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Climate Shocks and Unemployment Claims

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Abstract

Using a US state–level climate risk measure and the local projections (LP) framework, this study analyzes both linear and asymmetric effects of climate shocks on unemployment claims. The results provide strong evidence that climate shocks significantly increase both initial and continuing claims, with the linear estimates showing a stronger impact on initial claims. In the nonlinear framework, where climate risk and economic condition indices are used as regime-switching variables, we also find asymmetric effects of climate shocks across both types of claims. Specifically, climate shocks exert stronger pressure on initial claims under high–climate-risk regimes, while continuing claims respond more under low-risk regimes. When the economic condition index is applied as a regime-dependent variable, climate shocks are more influential during expansions than during recessions, when claims are already elevated and labor markets are slack. Overall, the findings highlight that climate shocks affect labor markets in complex, state-dependent ways, offering valuable insights for policymakers aiming to design effective mitigation strategies and enhance labor market resilience.

Keywords: Climate shocks; Linear and Non-Linear frameworks; Unemployment.

JEL Classifications: C23; E24; Q54.

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1. Introduction

Climate change—manifesting as abnormal weather shocks—has become a major source of macroeconomic volatility, as increasingly frequent and intense extreme events threaten economic stability and livelihoods. In the United States (US) and globally, physical climate shocks – such as hurricanes, floods, wildfires, and extreme temperature anomalies – have grown more frequent and severe over the past decades.[1] These events can inflict billions of dollars in damages and disrupt economic activity across sectors. A critical but often overlooked consequence of such climate extremes is their impact on the labor market, particularly on employment and the social safety nets that support workers. When a hurricane ravages a region or a heatwave stifles productivity, businesses may be forced to scale back or shut down, leading to sudden job losses. For instance, recent research shows that hurricanes significantly increase initial unemployment insurance claims, with larger spikes following more intense storms (Hancevic and Sandoval, 2025). Similarly, extreme temperature days have been found to freeze hiring and trigger layoffs, resulting in higher unemployment insurance claims and recipients (Rujiwattanapong and Yoshida, 2025). These findings underscore that acute weather shocks can translate swiftly into surges in unemployment claims, as workers lose jobs and turn to unemployment insurance for support.

The labor market disruptions caused by climate shocks operate through multiple channels. In the short run, climate-related disasters create cyclical unemployment: businesses facing damages or interruptions may lay off workers, pushing more individuals to file for unemployment benefits. Over a longer horizon, repeated climate shocks can also contribute to structural unemployment. Workers in climate-vulnerable industries (for example, agriculture during droughts or tourism in the wake of coastal storms) may find their skills less applicable if those industries contract or if production shifts towards more climate-resilient technologies. Moreover, the broader push for a low-carbon economy, while crucial for mitigation, can itself induce labor market shifts. As carbon-intensive industries downsize or transform, workers in those sectors may be displaced unless they retrain, echoing elements of transition risk in the labor market. In this regard, climate change poses a dual threat: physical risks from the direct impact of abnormal weather and transition risks from policy and market shifts in response to climate change (Deryugina, 2017, Liu and Lin, 2023). Both

[1] https://www.ncei.noaa.gov/access/billions/time-series#:~:text=Visualize%20the%20frequency%20and%20cost,using%20the%20interactive%20time%20series

types of shocks can increase friction in job matching and elevate unemployment, either temporarily or persistently. Households bear the immediate brunt through lost income, while governments face mounting pressure to finance relief and adaptation programs. Recent evidence from the United States highlights these fiscal pressures: hurricanes lead to substantial long-term increases in government transfers like unemployment insurance and public assistance in affected areas. In other words, climate shocks not only displace workers, but also strain public finances via higher outlays on social safety nets.

Against this backdrop, the present study examines how climate shocks affect unemployment insurance claims – a high-frequency indicator that captures both individual job losses and the resulting government support provided. Most existing literature on climate change and labor markets has focused on broader measures like the unemployment rate or employment levels (e.g. the share of people employed) (Gray et al., 2023; Kim et al., 2025). These studies provide important insights, such as evidence that global warming tends to raise unemployment rates through channels like reduced agricultural output and higher inflation (Liu and Lin, 2023), and that climate variability can alter labor productivity and migration patterns with labor market repercussions (Mueller et al., 2020). In specific national contexts, researchers have found mixed effects – for example, climate change has been associated with higher unemployment in some regions but lower in others, and with gender- or sector-specific impacts (women and agriculture often being more vulnerable)[2]. However, a critical gap remains in understanding the link between climate shocks and unemployment insurance claims, which are a more direct measure of labor market stress and an automatic fiscal stabilizer. Unemployment claims spike when people lose jobs suddenly, making them a leading indicator of rising unemployment. They also represent an immediate fiscal cost to the government through unemployment insurance payouts. Focusing on claims, rather than only the unemployment rate, enables us to capture the dual transmission of climate shocks: the microeconomic impact on households (via increased jobless claims) and the macroeconomic impact on public finances (via greater insurance payments). Furthermore, claims data are available at higher frequency (weekly in the U.S.), allowing for a timely assessment of climate shock impacts which might be diluted or delayed in monthly unemployment statistics. By examining both initial claims (new filings for unemployment insurance) and continuing claims

[2] https://www.nelp.org/october-jobs-report-climate-disasters-contribute-to-slowing-job-growth/

(ongoing benefit rolls), we differentiate between the immediate inflow of newly unemployed individuals and the persistence of unemployment over time. This distinction is important because climate shocks might cause a sudden influx of layoffs (affecting initial claims) and potentially longer spells of joblessness (affecting continuing claims) if recovery and re-employment are slow.

This study contributes to the literature by providing the first empirical analysis of climate shock impacts on unemployment claims in the US. Following the approach of Caporin et al., (2025), we construct the state-level climate risk measure that captures abnormal weather patterns and extreme climate conditions across the 50 US states. This comprehensive climate risk measure encompasses meteorological anomalies – such as deviations in temperature (e.g. extreme heat or cold), precipitation (heavy rainfall or drought), and wind activity – which are directly linked to physical climate risks. By using state-level data from 1995 to 2025 at a weekly frequency, we can exploit variation in climate shocks and labor market responses both over time and across regions. Our empirical approach employs the local projections (LP) framework of Jordà (2005) to estimate the dynamic effect of a climate shock on unemployment claims. The LP method is well-suited for this analysis as it enables flexible estimation of impulse response functions without imposing strong restrictions on a specific structural model. While this approach is standard in macroeconomic analysis (and thus not a methodological innovation per se), it allows us to easily extend the model to explore nonlinear, state-dependent effects (following Auerbach and Gorodnichenko, 2013). We estimate both linear models and regime-switching models where the impact of a climate shock can differ depending on the prevailing climate risk level or the general economic conditions. This asymmetric framework recognizes that the labor market fallout from a climate shock may be more severe in certain contexts – for example, an extreme weather event hitting an already fragile economy might push far more workers into unemployment than the same event would during a robust expansion. Likewise, when climate risks are chronically high (e.g. during a season of repeated storms or persistent drought), the marginal effect of an additional shock could be amplified compared to periods of low climate risk. We incorporate a broad set of control variables (such as state-level economic conditions indices, stock market returns, and national financial indicators including interest rates, credit spreads, economic uncertainty, and sentiment indices) to isolate the specific influence of climate shocks on unemployment claims amidst other concurrent economic fluctuations.

Our analysis yields several important findings. Climate shocks have a significant positive effect on both initial and continuing unemployment claims in the US. In the linear specification, a one-standard deviation rise in the climate risk index (i.e. an abnormal climate shock) leads to a notable increase in new unemployment claims, peaking within a few months of the shock. Continuing claims also rise in response, though somewhat less sharply and for a shorter duration than initial claims. This indicates that climate-induced layoffs occur quickly, which is reflected in the initial claims surge, while the effect on prolonged unemployment (those staying on benefits) is present but relatively moderate. Notably, the impact on initial claims is stronger, suggesting that climate shocks manifest first as a wave of new job losses, many of which may be resolved or recalled relatively soon (thereby not all translating into long-term unemployment). These results align with our expectations and with anecdotal evidence from disaster episodes: for example, after a major hurricane strikes, initial claims tend to jump immediately as businesses close and workers file for benefits, and then in subsequent months many workers return to work as reconstruction begins, tempering the rise in continuing claims.

When we allow for nonlinear, state-dependent effects, we uncover clear asymmetries in how climate shocks impact unemployment claims. First, using the climate risk level itself as the regime variable, we find that under high-risk conditions, climate shocks induce a larger increase in initial claims than under low-risk conditions. Intuitively, in states or periods already facing elevated climate stress (e.g. multiple disasters or ongoing extreme weather), an additional shock can overwhelm employers' coping capacity, leading to outsized layoffs. In contrast, continuing claims respond more under the low-climate risk regime: when a surprise climate shock hits an area that is typically more climate-stable, it may lead to longer-lasting unemployment for those affected (perhaps due to less preparedness or experience of recovery, causing a slower return to work). These asymmetric patterns suggest that the persistence and magnitude of job losses from climate events depend on the broader climate risk environment. Second, using the economic cycle as a regime variable, we observe that climate shocks have a bigger impact on unemployment claims during economic expansions than recessions. In an expansionary period with low baseline unemployment, a climate disaster's layoffs represent a more significant departure from the norm, and the availability of other jobs might be limited if the shock disrupts the local economy's core activities. Paradoxically, during recessions, the marginal effect of a climate shock on claims is muted – not because the shock is less severe, but because unemployment is already elevated and many firms are already strained. In downturns, some of the workers hit by a climate event might have already been unemployed or find it easier to be absorbed in existing relief programs, whereas in good times a climate event creates a stark spike from a low baseline. This result aligns with the idea of unemployment insurance acting as an automatic stabilizer: in a recessionary regime, the safety net is already engaged at high levels, so an additional climate shock adds comparatively less to the total claims than it would during a boom when claims are low (Deryugina, 2017). Overall, these nonlinear findings highlight that climate shocks affect labor markets in complex, state-dependent ways. High underlying climate risk can exacerbate immediate layoffs, while strong economic conditions can paradoxically amplify the shock's relative impact on jobless claims. Any analysis that treated the climate–labor linkage as uniform would miss these important nuances.

In summary, our study provides new evidence that abnormal climate events have significant and multifaceted repercussions for the labor market, as captured by unemployment insurance claims. By focusing on the US, which features one of the world's largest and most institutionalized unemployment insurance systems, our findings carry implications not only for national policymakers but also more broadly. In the US, unemployment insurance program covers over 140 million workers and disburses critical support in times of economic distress (Von Wachter, 2019). Understanding how climate shocks drive claims in this context can inform how other economies might need to bolster their social protection systems in the face of climate change. The results underscore the importance of integrating climate risk considerations into labor market policies and fiscal planning. Policymakers may need to prepare for surges in unemployment claims following extreme weather events by enhancing the responsiveness of unemployment insurance and disaster unemployment assistance programs3, budgeting for higher contingent liabilities, and encouraging businesses to develop adaptation strategies that minimize layoffs (such as climate-proofing infrastructure or flexible work arrangements during disasters). In high climate risk regions, proactive measures – like investments in resilient infrastructure, job transition programs for at-risk industries, and emergency employment schemes – could mitigate the impact of recurrent shocks

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[3] https://www.usa.gov/disaster-unemployment#:~:text=Unemployment%20benefits%20after%20a%20disaster,eligible%20and%20how%20to%20apply

on workers. Likewise, during economic expansions, incorporating climate resilience into growth strategies can prevent climate setbacks from undoing employment gains. Moreover, our work also contributes to the growing literature at the intersection of climate economics and labor economics by shifting the focus to high-frequency labor market indicators and by revealing nonlinear impact dynamics.

The remainder of this study is organized as follows. Section 2 reviews the related literature and identifies the gap addressed by this paper. Section 3 outlines the data and methodological framework guiding the empirical analysis. Section 4 presents and discusses the results, and Section 5 concludes and offers some policy implications.

2. Literature Survey and Gap

Climate change constitutes a systemic risk to the global economy, affecting key sectors such as agriculture, energy, transportation, and real estate, which also serve as major sources of employment. Consequently, the literature is extensive, with discussions broadly classified in this study into four strands: (i) those that measure climate change and its associated risks (Engle et al., 2020; Eckstein et al., 2021; Faccini et al., 2023; Bua et al., 2024; Ma et al., 2024a,b, 2025; Caporin et al., 2025; Salisu and Salisu, 2025); (ii) those that link such risks to broader macroeconomic and social fundamentals including poverty, forced migration, inflation, and growth (Skoufias et al., 2011; Leichenko and Silva, 2014; McNamara et al., 2015; Maurel and Tuccio, 2016; Cattaneo and Bosetti, 2017; Hallegatte et al., 2018; Marotzke et al., 2020; Maganga et al., 2021; Mukherjee and Ouattara, 2021; Nguyen and Sean, 2021; Almajali, 2023; Li et al., 2023; Beirne et al., 2024; Cevik and Jalles, 2024; Gupta et al., 2024; Yusifzada, 2024; Salisu and Salisu, 2025)[4]; (iii) those that specifically examine the consequences for unemployment (Babiker and Eckaus, 2007; Mueller et al., 2020; Liu and Lin, 2023; Castellanos and Heutel, 2024; Yunus et al., 2024; Abdullahi et al., 2025); and (iv) those emphasizing adaptive and mitigating strategies, including financing climate actions (Jones et al., 2007; Laukkonen et al., 2009; Marangoni et al., 2021; Wang et al., 2023; Shang et al., 2024).

[4]Tracing the channels of climate risks through macroeconomic and social fundamentals such as inflation, growth, poverty, and migration is essential, as disruptions in these areas ultimately feed into unemployment dynamics, and by extension, unemployment claims.

Specifically, some of the measures of climate risks focus specifically on extreme weather events such as storms, floods, heatwaves, snowfalls, and wind speed (Eckstein et al., 2021; Caporin et al., 2025). Others have explored the uncertainty surrounding climate change in developing climate change indices (Ma et al., 2024a, b, 2025). Additionally, some other studies have classified climate risks into physical and transition risks, given their distinct impacts on various sectors of the economy (Engle et al., 2020; Faccini et al., 2023; Bua et al., 2024). Essentially, physical-related climate risks refer to the direct disruptive effects of extreme weather events, such as droughts and wildfires driven by extreme heat, or floods caused by intense rainfall on an economy. These events often have a particularly severe impact on public infrastructure, placing significant strain on government budgets due to the need for emergency interventions. The attendant effect of these is in hindrance of economic growth and development prospects. In contrast, transition risks arise from the unintended consequences of climate mitigation strategies such as climate policies and the uncertainties surrounding same. These include adverse effects on businesses, labor market disruptions due to forced migration, and the challenges associated with adopting eco-friendly technologies in production processes.

Consequent upon the above, efforts to mitigate climate risks have gained significant traction in recent years, particularly following Mark Carney's landmark 2015 speech[5] highlighting the threat climate change poses to financial stability. This catalysed cross-border collaboration, with central banks such as the ECB echoing similar concerns and leading to the inclusion of finance and capital markets in the 2015 Paris Agreement and COP21. The Agreement seeks to keep global warming significantly below 2 degree Centigrade above pre-industrial levels, aiming for a limit of 1.5°C by 2050 through substantial reductions in carbon emissions. Supporting this momentum, the G20's Financial Stability Board created the Task Force on Climate-related Financial Disclosures (TCFD) to improve investor transparency. Meanwhile, both the European Central Bank (ECB) and the Bank of England began incorporating climate factors into their monetary policy and asset purchase schemes in 2021. Other institutions, including the Basel Committee on Banking Supervision (BCBS) and the United Nations Environment Programme (UNEP) also issued guidance[6] to help

[5]https://www.google.com/search?q=Mark+Carney%E2%80%99s+2015+inaugural+speech+on+the+harm+caused+by+climate+risks+to+financial+systems&oq=
[6]https://www.unepfi.org/industries/banking/from-disclosure-to-action/

identify and manage financial risks linked to climate change. Furthermore, the Helsinki Principles, endorsed by nearly 100 finance ministries, promote fiscal policy coordination to support climate goals (see Adeyemi et al., 2025).

Despite these efforts as well as the empirical attempt to examine the impact of climate shocks on macroeconomic variables and mitigation strategies (see Batten, 2018, for a discussion on the importance of aligning policymaking and macroeconomic modelling with climate concerns), little attention has been given to their effects on unemployment, with existing work largely skewed towards other economic fundamentals. Yet, this dimension is crucial, as climate risks may affect different forms of unemployment (e.g., frictional, structural, cyclical) in distinct ways, while also shaping the trajectory of aggregate unemployment. Assessing this channel is crucial for understanding the broader implications of climate change for labor markets and fiscal policy, particularly in relation to increased social security spending. This study addresses this gap by investigating the implications of climate shocks for unemployment claims within both linear and non-linear frameworks. Extending the analysis to include non-linear specifications is essential to capture potential asymmetries, as the effects of low versus high climate risk regimes are unlikely to be identical.

As a summary of existing empirical findings, the various measures of climate-related risks have been employed to examine the influence of climate risks on economic fundamentals, with various mitigation strategies being proposed. These economic channels double as the medium through which the influence of climate-related disasters are transmitted to the aggregate economy and particularly, to the labor market (see the preceding discussion).

Within this context, labor market outcomes, particularly unemployment, have also been examined (Babiker and Eckaus, 2007; Kono, 2020; Ngepah and Conselho, 2022; Mueller et al., 2023; Liu and Lin, 2023; Adekunle, 2024; Castellanos and Heutel, 2024; Yunus et al., 2024; Abdullahi et al., 2025; Ntamack and Song, 2025). Evidence at the national level is mixed. For example, climate change exerts a negative effect on the unemployment rate in Somalia (Abdullahi et al., 2025), whereas in South Africa, it has a positive impact (Adekunle, 2024). Meanwhile, Ngepah and Conselho (2022) find that climate change lowers the likelihood of employment more for men than for women, whereas extreme events exert a stronger negative effect on female employment relative to males in South Africa. Yunus et al. (2024) find that temperature variability does not directly affect cyclical unemployment in Indonesia but does so indirectly through its negative effect on productivity. Castellanos and Heutel (2024), using a computable general equilibrium model for the U.S., show that the effect of climate policy (carbon tax per ton) on aggregate unemployment is small and similar across two labor mobility assumptions. However, the unemployment effect in fossil fuel sectors is much larger under the immobility assumption, suggesting that models excluding labor mobility frictions may substantially under-predict sectoral unemployment effects.

At the international level, Liu and Lin (2023) demonstrate that global warming raises unemployment through channels such as inflation, agricultural production, and urbanization. Their results also reveal heterogeneity across regions and groups: unemployment rises with global warming in countries located between 20 degrees and 40 degrees latitude, while the effect is negative in countries above 40 degrees. Moreover, global warming significantly increases unemployment among men but not women, and the effect is stronger in middle-income countries compared to low- and high-income ones. In a related finding, Ntamack and Song (2025) demonstrate that climate change significantly reduces women's labor market participation in Africa, largely because of their heightened vulnerability in agriculture which doubles as their primary source earning. Mueller et al. (2020) further highlight migration as a key channel linking climate change to unemployment in middle-income African countries.

Babiker and Eckaus (2007) emphasize the importance of offsetting policies to cushion the adverse labor market effects of emission reductions. Building on the compensation hypothesis, Kono (2020) shows that legislators from carbon-intensive constituencies are less likely to support carbon restrictions, though this effect weakens when unemployment benefits are generous. In fact, generous unemployment insurance is found to increase the likelihood of voting for carbon restrictions, particularly in carbon-intensive regions.

Despite these insights, how climate risks affect unemployment claims remains empirically unexplored, a gap this study seeks to address. The closest is Kono's (2020) work, which centers on political considerations surrounding compensation for climate-related disruptions, but does not examine the direct link between climate risks and unemployment claims which have a broader implication for climate-related unemployment phenomenon.

3. Data and Methodology

3.1 Data

We collect daily weather data also from the Bloomberg terminal, as compiled by the National Climatic Data Center (NCDC), for the 50 states. The weather data captures meteorological phenomena along several dimensions, including temperature, precipitation, number of heating degree days (HDD), number of cooling degree days (CDD), and wind speed as described below

- *Temperature ($temp_t$)*: The average temperature (usually of the high and low) that was observed between 7am and 7pm local time, expressed in Fahrenheit.
- *HDD (HDD_t)*: The number of degrees that the day's average temperature is below 65 degrees Fahrenheit. It's used to calculate the heating requirements of a building.
- *CDD (CDD_t)*: The number of degrees the day's average temperature is above 65 degrees Fahrenheit, aiding in estimating a building's cooling needs.
- *Precipitation ($precip_t$)*: The amount of rain, snow, sleet, or hail that falls in a specific location.
- *Wind speed ($wind_t$)*: The average speed of the wind, not accounting for gusts, represented in knots.

Following Choi et al. (2020) and Caporin et al., (2025), we decompose the weather-related variables into three components that account for seasonal, predictable, and abnormal patterns. In particular, for each day, t, we compute the daily weather measure (W_t) for each of the states, using the following formula:

$$W_t = W_t^M + W_t^P + W_t^A$$

where $W_t = \{temp_t, HDD_t, CDD_t, precip_t, wind_t\}$, and the term W_t^M denotes the mean of W_t for a specific state spanning 10 years prior to t. Moreover, the variable W_t^P denotes the difference of the mean of the deviation of the W_t from the daily average temperature for a particular state in the same calendar day over the last ten years and W_t^M . Finally, the variable W_t^A is the remainder (i.e., the abnormal deviation of weather conditions) and, hence, captures extreme departures from normal weather conditions. For this reason, we focus on this variable in our analysis. We standardize (denoted by std.) the abnormal deviations, commonly known as the standardized anomaly, to obtain the following comprehensive climate risk (*CR*) measure:

$$CR_t = \frac{std(temp_t^A) + std(precip_t^A) + std(CDD_t^A) - std(HDD_t^A) + std(wind_t^A)}{5}$$

Since the unemployment claims data, which we describe below is weekly, we convert the daily CR values to weekly by taking seven-day averages.

The unemployment insurance claims data are published weekly by the U.S. Department of Labor, Employment & Training Administration (ETA) through its Unemployment Insurance Weekly Claims Report (ETA 539). We downloaded the official dataset directly from the Department of Labor. The data include two key measures: initial claims (*claims_in)* and continuing claims (*claims_co)*. Initial claims represent the number of individuals filing for unemployment insurance for the first time in a given week (or reopening a claim after reemployment). This metric is used as an early indicator of new layoffs and provides a high-frequency view of emerging labor market conditions. By contrast, continuing claims (also called insured unemployment) capture the number of individuals who remain on unemployment insurance after their initial claim. This figure reflects the ongoing level of insured unemployment, showing how many people continue to rely on benefits week after week.

Furthermore, we control various state- and national-level factors. At the state level, the controls include an economic conditions index (*ECI*)[7] – which captures whether the state-economy is in expansion or contraction – adjusted distinctly[8] for initial and continuing claims to mitigate possible multicollinearity, given that unemployment-related variables (including claims, our dependent variable), are among the variables used in its construction. We use state-level stock returns *(stock_ret*) as an additional state-level control. At the national level, we incorporate several financial and macroeconomic variables, including the corporate bond spread (*bond*), the Federal

[7]The economic conditions index is constructed by aggregating weekly, monthly and quarterly data that cover multiple dimensions namely, mobility measures, labor market indicators, real economic activity, expectations measures, financial indicators, and household indicators, into a single composite measure that tracks fluctuations in US state-level economic performance (see, Baumeister et al., 2024).

[8] We basically regress the ECI for each state on unemployment insurance and recover the residual and use it in our analysis, to capture filtered ECIs.

Reserve Bank of San Francisco's news-based economic sentiment index (*eco_sent*), the federal funds effective rate (*ffer*), the US economic policy uncertainty index (*EPU*) of Baker et al. (2016), the CBOE volatility index (*VIX*), Caldara and Iacoviello's (2022) geopolitical risk index (*GPR*), and the term spread (*TS*). A summary of these variables is provided in the appendix (see Table A1). In particular, our weekly data cover January 1995 through January 2025, and the sources are provided as follows: state-level unemployment claims (US Department of Labor)[9], the economic conditions index (Baumeister et al., 2024)[10], bond, term spread, and stock price data (Bloomberg)[11], the news sentiment index[12], the federal funds effective rate[13], the economic policy uncertainty index[14], CBOE volatility index[15], and the geopolitical risk index (Caldara and Iacoviello, 2022)[16]. The descriptive statistics of the data presented in Table A2a-c of the appendix[17].

Furthermore, we conduct pairwise correlation analysis among the dependent, independent, and control variables to assess potential multicollinearity issues prior to model estimation. This approach ensures that the predictor variables are not excessively correlated. The correlation results, along with statistical significance levels, are presented in Table A3. Our findings indicate that none of the variables of interest exhibit problematic multicollinearity, except for the pairs of initial and

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[9] https://oui.doleta.gov/unemploy/claims.asp
[10] https://sites.google.com/site/cjsbaumeister/datasets
[11] https://www.bloomberg.com/professional/products/data/enterprise-catalog/investment-research-data/?utm_source=google&utm_medium=paid_search&utm_campaign=global_techdata_bsss_2025_ao&utm_content=text_research-data&tactic=951953&gclsrc=aw.ds&gad_source=1&gad_campaignid=22294252522&gbraid=0AAAAADdH1c_beIJOJG48brvGadKd1qa2A&gclid=Cj0KCQjw5onGBhDeARIsAFK6QJaUS85V7K03RE1TKlvJp65gxNIqXvpDyRyCl46ZwrfJOk_uTONgAkwaAgUDEALw_wcB
[12] https://www.frbsf.org/research-and-insights/data-and-indicators/daily-news-sentiment-index/
[13] https://fred.stlouisfed.org/series/FEDFUNDS
[14] https://www.policyuncertainty.com/categorical_epu.html
[15] https://fred.stlouisfed.org/series/VIXCLS
[16] https://www.matteoiacoviello.com/gpr.htm
[17] Table A2 (a–c) reports descriptive statistics for climate risk and unemployment claims, showing that California consistently records the highest means and variability for both initial and continuing claims, while South Dakota and Wyoming exhibit the lowest levels and most stability. This contrast suggests stronger labor market volatility in larger, climate-vulnerable states like California, compared to smaller, more stable states. Both claims measures are positively skewed and leptokurtic, reflecting heavy-tailed distributions with greater likelihood of extreme values, whereas climate risk distributions vary across states in skewness and kurtosis. Overall, continuing claims tend to have higher averages and dispersion, but initial claims are more skewed and peaked, indicating sharper spikes in unemployment at the onset of labor market stress potentially influenced by climate risk.

continuing claims (*Claim-in* and *Claim-co*) as well as *ECI-in* and *ECI-co*, which are not included in the same model specification[18].

3.2 Methodology

This study adopts the local projections (LPs) approach of Jordà (2005) to examine the implications of climate risk for unemployment claims in the US. This approach offers a more recent alternative to the conventional VAR framework for estimating impulse response functions (see also, Olubusoye et al., 2023; Salisu et al., 2023). Unlike SVARs, LPs use single-equation estimations, which makes them especially useful for studying (non)linear dynamics or state-dependent effects (Jordà and Taylor, 2025), which is also the focus of this study. Moreover, Plagborg-Moller and Wolf (2021) show that the impulse responses obtained from local projections are generally equivalent to those derived from SVARs.

The linear model for computing impulse response functions (IRFs) using the LPs approach of Jordà (2005) is specified as follows:

$$UC_{i,t+s} = \alpha_{i,s} + \beta_s CRShocks_{i,t} + \gamma_s Z_{i,t} + \epsilon_{i,t+s}, \text{ for } s = 0,1,2,\dots H \tag{1}$$

where $UC_{i,t+s}$ is the levels of unemployment claims in the US state i in week $t + s$, and s is the forecast horizon.[19] The coefficient β_s captures the response of $UC_{i,t+s}$ in week $t + s$ to $CRShock_{i,t}$ in week *t,* and the shock is given by the innovation of the climate risk in the US state i in week *t*.[20] The local projections impulse response functions (LPs-IRFs) are computed as a series of β_s estimated separately for each horizon. We also account for unobserved heterogeneity across different US states and include an individual fixed effect in a panel specification (as captured by $\alpha_{i,s}$). Z_t is a vector of control variables (including state-level economic conditions index – which captures whether the economy is in expansion or contraction – adjusted distinctly for initial and

[18]In addition to these tests, we examine the stationarity of status of our series and find that all of them pass the unit root tests (see appendix for details). Ensuring stationarity is crucial for the validity of LP, as non-stationary series may yield biased impulse response estimates (Herbst and Johannsen, 2024), and the LP framework generally assumes stationarity (Plagborg-Moller and Wolf, 2021).

[19]The maximum length of forecast horizon is set to 52 in this study, corresponding to a maximum length of the 52-week ahead forecast horizon.

[20]$Shocks_{i,t}$ are obtained from the residuals of the AR (1) panel data model regressing the climate risks (and ECI) of the US states on its lag.

continuing claims, and state-level stock returns; national variables such as bonds, dollar index, economic sentiment, US Federal Funds Effective Rate, geopolitical risk, term spread, economic policy uncertainty, and volatility measure – VIX).

Following Auerbach and Gorodnichenko (2013) and Jordà et al. (2021), we employ two regime-dependent models to examine the asymmetric effects of climate risk shocks on unemployment claims across high- and low-regimes states of climate risks and economic conditions.

$$UC_{i,t+s} = \left(1 - F\left(z_{i,t}\right)\right)\left[\alpha_{i,s}^{High} + \beta_s^{High} Shocks_{i,t} + \gamma_s^{High} Z_{i,t}\right] + F\left(z_{i,t}\right)\left[\alpha_{i,s}^{Low} + \beta_s^{Low} Shocks_{i,t} + \gamma_s^{low} Z_{i,t}\right] + \epsilon_{i,t+s}, \quad \text{for } s = 0,1,2, \dots H \tag{2}$$

$$F\left(z_{i,t}\right) = \exp(-z_{i,t})/1 + \exp(-z_{i,t}), \tag{3}$$

Here $Shocks_{i,t}$ denote the shock variables, namely climate risk and economic conditions. The model(s) incorporate a smooth transition function $F\left(z_{i,t}\right)$ to distinguish between the high and low regimes of these variables. $z_{i,t}$ is a switching variable capturing state-level climate risks and economic conditions and is normalized to have a zero mean and unit variance. $F\left(z_{i,t}\right)$ is the smooth transition function that has a bound between 0 and 1, with values close to 1 representing the low regime of climate risks (and economic conditions), and 0 otherwise. Superscripts *High* and *Low* are used to denote the respective regimes.

Although the LP method is widely used in macroeconomic analysis owing to its simplicity, flexibility, and robustness to model misspecification (see Ramey, 2016), it is not without limitations. Herbst and Johannsen (2024) show that when LPs are applied to persistent time series with small samples, the resulting impulse response estimates may be biased. In addition, Gonçalves et al. (2024) highlight that, within a regime-dependent framework, if the state variable is endogenous, the LP estimator cannot recover the true population response.

These concerns, however, do not affect our analysis. First, our weekly series is long and not persistent (see Table A4 and the associated discussion). Second, the climate shocks can reasonably be treated as exogenous. That is, the unemployment claims impulse responses are not state-dependent with respect to the occurrence of shocks.

4. Results and Discussion

This section reports the findings from our linear and nonlinear analyses of how climate shocks influence unemployment claims in the US. We examine the behavior of both initial and continuing claims in relation to the US state specific climate risks measure based on abnormal weather shocks. The findings, particularly across the 52-week forecast horizons and under the asymmetric (high vs. low regimes) effects of climate shocks, provide a basis for targeted policy recommendations. It is important to note that for the non-linear analysis, we report IRFs in the high and low regimes of two switching variables: climate risks and economic conditions. The latter is particularly relevant, as economic conditions are closely tied to carbon emissions, consistent with the Kuznets hypothesis. Thus, we also trace the response of unemployment claims to climate shocks through the lens of prevailing economic conditions.

As previously mentioned, the responses of our dependent variable to climate shocks are examined alongside several macroeconomic and financial fundamentals. Specifically, the LP models incorporate controls such as bond markets, the adjusted economic conditions index, economic sentiment, the geopolitical risk volatility index, and economic policy uncertainty, amongst others. This ensures that the influence of climate-related shocks is assessed not in isolation but in comparison with other systemic sources of uncertainty known to affect macroeconomic and labor market dynamics – including unemployment claims. In doing so, our framework offers a more robust and comprehensive understanding of the drivers of labor market outcomes alongside climate shocks.

4.1 Linear Results

Figure 1a depicts the impulse response of initial unemployment claims to a one-standard-deviation climate shock, while Figure 1b shows the corresponding response for continuing claims, both over a 52-week horizon with 95% confidence intervals. The shocks are identified from the residuals of an AR(1) model, and the forecast horizon spans 52 weeks. The patterns in these figures reveal important dynamics. Initial claims rise sharply in the wake of the climate shock, peaking around 14 weeks after the shock, before gradually tapering off. In contrast, continuing claims exhibit a more muted increase that dissipates faster, returning toward baseline well before the one-year mark. The early peak in initial claims indicates that the bulk of new unemployment filings occur within the first few months of the climate disruption, whereas the faster reversion of continuing claims suggests that many affected workers either return to work or exit unemployment insurance rolls relatively quickly. Notably, the 95% confidence bands in Figure 1a confirm that the surge in initial claims is statistically significant in the first several months (i.e. the impulse response is distinctly above zero), reflecting a robust spike in layoffs or separations triggered by the climate shock. By the later half of the year, the bands widen and encompass zero, indicating that initial claims effects subside and are no longer statistically distinguishable from no-change. For Figure 1b, the confidence intervals are narrower in the very short run – underscoring a significant but short-lived jump in continuing claims – and they contract toward zero more rapidly. In practical terms, this means the increase in ongoing benefit claimants is brief: the climate shock causes a transient swell of people staying on unemployment benefits, but that swell recedes within months as the labor market readjusts.

These impulse response functions can be understood through the lens of labor market flows and the nature of climate shocks. Initial claims measure the inflow of newly unemployed individuals. A climate shock – for example, an extreme weather event or an anomalous season – often produces an immediate wave of layoffs or work interruptions. Indeed, it is well documented that major natural disasters lead to sudden spikes in unemployment insurance applications (Martinez, 2025). For instance, in the week following a recent US hurricane (Hurricane Helene in 2024), initial jobless claims surged to their highest level in a year as businesses in the disaster-hit regions temporarily shut down, while continuing claims remained somewhat elevated in those states during the aftermath[21]. The pronounced rise in initial claims around weeks 2–18 in Figure 1a aligns with this intuition: the climate shock rapidly translates into job separations as firms in affected industries (e.g. construction, agriculture, tourism) either lay off workers or delay hiring. Some of these separations occur immediately (e.g. workers unable to work due to facility damages or

[21] https://home.treasury.gov/news/press-releases/jy2689#:~:text=low%20levels%20through%20the%20third,impacted%20states

weather-related closures), and some occur with a lag as second-round effects set in – for example, supply-chain disruptions or declines in local demand leading to additional layoffs weeks after the initial event. The fact that the initial claims response culminates at about 4½ months suggests that these cascading effects are largely front-loaded: the labor market absorbs the shock relatively quickly, with the highest inflows of unemployment happening in the first quarter after the shock.

Meanwhile, continuing claims represent the number of people remaining unemployed and claiming benefits week after week. The quicker peaking and faster decline of continuing claims (Figure 1b) indicate that the unemployment spells induced by the climate shock tend to be short-lived on average. In other words, many of the workers who lose jobs due to the shock either find re-employment or otherwise stop claiming benefits within a few months. This pattern can arise for several reasons grounded in economic and institutional mechanisms. First, climate shocks (such as storms or heatwaves) are typically transitory disruptions rather than permanent shocks to labor demand. Many affected businesses reopen or resume operations within weeks, and reconstruction or recovery efforts can spur hiring, allowing displaced workers to return to work relatively quickly. Empirical research on disaster impacts supports this transient effect: for example, in an analysis of US hurricanes, local employment initially falls by roughly 1.5–5% in the quarter of the disaster, but then partially rebounds in subsequent quarters as rebuilding activity picks up (Belasen and Polachek, 2008). This "cobweb" pattern of initial decline followed by recovery over the next year or two is consistent with the idea that climate-induced job losses are largely made up later by reconstruction and re-hirings. Second, the design of the unemployment insurance (UI) system imposes a natural time limit on continuing claims. Standard UI benefits in the US last about 26 weeks (approximately half a year) in normal times. Thus, even if some individuals remain unemployed beyond several months, they may drop out of the continuing claims statistics once their benefits are exhausted. The relatively quick dissipation of the continuing claims response could partly reflect this effect – the impulse response in Figure 1b falls toward zero by month 6–9, which is around the typical duration after which UI recipients either find jobs or exhaust benefits. In summary, the climate shock causes a surge in short-term unemployment (captured by initial claims) but does not translate into prolonged joblessness for most workers, as evidenced by the swift normalization of continuing claims.

[INSERT FIGURE 1A&B HERE]

4.2 Non-Linear Results

Since it is not immediately obvious that low and high climate-related shocks would affect labor market dynamics, and thus unemployment claims, in the same way, we extend our analysis to test for asymmetry in the relationship between climate-related shocks and unemployment claims (both initial and continuing). In this setting, we use climate risk (CR) as a regime-dependent variable and, also, employ the economic conditions index as an additional regime variable, given its close link with (un)employment dynamics. The corresponding results are presented in Figure 2 (a&b) and 3 (a&b), respectively.

Figure 2 (a&b) presents the non-linear LP results for initial and continuing unemployment claims in response to one-standard-deviation climate shocks. Overall, we find that climate shocks exert a stronger effect on initial unemployment claims under the high-climate-shock regime, whereas continuing claims respond more under the low regime (see Figure 2a&b). This suggests asymmetric effects of climate shocks on unemployment claims. Breaking this further, for the initial claims under the high-climate-risk regime (LHS of Figure 2a), the response initially declines, turns positive over the 12–22 week horizons, and then becomes negative until around the 36th week. In contrast, under the low-climate-risk regime (RHS of Figure 2a), the short-term response resembles that of the high regime but diverges in the long run (28–52 weeks), where it becomes significantly positive. These results indicate that the asymmetric effect of climate shocks on initial claims is most pronounced at longer horizons.

The findings for continuing claims broadly mirror those for initial claims (Figure 2b). Under the high-climate-risk regime, asymmetry appears along the medium-term horizons (14–32 weeks), whereas under the low regime, it emerges slightly earlier, between 8–30 weeks. At longer horizons, the divergence becomes more evident: the response declines under the high regime but remains elevated under the low regime. By contrast, in the short term, the responses are largely similar across regimes.

The differing asymmetric impacts observed between initial and continuing claims suggest important distinctions in how climate shocks propagate through the labor market. For initial claims, asymmetry emerges primarily at longer horizons, with the low-climate-risk regime showing significantly positive responses from 28–52 weeks, while the high-risk regime turns negative after the medium-term rebound. This pattern indicates that climate shocks under lower-risk conditions may have more persistent consequences for new unemployment entries, reflecting slower recovery and weaker adjustment mechanisms when shocks are less anticipated. By contrast, for continuing claims, asymmetry is evident earlier—along the medium-term horizons (8–32 weeks)—with responses diverging across regimes at longer horizons, where the high-risk regime declines and the low-risk regime remains elevated. These results imply that while initial claims capture delayed but persistent effects of climate shocks, continuing claims are more sensitive to medium-term labor market frictions and institutional responses. Taken together, the findings underscore that the persistence of unemployment following climate shocks is conditional on both the type of claim and the prevailing climate risk environment, both of which have implications for the timing and policy intervention designs (see the concluding section).

Moreover, when the economic condition index (ECI) serves as the regime-switching variable, the effects indicate that climate risk shocks are more pronounced under economic expansions (high-ECI regime). In contrast, during recessions (low-ECI regime), when labor markets are already slack and claims are elevated, the marginal effect of climate risk shocks on unemployment claims is considerably weaker. This asymmetry suggests that the impact of climate risk is state-dependent, with stronger effects materializing in periods of economic expansion (see Figure 3a&b).

[INSERT FIGURES 2A-3B HERE]

5. Conclusion and policy implications

5.1 Conclusion

This study provides new evidence that abnormal climate events can destabilize labor markets, causing sharp spikes in unemployment insurance claims and straining public support systems. By analyzing high-frequency data on US unemployment claims from 1995 to 2025, the research demonstrates that climate shocks, such as extreme weather anomalies or natural disasters, lead to significant surges in jobless claims. A one-standard deviation increases in the climate risk index, which measures extreme deviations in temperature, precipitation, and related factors, results in a pronounced rise in initial unemployment claims, reflecting immediate layoffs and work disruptions. The effect on continuing claims is more moderate and short-lived, suggesting that many displaced workers either return to work or stop claiming benefits within a few months. In practical terms, climate disasters create a wave of sudden unemployment but do not necessarily translate into prolonged joblessness for most affected workers. For instance, recent findings indicate that hurricanes can increase unemployment insurance claims by about 25% on average, with major storms doubling claims and effects persisting for several months ((Hancevic and Sandoval, 2025). Likewise, extreme temperature days can freeze hiring, trigger layoffs, and temporarily drive-up claims. These results confirm that acute climate shocks rapidly translate into labor market dislocation, as businesses shut down or scale back and workers turn to safety nets for support.

Beyond these average effects, the analysis reveals important nonlinearities in how climate shocks affect labor markets. When baseline climate risk is already high, an additional shock causes a disproportionately large spike in unemployment claims, since employers and infrastructure are already stressed. Conversely, in areas with low climate risk, extreme events lead to more persistent continuing claims, reflecting slower recovery. This suggests that chronically exposed regions experience sharper but shorter-lived disruptions, while more stable areas face longer recovery times. Economic conditions also shape outcomes: climate shocks have a bigger impact during expansions, when they cause sudden spikes against a backdrop of low unemployment, while in recessions their marginal effect is muted because unemployment is already high. This aligns with the role of unemployment insurance as an automatic stabilizer, absorbing additional shocks when systems are already active.

Overall, our study highlights that climate change poses a multifaceted threat to labor markets, influencing both the frequency of job loss shocks and the duration of unemployment spells in ways that depend on prior risk exposure and macroeconomic conditions. By focusing on unemployment insurance claims, we capture both the immediate household impact and the short-term public finance implications of climate disasters. The findings underscore that extreme weather events quickly translate into surges in claims, adding nuance to anecdotal evidence from past disasters. Importantly, the analysis documents state-dependent dynamics: the effects of climate shocks vary based on local climate risks and broader economic environments. This finding is crucial for forecasting and policy design, as climate change emerges as a source of macro-labor volatility that heightens cyclical unemployment risks and imposes fiscal burdens on governments.

5.2 Policy implications

From a policy perspective, several implications arise. First, unemployment insurance systems should be strengthened to handle climate-induced surges, including adequate reserves, faster processing, and flexible rules during disasters. Disaster Unemployment Assistance programs should also be reinforced to extend benefits to nontraditional workers. Second, promoting climate-resilient business practices and infrastructure can reduce the need for mass layoffs in the first place, with targeted investments in high-risk regions yielding significant labor market benefits. Third, labor market reforms are needed to prepare workers for a climate-changed economy, including retraining for green and resilient jobs and strengthening social safety nets to enable a just transition. Fourth, climate-related labor risks should be integrated into macro-fiscal planning and international frameworks, with contingency funds, risk monitoring, and global cooperation supporting resilience. Finally, resilience planning must extend beyond infrastructure to livelihoods, combining adaptation, diversification, and job creation strategies that can shorten unemployment durations and build long-term economic security.

In conclusion, climate risk must be treated as a serious economic hazard requiring coordinated action by policymakers, businesses, and communities. Strengthening unemployment systems, encouraging adaptive practices, and embedding climate considerations into fiscal and labor policies will help safeguard workers and economies. For economists, these findings highlight the importance of incorporating climate variables into models of employment and public finance, as traditional analyses risk underestimating volatility by ignoring weather impacts. Climate change is no longer just an environmental issue; it is a present force shaping employment and welfare. Acting on these insights can help protect livelihoods and economic stability in an increasingly climate-uncertain future.

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Figures and Tables:

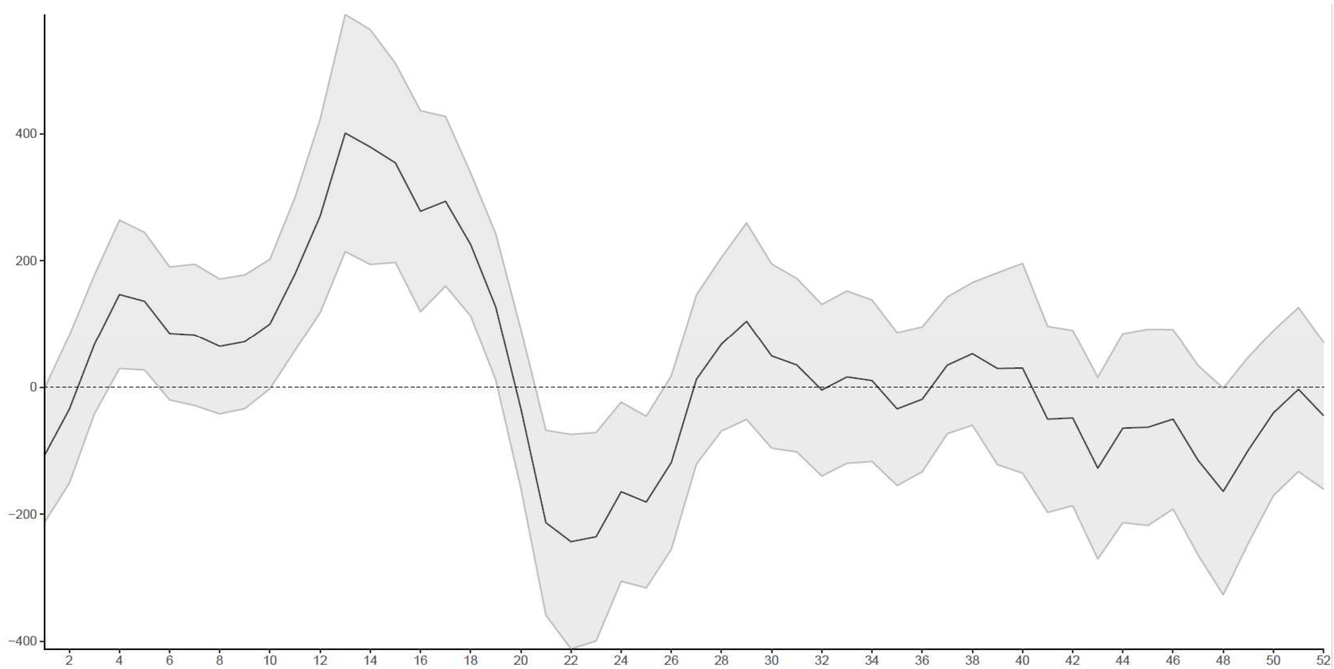

Figure 1a: LPs for the linear relationship between climate-related shocks and initial unemployment claims. Confidence intervals are reported at the 95% significance level.

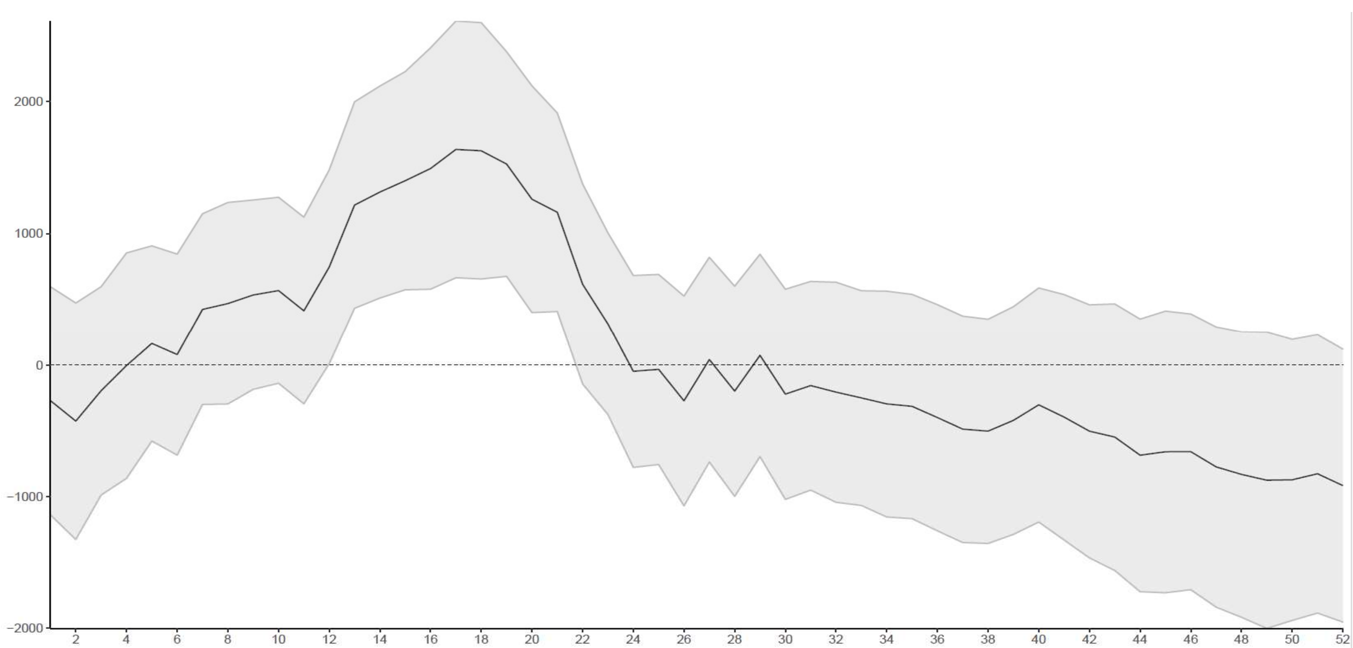

Figure 1b: LPs for the linear relationship between climate-related shocks and continuing unemployment claims. Confidence intervals are reported at the 95% significance level.

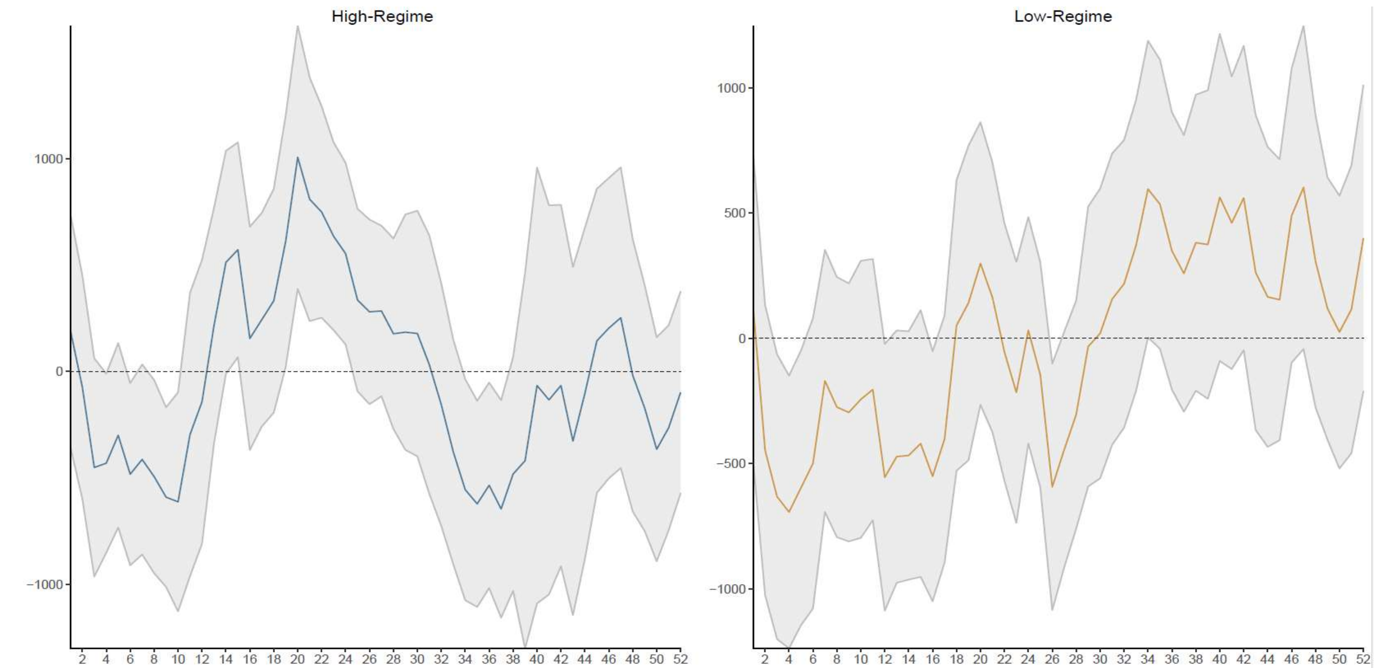

Figure 2a: LPs for the non-linear relationship between climate-related shocks and initial unemployment claims under high- and low-regime of climate risks. Confidence intervals are reported at the 95% significance level.

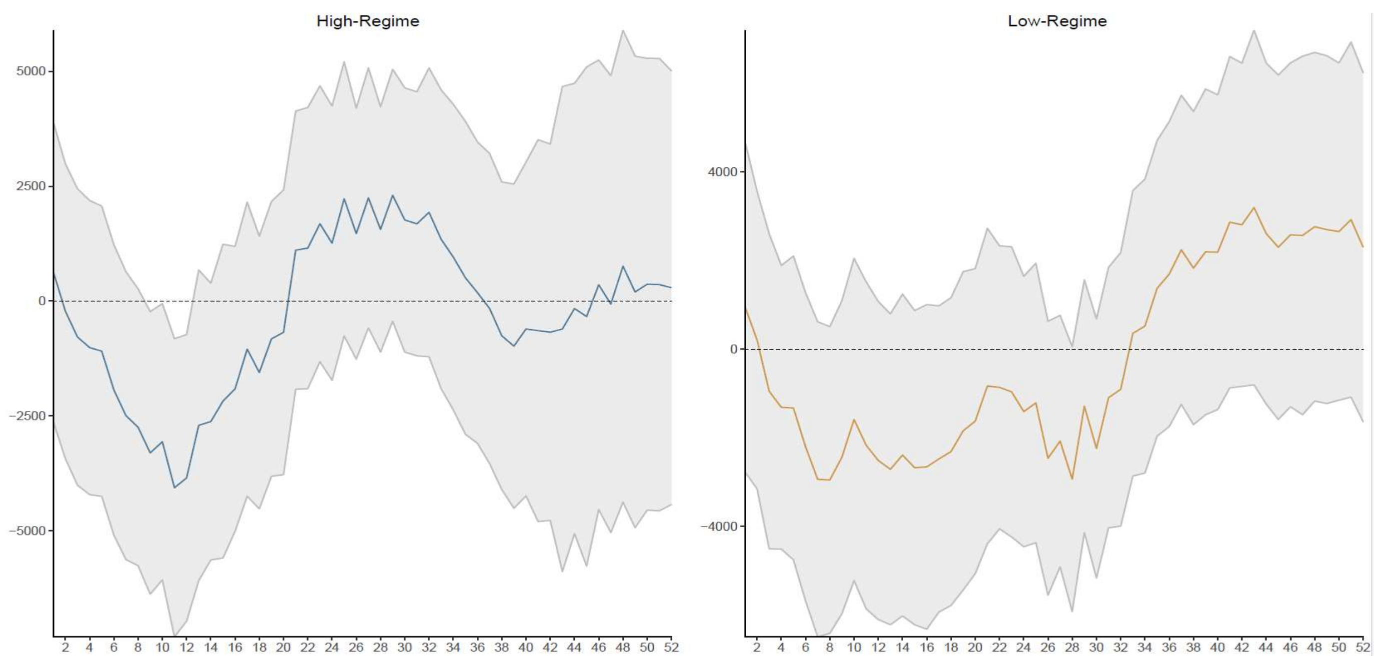

Figure 2b: LPs for the non-linear relationship between climate-related shocks and continuing unemployment claims under high- and low-regime of climate risks. Confidence intervals are reported at the 95% significance level.

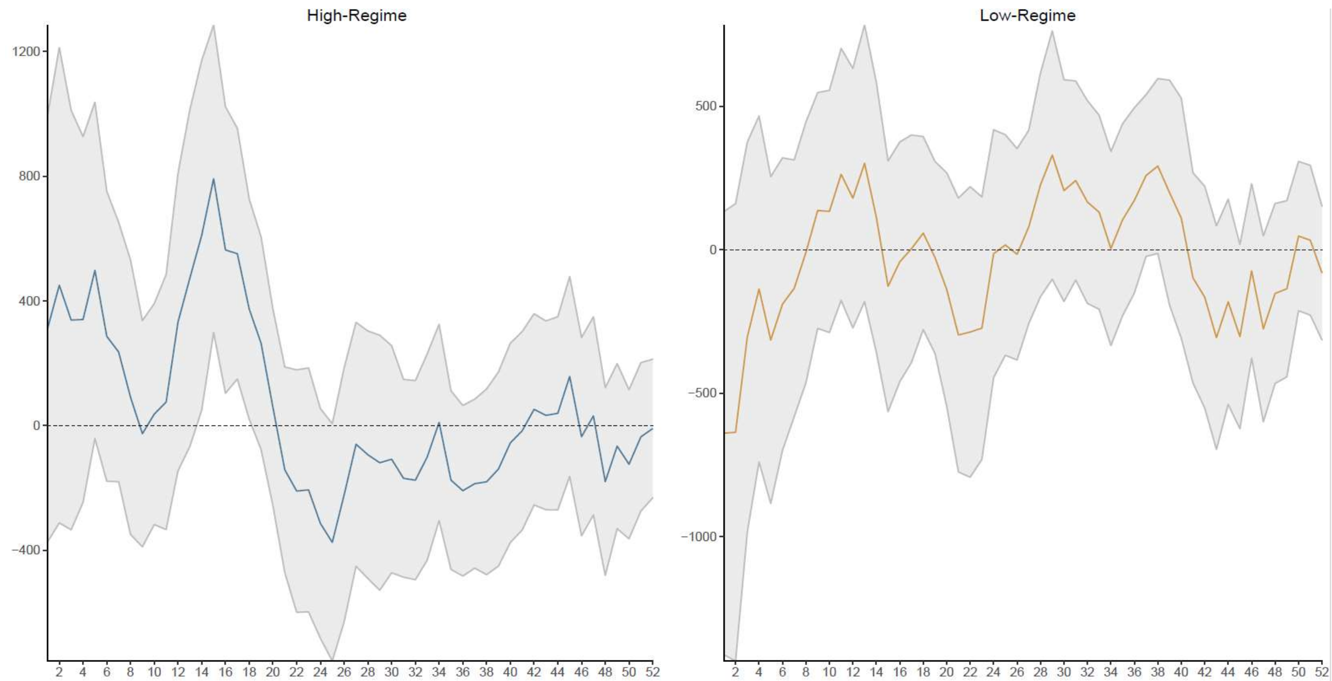

Figure 3a: LPs for the non-linear relationship between climate-related shocks and initial unemployment under high- and low-regime of Economic Condition Index – ECI (filtered for initial claims). Confidence intervals are reported at the 95% significance level.

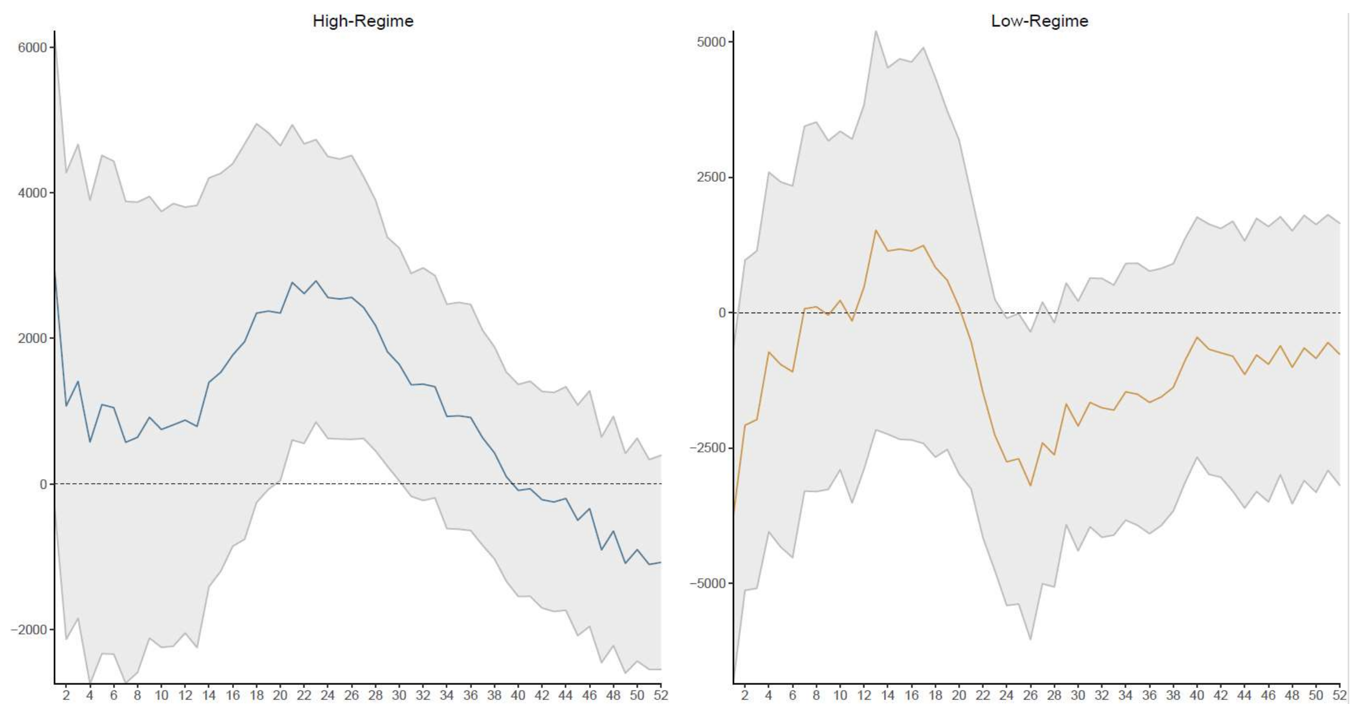

Figure 3b: LPs for the non-linear relationship between climate-related shocks and continuing unemployment claims under high- and low-regime of Economic Condition Index – ECI (filtered for continuing claims). Confidence intervals are reported at the 95% significance level.

Appendix

Table A1: Variable Descriptions

Variable	Acronym	Position	Measurement	Source
1. Climate Risk	CR	Independent Variable	Index	Caporin et al., 2025
2a. Unemployment Claims - Initial	Claims-in	Dependent Variable	Unit: Number	United States Department of Labor, Employment & Training Administration
2b. Unemployment Claims - Continuous	Claims-co	Dependent Variable	Unit: Number	United States Department of Labor, Employment & Training Administration
3a. Economic condition index adjusted for initial claims	ECI-in	State-level control variable	Index	Baumeister et al., 2024
3b. Economic condition index adjusted for continuous claims	ECI-co	State-level control variable	Index	Baumeister et al., 2024
4. Stock prices	Stocks	State-level control variable	USD	Bloomberg
5. Corporate bond spread	Bonds	National-level control variable	Rate	Bloomberg
6. US economic sentiment	Eco-sent	National-level control variable	Index	US Federal Reserve Bank of San Francisco
7. US Federal Funds Effective Rate	FFER	National-level control variable	Rate	Federal Reserve Bank of St. Louis
8. US Economic Policy Uncertainty Index	EPU	National-level control variable	Index	Economic Policy Uncertainty (see the link in the footnote)
9. Chicago Board Options Exchange volatility index	VIX	National-level control variable	Index	Federal Reserve Bank of St. Louis
10. Geopolitical risk index	GPR	National-level control variable	Index	Caldara and Iacaviello (2022)
11. Term spread	TS	National-level control variable	Rate	Bloomberg

Table A2a: Summary Statistics – initial claims

State	Mean	Std. Dev.	Skew.	Kurt.	Obs.
Alabama	5537.52	5546.61	9.56	137.42	1569
Alaska	1772.32	1102.61	4.72	40.94	1569
Arizona	4807.49	5707.71	14.10	254.90	1569
Arkansas	3691.53	2701.97	8.96	160.89	1569
California	58905.54	48115.97	12.21	209.07	1569
Colorado	3251.18	4142.64	15.26	304.71	1569
Connecticut	4597.58	3701.51	14.19	332.36	1569
Delaware	1041.73	1050.01	9.21	132.77	1569
Florida	13249.32	23118.30	13.12	226.22	1569
Georgia	11882.27	21354.98	10.47	137.84	1569
Hawaii	1826.98	2334.22	15.28	290.13	1569
Idaho	2149.14	1656.79	8.89	144.38	1569
Illinois	15114.35	13067.19	7.53	78.02	1569
Indiana	6756.88	7191.44	10.50	163.99	1569
Iowa	3576.66	3345.73	9.26	135.51	1569
Kansas	2936.96	2905.10	7.10	72.27	1569
Kentucky	5770.61	7567.54	9.69	123.76	1569
Louisiana	4056.29	6692.92	9.49	109.81	1569
Maine	1451.57	1429.30	11.57	192.82	1569
Maryland	5115.74	5397.24	10.37	151.08	1569
Massachusetts	8352.94	8845.67	11.46	180.50	1569
Michigan	15154.36	16379.99	13.14	254.87	1569
Minnesota	5702.99	6396.05	11.78	179.09	1569
Mississippi	3031.89	2955.42	7.89	89.88	1569
Missouri	7232.76	5710.25	9.72	144.18	1569
Montana	1245.55	1093.90	10.77	171.82	1569
Nebraska	1395.72	1270.51	12.27	215.46	1569
Nevada	3611.41	4374.66	13.47	227.12	1569
New Hampshire	1101.73	1849.08	13.49	225.85	1569
New Jersey	11561.75	10241.14	13.29	225.52	1569
New Mexico	1432.10	1514.20	9.89	137.09	1569
New York	23318.42	21741.32	10.39	145.14	1569
North Carolina	11932.00	11267.10	5.55	58.30	1569
North Dakota	611.78	725.91	10.68	169.32	1569
Ohio	13319.35	14439.86	10.14	139.26	1569
Oklahoma	2879.45	5506.28	11.00	140.86	1569
Oregon	6995.58	4024.75	5.95	63.49	1569
Pennsylvania	21748.75	16703.61	13.60	261.34	1569
Rhode Island	1862.93	1955.86	8.92	117.93	1569
South Carolina	5513.40	5550.60	8.18	101.14	1569
South Dakota	391.02	444.58	10.48	144.02	1569
Tennessee	6722.96	6234.33	7.27	93.12	1569
Texas	18927.89	19437.54	10.06	125.24	1569
Utah	1718.13	1594.02	12.01	195.37	1569
Vermont	806.15	757.98	11.66	205.75	1569
Virginia	6109.70	7325.21	10.41	155.32	1569
Washington	10198.36	10516.45	11.10	149.54	1569
West_Virginia	1656.58	1704.77	16.00	368.61	1569
Wisconsin	10728.17	7107.45	4.84	53.31	1569
Wyoming	523.65	401.62	7.64	94.73	1569
All	7265.58	14443.56	17.48	767.06	78450

Note: Std. Dev., Skew., Kurt., and Obs. denote standard deviation, skewness, kurtosis and number of observations, respectively.

Table A2b: Summary Statistics – continuing claims

State	Mean	Std. Dev.	Skew.	Kurt.	Obs.
Alabama	30450.95	19524.92	3.80	29.68	1569
Alaska	12195.98	5715.78	2.28	14.61	1569
Arizona	38709.85	29684.50	3.62	19.88	1569
Arkansas	26886.92	14396.12	2.11	13.03	1569
California	482059.80	340344.10	6.29	50.96	1569
Colorado	34165.85	28397.54	4.84	33.11	1569
Connecticut	47347.47	30494.32	5.10	36.92	1569
Delaware	8366.50	5261.67	4.63	33.05	1569
Florida	107472.90	103819.90	7.84	116.26	1569
Georgia	67906.04	85307.44	5.87	43.16	1569
Hawaii	12585.25	14950.86	6.53	48.82	1569
Idaho	13788.49	8764.38	1.90	9.14	1569
Illinois	151735.20	83664.98	3.69	22.33	1569
Indiana	47115.86	33313.47	2.64	13.57	1569
Iowa	25752.61	18048.98	4.25	31.28	1569
Kansas	19909.92	13175.89	2.21	10.69	1569
Kentucky	31993.79	23654.12	4.70	36.31	1569
Louisiana	33546.91	38229.48	5.56	37.11	1569
Maine	11860.07	9441.08	6.59	77.61	1569
Maryland	44870.16	27227.31	4.33	29.24	1569
Massachusetts	90464.47	60735.46	5.48	39.83	1569
Michigan	116225.50	93458.20	4.85	38.50	1569
Minnesota	55558.49	42808.71	4.97	36.82	1569
Mississippi	22104.93	17023.97	4.87	40.18	1569
Missouri	48617.06	28604.67	2.86	18.09	1569
Montana	9958.40	6280.24	3.39	23.48	1569
Nebraska	10094.17	7247.46	4.11	29.79	1569
Nevada	32258.57	36093.83	6.09	46.06	1569
New Hampshire	8642.37	10712.55	6.17	51.47	1569
New Jersey	121233.20	57330.13	5.37	41.02	1569
New Mexico	15533.37	12063.68	4.92	32.00	1569
New York	227678.30	193963.50	6.70	53.51	1569
North Carolina	72862.15	63296.89	3.71	25.93	1569
North Dakota	4379.96	3624.33	4.21	30.54	1569
Ohio	98180.14	69185.55	4.47	34.42	1569
Oklahoma	21006.87	17190.01	5.45	40.16	1569
Oregon	50453.77	30284.11	3.72	24.60	1569
Pennsylvania	176455.00	101615.00	4.47	33.65	1569
Rhode Island	14308.22	8560.62	5.03	39.27	1569
South Carolina	36235.02	27659.14	3.56	22.87	1569
South Dakota	2811.46	2332.55	4.57	34.38	1569
Tennessee	45045.52	34753.02	4.69	34.00	1569
Texas	168253.80	138370.60	6.25	46.54	1569
Utah	14289.97	10103.40	3.54	21.00	1569
Vermont	6794.73	5549.67	5.65	50.35	1569
Virginia	39190.35	40962.15	6.15	48.45	1569
Washington	79583.56	57555.13	7.27	84.95	1569
West Virginia	16132.07	9596.14	5.36	50.85	1569
Wisconsin	67961.53	40746.66	1.81	8.82	1569
Wyoming	3944.95	2331.14	1.77	8.36	1569
All	58499.57	105827.20	10.30	229.09	78450

Note: Std. Dev., Skew., Kurt., and Obs. denote standard deviation, skewness, kurtosis and number of observations, respectively.

Table A2c: Summary Statistics – climate risk

State	Mean	Std. Dev.	Skew.	Kurt.	Obs.
Alabama	-0.04	0.60	0.27	3.80	1569
Alaska	-0.03	0.59	0.57	6.46	1569
Arizona	-0.10	0.46	-0.16	3.03	1569
Arkansas	-0.02	0.61	0.10	3.21	1569
California	-0.04	0.53	0.60	4.47	1569
Colorado	-0.03	0.53	-0.14	3.28	1569
Connecticut	0.00	0.55	0.16	3.25	1569
Delaware	0.00	0.54	0.17	3.01	1569
Florida	-0.04	0.60	-0.14	4.27	1569
Georgia	-0.06	0.55	0.22	3.85	1569
Hawaii	-0.12	0.47	0.20	3.29	1569
Idaho	-0.02	0.58	0.13	4.32	1569
Illinois	-0.01	0.59	0.06	2.95	1569
Indiana	-0.02	0.60	0.06	2.94	1569
Iowa	-0.01	0.58	0.00	3.02	1569
Kansas	-0.02	0.57	0.03	3.11	1569
Kentucky	-0.02	0.60	0.21	3.33	1569
Louisiana	-0.03	0.60	0.31	3.99	1569
Maine	-0.02	0.56	0.29	3.52	1569
Maryland	-0.02	0.55	0.15	3.02	1569
Massachusetts	-0.03	0.56	0.19	3.03	1569
Michigan	-0.05	0.58	0.11	2.97	1569
Minnesota	-0.02	0.57	0.09	2.81	1569
Mississippi	-0.05	0.61	0.31	3.91	1569
Missouri	-0.04	0.60	-0.02	2.87	1569
Montana	-0.03	0.53	-0.34	3.78	1569
Nebraska	0.01	0.57	0.02	3.16	1569
Nevada	-0.11	0.45	0.15	3.44	1569
New Hampshire	0.03	0.55	0.21	3.23	1569
New Jersey	-0.07	0.53	0.18	3.18	1569
New Mexico	0.00	0.48	0.01	3.20	1569
New York	-0.06	0.52	0.90	10.80	1569
North Carolina	-0.04	0.58	0.29	3.68	1569
North Dakota	-0.03	0.55	0.00	3.20	1569
Ohio	-0.02	0.60	0.09	2.94	1569
Oklahoma	-0.01	0.58	0.03	3.23	1569
Oregon	-0.04	0.62	0.35	3.89	1569
Pennsylvania	-0.07	0.52	0.12	2.98	1569
Rhode Island	-0.01	0.57	0.22	3.30	1569
South Carolina	-0.05	0.56	0.24	3.84	1569
South Dakota	-0.02	0.56	0.05	2.97	1569
Tennessee	-0.06	0.60	0.18	3.39	1569
Texas	-0.01	0.59	0.05	3.52	1569
Utah	-0.02	0.57	0.15	3.58	1569
Vermont	-0.03	0.58	0.15	2.92	1569
Virginia	-0.04	0.57	0.25	3.30	1569
Washington	-0.03	0.62	0.28	3.92	1569
West Virginia	-0.03	0.57	0.07	2.91	1569
Wisconsin	-0.06	0.58	0.10	2.96	1569
Wyoming	-0.05	0.52	-0.10	3.77	1569
All	-0.03	0.56	0.16	3.62	78450

Note: Std. Dev., Skew., Kurt., and Obs. denote standard deviation, skewness, kurtosis and number of observations, respectively.

Table A3: Correlation Matrix

Correlation	CR2	Claims_in	Claims _co	Bonds	DI	ECI_co	ECI_in	ECO_sent	EPU	FFER	GPR	Stock_Ret	TS	VIX
CR2	1.00													
Claims_in	-0.02[a]	1.00												
Claims _co	-0.01[a]	0.80[a]	1.00											
Bonds	-0.04[a]	0.10[a]	0.11[a]	1.00										
DI	0.01[a]	-0.02[a]	-0.06[a]	-0.12[a]	1.00									
ECI_co	0.02[a]	-0.03[a]	0.03[a]	-0.40[a]	-0.02[a]	1.00								
ECI_in	0.03[a]	0.01[a]	-0.19[a]	-0.44[a]	0.11[a]	0.70[a]	1.00							
ECO_sent	0.00	-0.17[a]	-0.18[a]	-0.62[a]	0.16[a]	0.33[a]	0.45[a]	1.00						
EPU	-0.01[c]	0.26[a]	0.22[a]	0.36[a]	0.02[a]	-0.15[a]	-0.26[a]	-0.63[a]	1.00					
FFER	-0.03[a]	-0.09[a]	-0.13[a]	-0.37[a]	0.33[a]	0.17[a]	0.30[a]	0.45[a]	-0.31[a]	1.00				
GPR	0.01	-0.03[a]	-0.02[a]	0.02[a]	0.22[a]	-0.11[a]	-0.07[a]	-0.14[a]	0.15[a]	-0.13[a]	1.00			
Stock_Ret	-0.01[b]	0.04[a]	0.02[a]	-0.03[a]	-0.02[a]	-0.01	-0.01[a]	0.02[a]	-0.03[a]	0.00	-0.03[a]	1.00		
TS	-0.05[a]	0.06[a]	0.11[a]	0.39[a]	-0.44[a]	-0.17[a]	-0.33[a]	-0.28[a]	0.12[a]	-0.73[a]	0.13[a]	0.02[a]	1.00	
VIX	-0.04[a]	0.15[a]	0.12[a]	0.69[a]	0.14[a]	-0.21[a]	-0.25[a]	-0.53[a]	0.49[a]	-0.11[a]	0.05[a]	-0.16[a]	0.17[a]	1.00

Note: CR2 – climate risk, Claims_in – initial claims, Claims_co – continuing claims, Bonds – corporate bond spread, DI – Dollar Index, ECI_in – ECI filtered for initial claims, ECI_co – ECI filtered for continuing claims, ECO_sent - the Federal Reserve Bank of San Francisco's news-based economic sentiment index, EPU – the US Economic Policy Uncertainty, FFER - the federal funds effective rate (ffer), GPR - geopolitical risk index, Stock_Ret – Stock returns, TS – Term spread rate and VIX - the CBOE volatility index .

Panel unit root test

We examine the stationarity of our series as required for the use of Local Projections (LPs). Non-stationary series can lead to biased impulse response estimates (Herbst and Johannsen, 2024), and the LP framework generally assumes stationarity (Plagborg-Moller and Wolf, 2021). To ensure that this condition for the use of LP is satisfied, we test unit roots in our variables. Specifically, we implement several unit root tests: Levin et al. (2002) LLC test, Breitung (2001) test, Im et al. (2003) IPS test, and the Hadri (2000) Lagrange Multiplier test. We also use the Augmented Dickey-Fuller (ADF) test, which accounts for lagged differences to address serial correlation, and the Phillips-Perron (PP) test, which handles serial correlation and heteroskedasticity. In all tests except Hadri, the null hypothesis is non-stationarity.

We group these tests by their null hypotheses. The non-stationarity tests – LLC, Breitung, and IPS – assess the presence of unit roots, with alternative hypotheses that differ in scope. The LLC and Breitung tests assume a common autoregressive (AR) structure across series (Panel A in Table A4). The Hadri test, by contrast, assumes stationarity as the null and tests for unit roots as the alternative, though it also allows for a common AR structure (Panel B). The IPS test permits heterogeneity in unit root processes across cross-sections, while the ADF and PP tests address serial correlation and heteroskedasticity (Panel C in Table A4).

The results, summarised in Table A4, show that our series satisfy the stationarity condition: the null of non-stationarity is generally rejected (at least at first difference for DI and FFER). We also fail to reject the null of stationarity in the Hadri Z-stat test at first difference, except for stock return (stock_ret) that is stationary at level. Taken together, these results confirm that our variables are stationary, and this conclusion is consistent across all tests, underscoring the robustness of our findings and supporting the use of the LP approach in our analysis.

Table A4: Unit root tests' results

Variables	Panel A		Panel B	Panel C		
	LLC	Breitung test	Hadri Z-stat	IPS	ADF	PP
CR2	-155.66^{a***}	-16.70^{a***}	-0.48^{b}	-117.75^{a***}	9308.80^{a***}	13169.50^{a***}
Claims_in	-207.57^{a***}	-106.96^{a***}	1.04^{a}	-171.95^{a***}	13022.60^{a***}	4598.33^{a***}
Claims_co	-12.30^{a***}	-35.95^{a***}	-9.31^{b}	-35.66^{a***}	1457.97^{a***}	1074.93^{a***}
Bonds	-130.49^{b***}	-13.12^{a***}	-7.61^{b}	-7.39^{a***}	194.68^{a***}	214.38^{a***}
DI	-175.75^{b***}	-6.62^{a***}	-2.67^{b}	-122.87^{b***}	9879.90^{b***}	13169.50^{b***}
ECI_co	-5.13^{a***}	-23.47^{a***}	-7.11^{b}	-32.21^{a***}	1302.45^{a***}	1587.92^{a***}
ECI_in	-21.15^{a***}	-26.08^{a***}	-6.42^{b}	-30.31^{a***}	1145.05^{a***}	1652.40^{a***}
ECO_sent	-3.10^{a***}	-24.36^{a***}	-9.25^{b}	-25.00^{a***}	828.42^{a***}	774.10^{a***}
EPU	-30.61^{a***}	-9.64^{a***}	-7.08^{b}	-44.16^{a***}	2000.91^{a***}	11919.00^{a***}
FFER	-143.79^{b***}	-26.81^{b***}	1.03^{b}	-123.00^{b***}	9894.56^{b***}	9736.05^{b***}
GPR	-70.05^{a***}	-58.05^{a***}	-7.62^{b}	-59.41^{a***}	3230.12^{a***}	4762.03^{a***}
Stock_Ret	-177.87^{a***}	-57.80^{a***}	-2.20^{a}	-138.32^{a***}	11582.10^{a***}	13169.50^{a***}
TS	-4.10^{a***}	-5.11^{a***}	-1.50^{b}	0.88^{a***}	54.45^{a***}	37.87^{a***}
VIX	-185.49^{a***}	-137.19^{a***}	-8.11^{b}	-157.03^{a***}	13169.50^{a***}	13169.50^{a***}

Notes: The null hypothesis for Panel A is a unit root with a common process, as tested by Levin, Lin and Chu (LLC, 2002) and Breitung (2001); in Panel B, the null hypothesis is no unit root with a common unit root process (i.e. Hadri, 2000; Lagrange Multiplier test); while Panel C assumes a unit root with an individual unit root process, and applies tests such as Im, Pesaran and Shin (IPS, 2003), ADF-Fisher, and PP-Fisher. The terms a and b denote stationarity at the level and at the first difference, respectively, while ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. While the panel consists of 50 cross-sections, the total number of observations ranges from 78100 and 78400, depending on the lags utililised in the respective tests. Meanwhile, the time dimension covers 1569 periods, spanning from the first week of July 1995 until the last week of January 2025. CR2 depicts climate risk; Claims_in is initial claims; Claims_co means continuing claims; Bonds denotes corporate bond spread, DI represents Dollar Index; ECI_in is computed by filtering ECI for initial claims; ECI_co denotes ECI filtered for continuing claims; ECO_sent is the Federal Reserve Bank of San Francisco's news-based economic sentiment index; EPU is the US Economic Policy Uncertainty; FFER means federal funds effective rate; GPR is geopolitical risk index by Caldara and Iacoviello (2022), Stock_Ret means Stock returns computed from price series as $stock_{ret} = 100 * \log(\frac{p_t}{p_{t-1}})$; TS denotes Term spread rate and VIX is the CBOE volatility index.