Hearing the Alarm: Do Donors Follow Institutional Crisis Signals?

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Abstract

Donors rely on institutionalized alert systems to identify where hunger is most severe and to mobilize life-saving aid. The Integrated Food Security Phase Classification (IPC) is the primary global tool for this purpose, acting as a standardized emergency signal to direct resources toward acute food crises. Despite the importance of this system, its effectiveness remains unknown due to a lack of granular data tracking whether alerts actually result in donor aid allocation. This paper addresses this gap by using Natural Language Processing method to construct a novel dataset of geocoded aid flows in Afghanistan. Using a staggered difference in differences design, I estimate the causal impact of official food security emergency alerts. The analysis reveals that while an alert triggers a rapid increase in aid, the response is transitory and insufficient. The surge of resources fades quickly after the initial months and falls substantially short of the affected population's basic needs. These findings provide the first granular evidence of a critical gap between the severity of crisis and the actual amount of aid allocated.

Keywords: Humanitarian Aid, Food Security, Integrated Food Security Phase Classification, Natural Language Processing

JEL Codes: F35, H84, Q18, O19, C23, C81, C55

1 Introduction

The number of individuals experiencing food insecurity worldwide has doubled between 2016 and 2022, with an estimated 735 million people currently facing hunger [FAO et al., 2023]. Of these, approximately 250 million are classified as *acutely food insecure*, a condition defined as *"a person's inability to consume adequate food puts their lives or livelihoods in immediate danger"* [FAO et al., 2023, FSIN and Global Network Against Food Crises, 2023, WFP, 2023]. Timely intervention is essential to mitigate the most severe consequences of acute hunger [Hoddinott et al., 2008, Ruel et al., 2008]. To coordinate these efforts, international stakeholders rely on the Integrated Food Security Phase Classification (IPC), a multi-partner initiative that signals the severity of food crises and guides the allocation of billions of dollars in humanitarian aid annually [IPC, 2023].

While the IPC is intended to facilitate needs-based targeting, the broader literature on humanitarian assistance suggests that allocations are frequently shaped by a mix of altruism and donor self-interest, including political priorities and media attention [Olsen et al., 2003, Neumayer, 2005a, Fink and Redaelli, 2011, Rost and Clarke, 2025]. This raises a critical empirical question: does a technical, evidence-based tool like the IPC effectively direct resources to the most affected populations? Existing evidence on the IPC's influence is limited, focusing primarily on descriptive, country-level analyses of the most extreme Phase 5 "Famine" declarations [Maxwell et al., 2023]. A significant gap persists, as most research on aid allocation operates at the national level and uses broad proxies for need, leaving the causal effectiveness of institutional alerts at the subnational scale empirically unexplored.

This paper provides the first subnational evaluation of humanitarian aid responsiveness to IPC alerts by leveraging a novel dataset of funding flows in Afghanistan from 2017 to 2022. I apply Natural Language Processing (NLP) methods to georeference financial transactions and classify their purpose at the regional level. Using a staggered difference-in-differences design, I estimate the financial response to escalations into *IPC Phase 4* ("Emergency"), which indicates life-threatening food crises.

I further demonstrate the robustness of this causal link by ruling out alternative drivers. I show that humanitarian aid does not exhibit a similar immediate response to idiosyncratic shocks such as conflict intensity, food price inflation, or severe drought. Instead, the response is uniquely tied to the IPC's role as a comprehensive institutional signal. These findings provide granular evidence of a critical gap in the humanitarian system. While institutional signals successfully trigger an initial mobilization, the response ultimately falls far short of the support necessary to address the crisis effectively. The study also identifies heterogeneity in responsiveness across different donors, adding a subnational dimension to the literature on aid allocation and offering a more nuanced understanding of the operationalization of the needs-based principle.

The remainder of this paper is organized as follows. Section 2 provides a review of the relevant literature on development and humanitarian aid allocation. Section 3 describes the background of the IPC system and provides the specific context for the humanitarian crisis in Afghanistan. Section 4 details the construction of the geocoded aid dataset using NLP techniques, while Section 5 outlines the staggered difference in differences empirical strategy and identifying assumptions. Section 6 presents the main results, heterogeneity analysis, and robustness checks. Finally, Section 7 concludes with a discussion of policy implications for the global humanitarian financing system.

2 Literature Review

The literature that informs the study of aid allocation falls into two strands. The first examines patterns in *development aid*, where allocations are typically long-term and shaped by both recipient need and donor interests [Alesina and Dollar, 2000a, Berthélemy, 2006, Feeny and McGillivray, 2008, Hoeffler and Outram, 2011]. The second focuses on *humanitarian aid*, which is shorter-term and oriented toward crisis response, but is also influenced by factors beyond need, such as political priorities and media attention [Olsen et al., 2003, Neumayer, 2005a, Fink and Redaelli, 2011, Rost and Clarke, 2025]. By distinguishing between these two bodies of work, the review highlights both the commonalities and differences in how aid decisions are made, and sets the stage for assessing whether institutionalized food crisis classifications like the IPC influence allocations [Maxwell et al., 2023].

Research on development aid, often referred to as Official Development Assistance (ODA), emphasizes that allocations are shaped by both recipient needs and donor interests. Aid reflects a mix of altruistic and self-interested motives, with the balance differing across donors [Berthélemy, 2006, Feeny and McGillivray, 2008]. Historical and geopolitical ties are recurring themes, as colonial history, trade links, and political alignment have been shown to strongly predict allocation patterns [Alesina and Dollar, 2000b, Hoeffler and Outram, 2011]. Broader structural factors, such as donor income, institutional arrangements, and colonial legacies, also play a role [Fuchs et al., 2014]. This literature suggests that development aid reflects a combination of need and donor strategic concerns, with interests often exerting substantial influence.

Humanitarian assistance, on the other hand, also referred to as emergency aid, aims to provide rapid, life-saving support in crises where populations face acute vulnerability, such as during wars, natural disasters, or displacements [VanRooyen, 2013]. [Kuhlgatz et al., 2010, Kuhlgatz and Abdulai, 2012] show that emergency food aid responds to need, while also facing inertia and media bias. Young and Abbott [2008] highlights the importance of factors such as chronic hunger, poverty, and conflict, though responsiveness is not consistent across time or contexts. Olsen et al. [2003] argue that crises receiving more coverage tend to attract higher levels of aid, though they also note cases where substantial support was provided despite limited visibility, often due to political interests or strong institutional engagement. Rost and Clarke [2025] also identify media coverage as the most consistent factor driving appeal funding, but also find that crises involving severe human rights violations tend to receive less support.

Political and strategic considerations are also important. Fink and Redaelli [2011] point to biases toward smaller, geographically proximate, and resource-exporting countries, while Neumayer [2005b] emphasizes that food aid often favors recipients with geographic or political proximity to donors. Evidence of "bandwagon effects" is also present, where donor participation increases when other major donors have already committed resources Fink and Redaelli [2011]. By contrast, multilateral organizations appear to operate with somewhat greater independence from donor-specific interests. Dellmuth et al. [2021] show that disaster aid distributed through these institutions is more strongly linked to hazard severity and urgent need, suggesting that multilateral channels may provide a mechanism for allocations that are more consistently needs-based.

While both development and humanitarian aid literatures identify a mix of needs and interests in shaping allocation patterns, most studies evaluate these dynamics at the country level[Kuhlgatz et al., 2010, Neumayer, 2005a, Young and Abbott, 2008, Dellmuth et al., 2021, Maxwell et al., 2023]. This leaves less clarity on how aid responds to needs defined at subnational scales, where crises are experienced most directly. Moreover, measures of "need" in past work often rely on broad proxies, such as GDP per capita or national food production, which may not fully capture localized vulnerabilities Alesina and Dollar [2000a], Kuhlgatz et al. [2010], Neumayer [2005a], Young and Abbott [2008], Findley et al. [2011].

This study addresses these gaps by examining whether aid allocation corresponds with institutionalized food crisis classifications such as the IPC at the subnational level. The IPC provides a standardized, multi-dimensional assessment of food insecurity, making it a more precise indicator of humanitarian need than national-level proxies. By linking IPC classifications with subnational aid flows, the research investigates whether formal crisis signals influence the distribution of resources, and whether aid reaches the areas identified as being in the most severe phases of food insecurity. In doing so, the study connects the broader literature on aid allocation with emerging approaches that emphasize granularity, institutionalized indicators of need, and localized decision-making [Findley et al., 2011, Callen et al., 2023, Beath et al., 2025].

3 Background

3.1 IPC Acute Food Insecurity (AFI)

The IPC's Acute Food Insecurity (AFI) classification provides strategically critical information to decision-makers, focusing on immediate objectives to prevent, alleviate, or address severe food insecurity that poses risks to lives and livelihoods IPC [2021]. The IPC AFI follows a systematic, structured approach to enhance accuracy and reduce bias, progressing from data collection to classification outcomes to identify regions experiencing acute food insecurity [IPC, 2021]. Utilizing diverse data sources, the IPC assesses key drivers of food security, including vulnerability, resource availability, and the impacts of conflict and natural disasters. Primary indicators such as food consumption and livelihoods also play a central role in determining phase classifications [IPC, 2021].

Technical Working Groups (TWGs), comprising local government officials, non-governmental organizations (NGOs), and United Nations (UN) representatives, use a consensus-driven approach to generate subnational classifications of AFI. These classifications span from Phase 1 (None/Minimal) to Phase 5 (Catastrophe/Famine), representing the severity of acute food crises. Classifications at Phase 3 or higher indicate "crisis" levels, where households meet basic needs only by depleting essential assets or employing crisis coping strategies, highlighting the urgency for intervention [IPC, 2021].

The IPC seeks to ensure reliability by incorporating diverse data, standardizing its consensus process, and applying a rigorous analytical framework. However, challenges related to potential inaccuracies persist, particularly in complex or data-limited contexts [Enten, 2023, Lentz et al., 2024].

3.2 Socio-Political Instability, Food Insecurity, and Humanitarian Response in Afghanistan

Afghanistan faces significant political and economic instability, exacerbated by the Taliban's return to power in August 2021, which led to the suspension of international aid. This aid previously accounted for 40% of the country's GDP and over half of its government budget [Islam et al., 2022, Runde et al., 2024, The World Bank and Afghanistan Futures, 2023]. The abrupt cessation of funding triggered a severe economic downturn, intensifying both financial and humanitarian crises [Runde et al., 2024].

To address these challenges, large-scale humanitarian aid began flowing into Afghanistan in late 2021, amounting to over $2.9 billion to support essential services, salaries, and import costs for approximately 23.7 million people [Runde et al., 2024, The World Bank and Afghanistan Futures, 2023][1]. Despite these interventions, Afghanistan's economic and food security conditions remain precarious [OCHA, 2023]. Ranked 182 out of 193 on the Human Development Index, the country continues to experience acute food insecurity, with an estimated 15.8 million people projected to face crisis or emergency conditions (IPC 3+) through March 2024 due to drought, limited livelihoods, and other climate shocks [UNDP, 2024, OCHA, 2023]. Given Afghanistan's fragile economy, persistent food insecurity, and the critical role of humanitarian aid, evaluating the IPC's role in guiding allocation can provide insights into how response strategies might be strengthened to mitigate the impacts of severe food crises.

[1] Figure 22 in the appendix highlights this shift, showing the inverse trend between humanitarian and non-humanitarian aid starting in late 2021.

4 Data

4.1 IPC AFI

I leverage the IPC AFI data to assess whether IPC effectively prompt timely resource allocation in Afghanistan's humanitarian response. Since 2017, the IPC has consistently provided AFI classifications for Afghanistan's 34 Administrative Level 1 (ADM1) regions, including population estimates and phase outcomes accessible through its API. This panel dataset enables a longitudinal analysis of how humanitarian responses align with IPC phase changes.

The IPC framework categorizes AFI into five phases, ranging from Phase 1 (None/Minimal) to Phase 5 (Catastrophe/Famine). Phase 3 indicates severe food insecurity with heightened malnutrition risks, warranting urgent intervention, while Phase 4 signals life-threatening food shortages and increasing mortality risks. Although Phase 5 represents famine conditions, Afghanistan has not reached this level during the study period. Each classification includes estimates of the population proportion affected at each phase, allowing the calculation of "people in need."

Table 1 presents summary statistics of IPC AFI classifications across the 34 districts included in the sample.

(Insert Table 1 here.)

Table 1 indicates that a substantial proportion of IPC AFI observations are classified as Phase 3 (Crisis) or above, with 88% of observations in Phase 3+ and 16% specifically categorized as Phase 4 (Emergency). Furthermore, 57% of regions experienced IPC Phase 4+ at least once, while 15 regions (44%) never escalated to Phase 4. Given the common occurrence of IPC Phase 3, the high frequency of these classifications underscores the potential importance of transitions from IPC Phase 3 (Crisis) to IPC Phase 4 (Emergency) or higher as a critical trigger for mobilizing humanitarian aid in Afghanistan.

Treatment or Event Definition

My primary empirical approach, outlined in the following section, employs a Difference-in-Differences (DiD) method combined with an event study framework to analyze how transitions to severe levels of food insecurity influence aid allocation. The treatment is defined as the ***initial***

transition of a region from IPC AFI Phase 3 to Phase 4, representing a critical deterioration in food security that demands urgent humanitarian intervention. By focusing on these transitions, this analysis examines shifts in aid allocation, providing a framework to evaluate the IPC's role in mobilizing resources during crises.

Figure 1 illustrates IPC AFI classifications over time for Afghanistan's 34 Administrative Level 1 (ADM1) regions, with publicly available data starting in August 2017. The figure tracks transitions across Phases 2 to 4, where Phase 4 represents a state of *Food Emergency*. The figure highlights the widespread prevalence of Phase 3 (Crisis) and Phase 4 (Emergency) across many regions, some of which have persistently remained at these critical levels of food insecurity. Initially, IPC AFI classifications were conducted annually from 2017 to 2019; however, beginning in 2020, the assessments increased to a biannual frequency, typically conducted in March/April and August/September. The transitions between phases underscore the dynamic and volatile nature of acute food security in Afghanistan.

(Insert Figure 1 here.)

Figure 2 simplifies the staggered adoption of 'treatment' status, marking the point at which each region first reaches Phase 4 (Food Emergency) status. Darker red shading denotes the post-period following a region's initial Phase 4 classification. This figure illustrates the varied timing of Phase 4 entries across regions, highlighting differences in when severe food emergencies emerge. The complexity of these transitions between phases underscores the importance of an empirical strategy that captures the dynamic nature of IPC AFI classifications and the heterogeneous timing of these critical events, thereby enabling a more reliable estimation of their impact on humanitarian aid allocation.

(Insert Figure 2 here.)

In Figure 3, I show the geographic distribution of treated and non-treated units across ADM1 regions in Afghanistan. Of the total, 19 units are treated, while 15 remain non-treated. Treated regions are more dispersed throughout the country, spanning both northern and southern areas, whereas non-treated regions are more concentrated in the eastern and central parts of Afghanistan.

(Insert Figure 3 here.)

4.2 Humanitarian Aid Flow: Financial Tracking Service (FTS) Data

The analysis of humanitarian aid in this study draws on the Financial Tracking Service (FTS), a platform managed by the United Nations Office for the Coordination of Humanitarian Affairs (UN-OCHA). FTS functions as a centralized repository of humanitarian funding information, documenting contributions to crises and appeals since 1992. It provides curated, near real-time data on financial flows, including sectoral allocations, progress against response plans, and funding gaps [Kim, 2024]. Compared to OECD datasets, FTS is less frequently used in academic research, though it has served several purposes. For instance, [Fink and Redaelli, 2011] linked FTS data to individual disaster responses, while [Rost and Clarke, 2025] examined why some humanitarian appeals receive more funding than others. They highlight that FTS is considered to be “the most comprehensive and timely source of humanitarian financing data” and the provider of “the most frequently updated, openly accessible, and detailed information about international humanitarian aid flows”. Key features of the dataset are summarized in Table 2. Each transaction includes a monetary amount (USD), information on source and destination at the country level, timestamps that enable temporal analysis, keywords describing aid types, and the funding status (committed or disbursed). In addition, many records contain descriptions of activities, which describe details of allocation patterns.

(Insert Table 2 here.)

4.2.1 Leveraging Text Analysis to Address Data Limitations of FTS

1) Lack of Geocoded Data

However, a key challenge in using FTS data for this study is the lack of geocoded information, which complicates tracking of aid distribution at the subnational level. To address this issue, I develop a simple text-matching algorithm to identify ADM 1 region destinations within aid transaction descriptions. The algorithm accounts for common misspellings and variations in regional names (e.g., recognizing 'Sar-e-pul' as 'Saripol') and differentiates between similarly named regions, such as 'Paktika' and 'Paktya.'

When multiple ADM 1 regions are mentioned in a single aid record, aid (USD) is distributed across the detected regions, either evenly or weighted by the severity of food insecurity in each region. This study adopts an evenly distributed approach to avoid potential concerns of overestimation [2]. Among the 3,017 aid records in Afghanistan during the study period, 22% (658 transactions) explicitly mention ADM 1 regions as final aid destinations.

2) Categorization of Aid Transactions by Purpose

A second challenge involves the inconsistent availability of keywords categorizing aid transactions, complicating the interpretation of each allocation's purpose. While some transactions include clear labels such as "Food Security" or "Nutrition," others lack these tags, making it difficult to ascertain the intended use of the aid.

Figure 4 illustrates the distribution of humanitarian aid, totaling 355.86 million USD, across the top 10 keyword categories during the study period (January 2017 to December 2022). The categories "Food Security" and "Health" dominate the allocations, reflecting their prioritization in humanitarian responses. Other categories such as "Water, Sanitation, Hygiene" and "Protection," also represent significant portions of the funding. However, the "NA" category, representing missing or uncategorized entries, constitutes a substantial share (27.54%) of the total aid.

(Insert Figure 4 here.)

To address this challenge, I develop a Natural Language Processing (NLP) model trained on a global dataset comprising **42,024** aid records with categorized labels and descriptions. The model utilizes transaction descriptions as input to predict missing keywords, allowing for the categorization of transactions even when explicit labels are absent. This approach enhances the analysis of aid allocation by category by supplementing records lacking descriptive keywords with model-generated predictions.

The NLP model achieves high recall (95%), effectively identifying true "Food Security" cases, but exhibits lower precision (16%), indicating a tendency to misclassify non-"Food Security" cases as "Food Security." To improve classification accuracy, I apply an additional filtering step, searching

[2] Details of the allocation scheme is in the appendix.

for "Food Security"-related terms within the transaction descriptions. Further technical details, including the model architecture, performance metrics, and a confusion matrix, are presented in the Appendix.

4.2.2 Filtering and Aggregation of FTS Humanitarian Aid Flow Data

I filter the geocoded and keyword-recovered aid flow data using four criteria to conduct heterogeneity analysis: (1) the funding entity, (2) the objective or keywords describing the aid, (3) the funding status, categorized as commitments or disbursed contributions, and (4) whether the aid represents new funding or reallocated resources. The classification of funding status into commitments and disbursed contributions enables tracking aid allocation from initial pledges to actual disbursements. Differentiating between new and existing funding highlights whether the aid constitutes additional resources or reallocations within existing budgets. I aggregate the filtered data at the ADM 1 regional level, aligning it with historical IPC AFI classifications to conduct heterogeneity analysis in subsequent stages.

Figure 5 to 8 below provide an overview of the distribution of humanitarian aid to Afghanistan from 2017 to 2022, highlighting key patterns by source, sector, funding status, and resource origin. Figure 5 reveals that the United States is the largest individual donor in the original categorization (15.59%), followed by the European Commission (12.96%) and Germany (12.67%). However, in the recategorized view, European sources collectively dominate with 54.50%, underscoring Europe's pivotal role in Afghanistan's humanitarian aid landscape. Figure 6 categorizes aid by sector, enhanced by NLP-predicted keywords, addressing the initial 27.54% of entries labeled as "NA." The reclassification highlights "Food Security" as the largest category, growing from 10.34% to 36.59%, followed by "Protection" (13.00%) and "Health" (10.33%), reflecting an emphasis on food security in aid allocations. Figure 7 illustrates the funding status, indicating that 78.08% of the total 355.86 million USD had been disbursed by the time of data collection, while 21.92% remained in commitment. Figure 8 examines the funding composition, showing that 71.35% of the total funding comes from reallocated resources, while 28.65% originates from new funding.

(Insert Figure 5 - 8 here.)

Figure 9 illustrates variations in humanitarian aid trends across four dimensions. Aid from

European organizations shows consistent contributions, with prominent increases in 2020 and late 2022. Other contributors, including the United States and UN agencies, follow a similar pattern, though at lower levels. Sectoral funding, based on predicted labels, reveals steady trends in Food Security funding, while Non-Food Security funding exhibits episodic peaks, particularly in 2020 and late 2022. Regarding funding status, paid contributions constitute the majority, displaying consistent patterns and sharp increases in late 2022 corresponding to major disbursement events. Commitments, in contrast, show more irregular trends, with smaller peaks coinciding with those of paid contributions. Reallocated resources (i.e., New Money = False) dominate funding sources, providing consistent contributions and notable spikes in 2020 and late 2022, whereas new money displays a more sporadic pattern with smaller, less frequent peaks.

(Insert Figure 9 here.)

4.3 Other Data Sources

In Afghanistan, conflict, food price shocks, and extreme weather events are recognized drivers of food insecurity [D'Souza and Jolliffe, 2013a, D'Souza and Jolliffe, 2014, Oskorouchi and Sousa-Poza, 2021]. To account for these influences, I incorporate three monthly, subnational datasets as covariates: the Armed Conflict Location & Event Data Project (ACLED), the Standardized Precipitation-Evapotranspiration Index (SPEI-24), and the Real-Time Food Prices (RTFP) dataset.

ACLED provides detailed information on political violence, demonstrations, and related events, including fatalities, actors, dates, and locations [Raleigh et al., 2010]. SPEI-24 measures long-term drought conditions by combining precipitation and temperature data over a 24-month period, offering a widely used indicator of climatic stress on agriculture and food security [Vicente-Serrano et al., 2010]. RTFP integrates observed market data with machine-learning estimates to produce near real-time monthly food price series at the subnational level, addressing data gaps in areas without direct observations [Andree, 2021, Andrée and Pape, 2023, Penson et al., 2024].

For the analysis, I construct three variables: *conflict-related fatalities* from ACLED, *SPEI-24 drought values*, and *food price inflation* from RTFP. Each dataset is aggregated to the ADM1–month level. A five-month rolling mean is applied to smooth short-term fluctuations and align with

Afghanistan's biannual IPC cycle, which relies on information from prior months. These covariates are then integrated with IPC and FTS data in the econometric model.

5 Method

5.1 Identification Strategy

I use a staggered Difference-in-Differences (DiD) approach to estimate the causal effect of IPC AFI Phase 4 (Food Emergency) transitions on humanitarian aid allocation. I examine whether and to what extent transitions into critical states of food insecurity—the escalation from Phase 3 to Phase 4—trigger immediate aid responses, focusing on aid allocated within the first three months following the initial transition. This approach captures the short-term impact of worsening food insecurity on humanitarian response efforts. The DiD specification for this analysis is as follows:

$$\text{Humanitarian Aid}_{it} = \alpha + \beta \cdot \mathbf{1}[\text{Phase 4 (Food Emergency)}]_{it} + X_{it}'\gamma + \lambda_i + \delta_t + \epsilon_{it}$$

where Humanitarian Aid_{it} denotes the amount of humanitarian aid allocated to region i at time t. The variable $\mathbf{1}[\text{Phase 4 (Food Emergency)}]_{it}$ is a binary indicator equal to 1 if region i *first* enters Phase 4 (Food Emergency) at time t, and it remains set to 1 throughout the post-period. The vector X_{it} includes control variables such as conflict intensity (measured by fatalities), drought conditions (measured by SPEI-24), and food price fluctuation (measured by food price inflation). Region-specific fixed effects, λ_i, control for time-invariant characteristics unique to each region, while year-month fixed effects, δ_t, capture common shocks affecting all regions at a given time. Finally, ϵ_{it} represents the error term, accounting for any unobserved factors.

5.2 Addressing Identification Challenges

Identifying the causal impact of IPC AFI Phase 4 transitions on humanitarian aid poses several challenges. A primary issue is that IPC classifications are not assigned randomly. The decision to categorize a region as Phase 4 may depend on various observed and unobserved factors that influence the likelihood and timing of aid allocation, introducing potential endogeneity. These factors could drive both IPC classifications and aid responses, thereby biasing the estimates. Additionally, staggered treatment timing and the possibility of regions moving in and out of Phase 4 status complicate a straightforward DiD estimation. Standard DiD methods, which assume simultaneous treatment onset, are not directly applicable to staggered treatment timing and treatment switching, requiring a more flexible approach [Baker et al., 2022, Callaway and Sant'Anna, 2021].

To address identification challenges, I focus on each region's ***first transition from IPC AFI Phase 3 (Crisis) to Phase 4 (Food Emergency)*** to capture the immediate humanitarian response to a critical escalation in food insecurity. Restricting the analysis to the first three months following this initial transition isolates short-term aid responses and minimizes confounding effects from subsequent phase changes, enhancing causal clarity [Deryugina, 2017]. The biannual timing of IPC assessments in Afghanistan, typically conducted in March/April and August/September, further supports identification. For instance, even if significant events occur between these periods, IPC classifications remain unchanged until the next scheduled update, ensuring consistency in the analysis. To rule out alternative mechanisms, I conduct tests using variables such as spikes in political-violence-related fatalities, inflation shocks, and severe drought conditions. These tests vary intervention timing and reassign control and treated units, enabling an assessment of whether observed humanitarian responses are influenced by potential confounders.

5.3 Identifying Assumption and Verification

The key identifying assumption for the DiD approach is that the timing of a region's first transition to Phase 4 is uncorrelated with unobserved shocks that could also influence aid allocation. I assume that, after accounting for key covariates, as well as region and time-fixed effects, treated and control regions exhibit parallel trends in aid allocation in the absence of a Phase 4 transition. To verify this parallel trends assumption, I use a flexible event study framework, which enables a visual and statistical examination of whether treated regions show similar trends in aid allocation to control regions in the periods before the Phase 4 transition. If these pre-treatment trends are parallel, this supports the validity of the identifying assumption.

5.4 Event Study Specification

The event study model is specified as follows:

$$Y_{it} = \alpha_i + \lambda_t + \sum_{k=-K}^{-1} \beta_k \, \mathbf{Pre}_{i,t+k} + \sum_{k=0}^{K} \beta_k \, \mathbf{Post}_{i,t+k} + X_{it}'\gamma + \epsilon_{it},$$

where Y_{it} represents the amount of humanitarian aid (USD) received by region i at time t. Unit fixed effects, α_i, control for unobserved, time-invariant heterogeneity across regions, while time fixed effects, λ_t, account for shocks common to all regions at a given time, ensuring robust temporal comparability. The **Pre** and **Post** variables distinguish between periods before and after a region's **first escalation from Phase 3 (Crisis) to Phase 4 (Food Emergency)**, marking the onset of critical food insecurity.

The term $\sum_{k=-K}^{-1} \beta_k \, \mathbf{Pre}_{i,t+k}$ captures trends leading up to the escalation, allowing for the assessment of pre-trend validity, while $\sum_{k=0}^{K} \beta_k \, \mathbf{Post}_{i,t+k}$ estimates the temporal dynamics of aid allocation following the transition. This structure enables an evaluation of the timing and persistence of humanitarian aid responses. The vector X_{it}' incorporates relevant time-varying covariates—political-violence-related fatalities, food price inflation, and a drought indicator—to control for potential confounders influencing aid allocation. The coefficients γ quantify the impact of these covariates, and ϵ_{it} represents the idiosyncratic error term, capturing region-time-specific shocks not explained by the model.

5.5 Choice of Estimator: Callaway and Sant'Anna (2021)

I use the Callaway and Sant'Anna [2021] estimator for staggered DiD analysis to account for the staggered treatment timing and potential heterogeneity in Phase 4 transitions across regions. This estimator addresses scenarios with dynamic treatment effects and varying treatment timing. Formally, the estimator is expressed as:

$$ATT(g,t) = E[Y_t(1) - Y_t(0) \mid G = g, G \leq t]$$

where $ATT(g,t)$ represents the Average Treatment Effect on the Treated (ATT) for the group first treated in period g, evaluated at time t. Here, $Y_t(1)$ is the potential outcome (aid received) at time t under treatment, while $Y_t(0)$ is the potential outcome at time t without treatment. $G = g$ indicates the group first treated in period g, and $G \leq t$ denotes that treatment has already been received by group g by time t. By adjusting for dynamic treatment effects and allowing for heterogeneous treatment effects across groups and over time, the estimator provides a robust framework for analyzing the causal impact of IPC Phase 4 transitions on immediate aid allocation.

6 Results

6.1 Demographic Differences between Treated and Control Units at Baseline (2015)

To assess demographic differences between the treated and control ADM 1 region units, I use data from the latest available Demographic and Health Survey (2015) [ICF, 2015]. This captures baseline characteristics of both groups prior to the implementation of the IPC system in Afghanistan in 2017.

(Insert Table 3 here.)

The comparison between the treated and control regions shows minor demographic differences. The treatment group has slightly fewer household members, lower access to electricity, and less agricultural land ownership, along with a marginally lower wealth index, suggesting they may be more economically disadvantaged. However, differences in the number of eligible women, men, and children under 5 are minimal. These small but consistent disparities indicate that the treatment group may face slightly greater economic challenges, though the overall difference is marginal.

6.2 Summary Statistics of Key Variables

Table 4 presents summary statistics for key variables, comparing treated and controlled ADM 1 regions throughout the study period. Treated regions exhibit higher overall vulnerability, characterized by higher average IPC phases, larger proportions of the population in IPC Phase 3+ and Phase 4+, and more severe drought conditions, as reflected by the SPEI-24 index. These regions also receive greater allocations of food security-related and general humanitarian aid, aligning with their heightened needs.

(Insert Table 4 here.)

6.3 Main Results: Humanitarian Aid Response Against Acute Food Emergency

As discussed in the previous section, the key identifying assumption for the staggered DID model is that humanitarian responses would have followed parallel trends in both the treatment group (regions that experienced an escalation from Phase 3 to Phase 4) and the control group (regions that never experienced a Phase 4 escalation within the same period). To verify this parallel trends assumption, I conduct an event study analysis and test the pre-treatment parallel trend.

Figure 10 illustrates the average differences in total humanitarian aid (USD) between treatment and control units from 10 months before to 10 months after the treatment period. I employ multiple estimators to assess this trend, including Two-Way Fixed Effects (TWFE) models with and without covariates, a stacked regression model [Cengiz et al., 2019], and the Callaway and Sant'Anna method Callaway and Sant'Anna [2021] with and without covariates. The results indicate a clear separation between the pre-intervention and intervention periods, with no observable trend differences between treated and control ADM1 units before the intervention.

(Insert Figure 10 here.)

Humanitarian aid allocation for treated units trends upward following the first escalation to Phase 4, with a notable increase within the first three months post-intervention. This increase reflects a transitory effect, with fluctuations in aid allocation observed over the 10 months following treatment. These variations likely result from changing circumstances, including sustained Phase 4 status or repeated transitions between Phases 3 and 4. These dynamics suggest that aid responsiveness adapts to shifting severity levels rather than indicating a consistent escalation of need.

As I describe in the method section, I use the staggered DiD approach developed by Callaway and Sant'Anna (2021) to evaluate the impact of IPC AFI Phase 4 escalations on humanitarian aid allocation. I compare treated regions with "Never-Treated" and "Not-Yet-Treated" control groups to capture heterogeneous and dynamic treatment effects. I focus on the first three months following escalation to IPC Phase 4 to reduce potential contamination from subsequent fluctuations or transitions back to Phase 3. Table 5 shows the dynamic response of humanitarian aid (in millions of USD) to these escalations, while Table 6 presents results using log-transformed aid values as the outcome.

(Insert Table 5 here.)

1) Dynamic Effect

Following the initial escalation to IPC Phase 4, a significant increase in humanitarian aid emerges starting in the first month post-escalation. In the second month, the aid response peaks, with estimates ranging from 0.539 million USD in column (3) to 0.731 million USD in column (2), both statistically significant at the 5% level. This initial surge in aid reflects the rapid mobilization of resources in response to the escalation. However, by the third and fourth months, the aid response diminishes and loses statistical significance, suggesting that the initial increase represents a temporary surge rather than a sustained flow of resources.

2) Average Effect of the First Three Months

The average immediate effect (0-2 month average) in Table 5 captures the average aid allocation within the crucial early response period. For instance, column (2) reports an average effect of 0.369 million USD, while column (3) shows 0.285 million USD, emphasizing the substantial focus on aid delivery in the months immediately following the Phase 4 escalation. Summing the average effects across the initial 0-2 month period provides a bounded cumulative impact of the response, with a maximum total aid allocation of approximately 1.107 million USD and a minimum of 0.819 million USD. These cumulative effects underscore the concentrated and intensified humanitarian response targeted at regions facing heightened food insecurity shortly after the crisis intensifies to Phase 4.

3) Calculating the Need Gap

I further assess the adequacy of humanitarian aid among treated units following an escalation to IPC Phase 4 by using the minimum and maximum estimates of the average 3-month aid increase outlined in Table 5. These estimates provide a bound for the per capita aid allocation targeting populations affected by severe food insecurity, with the key metrics summarized in Table 7.

(Insert Table 7 here.)

Before the escalation to IPC Phase 4, among treated units, the per capita humanitarian aid for food-insecure populations averaged less than 20 USD, with aid distributed across both Phase 3 and Phase 4 populations. Following the first Phase 4 escalation, the estimated 3-month increase in aid ranges from approximately 819,000 USD to 1,107,000 USD per administrative unit. During this period, the average population in IPC Phase 4 per treated unit increased from 79,425 before the escalation to 186,661 after, with an additional 107,236 individuals, on average, entering IPC Phase 4 conditions.

As shown in Table 7, dividing the total aid increases by the number of new IPC Phase 4 entrants results in a per capita aid range of 7.64 USD to 10.32 USD over three months. This equates to approximately 2.55 USD to 3.44 USD per person per month. Even when combined with the pre-event per capita aid of less than 20 USD, the cumulative aid allocation remains below the estimated monthly food requirement cost of 98 USD per person in Afghanistan, based on a daily cost of 2.94 USD over a 30-day period [Numbeo, 2024].

Phase 4 (Emergency) conditions are associated with life-threatening food shortages and an increased risk of death. The result indicates that the level of additional humanitarian aid provided, after the escalation, is not sufficient to meet the estimated food needs of populations in IPC Phase 4. These findings suggest a gap between the aid allocated and the requirements associated with Phase 4 conditions.

6.4 Heterogeneity in Humanitarian Aid: By Source Organization, Temporal Context, Funding Type, and Aid Purpose

1) By Source Country

I examine variations in humanitarian aid allocation by funding source, focusing on contributions from the European Union (EU), non-United States (US) entities, and the US. Figure 11 illustrates the average treatment effects of aid for regions experiencing Phase 4 food insecurity, disaggregated by source. Each panel displays monthly aid responses from the escalation month (0 month) to four months post-escalation, along with a cumulative 0–2 month average effect indicated by the blue dashed line.

The left panel, representing EU-funded aid, reports a 0–2 month average effect of approximately 0.079 million USD. A statistically significant response emerges in the second month, suggesting timely mobilization of EU resources following Phase 4 escalations. However, the response appears to decline in magnitude in the subsequent months, indicating a limited persistence of aid flows. The middle panel, focusing on non-US funds, exhibits a relatively larger 0–2 month average effect of approximately 0.166 million USD. This panel highlights a notable and statistically significant response during the second month, suggesting that non-US funders, which include all other international agencies or regional contributors, provide a stronger and more immediate response within the early phase of a crisis. The right panel, displaying US-funded aid, shows a 0–2 month average effect of approximately 0.139 million USD. While the aid response is positive, no statistically significant effects are observed in any individual month.

These findings suggest that the magnitude and timing of humanitarian aid allocation vary by funding source, potentially reflecting differences in operational structures, funding mechanisms, or strategic priorities.

(Insert Figure 11 here.)

2) Before and After Taliban Offensive (2021)

I examine variations in humanitarian aid allocation by analyzing the timing of escalations to Phase 4, distinguishing between regions affected before and after the Taliban offensive in May 2021, a pivotal moment in Afghanistan's political history since 2017. Figure 12 presents the average treatment effect of humanitarian aid allocation before and after the Taliban offensive, delineating treated units based on whether they escalate to Phase 4 food insecurity before or after May 2021, which serves as the marker for the offensive period. The left panel, labeled "Before Conflict," shows the monthly aid response within the 0–4 month period following escalations to Phase 4 food insecurity prior to May 2021. During this period, the estimated average aid response within the first three months post-escalation remains modest, with a mean of approximately 0.033 million USD, indicating a limited scale of humanitarian aid mobilization in response to severe food insecurity. On the other hand, the right panel, labeled "After Conflict," shows the same time frame for treated units escalating to Phase 4 after May 2021. In this case, the average aid response within the first three month increases to approximately 0.340 million USD. Although this elevated response suggests a potential shift in aid prioritization following the escalation, the estimates lack statistical significance, necessitating cautious interpretation.

(Insert Figure 12 here.)

3) Food Security vs. Non-Food Security Aid

I also analyze how humanitarian aid allocation varies by purpose, focusing on food security-related and non-food security-related activities in regions experiencing Phase 4 food insecurity. Figure 13 compares the average treatment effects for these categories. The left panel, representing food security-related aid, shows a 0–2 month average effect of approximately 0.089 million USD, while the right panel, representing non-food security-related aid, shows a higher first-three-month average effect of approximately 0.182 million USD. None of the results are statistically significant, indicating that the observed aid responses likely reflect broader trends in total humanitarian aid allocation rather than being driven by one specific category of aid.

(Insert Figure 13 here.)

4) Paid vs. Committed

In Figure 14, I compare the average treatment effect of humanitarian aid by payment status: "Paid" versus "Committed." The left panel, representing the "Paid" category, shows an average treatment effect of 0.262 million USD over the 0–2 month period, with statistically significant effects observed in specific months. This suggests that aid marked as "Paid" is mobilized promptly in response to Phase 4 escalations. In contrast, the right panel, representing the "Committed" category, reports a smaller 0–2 month average treatment effect of 0.010 million USD, with no statistically significant effects observed. These findings indicate that aid marked as "Paid" exhibits a stronger response within the early months post-escalation, while the results for "Committed" funds show limited immediate mobilization.

(Insert Figure 14 here.)

5) New Allocations vs. Reallocated Budgets

Figure 15 presents the average treatment effects of humanitarian aid allocation based on funding type, comparing "New Fund" (left panel) and "Existing Fund" (right panel). "New Fund" refers to humanitarian aid sourced from freshly allocated resources, designated to address emerging or ongoing crises. In contrast, "Existing Fund" represents aid reallocated from previously committed resources. The "New Fund" category shows a 0–2 month average treatment effect of 0.241 million USD, as indicated by the dotted blue line, while the "Existing Fund" category shows a lower 0–2 month average of 0.075 million USD. Although it highlights some statistically significant effects for "Existing Fund," the estimates for "New Fund" do not show statistical significance across the months. These results suggest differences in the scale and timing of aid responses depending on the funding type, with "New Fund" showing a larger average effect over the 0–2 month period and "Existing Fund" demonstrating smaller but statistically significant effects in specific months.

(Insert Figure 15 here.)

Figure 16 illustrates the average immediate (0–2 month) treatment effects of humanitarian aid outcomes in response to Phase 4 escalations, disaggregated by funding source, payment status, new versus existing funds, and food security-related aid. The effects are further compared between units treated before and after the Taliban offensive in May 2021. Aid outcomes after the offensive (orange markers) generally show higher average immediate effects compared to those before the offensive (blue markers), though confidence intervals for many estimates overlap with zero, indicating limited statistical significance.

(Insert Figure 16 here.)

For "Funding Source," non-US and EU-funded aid exhibit larger immediate effects after the offensive, while US-funded aid shows smaller differences between the two periods. Within "Paid Status," disbursed (paid) aid demonstrates a stronger immediate response after the offensive, while committed aid shows minimal immediate effects in both periods. In the "New vs Existing Fund" category, newly allocated funds show higher immediate effects after the offensive, whereas existing funds exhibit more stable effects across both periods. Finally, under "Food Security Related Aid," non-food security-related aid demonstrates larger immediate effects after the offensive compared to food security-related aid, though statistical significance remains limited.

These results indicate shifts in the immediacy and magnitude of aid responses across funding categories following the Taliban offensive. Aid funded by non-US and EU sources, disbursed funds, and newly allocated resources show stronger immediate responses post-offensive, while pre-offensive units display more stable or weaker effects. Nonetheless, the lack of consistent statistical significance calls for cautious interpretation of these findings.

6.5 Ruling out Alternative Mechanisms

To ensure the robustness of the main results on humanitarian aid response to IPC AFI Phase 4 escalations, I investigate alternative mechanisms that may influence humanitarian responses, focusing on political, weather, and economic shocks. These factors are incorporated as covariates in the main specification, given their documented impact on food insecurity in Afghanistan [D'Souza and Jolliffe, 2013a,b, The World Bank and Afghanistan Futures, 2023].

Figure 17 demonstrates that the intensity of these indicators—political violence-related fatalities, food inflation rate, and drought index—does not consistently align with IPC phases, highlighting the complex relationship between these factors and food insecurity classification. For example, some periods and regions show high levels of fatalities or severe drought without a corresponding escalation to IPC Phase 4 (Emergency). Conversely, certain regions exhibit elevated IPC phases even when conflict or drought levels are moderate, suggesting that no single indicator is solely driving the IPC classification.

(Insert Figure 17 here.)

Figure 18 illustrates the timing of treatment entry and treatment status, defined by extreme events across three key indicators, along with the composition of control and treated units.

(Insert Figure 18 here.)

The misalignment between the timing of extreme events—conflict, food inflation, and drought—and IPC phases, as shown in Figure 18, provides a framework for testing whether humanitarian aid responds to Phase 4 escalations as a composite measure rather than to the intensity of individual indicators. If aid allocation primarily aligns with elevated IPC phases instead of individual shocks, such as political violence, economic disruptions, or environmental stressors, it suggests that aid responses are triggered by IPC rather than single-event drivers.

To investigate this, I examine whether humanitarian aid responds immediately to extreme events across conflict, food inflation, and drought. Figure 19 reveals no statistically significant evidence of immediate responses to these individual indicators, suggesting that aid allocation aligns more closely with IPC as a comprehensive measure rather than being influenced by any single stress indicator.

(Insert Figure 19 here.)

In Table 8, I report both dynamic effects and the average immediate effect (over 3 months) using the Callaway-Sant'Anna estimator without covariates, comparing against both never-treated and not-yet-treated groups. Neither the near-term dynamic effects nor the immediate effects show significant estimates. Altogether, these findings suggest that none of these alternative mechanisms drive an immediate humanitarian response.

(Insert Table 8 here.)

7 Conclusion

This study investigates the responsiveness of humanitarian aid to acute food security crises, using the Integrated Food Security Phase Classification (IPC) as a formal signal of need. By applying a staggered difference-in-differences approach to subnational data from Afghanistan (2017–2022), the analysis provides robust evidence that an escalation to IPC Phase 4 triggers a statistically significant increase in humanitarian aid. The response is both rapid, peaking in the second month, and transitory, diminishing quickly thereafter. Critically, this mobilized aid is insufficient, creating a substantial "need gap" where the assistance provided falls dramatically short of the resources required to meet the basic survival needs of the affected population.

These findings contribute to the long-standing discussion in the humanitarian literature regarding the interplay between needs-based principles and the complex array of factors that shape aid allocation. On one hand, the immediate surge in aid following an IPC alert supports the view that assistance is responsive to need, as noted by [Kuhlgatz et al., 2010, Kuhlgatz and Abdulai, 2012, Dellmuth et al., 2021]. The IPC classification system, as a formal mechanism, appears to trigger action by signaling the severity of conditions. On the other hand, the observed heterogeneity—such as stronger responses from non-US/EU sources, disbursed ("Paid") funds, and allocations following the 2021 Taliban offensive—aligns with research emphasizing the influence of donor-specific priorities and the broader geopolitical landscape on aid allocation [Olsen et al., 2003, Neumayer, 2005a, Fink and Redaelli, 2011].

This research makes two primary contributions that directly address the gaps highlighted in the literature review. First, by shifting the analysis to the subnational level, it moves beyond the country-level averages that dominate existing researchNeumayer [2005a], Young and Abbott [2008], Kuhlgatz et al. [2010], Fink and Redaelli [2011], Dellmuth et al. [2021]. This provides a more granular view, demonstrating that even when a country is a priority, the allocation of aid within its borders is dynamic and responsive to localized crisis alerts. It provides the first systematic evidence on how an institutional signal like the IPC influences funding at the scale where crises are actually experienced.

Second, this study moves beyond the broad proxies for need (e.g., GDP per capita) common in previous work by using the IPC—an institutionalized, operational measure of acute food insecurity[Neumayer, 2005a, Kuhlgatz et al., 2010, Young and Abbott, 2008]. In doing so, it directly tests the influence of the very mechanisms designed to guide humanitarian action. While [Maxwell et al., 2023] noted mixed evidence on the IPC's role at the national level, this study provides clear subnational evidence that its alerts do matter for upstream financial allocations, even if the resulting aid is inadequate.

In conclusion, this paper provides a more nuanced understanding of the needs-based principle in practice. While formal crisis signals work as a trigger, the subsequent response is constrained by funding mechanisms, donor priorities, and a lack of sustained commitment.

7.1 Limitation

This analysis has several constraints related to data and scope, but these reflect design choices for the research question at hand. The study relies on the geocoded subset of FTS transactions[3]; while this may not capture every transfer, geocoding signals intentionally targeted subnational responses and is therefore the most relevant ways for testing whether donors react to localized IPC alerts. Also, we use financial flows as outomces not last-mile deliveries; this assesses responsiveness at the first stage of the aid pipeline, where commitments and paid disbursements are the primary observable indicators of decision-making, although on-ground delivery can lag.

The setting—Afghanistan during a period of political transition and conflict—limits direct generalization of magnitudes, yet provides a rich case to study how institutional crisis signals translate into financing under operational constraints; the qualitative patterns are informative for similar complex emergencies. The "need gap" benchmark offers a transparent, conservative scale for interpreting shortfalls; it may not capture local price variation or non-food needs, but it clarifies orders of magnitude and supports cautious inference. Finally, although unobserved factors (e.g., shifting media attention or access conditions) cannot be completely ruled out, the empirical design incorporates unit and time fixed effects and time-varying controls for conflict, climate, and prices to reduce confounding; event-time diagnostics further help assess pre-trend comparability.

The approach prioritizes subnational relevance, decision-stage observability, and transparent benchmarking, while acknowledging where results should be interpreted with care.

(Insert Figure 20 here.)

7.2 Policy Considerations

The findings suggest that standardized, evidence-based alerts on food insecurity can effectively draw the attention of the international aid community. The observed response to a shift in food security classification indicates that these formal signals are influential. However, the analysis also points to several areas where the subsequent aid allocation could be enhanced. The significant

[3] Figure 20 highlights trends in humanitarian aid amounts recorded in the Financial Tracking Service (FTS) data from 2017 to 2022, distinguishing between aid with and without specific regional allocation.

"need gap" and the transitory nature of the funding surge suggest a need for responses that are not only rapid but also sufficient in magnitude and duration.

To strengthen this evidence-based approach, improving the granularity and consistency of sub-national aid data is critical. Better reporting on the final destination of funds would enhance accountability and enable a more accurate evaluation of whether resources are effectively reaching the specific areas identified as having the greatest need. Such transparency is fundamental for learning and adapting, ensuring that the humanitarian system can better align its resources with evidence of localized crises, regardless of the specific analytical tool used to identify them.

7.3 Future Research

Cross-country comparative analyses can hold great potential for advancing knowledge in this field. Examining patterns of aid responsiveness across various crisis contexts, including high-profile countries such as Ethiopia, Lebanon, South Sudan, Somalia, and the Democratic Republic of Congo, could reveal how regional dynamics, political contexts, and crisis severity shape aid flows. Such analyses could uncover trends and variations in allocation strategies that are not observable in single-country studies, offering a broader perspective on humanitarian responses.

A deeper line of inquiry could move beyond financial flows to examine the entire aid delivery chain. Research that tracks funding down to programmatic outputs and ultimately to household-level outcomes is needed to determine how effectively these financial responses translate into measurable improvements in welfare. Qualitative analysis through interviews with policymakers could uncover the specific bureaucratic and political factors that drive funding delays and gaps, answering the critical question of "why" these patterns of response occur. These lines of inquiry could move the field toward a more holistic understanding of the humanitarian financing ecosystem, from the initial trigger of a crisis signal to the ultimate on-the-ground impact.

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8 Appendix

8.1 Distribution Scheme for Geocoding Aid Data

This section explains the distribution scheme used to allocate aid when geocoding FTS data. The methods include even distribution, weighted distribution, and their application to specific cases. The allocation scheme for region i can be summarized as:

$$\text{Aid (USD)}_i = \begin{cases} A, & \text{if } n = 1, \text{ i.e., only one region is detected,} \\ \\ \frac{A}{n}, & \text{if aid is evenly distributed across } n \text{ regions,} \\ \\ A \cdot \frac{P_i}{\sum_{j=1}^{n} P_j}, & \text{if population data } (P_i) \text{ is available (weighted distribution).} \end{cases}$$

A represents the total aid amount (in USD) for a given record, n is the number of identified ADM1 regions within that record, P_i denotes the IPC Phase 3+ population of region i for the record, and $\sum_{j=1}^{n} P_j$ represents the total IPC Phase 3+ population across all n detected regions for that record.

The following examples illustrate how aid allocations are determined based on descriptive information in transaction records:

- **Case 1: Single Region Allocation**

  The description specifies: *"Emergency food assistance for acutely vulnerable people in Badakhshan Province facing crisis-level food insecurity."* In this scenario, the entire \$1,000,000 USD allocation is assigned solely to Badakhshan, as only one region is explicitly mentioned.

- **Case 2: Equal Distribution Across Multiple Regions**

  The description reads: *"Integrated Nutrition, Food Security, and WASH Drought Response in the Most Affected Districts of Bamyan and Daikundi Provinces."* Here, the \$1,000,000 USD allocation is divided equally between the two regions. Each region receives \$500,000 USD, as no additional weighting information is provided.

- **Case 3: Weighted Distribution Based on Population Estimates**

  Suppose the description states: *"Food security assistance for populations in crisis-level food insecurity in Herat and Ghor Provinces."* If population estimates for IPC Phase 3+ are available (e.g., 200,000 people in Herat and 100,000 people in Ghor), the allocation is weighted proportionally. Herat receives two-thirds of the aid ($666,667 USD), while Ghor receives one-third ($333,333 USD), based on the relative population sizes.

Figure 24 illustrates the distribution of humanitarian aid across Afghan regions from 2017 to 2022 under two allocation schemes: evenly distributed aid amounts (blue lines) and Phase 3+ population-weighted aid amounts (orange lines). While the allocation patterns show alignment in many regions, certain cases reveal differences between the two distribution schemes. However, for the majority of regions, the differences between these schemes remain relatively minor.

(Insert Figure 24 here.)

8.2 Natural Language Processing Model Predicting Aid Keyword [Main Text]

To classify humanitarian aid descriptions by destination cluster name, I develop a machine learning pipeline that combines text preprocessing, feature extraction, and ensemble classification methods. I filter the dataset for non-missing cluster definitions, obtaining a subset of descriptions and labels that serve as the feature and target sets, respectively.

The dataset, refined for complete keyword definitions, includes descriptions of humanitarian aid efforts and their keyword labels per record. Descriptions function as feature inputs, while destination clusters act as target labels. I split the data into training and test sets (75% training, 25% testing).

1) Model Pipeline

The pipeline includes TF-IDF vectorization to transform text into numerical vectors, preserving key textual features. For the base model, I use a Naive Bayes classifier and fine-tune hyperparameters through grid search. To enhance performance further, I implement an ensemble model combining Complement Naive Bayes, Random Forest, and Logistic Regression, each with balanced class weights and configured with soft voting for probability-based predictions.

2) Hyperparameter Tuning and Scoring

For hyperparameter optimization, I focus on TF-IDF parameters such as maximum document frequency (`max_df`), minimum document frequency (`min_df`), and n-gram range, along with classifier-specific parameters. I employ GridSearchCV with custom scorers to optimize precision, recall, and F1-score specifically for the "Food Security" label, aligning with the model's goal to prioritize accuracy in aid-related classifications.

3) Evaluation Metrics

I weigh precision, recall, and F1-scores for the "Food Security" label, using custom scoring functions to capture performance effectively. After identifying the optimal configuration, I assess the pipeline's predictive capability with precision and recall metrics, complemented by a confusion matrix display.

This approach provides a robust and domain-sensitive classification model, tailored to the complexities of humanitarian aid text and capable of supporting critical decision-making processes. As summarized in Table 7 the NLP model performs effectively in predicting the true "Food Security" category. The model's high recall ensures reliable identification of "Food Security" cases, although lower precision indicates occasional misclassification of non-"Food Security" transactions within this category.

(Insert Table 8 here.)

Figure 14 presents the confusion matrix for the classification model, illustrating its performance across different categories. The model accurately classifies 161 transactions as "Food Security," while demonstrating lower accuracy for other categories. Misclassifications frequently occur in categories such as "Coordination and Support Services," "Emergency Shelter and NFI," and "Water, Sanitation, and Hygiene," which are often incorrectly labeled as "Food Security." This misclassification may stem from overlapping terms in transaction descriptions or the predominance of "Food Security" labels in the training set. Additionally, less common categories, such as "Education" and "Protection - Child Protection," show lower classification accuracy, likely due to limited distinguishing features in their descriptions or small sample sizes. To address these issues and enhance accuracy, predictions are further refined by searching for terms explicitly related to "Food Security", such as "Food, Nutrition, Health" within the descriptions.

(Insert Figure 14 here.)

8.3 Contextualing Humanitarian Aid in Afghanistan

Figure 22 depicts a sharp rise in humanitarian aid beginning in late 2021, with amounts surpassing non-humanitarian aid in several subsequent quarters. This surge coincides with Afghanistan's escalating crisis following the Taliban's return to power in mid-2021, which abruptly halted most international assistance. Previously, such aid accounted for roughly 40% of Afghanistan's GDP and more than half of its government budget, highlighting the significant gap left by its cessation.

Figure 23 provides a detailed overview of the humanitarian aid data contextualized within the broader International Aid Transparency Initiative (IATI) framework. Out of a total aid amount of 84.61 billion USD, humanitarian aid accounts for 23.62 billion USD (27.9%). Of this, 6.97 billion USD (29.5%) is reported to the Financial Tracking Service (FTS). Within the FTS-reported aid, 1.04 billion USD (14.9%) is allocated specifically to food security and nutrition. However, only 0.38 billion USD (5.5% of FTS-reported aid) includes specified final destination information, underscoring challenges in tracking aid flows.

9 Figures and Tables

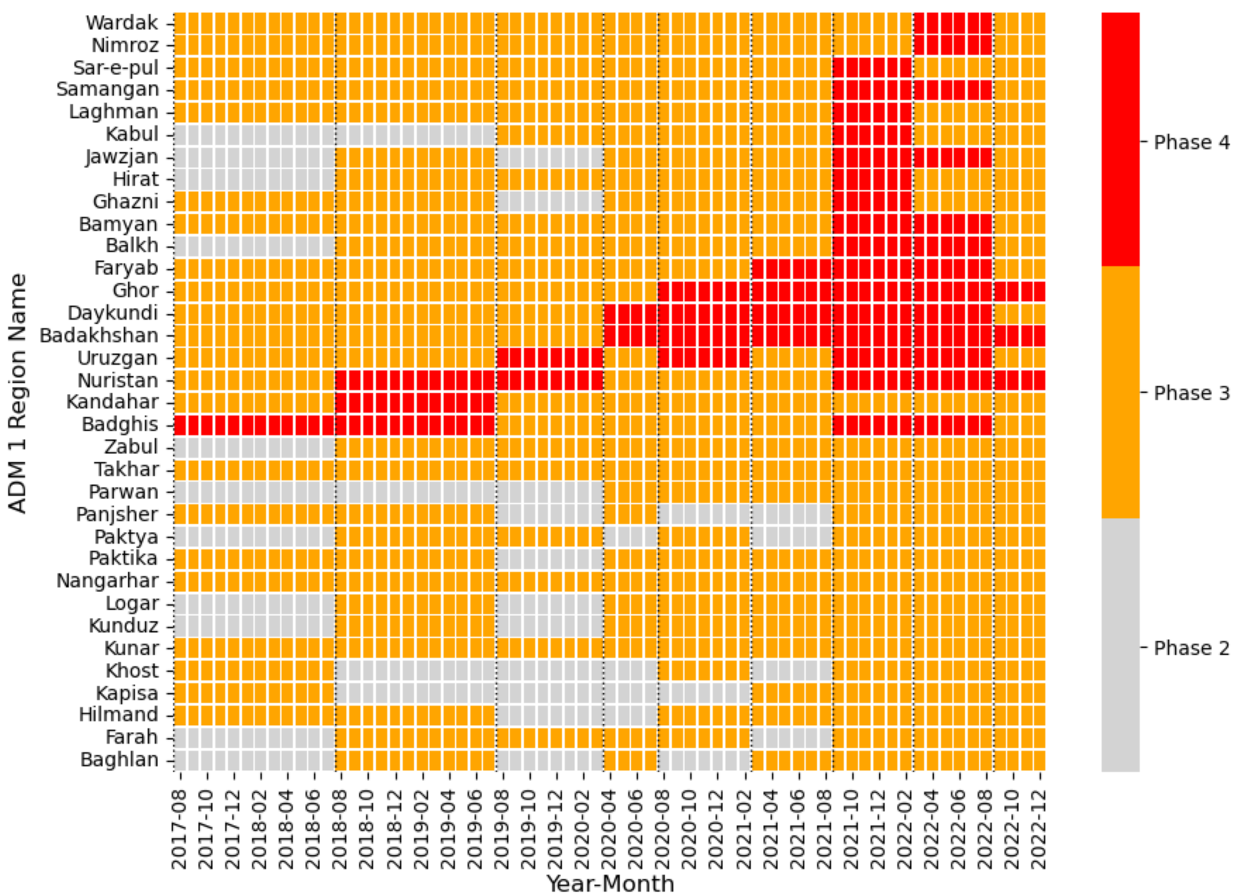
Table 1: **Distribution of IPC AFI Classifications from Jan, 2017 to Dec, 2022**

IPC Phase Outcome	Frequency (n = 306)	Percentage
Phase 1 (None/Minimal)	0	0%
Phase 2 (Stressed)	37	12%
Phase 3 (Crisis)	221	72%
Phase 4 (Emergency)	48	16%
Phase 5 (Catastrophe/Famine)	0	0%

% of Time Each District Spent in IPC Phase 4+	Frequency (n = 34 ADM1 Regions)
0	15 (Potential Control Group)
14	2
22	9
31	1
40	1
46	2
57	1
74	2
90	1

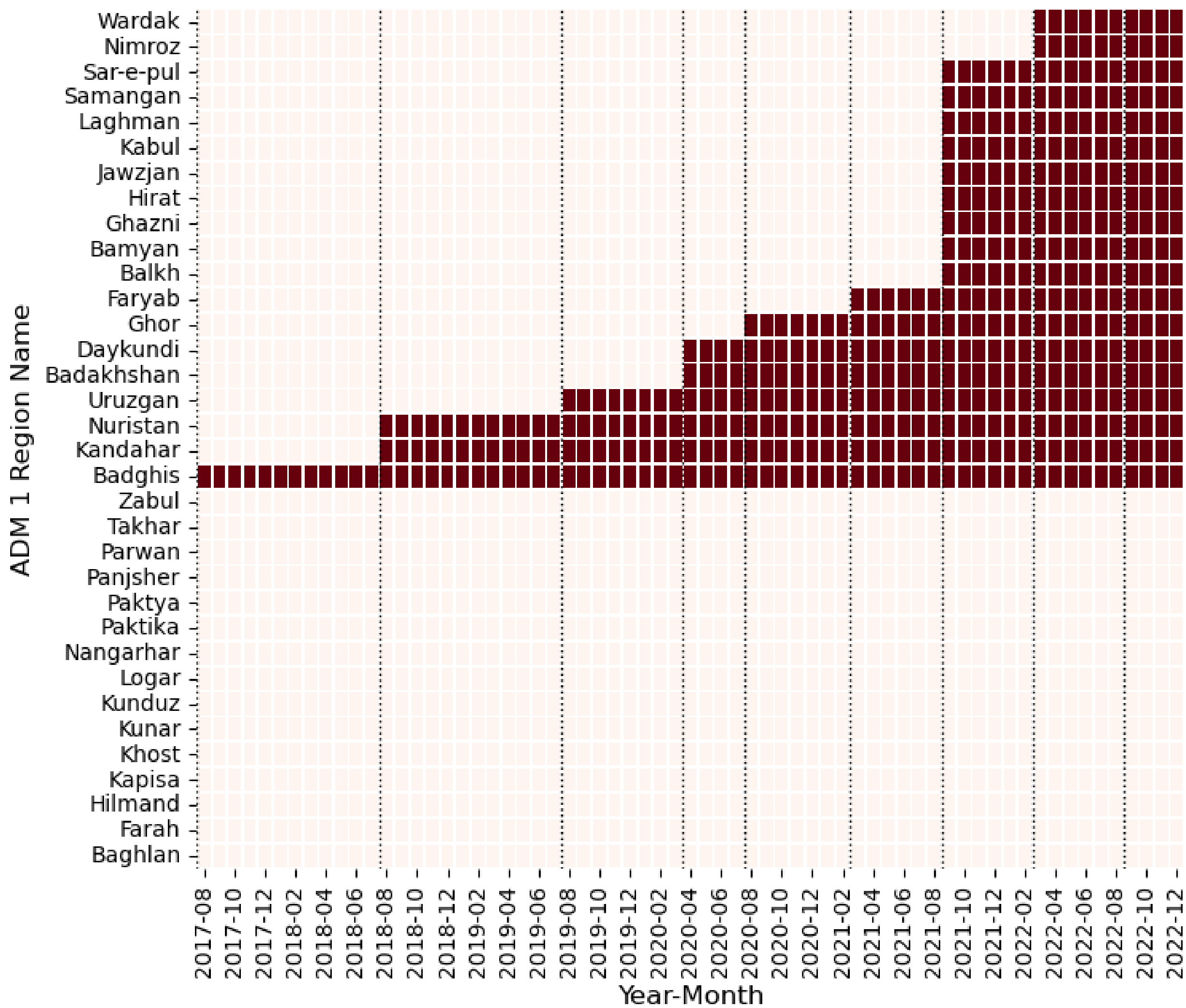
Note: Summary of IPC AFI classifications across regions during the study period, showing the frequency and percentage of regions in each IPC phase and the proportion of time each district spent in Phase 4 or higher. *Phase 3 (Crisis)* reflects severe food insecurity with elevated malnutrition risks, requiring urgent intervention, while *Phase 4 (Emergency)* indicates life-threatening food shortages and rising mortality rates. Although **Phase 5 (Famine)** represents the most severe conditions, Afghanistan did not experience this level during the study period. This analysis is restricted to *rural* classifications for consistency. [◃ Back]

Figure 1: **IPC AFI Distribution (2017 to 2022)**



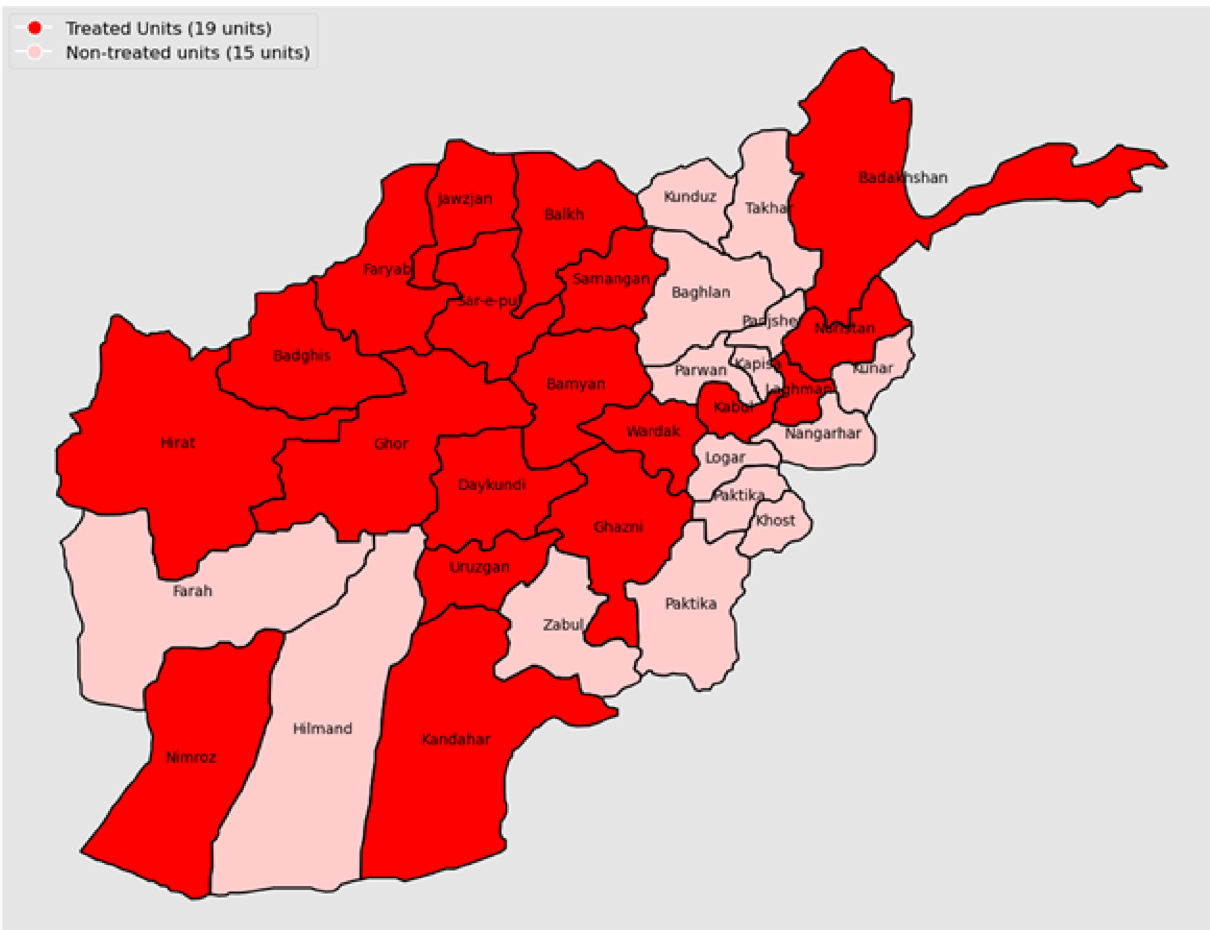
Note: This figure shows the transitions between different IPC AFI classifications for each region, with Phase 4 indicating a Food Emergency. It demonstrates how regions shifted between Phases 2 (Stress) to 4 (Emergency) over the years. The phase outcome was constructed by filling missing values forward within each region and time period, ensuring a continuous representation of AFI trends. ◃ Back

Figure 2: **Treatment Status: Following Initial Phase 4 (Emergency) Escalation**



Note: This figure visualizes the staggered treatment status of regions as they enter IPC AFI Phase 4 for the first time, with darker shades indicating regions classified as being in a food emergency for longer durations. The staggered nature of transitions into Phase 4 highlights the varying timing of these events across regions from 2017 to 2022. ◁ Back

Figure 3: **Treatment and Control Group Mapping**



Note: The map displays the geographic distribution of treated and non-treated units across ADM1 regions in Afghanistan. Regions colored in red represent treated units, while those in light red or pink indicate non-treated units. ◃ Back

Table 2: **Key Features Available in the Humanitarian Aid Flow Data (FTS)**

Feature	Description
Timestamp	Date (day-month-year) of the aid transaction, allowing for temporal analysis of aid flows.
Keywords	Categories such as Food Security, Nutrition, and Protection, used for classifying aid types.
Source & Destination	Country-level information on the origin and destination of aid.
Description	Detailed narrative of the aid transaction (e.g., "Emergency food assistance for acutely vulnerable people in Badakhshan Province facing crisis-level food insecurity").
Amount (USD)	Monetary value of the aid transaction in USD.
Funding Status	Indicates whether the contribution is 'Commitment' or 'Paid'; analysis focuses on 'Paid' contributions.
New Money	Identifies whether the transaction involves newly allocated funds or reallocated resources.

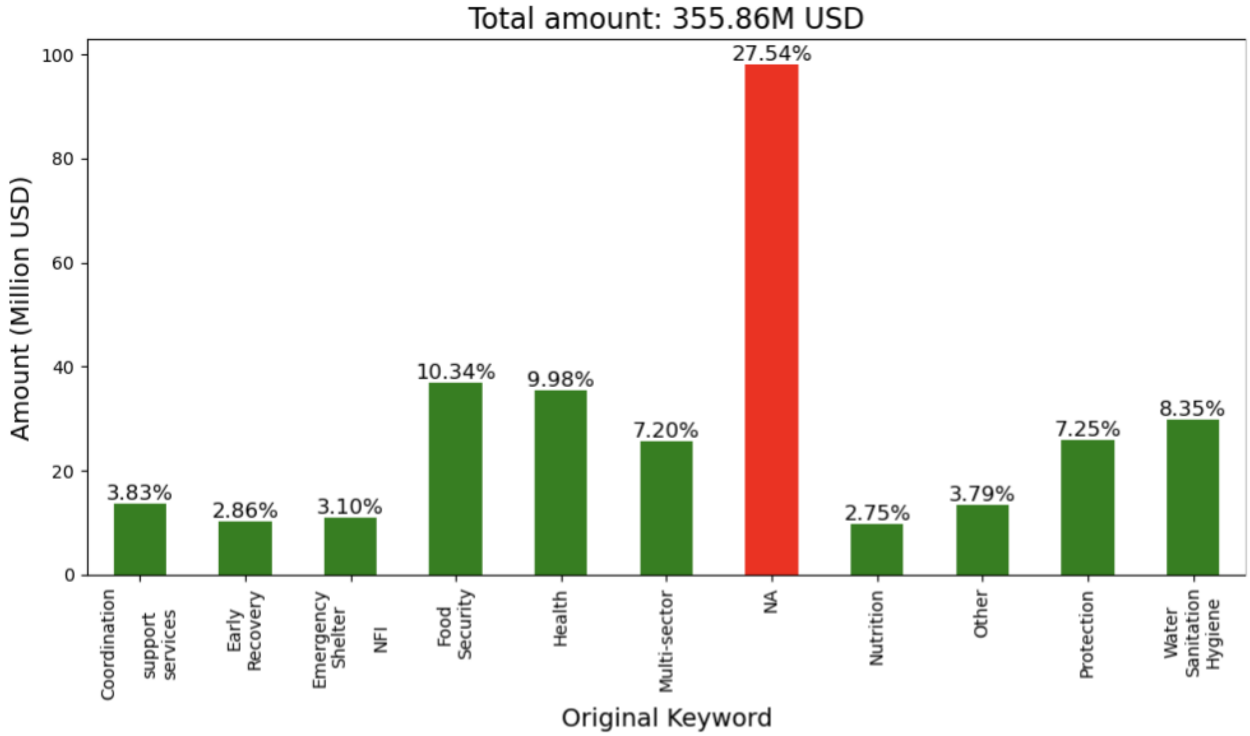
Note: This table summarizes key features of the Financial Tracking Service (FTS) data, which offer detailed information on aid flows and funding statuses. ◁ Back

Table 3: **Demographic Differences Before the Introduction of IPC**

Variable	Treated Mean	Control Mean	Mean Difference (T - C)
Household Members	8.091	8.686	-0.595
Eligible Women in Household	1.241	1.278	-0.037
Eligible Men in Household	0.483	0.498	-0.015
Children Under 5 in Household	1.602	1.650	-0.048
Has Electricity	0.626	0.670	-0.044
Female Household Head	0.015	0.010	0.005
Owns Agricultural Land	0.640	0.687	-0.047
Wealth Index (1=Poorest, 5=Richest)	2.379	2.738	-0.359

Note: Data from the 2015 Afghanistan Demographic Household Survey (DHS), weighted by household-level weight factors. The dataset primarily covers rural areas, with urban-only data for Kapisa and Zabul. The sample includes 19 treated units and 15 control ADM 1 units. ◁ Back

Figure 4: **Distribution of Humanitarian Aid by Top 10 Keywords (Jan 2017 - Dec 2022)**



Note: This figure displays the distribution of humanitarian aid (totaling 355.86 million USD) across the top 10 keyword categories during the study period (January 2017 to December 2022). The "NA" category represents missing or uncategorized entries. ◁ Back

Table 4: **Summary Statistics for Never Treated vs. Treated ADM 1 Regions**

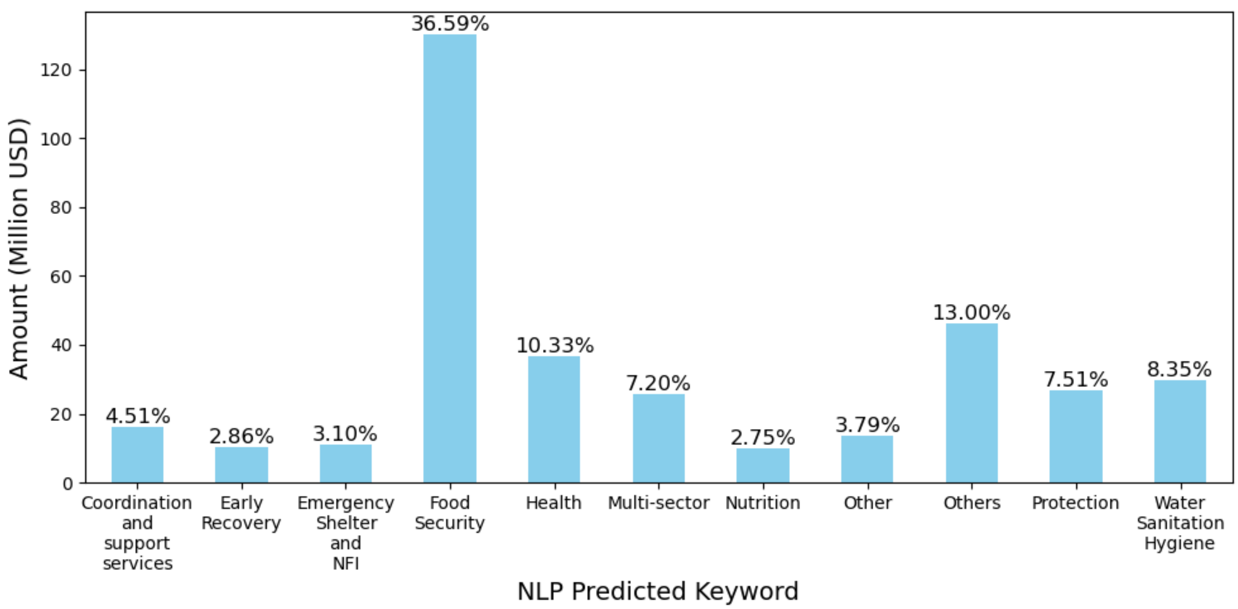
Variable Name	**Control Regions**	**Treated Regions**
IPC Phase	2.78	3.24
IPC Phase 3+ Population Estimates (%)	0.32	0.44
IPC Phase 4+ Population Estimates (%)	0.09	0.14
Estimated Population Mean (1,000)	791.84	831.70
(log-transformed) Food Security related Aid (USD)	1.95	2.66
(log-transformed) Total Humanitarian Aid (USD)	2.24	3.11
(log-transformed) Phase 3+ Population Weighted Food Security related Aid (USD)	1.92	2.64
(log-transformed) Phase 3+ Population Weighted Ttal Humanitarian Aid (USD)	2.20	3.09
Inflation Food Price Index (5-month lagged mean, RTFP)	7.30	7.91
Number of Fatalities from *Political Violence* (5-month lagged mean, ACLED)	1015.87	953.34
Drought Index (5-month lagged mean, SPEI-24)	-0.33	-0.49

Note: This table reports average values for key variables in control regions (15 regions that never transitioned to IPC Phase 4+) and treated regions (19 regions that transitioned from IPC Phase 3 to Phase 4). Variables include IPC population percentages, log-transformed aid amounts (USD), food inflation, political-violence-related fatalities (proxy for conflict intensity), and drought conditions (SPEI-24). ◁ Back

Figure 5: **Humanitarian Aid by Source Organization (2017-2022)**

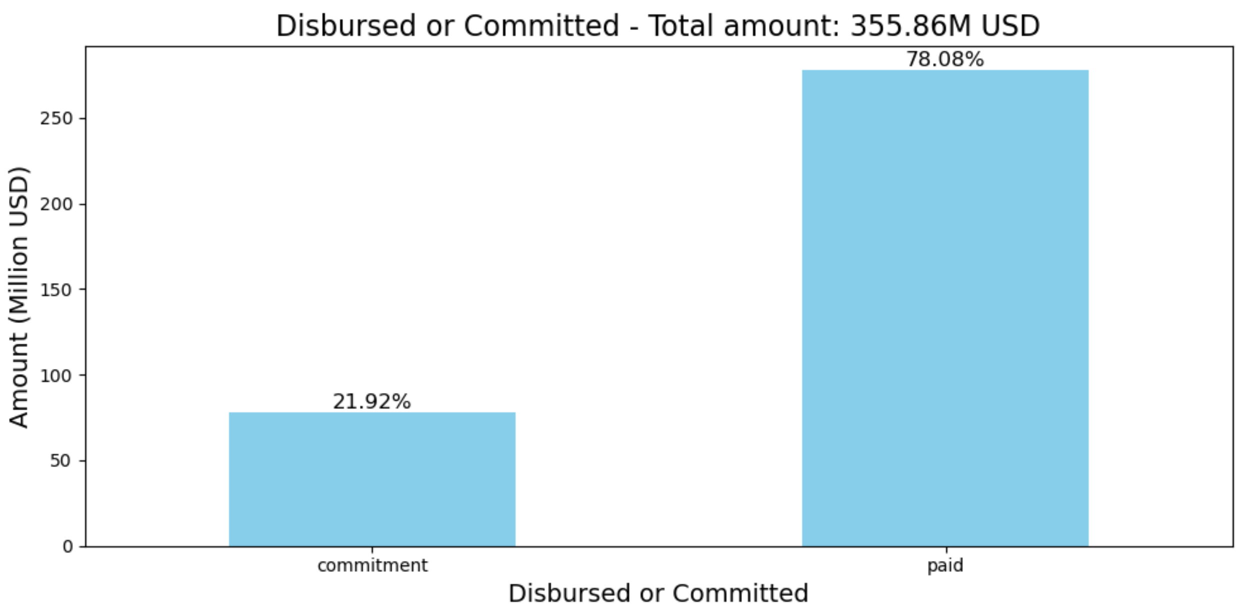
Note: The top panel shows the top 10 donors of humanitarian aid in Afghanistan by original organization category. The United States government is the largest bilateral contributor, accounting for 15.59% of total aid, followed by the European Commission's Humanitarian Aid and the German government. The bottom panel categorizes donors into larger groups, such as the EU and other collective entities, illustrating aggregate contributions by region or organization type. ◃ Back

Figure 6: **Distribution of Aid by Predicted Keyword Categories (2017-2022)**



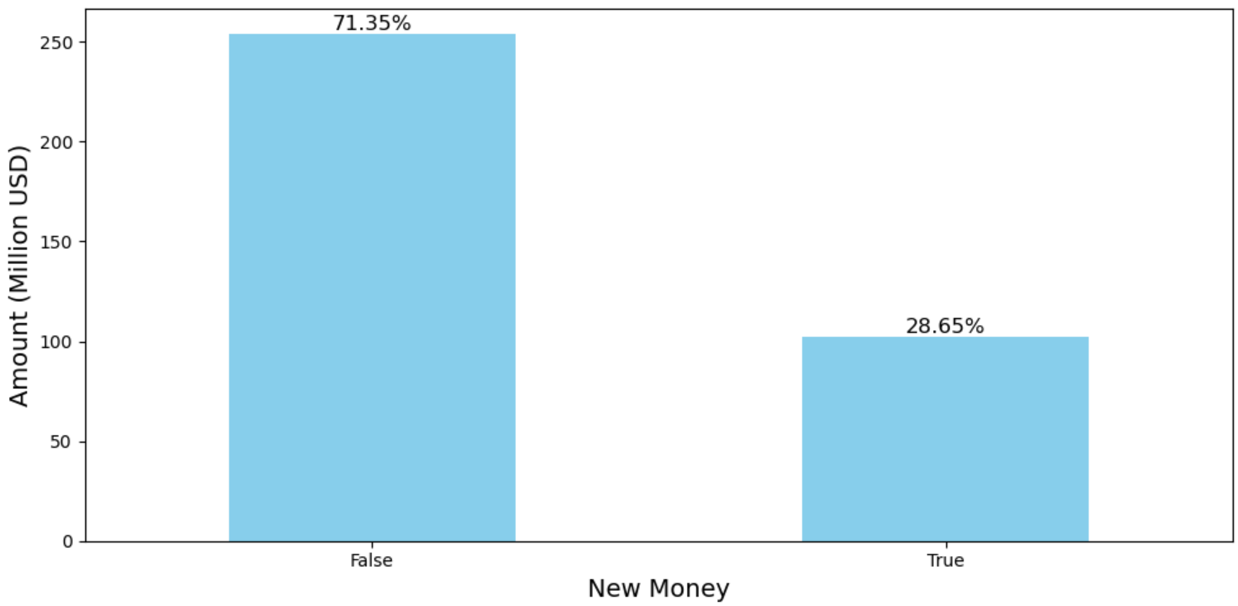
Note: This figure categorizes humanitarian aid allocations using keywords predicted by an NLP model, highlighting the prioritization of different aid sectors. "Food Security" dominates the distribution with 36.59% of total aid, followed by "Health" at 10.33%. Other categories such as "Water, Sanitation, Hygiene" and "Protection" received comparatively smaller shares. ◁ Back

Figure 7: **Disbursed vs. Commitment Status of Humanitarian Aid in Afghanistan (2017-2022)**



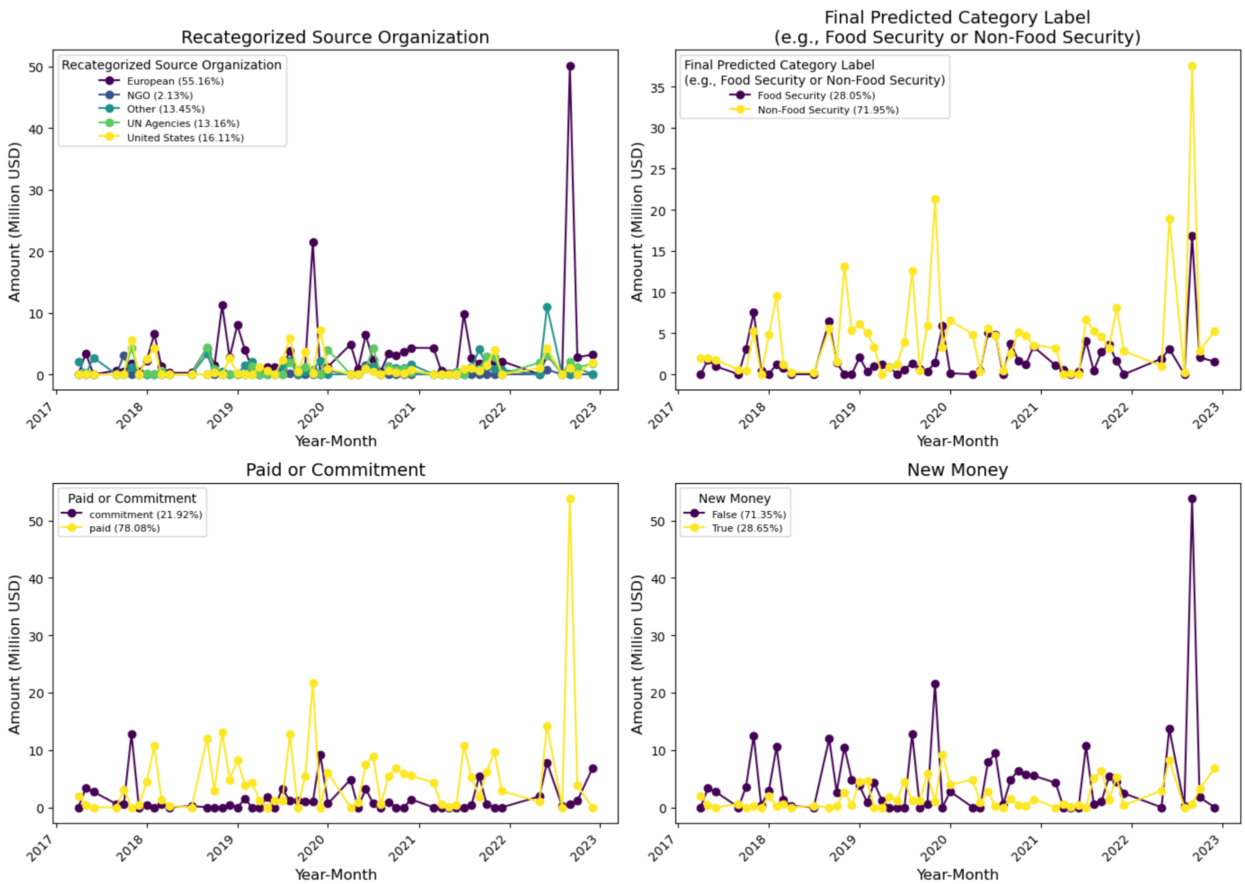
Note: This figure shows the allocation of humanitarian aid by funding status, distinguishing between committed and paid contributions. Of the total 355.86 million USD tracked in the study period, 78.08% has been disbursed as paid contributions, while 21.92% remains in the commitment phase. ◃ Back

Figure 8: **New Money vs. Reallocated Resources in Humanitarian Aid**



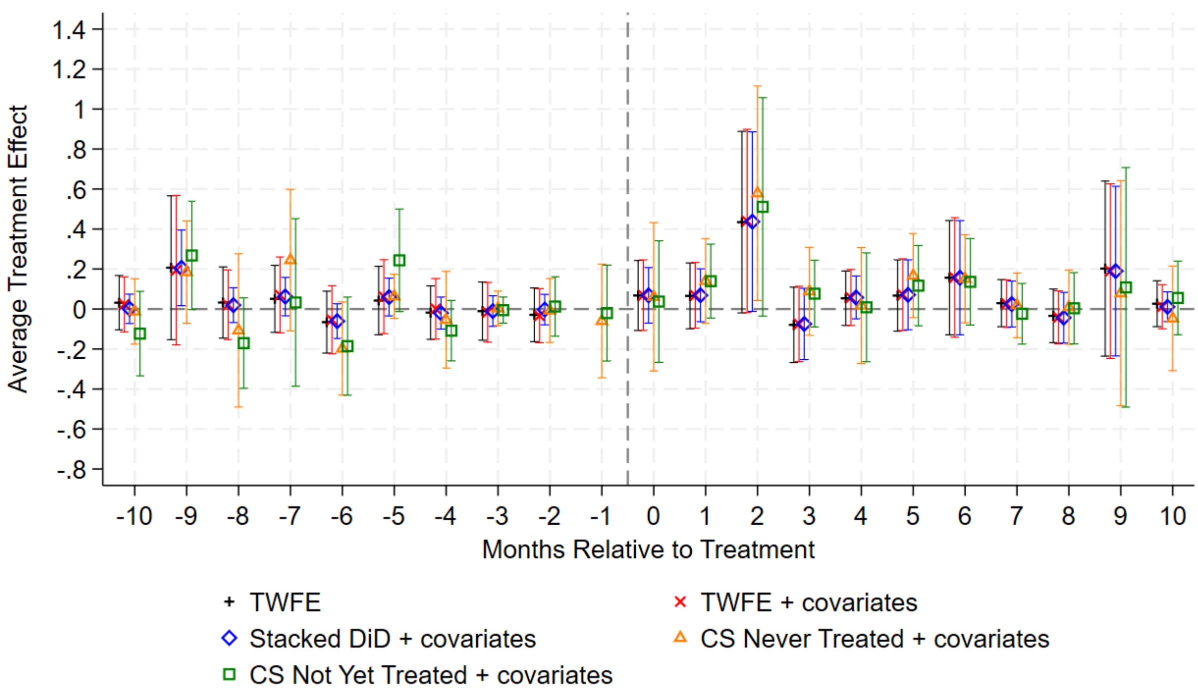
Note: This figure illustrates the distribution of humanitarian aid between new funding and reallocated resources. Of the total aid analyzed, 71.35% represents reallocated resources, while 28.65% constitutes new funding. ◁ Back

Figure 9: **Trends in Humanitarian Aid by Key Dimensions (2017-2023)**



Note: This figure shows the distribution of humanitarian aid across four dimensions. The top-left panel presents the aid distribution by recategorized source organizations. The top-right panel illustrates aid categorized by predicted sector labels using NLP. The bottom-left panel compares funding status as Paid or Committed. The bottom-right panel shows the distribution of aid between New Money and Reallocated Resources. ◁ Back

Figure 10: **Event Study Results (Total Humanitarian Aid $)**



Note: This event study plot shows the impact of phase escalation from Phase 3 to Phase 4 on ***total humanitarian aid (in million USD)*** over a 20-month period. The vertical gray line at time zero marks the first time this escalation occurs. The points represent estimated coefficients across different months relative to the escalation, with 95% confidence intervals. The models used are Two-Way Fixed Effects (TWFE), Stacked Difference-in-Difference (Cengiz et al., 2019), and Callaway and Sant'Anna (2021) estimator (CS) with comparison groups of "Never Treated" and "Not Yet Treated." Covariates include fatalities, food price inflation, and drought indicator as explained in section 4.3. ◁ Back

Table 5: Total Humanitarian Aid (Million USD)

	(1)	(2)	(3)	(4)
Dynamic Effect				
Treated X $\mathbb{1}$ (0 month)	0.183	0.068	0.122	0.088
	(0.176)	(0.176)	(0.136)	(0.140)
Treated X $\mathbb{1}$ (1 month)	0.168	0.308*	0.159	0.183*
	(0.108)	(0.108)	(0.106)	(0.097)
Treated X $\mathbb{1}$ (2 month)	0.552*	0.731	0.539*	0.585
	(0.290)	(0.290)	(0.292)	(0.294)
Treated X $\mathbb{1}$ (3 month)	0.010	-0.051	-0.011	-0.085
	(0.101)	(0.101)	(0.101)	(0.139)
Treated X $\mathbb{1}$ (4 month)	0.113	0.080	0.105	0.042
	(0.094)	(0.094)	(0.088)	(0.133)
Average Immediate Effect				
Treated X $\mathbb{1}$ (0-2 month)	0.301	0.369	0.273	0.285
	(0.144)	(0.151)	(0.137)	(0.138)
Observations	2448	2448	2448	2448
Number of Distinct ADM1 Units	34	34	34	34
ADM1 Unit FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Covariates (Conflict, Food Inflation, Drought)	No	Yes	No	Yes
Comparison Group	Never-Treated	Never-Treated	Not-Yet-Treated	Not-Yet-Treated

Note: One unit of observation is an Administrative Level 1 unit (or ADM 1 region), and only rural AFI classifications are included in the analysis. All variables are averaged at the monthly level, with the data covering the period from January 2017 to December 2022. I choose five post-treatment period spans from the treatment month (0). I present both the dynamic effects and three-month average effects. Covariates include fatalities, food price inflation, and drought indicator as explained in section 4.3. I employ the Callaway and Sant'Anna (2021) method (which implements doubly robust Difference in Difference estimator based on inverse-probability weighted and ordinary least squared regression), with two different comparison groups: "Never Treated" and "Not Yet Treated." Standard errors are clustered at the ADM1 level (in parentheses), and all models include ADM 1 region and year-month fixed effects (FE).*P $<$ 0.1; $<$0.05; *P$<$0.01. ◃ Back

Table 6: Log-Transformed Total Humanitarian Aid

	(1)	(2)	(3)	(4)
Dynamic Effect				
Treated X 𝟙 (0 month)	1.500	0.335	1.693	1.506
	(4.367)	(4.367)	(3.618)	(3.521)
Treated X 𝟙 (1 month)	4.180*	4.741*	4.958	5.765
	(4.886)	(4.886)	(4.922)	(4.902)
Treated X 𝟙 (2 month)	4.477*	5.460*	4.590*	5.572*
	(3.224)	(3.224)	(3.374)	(3.411)
Treated X 𝟙 (3 month)	0.328	-0.613	0.382	-0.105
	(3.907)	(3.907)	(3.614)	(3.890)
Treated X 𝟙 (4 month)	2.508	1.212	2.787	2.666
	(3.542)	(3.542)	(3.469)	(3.521)
Average Immediate Effect				
Treated X 𝟙 (0-2 month)	3.386	3.512	3.747*	4.281*
	(1.489)	(1.602)	(1.442)	(1.396)
Observations	2448	2448	2448	2448
Number of Distinct ADM1 Units	34	34	34	34
ADM1 Unit FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Covariates (Conflict, Food Inflation, Drought)	No	Yes	No	Yes
Comparison Group	Never-Treated	Never-Treated	Not-Yet-Treated	Not-Yet-Treated

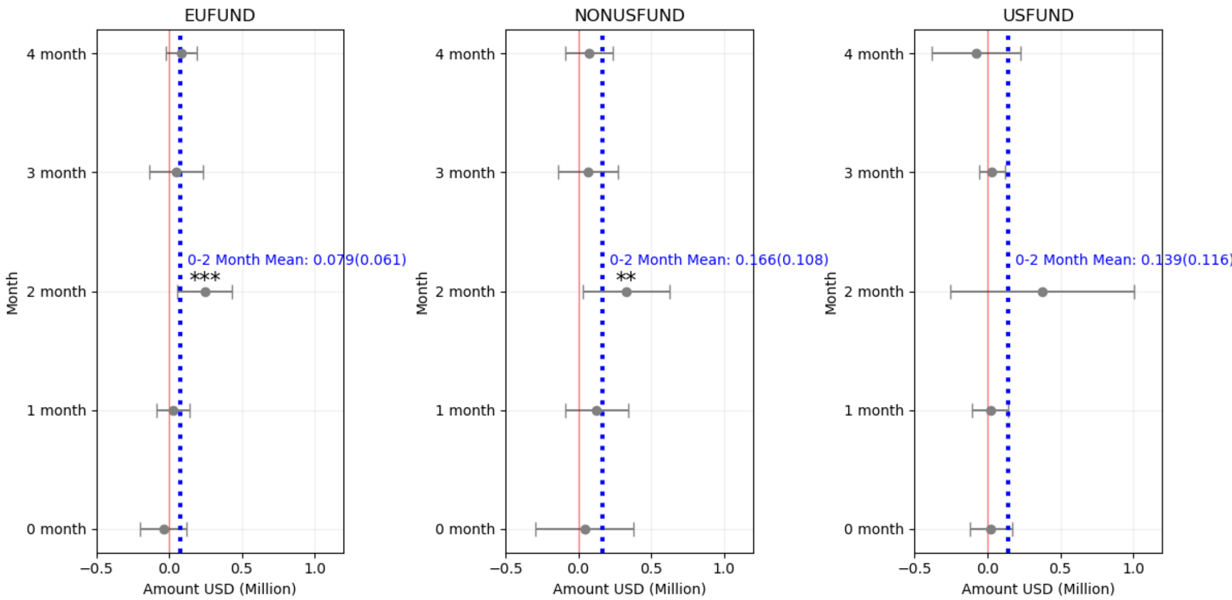
Note: Observations are at the Administrative Level 1 unit level, with data spanning from January 2017 to December 2022. All values reflect the log-transformed total humanitarian response (in million USD). Covariates include conflict data from ACLED, food inflation from RTFP, and drought data from SPEI24, each averaged over a three-month rolling window. The Callaway and Sant'Anna (2021) method is applied, utilizing both "Never-Treated" and "Not-Yet-Treated" groups as comparisons. Standard errors are clustered at the ADM1 level (in parentheses), and all models include ADM 1 region and year-month fixed effects (FE). *P < 0.1; P<0.05; *P<0.01. ◁ Back

Table 7: **Humanitarian Aid Pre- and Post-Event among Treated ADM1 Regions**

Metric	**Pre-Treatment (3 Months)**	**Post-Treatment (3 Months)**
Total Humanitarian Aid (USD)	4,777,206	819,000 - 1,107,000 (Additional)
Population in Phase 3 (per unit)	293,399	437,278
Population in Phase 4 (per unit)	79,425	186,661
Per Capita Aid (USD) (When distributed to Phase 3 populations only)	16.28	-
Per Capita Aid (USD) (When distributed to Phase 3 & 4 populations)	12.81	-
Range of Additional Per Capita Aid (USD)	-	7.64 - 10.32

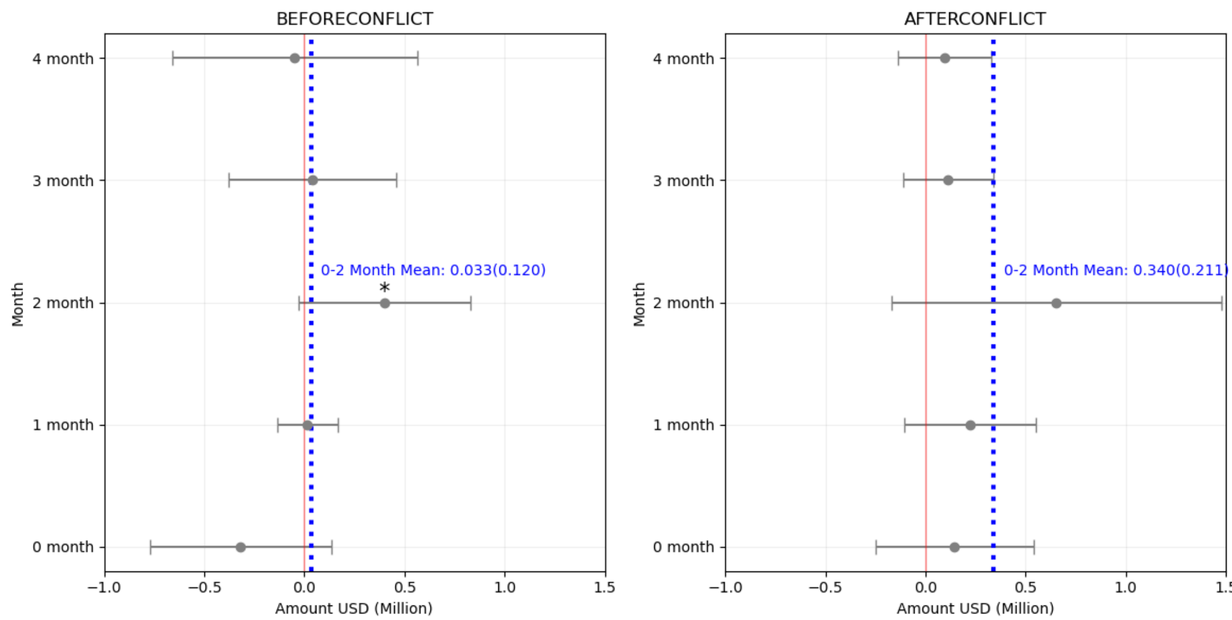
Note: Aid represents total humanitarian assistance measured in USD. The pre-treatment period encompasses the three months preceding the first escalation to IPC AFI Phase 4, while the post-treatment period captures additional aid allocated during the three months following the escalation. All values are reported as averages per ADM1 region. ◁ Back

Figure 11: **Treatment Effect by Funding Source**



Note: This figure presents the dynamic and average treatment effects of humanitarian aid for regions in Phase 4 food insecurity, estimated using the Callaway and Sant'Anna (2021) approach, include three covariates—fatalities, food price inflation, and drought (SPEI-24)—and are compared against the never-treated group. The left panel shows aid funded by the EU, the middle panel by non-US entities, and the right panel by the US. Each plot includes a 0–2 month average effect (indicated by the blue dashed line) as well as the monthly effects from 0 to 4 months post-escalation. The red vertical line at zero denotes the baseline, where positive values suggest an increase in aid compared to control regions. Statistical significance is indicated by * annotated above the corresponding coefficients(*P < 0.1; P<0.05; *P<0.01.). ($n = 2448$) ◁ Back

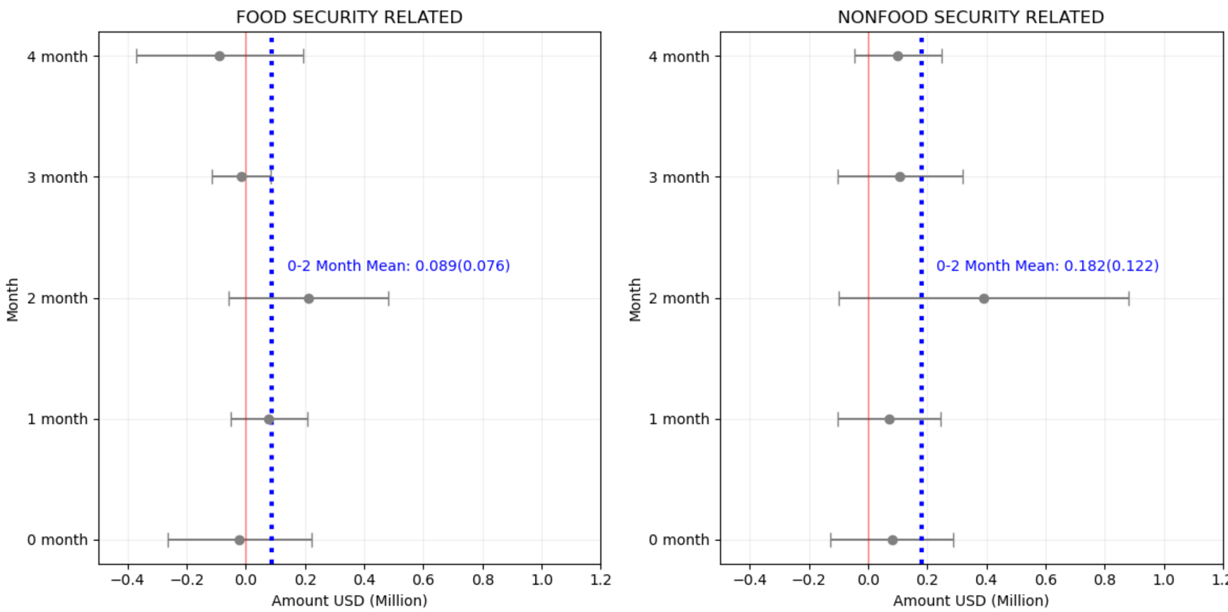
Figure 12: **Humanitarian Aid Response Before and After Taliban Offensive (May-2021)**



Note: This figure compares the dynamic and average treatment effects of humanitarian aid in the 0–4 month range before and after conflict, estimated using the Callaway and Sant'Anna (2021) approach, include three covariates—fatalities, food price inflation, and drought (SPEI-24)—and are compared against the never-treated group. The left panel shows the response before the conflict, and the right panel shows the response after the conflict. Each plot includes a 0–2 month average effect (indicated by the blue dashed line) as well as the monthly effects from 0 to 4 months. The red vertical line at zero denotes the baseline, where positive values suggest an increase in aid compared to control regions. Statistical significance is indicated by * annotated above the corresponding coefficients (*P < 0.1; P < 0.05; *P < 0.01.). ($n = 2448$)

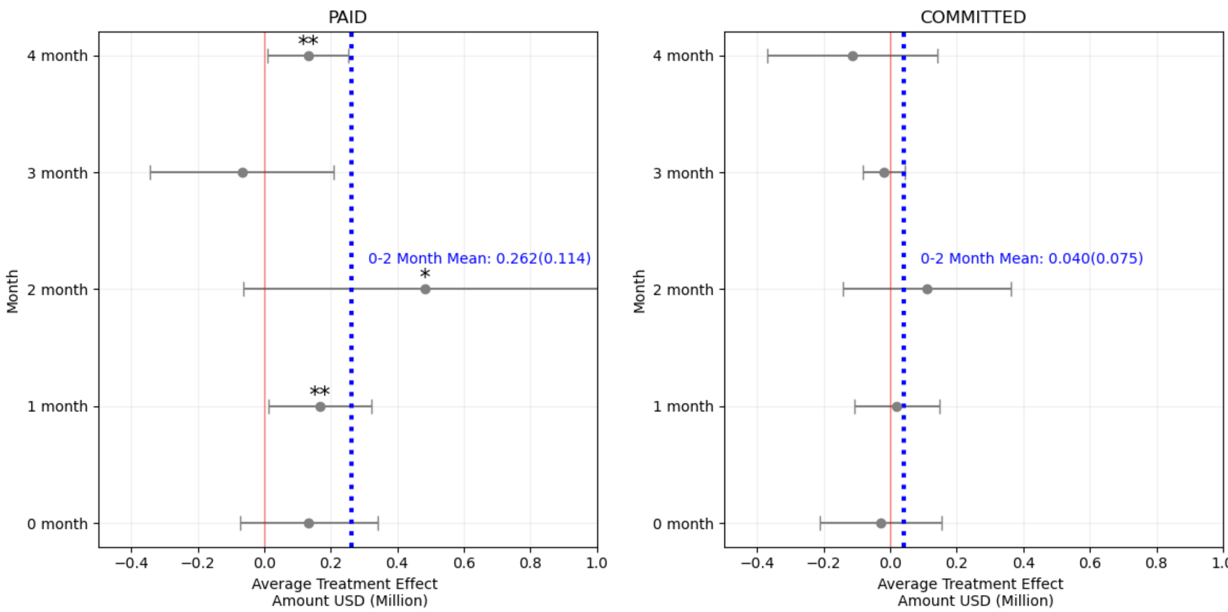
◃ Back

Figure 13: **Treatment Effect by Funding Type - Food Security vs. Non-Food Security**



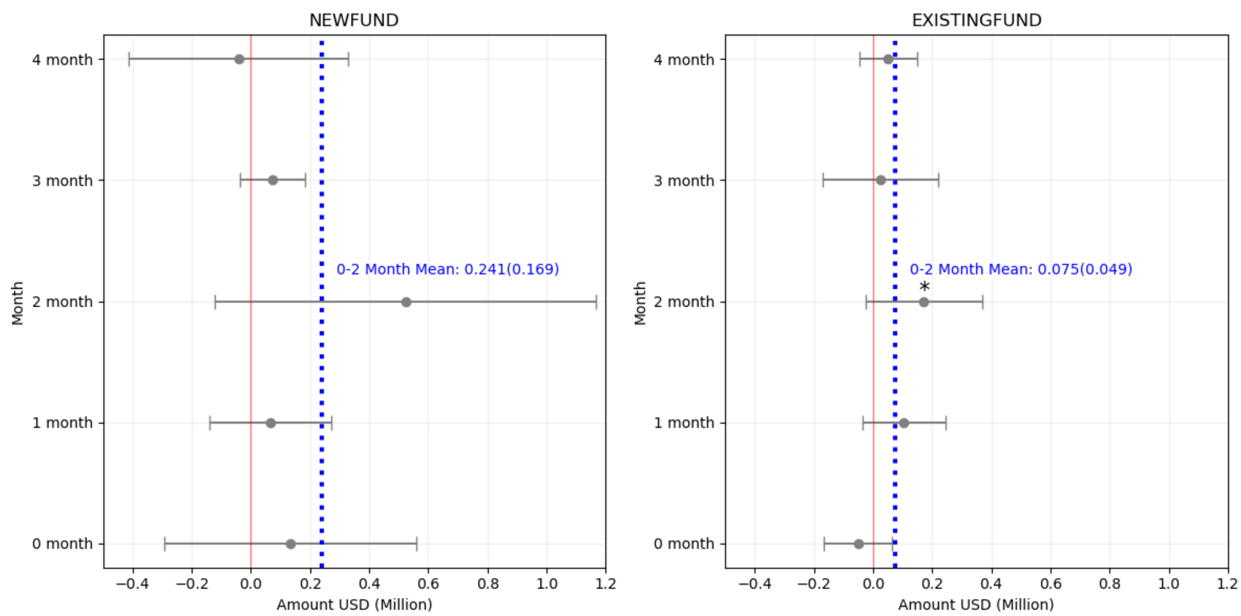
Note: This figure presents the dynamic and average treatment effects of humanitarian aid allocated to food security and non-food security activities, estimated using the Callaway and Sant'Anna (2021) approach, include three covariates—fatalities, food price inflation, and drought (SPEI-24)—and are compared against the never-treated group. Aid categories are identified using FTS data complemented by NLP-predicted keywords. The left panel ("NON FOOD SECURITY") and the right panel ("FOOD SECURITY") include a 0–2 month average effect (indicated by the blue dashed line) and monthly effects from 0 to 4 months relative to the initial Phase 4 escalation (0 month). The red vertical line at zero denotes the baseline, where positive values suggest an increase in aid compared to control regions. Statistical significance is indicated by * annotated above the corresponding coefficients (*P < 0.1; P < 0.05; *P < 0.01.). ($n = 2448$) ◃ Back

Figure 14: **Treatment Effect by Payment Status: Paid vs. Committed**



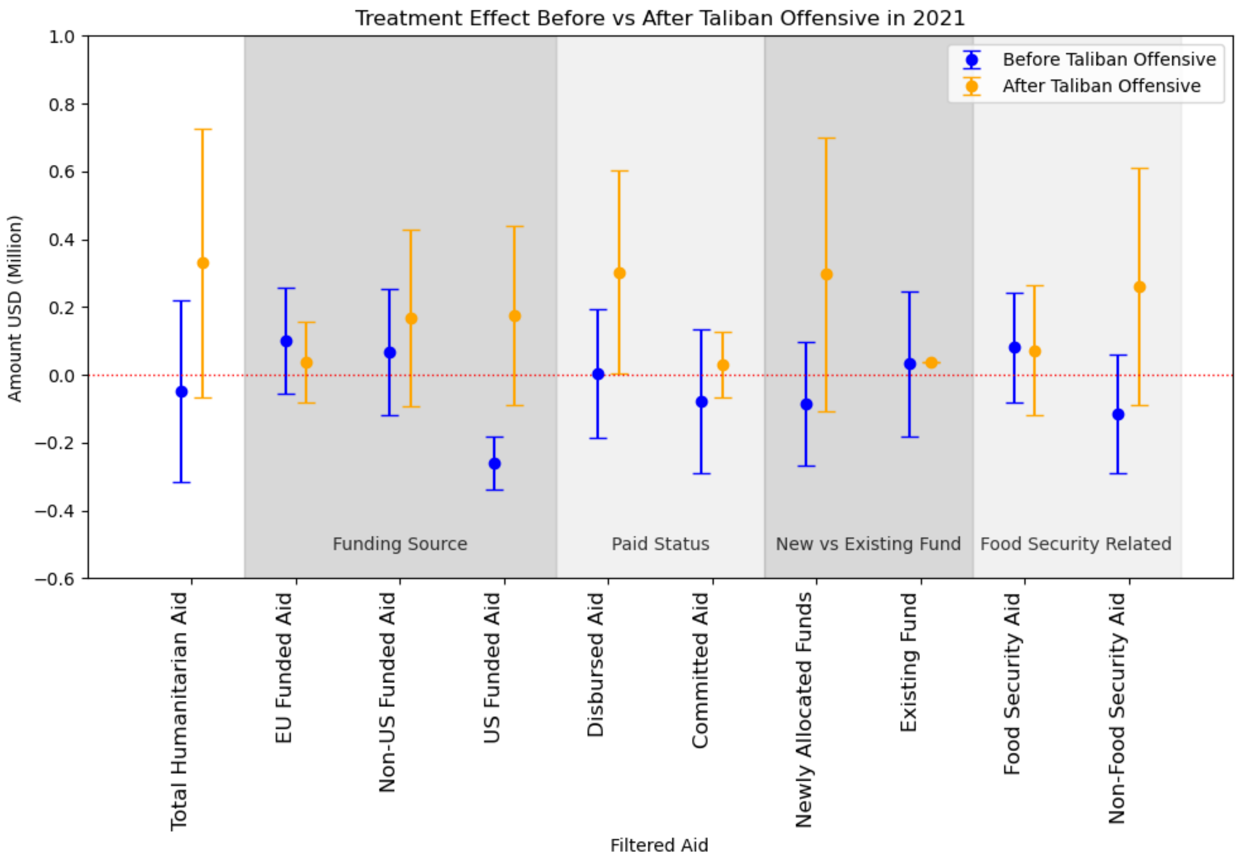
Note: This figure presents the dynamic and average treatment effects of humanitarian aid based on payment status, estimated using the Callaway and Sant'Anna (2021) approach, include three covariates—fatalities, food price inflation, and drought (SPEI-24)—and are compared against the never-treated group. The left panel shows aid categorized as "Paid," and the right panel shows aid categorized as "Committed." Each plot includes a 0–2 month average effect (indicated by the blue dashed line) and monthly effects from 0 to 4 months relative to the initial Phase 4 escalation (0 month). The red vertical line at zero denotes the baseline, where positive values suggest an increase in aid compared to control regions. Statistical significance is indicated by * annotated above the corresponding coefficients (*P < 0.1; P < 0.05; *P < 0.01.). ($n = 2448$) ◃ Back

Figure 15: Treatment Effect by Funding Source: New Allocations vs. Reallocated Budgets



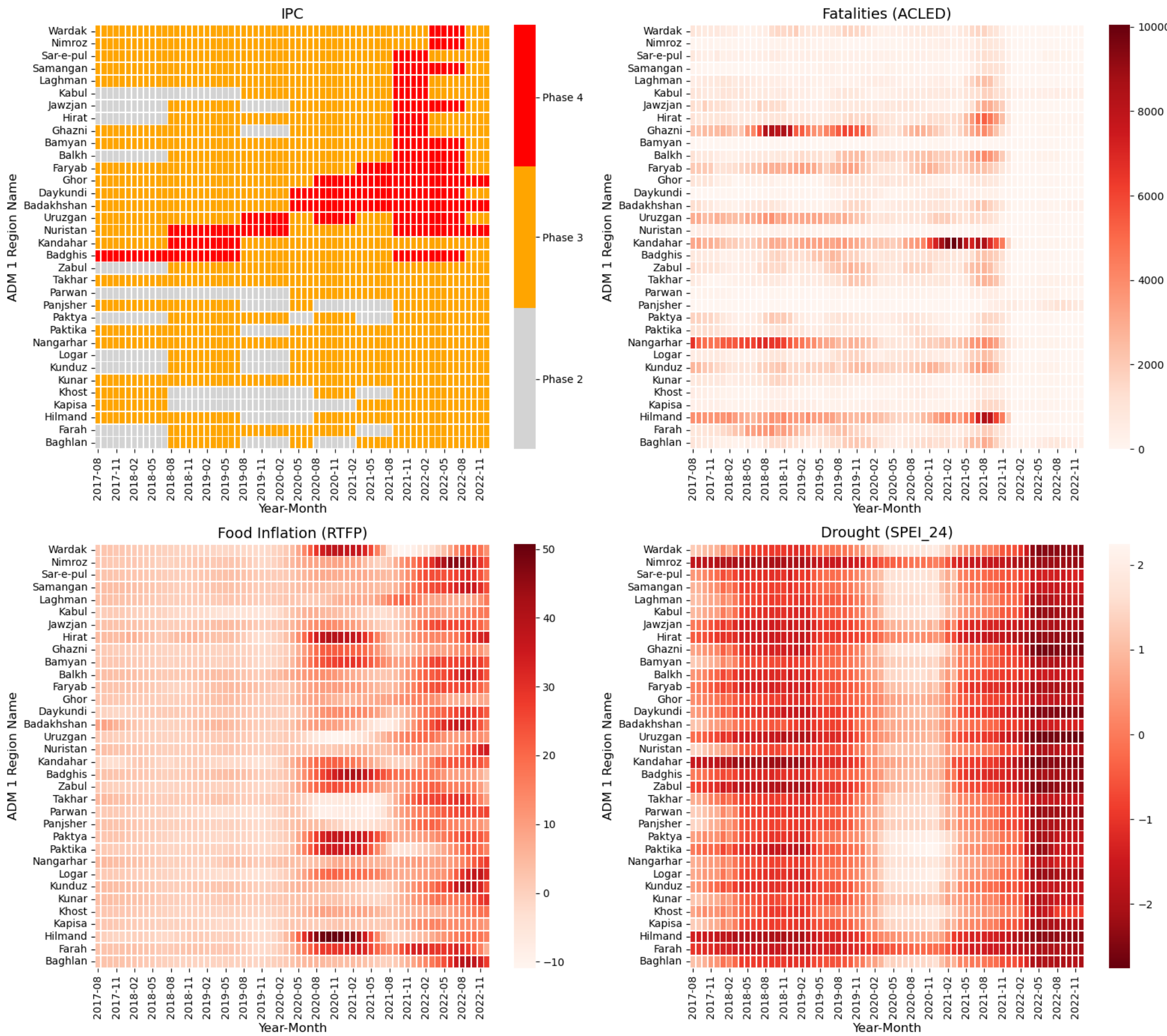
Note: This figure presents the dynamic and average treatment effects of humanitarian aid based on funding type, estimated using the Callaway and Sant'Anna (2021) approach, include three covariates—fatalities, food price inflation, and drought (SPEI-24)—and are compared against the never-treated group. The left panel shows aid categorized as "New Fund," and the right panel shows aid categorized as "Existing Fund." Each plot includes a 0–2 month average effect (indicated by the blue dashed line) and monthly effects from 0 to 4 months relative to the initial Phase 4 escalation (0 month). The red vertical line at zero denotes the baseline, where positive values suggest an increase in aid compared to control regions. Statistical significance is indicated by * annotated above the corresponding coefficients (*$P < 0.1$; $P < 0.05$; *$P < 0.01$.). ($n = 2448$) ◁ Go back

Figure 16: Average immediate (0–2 month) treatment effects of humanitarian aid before and after the Taliban offensive



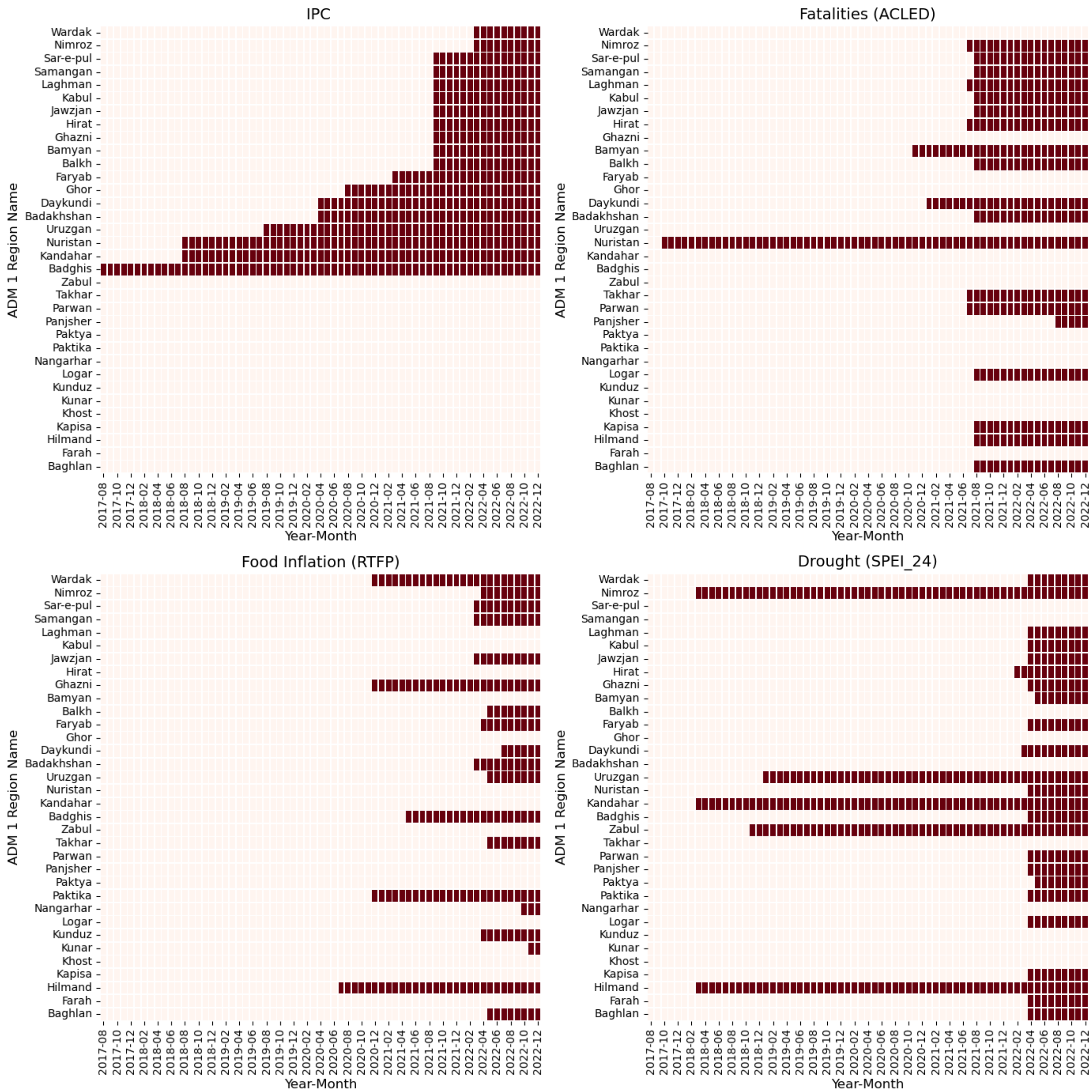
Note: This figure presents the average immediate (0–2 month) treatment effects of humanitarian aid in response to Phase 4 food insecurity escalations, estimated using the Callaway and Sant'Anna (2021) approach, include three covariates—fatalities, food price inflation, and drought (SPEI-24)—and are compared against the never-treated group. The effects are disaggregated by funding source, payment status, new versus existing funds, and food security-related aid. Blue markers indicate effects for units treated before the Taliban offensive in May 2021, while orange markers indicate effects for units treated after the offensive. Error bars represent 95 % confidence intervals, and the red dashed horizontal line denotes the baseline, where values equal to zero indicate no effect. ($n = 2448$) ◃ Go back

Figure 17: **Trends in IPC Phase and Other Drivers of Food Insecurity (2017 to 2022)**



Note: This figure presents temporal trends across indicators of political, economic, and environmental factors from 2017 to 2022. The top-left panel displays IPC phase classifications by region, with Phase 4 representing severe food crises. The top-right panel highlights fatalities from political violence, sourced from ACLED data. The bottom-left panel shows food inflation rates derived from Real-Time Food Prices (RTFP), while the bottom-right panel illustrates drought conditions using SPEI-24 values, with darker shades indicating greater severity of drought. ◁ Back

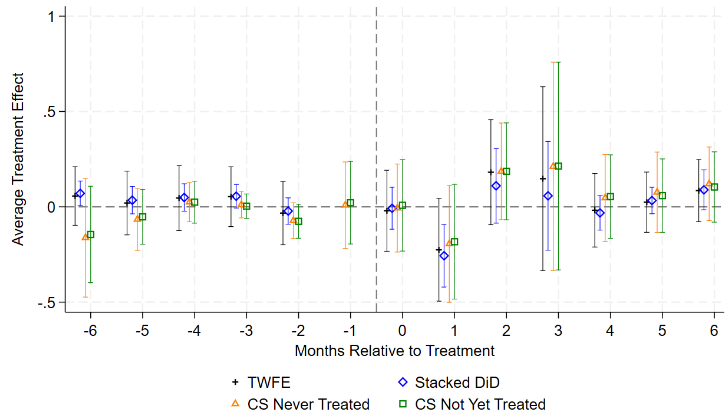
Figure 18: **Treatment Status Defined by IPC and Other Extreme Events (2017 to 2022)**



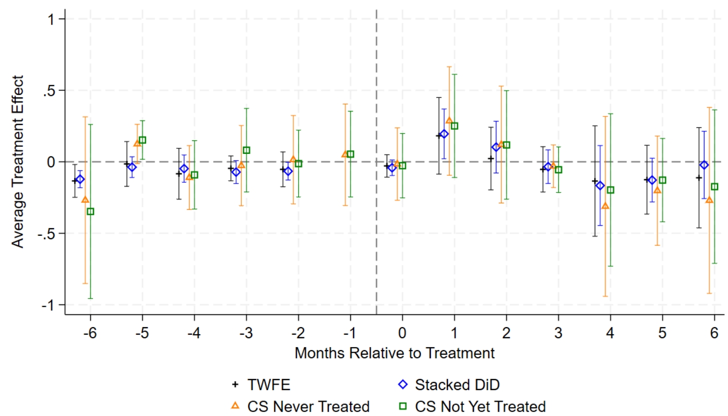
Note: This figure presents the treatment status of extreme events across four indicators, documenting occurrences from 2017 to 2022. The top-left panel shows IPC Phase 4 escalations, indicating Food Emergencies. Extreme events for the remaining indicators are defined as follows: food price inflation is flagged as extreme when values exceed 1.96 standard deviations (95% confidence level) above the regional and monthly mean, accounting for regional and seasonal variations. Fatalities are flagged as extreme when they exceed 2.8 standard deviations (99.5% confidence level) above the regional mean. Severe drought conditions are identified using a binary indicator set to 1 when SPEI-24 values are less than or equal to -1.96. For all three indicators, once flagged as extreme (set to 1), the status remains at 1 for subsequent months regardless of whether the values return below the threshold. The top-right panel illustrates extreme fatalities from political violence (ACLED), the bottom-left panel highlights periods of food inflation (RTFP), and the bottom-right panel depicts severe drought conditions (SPEI-24). ◁ Back

Figure 19: **Event Study of Average Treatment Effect by Indicator (Fatalities, Inflation, and Drought)**

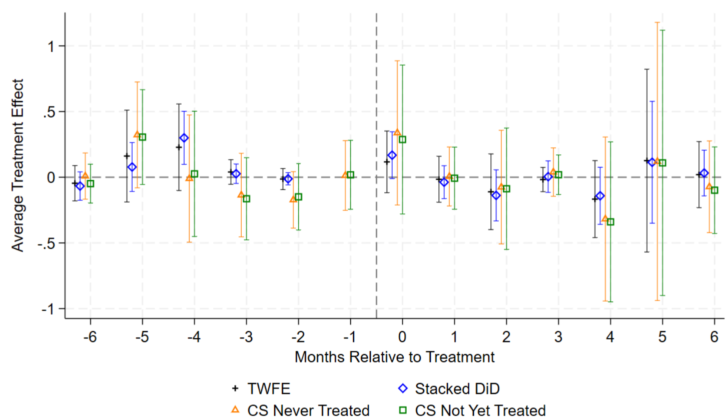
(a) Fatalities



(b) Food Inflation



(c) Drought



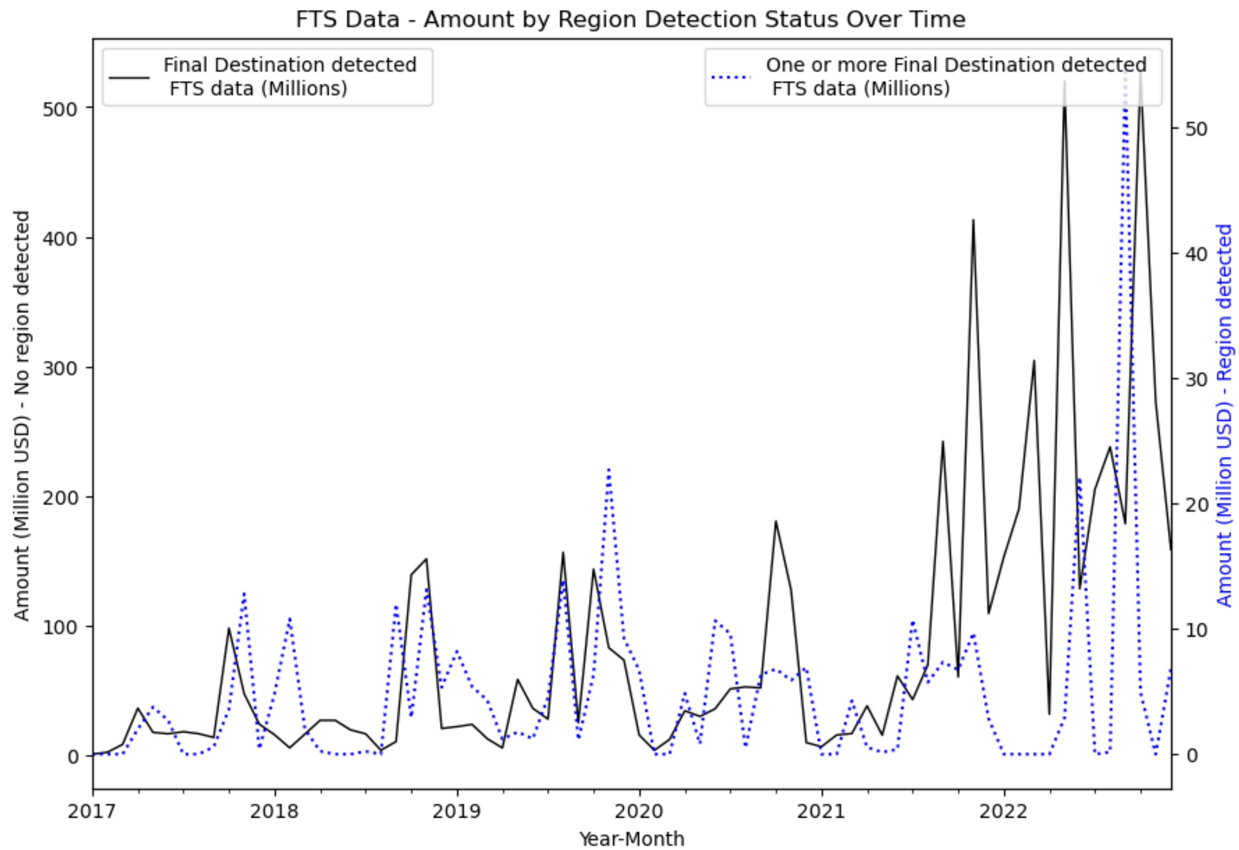
Note: This figure presents the event study of the average treatment effect over months relative to treatment for three indicators: extreme fatalities from political violence (top), food inflation (middle), and drought (bottom). Each plot displays the estimated average treatment effects derived from various models, including TWFE, Stacked DiD all without covariates, and Callaway & Sant'Anna estimators (Not Yet Treated and Never Treated). These models enable a comparison of responses across different methodologies and event types. ◁ Back

Table 8: **Dynamic Effects and Average Immediate Effects by Indicator**

	Fatalities (ACLED)		Food Inflation (RTFP)		Drought (SPEI 24)	
Dynamic Effect	(1)	(2)	(3)	(4)	(5)	(6)
Treated X $\mathbb{1}$ (0 month)	-0.006	0.008	-0.016	-0.027	0.338	0.287
	(0.118)	(0.123)	(0.129)	(0.115)	(0.280)	(0.289)
Treated X $\mathbb{1}$ (1 month)	-0.194	-0.183	0.285	0.251	0.006	-0.007
	(0.157)	(0.154)	(0.194)	(0.184)	(0.115)	(0.121)
Treated X $\mathbb{1}$ (2 month)	0.186	0.186	0.121	0.118	-0.075	-0.088
	(0.129)	(0.130)	(0.209)	(0.194)	(0.221)	(0.236)
Treated X $\mathbb{1}$ (3 month)	0.212	0.214	-0.031	-0.056	0.039	0.019
	(0.279)	(0.278)	(0.076)	(0.081)	(0.094)	(0.077)
Treated X $\mathbb{1}$ (4 month)	0.047	0.054	-0.312	-0.197	-0.318	-0.340
	(0.116)	(0.112)	(0.321)	(0.272)	(0.319)	(0.311)
Treated X $\mathbb{1}$ (5 month)	0.076	0.059	-0.202	-0.128	0.120	0.109
	(0.108)	(0.098)	(0.195)	(0.149)	(0.540)	(0.515)
3-Month Average Effect						
Treated X $\mathbb{1}$ (0-2 month)	-0.005	0.004	0.130	0.114	0.089	0.064
	(0.110)	(0.112)	(0.126)	(0.114)	(0.135)	(0.153)
Observations	2448	2448	2448	2448	2448	2448
Number of Distinct ADM1 Units	34	34	34	34	34	34
ADM1 Unit FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates (Conflict, Food Inflation, Drought)	No	No	No	No	No	No
Comparison Group	Never-Treated	Not-Yet-Treated	Never-Treated	Not-Yet-Treated	Never-Treated	Not-Yet-Treated

Note: This table reports the dynamic effects and average immediate effects for treated regions based on the Conflict, Food Inflation, and Drought (SPEI_24) indicators. Conflict is measured as extreme fatalities from political violence, defined as exceeding a 5-month rolling average anomaly by 2.8 standard deviations. Food Inflation is identified as periods where the 5-month rolling average of regional food price indices exceeds 1.96 standard deviations above the mean. Drought is defined using SPEI_24 values, where severe drought conditions correspond to values less than or equal to -1.96. Standard errors are reported in parentheses. Observations cover the period from 2017 to 2022 (n = 2,448). Fixed effects for ADM1 units and time (monthly) are included in all models. The Callaway and Sant'Anna difference-in-differences estimator is used, with never-treated units as the comparison group and not-yet-treated units considered in the estimation. ◃ Back

Figure 20: **Humanitarian Aid by Region Detection Status Over Time (2017-2022)**



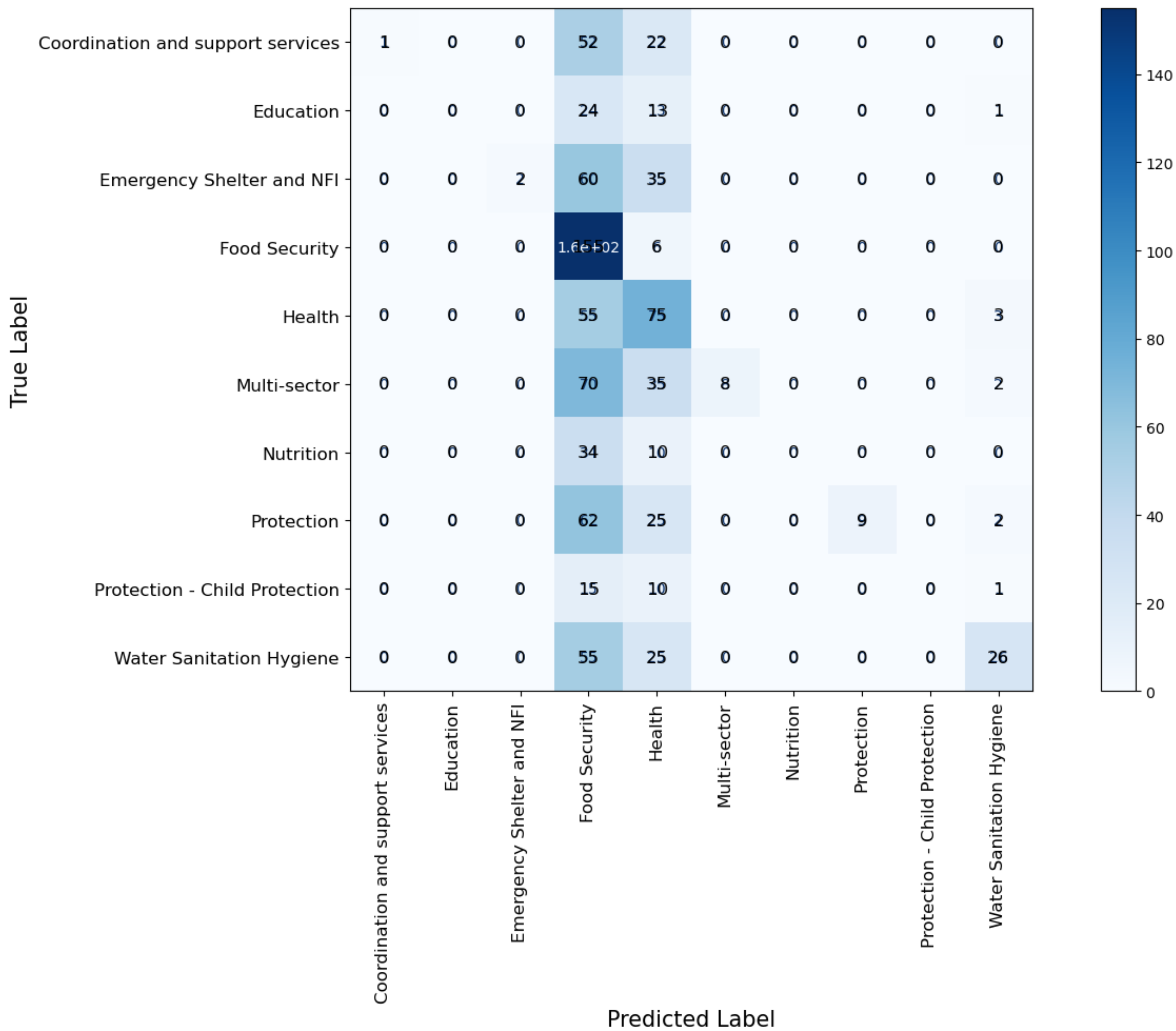
Note: This figure displays the trend in humanitarian aid amounts recorded in the Financial Tracking Service (FTS) from 2017 to 2022, distinguished by final ADM1 destination detection status. The solid black line represents aid amounts with no specific final destination region detected, while the dotted blue line indicates aid amounts where one or more final destinations were detected. ◁ Back

Table 9: **Results of NLP-Based Keyword Predictions**

Category	**Precision**	**Recall**	**F1-Score**	**Support**
Agriculture	0.00	0.00	0.00	9
COVID-19	0.00	0.00	0.00	6
Camp Coordination / Management	0.00	0.00	0.00	8
Coordination and Support Services	0.33	0.05	0.09	75
Early Recovery	0.00	0.00	0.00	50
Education	0.00	0.00	0.00	38
Emergency Shelter and NFI	1.00	0.03	0.06	97
Emergency Telecommunications	0.00	0.00	0.00	1
Food Security	0.14	0.96	0.25	161
Health	0.19	0.35	0.24	133
Logistics	0.00	0.00	0.00	26
Multi-Sector	0.33	0.05	0.09	115
NA	0.00	0.00	0.00	321
Nutrition	0.00	0.00	0.00	44
Other	0.00	0.00	0.00	33
Protection	0.89	0.08	0.15	98
Protection - Child Protection	0.00	0.00	0.00	26
Protection - Gender-Based Violence	0.00	0.00	0.00	26
Protection - Housing, Land and Property	0.00	0.00	0.00	1
Protection - Human Trafficking & Smuggling	0.00	0.00	0.00	1
Protection - Mine Action	0.00	0.00	0.00	24
Water Sanitation Hygiene	0.42	0.09	0.15	106

Note: This table presents the performance of an NLP model in predicting keywords for humanitarian aid transactions based on description text. The table includes precision, recall, and F1-scores for each aid category. Although the model shows high recall for ”Food Security,” meaning it rarely misses true cases, its lower precision indicates occasional misclassification of transactions. ◃ Back

Figure 21: **Confusion Matrix of Classification Model Performance**



Note: The confusion matrix summarizes the model's performance across humanitarian aid categories, showing high accuracy for **Food Security** but frequent misclassifications in less common categories. ◁

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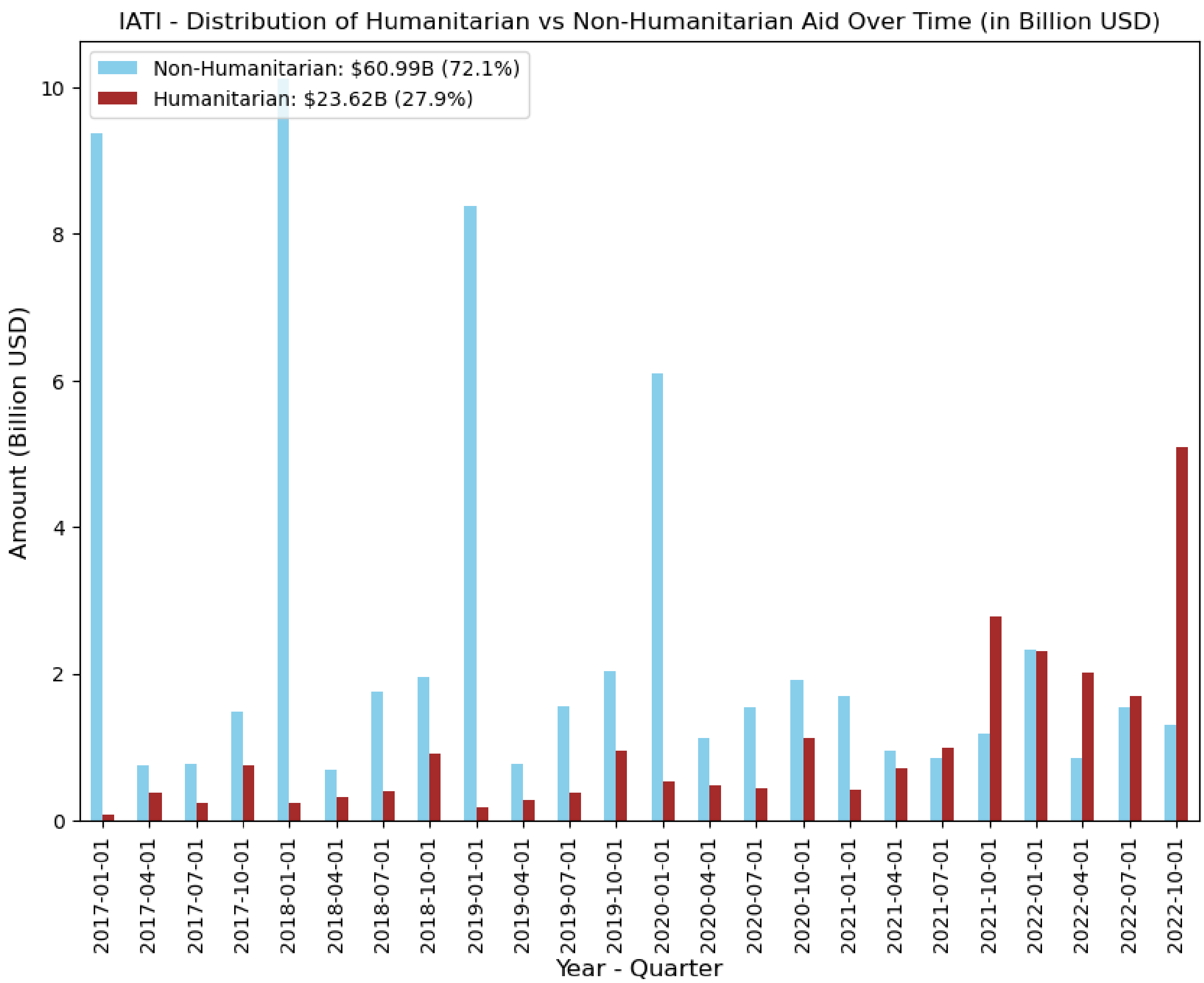
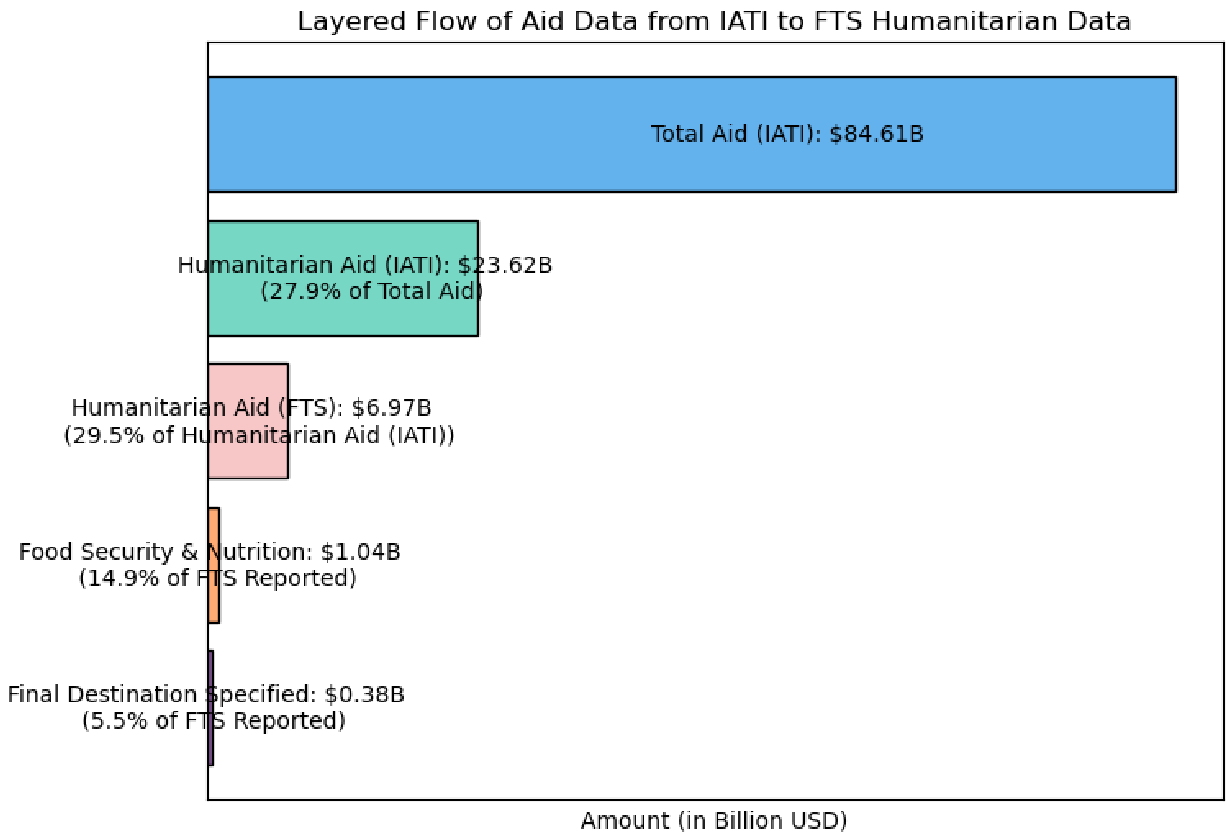
Figure 22: **Distribution of Humanitarian vs Non-Humanitarian Aid Over Time in Afghanistan (2017-2022) (in Billion USD)**



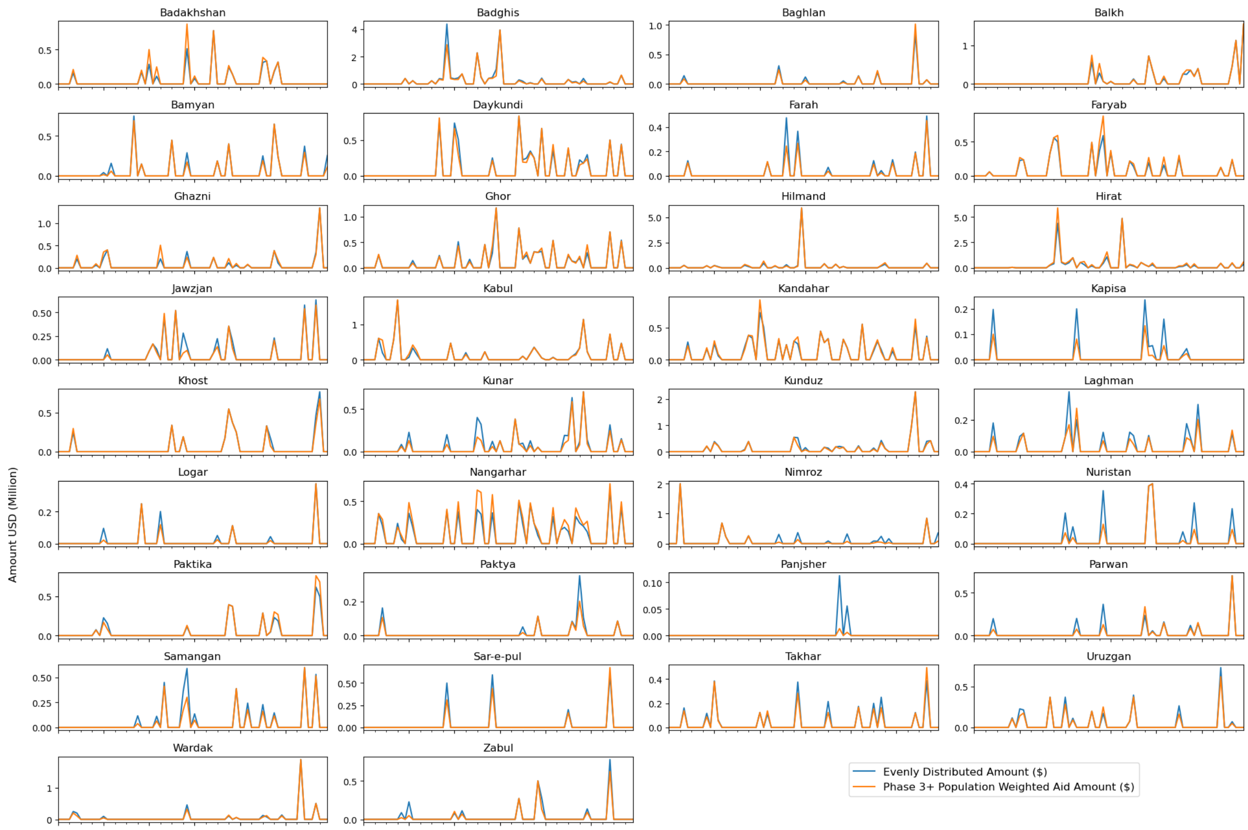
Note: This figure illustrates the trend in international aid distribution in Afghanistan, as tracked by the International Aid Transparency Initiative (IATI) from 2017 to 2022, differentiating between humanitarian and non-humanitarian aid. ◃ Back ◃ Appendix Back

Figure 23: **Layered Aid Data from IATI to FTS Humanitarian Data in Afghanistan (2017-2022)**



Note: This figure represents the flow of international aid data as tracked by the International Aid Transparency Initiative (IATI) through various stages, narrowing down to food security and nutrition-related aid, and finally to aid with a specified final destination in Afghanistan over the period from 2017 to 2022. ◃ Back

Figure 24: **Humanitarian Aid Distribution in Afghanistan by Region (2017-2022)**



Note: This figure compares humanitarian aid distribution across Afghan regions from 2017 to 2022. The blue lines represent aid amounts evenly distributed across regions, while the orange lines reflect Phase 3+ population-weighted aid amounts. The chart illustrates variations in aid distribution when accounting for the population under severe food insecurity (IPC Phase 3 and above). ◁ Back