When Wildfires Hit the Market: Detecting Shock Patterns in Insurer Stocks Using an ML Framework

The frequency and severity of climate-related extreme events have increased markedly over recent decades. These events are generating rapidly rising economic losses, with long-term implications for fiscal sustainability and recovery capacity (Kraehnert et al., 2021; Lamperti et al., 2019; Mills, 2009; Venturini, 2022; Zhou et al., 2023). Global economic damages from natural disasters between 2000 and 2025 are estimated at approximately US$3.8 trillion. Wildfires alone account for roughly US$170 billion of these losses (Ritchie et al., 2022).

In this setting, property and liability (P&L) insurers play a central role in the climate-risk ecosystem. They transfer risk, provide post-disaster liquidity, and enable reconstruction by allowing households and firms to absorb losses. Through these functions, insurance coverage supports economic continuity and stabilizes recovery processes after extreme events (Giuzio et al., 2025). When insurers reduce coverage or withdraw from high-risk climate assets, reconstruction costs shift to households, firms, and public budgets. Such withdrawal constrains investment, slows rebuilding, and weakens long-term socio-economic sustainability in exposed regions (Kousky et al., 2024; Von Peter et al., 2024).

Climate change increasingly threatens the solvency of P&L insurers. As extreme events intensify, losses place growing pressure on capital buffers and underwriting capacity. When insurers remain solvent, they support rehabilitation and stabilize credit conditions. When financial strength weakens, losses spill over to households, firms, and public budgets. This dynamic poses a direct risk to adaptation in a climate-changing world, as reduced insurance capacity constrains investment in resilient infrastructure and discourages long-term planning in high-risk regions. For this reason, insurance market stability is not only a board-level concern but a regulatory and societal one.

This paper examines whether extreme, sudden-onset wildfire events generate distinctive and predictable structural patterns in the stock returns of P&L insurers, and whether these patterns provide decision-relevant signals for monitoring insurance market stability and long-term socio-economic sustainability.

Recent research has examined the economic and financial consequences of natural disasters from multiple perspectives. Systematic reviews document a wide range of methodologies for assessing disaster-related costs and highlight the scale and persistence of economic losses (Eckhardt et al., 2019). Within financial markets, recent studies link extreme events to heightened stress in the insurance sector. Puławska et al. (2025) show that among climate, geopolitical, and cybersecurity risks, climate risk drives the strongest insurer stock-price reactions and is systematically priced into insurer equity risk premia. Montero et al. (2024) provide a rigorous and influential contribution, showing that natural disasters elevate short- and medium-term volatility in P&L insurers and materially reshape Value-at-Risk (VaR) forecasts using a multi-event GARCH framework.

Despite these advances, both Puławska et al. and Montero et al. still frame the core market response primarily through a volatility-based (GARCH-type) framework. They quantify how much returns fluctuate but offer limited insight into how prices evolve through time following a shock. As a result, differences in reaction speed, asymmetry, and recovery patterns remain misinterpreted. In addition, much of the literature aggregates heterogeneous disaster types. This can obscure differences between forecastable events, such as hurricanes or winter storms, and sudden-onset shocks, such as wildfires or flash floods. These limitations leave a gap in event-specific and interpretable characterization of insurer return dynamics under truly unexpected climate shocks. Moreover, many event-volatility studies do not include matched non-event windows, so the estimated "post-disaster" volatility shifts may not reflect a pattern specific to disaster timing, but instead coincide with broader market-wide volatility regimes.

To address these gaps, we introduce a data-driven framework that combines Structural Return Features (SRFs) - metrics that summarize the shape of return trajectories - with machine learning (ML). This design aligns with evidence that ML-based volatility forecasting can outperform traditional benchmarks and deliver economically meaningful gains in volatility-timing decisions (Chun et al., 2025). We focus on wildfires because they are typically sudden-onset shocks relative to forecastable hazards (e.g., hurricanes), reducing anomalies from pre-event pricing. To distinguish event-driven effects from calendar-related patterns, observed SRFs during wildfire windows are benchmarked against a counterfactual placebo calendar constructed by shifting event dates to break seasonal alignment. Structural patterns that emerge in true event windows but not in placebo periods are therefore more plausibly attributable to the climate shock itself.

The analysis proceeds in four steps. We construct a dual-source dataset of daily stock returns for U.S. insurers and a validated wildfire event timeline, alongside placebo windows for counterfactual comparison. We then focus on tail behavior by stratifying event-day outcomes into return-quantile groups, reflecting the solvency relevance of extreme moves. Structural Return Features are computed to capture trajectory characteristics across multiple windows, and machine learning models are applied to predict these patterns.

Predictive performance is evaluated by comparing true wildfire windows with matched placebo periods. We find evidence that forecast performance is maintained during wildfire windows and remains broadly comparable to placebo periods, implying that return dynamics can stay stable even under extreme shocks. Notably, the strongest predictive results are concentrated in episodes with large positive wildfire-day moves rather than the largest losses, suggesting that upside adjustments may be more predictable than downside drawdowns. We also observe feature- and horizon-specific improvements, such as higher predictability of symmetry over short-to-medium post-wildfire horizons, which can support more targeted risk monitoring and management.

The importance of this study lies in translating climate-induced financial signals into actionable diagnostics for insurance regulatory oversight, and long-term adaptation planning. When insurers misjudge tail exposure or fail to interpret rapid post-disaster repricing, pressures emerge to raise premiums, restrict coverage, or withdraw from high-risk regions. Such responses weaken slow recovery, and increase inequality in adaptation capacity. By identifying structural return patterns that signal abnormal post-disaster dynamics, this study contributes an early diagnostic layer that can strengthen insurer risk management and improve regulatory visibility into emerging solvency risks under escalating climate extremes.