Extreme Weather, Economic Implications, and Energy Consumption

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Abstract

This study investigates the impact of extreme weather on Australia's economy using the Australian Actuaries Climate Index (AACI). Incorporating temperature, rainfall, drought, wind, and sea level, the AACI provides a comprehensive measure of extreme weather conditions. Employing a vector autoregression model, our findings reveal persistent negative effects of extreme weather shocks on gross domestic product (GDP). Initially, consumer prices decline, later transitioning to positive due to supply-side effects. Moreover, interest rates initially decrease, unemployment rates rise, and energy consumption increases in the aftermath of extreme weather shocks. This research unveils the intricate relationship between extreme weather and key economic indicators.

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1. Introduction

Extreme weather plays an important role in understanding the impact of climate change on the economy. Different approaches have been used to measure extreme weather. Some studies use self-reported disaster counts and losses (Hsiang and Narita, 2012; Kahn, 2005; Noy, 2009). This measure has been argued to have an issue as it might underestimate actual losses from disaster and it might be affected by endogenous problems as the quality and completeness of self-reported measures depend on the local economic and political conditions (Hsiang and Jina, 2014; Kahn, 2005; Kim et al., 2022). Other measures are based on historical temperature and precipitation data (Acevedo et al., 2020; Dell et al., 2012). These measures might not capture other extreme weather events such as disasters from wind or drought.

Recently the Actuaries Institute Australia introduced the Australian Actuaries Climate Index (AACI) to measure extreme weather conditions in Australia. This index is constructed by including high and low temperatures, rainfall, drought, strong wind, and sea level. It can improve the accuracy of estimating the frequency of extreme events that could not be identified from only temperature or precipitation data. Also, this index is less subject to endogeneity and quality issues. It provides a better understanding of how climate change affects the economy. The weather in Australia has warmed by over 1°c since 1910, which leads to an increase in the frequency of extreme heat events, and severity of drought conditions, and consequently associated with a reduction in Australia's gross domestic product (GDP) by 1% annually (Bureau of Meteorology, 2018). The Actuaries Climate Index was first developed in the United States and Canada to provide the climate trend and potential impact of climate changes. It was only recently developed for Australia. Using this index, we examine the impact of extreme weather shocks on various economic indicators in the Australian economy, including the gross domestic product, consumer prices, interest rates, unemployment rates, and energy consumption.

Our finding shows that extreme weather shocks have a negative impact on GDP, interest rates, and consumer price index (CPI), while we observe a positive effect on energy consumption. We also provide an additional explanation by analyzing the following CPI components: core CPI, energy price, and food price. We find that energy and food prices increase after extreme weather shocks because of higher energy demand for cooling and heating and lower agriculture output. The increase in energy and food prices offsets the negative effect on CPI, causing the impact on core CPI to be more negative because energy and food prices are excluded in core CPI. In line with the economic growth decline, unemployment rate increases as extreme weather shocks lead to reducing output. In addition, energy consumption increases after extreme weather shocks because individuals demand more energy for cooling or heating during hostile weather conditions.

The rest of this paper is structured as follows. Section 2 presents the literature review. Section 3 provides a description of the data while Section 4 describes the model. Section 5 discusses results. Section 6 concludes.

2. Literature review

One strand of literature on the impact of climate change on the economy focuses on the relationship between the weather condition and economic activity. Earlier studies mainly investigate the relationship between changes in temperature or rainfall and agricultural productivity, such as crop production (Key and Sneeringer, 2014; Lobell and Asner, 2003; Schlenker and Roberts, 2009). Schlenker and Roberts (2009) report that temperature increases up to a critical threshold of 29°C (i.e., 84°F) may benefit crop production such as corn. If temperature increases beyond that threshold, crop production deteriorates. In addition, McCarl et al. (2008) examine the impact of climate change on crop yields and find that higher climate variability results in lower average crop yields. The result is also confirmed by Mukherjee et al. (2013) and Lobell and Asner (2003).

Some recent studies examine the impact of changes in temperature on aggregate economic activity (Burke et al., 2015; Colacito et al., 2019; Dell et al., 2014; Palareti et al., 2019; Raddatz, 2007). For example, Dell et al. (2009) provide cross-sectional evidence of the relationship between climate change and income for 12 countries. Their result shows a negative temperature-income relationship, with 1°c increase in temperature leading to a 1.2-1.9% reduction in per capita income and the short-run effect is more impactful than the long-run. Dell et al. (2012) examine the impact of temperature and precipitation fluctuation on aggregate economic outcomes in 125 countries in the world. They find that higher temperatures decrease economic growth in developing countries, particularly reducing the agricultural output, industrial output, and political stability. In addition, Donadelli et al. (2017) analyze the impact of temperature shocks on productivity for the US economy. Their results show that temperature shocks negatively impact total productivity, output, and labor productivity. Specifically, a one-standard deviation temperature shock decreases productivity growth by 1.4 percentage points.

The existing literature mainly focuses on specific climate events, particularly on temperature variation and precipitation (Colacito et al., 2019; Mendelsohn et al., 1994), cyclones or hurricanes (Deryugina, 2017; Hsiang and Narita, 2012; Knutson et al., 2010; Strobl, 2011), earthquake (Cavallo et al., 2014), flooding (Kirshen et al., 2008; Rojas et al., 2013). For example, Hsiang (2010) examines the effect of cyclones and temperature on economic production in the Caribbean and Central America and finds that cyclone events have a negative effect on the production in the agriculture and tourism sector, while average temperatures have a negative relationship with total domestic output. Hsiang and Jina (2014) also investigate the effect of tropical cyclones on economic growth rate and show that GDP growth rate decreases by 3.6 percentage points due to cyclone events. Yang (2008) investigates the impact of hurricanes on international finance flows in developing countries and shows that the hurricanes lead to higher economic losses and larger international flows of foreign aid. Colacito et al. (2019) find that seasonal temperatures significantly affect the U.S. economy. They find that average temperature increase reduces the U.S. economic growth. These findings are also supported by Dell et al. (2012) and Acevedo et al. (2020), who find that higher temperatures decrease economic growth rates. Overall, most studies conclude that the climate shock negatively impacts economic activities (Akter et al., 2023; Balvers et al., 2017; Bansal and Ochoa, 2011; Campbell and Spencer, 2021; Colacito et al., 2019; Dell et al., 2009; Dunz et al., 2021).

Another strand of literature focuses on how climate shocks influence energy consumption. Most studies focus on residential energy demand, where the impact of extreme temperature varies depending on season or location (Auffhammer and Mansur, 2014; Sailor, 2001). Deschênes and Greenstone (2011) document the relationship between temperatures and annual residential energy consumption. They find that there is a proportionately higher increase in energy consumption when the temperature exceeds 90° F, suggesting a U-shaped response function where electricity consumption is higher on extremely cold and hot days. Auffhammer and Aroonruengsawat (2011) also support the finding that the relationship between household electricity consumption and temperature is U-shaped, but the electricity consumption response to temperature is different across climate zones. Ahmed et al. (2012) examine how climate change affects electricity demand in New South Wales, Australia by using cooling and heating degree days to measure the temperature variation and find that climate change leads to a surge in electricity demand, especially during the summer and spring seasons. Ruth and Lin (2006) analyze the impact of climate change on energy consumption in the state of Maryland, U.S., by using the historical monthly average temperature data as a proxy for climate change. They demonstrate a statistically significant relationship between electricity demand and climate change. Specifically, the commercial sector is more affected by climate-related increases in electricity demand than the residential sector. These effects are particularly noticeable in summer.

Overall, previous studies of the impact of weather shocks on energy consumption predominantly use the temperature data or heating degree days (HDD) and cooling degree days (CDD) to estimate the effect of weather shocks on energy consumption (Auffhammer and Aroonruengsawat, 2011; Deschênes and Greenstone, 2011; Eskeland and Mideksa, 2010; Pardo et al., 2002). Regarding the influence of weather shocks on the economy, the existing literature presents mixed results, as the economic repercussions of weather shocks are contingent upon several factors such as income levels, government expenditure, and financial conditions specific to each nation. (Acevedo et al., 2020; Noy, 2009). Moreover, the quality of extreme weather shock measures also leads to different results. Some studies employ self-reported disaster counts and losses from the Emergency Events Database (EM-DAT) to construct the weather events (Dell et al., 2014; Hsiang and Narita, 2012; Kahn, 2005; Loayza et al., 2012; Noy, 2009). However, there are some issues associated with this self-reported data. Loayza et al. (2012) contend that accurately discerning whether reported statistics regarding incidents involving casualties, affected individuals, or economic losses are genuinely missing or merely recorded as zero poses a challenge. Measurement errors further compound this issue, stemming from erroneous data harmonization and compilation. Moreover, the self-reported measure is susceptible to underestimating true losses and influenced by endogenous factors linked to local economic and political circumstances (Hsiang and Jina, 2014; Kim et al., 2022; Kishore et al., 2018). Another climate change measure used in the literature is historical weather and precipitation data (Acevedo et al., 2020; Dell et al., 2012). This measure might not capture other extreme weather events, such as disasters from wind or drought.

In this study, we aim to fill this gap by using the Actuaries Climate Index (ACI) to measure extreme weather conditions. This index is constructed by including high and low temperatures, rainfall, drought, strong wind, and sea level so it can more precisely reflect the frequency of extreme events which cannot be identified only from temperature data (Hsiang and Jina, 2014; Kim et al., 2022). The ACI was first developed in the U.S. and Canada and has been utilized in a few recent articles (Kim et al., 2022; Natoli, 2022; Pan et al., 2022). Kim et al. (2022) use the ACI to measure extreme weather shocks and examine their macroeconomic effect in the U.S. They find that an increase in extreme weather causes a persistent decline in economic growth and inflation and an increase in the unemployment rate. Pan et al. (2022) also employ the ACI to estimate its effectiveness on predicting crop yields in the U.S. They show that the ACI has reasonable predictive power on corn yields and provides accurate information on extreme weather events when calculating and modelling climate-related insurance and financial risk.

Since the ACI was first developed in North America, the existing literature mainly leverages this data in the U.S. and Canadian markets. In contrast, we investigate the recently developed ACI for Australia. To the best of our knowledge, our study is one of the first employing the ACI in Australia.

3. Data

3.1 Australian Actuaries Climate Index (AACI)

The AACI is built on six individual components, i.e., high temperatures, low temperatures, precipitation, wind, consecutive dry days (CDD), and sea level. The high temperature component is defined as the change in frequency of daily maximum and minimum temperatures which exceed the 99th percentile in a month, while the low temperature component is defined as the change in frequency of daily maximum and minimum temperatures which exceed the 1st percentile in a month. The precipitation component is measured by the frequency of rainfall over five consecutive days, which exceeds the 99th percentile. This extreme precipitation could measure the flood risk or storm damage. Next, the wind component is defined as the monthly frequency of daily maximum wind gusts exceeding the 99th percentile. The highest wind gusts are likely to cause more danger and damage during extreme wind weather like storms and cyclones. The consecutive dry days (CDD) component measures the drought condition, which is defined as the annual maximum number of consecutive days with less than 1mm of rain. The last component is the sea level, measured by the track movement in the monthly maximum observed sea level via tide gauges. It measures the risk for coastal inundation; however, it does not measure the land movements because the land movements can be caused by a combination of climate-related and non-related factors such as tectonic movements. For each component, the data is collected from the Bureau of Meteorology (BoM)[2]. All data starts in 1981, except for wind data which starts in 2002 in Australia. The summary statistics of each component are presented in Table 1.

The combination of all components aims to bring extreme conditions into a single index e.g., AACI. One of the challenges to aggregate all components into a single index is the fact that each component has different measurement units across weather variables. Therefore, the following standardization method is implemented to make these measures comparable. All standardized anomalies are based on the reference period from 1981-2010, which is calculated as follows:

$$X_{i,t}^{std} = \frac{x_{i,t} - \mu_{x,i}^{1981-2010}}{\sigma_{x,i}^{1981-2010}}, \tag{1}$$

where the X_t^{std} is the standardized anomaly of the weather variable x at location i and time t. $x_{i,t}$ is the value of weather variable, $\mu_{x,i}^{1981-2010}$ is the average of weather variable x at location i for the same period during the reference period 1981-2010, $\sigma_{x,i}^{1981-2010}$ is the standard deviation of weather variable x at location i for the same period during the reference period 1981-2010. Following this standardization, all the standardized anomalies can be combined to create a single index.

Next, since the extreme temperature, precipitation, and wind track the frequency of events above the 99th percentile thresholds, we calculate these thresholds based on the standardized anomaly we observed. For example, to calculate the threshold on 5th January for the high temperature variable, we use all daily maximum temperature values on January 5th between the period 1981 and 2010 (30 years). This gives us 30 observations. To increase the number of observations, we also collect the data five days before and after January 5th. This finally gives us 330 observations.

[2] The Bureau of Meteorology (BoM) is the Australia's national weather, climate, and water agency. The Bureau provides the information related to natural environment, including tropical cyclones, drought, floods, fires, storms, and tsunami.

From this data, we determine the threshold of 99th percentile temperature to be the 4th warmest of the 330 days. Thus, the index tracks the proportion of temperature values that are higher than the threshold. Calculations of weather variables are performed at each station level. Then, the average across all stations is taken within a region to aggregate to into the regional level. Next, we aggregate the index at station level to national level by taking the average across regions. Thus, this results in six aggregate time series of weather variables including standardized anomaly for high temperature ($HighTemp_t^{std}$), low temperatures ($LowTemp_t^{std}$), precipitation ($Precip_t^{std}$), wind ($Wind_{i,t}^{std}$), consecutive dry days (CDD_t^{std}), and sea level ($SeaLevel_t^{std}$).

When aggregating these components into a composite index, the approach employed involves computing a simple average of each standardized component. However, the Actuaries Institute report (2018) mentions that the public AACI developed by the Australian Actuaries takes a simple average of only three individual component indices (high temperature, precipitation, and sea level). The reason for excluding other components is that the wind gust data is not available back to 1981 (it only becomes available in 2002 in Australia), so it is excluded from the composite index. The consecutive dry days index is also excluded because it has a strong inverse relationship with the precipitation measure, while the low temperature component is excluded to ensure that the composite index does not overweigh temperature metrics. Thus, the composite AACI combines only three standardized components (high temperature, precipitation (rainfall), and sea level), which is constructed as follow:

$$AACI_t = (HighTemp_t^{std} + \ Precip_t^{std} + SeaLevel_t^{std})/3. \qquad (2)$$

A positive index value represents an increase in relevant climate extremes relative to the 1981-2010 reference period. Since the value is in the form of a standardized anomaly, an index value of 0.5 indicates that a component making up the aggregate index has increased on average by 0.5 standard deviation. This composite index is the main index we used in this study[3]. The data is available at quarterly frequency and covers the period from 1981:1 to 2021:4.

Figure 1 illustrates the trend of AACI during the period 1981-2021. The bar plots the quarterly values of the index relative to the reference period of 1981-2010, with the green bar indicating the positive value while the red bar indicates the negative value. The solid black line presents the five-year moving average of AACI. The graph shows that after 2000, the index exhibits a high frequency of positive value. This suggests an increase of extreme climate events in Australia compared to the reference period. This pattern is more pronounced post 2010[4].

The trend of each standardized component in the index is plotted in Figure 2. Among all components, the high temperature and sea level components exhibit the most significant extreme changes. These findings suggest that the factors contributing to an upsurge in the AACI predominantly originate from the components associated with elevated temperatures and sea levels. In contrast, the component related to rainfall exhibits greater consistency and relative stability compared to the other components during the same time frame. Overall, the graph shows that the AACI and all component indices significantly increased over the period of 1981-2021, confirming the surge in extreme climate instances. Notably, extreme climate risks related to higher temperatures and higher sea levels have increased. This leads to greater concern about climate change risk in Australia.

3.2 Explanatory variables

While analyzing the impact of extreme weather shocks on the economy, we employ the year-on-year growth rate of following variables in our analysis: the gross domestic production (GDP), consumer price index (CPI), core CPI, CPI energy, CPI food and the unemployment rate. All data is collected from Federal Reserve Bank of St. Louis' Federal Reserve Economic Data (FRED) at a quarterly frequency.

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[3]Refer to the Actuaries Institute in Australia: https://actuaries.asn.au

[4] We also plot the trend of each AACI component in Appendix A.

We also employ energy consumption to examine the impact of extreme weather on energy consumption. We use the energy consumption and energy production data from the International Energy Agency (IEA) energy database. The variables are measured as the year-on-year growth rate.

Table 2 presents the summary statistics of variables used in our analysis. Panel A of Table 2 presents summary statistics of AACI and its components. The high temperature and sea level have the largest average value of extreme changes. This observation substantiates the findings depicted in Figure 2, which highlight that the ACCI is primarily influenced by the sea level and high temperature components, demonstrating the highest average values of 0.163 and 0.149, respectively. The standard deviation of the components varies approximately between 0.3 and 0.6, and the high temperature and sea level are still the most significant volatile components. Panel B of Table 2 shows the summary statistics of macroeconomic variables. All variables are expressed as the year-on-year growth rate. The average value of all consumer price growth rates is approximately 3% across our sample period. However, the growth rate of the consumer price index for the energy component is the highest of all at 5.3% on average. This is because Australia's energy price has increased by 72% over the past ten years (ABS, 2021).

4. Methodology

To analyze the impact of extreme weather shocks on the economy, we employ the vector autoregressive (VAR) model with exogenous variables. Our model enables the integration of exogenous predictor variables and analysis of their effects on endogenous response variables. We incorporate the extreme weather index as the exogenous climate factor. The VAR model takes the following form:

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} a_0 \\ c_0 \end{pmatrix} + \begin{pmatrix} A_1 & B_1 \\ 0 & C_1 \end{pmatrix} \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \cdots + \begin{pmatrix} A_p & B_p \\ 0 & C_p \end{pmatrix} \begin{pmatrix} y_{t-p} \\ x_{t-p} \end{pmatrix} + \begin{pmatrix} U_t \\ V_t \end{pmatrix}, \tag{3}$$

where y_t represents the $(k \times 1)$ vector of endogenous variables and p is the number of lags included in the model. x_t represents the $(m \times 1)$ vector of exogenous variables and:

$$\begin{pmatrix} U_t \\ V_t \end{pmatrix} \sim i.i.d\ N_{k+m} \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \epsilon_{11} & \epsilon_{12} \\ \epsilon_{21} & \epsilon_{22} \end{pmatrix} \right].$$

The vector of endogenous variable (y_t) includes the GDP growth rate, CPI growth rate, the change in the interest rate (INT), and the change in the unemployment rate (UEM). It can be written in the vector form as: $y_t = [\Delta GDP_t \quad \Delta CPI_t \quad \Delta INT_t \quad \Delta UEM_t]'$. The exogenous variable (x_t) is the extreme weather shock, which is the Australian Actuaries Climate Index (AACI) as described in Section 3.1.

We can rewrite equation (3) in the lag operation notation (L) as:

$$\beta(L)Y_t = \Phi(L)X_t + U_t \ , \tag{4}$$

where:

$$\beta(L) \ = I_k - \beta_1 L - \ldots - \beta_P L^p \ , \tag{5}$$

and:

$$\Phi(L) \ = \Phi_0 - \Phi_1 L - \ldots - \Phi_j L^j \ . \tag{6}$$

To assess the effect of a change in exogenous variable on the endogenous variables, we multiply equation (4) by $\beta(L)^{-1}$:

$$\beta(L)^{-1}\beta(L)Y_t = \beta(L)^{-1}\Phi(L)X_t + \beta(L)^{-1}W_t \ , \tag{7}$$

$$Y_t = \beta(L)^{-1}\Phi(L)X_t + \beta(L)^{-1}W_t \ . \tag{8}$$

We set $\mathrm{D}(L) = \beta(L)^{-1}\Phi(L)$ and rewrite the equation (8) as:

$$Y_t = \mathrm{D}(L)X_t + \beta(L)^{-1}W_t \tag{9}$$

The term $\mathrm{D}(L)$ measures the effect that changes in exogenous variables have on endogenous variables. Thus, the impact of extreme weather shocks on economic variables can be captured by $\mathrm{D}(L) = \beta(L)^{-1}\Phi(L)$.

5. Results

5.1 Unit root test

Before estimating the VAR model, we first conduct the unit root testing to ensure that the variables in the model are stationary to avoid the spurious regression problem. We apply the standard Augmented Dickey–Fuller (ADF) and Phillips Perron (PP) test to perform unit root test in this study. The null hypothesis of both methodologies is that the unit root exists in the series.

We also analyze the unit root test with and without time trend in the regression. For all variables, we reject the null hypothesis at 1% significant level for both the Augmented Dicky Fuller and Phillips–Perron tests and both unit root test with trend and without trend. This suggests that all variables are stationary and can be included in the VAR model.

5.2 Economic indicator response to extreme weather shocks

In this section, we estimate the VAR model as specified in equation (3). We use 6 lags of VAR based on the Akaike Information criterion (AIC). We then plot the dynamic multiplier function, which is used to measure the impact of a unit increase in an exogenous variable on the endogenous variable. This allows us to estimate the impact of extreme weather shocks on economic variables.

Figure 3 illustrates the dynamic response of economic variables to one standard deviation of extreme weather shock. The solid line shows the median response while the dash line represents a 90% confidence interval. We find that the GDP growth rate responds negatively to extreme weather shocks. An increase of extreme weather shock by one standard deviation decreases the GDP growth rate by 0.7 percentage point contemporaneously and the impact is continuously negative over time for almost 10 quarters, although it gradually converges to zero. This suggests that the effect is quite persistent. Our finding is consistent with the literature, which finds that the GDP growth rate steadily decreases in the long term after cyclone events and temperature shocks (Burke et al., 2015; Dell et al., 2012; Hsiang and Jina, 2014; Natoli, 2022). However, our result also shows a gradually rising GDP growth rate, suggesting a recovery in the economy. This is because subsequent government spendings, such as financial aid activities, investment, and reconstruction works, help the economy to recover from such extreme weather shock (Mohan et al., 2019; Rasmussen, 2006).

The CPI growth rate results demonstrate that extreme weather shocks have a contemporaneous negative impact of approximately 0.3 percentage points immediately after the initial shock, but the impact gradually increases in the next quarter and reverses to a positive impact within 8 quarters after the shock. The initial decrease in the CPI growth rate can be attributed to the dual impact of extreme weather shocks on both supply and demand sides, resulting in a significant reduction in aggregate demand within the Australian economy, surpassing the supply-side (Natoli, 2022; Parker, 2018). Post the weather shock, constrained spending patterns and a focus on essential items may contribute to an initial decrease in overall pricing inflation. However, beyond the initial quarter, the supply-side impact of extreme weather shock leads to output (Faccia et al., 2021; Fomby et al., 2013; Noy, 2009; Strobl, 2011) and labor supply (Cachon et al., 2012; Graff Zivin and Neidell, 2014; Somanathan et al., 2021) shortages, resulting in an upward pressure on the consumer price index (Cavallo et al., 2014; Keen and Pakko, 2011).

Following a weather shock, interest rates exhibit a decline for five quarters, subsequently transitioning to a positive trajectory after nine quarters. The decrease amounts to approximately 4 percentage points within the initial five quarters. This decline aligns with the reduction in the consumer price index (inflation) during the onset of weather shocks. Consequently, an expansionary monetary policy response is observed, whereby interest rates are lowered and the money supply is increased, aiming to address the declining inflation and uphold economic stability. Subsequently, nine quarters after the weather shock, interest rates exhibit a positive trend, rising by approximately 2% in response to a one-standard-deviation increase in extreme weather shock. This suggests the implementation of a contractionary monetary policy, wherein interest rates are increased to mitigate inflationary pressures by reducing the money supply, economic growth, and consumer spending. Our findings align with Natoli (2022) indicating a decline in interest rates following weather shocks, followed by a gradual increase in the medium term. This supports the notion that an effective monetary policy response is crucial to address inflation dynamics and sustain economic stability (Keen and Pakko, 2011).

Furthermore, extreme weather shocks have a positive impact on the unemployment rate, with a one-standard-deviation increase in shocks associated with a 2-percentage-point rise. This effect remains positive before gradually declining over 4 quarters following the shock. This outcome is consistent with the observed decrease in economic growth, indicating reductions in output and total factor productivity, leading to a decrease in hours worked and an increasing unemployment rate (Babiker and Eckaus, 2007; Graff Zivin and Neidell, 2014). Subsequently, our findings indicate a decrease in the unemployment rate following extreme weather shocks, turning negative within 10 quarters, implying a recovery effect. This observation aligns with the trajectory of gross domestic product (GDP) growth, which exhibits an increasing or recovering trend within the same 10-quarter period after extreme weather shocks.

5.3 The price impact of extreme weather shocks

To gain further insight into the price impact, we augment our analysis by employing the core consumer price index (Core CPI) as an alternative to the overall CPI in our model. The Core CPI excludes energy and food prices. Subsequently, we re-estimate the VAR model and present the dynamic response function in Figure 4, providing a comprehensive understanding of the price dynamics. The graphical representation reveals that the Core CPI is negatively impacted by extreme weather shocks, with a larger impact observed at the onset of the shock period compared to the CPI results shown in Figure 3. This disparity in findings can be attributed to the exclusion of energy and food prices in the Core CPI, emphasizing the significance of energy and food price dynamics in shaping the observed impact.

To further explore the impact of extreme weather shocks on specific components of the CPI, namely energy prices and food prices, we conduct a separate analysis. The dynamic response function, illustrated in Figure 5, demonstrates that the response of energy prices to extreme weather shocks is positive. A one-standard-deviation positive shock corresponds to an increase of approximately 0.4 percentage points in energy prices, which further amplifies to around 0.9 percentage points within a year. Subsequently, the energy price gradually decreases and dissipates over time. This observation indicates that extreme weather shocks lead to increased energy demand, as individuals require more energy for heating purposes. Simultaneously, the productivity of energy infrastructure can diminish due to the impact of extreme weather shocks, affecting energy supply. Consequently, higher energy prices arise because of reduced supply and heightened demand for energy (Cashin et al., 2017; Mukherjee and Ouattara, 2021).

Similarly, the analysis reveals a positive impact of extreme weather shocks on food prices. Specifically, a one-standard-deviation increase in extreme weather shock corresponds to an approximate 0.2 percentage point increase in food prices. Subsequently, the impact gradually diminishes to zero and transitions into a negative effect, resulting in a decline of 0.4 percentage points within six quarters following the shock. This finding aligns with the understanding that extreme weather shocks lead to reduced agricultural output and productivity, as climatic conditions significantly influence agricultural productivity. Extreme weather conditions can disrupt agricultural systems by altering the prevalence of pests and diseases and diminishing the availability of land, soil moisture, and water supply. These changes pose significant challenges and expenses to the agricultural sector and the production of food commodities (Adams et al., 1998; Aydinalp and Cresser, 2008). Such disruptions in agricultural systems have the potential to contribute to food scarcity issues. As the demand for food surpasses the available supply, a situation of excess demand can arise, leading to longer-term increases in food prices. (Acevedo et al., 2020; Mukherjee and Ouattara, 2021; Wang and McPhail, 2014).

In summary, our findings indicate that extreme weather shocks have a larger negative impact on the core CPI compared to the overall CPI. This disparity can be attributed to the subsequent increase in energy and food prices following extreme weather events, which are excluded from the Core CPI calculation. The rising energy and food prices counterbalance the negative impact, resulting in a smaller effect on the overall CPI. Nevertheless, both CPI and Core CPI exhibit negative responses to extreme weather shocks, suggesting that these shocks primarily reduce aggregate demand rather than supply.

5.4 Extreme weather and energy consumption

In this section, we examine the effects of extreme weather shocks on energy consumption by incorporating it as an additional variable in our VAR model. We present the dynamic response function in Figure 6, which demonstrates the response of energy consumption to a one-standard-deviation increase in extreme weather shock.

The depicted graph illustrates that energy consumption exhibits a positive response to extreme weather shocks. Following the shock, energy consumption experiences a gradual increase, peaking at 0.8 percentage points in the initial quarter and reaching 0.4 percentage points immediately after the shock. Subsequently, energy consumption gradually declines as the intensity of the extreme weather shock increases by one standard deviation. These findings indicate that extreme weather conditions stimulate higher energy consumption as individuals require increased energy for heating or cooling during such events (Akhmat et al., 2014; Auffhammer and Mansur, 2014). Nevertheless, individuals may learn to adapt their energy consumption patterns over the long run, potentially through the adoption of more efficient technologies. This could involve the purchase of energy-saving equipment, resulting in reduced energy consumption. This observation aligns with our findings, indicating a gradual decrease in energy consumption in the medium and long term. These results are in line with the findings presented in Figure 5, which demonstrate an increase in energy prices due to heightened energy demand.

5.5 The impact of each component of AACI on energy consumption

To gain further insights into the impact of extreme weather events on energy consumption, we analyze the individual components of the AACI, namely high temperature, precipitation, and sea level. Additionally, we extend our analysis to include low temperature, drought, and wind indices, which are not encompassed in the main AACI. By incorporating each specific component into separate VAR models, we assess the unique effects of these weather events on energy consumption.

The dynamic response function in Figure 7 depicts the impact of extreme weather shocks on energy consumption, focusing on the components of high temperature and low temperature. Our analysis reveals a positive influence of both high and low temperatures on energy consumption, with an average increase of 5 percentage points. The impact follows a similar pattern for both temperature extremes, gradually returning to zero within 7 quarters after the shocks. This finding aligns with previous literature examining the relationship between climate change, temperature, and electricity consumption, suggesting that climate change is likely to contribute to higher electricity consumption (Mansur et al., 2008; Sailor and Muñoz, 1997).

In addition to temperature, we also analyze the impact of other components of the AACI on energy consumption. Our findings indicate that precipitation (rainfall) has a small and insignificant positive effect on energy consumption, which diminishes within 8 quarters. Similarly, the sea level component initially increases energy consumption by 2 percentage points, followed by a gradual decline and return to zero within 8 quarters. However, the consecutive dry days and wind index have negligible effects on energy consumption, with an impact magnitude of approximately 0.2 percentage points. These results suggest that temperature fluctuations have a more substantial influence on energy consumption compared to other weather factors.

Overall, our analysis indicates that temperature and sea level are the primary components of extreme weather that significantly impact energy consumption. These factors exhibit the most substantial magnitude of impact, while precipitation, drought, and wind have a relatively smaller contribution to the effect on energy consumption. Understanding the relative importance of each weather component can help policymakers and energy planners prioritize their efforts in mitigating the impact of extreme weather events on energy consumption and developing appropriate adaptation strategies.

6. Conclusion

This study investigates the impact of extreme weather on Australia's economy using the Australian Actuaries Climate Index (AACI), a comprehensive measure that incorporates high and low temperatures, rainfall, drought, strong wind, and sea level. By including multiple weather components, the AACI improves the accuracy of capturing the frequency of extreme events and their potential effects on the economy. Utilizing a VAR model, we analyze the influence of extreme weather shocks on key economic indicators, such as the gross domestic product, interest rate, consumer prices, unemployment rate, and energy consumption. This approach allows us to assess the broader implications of extreme weather on Australia's economic performance.

Our study reveals that extreme weather shocks have a lasting negative impact on gross domestic product (GDP) in Australia. Furthermore, we observe an initial negative effect on the consumer price index, reflecting a decrease in aggregate demand following the weather shock. However, over the medium term, the impact shifts to a positive effect, indicating the supply side consequences of extreme weather events, such as output and labor supply shortages. These findings emphasize the complex dynamics and interplay between weather shocks, economic activity, and price levels.

Additionally, we analyze the components of the consumer price index (CPI) to gain further insights. Specifically, we decompose the CPI into Core CPI, energy price index, and food price index, and assess the impact of extreme weather shocks on each component. Our findings reveal that both CPI and Core CPI experience negative effects, but the impact on Core CPI is more pronounced compared to CPI. This disparity can be attributed to the increase in energy and food prices, which offset the negative impact on CPI. Extreme weather shocks drive higher energy demand, leading to increased energy prices, while agricultural output decline contributes to elevated food prices.

Furthermore, our analysis reveals a decrease in the interest rate in response to extreme weather shocks, indicating an expansionary monetary policy that aims to address declining inflation. Consistent with the decrease in economic growth, the unemployment rate rises due to reduced output and fewer hours worked. Interestingly, we observe an increase in energy consumption following extreme weather shocks, driven by the heightened demand for cooling or heating during adverse weather conditions.

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Table 1: AACI Component index

This table presents the description and data sources of Australian Actuaries Climate Index (AACI) and its components. The AACI consists of six components: high temperature, low temperature, precipitation, wind, consecutive dry days, and sea level.

Component	Detail	Source
High Temperature	Frequency of daily maximum and minimum temperatures which exceed the 99th percentile	112 ACORN-SAT BoM weather stations across Australia
Low Temperature	Frequency of daily maximum and minimum temperatures which exceed the 1st percentile	112 ACORN-SAT BoM weather stations across Australia
Precipitation	Frequency of rainfall over the five consecutive days exceed the 99th percentile	Approximately 2,000 BoM weather stations that collect rainfall data across Australia
Wind	Frequency of daily wind speed exceed the 99th percentile	38 BoM weather stations that provide the most reliable wind data
Consecutive Dry Days	Seasonal maximum consecutive dry days	Approximately 2,000 BoM weather stations that collect rainfall data across Australia
Sea Level	Seasonal maximum sea level	16 tide gauges across Australia and BoM's Baseline Sea Level Monitoring Project

Table 2: Descriptive statistics

This table presents the summary statistics of variables included in our analysis. Panel A presents the summary statistics of the Australian Actuaries Climate Index (AACI) and its six components constructed as described in Section 3.1. Panel B shows the summary statistics of macroeconomic variables, collected from Federal Reserve Bank of St. Louis' Federal Reserve Economic Data (FRED). All data is based on the quarterly frequency from 1981-2021.

	Mean	S.D.	Median	Min	Max
Variables	(1)	(2)	(3)	(4)	(5)
Panel A: AACI Index and components					
AACI	0.111	0.317	0.100	-0.630	1.000
High Temperature	0.149	0.492	0.050	-0.530	2.520
Low Temperature	0.058	0.293	0.140	-0.810	0.520
Rainfall	0.021	0.280	0.000	-0.420	1.360
Sea Level	0.163	0.592	0.190	-1.250	1.920
CDD	-0.002	0.383	-0.035	-0.870	1.190
Wind	-0.044	0.323	-0.035	-0.770	1.070
Panel B: Macroeconomic variables (Ch. in %)					
CPI	0.029	0.019	0.024	-0.003	0.085
Core CPI	0.037	0.031	0.024	-0.011	0.131
CPI-Energy	0.053	0.073	0.057	-0.135	0.259
CPI-Food	0.040	0.036	0.032	-0.060	0.133
GDP	0.069	0.039	0.067	-0.061	0.167
Interest Rate	-0.059	0.290	-0.042	-0.978	0.696
Unemployment Rate	0.006	0.154	-0.040	-0.346	0.559
Energy Consumption	0.025	0.021	0.024	-0.032	0.063

Figure 1: Trend of the Australian Actuaries Climate Index (AACI)

This figure illustrates the trend of the Australian Actuaries Climate Index (AACI) during the period 1981-2021. The AACI is constructed as described in Section 3.1. The bar plots the quarterly values of index relative to the reference period of 1981-2010, with the green bar indicating the positive value while the red bar indicates the negative value. The black solid line presents the five-year moving average of the AACI.

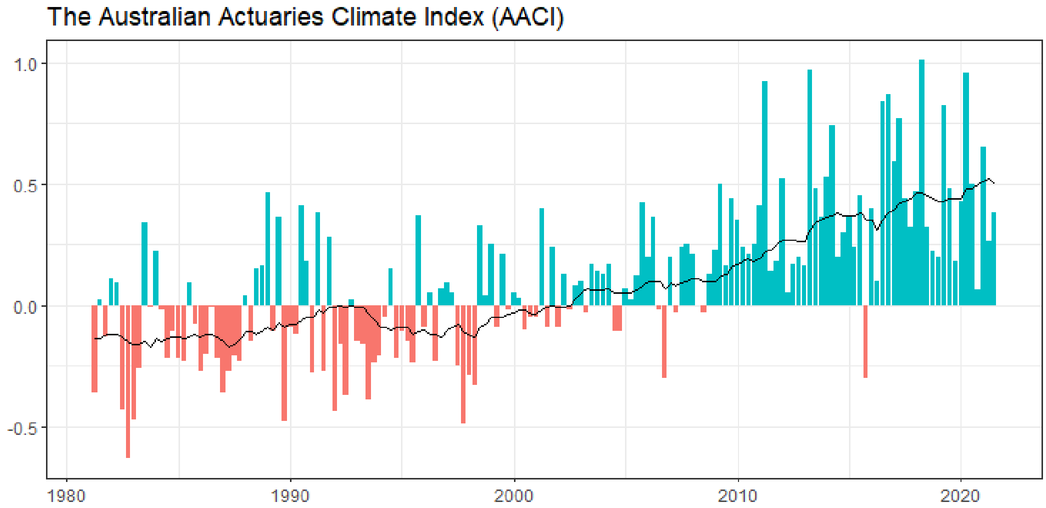


Figure 2: Trend of each Australian Actuaries Climate Index (AACI) component

This figure illustrates the trend of Australian Actuaries Climate Index (AACI) components during the period 1981-2021. The AACI consists of six components: high temperature, low temperature, precipitation, wind, consecutive dry days, and sea level. Index values are standardized.

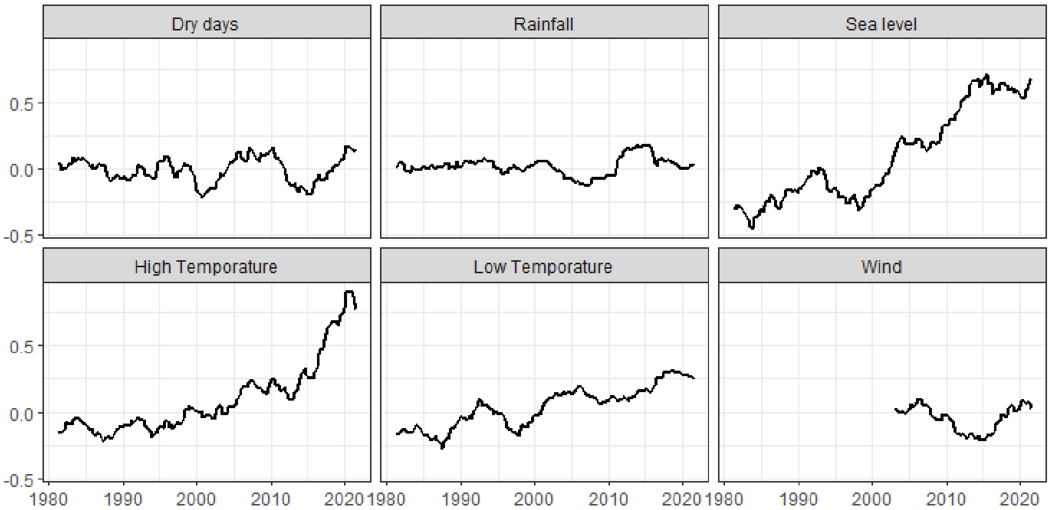


Figure 3: Response of economic variables to extreme weather shock

Figure 3 presents the estimated dynamic response functions of key economic variables, including gross domestic product (GDP), consumer price index (CPI), interest rate, and unemployment rate, to extreme weather shocks. The responses are derived from a vector autoregression (VAR) model using data at a quarterly frequency from 1981 to 2021. Extreme weather shocks are constructed based on the Australian Actuaries Climate Index (AACI), as detailed in Section 3.1. The solid line represents the median response, while the dashed lines depict the 90% confidence intervals.

Figure 4: Response of Core CPI to extreme weather shock

Figure 4 illustrates the dynamic response function of Core CPI to extreme weather shocks. The response function is estimated using a vector autoregression (VAR) model. The model incorporates the Australian Actuaries Climate Index (AACI) to construct extreme weather shocks, as explained in Section 3.1. Data at a quarterly frequency from 1981 to 2021 are employed for the regressions. The solid line represents the median response, while the dashed lines indicate the 90% confidence intervals. The analysis focuses on gross domestic product (GDP), Core CPI, interest rate, and unemployment rate.

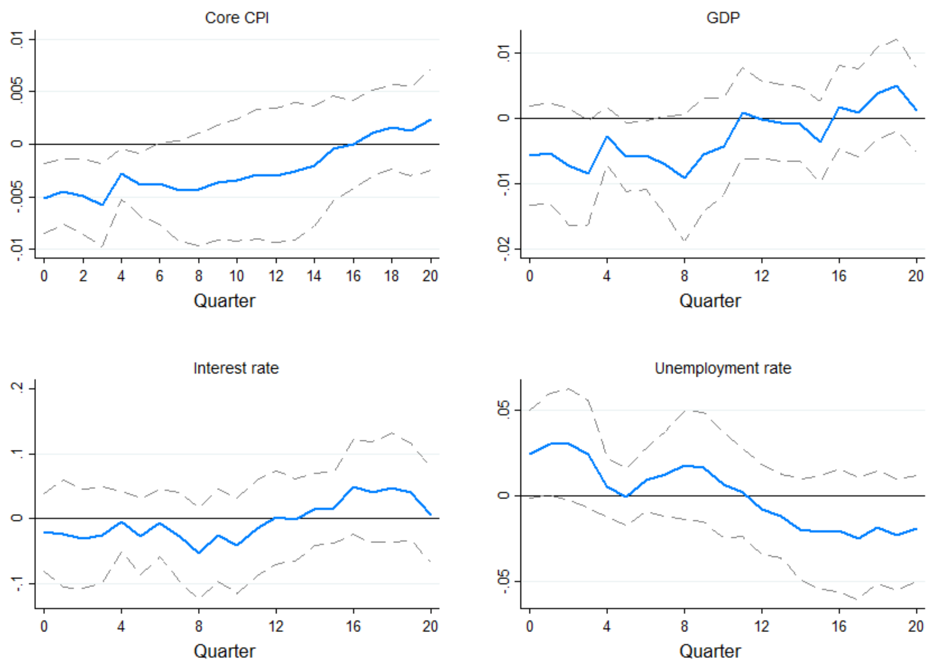


Figure 5: Response of energy and food prices to extreme weather shock

Figure 5 displays the dynamic response function of energy price and food price to extreme weather shocks. The response function is estimated using a vector autoregression (VAR) model, with extreme weather shocks constructed from the Australian Actuaries Climate Index (AACI) as explained in Section 3.1. The analysis is based on quarterly data from 1981 to 2021. The solid line represents the median response, while the dashed lines indicate the 90% confidence intervals.

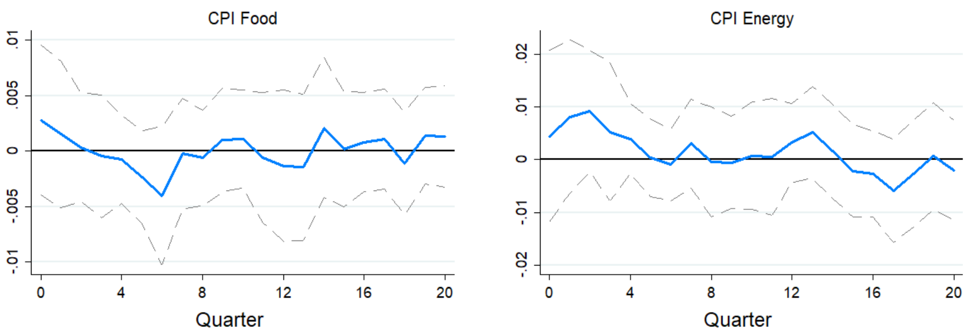


Figure 6: Response of energy consumption to extreme weather shock

Figure 6 illustrates the dynamic response function of energy consumption to extreme weather shocks. The response function is estimated using a vector autoregression (VAR) model, with extreme weather shocks constructed from the Australian Actuaries Climate Index (AACI) as outlined in Section 3.1. The analysis utilizes quarterly data from 1981 to 2021. The solid line depicts the median response, while the dashed lines represent the 90% confidence intervals.

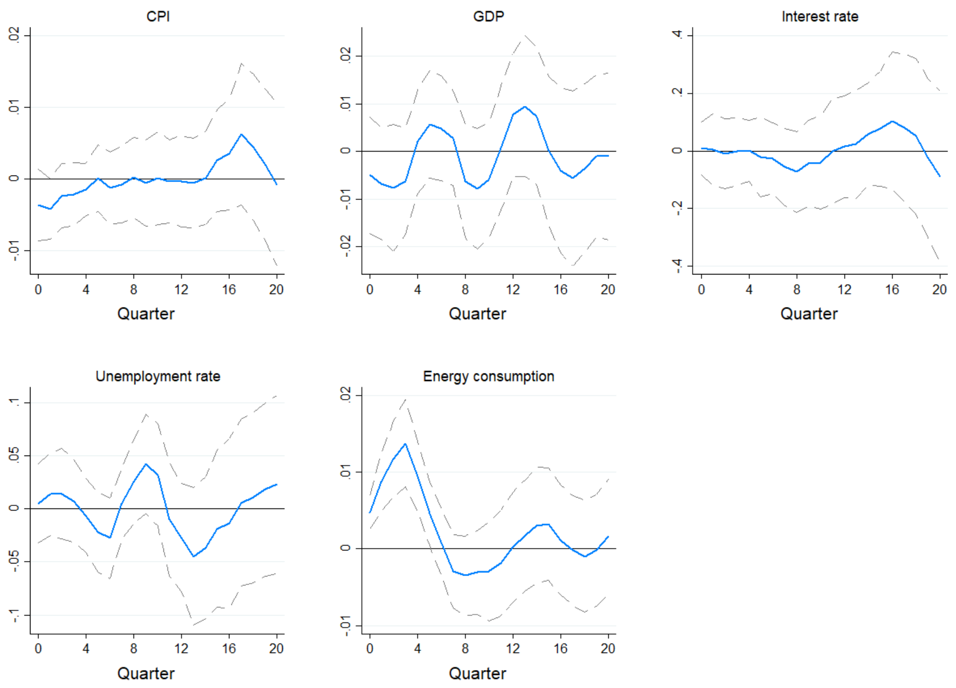
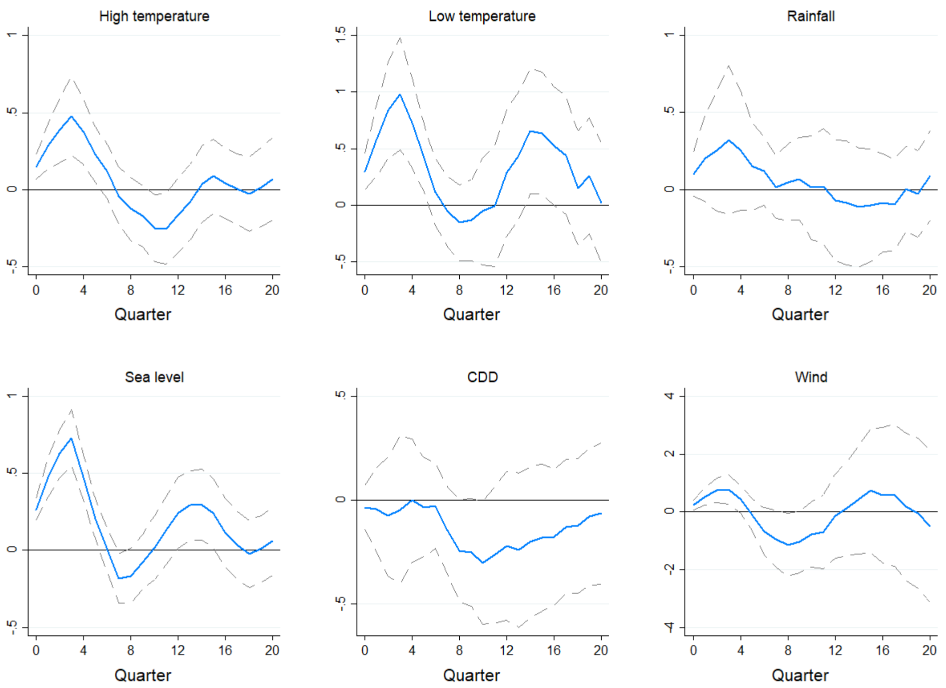


Figure 7: Response of energy consumption to each component of extreme weather shock

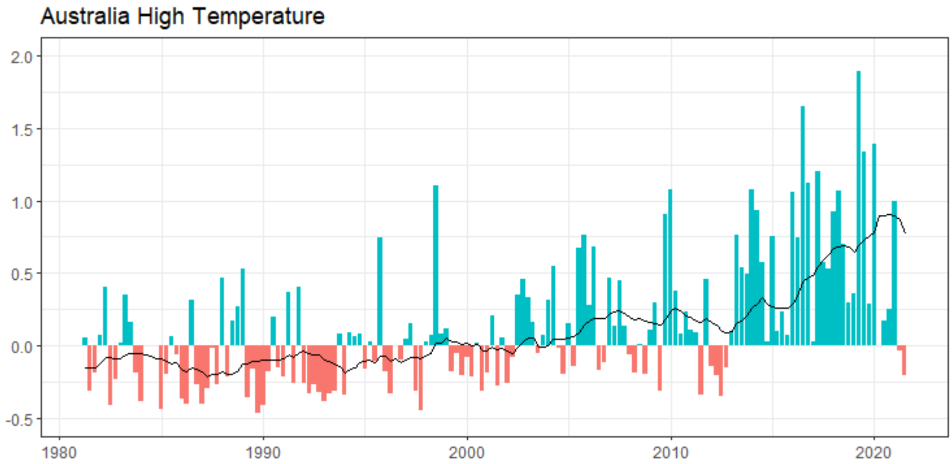
Figure 7 presents the dynamic response function of energy consumption to each component index of extreme weather shocks, including high temperature, low temperature, rainfall, sea level, consecutive dry days (CDD), and wind. The response function is estimated using a vector autoregression (VAR) model, with each component index constructed as described in Section 3.1. The analysis utilizes quarterly data from 1981 to 2021, except for the wind index which is based on data from 2002 to 2021. The solid line represents the median response, while the dashed lines indicate the 90% confidence intervals.

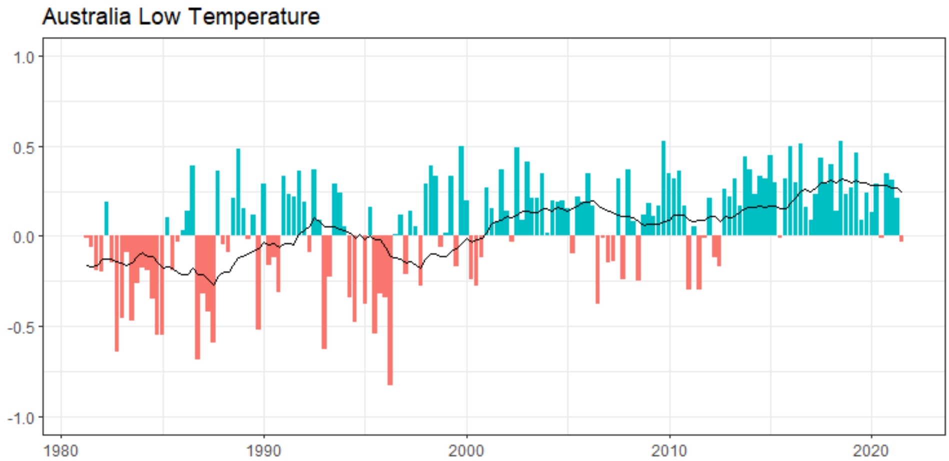


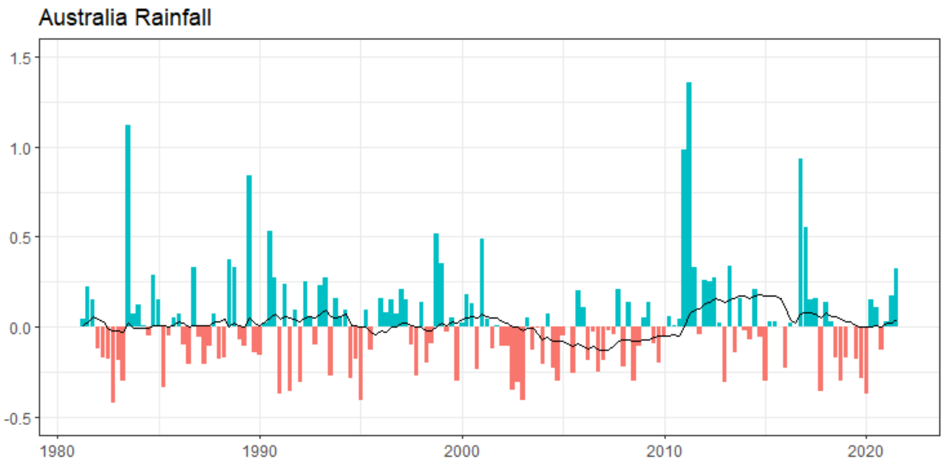
Appendix A

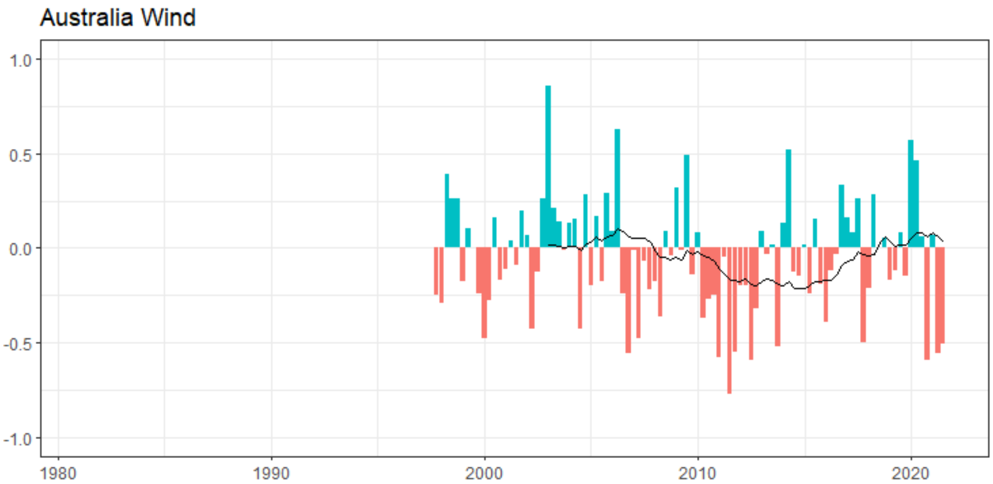
Figure A.1: Trend of the Australian Actuaries Climate Index (AACI) components

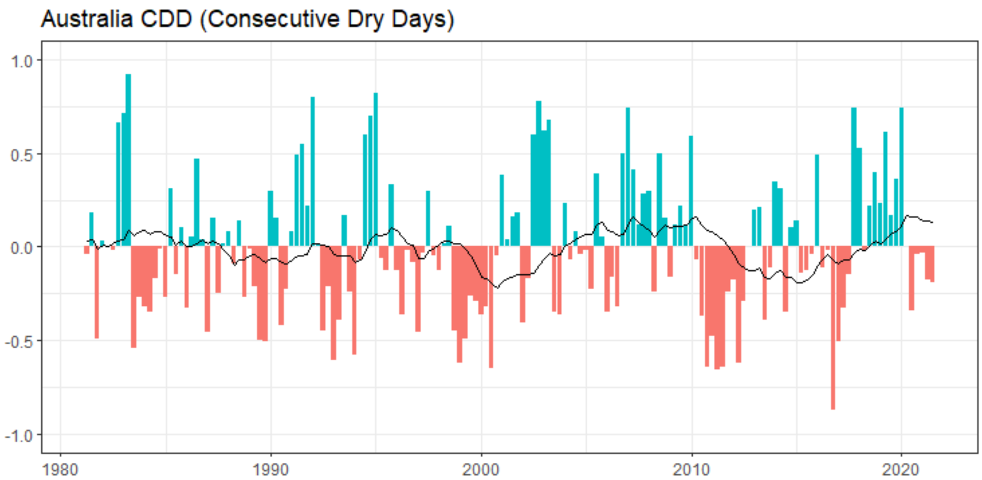
This figure illustrates the trend of each AACI component during the period 1981-2021. The index is constructed as described in Section 3.1. It shows six components: high temperature, low temperature, precipitation, wind, consecutive dry days, and sea level. The value of each index is standardized. The bar plots the quarterly values of the index relative to the reference period of 1981-2010, with the green bar indicating the positive value while the red bar indicates the negative value. The black solid line presents the five-year moving average of AACI.






Australia Rainfall
1.5
1.0
0.5
0.0
-0.5
1980
1990
2000
2010
2020


Australia Wind
1.0
0.5
0.0
-0.5
-1.0
1980
1990
2000
2010
2020


Australia CDD (Consecutive Dry Days)
1.0
0.5
0.0
-0.5
-1.0
1980
1990
2000
2010
2020

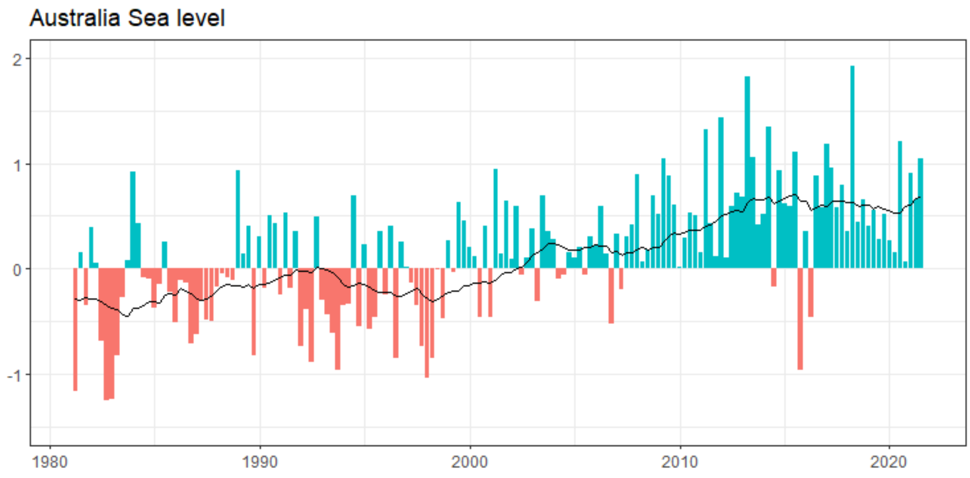

Australia Sea level
2
1
0
-1
1980
1990
2000
2010
2020

Figure A.2: Actuaries Climate Index for the U.S., Canada, and Australia

This figure illustrates the trend of the Actuaries Climate Index (ACI) for U.S., Canada, and Australia during the period 1981-2021. The ACI is the index for U.S. and Canada market, which is the green line and the AACI is the Australian index, which is red line. Index values are standardized.