UNIVERSITÀ DI PAVIA

Department of Economics and Management

Master's Programme in Economics, Development and Innovation

Food Insecurity and Extreme Weather Events

Evidence from Tropical Cyclone Freddy in Malawi

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Pavia, 29th June 2026

Academic Year 2023/2024

Acknowledgements

First and foremost, I would like to thank my supervisor, Prof. Leone, for giving me the opportunity to write this thesis. Investigating a topic that is still under-researched and requires climate datasets not included in the standard training for a Master's in Economics increased the risk of complications. I consider it a strong vote of confidence that Prof. Leone, despite these challenges, let me choose this topic. Her advice and guidance have been very valuable throughout this entire journey.

I am profoundly grateful to my parents and my brother for their encouragement throughout my studies. During my stays abroad and the COVID-19 pandemic, they were an invaluable cornerstone. I would also like to thank my closest friends and flatmates, who have accompanied me throughout my studies and the writing of this thesis. Our shared experiences and conversations were always incredibly fruitful and deeply shaped who I am today.

Finally, I would like to express my deep gratitude and unconditional love to my partner, Samy, who carried me through challenging times. Despite not always being able to be close to her, her love and confidence in me are the greatest gifts I could get. I am incredibly thankful to have her by my side, as her enduring patience during stressful periods has been invaluable. She gives me the energy and reassurance to overcome all future challenges together.

English Abstract

While the literature identifies extreme weather events as a major driver of food insecurity, no empirical study has attributed food insecurity to a single event. This paper develops a conceptual framework that maps the impact of an extreme weather event across all dimensions of food security. By illustrating the effects on agricultural output, prices, and income, the framework shows how households' consumption and production are altered and how this, ultimately, triggers food insecurity.

Utilising the Integrated Food Security Phase Classification (IPC) and ERA5-Land climate data, this study assesses the impact of Tropical Cyclone Freddy (TC Freddy) on rural food insecurity in Malawi between 2019 and 2025. A district-level difference-in-differences and event-study design, including rigorous controls and fixed effects, are employed to isolate the effect from concurrent weather and social phenomena. By developing a measure that compares rainfall during the cyclone with long-term local baselines, this study successfully quantifies the district's exposure to TC Freddy, thereby categorising districts as affected or unaffected. The results indicate that TC Freddy increased food insecurity and the effect persists across multiple agricultural cycles. The impact is more pronounced during lean periods. When averaged over all periods, the estimated increase in the share of the food-insecure population is around 3.6 percentage points, equivalent to about one-quarter of the pre-Freddy baseline. The results are robust to several specifications.

This paper provides a conceptual framework, a rigorous identification strategy, and a case study for attributing food insecurity to single extreme weather events. Thus, when combined with studies attributing extreme weather events to climate change, this work can help examine the role of climate change in socioeconomic outcomes, such as food insecurity.

Italian Abstract

Sebbene la letteratura identifichi gli eventi meteorologici estremi tra i principali fattori all'origine dell'insicurezza alimentare, nessuno studio empirico ha mai attribuito l'insicurezza alimentare a un singolo evento. Il presente articolo sviluppa un quadro concettuale che mappa l'impatto di un evento meteorologico estremo su tutte le dimensioni della sicurezza alimentare. Illustrando gli effetti sulla produzione agricola, sui prezzi e sul reddito, il quadro mostra come il consumo e la produzione delle famiglie subiscano variazioni e come ciò, in ultima analisi, determini l'insicurezza alimentare.

Utilizzando la Classificazione integrata delle fasi di sicurezza alimentare (IPC) e i dati climatici di ERA5-Land, questo studio valuta l'impatto del ciclone tropicale Freddy (TC Freddy) sull'insicurezza alimentare rurale in Malawi tra il 2019 e il 2025. Un disegno empirico a livello distrettuale di tipo difference-in-differences ed event-study, che include controlli rigorosi ed effetti fissi, viene impiegato per isolare l'effetto da fenomeni meteorologici e sociali concomitanti. Sviluppando una misura che confronta le precipitazioni durante il ciclone con le medie storiche locali, questo studio quantifica con successo l'esposizione del distretto al TC Freddy, classificando i distretti come colpiti o non colpiti. I risultati indicano che il TC Freddy ha aumentato l'insicurezza alimentare e che l'effetto persiste per più cicli agricoli. L'impatto è più pronunciato durante i periodi di saldatura. Se calcolata come media su tutti i periodi, l'aumento stimato della percentuale della popolazione in condizioni di insicurezza alimentare è di circa 3,6 punti percentuali, pari a circa un quarto del valore di riferimento pre-Freddy. I risultati sono robusti rispetto a diverse specifiche.

Questo articolo fornisce un quadro concettuale, una strategia di identificazione rigorosa e un caso di studio per attribuire l'insicurezza alimentare a singoli eventi meteorologici estremi. Pertanto, se combinato con studi che attribuiscono gli eventi meteorologici estremi al cambiamento climatico, questo lavoro contribuisce a esaminare il ruolo del cambiamento climatico nei risultati socioeconomici, come l'insicurezza alimentare.

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List of Abbreviations

DiD	Difference in Differences
FAO	Food and Agriculture Organization of the United Nations
FEWS NET	Famine Early Warning Systems Network
GDP	Gross Domestic Product
GoM	Government of Malawi
HLPE	High Level Panel of Experts
IFAD	International Fund for Agricultural Development
IPC	Integrated Food Security Phase Classification
IPCC	Intergovernmental Panel on Climate Change
OCHA	United Nations Office for the Coordination of Humanitarian Affairs
SHDI	Subnational Human Development Index
SDG	Sustainable Development Goal
TC	Tropical Cyclone
UK Gov	Government of the United Kingdom
UN	United Nations
UNICEF	United Nations International Children's Emergency Fund
WASH	Water, Sanitation and Hygiene
WFP	World Food Programme
WMO	World Meteorological Organization

1 Introduction

Even though hunger has declined slightly in recent years, around 8% of the global population suffers from hunger (FAO et al., 2025). In their annual report, all organisations of the United Nations [UN] that work in the field of food systems repeatedly highlight that the world remains far off track to achieve the Sustainable Development Goal 2 [SDG 2], which mandates the eradication of hunger by 2030 (FAO et al., 2018, 2024, 2025; United Nations [UN], 2024). As hunger in Africa has risen in recent years, the situation in Africa is even more concerning (FAO et al., 2025). According to figures from 2024, 22.2% of the African population is affected by severe food insecurity, and 37.7% by moderate food insecurity. This implies that more than half a billion people in Africa alone do not always have "physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life" (World Food Summit, 1996, par. 1). Extreme weather events are considered one of the main drivers of food insecurity (Bezner Kerr et al., 2023; Dasgupta & Robinson, 2022; FAO et al., 2018; Food Security Information Network [FSIN], 2024; Hasegawa et al., 2021; Mbow et al., 2019). Nevertheless, a study design capable of identifying the effect of a single event on food insecurity is still lacking. To close this gap, the present work develops a framework for such an analysis and applies it by assessing the impact of Tropical Cyclone Freddy on food insecurity in Malawi.

Amondo et al. (2023) state that most of the mechanisms linking extreme weather events to food insecurity remain unclear. To address this, the present paper develops a framework illustrating them. The framework aims to show how agricultural losses and infrastructure damage caused by such an event can affect market and social outcomes, such as prices, income, and sanitary conditions. Furthermore, it explains the complex interactions of the mechanisms shaping the food consumption of a household. Since households in agricultural economies are both producers and consumers of agricultural goods, the framework is divided into a production and consumption side. To account for the multidimensionality of food insecurity, the effects are mapped on the different dimensions, i.e., availability, access, utilisation, stability, agency and sustainability (High Level Panel of Experts on Food Security and Nutrition [HLPE], 2020). The framework also explains how external factors, such as humanitarian assistance, shape food insecurity and how mechanisms can reinforce themselves, leading to the persistence of the effects over several growing periods.

The Tropical Cyclone Freddy (TC Freddy), which struck Malawi in March 2023, serves as a case study for testing the new framework. Malawi is a suitable setting for analysis because, according to the Global Adaptation Index of the Notre Dame Global Adaptation Initiative (2026), it is one of the most vulnerable and exposed countries to climate change and extreme weather events worldwide. Furthermore, as Malawi's economy depends heavily on agricultural production, the effect is likely to be especially pronounced (Government of Malawi [GoM], 2023). Although the exposure to a tropical cyclone (TC) is difficult to quantify, there are several reasons to test the framework with a TC rather than another extreme weather event. In comparison to droughts or heat waves, TCs are sudden-onset events, and therefore it is less challenging to define the time of impact (Food and Agriculture Organization [FAO], 2023). Furthermore, their direct repercussions are more geographically confined than those of droughts. In contrast to floods, for TCs, high-resolution data are available, covering rainfall and wind speed. TC Freddy is considered an event suitable for the analysis, as it struck Malawi when most crops were still in the fields and therefore exposed to the TC (GoM, 2023). Moreover, TC Freddy did not affect the entire country, allowing for within-country comparisons (United Nations Office for the Coordination of Humanitarian Affairs [OCHA], 2023c). Additionally, food insecurity data are available for several years around the event, facilitating comparisons over time (Integrated Food Security Phase Classification [IPC], 2025a).

The framework indicates that the mechanisms affecting food insecurity differ between rural and urban populations. As Malawi's economy is primarily based on agriculture, this work focuses on the rural parts of the country. To test whether TC Freddy increased food insecurity, it draws on data from the Integrated Food Security Phase Classification (IPC) and combines it with rainfall data from the ERA5-Land dataset. Moreover, it includes controls on other extreme weather events in the time frame and uses data on humanitarian assistance. The identification strategy is based on time and regional variation, assuming that food insecurity in affected districts rises relative to unaffected districts after the TC. To test this, it employs a difference in differences (DiD) and an event-study design. Based on the literature and motivated by the data structure, the event study uses the average of two periods as the baseline following the approach of Miller (2023).

The results suggest that TC Freddy increased food insecurity in rural districts affected by it. The estimated effect is significant with and without including controls. In line with the literature and the developed framework, the event-study analysis indicates that the effect persisted across several growing periods and was concentrated on lean periods. The robustness of the results was tested using wild bootstrap confidence intervals, including the urban population and using a continuous treatment variable. Similar to other authors and due to limited data availability, the mechanisms behind the effect are explained by the framework, but could not be tested in detail by the statistical analysis, leaving the opportunity for further research (Keller & Mulangu, 2025).

Since this work is one of the first in the area, it makes three important contributions to the literature. First, the newly developed framework illustrates the channels through which extreme weather events affect food insecurity, thereby laying the groundwork for future research. Second, the analysis of the effect of TC Freddy on food insecurity contributes to the literature assessing the extent to which extreme weather events contribute to food insecurity. Third, the paper integrates into the literature assessing the role of climate change in food insecurity.

Several authors recognise extreme weather events as one driver of food insecurity (Amondo et al., 2023; FAO et al., 2018; FSIN, 2024; Galanakis et al., 2025; Hasegawa et al., 2021; IPC, 2023; Keller & Mulangu, 2025; Ortiz et al., 2023; Tidiane Ndour et al., 2025). Nevertheless, Amondo et al. (2023) state that the mechanisms behind the effect remain unclear. Hence, the comprehensive framework mapping the impact of extreme weather events on food insecurity developed in Section 3 is a crucial contribution to the literature. Prior frameworks focused either on food insecurity or extreme weather events. This work builds on these and combines them into one comprehensive framework. The framework is primarily grounded in the work of Amondo et al. (2023), in which they examine how extreme weather events can influence child undernutrition. They identify changes in agricultural production and infrastructure and asset damage as the primary factors contributing to the effect. Subsequently, they show that all other effects can be derived from these. For instance, reduced yields lead to lower agricultural supply, and infrastructure damage increases transportation costs, both of which lead to higher agricultural prices. Although they do not explicitly mention this, their framework indicates that households are both producers and consumers. Rising prices of agricultural goods affect them on the one hand, as their purchasing power decreases, and on the other hand, as their income increases. Hence, the effects go in opposite directions and can therefore potentially offset each other. The framework of Amondo et al. (2023) also features adaptation and coping mechanisms. These are depicted as external to the other effects, suggesting that they moderate the other mechanisms. Even though the framework focuses on nutrition and, therefore, more on the nutrient content of crops, most of the mechanisms proposed by the authors also apply to the framework of this work. Although not addressed by Amondo et al. (2023), an important characteristic of food insecurity is its multidimensionality. In their framework on food insecurity Spieker et al. (2022) distributed the various mechanisms across the different dimensions. For example, availability is shaped by production and agricultural stock. Utilisation depends mainly on sanitary conditions. Economic access is driven by prices and income. Hence, although Spieker et al. (2022) developed a general framework and do not focus on extreme weather events, they contribute an important aspect to research on the effect of extreme weather events on food insecurity. Moreover, when trying to understand food systems, it is crucial to understand the feedback mechanisms inherent to them (HLPE, 2020). The framework of the HLPE (2020) shows how food insecurity can influence its own drivers and is therefore an important contribution to this paper. For instance, lower levels of utilisation may undermine economic access because insufficient sanitation infrastructure results in poorer health, which can diminish work capacity and consequently limit household income (HLPE, 2020). This is crucial in the context of extreme weather events as it explains how they can trigger a chain of effects that extends well beyond the original impact. Furthermore, it shows how effects can extend from one growing period to another. Together, these works provided the foundation for building the framework proposed by this paper. By combining the mechanisms and the idea of multidimensionality and persistence into a single comprehensive framework, it not only provides the theoretical background for future research on the effects of extreme weather events on food insecurity but also enhances the understanding of the mechanisms that lead to it.

A second significant contribution of this study lies in its enrichment of the research identifying the drivers of food insecurity. In a meta-analysis Galanakis et al. (2025) list over 100 drivers. They categorise them into groups, including food value chain performance drivers, economic and market drivers and biophysical and environmental drivers. By showing the effect of TC Freddy on food insecurity, this work integrates into existing literature, which identifies extreme weather events as an important driver of food insecurity. Even though most of the authors focus on the connection between climate change and food insecurity and do not consider the important role of extreme weather events, there are some relevant scientific contributions to this topic (Hasegawa et al., 2021; Tidiane Ndour et al., 2025). According to Galanakis et al. (2025), extreme weather events affect every dimension of food insecurity in the long as well as in the short term. In line with this, the 6th IPCC report states that extreme weather events reduce access to food and increase prices, thereby influencing all other dimensions of food insecurity (Bezner Kerr et al., 2023). The examples in the report show that Sub-Saharan Africa is particularly affected by this phenomenon. Regarding the food crises in 2024, extreme weather events are considered the main driver for nearly one-third of them (FSIN, 2024). Hasegawa et al. (2021) quantify how the prevalence of food insecurity worldwide will change due to more frequent and intense extreme weather events caused by climate change. First, they compute the impact of climate-induced extreme weather events on future yields of rice, spring and winter wheat, maize, and soybeans. Based on this, they estimate the change in the probability distribution function for calorie intake and its effect on the share of people at risk of hunger in 2050. While this increases by 11% for low-emission scenarios, it rises by 36% for high-emission scenarios. In conclusion, regardless of differences in types of extreme weather events, research provides strong evidence that extreme weather events, in general, increase food insecurity.

Fewer authors focus on a single type of extreme weather event. Amondo et al. (2023) provide important insights into the effect of dry spells and heat waves on child undernutrition in Uganda. They state that calorie and protein intake of children is affected negatively if previous growing seasons were affected by such an event. Keller and Mulangu (2025) assess the effect of the 2022 cyclone season in Madagascar on households' welfare. Using a DiD approach, they compare data from 2020 and 2022 to assess how expenditure and food consumption changed over time in households affected and unaffected by the cyclones. Using wind speed data, they categorise households as affected or unaffected. To account for sociodemographic differences between these two groups, they employ propensity score matching. They reveal that the cyclones of the 2022 season not only increased the percentage of people living in poverty but also reduced calorie intake and food diversity in Madagascar. Since the last data they use is from the same year as the TCs, they can only reveal short-term effects. Although data availability did not allow for testing the mechanisms behind it, the study of Keller and Mulangu (2025) is very valuable as it attributes changes in food insecurity to a group of cyclones. In several respects, this paper goes a step further than previous literature that examined the effects of extreme weather events in general or of certain types of them. First, to the best of the author's knowledge, it is the first to show the effect of a single TC on food insecurity. Second, it enhances the statistical approach of Keller and Mulangu (2025) as it includes several periods before and after the event, making the assessment of medium-term effects and the parallel trends assumption possible. Third, it not only focuses on food consumption but also considers all dimensions of food insecurity. Overall, this paper can be considered a very valuable contribution to the literature, identifying extreme weather events as an important driver of food insecurity.

The third important contribution of this paper is that its insights can be used to further develop the literature on the effect of climate change on food insecurity. The World Weather Attribution is an initiative of the Imperial College London and other institutions that aims to attribute single extreme weather events to climate change. When they started, most studies focused on the effect of climate change on extreme weather events in general (Otto, 2019). By enhancing their statistical methods, the World Weather Attribution can now assess how the intensity and probability of a single event have changed due to climate change. To some extent, this paper follows their approach. It builds on work showing the general effect of extreme weather events on food insecurity and seeks to assess the effect of a single extreme weather event. Combining the results of studies that attribute single events to climate change with the insights from this work, future research can develop a framework and statistical methods to evaluate how climate change influenced a specific extreme weather event and how this subsequently affected food insecurity. This would be a substantial change in the literature assessing the effect of climate change on food systems, which, to date, had a very general focus.

Although Dasgupta and Robinson (2022) state that literature still lacks a comprehensive description of the mechanisms by which climate change affects food insecurity and its quantification, there is strong evidence that climate change influences food insecurity or will do so in the future (Dasgupta & Robinson, 2022; FAO et al., 2018; Galanakis et al., 2025; Hasegawa et al., 2021; Mbow et al., 2019; Msowoya et al., 2016; Roy et al., 2022). An IPCC report states with high confidence that climate change already influences food insecurity today (Mbow et al., 2019). Comparable to the effect of extreme weather events, the effect extends across all dimensions of food insecurity (FAO et al., 2018; Galanakis et al., 2025). One of the effects of anthropogenic climate change is rising temperatures (Eyring et al., 2021). Dasgupta and Robinson (2022) assess the effect of increased temperatures on food insecurity. They use FAO data on the share of people experiencing severe and moderate food insecurity from 2014 to 2019 across 83 countries. To assess the effect of temperature anomalies, they combine it with climate data from the ERA5-Land database. The difference between the annual temperature and the 30-year annual mean is considered an anomaly. The results of Dasgupta and Robinson (2022) reveal that for every 1 °C of temperature anomaly, severe food insecurity rises by around 1.6% and moderate by 1.9%. Although they do not have a good explanation for this, they state that the effect becomes stronger over time, suggesting that the impact of the same temperature anomaly increased during the last decade. In an IPCC report Roy et al. (2022) compare the effects of 1.5 °C and 2 °C global warming. They estimate that the number of people exposed to lower yields increases tenfold from one scenario to the other. This means that with 2 °C global warming, approximately 300 million additional people are affected by lower yields than with 1.5 °C global warming. According to them, this poses a threat to reaching SDG 2. Both the results of Dasgupta and Robinson (2022) and Roy et al. (2022) suggest that the effect of global warming on food insecurity is non-linear. Even though research regarding this is still lacking, extreme weather events may be part of the explanation, as some of them increase disproportionately with global warming (Seneviratne et al., 2021).

Regarding the context of the study, Msowoya et al. (2016) assess the effect of global warming on maize production in Malawi. Feeding the results of climate models into an AquaCrop model, they predict changes in maize yields in Lilongwe, Malawi's largest district. Based on simulations of temperature and rainfall, they estimate that maize yields in that district will decline by 8% to 14% by 2050, depending on the climate change scenario. Until the end of the century, the decrease will be 13% to 33%. As maize is by far the most important crop, they consider climate change to have an effect on food insecurity in Malawi. Taken together, there is a broad consensus in the literature that climate change increases food insecurity globally and in Malawi. Even though not all mechanisms are revealed, various authors highlight that extreme weather events are an important channel of this effect, as climate change increases the probability and the intensity of extreme weather events which consequently cause food insecurity (FAO et al., 2018; Galanakis et al., 2025; Hasegawa et al., 2021; Mbow et al., 2019). This work contributes a methodology to assess the effect of one single extreme weather event on food insecurity to the academic literature.

Hence, it facilitates testing the causal chain from climate change through extreme weather events on food insecurity by assessing a single event.

The following paper is structured as follows. Section 2 gives some background information on food insecurity, Malawi and TC Freddy. In Section 3, the newly developed framework for assessing the effects of single extreme weather events on food insecurity is presented. This is followed by a section on the methods used to estimate the effect of TC Freddy on food insecurity. After presenting the results in Section 5, their validity and robustness are assessed in Section 6. This is followed by a discussion of the results, integrating them into the existing literature, in Section 7.

2 Background information

2.1 Food Insecurity

In the Second Sustainable Development Goal, adopted in 2015, the member states of the UN not only committed to eradicating hunger, but also to ending food insecurity by 2030 (UN General Assembly, 2015). Several decades earlier, the action plan of the Rome Declaration on World Food Security of the World Food Summit (1996, par. 1) defined food security as the state in which "all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life". Hence, food security is a concept that goes beyond mere food availability in a region. Moreover, it depends on the following six intertwined dimensions: availability, access, utilisation, stability, agency, and sustainability (HLPE, 2020).

The 15th report of the HLPE (2020) describes these dimensions as follows: Availability focuses on the quantity and safety of the food consumed. Access can be divided into economic, physical and social access. Economic access depends on market prices and the financial means of a household. The physical component is determined by market access. Social access ensures that all social groups have access to sufficient food and nutrients. The dimension of utilisation concerns the sanitation and health conditions that enable safe food consumption. Stability underlines the importance of achieving food security at all times, even during shocks. The dimension of agency underlines that people should be able to shape their own food consumption, and sustainability adds the intergenerational aspect, implying that present actions should safeguard future food security.

Even though the concept of food security has been well defined for several decades, and countries have agreed to achieve it for everyone by 2030, many people still suffer from food insecurity. In 2024, around 28% of the world population was affected by moderate or severe food insecurity (FAO et al., 2025). After an increase during the COVID-19 pandemic, food insecurity rates have fallen in most parts of the world (FAO et al., 2025). Nevertheless, in Africa, numbers are rising, leading to 22.2% of severe and 37.7% of moderate food insecurity (FAO et al., 2025). This means that more than half of the people in Africa suffer from food insecurity.

To create a systematic framework, Galanakis et al. (2025) identified in the literature over 100 drivers relevant for food insecurity. These span several categories, including biophysical and environmental drivers, market drivers and socio-cultural drivers. Their framework shows the large number of drivers and their strong connectedness. Without questioning the other drivers, several authors emphasise the role of climate variability and extreme weather events in shaping food insecurity (Dasgupta & Robinson, 2022; FAO et al., 2018; FAO, 2023; Hasegawa et al., 2021; Mbow et al., 2019). Since the literature still lacks reliable estimates of the extent to which climate change contributes to food insecurity (Dasgupta & Robinson, 2022), such works mostly rely on estimates of changes in agricultural output to quantify this effect. For this work, the effect of climate-induced changes in extreme weather events is particularly important. A flagship report of FAO (2023) estimates that natural disasters cause an annual loss in agricultural production of around USD 120 billion, equivalent to 5% of the agricultural GDP. In Eastern Africa, where Malawi is located, the loss even amounts to more than 14% of the agricultural GDP (FAO, 2023). Even though this also includes losses from disasters unrelated to climate change, such as earthquakes, most of these are caused by natural disasters that have become more likely due to climate change. As this results in a serious reduction of available crops, this can trigger food insecurity (FAO, 2023).

2.2 Malawi

Malawi is a fast-growing and, compared to neighbouring countries, densely populated country of approximately 20 million inhabitants in eastern Sub-Saharan Africa (Famine Early Warning Systems Network [FEWS NET], 2016). It spans around 900 km from north to south and 160 km from west to east (Thiery et al., 2024). The altitude of its districts varies from near sea level to 1,500 m above sea level (Pangapanga-Phiri, 2025). Transport costs are high and, especially for the rural population, market access can be challenging (FEWS NET, 2016; S&P Global, 2023). The subtropical climate of the country is characterised by a wet and a dry season (FEWS NET, 2016). Average annual rainfall increases from 1,048 mm in the South to 1,102 mm in the Central region and 1,687 mm in the North (Muñoz Sabater, 2019b). Malawi is one of the least developed countries in the world, and agriculture remains the backbone of the economy (GoM, 2023). Around 20% of the national Gross Domestic Product (GDP) is generated in the agricultural sector (GoM, 2026). Furthermore, the sector provides important employment opportunities, especially in February when the weeding must be done (FEWS NET, 2026c).

Malawi is endowed with suitable conditions for rainfed and irrigated agriculture (GoM, 2023). Smallholder farmers contribute approximately 75% to the total agricultural output (GoM, 2024). Due to the higher population density, land parcels in the South tend to be smaller (FEWS NET, 2016). Typically, the North and the Centre achieve an agricultural surplus, while the South runs a deficit (FEWS NET, 2026c). The main growing season goes from November to April (FAO, 2025). The most important crops are maize, sorghum, cassava and rice (FEWS NET, 2016). In terms of production volume, cassava is the most widely harvested crop (FEWS NET, 2026b). Nevertheless, maize is by far the most important crop in Malawi as it has a higher calorie density (FEWS NET, 2016; GoM, 2024). It is grown by nearly all farmers all around the country.

The most common livestock in rural Malawi are cattle, goats, pigs and poultry (FEWS NET, 2016).

2.3 Tropical Cyclone Freddy

Tropical Cyclone Freddy (TC Freddy) was the longest-lasting cyclone and the one with the most energy on record (World Meteorological Organization [WMO], 2024). In February 2023, it formed off the coast near Australia and travelled across the Indian Ocean, gathering water and energy. It hit the southern parts of Africa in March 2023 (WMO, 2024). Most of the damage was recorded in Mozambique, Malawi, and Madagascar (OCHA, 2023d). For Malawi, it brought heavy rains between the 11th and the 15th of March (Muñoz Sabater, 2019b). In several districts in the South, such as Chiradzulu, Mulanje, Nsanje, and Thyolo, the total rainfall over those 5 days averaged across each district exceeded 500 mm (Muñoz Sabater, 2019a). This represents approximately half of the normal annual total. At some stations, rainfall was even more than the normal annual total (GoM, 2023).

Most destruction was caused by floods and landslides triggered by the extraordinary rains (GoM, 2023). About 2.2 million people were directly affected by the cyclone, 1,200 people were reported dead or missing, and more than 600,000 were displaced (GoM, 2023). Total economic losses were estimated to be approximately 500 million USD, representing 5% of the national Gross Domestic Product (GoM, 2023). Apart from the economic losses, the cyclone led to significant shocks in the agricultural sector. About 200,000 hectares of agricultural land were either submerged or washed away (OCHA, 2023b). This resulted in damage and losses of about 110 million USD (GoM, 2023). Approximately 50% were direct crop losses, and around 40% were losses and damage to irrigation systems. The other 10% corresponded to livestock and fishery losses and damages. Hence, the numbers show that most of the economic cost in the productive sector is attributable to the crop sector. This stems from the timing of the shock. When TC Freddy hit, the maize harvest was still in the fields, and therefore the TC was able to destroy a significant share of Malawi's most important crop.

Even before TC Freddy, transport costs in Malawi were high due to poor road infrastructure (S&P Global, 2023). By destroying transport infrastructure worth 110 million USD, TC Freddy made food logistics even more challenging (GoM, 2023). It destroyed more than 10% of the national road network (GoM, 2023). Some areas in southern districts were rendered inaccessible for several weeks after the TC (OCHA, 2023b). Hence, infrastructure damage substantially affected the availability and physical access to food.

Concerning the utilisation of agricultural goods, the GoM (2023) reported damage to over 500 km of pipeline and over 1800 boreholes. Furthermore, nearly 90,000 private and public latrines were damaged, deteriorating WASH conditions (Aderinto, 2023; GoM, 2023; OCHA, 2023a). In the South, this worsened the cholera epidemic already impacting Malawi when TC Freddy hit (Braka et al., 2024). Additionally, over half a million Malawians were displaced by TC Freddy, and thousands moved to shelters where safe food consumption posed a challenge to camp management (OCHA, 2023a).

OCHA (2023a) estimated that 1.3 million Malawians required urgent life-saving food assistance after TC Freddy. Other authors refrained from providing specific estimates but projected, in the immediate aftermath of the event, that TC Freddy would exacerbate food insecurity (Bahaji, 2023; GoM, 2023). Immediately after TC Freddy, the World Food Programme targeted 715,000 Malawians in the southern part of the country with humanitarian assistance (FEWS NET, 2023). In the flash appeal for humanitarian assistance, OCHA (2023a) requested funding of 25 million USD for nine projects in the area of food insecurity. Across all sectors, including WASH, education and nutrition, OCHA estimated a financial requirement of approximately 70 million USD for recovery from TC Freddy.

There is no evidence showing whether TC Freddy itself or its extraordinary strength is attributable to climate change. In general, there is mixed literature on the effect of climate change on TCs (Hoegh-Guldberg et al., 2022). Some papers indicate that there are fewer TCs due to climate change, but that those that arise get stronger in terms of wind speed and rainfall (Hoegh-Guldberg et al., 2022; Knutson et al., 2020). Otto et al. (2022) exemplify this by showing that climate change, with a high probability, intensified rainfall during TC Ana and TC Batsirai, which hit Malawi and neighbouring countries in 2022. Hence, there is no literature showing whether climate change influenced TC Freddy.

3 Conceptual Framework

To better understand how an extreme weather event can affect food insecurity in low-income countries, the following describes the mechanisms at play. As other authors have noted, data availability in this area of research is very limited (Keller & Mulangu, 2025). Hence, most channels of impact cannot be tested empirically. Therefore, this section is central to explaining how extreme weather events influence food insecurity. The first subsection mathematically describes the composition of the income and the consumption of a typical household. Furthermore, it shows how a household is constrained in its decision-making. The framework presented in the second subsection illustrates how household food consumption is affected by an extreme weather event and reveals the underlying mechanisms. The third subsection applies the framework to TC Freddy and shows how the consumption possibilities of households, both affected and unaffected by the TC, change.

The conceptual framework focuses on mechanisms in developing countries, such as Malawi, and thus makes some important, but justified assumptions. Nevertheless, some of its elements can be transferred to other country groups. As farmers in developing countries tend to be smallholders, they are considered consumers and producers of agricultural goods. Whether they are net consumers or producers can change over the year, depending on their stock levels. Normally, they act as sellers after harvest and become buyers during the year. Due to small production and consumption quantities and following the work of Singh et al. (1986), the households are always considered price takers. As shown by the different dimensions of food insecurity, it is a household-level phenomenon influenced by some macro-level circumstances (HLPE, 2020). Thus, the household constraint presented in Section 3.1 focuses on the micro level, but the framework of Section 3.2 includes some macro elements. The latter are necessary to explain, for example, price changes in markets.

3.1 Mathematical description of the constraint an agricultural household faces

$$p_m X_m + p_a X_a = p_a Q_a(L, V, A, K) - p_v V + p_l(T - L - X_l) + E \tag{1}$$

Source: Adapted equation from Singh et al. (1986, p. 152)

Although Singh et al. (1986) developed their model in the 1980s, it still describes well under which constraint an agricultural household maximises utility. It includes all essential mechanisms for the framework without adding unnecessary complexity. Equation (1) shows the constraint and its derivation is provided in Appendix A.1. The left-hand side of the equation represents the consumption side. It indicates the total expenditure, which is the consumption of a market good (X_m) and an agricultural good (X_a) valued at their respective prices (p_m; p_a). The market good is a compound good of all commodities not produced by the household. For food-deprived households, food items represent a high share of the market good (X_m). The right-hand side characterises mechanisms on the production side. It contains the value of the agricultural output produced (Q_a) at market price (p_a). Agricultural output (Q_a) depends on the input of labour (L) and other production factors needed (V) as well as the quantity of land (A) and capital (K) available. The right-hand side is negatively affected by agricultural input expenditure, which is the product of the price (p_v) and quantity (V). Furthermore, it includes the income from external work. This is the product of the working hours ($T - L - X_l$) and the wage (p_l). The working hours are the difference between the total productive time available (T) and the sum of labour needed on the farm (L) and the leisure time (X_l). Lastly, the right-hand side of the equation contains the non-farm and non-labour income (E), such as humanitarian assistance or harvest stocks from previous years.

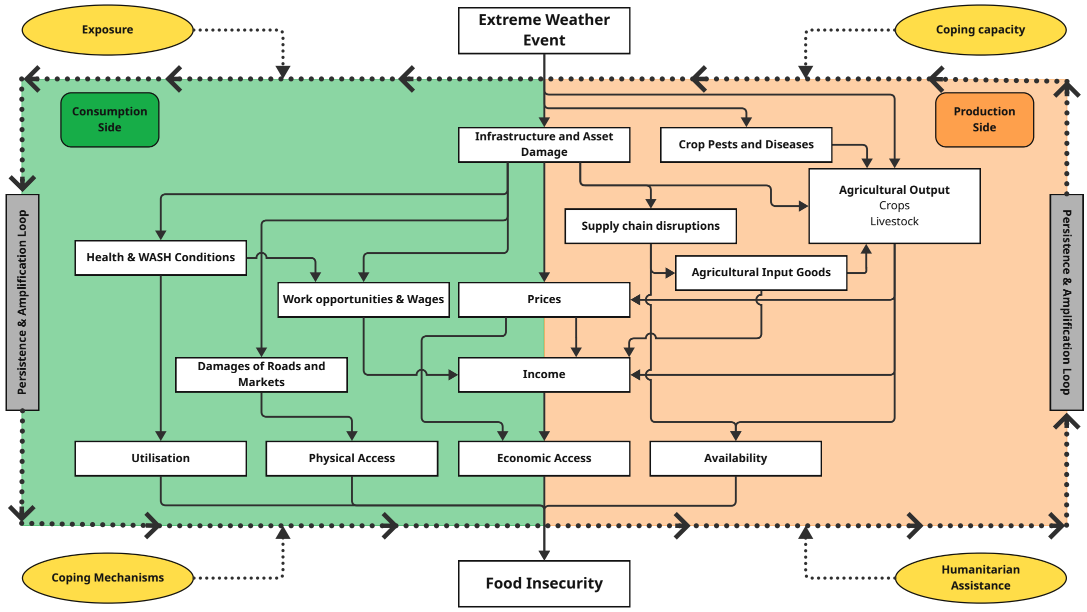
In summary, the total income available for consumption is the sum of the farm income, labour income, and income from other sources. Whether this allows for buying larger or smaller quantities depends on the market prices of the consumption goods. Therefore, market prices of agricultural goods play a pivotal role on the production and consumption side.

3.2 Mechanisms of the effect of an extreme weather event on food insecurity

To the best of the author's knowledge, there is, to date, no comprehensive framework that maps the effect of extreme weather events on food insecurity. Hence, the framework presented in Figure 1 is based on a framework that shows the effect of extreme weather events on child nutrition proposed by Amondo et al. (2023). Furthermore, it builds on ideas from Spieker et al. (2022) and includes the notion of feedback loops that can be found in the framework of the HLPE (2020). Most of the mechanisms presented are described in the work of Amondo et al. (2023). The framework is divided into a production and a consumption side to reflect that households produce and consume agricultural goods.

By definition, the effect of an extreme weather event on food insecurity is determined by the physical exposure of the household to the event. Its response is constrained a priori by its coping capacities, such as financial or agricultural reserves and the ability to generate income from other sources. Since some of the mechanisms discussed below can persist over multiple growing periods, the impact of an extreme weather event may extend over several agricultural cycles. This may occur if damages cannot be repaired within one year or if extreme weather events destroy the means of production for the following year. Furthermore, an amplification loop may arise if

Figure 1: Framework for the effect of an extreme weather event on food insecurity



Source: Own representation based on frameworks by Amondo et al. (2023), HLPE (2020), and Spieker et al. (2022)

coping strategies hinder agricultural production in the future, or if another extreme weather event strikes while coping capacities are still reduced by a previous shock. Besides these persistence and amplification loops, exogenous factors, such as weather, humanitarian assistance and coping mechanisms, shape the path of recovery.

The effects on production and consumption arise primarily from reduced agricultural output and damage to infrastructure and assets. Agricultural output can be affected directly if the extreme weather event destroys the crops in the field or kills livestock, or indirectly by triggering crop pests or diseases. Dry spells, for example, can cause infestations of the fall armyworm (FEWS NET, 2024; Kakara et al., 2026). Infrastructure or asset damage includes destroyed roads, bridges or markets, and the loss of irrigation systems or other tools essential to agriculture.

On the production side, agricultural output is a key factor. As shown in Section 3.1 it depends on labour, agricultural land, input goods, and capital. Extreme events can render land unusable for agriculture by flooding or submerging it, or by destroying the crops grown on it. Moreover, the supply of input goods, such as fertiliser, may be affected by damaged transport infrastructure. Additionally, capital input may be reduced as production tools are destroyed by the event. This may include the loss of livestock that were held for meat or milk production in the following years. Hence, the agricultural output of an affected household declines if the reduction in other input factors cannot be mitigated by higher labour input. This effect may persist, as infrastructure repair or the recovery of production assets may not be completed within one year. At the macro level, reduced agricultural output and damage to infrastructure or assets raise prices for agricultural and non-agricultural products. As shown in Equation (1), the household's agricultural income is the product of the price and the quantity produced minus the input costs. Thus, it is negatively affected by decreased output and by higher input prices, but positively affected by higher agricultural prices. Hence, the effect on agricultural income depends on the extent of damage caused to the household's agricultural production.

The consumption side describes the mechanisms outside the agricultural sector. As the extreme weather event perturbs the economy and destroys means of production in and outside agriculture, work opportunities and wages are affected. Lower yields, for example, decrease the demand for agricultural workers (Haile, 2005). This influences the household's disposable income in addition to the effect of lower farm income. Furthermore, an extreme weather event can impact food consumption by damaging roads and markets, making buying food a challenge. Moreover, if it renders sanitary installations unusable, this compromises safe food consumption and heightens the risk of waterborne diseases. Hence, it can lead to an inability to work, which in turn decreases labour income and reduces labour input in agricultural production.

When taking the effects of production and consumption side together, it appears that all dimensions of food insecurity may be affected by an extreme weather event. By definition, such an event compromises stability. Availability may be affected by a reduction of agricultural output or by supply chain disruptions. Economic access is influenced by changes in prices and income, and physical access is reduced by transport disruptions. The dimension of utilisation can be affected by deteriorating water and sanitation conditions. Agency is compromised by higher prices and lower availability of agricultural products. This makes it more difficult for households to choose their diet. The effect on sustainability depends on the coping and adaptation mechanisms implemented after the event. Sustainability decreases if coping strategies involve selling assets necessary for production in the following years or when funds allocated to programmes for sustainable agriculture are redirected towards post-disaster recovery. Nevertheless, an extreme weather event can also be the trigger for a change towards more sustainable farming. For example, after a drought, farmers may start to grow more heat-resistant crops, like cassava (FEWS NET, 2016). Strictly speaking, the latter cannot be considered an effect of the extreme weather event since it is not caused by it and could even be implemented more easily without it.

3.3 Applying the framework to TC Freddy

Even though most of the channels through which TC Freddy influenced food insecurity cannot be tested in the statistical model of Section 4 due to limited data availability, the literature on TC Freddy corroborates nearly every mechanism mentioned above. Using the mathematical description of the household income constraint and the framework, the following paragraphs illustrate how TC Freddy influenced every dimension of food insecurity. Hence, it is a very important complement to the empirical analysis, which is limited in its ability to reveal the underlying channels of impact.

As described in Section 2.3, availability in affected regions was directly impacted by major losses of crops and livestock in the South of the country (IPC, 2023). Additionally, there was an indirect impact on availability due to disruptions in the transport of goods and the destruction of production assets. The GoM (2023) reported that 10% of the road network was fully or partially destroyed by TC Freddy and that irrigation systems, worth 40 million USD, were made unusable, impacting the growth of winter harvest (GoM, 2023). Hence, primarily households whose harvests were affected by TC Freddy and those in the southern districts experienced shortages in agricultural goods. Nevertheless, there could be spillover effects, and thus households in other districts could be impacted by reduced availability.

Equation (1) of Section 3.1 describes the economic access. The left-hand side depicts expenditure, and the right-hand side income. Starting with income, the external component (E) is primarily driven by humanitarian assistance. Even if only a small share of the projects described in Section 2.3 was carried out, humanitarian assistance had an important influence on the model. Hence, it is included in the statistical model of this work.

Regarding labour income, the effect is driven by wage and labour time. Wages are influenced by contradicting effects on labour demand. While agricultural demand declines, humanitarian relief creates new employment opportunities (GoM, 2023). Since agriculture is by far the most important sector and because work in humanitarian assistance requires a high level of education, it can be suggested that the demand for low-skilled labour declines after TC Freddy. This leads to declining wages (p_l), particularly in rural areas. Through this channel, the non-agricultural labour force with comparable educational attainment is impacted by the decline in agricultural output as well. Furthermore, worse WASH conditions due to TC Freddy aggravated the cholera outbreak in Malawi (Braka et al., 2024). The total productive time T decreased for those who contracted cholera as they became unable to work. Taken together, this reduces labour income ($p_l(T - L - X_l)$) for households in the zones struck by TC Freddy.

The agricultural income $(p_a Q_a(L, V, A, K) - p_v V)$ is negatively affected because infrastructure damage led to higher transport costs, thereby increasing input prices (p_v) after TC Freddy. Additionally, the production quantity (Q_a) declines for farmers whose agricultural land (A) was submerged or washed away or whose production assets (K) were destroyed (OCHA, 2023a). Furthermore, repairing the damage of the TC required a lot of labour (L), thereby reducing the labour productivity of those farmers. Although this did not impact the 2022/23 growing season, input availability (V) remained limited until the infrastructure damage was repaired. Hence, TC Freddy reduced the agricultural production (Q_a) of the farmers in affected regions through several mechanisms. Regarding agricultural prices (p_a), distortions are difficult to attribute to TC Freddy, as they are influenced by various factors, including the war in Ukraine. Nevertheless, several sources report increased price pressure on maize after TC Freddy and link it to the TC (Bahaji, 2023; GoM, 2023; OCHA, 2023a). In conclusion, agricultural income might rise for farmers with low input costs whose production is not or less affected by TC Freddy and decrease for those directly affected.

The expenditure part of economic access is defined by the left-hand side of Equation (1). Since food items constitute a significant share of the market good (X_m) for food-deprived households, their consumption levels mainly depend on food prices. As previously stated, a portion of the rise in agricultural prices was attributed to TC Freddy. Hence, households could buy fewer nutrients with the same income.

In conclusion, TC Freddy did not affect the economic access of every household equally. Assuming the share of labour income is minimal and omitting the exogenous factor of humanitarian assistance for a moment, the effects are as follows: The economic access of households that are net consumers of agricultural products declined due to higher prices, regardless of individual crop losses. Households that are net producers gained economic access if their agricultural production was not altered or if higher prices could compensate for their reduced production. In general terms, farmers with larger farms in regions not affected by TC Freddy tended to experience stable or even increasing economic access, whereas those with smaller farms or those living in regions affected by the TC mainly experienced lower economic access. This disparity is further widened by the TC's effect on labour income, but could be narrowed by coordinated humanitarian assistance.

The effects on physical access and utilisation were primarily driven by infrastructure damage. In regions hit by Freddy, transport became more challenging as roads and bridges were washed away (GoM, 2023). Major parts of the districts Chikwawa, Nsanje, Chiradzulu, Mulanje, and Phalombe needed to be supplied via air transport for several weeks, as they were inaccessible via road (OCHA, 2023a). Similar to this, infrastructure for water supply and sanitation was destroyed by the TC. As shown in Section 2.3 this led to a higher prevalence of cholera in the South (Braka et al., 2024). In conclusion, infrastructural damage decreased physical access and deteriorated the safe utilisation of food items.

Since the effect of TC Freddy on stability, agency and sustainability was indirect, it is not mentioned in the framework. As described, the emergency situation following the TC disrupted consumption stability. Agency is primarily influenced by availability and economic access (HLPE, 2020). As shown before, availability decreased, prices increased, and many households experienced lower income. Hence, the cyclone constrained purchasing power and choices regarding food consumption. The high capital needs to repair the damage caused by TC Freddy will, on the one hand, pose a challenge for financing sustainability programmes, and, on the other hand, create a window of opportunity to implement more sustainable food systems (GoM, 2023). The latter can only be considered a secondary effect, not by nature related to the TC, but dependent on the reaction of the Malawian society.

Summing up this section, all the mechanisms linking food insecurity to an extreme weather event mentioned in the framework can be observed after TC Freddy. Nevertheless, not every household in Malawi suffered equally. Those whose agricultural production was directly affected suffered the largest increase in food insecurity. Nevertheless, even Malawians whose harvests remained unaffected experienced negative effects from TC Freddy as prices and the risk of infection increased and as employment opportunities decreased. In contrast, farmers in regions not struck by TC Freddy, being net agricultural producers, could even profit from the situation. This effect drives the regional variation between the heavily impacted South and the less-affected North, which will be exploited in the identification strategy.

4 Methods

4.1 Data structure

For the analysis, data from 2019 to 2025 are used. Although food insecurity data are available from 2017 onwards, the first two years of data are not included for two reasons. First, the data prior to 2019 were measured according to different guidelines, raising concerns about comparability. Second, during the 2017/2018 growing season, Malawi experienced a major infestation of the fall armyworm (FAO, 2018; Reuters, 2017). As the development of the fall armyworm is temperature-dependent and average temperatures differ across districts, the effect may not be nationwide (Kakara et al., 2026; Muñoz Sabater, 2019b). Since there are no measures available to control for such a plant pest in the analysis, the years of the most severe fall armyworm infestations are excluded to avoid biasing the results.

Food insecurity is a household-level phenomenon, but it strongly depends on regional characteristics. While food availability, for example, is similar across households in the same location, economic access depends heavily on household income. Despite the advantages that a household-level analysis would offer, this study is conducted at the district level due to data constraints. This makes it challenging to reveal the mechanisms behind the effects and to uncover which households are especially affected by the TC. Since such a research design makes it impossible to control for household characteristics, it is even more important that the households in the districts included in the analysis are as comparable as possible. Although most people in Malawi are farmers, there are some urban centres where income is generated from more diverse activities. In these areas, the ways in which TC Freddy affects food security differ from rural areas. Therefore, this paper focuses only on rural districts, where farming is by far the most important source of income. Thus, the three important urban centres, Blantyre City, Lilongwe City and Zomba City, are excluded. Furthermore, Likoma, an island in the middle of Lake Malawi, is not considered in the analysis, as consumption and production patterns there rely more on fishing than in other areas. Using only districts that are shaped mainly by smallholder farming makes it possible to apply the framework of Section 3 and to understand the mechanisms behind the effects better.

The data used consist mainly of food insecurity data and weather data. The weather during the growing season affects agricultural output, which in turn influences the availability of food over the next 12 months until the next harvest. Hence, food insecurity data are matched with weather data from the growing period prior to the observation. This follows the approach of Amondo et al. (2023) who even consider the climate conditions of the last 5 years to be important for nutrition outcomes.

4.2 Measures

4.2.1 Food Insecurity

As food insecurity is a latent construct, it cannot be measured directly (IPC, 2024; Lentz et al., 2026). This measurement challenge, alongside other financial and administrative constraints, explains the relative scarcity of longitudinal data on food insecurity (IPC, 2021). For this study, the measure for acute food insecurity of the Integrated Food Security Phase Classification (IPC) is used. The scale contains five phases ranging from 1 (minimal food insecurity) to 5 (catastrophe/famine). It aims at revealing in which phase an administrative unit, for example a country or a district, is in general and which percentage of its population is in each phase. In comparison to other measures, the IPC-scale comprises all dimensions of food insecurity (Machefer et al., 2025). It is based on the evaluation of a national stakeholder panel, which assesses all available data related to food insecurity using the IPC protocol and compares it against reference tables (IPC, 2021). As the stakeholder team includes representatives from the national government, national and international non-governmental organisations, and UN agencies, it has expertise at the regional and global levels and comprises a diverse set of views on the topic (IPC, 2021). To generate the data, they first collect data on different indicators of food insecurity, such as the Food Consumption Score or the Food Insecurity Experience Scale. Subsequently, the team compares the available data against the thresholds of a reference table (IPC, 2021). Based on this, the experts estimate for each administrative unit the distribution of the population across the five IPC-phases. In conclusion, the assessment of the expert team remains subjective but is informed by the best data available.

The data are published in IPC reports on acute food insecurity once or twice per year for each country. Such reports present subnational data for the current three-month period and a projection period covering the subsequent three to four months. Like this, there are at least two data points per year for each subnational unit. All IPC-phases of 3 or higher are considered phases of crisis, and further humanitarian assistance is recommended for the population located in regions categorised into these IPC-phases (IPC, 2021). Therefore, as this indicates the share of people in need of assistance, most authors use the percentage of people in phase $\geq$3 to characterise the situation of food insecurity in a country (Al Sharjabi et al., 2024; FAO et al., 2024; FAO, 2025; Lentz et al., 2025; OCHA, 2024).

Apart from being the measure with the most data available, the IPC scale is considered the most important tool for assessing food insecurity for policy purposes (Government of the United Kingdom [UK Gov], 2021; Lentz et al., 2026; Machefer et al., 2025). Although its technical manual explicitly states its use in time series analysis, up to now, few empirical studies have employed the data (IPC, 2021; Penson et al., 2024). As comparable IPC data for most countries are only available since 2017, sufficient data for time-series assessments have only recently become available. One of the main limitations of employing this measure in such analyses is that the data are projections and that there is uncertainty about the actual food insecurity. Nevertheless, when the IPC (2024) tested for the accuracy of the data, it found that the projections in Malawi reflected the actual outcome very well. In the end, the share of the population in IPC phase $\geq$3 is used as the dependent variable in this paper, because of its rigorous guidelines, wide use, and extensive longitudinal coverage.

As can be seen in Table 4 of the Appendix B.2, which presents the descriptive statistics for all variables of this work, the mean share of the population in IPC phase $\geq$3 is .147 in the timeframe and districts considered by this work. This means that, during the analysis period, nearly 15% of Malawi's population was in an IPC phase, indicating a food insecurity crisis. The standard deviation of the variable is .099, revealing that district and time variation are considerable. Districts in the South tend to have higher levels of food insecurity, and over the years, food insecurity has risen in Malawi. Figure 6 of the Appendix shows the distribution of the variable. As expected for a measure based on expert evaluation, the frequencies of the variable are concentrated at multiples of 5%. The wide distribution across the range from 0 to 60% yields good opportunities for further analysis.

4.2.2 Exposure to TC Freddy

The literature lacks a standardised methodology for identifying regional entities affected by a cyclone or a hurricane (Anderson et al., 2020). Some studies use trajectory data (Caillouët et al., 2008; Currie & Rossin-Slater, 2013; Keller & Mulangu, 2025) and others estimate wind speed using data from wind field models (Barattieri et al., 2023; Goulbourne et al., 2024; Hancevic &

Sandoval, 2025). Anderson et al. (2020) underline that both of these measures may have major disadvantages. They argue that damage can occur far from the eye of a cyclone and can also be triggered by heavy rains or tornadoes that come with the cyclone. Furthermore, the damages are not systematically centred around the track of the storm due to the Coriolis force (Anderson et al., 2020). Hence, for their dataset mapping tropical cyclone exposure in the United States, they combine information on the track, wind speed, rainfall, flooding, and tornadoes associated with the storm. Unfortunately, such a compound dataset is not available for TC Freddy. Therefore, this work builds on one metric. There are several reasons this work uses rainfall data. First, since Malawi is landlocked, the wind speed of TC Freddy was not as high as in other countries, making it difficult to assess different exposure levels. Second, the damage report of the GoM (2023) states that most of the harvest losses and infrastructure damage resulted from mudslides and flooding, and not from wind. Data on mudslides are not available because they are a geographically very limited phenomenon. Even though the flooded area during TC Freddy is depicted in maps, to the best of the author's knowledge, there is no geocoded dataset on flooded land during the TC. As rainfall is the trigger for both mudslides and floods, this paper focuses on rainfall data.

The Department of Climate Change and Meteorological Services of Malawi (2026) lists over 70 weather stations all across the country. Nevertheless, only a few of them provide long-term data, which is necessary for the identification strategy. Hence, this work could not rely on station data. In recent times, gridded climate datasets that are based on satellite or reanalysed data are increasingly used for analyses in regions with low or even high station coverage (Nkhoma et al., 2026). Nkhoma et al. (2026) compared several gridded datasets to station data in Malawi. Although being outperformed by other datasets in annual rainfall and dry-season rainfall, the ERA5-Land data showed the best results for daily rainfall. Since this study focuses on several days of heavy rain during Malawi's rainy season, ERA5-Land is considered the best dataset for capturing the effect of TC Freddy. The dataset is a reanalysis of the ERA5-dataset, which is based on a land surface model fitted to observational data (Copernicus Climate Change Service, n.d.). It has a native resolution of 9 km, implying that there are on average 30 grid cells per district (Copernicus Climate Change Service, n.d.; Muñoz Sabater, 2019a). Given its wide usage in climate research and its good performance, this paper uses the data from the ERA5-Land-dataset (Nkhoma et al., 2026). The data are extracted using the Google Earth Engine. During this process, the data are aggregated to the district level by computing the average across all grid cells that are part of the district. Furthermore, daily totals are derived from the hourly data.

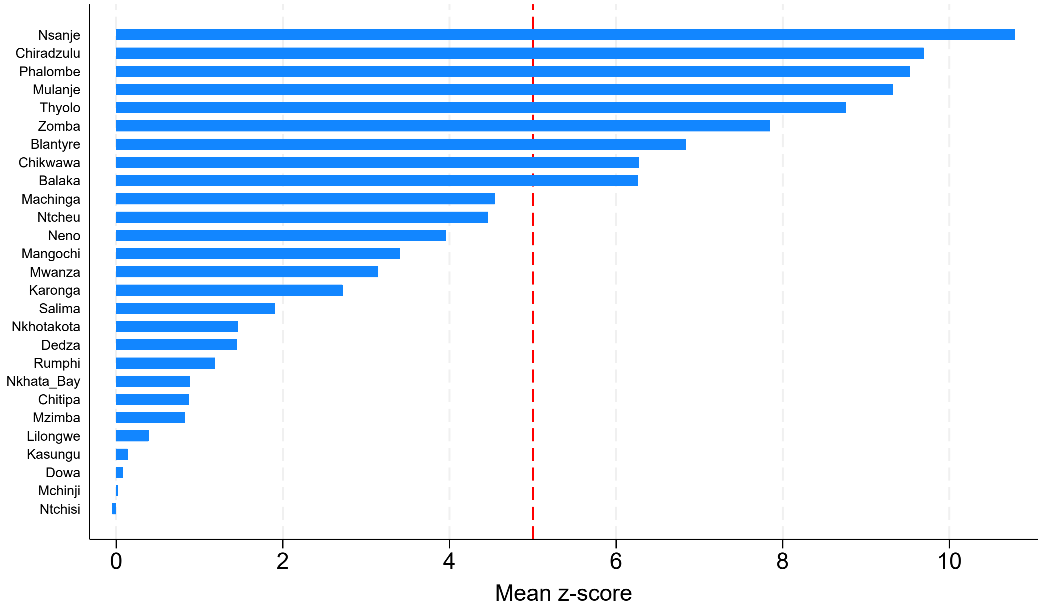
To identify the effect of TC Freddy, it is essential to have a measure that is as orthogonal as possible to other district characteristics. Taking the sum of the rainfall during TC Freddy in each district may not be orthogonal to other characteristics, as it is strongly influenced by topography and regional climate. Therefore, this work builds on the approach used by Burke et al. (2015) and Corno et al. (2020). They assess the effect of low economic productivity due to droughts on HIV in Africa and on marriage decisions in India and Sub-Saharan Africa, respectively. To identify periods of drought, they first build a long-term distribution of yearly rainfall specific to the local area. Subsequently, they consider all years with rainfall in the 15th percentile of this distribution to be droughts. Hence, they compare the rainfall to the normal rainfall at that specific location to define an extreme. Burke et al. (2015) argue that their measure is by definition uncorrelated to time-invariant confounders because every period in a location has the same probability of being considered a drought. This paper uses a similar approach to define the exposure to TC Freddy.

Using the ERA5-Land data from 1950 to 2025, the long-term distribution of daily rainfall in March is computed by district. Focusing only on data from March is important, as the rainfall during Freddy should be compared to what is expected for the location at that time. As rainfall in

Malawi varies strongly over the course of a year, the amount of normal rainfall not only depends on location but also on the season. The days with the heaviest rains during TC Freddy were the 11th to the 15th of March (Muñoz Sabater, 2019a). In nearly all districts, the rainfall of each of these days was in the top 5% of the long-term local month-specific distribution of daily rainfall. Hence, defining a threshold as done by Burke et al. (2015) and Corno et al. (2020) would not have been possible due to low heterogeneity in the data. Therefore, a z-score for each day from 11th to 15th of March is computed using the average and the standard deviation of the described distribution. This is similar to the z-score calculated by Amondo et al. (2023). In comparison to this work, they calculate it for total seasonal rainfall and use it to define dry spells. As this work focuses on extremely heavy rainfall, it employs daily rainfall. To define the district exposure to TC Freddy, the average z-score over the five days with the most rain is taken. Figure 2 shows the results. It reveals that in nearly all districts, the average daily rainfall during TC Freddy was significantly higher than on normal March days. In more than half of the districts, it even exceeded the average normal rainfall by 3 standard deviations, underlining the extraordinary strength of TC Freddy.

The reason this measure is orthogonal to district characteristics is comparable to that of Burke et al. (2015). The probability that any day in the long-term local rainfall distribution has a certain z-score is, by definition, uncorrelated to district-specific characteristics that influence rainfall, because these are already reflected in the distribution. This encompasses the district-specific probability of being hit by a TC, which is higher in the South than in the North. Each event increases the mean and the standard deviation and therefore decreases the z-score for any absolute level of rainfall. As the probability of each day having a certain z-score is uncorrelated to district-specific characteristics, the probability for the average of five consecutive days is as well. In

Figure 2: Average z-score for the rainfall in the days of Freddy by district



Notes: Z-scores are calculated by comparing the rainfall from the 11th of March to the 15th of March 2023 to the long-term daily district rainfall distribution for March (1950 to 2025); The red line indicates the threshold of $z = 5$
Source: Own representation using data from Muñoz Sabater (2019a)

conclusion, the measure used here is the average of five z-scores that are uncorrelated with district characteristics. Hence, the measure itself is orthogonal to these characteristics.

Similar to Burke et al. (2015) and Corno et al. (2020), this work must define a threshold to identify which districts were affected by TC Freddy. As there is no prior literature to rely on, the author uses visual inspection of the z-score distribution to establish a threshold. Figure 2 indicates a jump in z-scores between the district of Machinga (z = 4.542) and Balaka (z = 6.258). Hence, there is a group of districts that experienced rains with average z-scores below 5 and another that experienced rains with average z-scores of 6 or higher. This means that while in the first group of districts, daily rainfall during TC Freddy exceeded the normal rainfall on a March day by less than 5 standard deviations, in the second group, rainfall exceeded normal rainfall by more than 6 standard deviations. Using this jump in the distribution, the threshold is set to z = 5. As the threshold is arbitrary, the robustness of the results is assessed using alternative thresholds and using the z-score as a continuous treatment variable. Based on the exposure measure and the threshold of 5, 9 of the 27 districts are considered affected by TC Freddy. As shown in Figure 5 in Appendix B.2 they are all in the South region. OCHA (2023c) shows a map with areas flooded and affected by TC Freddy in the South of the country. As these areas match the districts identified as affected, OCHA (2023c) supports the validity of the proposed measure for the exposure to the TC.

4.2.3 Humanitarian Assistance

As the framework shows, humanitarian assistance has a significant impact on food insecurity in the aftermath of an extreme weather event. Following TC Freddy, various organisations provided humanitarian assistance. Ensuring food security was one of the main pillars of their work (OCHA, 2023a). Since humanitarian aid is limited to the post-Freddy time and targeted at specific areas, it is covered by neither time nor regional fixed effects. Measuring humanitarian assistance is challenging, and subnational-level data are scarce. In this paper, it is operationalised using the Malawian Flash Appeal report from 2023 (OCHA, 2023a). In this report, UN agencies, together with the national government, estimate the number of people requiring assistance across districts and humanitarian sectors following TC Freddy. Furthermore, they quantify the number of people their projects target. For this paper, data from the food assistance sector are used.

As the share of people in a district who received assistance is strongly correlated with the exposure to TC Freddy, including it in the analysis would absorb much of the explanatory power of the exposure variable. To address this, humanitarian assistance in this work is operationalised as the share of people in a district who would have needed assistance but did not receive it. This is considered the humanitarian assistance gap. Equation (2) defines the instrument mathematically. It is the number of people in a district who were in need after the cyclone (pop_i^{need}) minus those who were targeted by humanitarian aid (pop_i^{targeted}), divided by the district's population (pop_i^{total}).

Like this, it expresses the share of the population not targeted by humanitarian aid who would have needed assistance, relative to the district's total population. As it focuses on the assistance after TC Freddy, the measure is 0 prior to it. Using the data from OCHA (2023a), the humanitarian assistance gap is on average 1.3% after TC Freddy and has a standard deviation of 1.9%. This implies that around 260,000 people did not receive the assistance they urgently needed after the TC.

$$\text{Humanitarian assistance gap}_{it} = \begin{cases} 0, & \text{if } t < t_{\text{Freddy}}, \\ \dfrac{pop_i^{\text{need}} - pop_i^{\text{targeted}}}{pop_i^{\text{total}}}, & \text{if } t \geq t_{\text{Freddy}}. \end{cases} \tag{2}$$

4.2.4 Extreme weather conditions during the period of analysis

Since Malawi is highly vulnerable to extreme weather conditions, this work controls for such events during the period of analysis. Malawi is regularly hit by TCs affecting especially the South of the country (GoM, 2022). In the context of food insecurity, the literature names two TCs that had an influence during the study period. These are TC Ana and TC Gombe, which struck Malawi in January and March of 2022. According to humanitarian reports, both led to higher levels of food insecurity (FEWS NET, 2022a, 2022b; GoM, 2022; IPC, 2022). To account for their impact, a variable similar to the treatment variable for TC Freddy is used. First, the days with the heaviest rains are identified for each TC using graphical analysis of the ERA5-Land rainfall data. The strongest rainfall during TC Ana was observed from the 24$^{\text{th}}$ to the 26$^{\text{th}}$ of January, and for TC Gombe it was from the 11$^{\text{th}}$ to 13$^{\text{th}}$ of March 2022 (Muñoz Sabater, 2019b). For each of these days, the z-score within the district- and month-specific long-term rainfall distribution is calculated. Then the average for TC Gombe and TC Ana is taken. As for TC

Freddy, every district that experienced rainfall with an average z-value above 5 during TC Ana or TC Gombe was considered exposed to TC Ana or TC Gombe, respectively. For Ana, these are 3 districts, and for TC Gombe, these are 7 districts. All of them are in the South of the country. Similar to a DiD approach, the variables for TC Gombe and TC Ana take the value of one for all districts exposed to the respective TC in all periods following the cyclones and 0 otherwise. Hence, the coefficient of each variable can be interpreted as a DiD coefficient.

Since heavy rain can also occur without a cyclone event, this paper uses a measure of heavy rainfall during the growing period. It follows the same structure as the variables for TC Ana, TC Gombe and TC Freddy. For every day during the growing period, the z-score in the long-term district- and month-specific rainfall distribution is calculated using the ERA5-Land data. If the average z-score of three consecutive days exceeds 5, it is considered a heavy rain event. This is very similar to the definition used for the different TCs. The variable for heavy rain events is equal to 1 for each observation of a district that experienced such a heavy rain event in the previous growing season. In total, these are 126 observations which are dispersed all across the country and slightly concentrated at the beginning of the analysis period.

Several authors show that droughts can affect yields and therefore food insecurity (Amondo et al., 2023; Burke et al., 2015; Dasgupta & Robinson, 2022; Galanakis et al., 2025; Lesk et al., 2016). Since there are reports about droughts in Malawi during the period of analysis, especially due to the El Niño phenomenon, this work controls for this (FEWS NET, 2024). To operationalise it, the previously described approach of Burke et al. (2015) and Corno et al. (2020) is used, but instead of focusing on the whole year, this paper considers only the growing season. Like this, it is ensured that the measure is not biased by rain that occurs outside the growing season and therefore has very little influence on yields. Using the ERA5-Land data, the rainfall total for each season between 1950 and 2025 is calculated. Following Burke et al. (2015) and Corno et al. (2020) every growing season in the 15th percentile in this rainfall distribution is considered a drought. Since food insecurity depends on the harvest prior to the observation, the rainfall during the growing season before each observation is used. Based on this variable, 38 observations are classified as post-drought observations. They are all in 2024 or 2025 and spread across the country.

The relationship between temperature and agricultural output is well-researched. Even though rising temperatures have a positive effect at low baseline temperatures, the effect becomes negative when passing a plant-specific threshold (Antonelli et al., 2021; Hatfield & Prueger, 2015; Schlenker & Roberts, 2009). For Maize, the main crop in the Malawian agricultural system, this threshold is around 30 °C (Hatfield & Prueger, 2015; Schlenker & Roberts, 2009). This insight from agricultural economics might explain why Galanakis et al. (2025) state that temperature has a short and long-term effect on all dimensions of food insecurity, but find mixed effects on availability. Msowoya et al. (2016) assess the effect of global warming on Malawian maize production and reveal in their simulation a negative impact of temperature on production. Another important aspect of the connection between temperature and food insecurity is that the development of the fall armyworm, a common plant pest in Malawi, is temperature-dependent (Kakara et al., 2026). It shows the best growth, survival and reproduction rates at temperatures between 25 °C and 32 °C (Kakara et al., 2026). Taking into account these physiological characteristics of crops and the fall armyworm, this paper uses absolute temperature values. In comparison to the rainfall analysis, it does not compute temperatures relative to the normal temperature. Furthermore, it focuses on temperatures over 25 °C as they seem to be especially harmful for agricultural output. Nkhoma et al. (2026) state that the ERA5-Land not only provides good rainfall data for Malawi, but also good temperature data. Hence, this work uses hourly temperature data from the ERA5-Land dataset. To operationalise temperature, this paper follows the approach of Schlenker and Roberts (2009) who count how long a crop is exposed to each temperature during the growing period. Although they use temperature steps of 1 °C, this work follows Blom et al. (2022) to limit the number of variables and summarises temperature in ranges of 5 °C. Hence, it includes three distinct variables measuring the total hours a district is exposed to temperatures of the following ranges during each growing season: $25\ °C \leq T < 30\ °C$, $30\ °C \leq T < 35\ °C$, and $T \geq 35\ °C$. For better interpretation, the values are divided by 24. Thus, 1 unit represents one day at a certain temperature range. Of the 151 days of the growing season, districts experienced on average an equivalent of 38 days at temperatures between 25 °C and 30 °C and an equivalent of 8 days at temperatures between 30 °C and 35 °C. With the exception of Chikwawa and Nsanje, no district is exposed to temperatures ≥ 35 °C for more than the equivalent of two days. In general, the districts in the South experience significantly more hours of extreme heat than those in the North of the country.

4.3 Identification Strategy

The identification strategy builds on regional and time variation. It aims to assess whether, following TC Freddy, food insecurity increased more in the areas affected by the TC than in others. Spatial variation is defined at the district level and results from differences in exposure to TC Freddy across regions. Some districts were severely affected by the torrential rains of TC Freddy, and others less. While acknowledging that districts with lower exposure could also have been impacted by TC Freddy, this work groups districts into affected and unaffected to ensure clarity. As this group definition is to some extent arbitrary, there is a robustness check using a continuous treatment variable. Time variation is defined by the point in time the TC hit. All periods after March 2023 are considered post-periods, and those before pre-periods. The identification strategy hypothesises that food insecurity moved in parallel trends prior to the event and that districts affected by the TC diverged upwards from the common trend afterwards.

To test the hypothesis, a Difference-in-Differences [DiD] and an event-study design are implemented. By definition, both methods control for shocks at the global or national level, provided these affect both district groups equally and simultaneously. These properties are crucial, as inflation in Malawi was very high at the time of analysis and as the Russian war of aggression in Ukraine caused global shocks of agricultural input and output goods (IPC, 2022, 2023). Furthermore, during the analysis period, Malawi was affected by a cholera epidemic and the COVID-19 pandemic, which could also influence the trend of food insecurity. The DiD and the event-study analysis are first conducted with fixed effects only, and then controls considered important by the existing literature are added. Standard errors are clustered at the district level. As recommended by the literature, wild bootstrap estimation is used as a robustness check to account for the low number of clusters (Cameron & Miller, 2015; Miller, 2023; Roodman et al., 2019).

For the DiD-analysis, a traditional approach as described in Angrist and Pischke (2009) is employed. Equation (3) shows the specification of the DiD-analysis. Y_{it} represents food insecurity in district i in period t. Thus, it is the share of people being in IPC-phase $\geq$3 in district i in period t. Affected$_i$ is a dummy variable that is equal to 1 for all districts i that are affected by TC Freddy according to the exposure variable described in Section 4.2.2. Post$_t$ is equal to 1 for all periods after TC Freddy struck Malawi. Hence, β is the DiD-coefficient indicating the effect. The equation also includes a vector of variables X_{it} to control for time-variant district characteristics. It contains the values of the variables describing humanitarian assistance and extreme weather for district i at time t, which were described before. Moreover, district fixed effects α_i are included in the analysis to control for time-invariant district characteristics. λ_t

are time fixed effects and control for nationwide shocks, such as the repercussions of the war in Ukraine. ε_{it} represents the error term for district i at time t.

$$Y_{it} = \beta(\text{Affected}_i \times \text{Post}_t) + X'_{it}\gamma + \alpha_i + \lambda_t + \varepsilon_{it} \tag{3}$$

For the event study, modern research recommends making a deliberate decision on the reference periods (Borusyak et al., 2024; D. Clarke & Tapia-Schythe, 2021; Miller, 2023). In the traditional approach, the period prior to the event is used as reference. However, for some data, it is more appropriate to use the average of multiple periods. The last period with food insecurity data before TC Freddy was December 2022. This is in the middle of Malawi's lean period. In lean periods, households' food stocks get depleted. Hence, it can be assumed that the difference between food-secure and food-insecure households is more pronounced during these periods than during post-harvest periods, when even those households with a low harvest still have some food in stock. The food insecurity data consist of about the same number of lean and non-lean periods. Comparing the difference in food insecurity between affected and unaffected districts to the difference in a lean period would be adequate for lean periods, but not for non-lean periods. To resolve this issue, this paper follows the approach of Miller (2023). To represent lean and non-lean periods in the reference, the event study is baselined to the average difference between affected and unaffected districts during the two periods prior to TC Freddy. This is one lean and one post-harvest period. As the periods used are directly prior to TC Freddy and as they represent both types of growing periods, this is considered as comparable to the aftermath of the event as possible.

The approach is mathematically described by Equation (4) and its constraint represented in Equation (5). As in the DiD-analysis, Y_{it} represents the food insecurity in district i in period t, and X_{it} is the vector of controls for district i at time t. α_i, λ_t, and ε_{it} are the time fixed effects, the district fixed effects and the error term, respectively. In contrast to the DiD analysis, for every period, there is a dummy variable D_{it} that indicates whether a district i was affected by TC Freddy in period t. Hence, D_{it} becomes 1 for each observation from period t in a district i that is affected by TC Freddy and is otherwise 0. In comparison to a traditional event-study approach, such a dummy is included for every period of the analysis, and none is omitted. To ensure that there is no overspecification problem, the event-study equation is constrained by Equation (5). It indicates that the sum of the event-study coefficients of the two periods prior to TC Freddy is set to 0. This is the same as saying that their average is constrained to 0 and follows the approach of Miller (2023) directly. The coefficients δ_0 to δ_5 indicate the effect of TC Freddy as they show the difference between affected and unaffected districts regarding food insecurity relative to the average difference in the two periods prior to the TC.

$$Y_{it} = \sum_{t=-10}^{5} \delta_t \times D_{it} + X'_{it}\gamma + \alpha_i + \lambda_t + \varepsilon_{it} \tag{4}$$

$$\delta_{-2} + \delta_{-1} = 0 \tag{5}$$

The data cleaning and the administration of the DiD and event-study analyses are carried out using STATA 19. For the implementation of the constrained event study, the author closely follows the code provided in the appendix of Miller (2023).

5 Results

5.1 Descriptive statistics

5.1.1 Comparing affected and unaffected districts

To assess whether the districts considered unaffected by TC Freddy provide a good counterfactual for the affected districts, they are compared using measures relevant to the analysis. First, the comparisons are crucial for discussing the effect of TC Freddy on food insecurity and for understanding the mechanisms behind it. The insights on harvest data, for example, help to understand agricultural patterns in the country, and socioeconomic variables explain recovery possibilities. Second, they are important for assessing the parallel trends assumption of the DiD and event-study analysis. As for the subsequent DiD and event-study analyses, the exposure variable defined in Section 4.2.2 with a threshold of $z = 5$ is used to identify the affected districts. Table 1 indicates that TC Freddy affected 9 districts with a combined population of 5 million people, while 18 districts with a total of 12 million people remained unaffected. It also displays the mean outcomes of the control variables prior to TC Freddy. It indicates that the percentage of districts affected by TC Ana is 4 times higher among districts affected by TC Freddy. For TC Gombe, the percentage is even fivefold. The difference between affected and unaffected districts regarding the exposure to TC Gombe is significant. As all drought periods occur after TC Freddy, there is no difference in droughts prior to the TC. In the group of affected districts, there are slightly more observations with a heavy rain event during the prior growing period, but the difference is not significant at the given significance levels. Regarding heat exposure, a clear difference between unaffected and affected districts becomes evident. Affected districts are exposed to heat across all temperature ranges for more time than unaffected districts. While unaffected districts are, on average, exposed to temperatures between 30 °C and 35 °C for the equivalent of 5.6 days during one growing period, affected districts are exposed to these temperatures for more than twice that time. While affected districts are exposed to heat exceeding 35 °C for the equivalent of 2 full days, unaffected districts experience this extreme heat only a tenth of that time. The differences in heat exposure are significant at the 1% level for temperatures between 25 °C and 30 °C, and 30 °C to 35 °C. For heat above 35 °C, the difference is significant at the 5% level. In conclusion, Table 1 shows that the two groups differ across various dimensions even before TC Freddy. As these differences persist after TC Freddy, this underscores the importance of the control variables.

Table 1: Comparing affected and unaffected districts using variables included in the analysis

Variable	Unaffected	Affected	Sig. of Diff.
Number of districts†	18	9	-
Total Population†	12,141,234	5,228,147	-
Districts affected by TC Ana	5.6%	22.2%	n.s.
Districts affected by TC Gombe	11.1%	55.6%	**
Drought (gr. period)	0	0	n.s.
Heavy rain event (gr. period)	0.322	0.422	n.s.
Heat exposure 25 - 30 °C [24h]	31.436	48.108	***
Heat exposure 30 - 35 °C [24h]	5.567	12.657	***
Heat exposure > 35 °C [24h]	0.218	2.104	**

Notes: †The variable is not directly included in the analysis, but displayed here to understand the results better; Significance of the differences determined using OLS regressions; * $p < .1$, ** $p < .05$, *** $p < .01$
Source: Own representation using data from Muñoz Sabater (2019a, 2019b)

Food insecurity depends heavily on agricultural production and weather outcomes. Hence, Table 2 compares the affected and unaffected districts according to these dimensions. The average yearly temperature is approximately 1.5 °C higher in the affected districts than in others. The difference is significant at the 5% level. Although rainfall in the affected districts is lower, the difference is only significant at the 10% level. In general, the climate in affected districts is drier and warmer. Table 2 also indicates that only one-fifth of maize and cassava harvested in the main season comes from affected districts. This suggests that TC Freddy could affect up to 20% of total maize output. In terms of production per capita, unaffected districts have a higher output for both crops than affected districts. For maize, the difference is significant at the 1% level. Table 5 in Appendix C.1 presents supplemental harvest data. Although none of the differences displayed is significant, the table demonstrates that patterns similar to those of the main maize harvest emerge for rice and for the winter harvest of cassava and maize. It also indicates that yields per hectare are systematically higher in unaffected districts than in affected districts. In conclusion, affected districts have a lower agricultural output and productivity, but none of the differences, except for the difference in the per capita maize harvest, is significant.

Table 2: Comparing affected and unaffected districts using climate and harvest data

Variable	Unaffected	Affected	Sig. of Diff.
Average yearly temperature [°C]	20.93	22.482	**
Average yearly total rainfall [mm]	1,239	1,020	*
Maize harvested in main season [t]	2,268,011	614,166	n.s.
Cassava harvested in main season [t]	3,828,347	1,087,017	n.s.
Maize harvested in main season per cap. [t/cap]	0.221	0.108	***
Cassava harvested in main season per cap. [t/cap]	0.527	0.175	n.s.

Notes: Climate variables denote long-term averages calculated with data from Muñoz Sabater (2019b). Harvest data is computed using data from 2010 to 2019 retrieved from the FEWS NET (2026b); Significance of the differences determined using OLS regressions; * $p < .1$, ** $p < .05$, *** $p < .01$

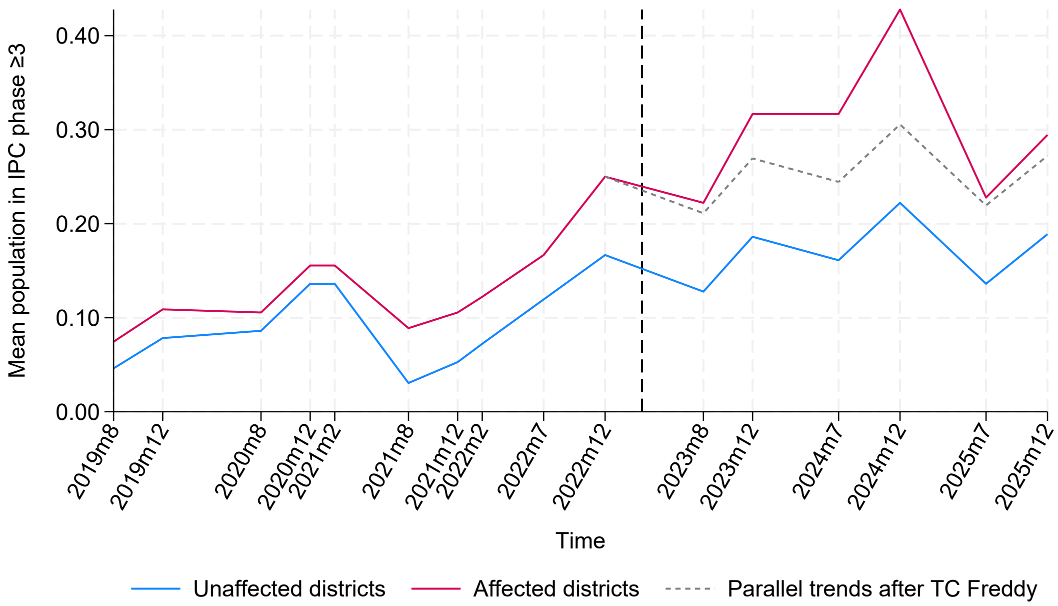
For adaptation and coping mechanisms, socioeconomic characteristics are particularly important. They are compared in Table 6 of the Appendix C.1. In general, the differences are minor. The Subnational Human Development Index (SHDI) differs only in the third digit after the comma. In the dimension of income, the SHDI index for affected districts is slightly higher, whereas in the dimension of education, it is higher in the other districts. Regarding average school years, the difference between affected and unaffected districts is less than 1 month. The districts also do not differ systematically regarding poverty. While the Multidimensional Poverty Index of the Oxford Poverty & Human Development Initiative (2026) indicates slightly more poverty in non-affected districts, the share of people in poverty in these districts is lower than in the others. In conclusion, the only significant difference between the groups is the educational HDI. The difference is minimal and only significant at the 5% level.

Taken together, the insights from all the variables reveal some differences between the affected and unaffected districts regarding weather phenomena. Hence, the paper controls for these in the analysis. Harvest seems to be biased towards the non-affected districts, but the effects are mostly insignificant. Socioeconomic characteristics do not differ substantially between the affected and the unaffected group.

5.1.2 Comparing trends in food insecurity

Before conducting the DiD and event-study analysis, the food insecurity outcomes in the group of affected and unaffected districts are compared over time. This is crucial for interpreting the results afterwards and for testing the parallel trends assumption. Figure 3 shows how the share of people in IPC phase $\geq$3 evolved over the period of analysis in the districts affected and unaffected by TC Freddy, respectively. Furthermore, it indicates how food insecurity in affected districts would have developed after TC Freddy if it had progressed in parallel with food insecurity in unaffected districts. As for the DiD and event-study analyses, a threshold of $z = 5$ is used to categorise the districts into the affected and unaffected group. The figure depicts the unweighted average of district-level food insecurity in each group. It shows that the share of people in IPC phase $\geq$3 rose in both groups until 2024 and dropped thereafter. In general, food insecurity is around 4 percentage points higher during the lean season, from November to February, than during the post-harvest periods. Over the entire analysis period, food insecurity is higher in districts considered affected by TC Freddy than in those unaffected. Until the 2020/21 harvest, the difference remained minimal at approximately 2 percentage points. In August 2021, food insecurity declined more in districts not affected by TC Freddy, raising the difference to around 5 percentage points. From July 2022 to December 2022, food insecurity increased significantly more in districts considered affected than in those not affected, and the gap rose to 8 percentage points. By the end of 2023, the gap widened further due to a disproportionately high increase in food insecurity in affected districts. In December 2024, the difference in food insecurity between the two groups reached its maximum at approximately 20 percentage points. In 2025, food insecurity in affected districts diminished disproportionately, closing the gap once more. In general, although food insecurity increases over time in unaffected districts as well, most of the difference between affected and unaffected districts is attributable to an increase in food insecurity in the affected districts in the lean seasons of 2022, 2023, and 2024.

Figure 3: Development of food insecurity in affected and unaffected districts over time



Notes: The red (blue) lines show the unweighted average of the share of people in IPC phase ≥ 3 in the group of affected (unaffected) districts. The short dashed line indicates how food insecurity would have developed in the affected districts if it had moved parallel to the unaffected districts after TC Freddy. The dashed vertical line indicates the time TC Freddy struck Malawi.
Source: Own representation using data from the IPC (2025a) and Muñoz Sabater (2019b)

5.2 Results – Difference-in-Differences Estimation

Table 3 presents the results of the DiD analysis. The DiD coefficient for TC Freddy is positive and significant at the 1% level in the model without control variables (M1) and in the model including controls (M2). The effect on food insecurity differs substantially between the models. The model without controls indicates that food insecurity rose after TC Freddy 9.0 percentage points more in districts affected by it than in unaffected districts. However, when control variables are included, this difference is reduced to 3.6 percentage points. All coefficients for the control variables except the one for TC Ana are positive, indicating a positive association with food insecurity. The coefficient of the gap in humanitarian assistance is significant at the 1% level. It indicates that for each percentage point of the population left unassisted after TC Freddy, although requiring assistance, there is approximately a 1-percentage-point rise in people in IPC phase ≥ 3 , denoting a state of food crisis. This suggests a proportional transmission of the lack of humanitarian assistance to food insecurity. While no significant effect of TC Ana is observed, the coefficient for TC Gombe is significant at the 1% level. The estimated coefficient appears even larger than that for TC Freddy. Droughts during the growing periods are also associated with higher food insecurity ($p < .05$). The coefficient for heavy rain events is relatively small compared with the others and is only significant at the 10% level. Regarding heat exposure, the DiD analysis indicates a positive association. The coefficient for temperatures between 25 °C and 30 °C is significant at the 10% level, the coefficient for temperatures between 30 °C and 35 °C is significant at the 1% level, and the coefficient for temperatures over 35 °C is not significant. The analysis indicates a 0.5 percentage-point increase for every 24 additional hours of exposure to temperatures between 30 °C and 35 °C. Overall, the DiD estimation suggests a disproportionately large rise in food insecurity in affected districts following TC Freddy. Moreover, it underlines the importance of the control variables, as they are mostly significant, and their inclusion substantially changes the effect size of the DiD coefficient.

Table 3: Results of the Difference-in-Differences Estimation

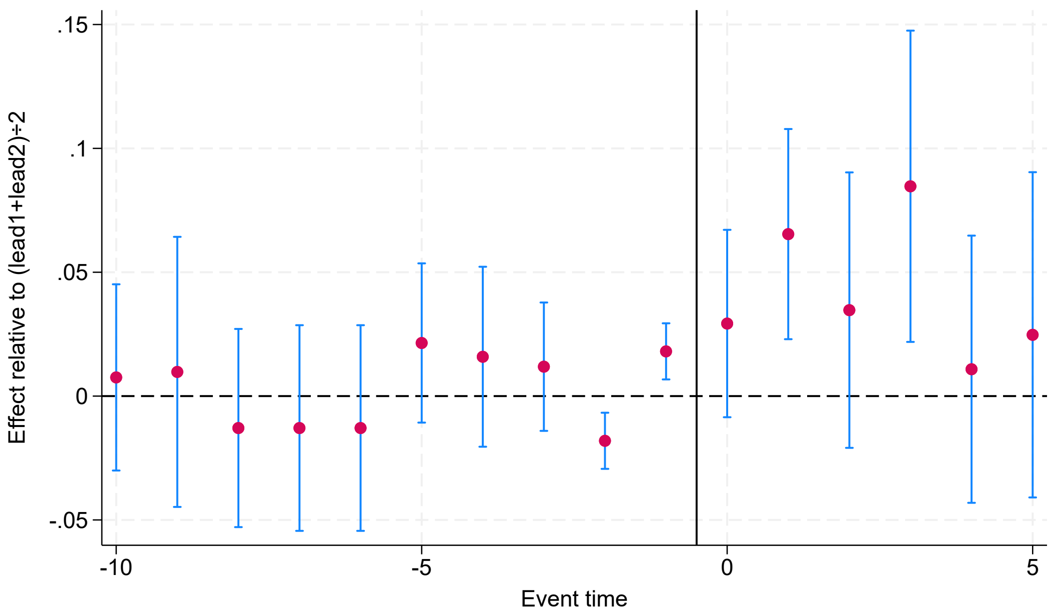
Variable	M1	M2
TC Freddy: Affected × Post	0.090*** (0.018)	0.036*** (0.012)
Humanitarian assistance gap		1.013*** (0.299)
TC Ana: Affected × Post		-0.001 (0.009)
TC Gombe: Affected × Post		0.074*** (0.012)
Drought		0.027* (0.015)
Heavy rain event		0.016* (0.009)
Heat exposure 25 - 30 °C		0.002* (0.001)
Heat exposure 30 - 35 °C		0.005*** (0.002)
Heat exposure > 35 °C		0.003 (0.004)
Number of observations	432	432
R^2	0.803	0.860
Time & District FEs	Yes	Yes

Notes: Standard errors clustered at district level and displayed in parentheses; * $p < .1$, ** $p < .05$, *** $p < .01$

5.3 Results – Event Study estimation

The results of the event study without controls are depicted graphically in Figure 7 of Appendix C.2, and those of the event study with controls are visualised in Figure 4. Table 7 in Appendix C.2 shows the results for both of them in table format. Regardless of whether controls are included, the post coefficients differ substantially from the pre-event coefficients. Except for the lead coefficients used to compute the reference, none of the lead coefficients is significant in any model. All coefficients for lead periods are close to zero. While in the model without controls, most are negative, in the model with controls, some are negative and some are positive. In general, none of the lead coefficients indicates a major difference from the reference. Regarding the two coefficients used for the calculation of the reference, the coefficient for Lead 1, a lean period, is higher than the one for Lead 2, a non-lean period, in both models. When not including the controls, all coefficients for the first four periods following TC Freddy are positive and significant at the 1% level. The effect size grows steadily from Lag 0, with $\delta_0 = .046$, to Lag 3, when the coefficient is equal to .157. The coefficients for Lag 4 and Lag 5 are substantially smaller and only significant at the 10% level.

Figure 4: Event study plot for the model with controls (M4)



Notes: Model with controls (M4) under the constraint of ($\delta_{-2} + \delta_{-1} = 0$) including district and time FE; Confidence bands calculated using clustered standard errors and the 5% significance level.

In the model with control variables, all coefficients for periods after TC Freddy hit are positive, but only those for Lag 1 and Lag 3 are significant at the 1% level. These are the lean periods. In the non-lean periods, none of the coefficients is significant. Furthermore, there is a sudden decrease in the coefficients for Lag 4 and Lag 5. For these observations from 2025, the effect is no longer significant, regardless of whether it is a lean period. Similar to the DiD results, the coefficients for all control variables are positive. The effect of the humanitarian assistance gap is significant at the 1% level and suggests that a 1-percentage-point increase in non-assisted population results in an additional percentage point of population in IPC phase ≥ 3 . As in the DiD analysis, the coefficient for TC Gombe is significant at the 1% level, whereas the coefficient for TC Ana is not. The coefficient for Droughts does not indicate a higher level of food insecurity in post-drought periods. The coefficient for heavy rain events is only significant at the 10% level. Regarding heat exposure, only the coefficient for the hours with temperatures between 30 °C and 35 °C is significant at the 5% level. The one for heat exposure to temperatures between 25 °C and 30 °C is significant at the 10% level, and the one for temperatures exceeding 35 °C is not significant. All remaining heat coefficients are insignificant. Overall, the event-study results underline the highly significant and strong effects of the absence of humanitarian assistance and of TC Gombe. The significance of the other control variables is limited. Regarding the effect of TC Freddy on food insecurity, the results reveal that it is more pronounced during lean periods and that it is no longer observed in 2025.

6 Validity of the identification strategy

6.1 Assessing the assumption of the identification strategy

The identification strategy assumes that food insecurity in affected and unaffected districts would have followed parallel trends without TC Freddy. By definition, this cannot be assessed directly. Hence, the work relies on Tables 1, 2, 5 and 6 comparing district characteristics between the two district groups, on the pre-event coefficients and on Figure 3 showing the development of food insecurity over time to evaluate the parallel trends assumption. The framework shows that weather conditions alongside the vulnerability and coping capacities of each household determine how the shock of an extreme weather event translates into food insecurity. If the districts in both the affected and unaffected group are as similar as possible in these aspects, this supports the plausibility of parallel trends. Tables 1 and 2 indicate some differences regarding climate. Because these can potentially violate the parallel-trends assumption, the analysis controls for them. Those aspects that are highly time- and district-variant, such as droughts or heavy rain events, are included as control variables. Those that change only in one dimension, such as average annual temperature or rainfall, were tested for inclusion in the analysis but appear to be fully absorbed by the district and time fixed effects.

Regarding harvest, the affected and unaffected districts differ, but most of the differences are not significant. Whether the lack of statistical significance stems from the low number of observations cannot be tested. For a similar reaction to external circumstances, it is important that the districts have a comparable agricultural output and distribution between the winter and the main harvest. The latter is decisive for recovery from the shock, as it defines how quickly the district can compensate for losses in agricultural production. As shown in Tables 2 and 5, there are significant differences for maize, but not for the other crops. Considering the importance of maize in overall consumption, it cannot be ruled out that the different agricultural structure of the districts leads to slightly divergent trends in food insecurity.

The socioeconomic characteristics are another important dimension that can shape trends in food insecurity. They are especially important for the recovery from a shock as they influence adaptation and coping mechanisms. Table 6 indicates that the differences in income, poverty and education are minimal. Consequently, it is highly improbable that after a nationwide shock, socioeconomic characteristics trigger a deviation from parallel trends. In general, comparing district characteristics does not yield a clear conclusion on the parallel trends assumption. While climate and harvest data cast doubt on the parallel-trends assumption, socioeconomic differences do not. Thus, it is recommended to focus on the interpretation of the model controlling for climate variation.

As recommended by Miller (2023), this work compares average food insecurity between affected and unaffected districts in Figure 3 to assess the parallel trends assumption further. With a minor exception in 2021, when there was a disproportionate decrease in food insecurity in unaffected districts, food insecurity moved in parallel trends until July 2022. From July 2022 to December 2022, meaning in the period before TC Freddy, this changed. While food insecurity rose by 4.7% in unaffected districts, it increased by 8.3% in affected districts. As anticipation effects can be ruled out in the case of a TC, this 3.6 percentage-point difference raises concerns about the validity of the parallel-trends assumption. The change coincided with the effects of TC Ana and TC Gombe. Given that districts affected by TC Freddy are disproportionately affected by TC Gombe, and that the DiD and event study estimate the effect of TC Gombe at around 7 percentage points, the difference in the plot may be attributable to TC Gombe. Hence, the graphical analysis of trends in food insecurity casts some doubt about the validity of the parallel trends assumption, but controlling for other extreme events might help to account for the observed differences.

Apart from the raw data, the pre-event coefficients of the event study analysis give some information about the validity of the parallel trends assumption (Miller, 2023). Since none of the coefficients, except those used in the constraint, is significant, there is no strong indication against the validity of the parallel trends assumption. The coefficients are very stable within each agricultural year and only indicate minor variation from one year to the other. This shows that, if the difference between the groups varies, it occurs only between agricultural years, not within a single year. Since including the control variables reduces the magnitude of the lead coefficients, the controls can be considered important for creating conditional parallel trends against which post-treatment outcomes are compared. In both models, the coefficients indicate that the districts deviate from the common trend significantly more after TC Freddy than before.

Using these three methods to check the parallel trends assumption, some uncertainty remains. Nevertheless, controlling for humanitarian assistance and other weather extremes helps to create conditional parallel trends. The concerns regarding the parallel trends limit the interpretation of the effect size of the impact of TC Freddy. Yet this section showed that the divergence from the parallel trends is minor and not systematic. Hence, the proposed strategy still serves for identifying the effect of TC Freddy.

6.2 Robustness Checks

The robustness of the results described in Section 5 is assessed by extending the dataset, by using wild bootstrap estimation and a continuous treatment variable, and by varying the z-score threshold. The results of the checks indicate a high robustness regarding the main findings of the paper. For the first robustness check, the temporal and regional scope of the data is extended. Since the framework indicates that the mechanisms underlying food insecurity may differ in urban districts, this work focuses on the rural population. Moreover, it does not include the data prior to 2019, as there was a major fall armyworm infestation in Malawi (FAO, 2018; Reuters, 2017). For this robustness check, both restrictions are relaxed at once, but if only the time or regional scope were increased, the results would be similar. The results, displayed in Appendix D.1, corroborate the main results of the paper. Food insecurity did not exhibit parallel trends before 2019, which may be attributable to the particularly strong influence of the fall armyworm on the affected districts. The significant difference observed in those periods (Lead 13 to Lead 14) might also explain why the DiD coefficient loses significance. The event study results indicate a positive and highly significant effect in the post-Freddy lean periods. The effect size and significance in post-harvest periods are slightly higher than in the main analysis. This is in line with the theory, as urban households, now added to the analysis, cannot rely on their own production in the months after the harvest. Hence, they are also affected during post-harvest periods by higher prices and lower availability, increasing the effects in those periods. In conclusion, the results using all data indicate an explicable divergence from the parallel trends prior to TC Freddy and underline the robustness of the effect of the TC.

To account for the low number of clusters, a robustness check using wild bootstrap estimation is carried out. Its results can be found in Appendix D.2. Compared to the estimation using OLS clustered standard errors, there are only minor differences. By definition, the coefficients remain unchanged. Confidence intervals increase slightly, but none of the coefficients regarding the effect of TC Freddy on food insecurity loses its significance. Only the DiD coefficient changes from being significant at the 1% level to the 5% level. Thus, the wild bootstrap estimation suggests a high robustness of the results.

Since there is no prior literature recommending a certain rainfall threshold to identify areas affected by a TC, this study relied on a graphical analysis of Figure 2 to establish one. As described in Section 4.2.2, the main results of this paper use the average daily z-score of the rainfall during TC Freddy within the long-term daily district- and the month-specific rainfall distribution. All districts with an average z-score above 5 for the days of TC Freddy were identified as affected. To check whether the results are sensitive to the threshold, different thresholds are used for a robustness check. First, a threshold of 4, meaning a threshold one standard deviation lower, is used. Appendix D.3 shows that the graphical analysis, the DiD, and the event study analysis yield extremely similar results when using $z = 4$ instead of $z = 5$ as the threshold. Where the effect sizes in the results differ, they differ only at the third decimal place. With the exception of the DiD coefficient in the model with controls, which becomes significant only at the 5% level rather than the 1% level, all other significance levels remain unchanged. When the z-score threshold is increased by one unit rather than decreased, the results are exactly the same as in the main analysis, because the districts considered affected are the same as when using a threshold of $z = 5$. Given that this is not an adequate robustness check, the work also tests the results using a threshold of $z = 7$. As shown in Appendix D.4, the results for the DiD analysis show slightly reduced effect size and significance when using the increased threshold. Nevertheless, the message about the effect of TC Freddy on food insecurity remains the same. In contrast, the post-Freddy coefficients in the event study analysis are not significant. This suggests that the robustness check using a z-threshold of 7 does not support the main results of this paper. Therefore, decreasing or increasing the threshold by 1 unit produces nearly identical results, whereas a 2-unit increase yields very different outcomes. Analysing in detail the group of districts considered unaffected using the threshold of $z = 7$ might explain this phenomenon. During TC Freddy, one-third of these districts experienced rainfall that was at least 3 standard deviations above the long-term mean. Hence, these districts may not serve as a good comparison, and the discussion of the robustness of the effect should focus on the results using lower thresholds. In conclusion, even when the threshold is varied, the same effects are observed, thereby indicating a high robustness of the results.

The paper considers strong rainfall an indicator for TC Freddy and, therefore, hypothesises that districts with heavy rainfall are affected by higher food insecurity after the TC. If that holds true, it can be expected that the stronger the rains during TC Freddy, the more destruction and therefore, the more food insecurity is caused afterwards. Hence, a robustness check using a continuous treatment variable is performed. This has the advantage of obviating the need to set a somewhat arbitrary rainfall threshold. For the robustness check, the z-score described in Section 4.2.2 is used, and the results are displayed in Appendix D.5. They support the main results of this paper. The coefficients for the effect of TC Freddy indicate that the more the rainfall during TC Freddy exceeded normal rainfall, the greater the increase in food insecurity afterwards. All coefficients in the DiD analysis with and without controls are positive and significant at the 1% level. Consistent with the main analysis, all coefficients for periods after TC Freddy are positive. The coefficients for the post-harvest periods become insignificant when controls are included. Those for Lag 1 and Lag 3, two lean periods, remain significant at the 5% level in both models. Hence, the results not only support the main finding that food insecurity rises disproportionately in affected districts after TC Freddy, but also that this effect is more pronounced in lean periods. As in the main results, the significant effect disappears in Lag 4 and Lag 5.

In conclusion, the robustness checks show that using all available data does not affect the results. Moreover, the low number of clusters is not optimal for the analysis, but it does not call the effect into question. Furthermore, the results remain stable when the rain threshold is varied within reasonable bounds. The robustness check using the continuous treatment variable shows that the more the rainfall exceeds normal rainfall, the more food insecurity is observed, linking food insecurity to the strength of the TC. Hence, the main message of this work is robust to changes in the assumptions made for the analysis.

7 Discussion

7.1 The Contribution of Cyclone Freddy to food insecurity in Malawi

The previously presented results suggest that TC Freddy increased food insecurity. Three aspects are crucial to this reasoning. First, the DiD and event-study estimations show across various specifications that food insecurity in affected districts followed different trends after TC Freddy than food insecurity in unaffected districts. Second, this difference in trends is driven by increasing food insecurity in affected districts rather than by a decline in unaffected districts. This is important because the framework shows that positive effects of such an event on unaffected agricultural households are theoretically possible. Figure 3, depicting the development of food insecurity in both district groups, affirms that an increase in food insecurity in affected districts is responsible for the effect. It indicates that food insecurity rose substantially in affected districts during the time frame relevant to the analysis and did not decrease in unaffected districts. Third, the observed deviation from parallel trends corresponds with the time TC Freddy struck Malawi. As shown in the section on the validity of the identification strategy, a slight increase in the gap between the two groups is observed one period before TC Freddy, but in broad terms the parallel-trends assumption holds prior to the TC. In conclusion, this work provides evidence showing that at least some of the food insecurity in Malawi in 2024 and 2025 is attributable to TC Freddy.

The high degree of confidence regarding this result is grounded in theoretical considerations presented in the framework section and the various robustness checks conducted. The framework plausibly explains how an extreme weather event impacts each dimension of food insecurity. Even though the DiD and event-study analyses cannot disentangle the effect by dimension, they consistently show an overall effect on food insecurity. As indicated by the main results and the robustness checks, the general effect of TC Freddy on food insecurity is not sensitive to the inclusion of control variables or changes in the specification. Furthermore, the effects of two other TCs during the analysis period, TC Ana and TC Gombe, are assessed by including treatment variables for them in the control section. For TC Gombe, the more severe of the two, the results indicate, across several specifications, an effect similar to that of TC Freddy, thereby underscoring the effect of such TCs on food insecurity.

The results of the event-study estimation reveal that the effect of TC Freddy is not uniformly distributed across the post-event periods but more pronounced in some of them. For example, the effect is stronger in lean periods than in post-harvest periods. This is in line with the consumption patterns of smallholder farmers. Since most of them produce primarily for subsistence, food availability depends on their own stock. Because maintaining a baseline level of consumption is critical for survival, complete consumption smoothing after a shock is not feasible for most Malawians. Consequently, food shortages intensify with time after harvest as stocks get depleted. Immediately after the harvest, all households whose harvest was not totally destroyed have some food available. Over time, those whose harvest was partially destroyed run out of stock, and only those with sufficient production or reserves from previous years have enough food. In the case of TC Freddy, this translates into a steady rise in food insecurity the longer it has been since the last harvest for those districts where harvests were particularly affected. The results of the event study reflect this, showing that after TC Freddy the difference in food insecurity between affected and unaffected districts is higher in lean periods, when food reserves are exhausted. The same mechanism may also explain why variations in the observed effect between lean and non-lean periods emerge only after TC Freddy and not before. Prior to the event, nothing triggered the early depletion of food reserves in some districts. Stock depletion occurred equally across the country, leading to greater levels of food insecurity during lean periods in Malawi in general and not restricted to certain districts.

Apart from the differences in the effect size between lean and non-lean periods, the effect of TC Freddy also changes considerably over time. It increases until December 2024 (lag 3), but decreases promptly afterwards. In the model without control variables, the increase over time is even stronger than in the model including controls. The data reveal that part of the increase observed in the model without controls stems from El Niño-induced droughts. Hence, when analysing the change in effect size over time, it is important to refer to the model with controls, as the other is biased by other weather phenomena. Even though the increase in effect size from the pre to post-periods is much higher, there is also a slight increase in effect size from the first to the second year after the cyclone. The framework explains the mechanisms through which such an effect can persist beyond the subsequent harvest and even be slightly intensified. If coping mechanisms affect agricultural potential in the coming years, or if infrastructure is not repaired before the next agricultural season, this reduces the following harvest, consequently leading to higher food insecurity. The high degree of destruction that TC Freddy left suggests that rebuilding everything is not possible within one year (GoM, 2023). In particular, eroded fields pose a problem far beyond the 2022/23 growing season. Furthermore, humanitarian aid, food reserves, and financial resources typically are high in the direct aftermath of the cyclone, allowing for mitigation of the effect, but once these resources are exhausted, the effects of the TC manifest more severely. The results suggest that this was the case for TC Freddy as well.

Explaining the decline of the effect in Lag 4 and Lag 5 is far more challenging. The coefficients for these periods remain positive and higher than in pre-event periods, but are not significant. The trend plot indicates that this decrease is driven by a strong decline in food insecurity in the affected districts and not by an increase in food insecurity in unaffected districts. In affected districts, the share of people in IPC phase ≥ 3 approximately halved between December 2024 and June 2025. Part of this decline may be explained by exceptionally poor harvests in the South in previous years and extremely elevated levels of food insecurity, which allowed for such a substantial reduction. Hence, the 2024/25 maize harvest, which was below the five-year average, but about 5% higher than the previous harvest, may have led to a mitigation of the increase in food insecurity observed in the years before (IPC, 2025b). Regarding climate, El Niño might have played a role during the 2024/25 growing season. While in most unaffected districts rainfall was considerably lower than the long-term average, all districts considered affected experienced above-normal rainfall (Muñoz Sabater, 2019b). IPC (2025b) links improvements in food insecurity in Chikwawa, Nsanje and Balaka, and therefore 3 of the 9 districts considered affected, to this increase in rainfall. Another reason for such a steep drop in food insecurity by the end of 2025 can be humanitarian assistance. The World Food Programme (WFP, 2026) reports very substantial humanitarian assistance in 4 of the 9 districts considered affected by TC Freddy during the 2025/26 lean season, and a map of FEWS NET (2026a) indicates that humanitarian assistance at that time was considerably higher in the South than in the North. Whether this or one of the other factors led to this decrease in food insecurity is challenging to assess. If assuming that food insecurity caused by an extraordinary event can transfer from one agricultural period to the next, such a substantial and sudden drop would require a plausible explanation. The literature offers hints for understanding the decline but does not provide a comprehensive explanation. Hence, because the end of the effect of TC Freddy on food insecurity cannot be explained well, this raises doubts about the estimated effect itself.

Although subject to further discussion below, the DiD and event-study analyses point to a substantial effect of TC Freddy on food insecurity. Before the TC, food insecurity in the affected districts averaged 13.3% and had a standard deviation of 6.6%. Regarding the effect size, there is a considerable difference between the models with and without controls. Given the importance of other climate events and humanitarian assistance, the focus here is on the models with control variables. The DiD estimates suggest that TC Freddy increased food insecurity in the affected districts by 3.6 percentage points. This is equivalent to about 27% of the previous food insecurity level. Considering the event-study results, the effect in the first two post-harvest periods is nearly the same as that estimated by the DiD analysis. In the first two lean periods after TC Freddy, the effect size is 6.6 percentage points and 9.1 percentage points, and therefore considerably larger. Thus, the increase in lean time represents around 50% and 68% of the normal food insecurity level, respectively. Assuming the results are not biased by unobservables, both the DiD and the event-study analysis suggest that the effect of TC Freddy was substantial.

The high robustness, the theoretical background, and the substantial effect size suggest that TC Freddy increased food insecurity. Nevertheless, the slight increase in food insecurity before the event and the lack of an explanation for its end leave some doubt about the actual size of the effect. Although this work controls for the effects of various climate phenomena, including heavy rains, TCs and droughts, it cannot be ruled out that the estimate is biased by other simultaneous climate or social phenomena. It might be possible that TC Freddy had an effect, but that it is not as strong as described. Since there is still no literature on the effect of this TC or comparable TCs, the results cannot be compared with benchmark estimates. Hence, some caution is recommended when interpreting the effect size.

7.2 Strengths and Limitations

7.2.1 Strengths

To the best of the author's knowledge, the present study is the first to attribute food insecurity to a single extreme weather event and, therefore, closes an important gap in the literature. A substantial body of literature estimates the effect of extreme weather events in general on socioeconomic outcomes (Amondo et al., 2023; Burke et al., 2015; Corno et al., 2020; Hsiang & Jina, 2014; Keller & Mulangu, 2025; Krichene et al., 2021; Tidiane Ndour et al., 2025). In contrast, there are very few papers assessing the effect of a single event (Clay & Ross, 2020; Salvucci & Santos, 2020; Warr & Aung, 2019). Nevertheless, such analyses are essential to complement the multi-event assessments and to discover localised effects specific to a singular event. Furthermore, as criticised by Cavallo et al. (2022) most of the studies in the area use country-level and not subnational data. As the effects of TCs, for example, are highly regional, using such data are essential. This work overcomes these issues and is the first to identify an effect of one TC on subnational food insecurity.

To identify the effect of a specific TC on food insecurity, it is crucial to have a measure for the exposure of a certain region to that TC which is not confounded by geographical characteristics. Informed by prior literature, this study develops a measure derived exclusively from rainfall data. As such data are available worldwide, over an extensive historical time span, and at high granularity, the measure can be computed for any event to be analysed. Even though it is based on only one dimension of the TC, it seems to measure exposure well. The robustness check with the continuous treatment variable suggests that the measure developed for this paper can proxy for the actual degree of destruction and therefore predicts the level of effect on food insecurity.

Even though this might not be transferable to other countries, the paper shows that for Malawi an effect can be expected if rainfall exceeds the long-term average by 4 standard deviations or more for at least 3 consecutive days. Developing an easily computable exposure measure is an achievement of this paper and facilitates future research.

Furthermore, this paper proposes a framework for further studies in the area. Although data availability does not permit the assessment of the mechanisms, visualising them and providing a theoretical background for the results goes beyond the contribution of other papers in the field. It allows the reader to understand the background of the effect, thereby grounding the empirical findings in a robust theoretical framework.

Another strength of the present work is the elaborate identification strategy, which includes a broad set of control variables. Since food insecurity has various causes and cannot be attributed to a single factor, the controls are crucial for distinguishing the effect of TC Freddy from other effects. Although there remains scope to further refine the identification strategy, it may serve as a good basis for future work. Using a DiD and event-study approach, this work is capable of controlling for shocks at the national and global level. As in recent years, several events, including the COVID-19 pandemic and the wars in Ukraine and Iran, have had serious repercussions for global food security and nutrition outcomes (FAO et al., 2024; IPC, 2022). Therefore, only comparing pre- and post-event socioeconomic outcomes, as done in other studies, would be insufficient for analysing food insecurity. Furthermore, by incorporating time-variant climate variables, this work enhances the validity of its results, as they allow controlling for the impact of climate phenomena such as El Niño and heavy rains. The difference between the models with and without controls indicates how important the control variables are for the identification strategy. In times of changing climate, this is an important asset for this kind of analysis.

The high robustness of the results is an indicator of the rigour of the identification strategy. As shown before, the results are barely sensitive to changes in the strategy. The statistical significance of the coefficients for TC Gombe, coupled with the observation that the effect does not depend on the threshold definition, increases confidence that the results are not biased by confounding factors.

7.2.2 Limitations

As this is the first study to attribute food insecurity to a single extreme weather event, it has some limitations. Since measuring such a multidimensional latent concept like food insecurity is challenging, measures are scarce, leading this work to use food insecurity data that is based on expert evaluation. Therefore, it needs to be acknowledged that some endogeneity could arise. It is possible that the experts rank areas impacted by a cyclone into higher categories of food insecurity because they were struck by the TC, rather than because there is a real change in food insecurity. Although this issue cannot be ruled out, it is mitigated by the strict IPC-guidelines and the obligation to use reference tables with other food insecurity variables to assess food insecurity. Furthermore, food insecurity depends on many factors which change simultaneously. Hence, the decision of the expert panel is informed by various inputs, including harvest and climate data, as well as data on humanitarian assistance. Based on that, these experts who come from different areas need to reach a consensus on the estimated level of food insecurity. Hence, their decision-making is multi-dimensional and depends on the agreement of various parties, making it improbable that a TC mechanically leads to a higher level of estimated food insecurity.

Furthermore, the IPC food insecurity measure used in this paper is designed to inform policy actions and is therefore always a projection based on the data available at the point of assessment. Hence, the measure might not always fully capture the level of food insecurity, which poses a limitation on the results. The concern can be partially mitigated by the fact that the IPC analyses are conducted in August, when all indicators of the past agricultural season are available. Based on the harvest and climate data, the level of food insecurity is broadly predictable. Harvest or climate shocks cannot happen at that point of the year. Hence, the most relevant shocks that could occur between the assessment period and the projection horizon are economic shocks. These are mostly nationwide. As the socioeconomic characteristics are comparable between the districts affected and unaffected by TC Freddy, it can be suggested that the shock impacts food insecurity in both groups equally. Hence, it would not interfere with the analysis that is focused on the difference between the two groups. Even though there are good arguments for using the share of people in IPC phase ≥ 3 as the dependent variable, the measure poses some limitations on the results. Hence, this work calls for further efforts to collect data on food insecurity using more objective measures. Further research might opt to employ these alternative measures.

Another limitation of the study is that it employs district-level, not household-level, data. The author designed the exposure measure so that it can also be computed for smaller areas, such as the county of each household, but food insecurity data for the period of analysis are only available at district level. This makes it challenging to test the underlying mechanisms that were described in the framework section. Apart from increasing the number of observations, household-level data would allow for checks of heterogeneity. It could, for example, be analysed whether households with lower economic capacity are less able to mitigate the effect of a TC.

As mentioned before, some concerns regarding the parallel trends assumption cannot be allayed. One period before TC Freddy, the difference between the district groups begins to rise. This coincides with TC Gombe and TC Ana. Nevertheless, the variables for those do not seem to capture all the effect. Hence, it cannot be ruled out that the observed effects are biased by an unobserved factor. Still, the large effect size, the various robustness tests and the observation that the coefficients for TC Gombe are highly significant and comparable in magnitude suggest that at least some of the observed effect is attributable to TC Freddy. In conclusion, it must be admitted that the size of the effect should be interpreted with caution.

One last limitation of the study is that the identification strategy does not allow for spill-over effects. TC Freddy destroyed a lot of the harvest in the South. Due to market frictions, such as high transport costs, the effect is first concentrated in the South, increasing prices there. Over time, merchants may adapt by shipping more agricultural goods to the South. This reduces supply in the North, and therefore, the effect of lower harvest can be transferred with a time lag from one region to the other. Some of the observed increase in food insecurity in the unaffected districts may stem from such an effect. If that is the case, it would lead to an underestimation of the effect of TC Freddy. Neither the framework nor the empirical strategy account for such effects and could therefore be enhanced in that dimension.

8 Conclusion

While several papers examine the effects of extreme weather events on food insecurity in general, to the best of the author's knowledge, this work is the first to attribute food insecurity to a single extreme weather event. As various UN organisations raise serious concerns about achieving the Sustainable Development Goal of eliminating food insecurity by 2030, it contributes to a strand of literature important for academic and public debate. Attributing extreme weather events to climate change was initially conducted at a general level and later complemented by analyses specific to single events. This paper contributes to establishing a line of research that attributes socioeconomic outcomes to single extreme weather events, rather than only showing general relationships.

Using the framework, the paper illustrates the mechanisms by which extreme weather events affect food insecurity among households engaged in subsistence farming. It demonstrates that the extent of the impact depends heavily on the specific household's consumption and production patterns. Furthermore, it shows that each dimension of food security may be affected by an extreme weather event, and that focusing on a single dimension will not capture the full effect.

The findings of this study indicate that food insecurity rose after TC Freddy and that this effect is more pronounced in lean periods. Moreover, the results suggest that the effect of a TC can persist beyond the initial agricultural periods. Furthermore, they show how the climate conditions during the growing season shape food insecurity and highlight the importance of humanitarian assistance after such an event. Some doubts about the validity of the parallel trends assumption and the lack of explanation for the end of the effect need to be acknowledged. Nevertheless, the magnitude of the observed effect, coupled with multiple robustness checks and the rigorous identification strategy that includes various control variables, supports considerable confidence that TC Freddy increased food insecurity.

The contribution of this paper to the academic and public discussion goes far beyond the empirical results. Regarding the scientific contribution, the framework helps readers understand the mechanisms that lead to food insecurity. Furthermore, the proposed identification strategy can serve as a basis for assessing the effect of further extreme weather events on food insecurity. Hence, if combined with the results of studies that attribute single extreme weather events to climate change, this work can also help identify the role climate change plays in food insecurity. For the public discussion, the latter point is particularly important. One reason to complement the general literature attributing single events to climate change with specific case studies was that the public understands the effects of climate change more easily when exemplified by a single event (Otto, 2019). The same may apply here. The public may better understand the socioeconomic effects of extreme weather events when explained with an example. Studies by the World Weather Attribution project indicate the factor by which anthropogenic climate change has augmented the probability of a specific extreme weather event. In some of the most recent papers, this factor is so high that the authors claim that these events would have been virtually impossible without climate change. Examples of this are the studies on the heat waves in Siberia in 2020 and in Western North America in 2026 (Ciavarella et al., 2021; B. Clarke et al., 2026). Hence, any change in food insecurity or other socioeconomic outcomes that can be attributed to this weather phenomenon may be considered a direct impact of climate change. By illustrating the relationship between climate change and food insecurity with a concrete example, the scientific community would have another valuable tool to raise awareness of the disastrous effects of climate change. With this, the call for a change in policies, as the IPCC has done for several years, becomes easier to understand for the public (Masson-Delmotte et al., 2022).

Extrapolating this logic further, analyses like the one presented could also play a role in judicial decisions. The literature discusses how studies attributing certain extreme weather events to climate change can be used by people affected by the event to justify their claims against mostly companies that contributed most to the rise in emissions (Lloyd & Shepherd, 2021; Marjanac & Patton, 2018). A report by the United Nations Environment Programme (2025) counts more than 3,000 cases of climate litigation by mid-2025, highlighting that it is not a marginal phenomenon in case law. In some legal proceedings, reports attributing single extreme weather events to climate change were yet introduced as evidence (Farand, 2025). Attributing food insecurity to a climate-induced extreme weather event would extend such possibilities even further. Even if not used in court, it could give countries hit by extreme weather events, which are mostly in the Global South, stronger arguments when negotiating recovery or adaptation funds with nations of the Global North. Hence, the results of attribution studies such as this one may also play a crucial role in future discussions of climate justice.

In conclusion, this work can be considered a starting point for attributing changes in socioeconomic outcomes, such as food insecurity, to single extreme weather events. Considering its limitations, the results for TC Freddy are not the main contribution of this paper, but the framework and the empirical strategy are. Future research can build on and refine them. This will help to adequately assess whether one extreme weather event triggered by climate change has caused food insecurity.

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A Framework section

A.1 Deriving the household constraint equation

Equation (1) shows the constraint under which the household maximises utility. Following Singh et al. (1986, pp. 152–153), this section indicates how to derive it.

According to Singh et al. (1986), an agricultural household has the following income constraint:

$$p_m X_m = p_a \left(Q_a - X_a\right) - p_l(L - F) - p_v V + E \tag{6}$$

$p_m X_m$ is the expenditure on a composite market good. p_a is the price of the produced agricultural commodity, and Q_a and X_a represent the quantities produced and consumed, respectively. Thus, the term $p_a(Q_a - X_a)$ constitutes the market value of the agricultural surplus. L describes the labour requirement of the farm and F the total labour input of the household. Consequently, $(L - F)$ is positive if the household hires labour from other households, and negative if the household provides labour to other households or firms. $p_v V$ denotes agricultural input goods, such as fertilisers, valued at market prices. E is external income.

Rearranging Equation (6) yields:

$$p_m X_m + p_a X_a = p_a Q_a - p_v V + p_l(F - L) + E \tag{7}$$

In addition to the income constraint, the household also faces a time constraint. Equation (8) describes the time distribution of a household. The total stock of household time, T, can be allocated to leisure (X_l) or labour (F). F can be on their own farm or for other households or firms.

$$X_l + F = T \tag{8}$$

The total production of the agricultural product Q_a is a function of farm labour input (L), the input goods (V), the quantity of land at disposal (A) and the capital (K) that can be used for production. Hence, Q_a can be expressed as: $Q_a(L, V, A, K)$.

Singh et al. (1986) combines all these notions into one function. Substituting the production function and the time constraint, Equation (8), into Equation (7) yields the following final equation, which is depicted as Equation (1) in the main section of this paper:

$$p_m X_m + p_a X_a = p_a Q_a(L, V, A, K) - p_v V + p_l(T - L - X_l) + E \tag{9}$$

B Variable description

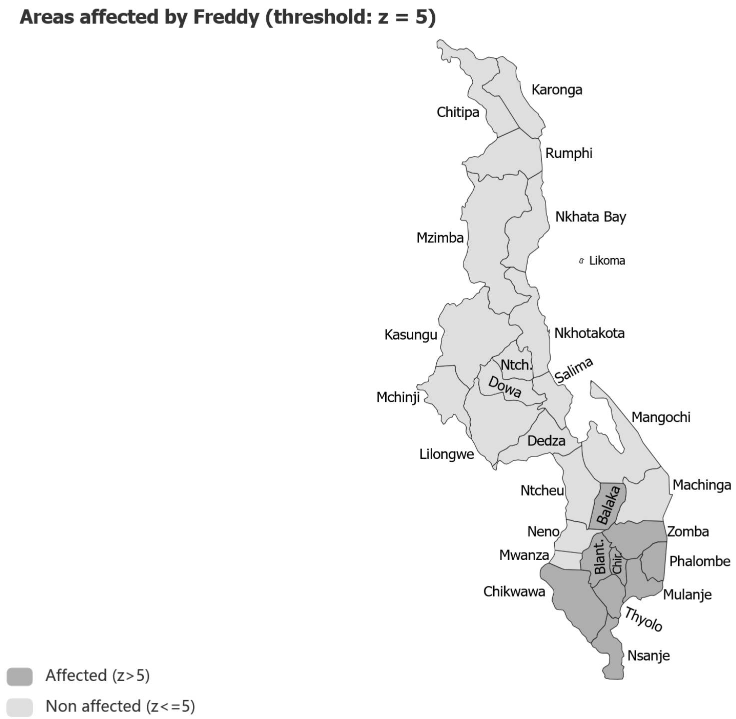
B.1 Districts considered affected by TC Freddy

Using a threshold of z = 5 the following districts are considered affected:

- Balaka
- Blantyre
- Chikwawa
- Chiradzulu
- Mulanje

- Nsanje
- Phalombe
- Thyolo
- Zomba

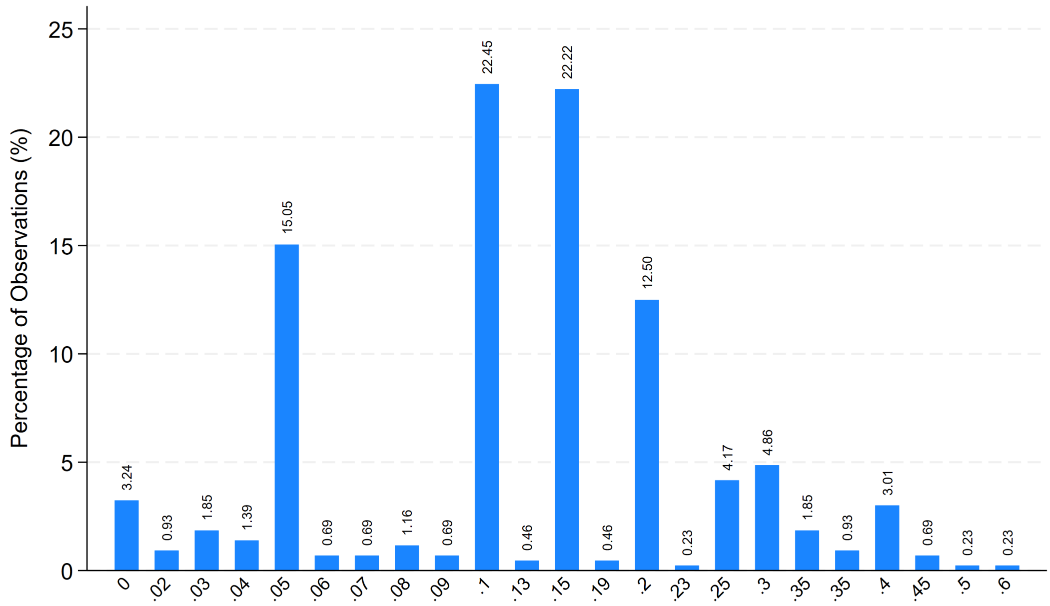
Figure 5: Map showing the districts considered affected (threshold z = 5)



Notes: Own representation using data from Muñoz Sabater (2019b)

B.2 Distributions of the variables

Figure 6: Distribution of the share of people in IPC phase 3 or higher



Notes: N = 432; Data from 2019 to 2025

Source: Own representation using data from IPC (2025a)

Table 4: Summary statistics of the main variables [N=432]

Variable	Mean	SD	Min	Median	Max
People in IPC phase ≥3 [%]	0.147	0.099	0	0.150	0.600
TC Freddy: Affected × Post	0.333	0.472	0	0	1
Humanitarian assistance gap	0.005	0.013	0	0	0.057
TC Gombe: Affected × Post	0.130	0.336	0	0	1
TC Ana: Affected × Post	0.062	0.242	0	0	1
Drought	0.083	0.277	0	0	1
Heavy rain event	0.292	0.455	0	0	1
Heat exposure 25 - 30 °C	38.104	15.921	7.500	38.625	74.500
Heat exposure 30 - 35 °C	7.865	7.534	0	6.104	37.375
Heat exposure > 35 °C	0.801	2.407	0	0	14.625

Notes: Own representation using data from IPC (2025a), Muñoz Sabater (2019a, 2019b), and OCHA (2023a)

C Results

C.1 Comparing affected and unaffected districts

Table 5: Comparing affected and unaffected districts using harvest data

Variable	Unaffected	Affected	Sig. of Diff.
People vulnerable to poverty [%]	29.484	29.873	n.s.
Rice harvested in main season [t]	68,079	33,798	n.s.
Rice harvested in main season per cap. [t/cap]	0.009	0.007	n.s.
Maize harvested in winter season [t]	361,667	144,841	n.s.
Cassava harvested in winter season [t]	62,709	1,109	n.s.
Rice harvested in winter season [t]	12,483	2,181	n.s.
Maize harvested in winter season per cap. [t/cap]	0.034	0.03	n.s.
Cassava harvested in winter season per cap. [t/cap]	0.008	0	n.s.
Rice harvested in winter season per cap. [t/cap]	0.002	0	n.s.
Yield of Cassava [t/ha]	21.229	18.98	n.s.
Yield of Maize [t/ha]	2.412	2.096	n.s.
Yield of Rice [t/ha]	1.221	1.28	n.s.

Notes: Data is computed using data from 2010 to 2019 retrieved from FEWS NET (2026b); Significance of the differences determined using OLS regressions; * p < .1, ** p < .05, *** p < .01

Table 6: Comparing affected and unaffected districts using socioeconomic indicators

Variable	Unaffected	Affected	Sig. of Diff.
Subnational Human Development Index†	0.507	0.505	n.s.
Income Index of HDI†	0.527	0.545	n.s.
Education Index of HDI†	0.688	0.657	**
Average years of schooling†	5.118	5.181	n.s.
Multidimensional Poverty Index‡	0.228	0.218	n.s.
People vulnerable to poverty [%]‡	29.484	29.873	n.s.

Notes: † data from 2022; ‡ Computed using data from 2019 and 2020; Significance of the differences determined using OLS regressions; * p < .1, ** p < .05, *** p < .01
Source: Own representation using data from Global Data Lab (2025) and Oxford Poverty & Human Development Initiative (2026)

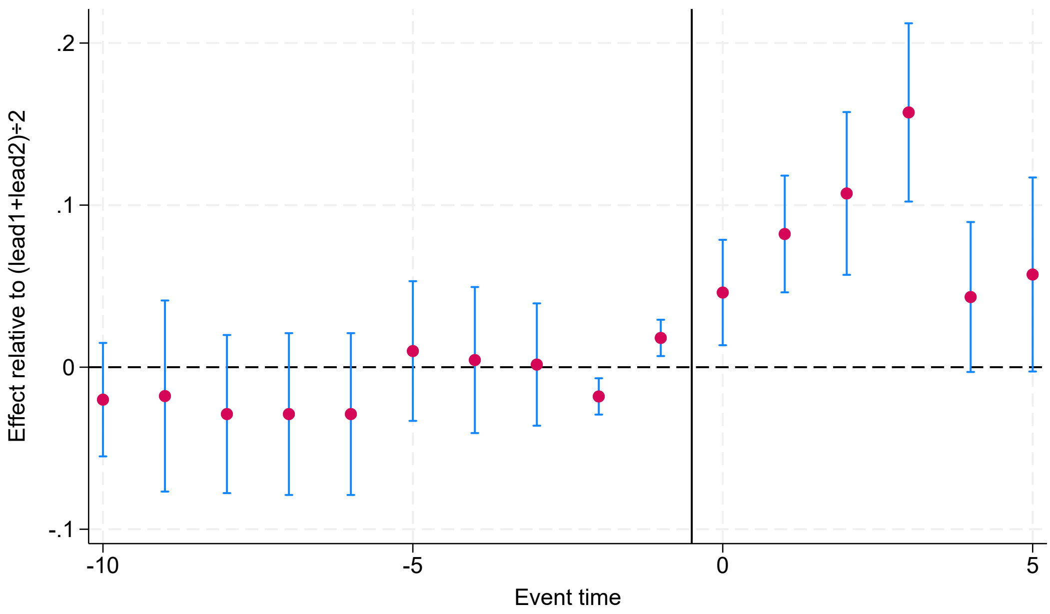
C.2 Results of the Event-Study Estimation using clustered standard errors

Table 7: Results of the Event-Study Estimation

Variable	M3	M4
Lead 10	-0.020 (0.017)	0.008 (0.018)
Lead 9	-0.018 (0.029)	0.010 (0.026)
Lead 8	-0.029 (0.024)	-0.014 (0.020)
Lead 7	-0.029 (0.024)	-0.014 (0.020)
Lead 6	-0.029 (0.024)	-0.014 (0.020)
Lead 5	0.010 (0.021)	0.020 (0.016)
Lead 4	0.004 (0.022)	0.015 (0.018)
Lead 3	0.002 (0.018)	0.011 (0.013)
Lead 2 [used to calculate the reference]	-0.018*** (0.005)	-0.018*** (0.006)
Lead 1 [used to calculate the reference]	0.018*** (0.005)	0.018*** (0.006)
Lag 0	0.046*** (0.016)	0.030 (0.019)
Lag 1	0.082*** (0.018)	0.066*** (0.021)
Lag 2	0.107*** (0.024)	0.041 (0.026)
Lag 3	0.157*** (0.027)	0.091*** (0.029)
Lag 4	0.043* (0.023)	0.007 (0.025)
Lag 5	0.057* (0.029)	0.021 (0.031)
Humanitarian assistance gap		0.954*** (0.298)
TC Ana: Affected × Post		0.006 (0.010)
TC Gombe: Affected × Post		0.072*** (0.012)
Drought		0.013 (0.016)
Heavy rain event		0.019* (0.010)
Heat exposure 25 - 30 °C		0.002* (0.001)
Heat exposure 30 - 35 °C		0.005** (0.002)
Heat exposure > 35 °C		0.003 (0.004)
Number of observations	432	432
Time & District FEs	Yes	Yes

Notes: Event study under the constraint of $(\delta_{-2} + \delta_{-1} = 0)$; Standard errors clustered at district level and displayed in parentheses; * p < .1, ** p < .05, *** p < .01

Figure 7: Event study plot for the model without controls (M3)



Notes: Model without controls (M3) under the constraint of $(\delta_{-2} + \delta_{-1} = 0)$ with district and time FE; Confidence bands calculated using clustered standard errors and the 5% significance level.

D Robustness checks

D.1 Robustness check using the whole sample

D.1.1 DiD Estimation using the whole sample

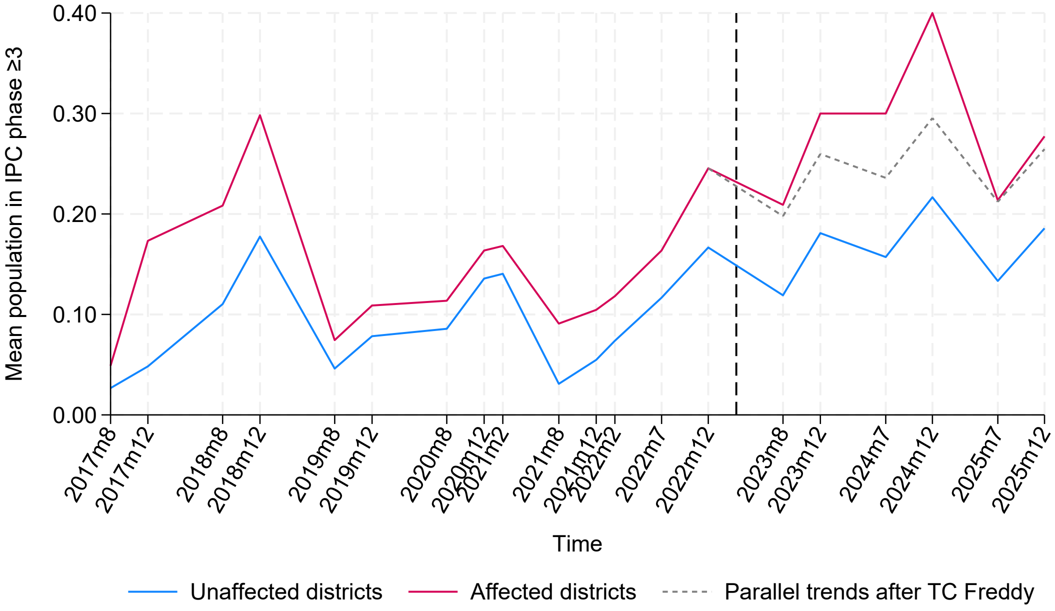
Table 8: Results of the DiD Estimation using the whole sample

Variable	M5	M6
TC Freddy: Affected × Post	0.065*** (0.019)	0.019 (0.013)
Humanitarian assistance gap		0.887*** (0.301)
TC Ana: Affected × Post		-0.009 (0.007)
TC Gombe: Affected × Post		0.078*** (0.010)
Drought		0.022* (0.013)
Heavy rain event		0.014* (0.007)
Heat exposure 25 - 30 °C		0.003** (0.001)
Heat exposure 30 - 35 °C		0.004*** (0.001)
Heat exposure > 35 °C		0.002 (0.003)
Number of observations	610	610
R^2	0.770	0.814
Time & District FEs	Yes	Yes

Notes: Standard errors clustered at district level and displayed in parentheses; * p < .1, ** p < .05, *** p < .01

D.1.2 Trend analysis using the whole sample

Figure 8: Development of food insecurity in affected and unaffected districts over the whole time frame and including the urban centres (threshold z = 5)



Notes: The red (blue) lines show the unweighted average of the share of people in IPC phase ≥3 in the group of affected (unaffected) districts. The short dashed line indicates how food insecurity would have developed in the affected districts if it had moved parallel to the unaffected districts after TC Freddy. The dashed vertical line indicates the time TC Freddy struck Malawi.
Source: Own representation using data from the IPC (2025a) and Muñoz Sabater (2019b)

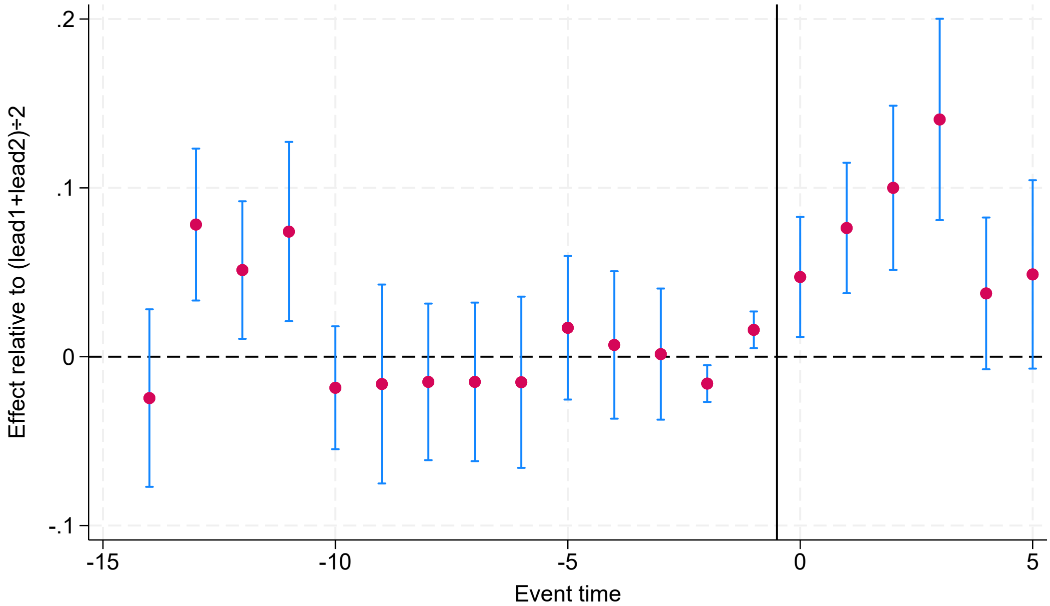
D.1.3 Event-Study Estimation using the whole sample

Table 9: Results of the Event-Study Estimation using the whole sample

Variable	M7	M8
Lead 14	-0.024 (0.026)	0.008 (0.021)
Lead 13	0.078*** (0.022)	0.111*** (0.025)
Lead 12	0.051** (0.020)	0.075*** (0.021)
Lead 11	0.074*** (0.026)	0.097*** (0.027)
Lead 10	-0.018 (0.018)	0.012 (0.018)
Lead 9	-0.016 (0.029)	0.014 (0.026)
Lead 8	-0.015 (0.023)	-0.003 (0.019)
Lead 7	-0.015 (0.023)	-0.003 (0.019)
Lead 6	-0.015 (0.025)	-0.003 (0.021)
Lead 5	0.017 (0.021)	0.026 (0.018)
Lead 4	0.007 (0.021)	0.016 (0.019)
Lead 3	0.002 (0.019)	0.010 (0.017)
Lead 2 [used to calculate the reference]	-0.016*** (0.005)	-0.016*** (0.005)
Lead 1 [used to calculate the reference]	0.016*** (0.005)	0.016*** (0.005)
Lag 0	0.047** (0.017)	0.037* (0.019)
Lag 1	0.076*** (0.019)	0.066*** (0.020)
Lag 2	0.100*** (0.024)	0.049* (0.024)
Lag 3	0.141*** (0.029)	0.090*** (0.030)
Lag 4	0.037* (0.022)	0.007 (0.024)
Lag 5	0.049* (0.027)	0.018 (0.028)
Humanitarian assistance gap		0.745** (0.323)
TC Ana: Affected × Post		0.004 (0.011)
TC Gombe: Affected × Post		0.080*** (0.012)
Drought		0.006 (0.016)
Heavy rain event		0.019** (0.008)
Heat exposure 25 - 30 °C		0.002** (0.001)
Heat exposure 30 - 35 °C		0.004*** (0.001)
Heat exposure > 35 °C		0.004 (0.004)
Number of observations	610	610
Time & District FEs	Yes	Yes

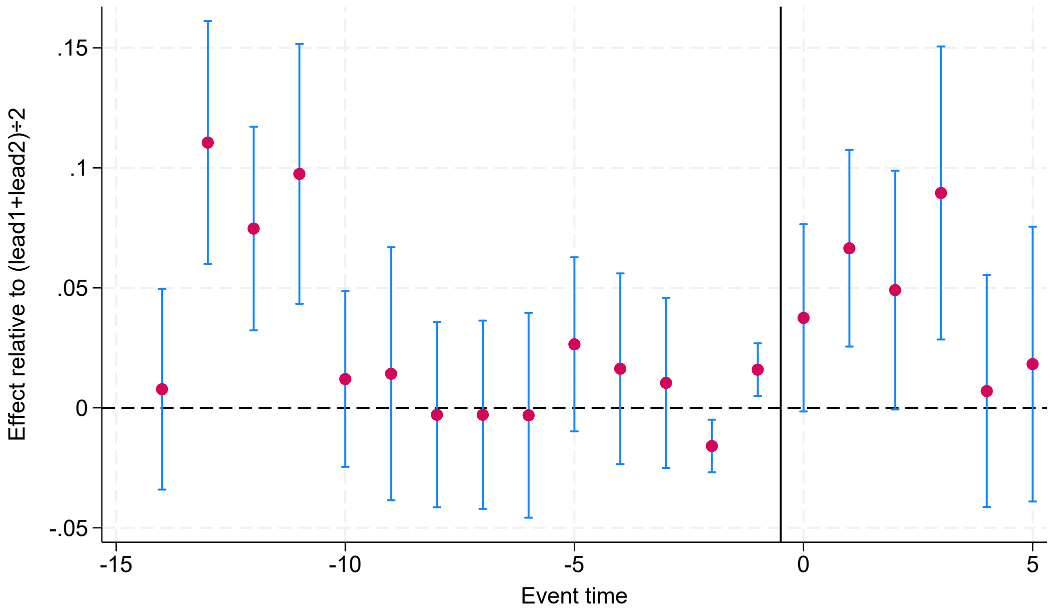
Notes: Standard errors clustered at district level and displayed in parentheses; * p < .1, ** p < .05, *** p < .01

Figure 9: Event study plot for the model without controls using data from the whole time frame and from urban centres



Notes: Model without controls and with district and time FE; Model constrained by: $\delta_{-2} + \delta_{-1} = 0$; Confidence bands calculated using clustered standard errors and the 5% significance level.

Figure 10: Event study plot for the model with controls using data from the whole time frame and from urban centres



Notes: Model with controls and with district and time FE; Model constrained by: $\delta_{-2} + \delta_{-1} = 0$; Confidence bands calculated using clustered standard errors and the 5% significance level.

D.2 Robustness check using wild bootstrap

D.2.1 DiD Estimation using wild bootstrap

Table 10: Results of the DiD Estimation using wild bootstrap

Variable	M9	M10
TC Freddy: Affected × Post	0.090*** (0.000)	0.036** (0.028)
Humanitarian assistance gap		1.013 (0.131)
TC Ana: Affected × Post		-0.001 (0.942)
TC Gombe: Affected × Post		0.074*** (0.000)
Drought		0.027* (0.082)
Heavy rain event		0.016* (0.095)
Heat exposure 25 - 30 °C		0.002* (0.068)
Heat exposure 30 - 35 °C		0.005*** (0.006)
Heat exposure > 35 °C		0.003 (0.609)
Number of observations	432	432
Time & District FEs	Yes	Yes

Notes: Analysis clustered at district level; P-values and confidence intervals calculated using wild bootstrap; P-values in parentheses; * p < .1, ** p < .05, *** p < .01

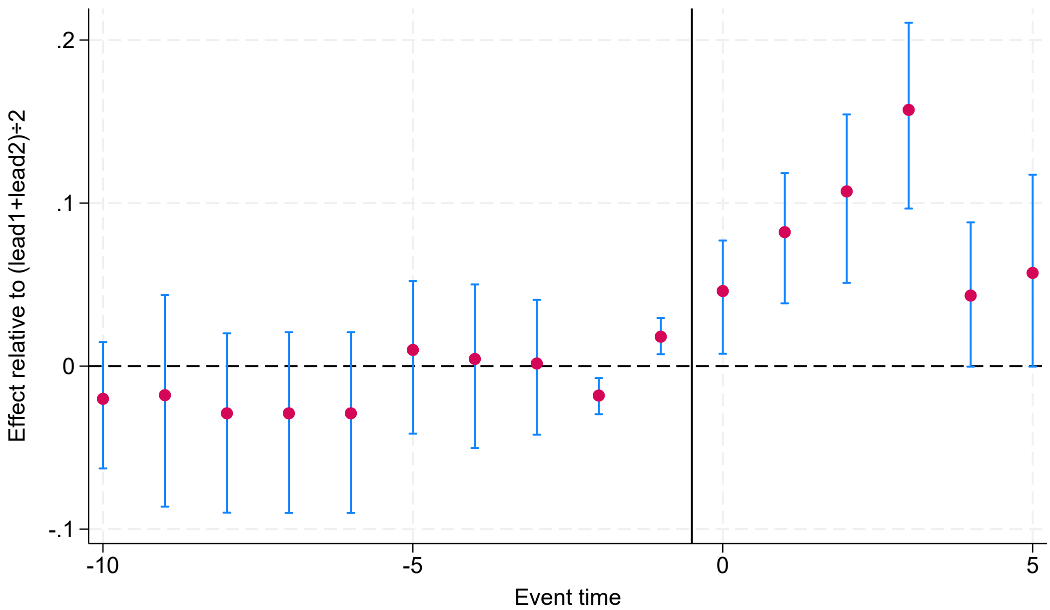
D.2.2 Event-Study Estimation using wild bootstrap

Table 11: Results of the Event-Study Estimation using wild bootstrap

Variable	M11	M12
Lead 10	-0.020 (0.277)	0.008 (0.683)
Lead 9	-0.018 (0.566)	0.010 (0.738)
Lead 8	-0.029 (0.241)	-0.014 (0.534)
Lead 7	-0.029 (0.249)	-0.014 (0.539)
Lead 6	-0.029 (0.249)	-0.014 (0.539)
Lead 5	0.010 (0.679)	0.020 (0.257)
Lead 4	0.004 (0.862)	0.015 (0.486)
Lead 3	0.002 (0.946)	0.011 (0.501)
Lead 2 [used to calculate the reference]	-0.018*** (0.006)	-0.018*** (0.006)
Lead 1 [used to calculate the reference]	0.018*** (0.006)	0.018*** (0.006)
Lag 0	0.046** (0.024)	0.030 (0.169)
Lag 1	0.082*** (0.000)	0.066*** (0.010)
Lag 2	0.107*** (0.002)	0.041 (0.219)
Lag 3	0.157*** (0.000)	0.091** (0.011)
Lag 4	0.043* (0.053)	0.007 (0.770)
Lag 5	0.057* (0.051)	0.021 (0.492)
Humanitarian assistance gap		0.954 (0.118)
TC Ana: Affected × Post		0.006 (0.518)
TC Gombe: Affected × Post		0.072*** (0.000)
Drought		0.013 (0.385)
Heavy rain event		0.019* (0.091)
Heat exposure 25 - 30 °C		0.002* (0.092)
Heat exposure 30 - 35 °C		0.005** (0.015)
Heat exposure > 35 °C		0.003 (0.560)
Number of observations	432	432
Time & District FEs	Yes	Yes

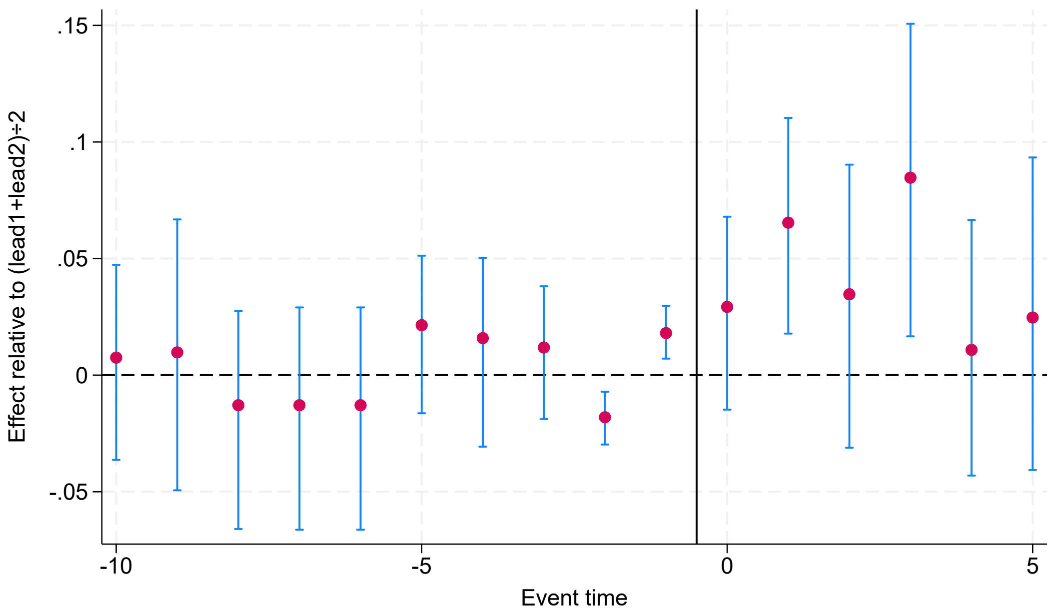
Notes: Analysis clustered at district level; P-values and confidence intervals calculated using wild bootstrap; P-values in parentheses; * $p < .1$, ** $p < .05$, *** $p < .01$

Figure 11: Event study plot for the model without controls using wild bootstrap estimation (M11)



Notes: Model M11 under the constraint of $(\delta_{-2} + \delta_{-1} = 0)$ with district and time FE without controls; CI calculated using wild bootstrap from boottest

Figure 12: Event study plot for the model with controls using wild bootstrap estimation (M12)



Notes: Model M12 under the constraint of $(\delta_{-2} + \delta_{-1} = 0)$ with district and time FE with controls; CI calculated using wild bootstrap from boottest

D.3 Robustness check using a threshold of z = 4

D.3.1 DiD Estimation using a threshold of z = 4

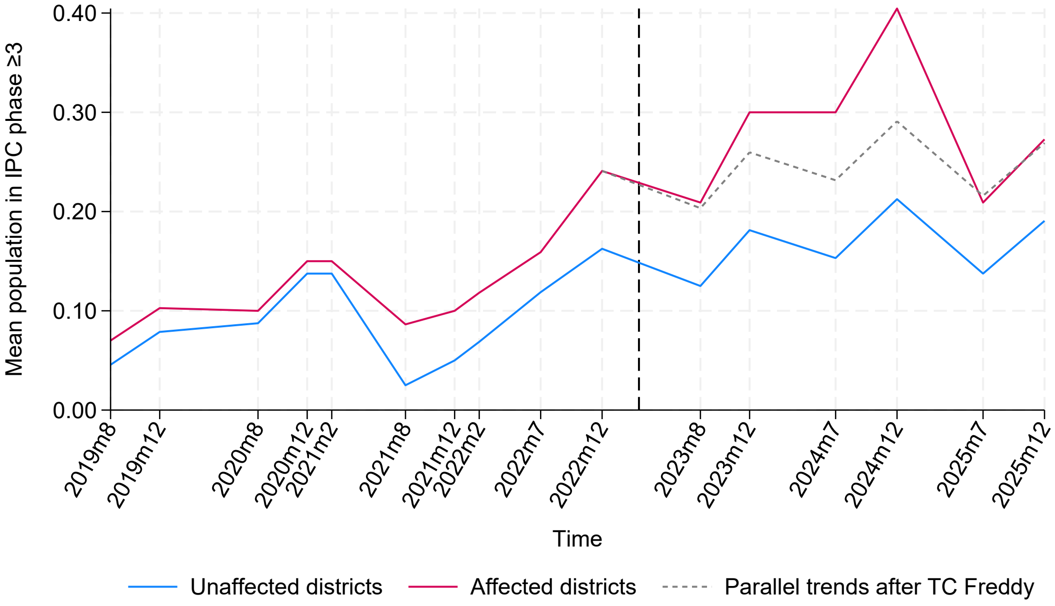
Table 12: Results of the DiD Estimation using a threshold of z = 4

Variable	M13	M14
TC Freddy: Affected × Post	0.079*** (0.020)	0.036** (0.015)
Humanitarian assistance gap		0.871** (0.344)
TC Ana: Affected × Post		-0.006 (0.007)
TC Gombe: Affected × Post		0.078*** (0.011)
Drought		0.035** (0.015)
Heavy rain event		0.016* (0.009)
Heat exposure 25 - 30 °C		0.002* (0.001)
Heat exposure 30 - 35 °C		0.005*** (0.002)
Heat exposure > 35 °C		0.003 (0.004)
Number of observations	432	432
R^2	0.797	0.861
Time & District FEs	Yes	Yes

Notes: Standard errors clustered at district level and displayed in parentheses; * $p < .1$, ** $p < .05$, *** $p < .01$

D.3.2 Trend analysis using a threshold of z = 4

Figure 13: Development of food insecurity in affected and unaffected districts over time (threshold z = 4)



Notes: The red (blue) lines show the unweighted average of the share of people in IPC phase ≥ 3 in the group of affected (unaffected) districts. The short dashed line indicates how food insecurity would have developed in the affected districts if it had moved parallel to the unaffected districts after TC Freddy. The dashed vertical line indicates the time TC Freddy struck Malawi.
Source: Own representation using data from the IPC (2025a) and Muñoz Sabater (2019b)

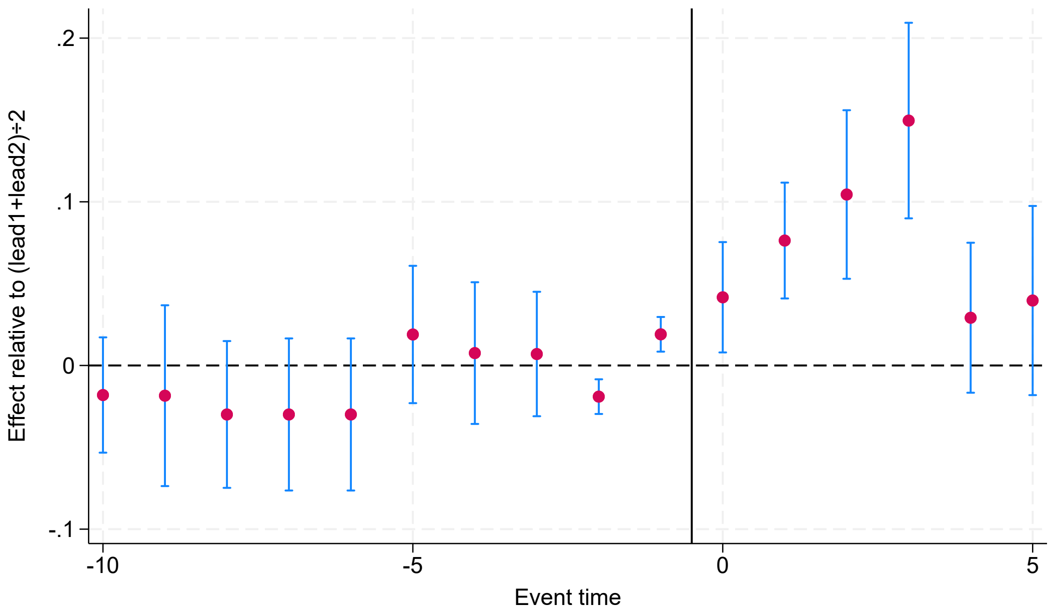
D.3.3 Event-Study Estimation using a threshold of z = 4

Table 13: Results of the Event Study Estimation using a threshold of z = 4

Variable	M15	M16
Lead 10	-0.018 (0.017)	0.008 (0.019)
Lead 9	-0.018 (0.027)	0.007 (0.026)
Lead 8	-0.030 (0.022)	-0.011 (0.017)
Lead 7	-0.030 (0.023)	-0.011 (0.018)
Lead 6	-0.030 (0.023)	-0.011 (0.018)
Lead 5	0.019 (0.020)	0.027* (0.015)
Lead 4	0.008 (0.021)	0.015 (0.017)
Lead 3	0.007 (0.018)	0.014 (0.013)
Lead 2 [used to calculate the reference]	-0.019*** (0.005)	-0.019*** (0.005)
Lead 1 [used to calculate the reference]	0.019*** (0.005)	0.019*** (0.005)
Lag 0	0.042** (0.016)	0.030 (0.021)
Lag 1	0.076*** (0.017)	0.065*** (0.021)
Lag 2	0.104*** (0.025)	0.042 (0.027)
Lag 3	0.150*** (0.029)	0.087** (0.033)
Lag 4	0.029 (0.022)	0.009 (0.024)
Lag 5	0.040 (0.028)	0.020 (0.029)
Humanitarian assistance gap		0.840** (0.371)
TC Ana: Affected × Post		0.000 (0.011)
TC Gombe: Affected × Post		0.076*** (0.012)
Drought		0.021 (0.017)
Heavy rain event		0.017* (0.010)
Heat exposure 25 - 30 °C		0.001 (0.001)
Heat exposure 30 - 35 °C		0.005** (0.002)
Heat exposure > 35 °C		0.003 (0.004)
Number of observations	432	432
Time & District FEs	Yes	Yes

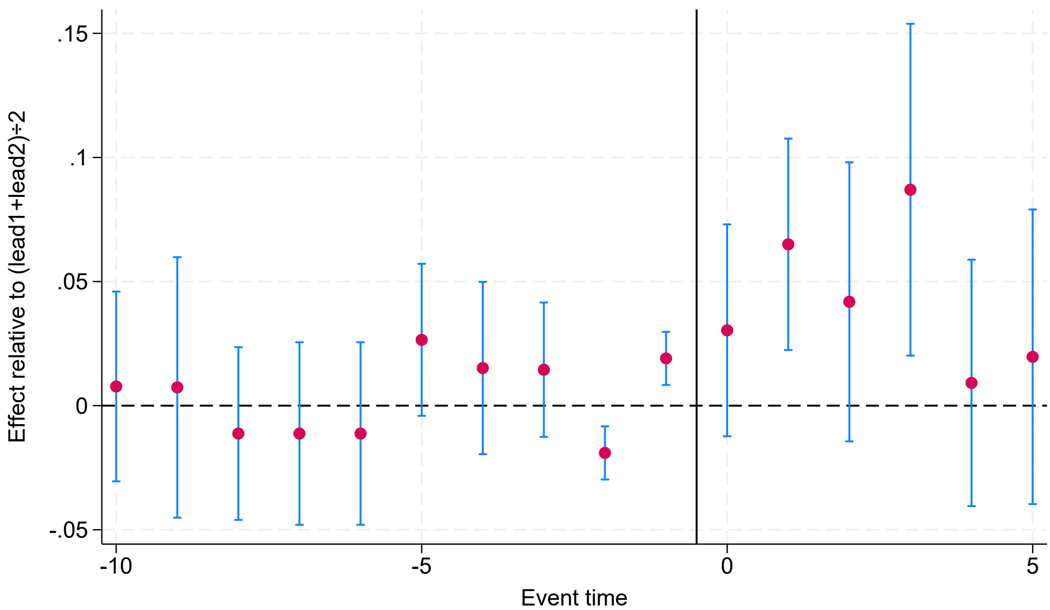
Notes: Standard errors clustered at district level and displayed in parentheses; * $p < .1$, ** $p < .05$, *** $p < .01$

Figure 14: Event-study plot for the model without controls using a threshold of z = 4



Notes: Model without controls and with district and time FE; Model constrained by: $\delta_{-2} + \delta_{-1} = 0$; Confidence bands calculated using clustered standard errors and the 5% significance level.

Figure 15: Event-study plot for the model with controls using a threshold of z = 4



Notes: Model with controls and with district and time FE; Model constrained by: $\delta_{-2} + \delta_{-1} = 0$; Confidence bands calculated using clustered standard errors and the 5% significance level.

D.4 Robustness check using a threshold of z = 7

D.4.1 DiD Estimation using a threshold of z = 7

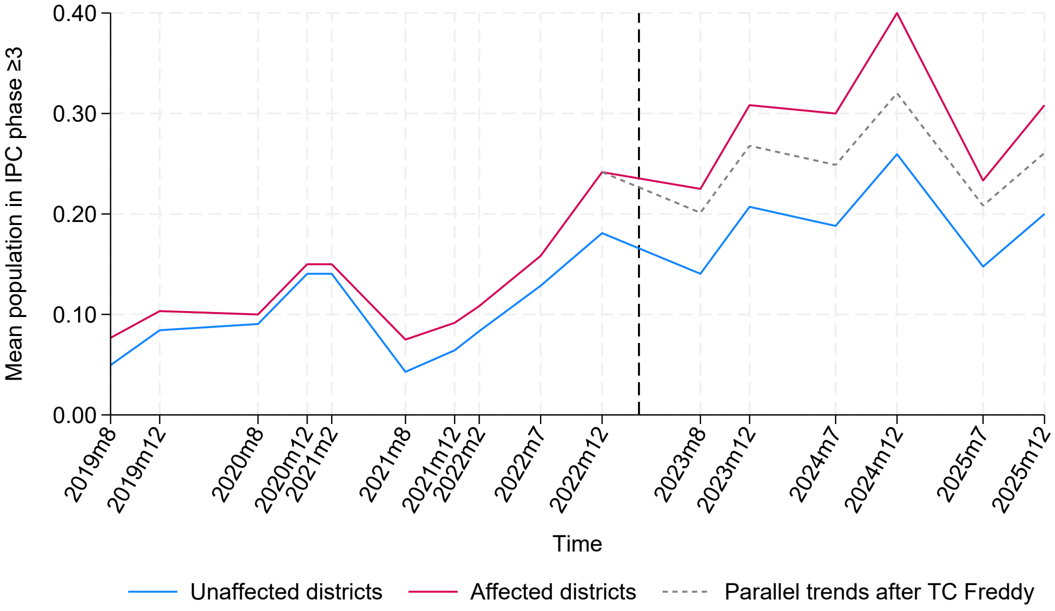
Table 14: Results of the DiD Estimation using a threshold of z = 7

Variable	M17	M18
TC Freddy: Affected × Post	0.080*** (0.021)	0.029** (0.013)
Humanitarian assistance gap		1.052*** (0.267)
TC Ana: Affected × Post		0.013 (0.010)
TC Gombe: Affected × Post		0.081*** (0.012)
Drought		0.032** (0.015)
Heavy rain event		0.016* (0.009)
Heat exposure 25 - 30 °C		0.002* (0.001)
Heat exposure 30 - 35 °C		0.005*** (0.002)
Heat exposure > 35 °C		0.003 (0.004)
Number of observations	432	432
R^2	0.787	0.860
Time & District FEs	Yes	Yes

Notes: Standard errors clustered at district level and displayed in parentheses; * p < .1, ** p < .05, *** p < .01

D.4.2 Trend analysis using a threshold of z = 7

Figure 16: Development of food insecurity in affected and unaffected districts over time (threshold z = 7)



Notes: The red (blue) lines show the unweighted average of the share of people in IPC phase ≥3 in the group of affected (unaffected) districts. The short dashed line indicates how food insecurity would have developed in the affected districts if it had moved parallel to the unaffected districts after TC Freddy. The dashed vertical line indicates the time TC Freddy struck Malawi.
Source: Own representation using data from the IPC (2025a) and Muñoz Sabater (2019b)

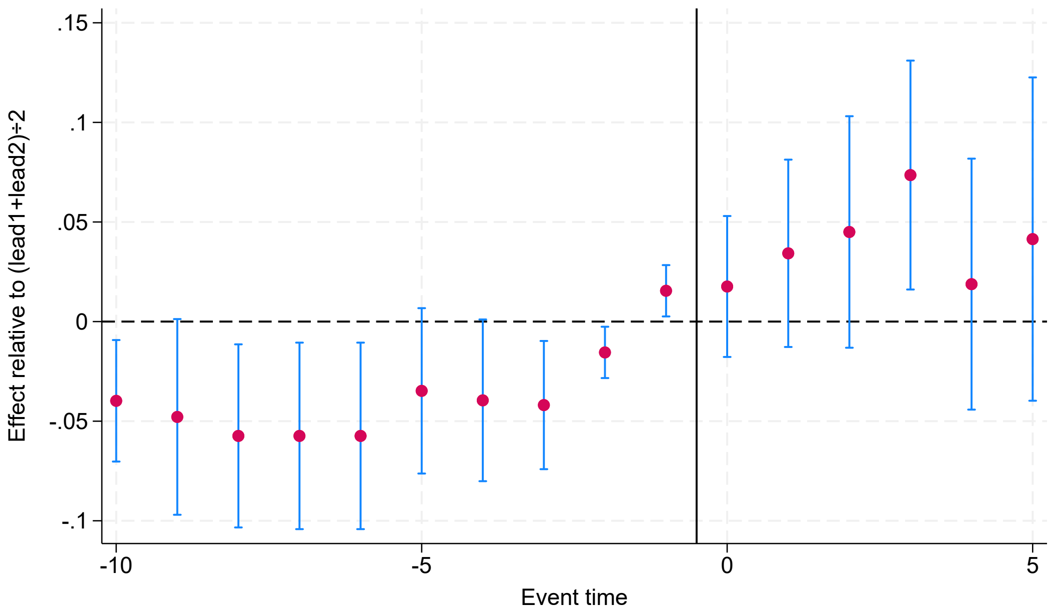
D.4.3 Event-Study Estimation using a threshold of z = 7

Table 15: Results of the Event Study Estimation using a threshold of z = 7

Variable	M19	M20
Lead 10	-0.040** (0.015)	0.003 (0.013)
Lead 9	-0.048* (0.024)	-0.005 (0.017)
Lead 8	-0.057** (0.022)	-0.022 (0.021)
Lead 7	-0.057** (0.023)	-0.022 (0.021)
Lead 6	-0.057** (0.023)	-0.022 (0.021)
Lead 5	-0.035* (0.020)	-0.003 (0.020)
Lead 4	-0.040* (0.020)	-0.008 (0.020)
Lead 3	-0.042** (0.016)	-0.008 (0.009)
Lead 2 [used to calculate the reference]	-0.015** (0.006)	-0.015** (0.006)
Lead 1 [used to calculate the reference]	0.015** (0.006)	0.015** (0.006)
Lag 0	0.018 (0.017)	0.020 (0.021)
Lag 1	0.034 (0.023)	0.036* (0.020)
Lag 2	0.045 (0.028)	-0.014 (0.029)
Lag 3	0.074** (0.028)	0.014 (0.029)
Lag 4	0.019 (0.031)	0.021 (0.028)
Lag 5	0.041 (0.039)	0.044 (0.036)
Humanitarian assistance gap		1.062*** (0.285)
TC Ana: Affected × Post		0.015 (0.010)
TC Gombe: Affected × Post		0.080*** (0.013)
Drought		0.041** (0.018)
Heavy rain event		0.015 (0.010)
Heat exposure 25 - 30 °C		0.002** (0.001)
Heat exposure 30 - 35 °C		0.005*** (0.001)
Heat exposure > 35 °C		0.003 (0.004)
Number of observations	432	432
Time & District FEs	Yes	Yes

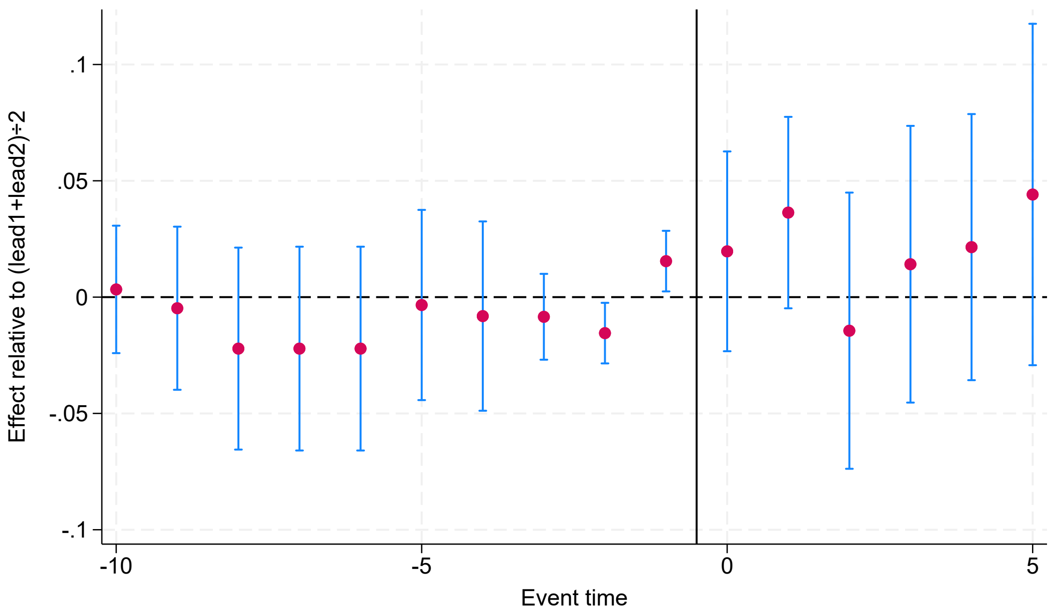
Notes: Standard errors clustered at district level and displayed in parentheses; * p < .1, ** p < .05, *** p < .01

Figure 17: Event-study plot for the model without controls using a threshold of z = 7



Notes: Model without controls and with district and time FE; Model constrained by: $\delta_{-2} + \delta_{-1} = 0$; Confidence bands calculated using clustered standard errors and the 5% significance level.

Figure 18: Event-study plot for the model with controls using a threshold of z = 7



Notes: Model with controls and with district and time FE; Model constrained by: $\delta_{-2} + \delta_{-1} = 0$; Confidence bands calculated using clustered standard errors and the 5% significance level.

D.5 Robustness check using the continuous treatment variable

In the following, the mean of the daily z-scores of the 11th to 15th of March 2023 within the district- and month-specific long-term daily rainfall distribution is used as continuous treatment variable. It is defined in Section 4.2.2. The effects need to be interpreted as the change of population in IPC phase ≥3 in percentage points per unit increase in z-score. Hence, it shows by how many percentage points food insecurity increased if the average daily rains during TC Freddy increased by one standard deviation of the long-term daily district March precipitation distribution.

D.5.1 DiD Estimation using the continuous treatment variable

Table 16: Results of the DiD Estimation using the mean z-score as continuous treatment variable

Variable	M21	M22
TC Freddy: Cont. treatment × Post	0.014*** (0.002)	0.008*** (0.002)
Humanitarian assistance gap		0.516 (0.306)
TC Ana: Affected × Post		0.001 (0.009)
TC Gombe: Affected × Post		0.070*** (0.012)
Drought		0.030** (0.014)
Heavy rain event		0.017* (0.009)
Heat exposure 25 - 30 °C		0.002** (0.001)
Heat exposure 30 - 35 °C		0.005*** (0.002)
Heat exposure > 35 °C		0.003 (0.004)
Number of observations	432	432
R^2	0.814	0.862
Time & District FEs	Yes	Yes

Notes: Standard errors clustered at district level and displayed in parentheses; * p < .1, ** p < .05, *** p < .01

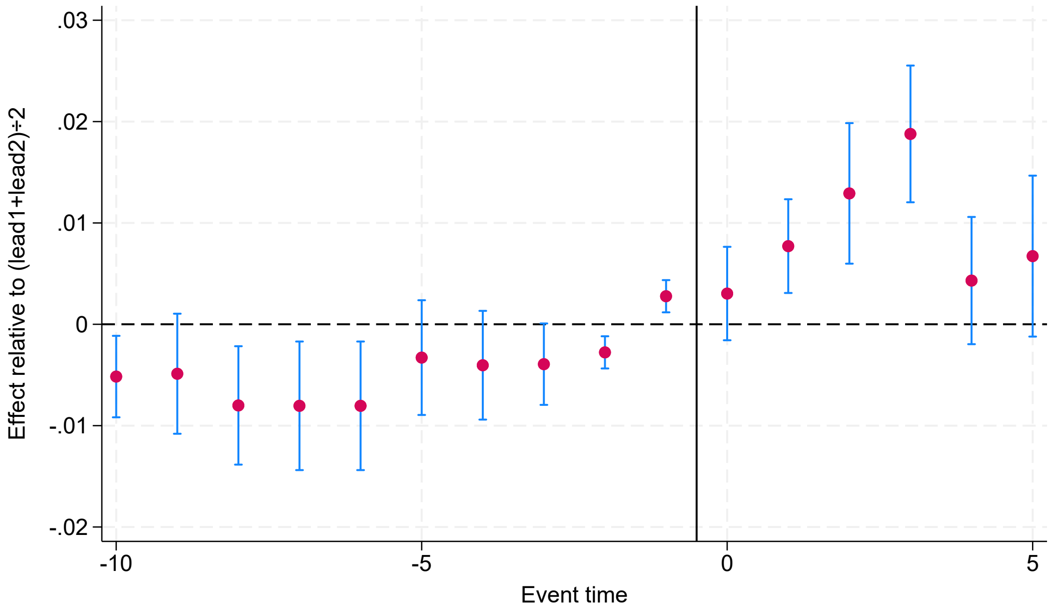
D.5.2 Event-Study Estimation using the continuous treatment variable

Table 17: Results of the Event-Study Estimation using the mean z-score as continuous treatment variable

Variable	M23	M24
Lead 10 (cont.)	-0.005** (0.002)	-0.000 (0.002)
Lead 9 (cont.)	-0.005 (0.003)	0.000 (0.003)
Lead 8 (cont.)	-0.008*** (0.003)	-0.006* (0.003)
Lead 7 (cont.)	-0.008** (0.003)	-0.006* (0.004)
Lead 6 (cont.)	-0.008** (0.003)	-0.006* (0.004)
Lead 5 (cont.)	-0.003 (0.003)	-0.003 (0.003)
Lead 4 (cont.)	-0.004 (0.003)	-0.004 (0.003)
Lead 3 (cont.)	-0.004* (0.002)	-0.003 (0.002)
Lead 2 (cont.) [used to calculate the reference]	-0.003*** (0.001)	-0.003*** (0.001)
Lead 1 (cont.) [used to calculate the reference]	0.003*** (0.001)	0.003*** (0.001)
Lag 0 (cont.)	0.003 (0.002)	0.003 (0.003)
Lag 1 (cont.)	0.008*** (0.002)	0.007** (0.003)
Lag 2 (cont.)	0.013*** (0.003)	0.004 (0.004)
Lag 3 (cont.)	0.019*** (0.003)	0.010** (0.004)
Lag 4 (cont.)	0.004 (0.003)	0.002 (0.004)
Lag 5 (cont.)	0.007* (0.004)	0.004 (0.005)
Humanitarian assistance gap		0.541 (0.326)
TC Ana: Affected × Post		-0.004 (0.009)
TC Gombe: Affected × Post		0.070*** (0.011)
Drought		0.015 (0.020)
Heavy rain event		0.016 (0.010)
Heat exposure 25 - 30 °C		0.003*** (0.001)
Heat exposure 30 - 35 °C		0.006*** (0.001)
Heat exposure > 35 °C		0.004 (0.005)
Number of observations	432	432
Time & District FEs	Yes	Yes

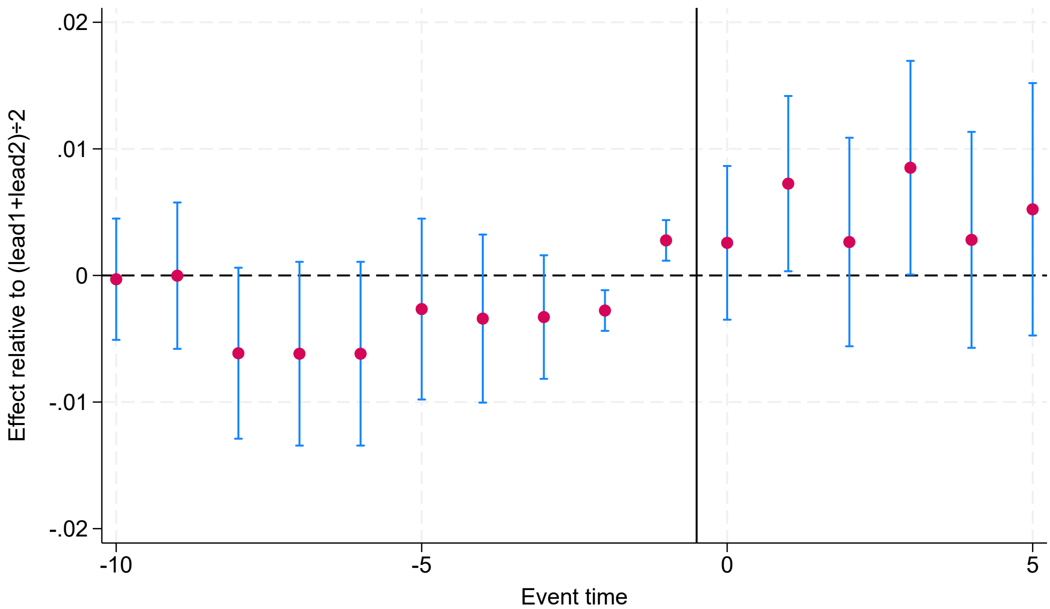
Notes: Event study under the constraint of ($\delta_{-2} + \delta_{-1} = 0$) for the continuous treatment variable; Standard errors clustered at district level and displayed in parentheses; * p < .1, ** p < .05, *** p < .01

Figure 19: Event study plot for the model without controls using the z-score as continuous treatment variable



Notes: Model without controls and with district and time FE; Model constrained by: $\delta_{-2} + \delta_{-1} = 0$; Confidence bands calculated using clustered standard errors and the 5% significance level.

Figure 20: Event study plot for the model with controls using the z-score as continuous treatment variable



Notes: Model with controls and with district and time FE; Model constrained by: $\delta_{-2} + \delta_{-1} = 0$; Confidence bands calculated using clustered standard errors and the 5% significance level.