(0.49)	(0.47)	(0.04)
Subjective well-being	Life satisfaction	2.81	2.76	2.85	-0.10 *
		(0.74)	(0.74)	(0.73)	(0.05)
Forest characteristics	Size of the estate (in ha)	56.64	58.05	55.36	2.69
		(53.45)	(54.51)	(52.52)	(3.99)
	Size of the productive estate (in ha)	43.23	44.32	42.23	2.09
		(42.65)	(42.35)	(42.95)	(3.18)
	Average tree age	48.15	48.13	48.16	-0.02
		(6.43)	(4.72)	(7.67)	(0.47)
	Average tree height (in meters)	13.05	14.42	11.81	2.60 ***
		(1.96)	(1.54)	(1.40)	(0.11)
	Average share of spruce	0.48	0.54	0.44	0.10 ***
		(0.09)	(0.07)	(0.07)	(0.01)
	Elevation	98.25	106.36	90.91	15.45 ***
		(67.52)	(67.91)	(66.40)	(5.01)
Individual characteristics	Male	0.80	0.82	0.78	0.04
		(0.40)	(0.38)	(0.41)	(0.03)
	Age	58.41	58.63	58.21	0.42
		(12.26)	(12.28)	(12.26)	(0.91)
	Low educated	0.36	0.41	0.32	0.09 **
		(0.48)	(0.49)	(0.47)	(0.04)
	Risk aversion	6.13	6.14	6.12	0.03
		(2.19)	(2.19)	(2.20)	(0.16)
	Monthly household income ('1000 kroners)	33.91	33.10	34.63	-1.53
		(16.81)	(16.87)	(16.74)	(1.25)
# obs.		722	343	379	

Source: statistics elaborated by the authors using the survey on forest owners and satellite data on forest characteristics. Standard deviations in parenthesis.

(a) Hit and not hit: defined using the subjective binary exposure question ("Was you forest hit?")

(b) Test of the difference with significativity level: *=10%, **=5%, ***=1%

Table A5: Correlates of Pre-Gudrun Insurance Coverage

Pre-Gudrun insurance takeup	(1)	(2)	(3)	(4)
Individual characteristics				
Male	0.062	0.029	0.020	0.020
	(0.045)	(0.039)	(0.041)	(0.041)
Age	-0.000	0.001	0.002	0.002
	(0.002)	(0.001)	(0.001)	(0.001)
Risk averse	0.027***	0.028***	0.031***	0.031***
	(0.008)	(0.007)	(0.006)	(0.006)
Skills and information				
Low education		-0.096**	-0.092**	-0.093**
		(0.034)	(0.034)	(0.034)
Knew about storm insurance (scale 1-6)		0.430***	0.416***	0.413***
		(0.044)	(0.043)	(0.043)
Economic factors				
Economic dep. on forest (scale 1-6)			0.036***	0.036***
			(0.010)	(0.010)
Income			0.002*	0.002*
			(0.001)	(0.001)
Perception of premium cost (in Kr/ha)			-0.169	-0.168
			(0.180)	(0.180)
Hit by Gudrun ("My forest was affected")				0.025
				(0.063)
County FE	YES	YES	YES	YES
Forest & terrain characteristics	YES	YES	YES	YES
# obs.	708	708	708	708
R2	0.091	0.236	0.249	0.249

Note: the table reports the results of a linear regression of holding a climate insurance before Gudrun on individual characteristics (socio-demographics & risk aversion), skills and information, economics factors, and being hit by Gudrun (using the binary variable "My forest was affected"), controlling for forest & terrain characteristics (% spruce, tree age, height, elevation) and county fixed effects. Standard error in parentheses are clustered at county level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Estimates of Post-Gudrun Insurance Coverage and Take-Up with Propensity Score Reweighting

Dep. Variable:	Post-Gudrun Coverage		Post-Gudrun Take-up
Post-Gudrun	(i)	(ii)	(iii)
Male	-0.024	-0.025	-0.006
	(0.021)	(0.023)	(0.041)
Age	-0.000	0.000	0.000
	(0.001)	(0.001)	(0.002)
Risk averse	0.016*	0.017*	0.023
	(0.009)	(0.008)	(0.014)
Low education	-0.003	-0.005	0.010
	(0.032)	(0.030)	(0.044)
Economic dep. on forest	0.007	0.006	0.015
	(0.011)	(0.011)	(0.016)
Income	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Perception of premium cost	0.114	0.118	0.133
	(0.175)	(0.166)	(0.170)
Pre-Gudrun insurance purchase	0.803***	0.793***	
	(0.033)	(0.032)	
Hit by Gudrun ("My forest was affected")		0.110***	0.138*
		(0.034)	(0.066)
County FE	YES	YES	YES
Forest & terrain characteristics	YES	YES	YES
# obs.	708	708	463
R2	0.673	0.680	0.229
Hit by Gudrun, relative to pre-Gudrun coverage (and rescaled in column iii):			
My forest was affected		32.4%***	26.5%*
Some acres affected		37.1%***	30.8%***
Some m3 of timber lost		32.4%**	23.3%**
Financially affected		17.1%*	13.3%

Note: the table reports the results of a linear probability model of holding a storm insurance post-Gudrun on individual characteristics (as specified), forest & terrain characteristics (% spruce, tree age, height, elevation), and county fixed effects. Observations are weighted by 1/PS for the treated and 1/(1-PS) for the untreated, with PS the propensity score from a probit estimation of the probability of being hit (subjective binary definition) on individual, forest and terrain characteristics. Standard error in parentheses are clustered at county level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Relative effects are estimates of being hit by Gudrun relative to pre-Gudrun coverage rate (34%), rescaled to total population size in column (iii).

Table A7: Estimates of Post-Gudrun Insurance Coverage with Heterogeneous Treatments

Dep: Post-Gudrun insurance holders	(a) Alternative treatments				
	My forest hit by Gudrun	Relatives' forest was hit	Neighbors' forest was hit	Friends' forest was hit	Forest of other people I know was hit
Treatment	0.179***	-0.010	0.047	-0.072	-0.023
	(0.059)	(0.058)	(0.045)	(0.055)	(0.053)
# obs.	708	706	708	708	707
R2	0.172	0.160	0.161	0.163	0.162

Dep: Post-Gudrun insurance holders	(b) Treatment interacted with past 10-year storm exposure			
	My forest hit by Gudrun	Some acres affected	Some m3 of timber lost	Financially affected
Treatment	0.103***	0.140***	0.082***	0.100**
	(0.030)	(0.022)	(0.026)	(0.044)
Treatment x Past Exposure	-0.020	-0.035	-0.025	-0.021
	(0.055)	(0.056)	(0.055)	(0.071)
# obs.	697	697	697	697
R2	0.644	0.649	0.644	0.645

Dep: Post-Gudrun insurance holders	(c) Treatment x future risk perception (climate change anxiety)			
	My forest hit by Gudrun	Some acres affected	Some m3 of timber lost	Financially affected
Treatment x low risk	0.046	0.058	0.010	0.051
	(0.038)	(0.042)	(0.031)	(0.043)
Treatment x high risk	0.109***	0.113***	0.075**	0.101**
	(0.036)	(0.031)	(0.035)	(0.044)
Difference in coeffs (p-value)	0.06	0.05	0.07	0.26
# obs.	708	708	708	708
R2	0.634	0.636	0.633	0.635

Note: the table reports the results of a linear probability model of holding a storm insurance post-Gudrun on individual characteristics (socio-demographics, risk aversion, skills, economically dependent on forest, income, perception of premium cost), forest & terrain characteristics (% spruce, tree age, height, elevation), and county fixed effects. Standard error in parentheses are clustered at county level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Treatment variables as indicated - in panel (b), Past Exposure is a binarized version of the question: "have you been hit by several storms over the past 10 years"; in panel (c), high/low risks derived from the question "Do you think that the climate is changing in such a way that it will affect your forest significantly over the next 25 years?" (scale 1 to 10).

Table A8: Heterogeneous Subjective Well-Being Estimates, Consistent with Feeling of Insecurity and Emotional Loss

Dep: Life satisfaction		My forest hit by Gudrun	Lost acres	Lost forest volume	Financially affected
Panel (a): Treatment x future risk perception (climate anxiety)					
high risk		-0.180*	-0.146***	-0.205***	-0.190**
		(0.095)	(0.038)	(0.069)	(0.065)
low risk		0.140	0.117	0.077	0.125
		(0.140)	(0.183)	(0.167)	(0.130)
# obs.		713	713	713	713
R2		0.221	0.212	0.219	0.218
Test: high = low risk (p-value)		0.02	0.20	0.07	0.02
Panel (b): Treatment x forest heritage (ownership duration in the family)					
0 to 20 years		0.043	0.011	-0.034	0.079
		(0.144)	(0.117)	(0.154)	(0.121)
20 to 40 years		-0.071	-0.129	-0.057	-0.124
		(0.090)	(0.085)	(0.086)	(0.088)
40 to 60 years		-0.149	0.010	-0.138	-0.130
		(0.176)	(0.087)	(0.143)	(0.098)
More than 60 years	x low econ.	-0.176	-0.144*	-0.245***	-0.210**
		(0.106)	(0.068)	(0.076)	(0.082)
	x high econ.	-0.253	-0.233	-0.260*	-0.246
		(0.176)	(0.232)	(0.141)	(0.166)
# obs.		713	713	713	713
R2		0.212	0.210	0.216	0.215
Test: low = high econ. dependence (p-value)		0.57	0.70	0.91	0.79
Panel (c): Treatment x proximity (lives on the property or not)					
lives on the property		-0.176*	-0.236***	-0.212***	-0.247***
		(0.084)	(0.054)	(0.059)	(0.049)
does not live on the property		0.020	0.064	-0.008	0.013
		(0.108)	(0.085)	(0.132)	(0.095)
# obs.		717	717	717	717
R2		0.052	0.055	0.054	0.058
Test: lives = does not live on site (p-value)		0.01	0.03	0.06	0.00

Note: the table represents the results of a linear regression of life satisfaction three years after storm Gudrun on treatment, individual characteristics (socio-demographics, risk aversion, income), forest & terrain characteristics (% spruce, tree age, height, elevation), and county fixed effects. Treatment captures whether the forest owner had damages, using alternative damage measure as specified. Standard error in parentheses are clustered at county level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Future risk perception in the first panel (high/low risks) is derived from the question "Do you think that the climate is changing in such a way that it will affect your forest significantly over the next 25 years?" (scale 1 to 10).

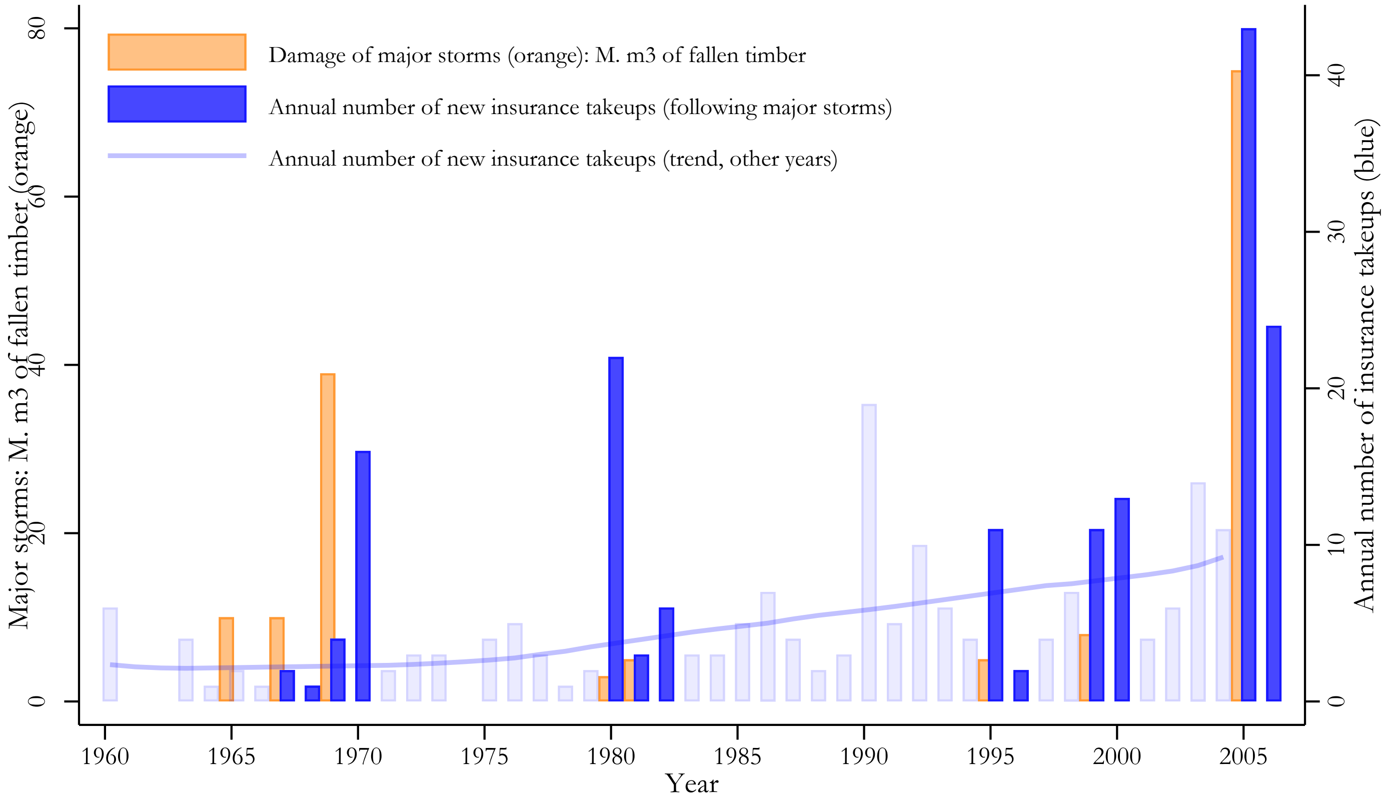
Table A9: Heterogeneous Subjective Well-Being Estimates, Being Hit interacted with Insurance Status

Dep: Life satisfaction		Treatment			
		My forest hit by Gudrun	Lost acres	Lost forest volume	Financially affected
(a) Baseline (Table 3, model 2)					
Treatment		-0.109	-0.096**	-0.148*	-0.140**
		(0.090)	(0.038)	(0.076)	(0.064)
(b) Controlling for pre-Gudrun insurance status					
Treatment		-0.143	-0.095**	-0.172**	-0.152**
		(0.095)	(0.036)	(0.080)	(0.058)
Insured pre-Gudrun		0.110**	0.103**	0.113**	0.115**
		(0.044)	(0.046)	(0.046)	(0.045)
(c) Interacting with pre-Gudrun insurance status (model 2')					
Treatment	x insured pre-Gudrun	-0.086	-0.047	-0.129	-0.113
		(0.112)	(0.076)	(0.090)	(0.096)
	x not insured pre-Gudrun	-0.168*	-0.130*	-0.187*	-0.163**
		(0.095)	(0.062)	(0.101)	(0.069)
Test "insured = not insured", p-value		0.310	0.490	0.580	0.650
(d) Interacting with post-Gudrun insurance status					
Treatment	x insured post-Gudrun	-0.083	-0.010	-0.117	-0.094
		(0.101)	(0.038)	(0.082)	(0.070)
	x not insured post-Gudrun	-0.187*	-0.205***	-0.221**	-0.214***
		(0.104)	(0.045)	(0.099)	(0.073)
Test "insured = not insured", p-value		0.160	0	0.190	0.100
County FE		YES	YES	YES	YES
Forest & terrain		YES	YES	YES	YES

Note: the table represents the results of a linear regression of life satisfaction three years after storm Gudrun on treatment, individual characteristics (socio-demographics, risk aversion, income), forest & terrain characteristics (% spruce, tree age, height, elevation), and county fixed effects. Treatment captures whether the forest owner had damages, using alternative damage measure as specified. Standard error in parentheses are clustered at county level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

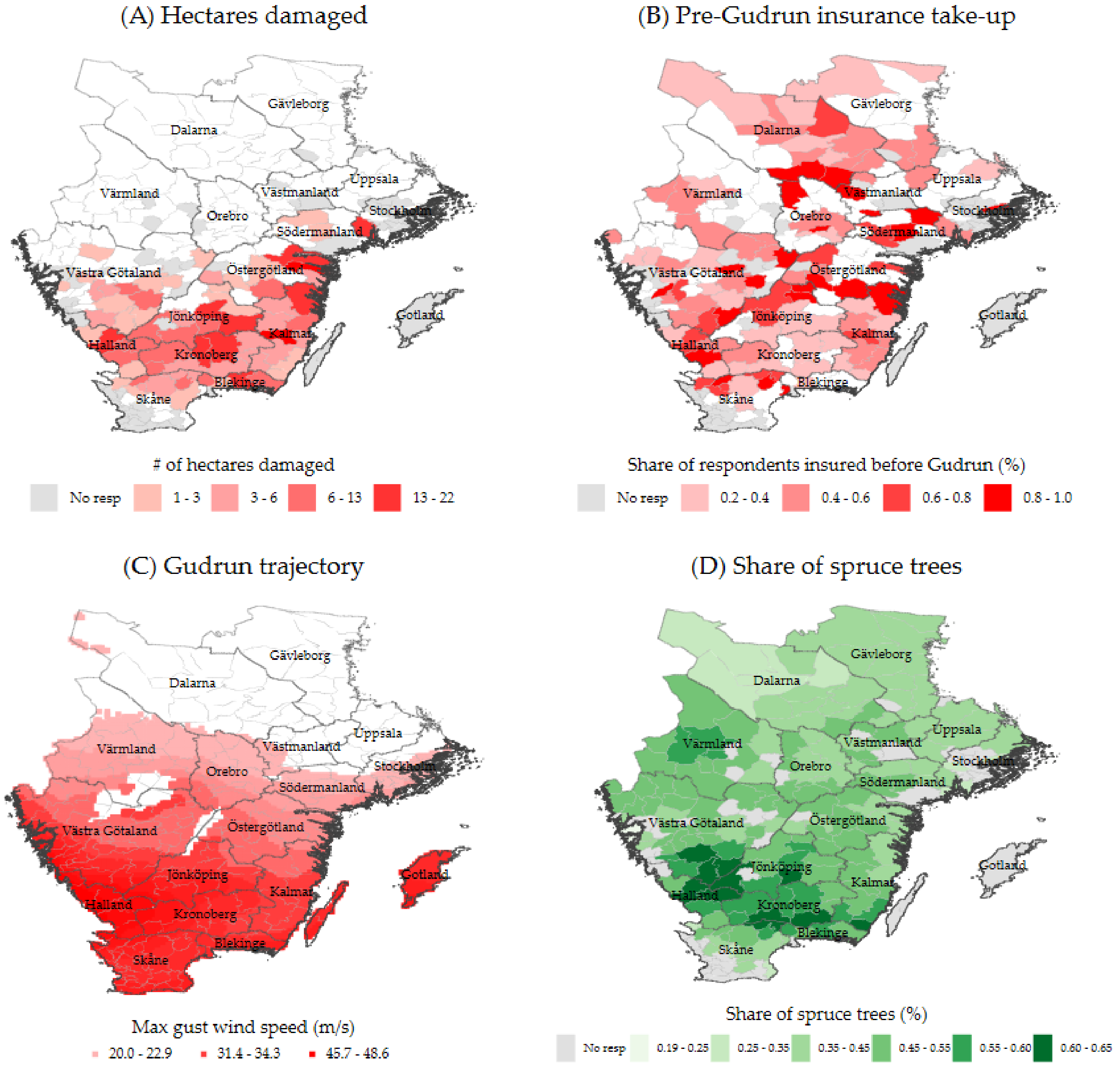
Figure A1: Pictures of Damaged Landscape

Figure A2: Storm Damages and New Insurance Take-up over the Long Run



The figure shows the extent of damage after each major storm (official statisics, orange bars, left axis) against the annual number of new insurance purchase (our survey), distinguising the two years after a major storm (blue bars, right axis) and the other years (local polynomial trend, light blue, right axis). We only observe insurance date for owners who were insured just before Gudrun, and remained insured, and for those who entered after Gudrun. Owners who insured earlier but later dropped coverage are not shown in this figure. Thus, the figure captures new take-ups only, not potential declines in coverage following spikes.

Figure A3: Mapping of Forest Damage, Ex Ante Insurance Take-Up, Wind Speed & Spruce Density (Municipality Averages)



Notes: Panel A shows the municipality-level average number of damaged hectares (source: our survey). Panel B reports the mean share of respondents insured against storm damage prior to Gudrun (source: our survey). Panel C displays Gudrun's trajectory as storm-force wind exposure in Beaufort scale (source: Copernicus Climate Change Service's (C3S)). Panel D presents the municipal-level share of spruce trees (SLU Forest Map).