From Food Crisis to Resource Allocation: Tracking Humanitarian Aid in Afghanistan

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Abstract

This study sheds light on a critical challenge for global humanitarian efforts: delivering timely, targeted aid to regions facing acute food insecurity. As hunger intensifies worldwide, the Integrated Food Security Phase Classification (IPC) system plays a pivotal role, alerting the world to regions in crisis and directing billions in relief aid to those in dire need. Yet, a fundamental question remains—does the IPC mobilize aid with the speed and precision necessary to meet escalating needs? Focusing on Afghanistan, a priority IPC country, this study introduces a novel dataset that aligns humanitarian funding flows with IPC regional classifications. Utilizing a staggered Difference-in-Differences approach, I investigate how IPC phase escalations impact immediate aid responses. The findings reveal a significant but insufficient increase in funding following transitions to IPC Phase 4, underscoring the gap between current aid allocations and the critical needs of populations facing severe food insecurity. This research offers a first-of-its-kind subnational analysis of IPC-driven aid allocation, providing policymakers with essential insights to strengthen future humanitarian response efforts.

Keywords: Humanitarian Aid, Acute Food Insecurity, Integrated Food Security Phase, Afghanistan
JEL Codes: I15, Q18, O12, F35, R58

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 humanitarian intervention is essential to mitigate the most severe consequences of acute hunger, with international stakeholders coordinating these efforts using the Integrated Food Security Phase Classification (IPC) system.

The IPC, a consortium of 15 organizations operating in over 30 countries, serves as the primary framework for signaling urgent food crises, emergencies, and famines. Beyond famine identification, the IPC enables humanitarian actors to identify critical situations that, while not reaching famine levels, still require immediate action to protect affected populations' well-being. The IPC system categorizes sub-national regions within member countries into five distinct phases of food insecurity, ranging from Phase 1 ("Minimal") to Phase 5 ("Famine"). These classifications, supported by detailed reports, are disseminated through humanitarian communication channels and widely covered by national and international media. Each year, IPC analyses guide the allocation of approximately six billion dollars in humanitarian food assistance across 30 crisis-affected countries [IPC, 2023].

The IPC's primary role is to provide information on food crisis severity to guide humanitarian resource allocation; however, its effectiveness in mobilizing timely and spatially targeted aid remains uncertain. Assessing aid allocation in response to IPC classifications, with a focus on its timing and effectiveness in targeting the appropriate locations to address acute hunger, is crucial from a humanitarian perspective. Research to date provides mixed findings: while Maxwell et al. [2023] found that aid increased after the IPC's famine declaration in Somalia in 2011, a similar declaration in South Sudan in 2017 led to only a modest increase in funding. Studies on the IPC's impact are descriptive, focusing on country-level analyses and famine declarations (Phase 5), with no empirical evidence on the IPC's broader effectiveness in directing aid to the most affected populations. However, conducting such analyses is challenging due to the lack of a comprehensive, subnational database tracking aid flows and the potential endogeneity that arises when factors influence both IPC classifications and aid distribution.

In this paper, I create a novel dataset of humanitarian funding flows geocoded to align with IPC's regional classifications. Using data from the UN OCHA Financial Tracking Service, I develop a text-finder algorithm to georeference final aid destinations at the provincial (Administrative 1) level and apply a natural language processing (NLP) model to recover purpose-related keywords for aid flows with missing records. With a staggered difference-in-differences approach, I estimate the immediate financial impact of IPC phase escalations, evaluate the gap between needs and aid allocated, and identify responsive actors. I use Afghanistan—a priority IPC country facing severe and persistent food insecurity—as a case study to examine humanitarian aid responsiveness to IPC classifications.

This study applies a staggered Difference-in-Differences (DiD) approach to examine the response of humanitarian aid to IPC Phase 4 escalations, which indicate severe food emergencies. The analysis identifies a marked increase in aid during the first three months following an escalation, with cumulative aid per administrative unit ranging from 0.819 to 1.107 million USD. This translates to a per capita allocation of 7.57 to 10.23 USD for new Phase 4 entrants, or 2.52 to 3.41 USD monthly. Given the negligible prior aid levels for these populations, this additional monthly support remains limited, particularly when compared to the estimated daily minimum food cost of 2.94 USD per person in Afghanistan. In the context of Phase 4 conditions, characterized by life-threatening food shortages and high mortality risks, the findings point to significant gaps in humanitarian aid coverage. The analysis further indicates that Non-US and EU funding shows a stronger response to IPC escalations, while US contributions, despite their overall scale, exhibit less alignment with these crises.

This paper addresses a critical gap in humanitarian aid research: the limited availability of subnational data on aid flows and the uncertainty surrounding the adequacy of aid responses to food crises identified by the IPC. To address this issue, it introduces a subnational dataset on humanitarian aid flows, utilizing an NLP model to analyze sectoral allocation patterns. It presents the first empirical assessment of humanitarian responsiveness to IPC classifications, examining whether regions classified as being in "Food Emergency" receive timely and sufficient aid. By focusing on subnational dynamics, this analysis contributes to the humanitarian aid literature by moving beyond country-level studies, such as Maxwell et al. [2023], and offering insights into aid allocation effectiveness in regions experiencing acute crises.

2 Literature Review

To evaluate whether aid aligns with IPC declarations, it is essential to examine broader patterns in how countries allocate aid. Donors frequently prioritize strategic interests over the needs of recipient countries. Davis and Swiss [2020] and Hoeffler and Outram [2011] identify three primary factors influencing aid allocation: recipient need, recipient merit, and donor self-interest. Aid based on need often correlates negatively with income per capita, suggesting that poorer countries should receive more aid [Hoeffler and Outram, 2011]. However, the influence of other donors can disrupt this dynamic, either reducing or increasing allocations depending on whether donors exhibit herding behavior [Berthélemy, 2006].

Merit-based aid tends to favor countries with sound economic policies, democratic governance, and respect for human rights, as these characteristics suggest more effective aid utilization [Burnside and Dollar, 2000]. However, since economic growth and governance can also reflect a country's level of need, the relationship between merit and aid allocation remains complex [Feeny and McGillivray, 2008]. Donor self-interest, including trade relationships and geopolitical alliances, also shapes aid flows, with donors often rewarding political alignment in organizations such as the United Nations [Alesina and Dollar, 2000, Berthélemy, 2006]. While these factors are well-documented, the causal mechanisms underlying these relationships continue to be debated.

Humanitarian assistance, including emergency food 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]. Food security related aid primarily addresses temporary food production shortfalls and increases most notably in response to violent conflicts and sudden natural disasters, while responses to slow-onset events like droughts are less pronounced [Kuhlgatz et al., 2010]. Neumayer [2005] highlights that food availability alone does not resolve food insecurity, as hunger often results from extreme poverty and barriers to food access, even when supplies are sufficient. Young and Abbott [2008] observe that while food security aid does not consistently target poorer countries, it tends to respond to severe production shortfalls and violent conflicts, which attract global attention and often lead to increased assistance. However, international political tensions and safety concerns for aid workers frequently hinder aid delivery during such crises [Kuhlgatz et al., 2010].

The Integrated Food Security Phase Classification (IPC) provides a key mechanism for assessing food insecurity crises at the global and national levels [Maxwell et al., 2011, 2023]. The IPC incorporates a range of evidence—spanning food availability, access, utilization, and acute events impacting food security—to evaluate the status of subnational regions [IPC, 2021]. Its adoption by humanitarian agencies and governments underscores its importance in guiding responses to acute and chronic food insecurity challenges.

However, the IPC's potential to influence external funding and targeted interventions remains uneven. High-profile cases, such as the 2011 Somalia crisis and South Sudan in 2017, demonstrate that IPC declarations do not consistently lead to substantial increases in external funding [Maxwell et al., 2023]. While the IPC is a central reference for strategic national-level planning, its capacity to shape subnational aid allocation directly is less established. For instance, the Office for the Coordination of Humanitarian Affairs (OCHA) and the Food Security and Nutrition Clusters primarily rely on IPC data for country-level coordination, often without extending its insights to localized interventions. This limited use of the IPC for subnational planning suggests a gap in fully leveraging its capabilities to guide targeted humanitarian responses.

This paper addresses this gap by analyzing how humanitarian aid aligns with IPC classifications at the subnational level. By providing the first systematic evaluation of aid responsiveness to IPC declarations, it examines whether regions classified as being in "Food Emergency" receive timely and sufficient support. This subnational focus advances the understanding of aid allocation dynamics and assesses the effectiveness of IPC-driven interventions in addressing acute food crises.

3 Background

3.1 Regional Acute Food Insecurity (AFI) as Captured by the IPC

The IPC's Acute Food Insecurity (AFI) analysis uses a structured framework to improve accuracy and minimize bias, systematically progressing from data collection to classification outcomes to identify acutely food-insecure regions [IPC, 2021]. Drawing on diverse data sources, the IPC evaluates key factors affecting food security, including vulnerability, resource availability, and the impacts of conflict and natural disasters. Primary indicators such as food consumption and livelihoods are integral to 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 food insecurity. 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]. Figure 22 in the appendix highlights this shift, showing the inverse trend between humanitarian and non-humanitarian aid starting in late 2021. 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 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 effectiveness in guiding aid allocation becomes crucial. Assessing whether aid aligns with population needs during phase transitions provides valuable insights to improve response strategies and mitigate the impacts of severe food crises.

4 Data

4.1 IPC

I use IPC's AFI data to evaluate whether IPC classifications effectively trigger timely resource allocation in Afghanistan's humanitarian response. Since 2017, the IPC has provided consistent AFI classifications for Afghanistan's 34 Administrative Level 1 (ADM1) regions, including population estimates and phase outcomes via its API. The panel structure of this dataset supports a longitudinal analysis of humanitarian response patterns in relation to IPC Phase changes.

The IPC framework categorizes AFI into five phases: Phase 1 (None/Minimal) to Phase 5 (Catastrophe/Famine). Phase 3 signals severe food insecurity with elevated malnutrition risks, requiring urgent intervention, while Phase 4 reflects 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, facilitating "people in need" calculations. The analysis focuses on *rural* classifications, aggregated across ADM1 regions, to maintain consistency.

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

(Insert Table 1 here.)

Table 1 indicates that a substantial proportion of IPC observations are classified as IPC Phase 3 (Crisis) or above, with 88% of observations in IPC Phase 3+ and 16% specifically categorized as IPC 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 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 Phase 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 IPC Phases 2 to 4, where Phase 4 represents a state of *Food Emergency*. The visualization highlights the widespread prevalence of IPC Phase 3 (Crisis) and IPC Phase 4 (Emergency) across many regions, some of which have persistently remained at these critical levels of food insecurity. Initially, IPC 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 IPC 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 IPC phases underscores the importance of an empirical strategy that captures the dynamic nature of IPC 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. Regions colored in red represent treated units, while those in pink indicate not-treated units. There are 19 treated units and 15 non-treated units, as indicated by the legend. The treated regions are more widely distributed across the country, covering both northern and southern areas, while the not-treated regions are more clustered in the eastern and central parts of the country.

(Insert Figure 3 here.)

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

The outcome variable in this study is the allocation of humanitarian aid, sourced from the Financial Tracking Service (FTS), managed by the United Nations Office for the Coordination of Humanitarian Affairs (UN-OCHA). The FTS acts as a centralized repository, providing curated, near real-time data on humanitarian funding flows. This platform offers a detailed view of financial contributions toward humanitarian operations, tracking funding progress against response plans, sectoral allocations, and identifying funding gaps [Kim, 2024]. By using the FTS data, I capture humanitarian aid allocations specifically following IPC phase escalations from Phase 3 (Crisis) to Phase 4 (Emergency), which allows to analyze the timeliness and adequacy of responses to food security needs flagged by the IPC.

The FTS provides extensive global coverage of humanitarian funding data, documenting contributions across various crises and appeals since its establishment in 1992. This broad temporal scope is particularly valuable for examining trends in humanitarian aid allocation in response to IPC classifications and understanding how international funding priorities have adapted to emerging needs. In the Appendix, I expand on the context of FTS data by relating it to the International Aid Transparency Initiative (IATI) data, which captures the full spectrum of international aid flows, offering a complementary perspective on funding trends in Afghanistan.

4.2.1 Features Available in the Data

The FTS includes several key features vital for understanding aid transactions as shown in Table 2. These features comprise timestamps, which enable temporal analysis, as well as keywords for categorizing aid types, and details on the source and destination of funds at the country level. Additionally, each transaction record includes a description, the monetary amount in USD, and funding status, distinguishing between committed and disbursed contributions. Together, these attributes facilitate an assessment of aid flows and their responsiveness to identified needs.

(Insert Table 2 here.)

4.2.2 Leveraging Text Analysis to Address Data Limitations in FTS

1) Lack of Geocoded Data

A key challenge in using FTS data for this study is the lack of geocoded information, which complicates efforts to track aid distribution at the subnational level. Geocoding aid data is inherently complex, as evidenced by initiatives such as Malawi's Open Aid Map [Weaver et al., 2014]. To address this issue, I develop a 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 is distributed across the detected regions, either evenly or weighted by the severity of food insecurity in each region. For this study, I apply the evenly distributed approach to mitigate potential concerns of overestimation [1]. Out of 3,017 aid records in Afghanistan during the study period, 22% (658 transactions) specifically mention ADM 1 regions as final aid destinations.

2) Categorization of Aid Transactions by Purpose

A second challenge is the inconsistent availability of keywords categorizing each aid transaction, which makes it challenging to interpret the purpose of each allocation. While some transactions are labeled with categories like "Food Security" or "Nutrition," others lack these tags, making it difficult to determine the intended use of the aid.

[1] The details of allocation scheme is explained in the appendix.

Figure 4 shows the distribution of humanitarian aid, amounting to 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" account for the largest shares, reflecting their prioritization in humanitarian aid allocations. Other categories, such as "Water, Sanitation, Hygiene" and "Protection," also receive considerable funding. Notably, the "NA" category, representing missing or uncategorized entries, comprises a significant portion (27.54%) of the total aid, emphasizing the challenges in obtaining comprehensive insights into sectoral funding.

(Insert Figure 4 here.)

To tackle this problem, I develop a Natural Language Processing (NLP) algorithm trained on a global dataset of **42,024** aid records with categorized labels and descriptions. The model uses transaction descriptions as input to predict missing keywords, enabling the approximation of transaction categories even when explicit labels are absent. This enhances the analysis of aid allocation by category. Records initially lacking descriptive keywords are supplemented with model-generated predictions. The NLP model demonstrates high recall (95%, rarely missing true "Food Security" cases) but shows lower precision (16%, many cases that falsely predicting non-"Food Security" as "Food Security"). To improve accuracy, I further filter predictions by searching for terms related to "Food Security" in the descriptions. Further technical details, including model architecture, performance metrics, and a confusion matrix, are provided in the Appendix.

4.2.3 Filtering and Aggregation of FTS Humanitarian Aid Flow Data

I filter the geocoded and keyword-recovered aid flow data based on four key criteria to enable a comprehensive heterogeneity analysis: (1) the funding entity, (2) the objective or associated 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. Funding status is classified into commitments and disbursed (or paid) contributions, enabling the tracking of aid allocation from initial commitment to actual disbursement. The distinction between new money and existing money highlights whether the aid represents additional resources or reallocated budgets. I aggregate the filtered data at the ADM 1 region level, aligning it with historical IPC AFI classifications to support 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 key drivers of food insecurity [D'Souza and Jolliffe, 2013a, D'Souza and Jolliffe, 2014, Oskorouchi and Sousa-Poza, 2021]. To account for these factors, the analysis incorporates three additional data sources—ACLED, SPEI, and RTFP—to capture subnational, monthly variations in fatalities, drought, and food price inflation, respectively. These datasets are included as covariates to control for external influences on food security dynamics beyond IPC classifications, enhancing the evaluation of IPC's role in guiding humanitarian aid allocation.

4.3.1 Armed Conflict Location & Event Data Project (ACLED)

The Armed Conflict Location & Event Data Project (ACLED) provides detailed data on political violence, demonstrations, and other significant events globally [Raleigh et al., 2010]. It documents event types, involved actors, dates, locations, and fatalities, offering comprehensive information on conflict dynamics. Updated weekly, ACLED covers both historical and current events, enabling the tracking of political disorder across time and regions.

4.3.2 Standardized Precipitation-Evapotranspiration Index (SPEI) 24 Data

The Standardized Precipitation-Evapotranspiration Index (SPEI) 24 is a climatic indicator designed to monitor long-term drought conditions by integrating precipitation and temperature data [Vicente-Serrano et al., 2010]. The index captures drought patterns over a 24-month period and is widely used to evaluate impacts on agricultural productivity and food security.

4.3.3 Real-Time Food Prices (RTFP) Data

The Real-Time Food Prices (RTFP) dataset combines market data with machine learning-based estimates to monitor food prices at the market or subnational level, addressing data gaps in areas lacking direct observations [Andree, 2021]. The dataset provides monthly near real-time estimates, used in modeling acute food insecurity risk [Andrée and Pape, 2023, Penson et al., 2024]. Food prices are a key component in IPC phase determinations, contributing to assessments within the IPC Food Security Analytical Framework [IPC, 2021].

Specifically, I use the *total number of fatalities related to political violence* from **ACLED**, *SPEI-24 values* to measure drought conditions, and *food price inflation* from **RTFP**. These datasets aggregate at the ADM1 regional level across months, capturing temporal and spatial dynamics affecting food security. A 5-month lagged rolling mean smooths short-term fluctuations, aligning with Afghanistan's biannual IPC publication schedule, which typically relies on data from preceding months. This ADM1-level aggregated data integrates with IPC and FTS datasets as covariates in the econometric model.

5 Identification

5.1 Identification Strategy

I use a staggered Difference-in-Differences (DiD) approach to estimate the causal effect of IPC 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 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 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—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)

Given the staggered treatment timing and the potential heterogeneity in Phase 4 transitions across regions, I primarily use the Callaway and Sant'Anna [2021] estimator for staggered DiD analysis. This estimator is well-suited for cases with dynamic treatment effects and heterogeneous treatment timing. Formally, the estimator is defined 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 level 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 provides summary statistics for key variables, comparing treated and control ADM1 regions over the study period. Treated regions demonstrate overall higher vulnerability, with higher average IPC phases, larger proportions of the population in IPC Phase 3+ and Phase 4+, and more severe drought conditions, as indicated by the SPEI-24 index. These regions also receive greater food security-related and general humanitarian aid.

(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 IPC 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.

I employ a staggered Difference-in-Differences (DiD) approach, following Callaway and Sant'Anna (2021), to evaluate the impact of IPC Phase 4 escalations on humanitarian aid allocation. This method compares treated regions with two control groups: "Never-Treated" and "Not-Yet-Treated," accounting for heterogeneous and dynamic treatment effects. The approach provides robust estimates of both monthly and short-term average impacts, focusing on the first five months post-escalation to IPC Phase 4 to reduce potential contamination from subsequent fluctuations or transitions back to Phase 3. Table 5 presents the dynamic response of humanitarian aid (in millions of USD) to these escalations, while Table 6 provides the corresponding results with 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 data 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 Organization

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 may include 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 also explore variations in humanitarian aid allocation based on the timing of escalations to Phase 4 food insecurity, distinguishing between regions affected before and after the Taliban offensive in 2021, a pivotal moment in Afghanistan's recent history. 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 0–2 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 food insecurity after May 2021. In this case, the average aid response within the first 0–2 months 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 0–2 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 markers highlight 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 food insecurity 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 suggest some shifts in the immediacy of aid responses across different funding categories following the Taliban offensive, but the lack of consistent statistical significance underscores the need for cautious interpretation.

6.5 Ruling out Alternative Mechanisms

To ensure the robustness of the main results on humanitarian aid response to IPC 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 IPC 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 exhibits an immediate response to extreme events across these indicators. Figure 19 shows that, despite the inclusion of these mechanisms in the analysis, there is no statistically significant evidence of an immediate humanitarian response to conflict, food inflation, or drought individually. This suggests that aid allocation is more closely tied to IPC Phase 4 escalations as a comprehensive measure, rather than being driven by any single indicator of stress.

(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 employs a staggered Difference-in-Differences (DiD) approach to analyze how humanitarian aid responds to Phase 4 escalations in the Integrated Food Security Phase Classification

(IPC). The findings indicate a rapid surge in aid during the first two months following an escalation, reflecting immediate mobilization efforts. However, this response diminishes in subsequent months, suggesting that while immediate needs are met, sustained support is limited. These results align with prior research highlighting that humanitarian assistance, though designed for rapid crisis response, often struggles to maintain adequate levels of aid over time, particularly in complex emergencies [VanRooyen, 2013, Kuhlgatz et al., 2010].

Over a three-month period, cumulative aid per administrative unit ranges from 0.819 to 1.107 million USD, translating to 7.57 to 10.23 USD per person. These levels fall significantly short of the estimated daily food requirement cost of 2.94 USD, revealing a substantial gap between humanitarian aid allocations and actual needs during crises. This shortfall underscores the challenges of aligning aid distribution with the severity of food insecurity, a misalignment often influenced by donor interests and strategic priorities rather than recipient needs [Davis and Swiss, 2020, Hoeffler and Outram, 2011].

The analysis reveals significant variation in aid responsiveness across donor sources, funding types, temporal contexts, and aid purposes. Non-US and EU donors exhibit faster and stronger responses compared to US-funded aid, despite the US being the largest overall donor. Aid classified as "Disbursed or Paid" is mobilized more effectively than "Committed" funds, while newly allocated funds show slightly larger immediate effects than existing budgets, although the latter contribute the majority of total aid quantities. Aid responsiveness also varies temporally, with higher immediate effects observed post-Taliban offensive compared to pre-offensive periods, though this difference lacks consistent statistical significance. Furthermore, the findings indicate that humanitarian aid responses are not narrowly focused on a single purpose but represent a collective effort across diverse aid categories. These variations likely reflect differences in operational structures, funding mechanisms, and broader donor strategies, consistent with literature emphasizing the role of donor self-interest, including geopolitical and trade considerations, in shaping aid flows [Alesina and Dollar, 2000, Berthélemy, 2006].

Alternative mechanisms such as political violence, food inflation, and drought intensity were also examined to test their influence on aid allocation. The analysis finds no consistent evidence that these factors alone directly drive humanitarian aid. Instead, aid flows appear more closely tied to IPC Phase 4 classifications, underscoring the IPC's role in guiding responses. While the

IPC provides a comprehensive framework that integrates multiple factors to assess food insecurity, challenges such as political tensions and logistical constraints often hinder effective delivery [Young and Abbott, 2008, Kuhlgatz et al., 2010].

This study addresses a critical gap in understanding humanitarian aid allocation at the subnational level. By providing a detailed analysis of aid responsiveness to IPC Phase 4 alerts, it highlights gaps in per capita aid allocation that align with broader concerns about the adequacy of aid flows during critical food crises [Alesina and Dollar, 2000, Kuhlgatz et al., 2010]. While humanitarian aid shows an initial surge following Phase 4 escalations, funding frequently falls short of addressing acute needs. Leveraging a novel subnational dataset, this study enhances the understanding of aid responsiveness and underscores the importance of improving mechanisms to ensure timely and sufficient support in response to acute food crises.

7.1 Limitation & Discussion

The geocoded humanitarian aid data used in this analysis represents a subset of the full dataset, as some entries lack detailed information on final destination regions. Figure 20 illustrates 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. This highlights a persistent challenge in tracking aid flows—particularly after the Taliban takeover in 2021—and underscores the need for improving data transparency and accuracy. Missing or unclear destination information may introduce inefficiencies in aid allocation or delays in distribution, potentially hindering the timely delivery of support to vulnerable populations. Addressing these gaps is essential for enhancing the effectiveness of humanitarian responses.

(Insert Figure 20 here.)

This limitation has two significant implications: **data curation** and **operational effectiveness**.

Data Curation: Improving the accuracy and completeness of geolocation data in aid allocation is critical to ensuring that humanitarian assistance reaches its intended targets efficiently. Better tracking of final destination data enables donors, NGOs, UN agencies, and local governments to optimize resource distribution, reducing risks such as over-saturation in some areas or under-support in others. Enhanced geolocation accuracy also mitigates issues like double-counting or gaps in coverage, promoting a more equitable and effective allocation of resources.

Operational Effectiveness: Strengthening communication between the Integrated Food Security Phase Classification (IPC), local governments, and operational stakeholders—including donors, NGOs, and implementing agencies—is crucial for addressing food security crises. Clear and timely dissemination of IPC assessments, particularly in regions experiencing rapidly escalating needs, ensures that all stakeholders are informed about the urgency of interventions. Improved communication channels foster better coordination and enable more responsive and targeted aid delivery, helping to align humanitarian responses with the actual needs on the ground.

7.2 Future Direction

Building on the findings of this study, future research offers significant opportunities to enhance understanding of the effectiveness and responsiveness of humanitarian aid, particularly in crisis-affected regions.

A critical priority for future work is geocoding humanitarian aid data at the subnational level on a global scale, given that the current Financial Tracking Service (FTS) data is not geocoded. Developing detailed geocoded datasets would provide valuable insights into the spatial distribution of aid flows, enabling a deeper analysis of how humanitarian assistance aligns with regional needs and IPC classifications. Expanding geocoding efforts globally would address existing gaps in data granularity and transparency, supporting a more precise understanding of aid allocation patterns and facilitating more effective and equitable resource distribution.

Cross-country comparative analyses also hold great potential for advancing knowledge in this field. Examining patterns of aid responsiveness across various crisis contexts, including IPC-priority countries such as Afghanistan, 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 visible in single-country studies, offering a broader perspective on the factors influencing humanitarian responses.

Additionally, investigating the role of governance quality and logistical constraints in shaping aid effectiveness is essential. Weak infrastructure, political instability, and governance challenges can significantly impede aid delivery in many crises. Understanding the impact of these factors on humanitarian operations would provide valuable insights into the barriers faced by donors and implementing agencies. Such research could also inform strategies to overcome these challenges, improving the timeliness and efficacy of aid delivery to affected populations.

By addressing these areas, future research could contribute to a more evidence-based and equitable humanitarian aid system. Enhancing data quality, conducting cross-country analyses, and examining operational challenges would provide critical insights for aligning aid efforts with acute needs and improving the overall effectiveness of humanitarian responses.

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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" 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

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 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 phase classifications observed between Jan 2017 and Dec 2022 across regions, indicating the frequency and percentage of regions in each IPC phase, and the proportion of time each district spent in Phase 4 or above. *Phase 3 (Crisis)* indicates severe food insecurity with high malnutrition risks, demanding urgent intervention. *Phase 4 (Emergency)* signals life-threatening food shortages and rising mortality rates. Although **Phase 5** represents famine conditions, Afghanistan has not reached this level during the study period. [◃ 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.

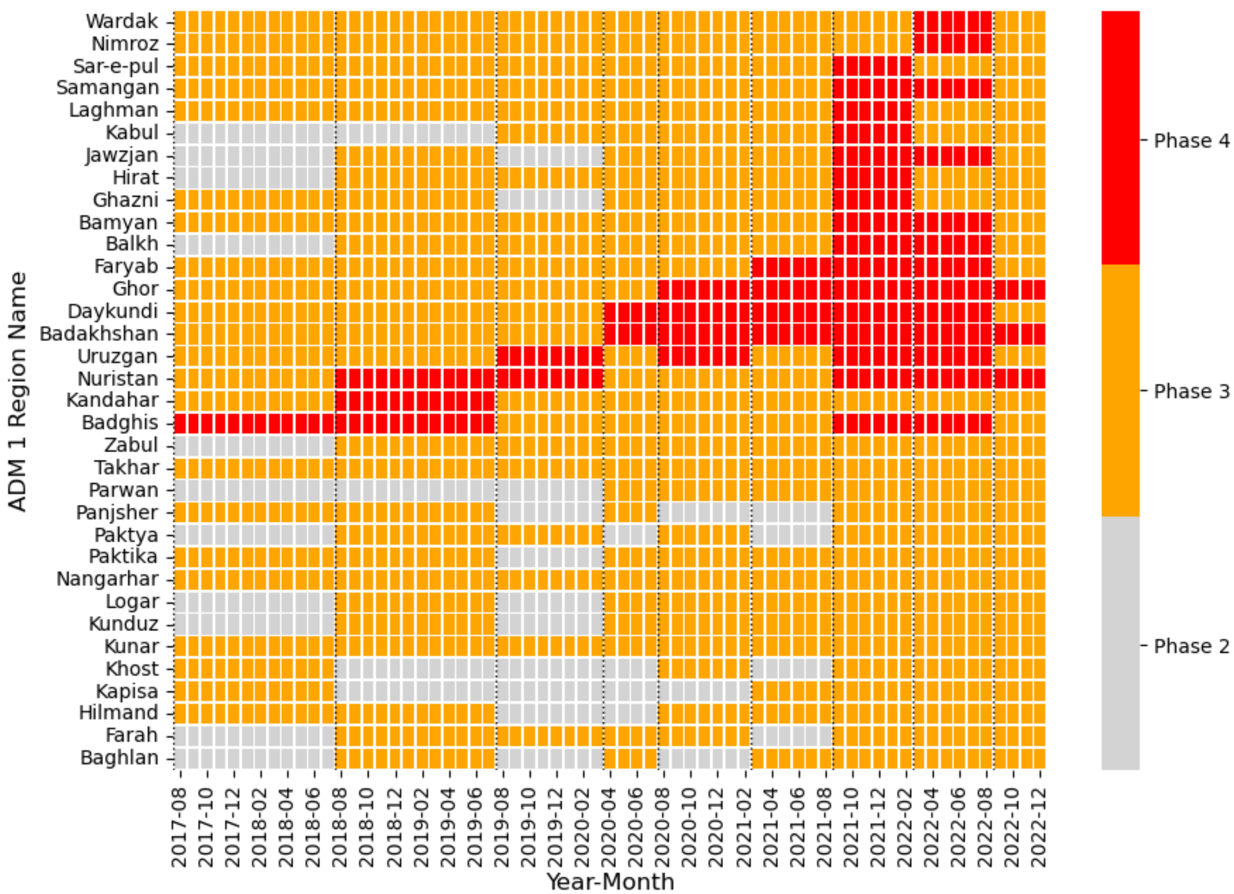
Note: This table summarizes key features of the Financial Tracking Service (FTS) data, including timestamps, classification keywords, and transaction descriptions, which offer detailed information on aid flows and funding statuses. ◃ Back

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

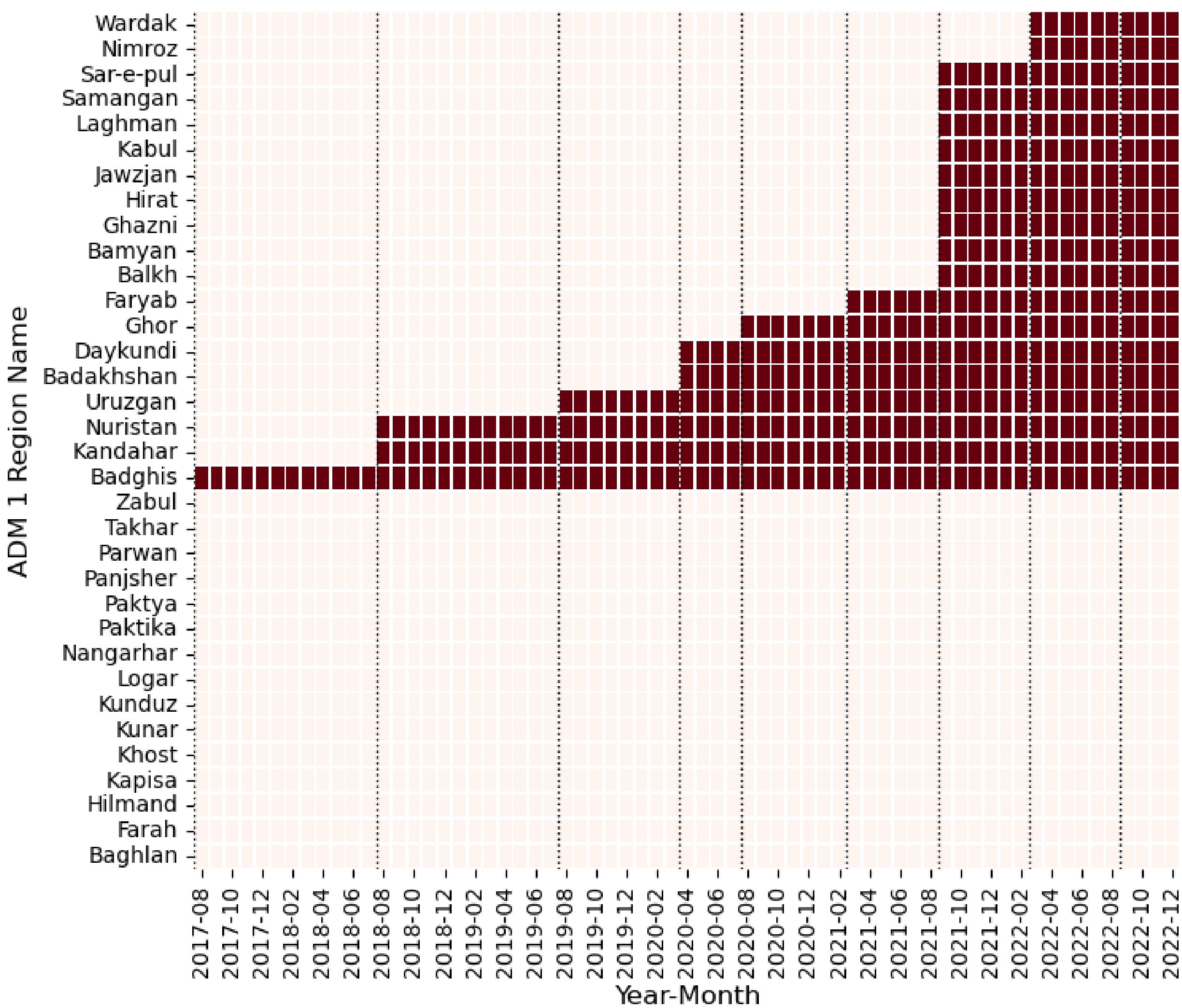
Note: Data from the 2015 Afghanistan Demographic Household Survey (DHS), weighted by household-level weight factors. The dataset primarily covers rural areas, with urban-only data for Kapisa and Zabul. The sample includes 19 treated units and 15 control ADM 1 units. ◃ Back

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



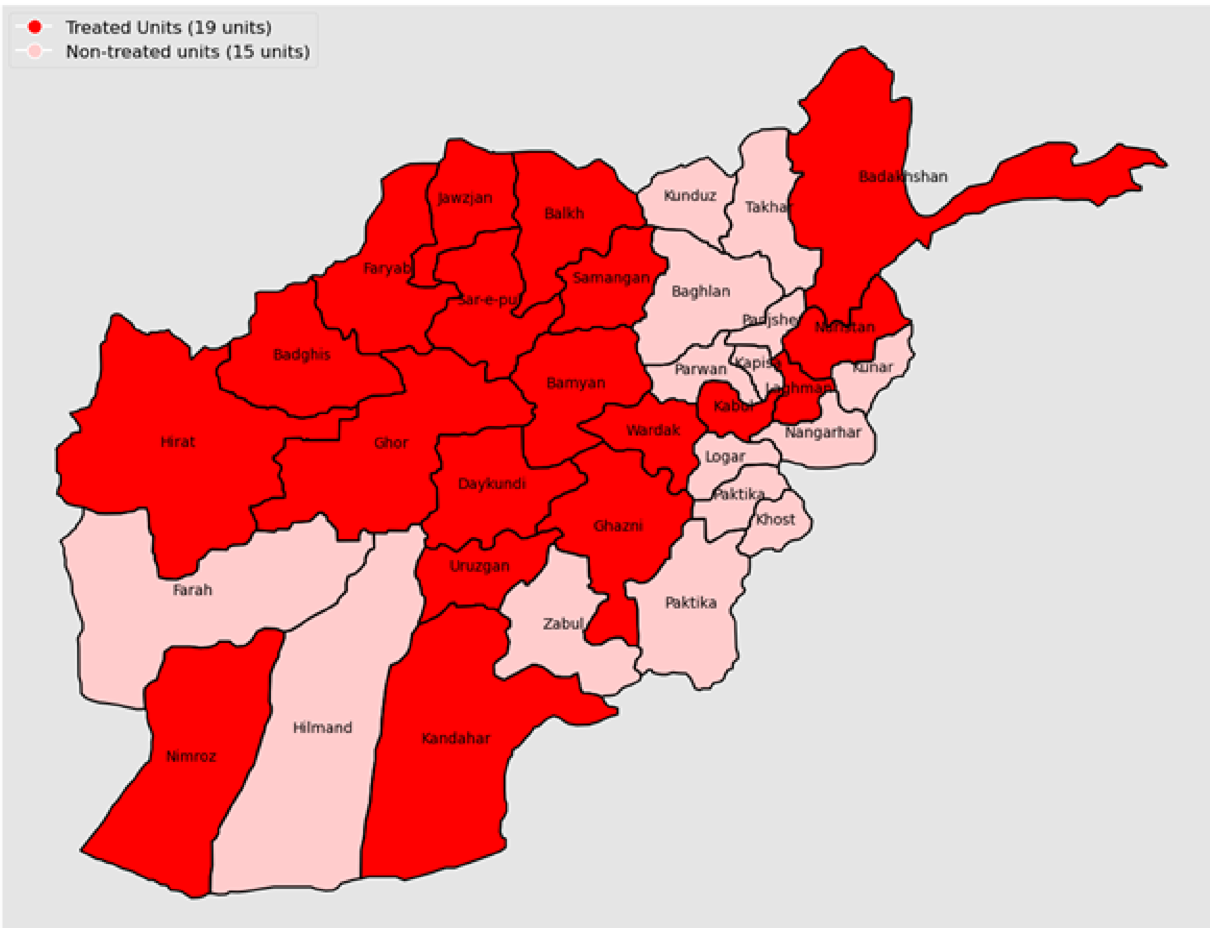
Note: This figure shows the transitions between different IPC phases for each region, with Phase 4 indicating a Food Emergency. It highlights how regions shifted between IPC Phases 2 (Stress) to 4 (Emergency) over the years, with some experiencing prolonged periods of food crises or emergencies. The phase outcome was constructed by filling missing values forward within each region and time period, ensuring a continuous representation of food insecurity trends. ◁ Back

Figure 2: **Treatment Status (Phase 4: Food Emergency) by Group: According to First Treatment Timing**



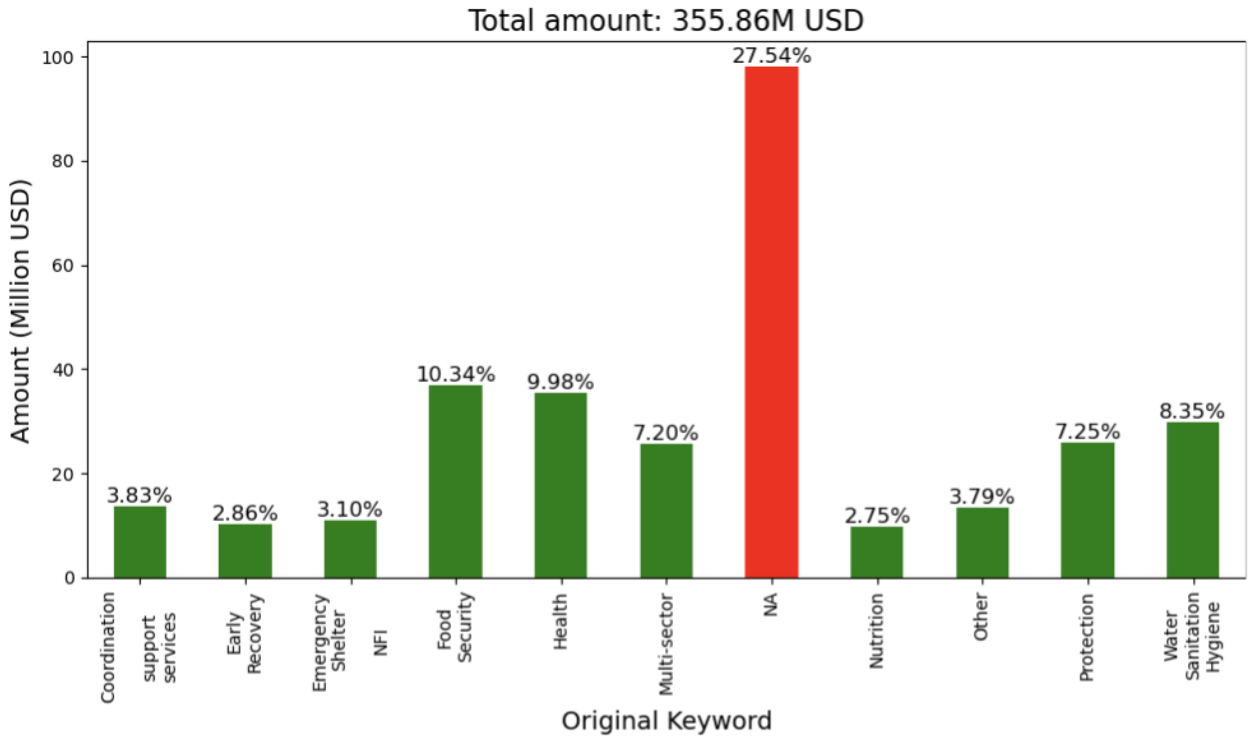
Note: This figure visualizes the staggered treatment status of regions as they enter IPC Phase 4 for the first time, with darker shades indicating regions classified as being in a food emergency for longer durations. The staggered nature of transitions into Phase 4 highlights the varying timing of these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

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). "Food Security" and "Health" receive the largest shares, underscoring their prioritization in humanitarian aid allocations. Categories like "Water, Sanitation, Hygiene" and "Protection" also received substantial allocations. The "NA" category represents missing or uncategorized entries, highlighting a significant portion of aid with unspecified allocation purposes. ◁ Back

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

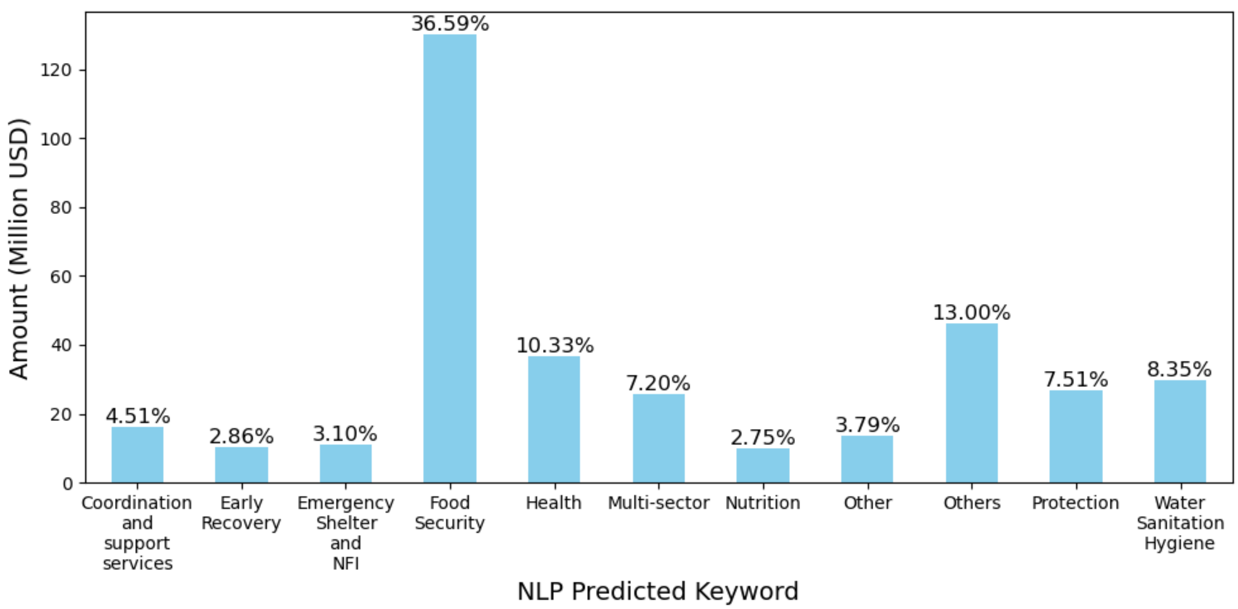
Variable Name	**Control Regions**	**Treated Regions**
IPC Phase	2.78	3.24
IPC Phase 3+ Population Estimates (%)	0.32	0.44
IPC Phase 4+ Population Estimates (%)	0.09	0.14
Estimated Population Mean (1,000)	791.84	831.70
(log-transformed) Food Security related Aid (USD)	1.95	2.66
(log-transformed) Total 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)**

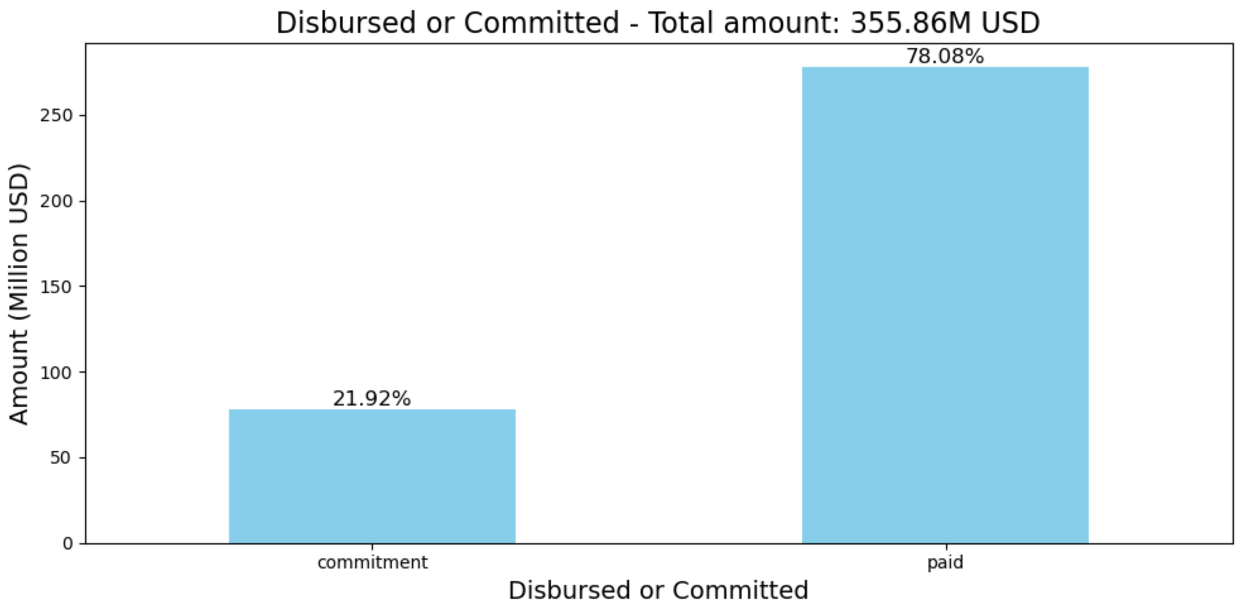
Note: The top panel shows the top 10 donors of humanitarian aid in Afghanistan by original organization category. The United States government is the largest bilateral contributor, accounting for 15.59% of total aid, followed by the European Commission's Humanitarian Aid and the German government. The 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)**



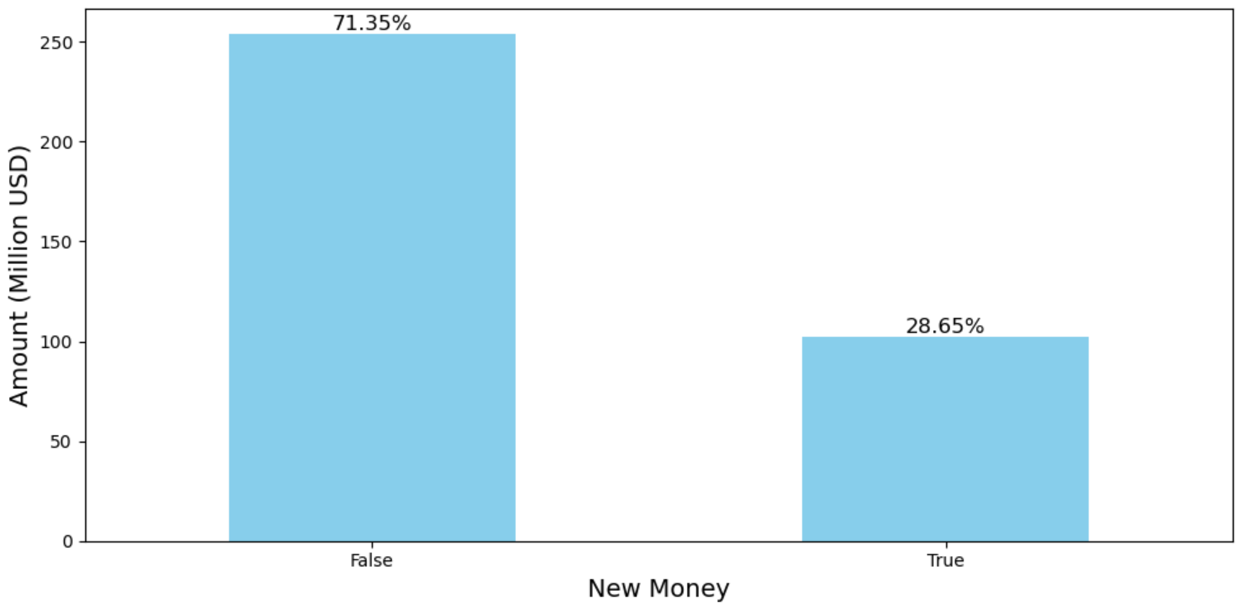
Note: This figure categorizes humanitarian aid allocations using keywords predicted by an NLP model, highlighting the prioritization of different aid sectors. "Food Security" dominates the distribution with 36.59% of total aid, followed by "Health" at 10.33%. Other categories such as "Water, Sanitation,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

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



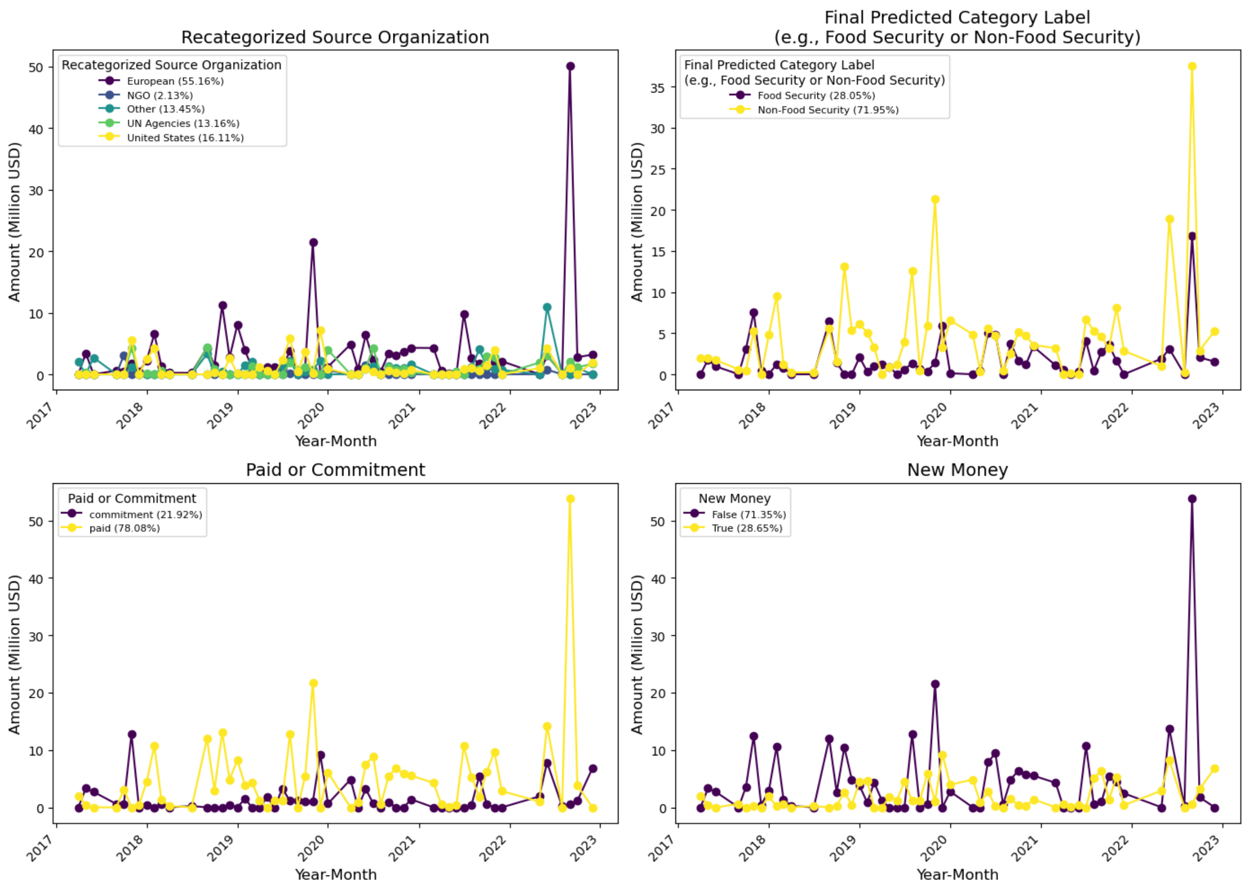
Note: This figure shows the allocation of humanitarian aid by funding status, distinguishing between committed and paid contributions. Of the total 355.86 million USD tracked in the study period, 78.08% has been disbursed as paid contributions, while 21.92% remains in the commitment phase. ◃ Back

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



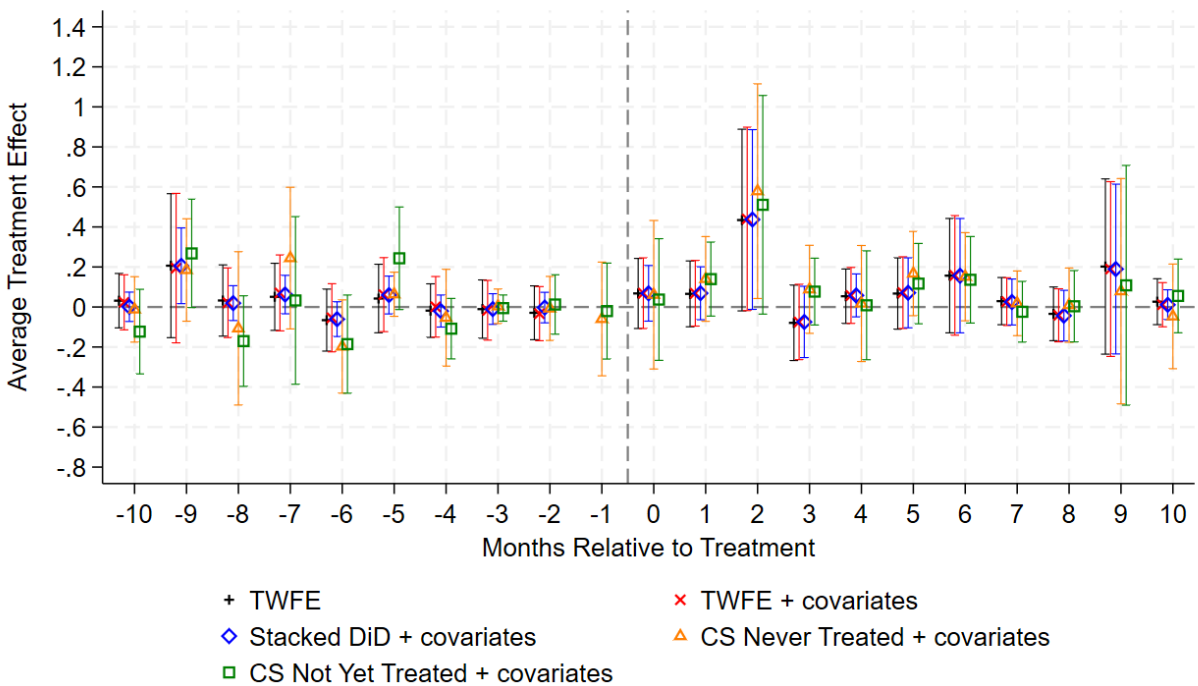
Note: This figure illustrates the distribution of humanitarian aid between new funding and reallocated resources. Of the total aid analyzed, 71.35% represents reallocated resources, while 28.65% constitutes new funding. ◃ Back

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, and only rural observations 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

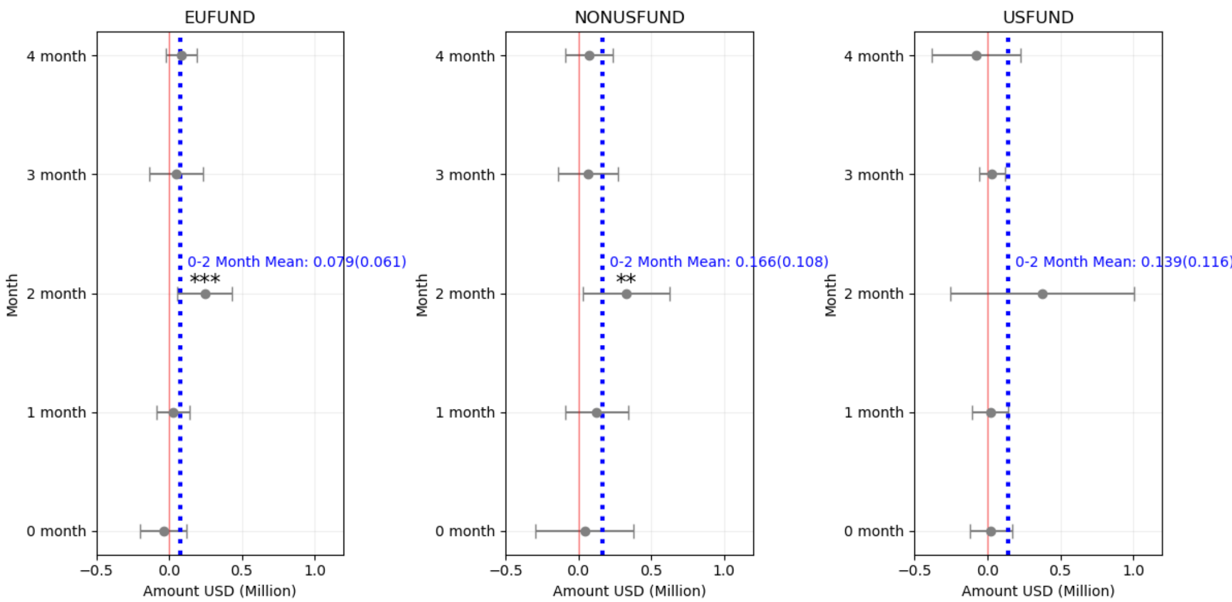
Note: Observations are at the Administrative Level 1 unit level, with data spanning from January 2017 to December 2022. All values reflect the log-transformed total humanitarian response (in million USD). Covariates include conflict data from ACLED, food inflation from RTFP, and drought data from SPEI24, 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

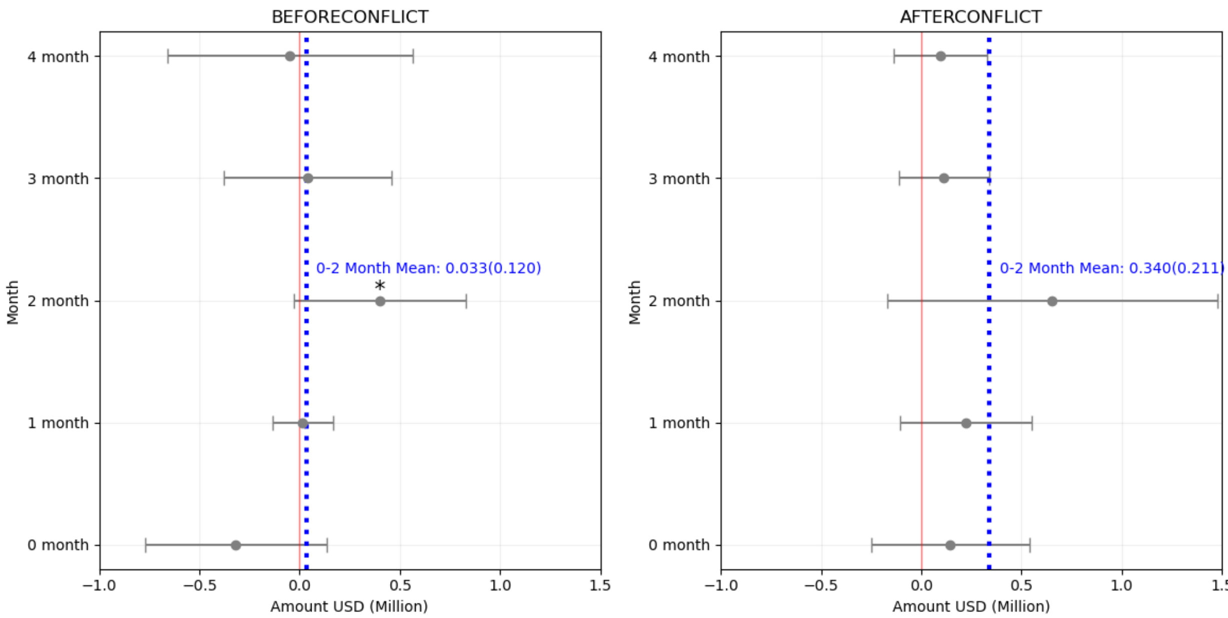
Note: Aid represents total humanitarian assistance measured in USD. The pre-treatment period encompasses the three months preceding the first escalation to IPC Phase 4, while the post-treatment period captures additional aid allocated during the three months following the escalation. All values are reported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

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



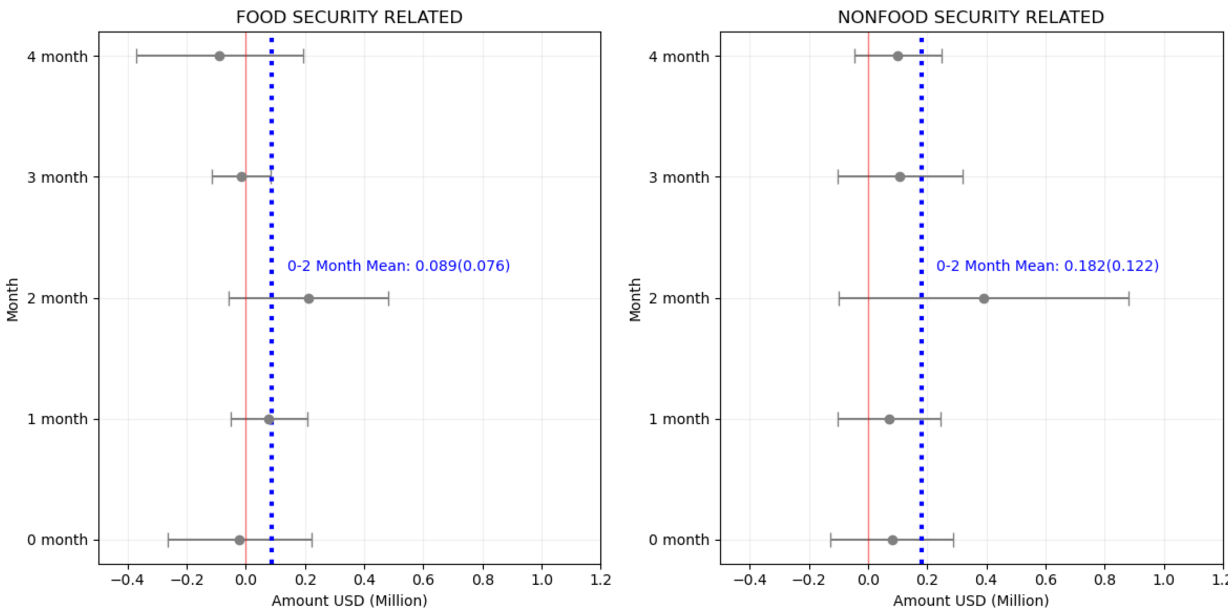
Note: This figure presents the dynamic and average treatment effects of humanitarian aid for regions in Phase 4 food insecurity, estimated using the Callaway and Sant'Anna (2021) approach with three covariates: fatalities, food price inflation, and drought (SPEI-24). The left panel shows aid funded by 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)**



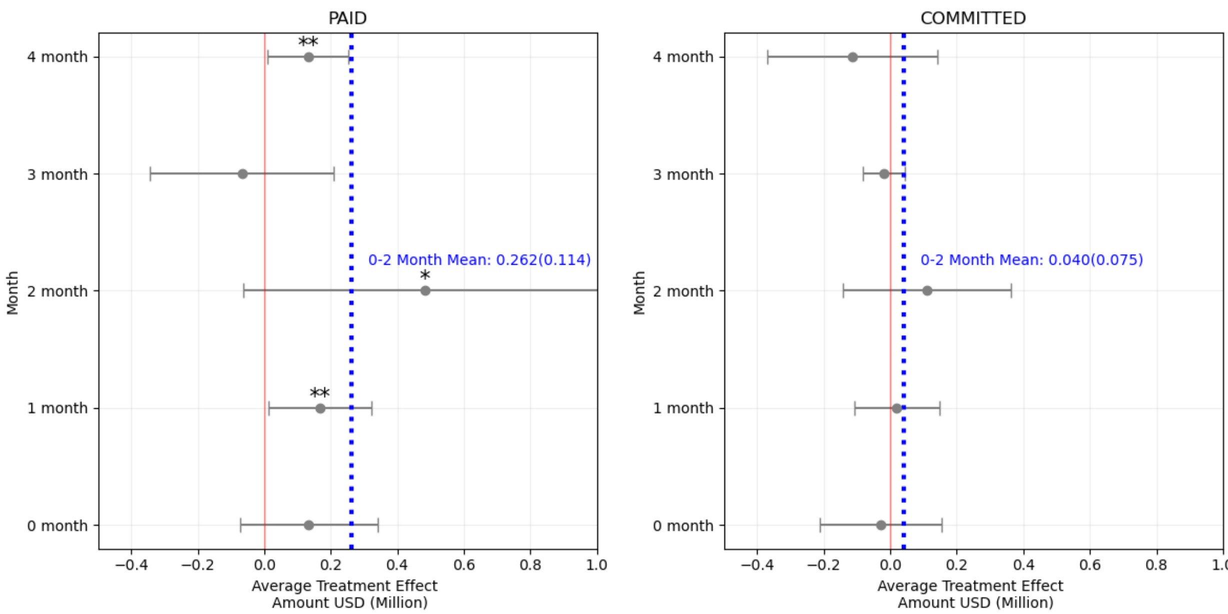
Note: This figure compares the dynamic and average treatment effects of humanitarian aid in the 0–4 month range before and after conflict, estimated using the Callaway and Sant'Anna (2021) approach with three covariates: fatalities, food price inflation, and drought (SPEI-24). The left panel shows the 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**



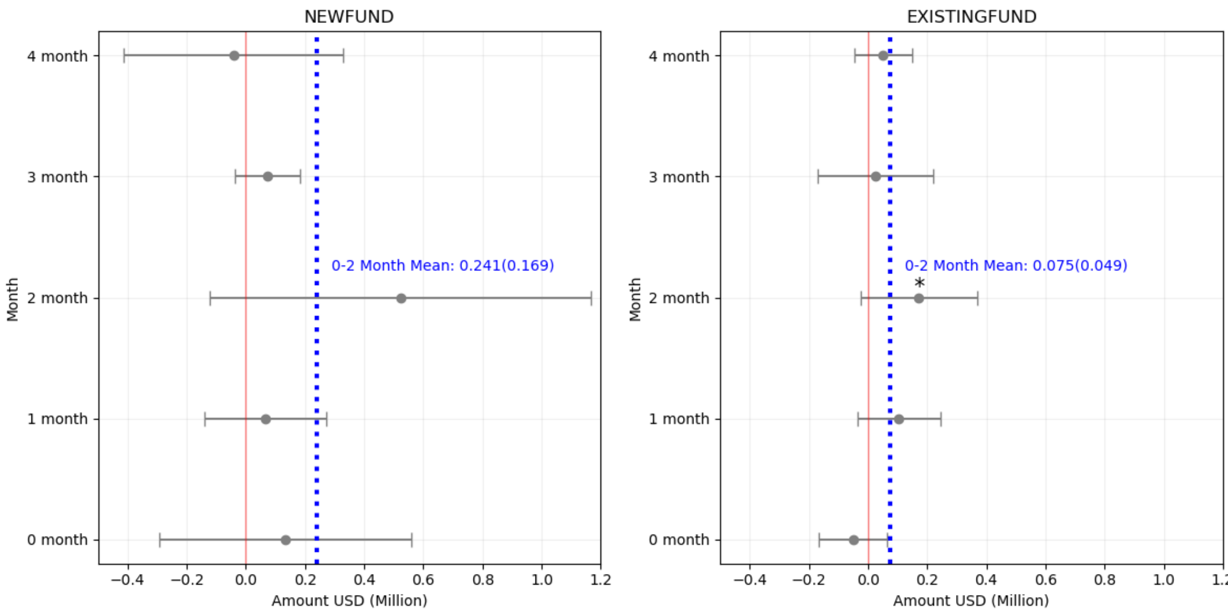
Note: This figure presents the dynamic and average treatment effects of humanitarian aid allocated to food security and non-food security activities, estimated using the Callaway and Sant'Anna (2021) approach with three covariates: fatalities, food price inflation, and drought (SPEI-24). Aid categories 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**



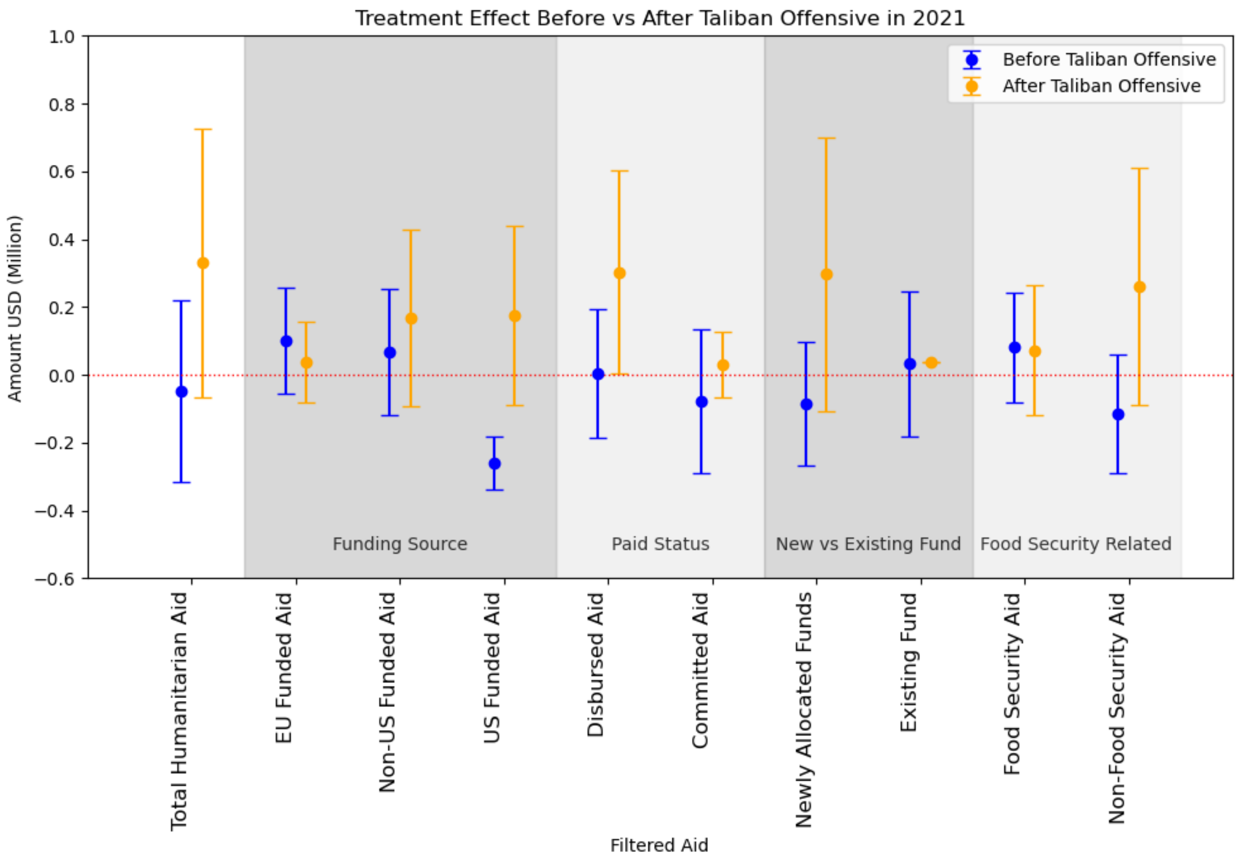
Note: This figure presents the dynamic and average treatment effects of humanitarian aid based on payment status, estimated using the Callaway and Sant'Anna (2021) approach with three covariates: fatalities, food price inflation, and drought (SPEI-24). The left panel shows aid categorized as "Paid," 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



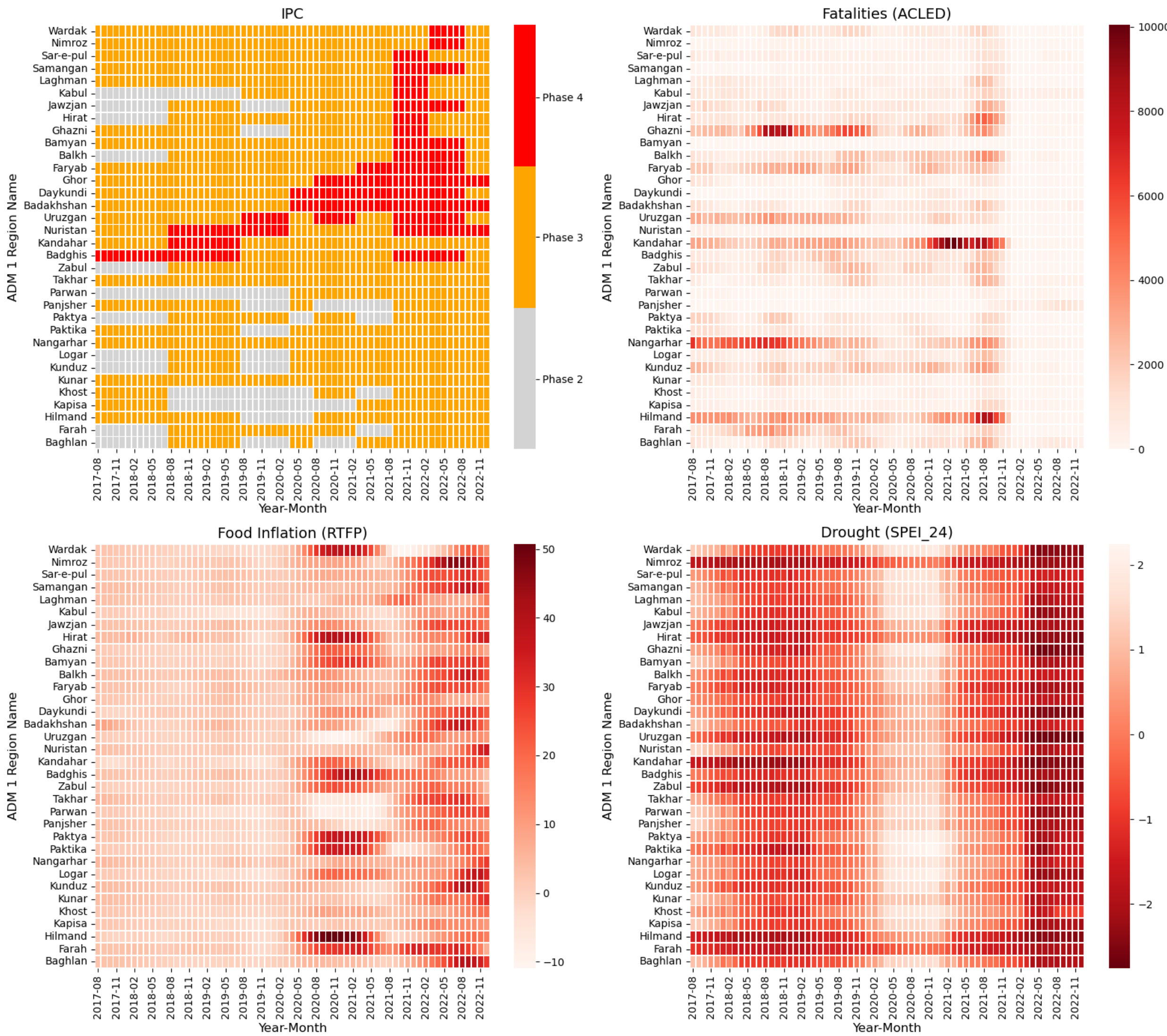
Note: This figure presents the dynamic and average treatment effects of humanitarian aid based on funding type, estimated using the Callaway and Sant'Anna (2021) approach with three covariates: fatalities, food price inflation, and drought (SPEI-24). The left panel shows aid categorized as "New Fund," 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



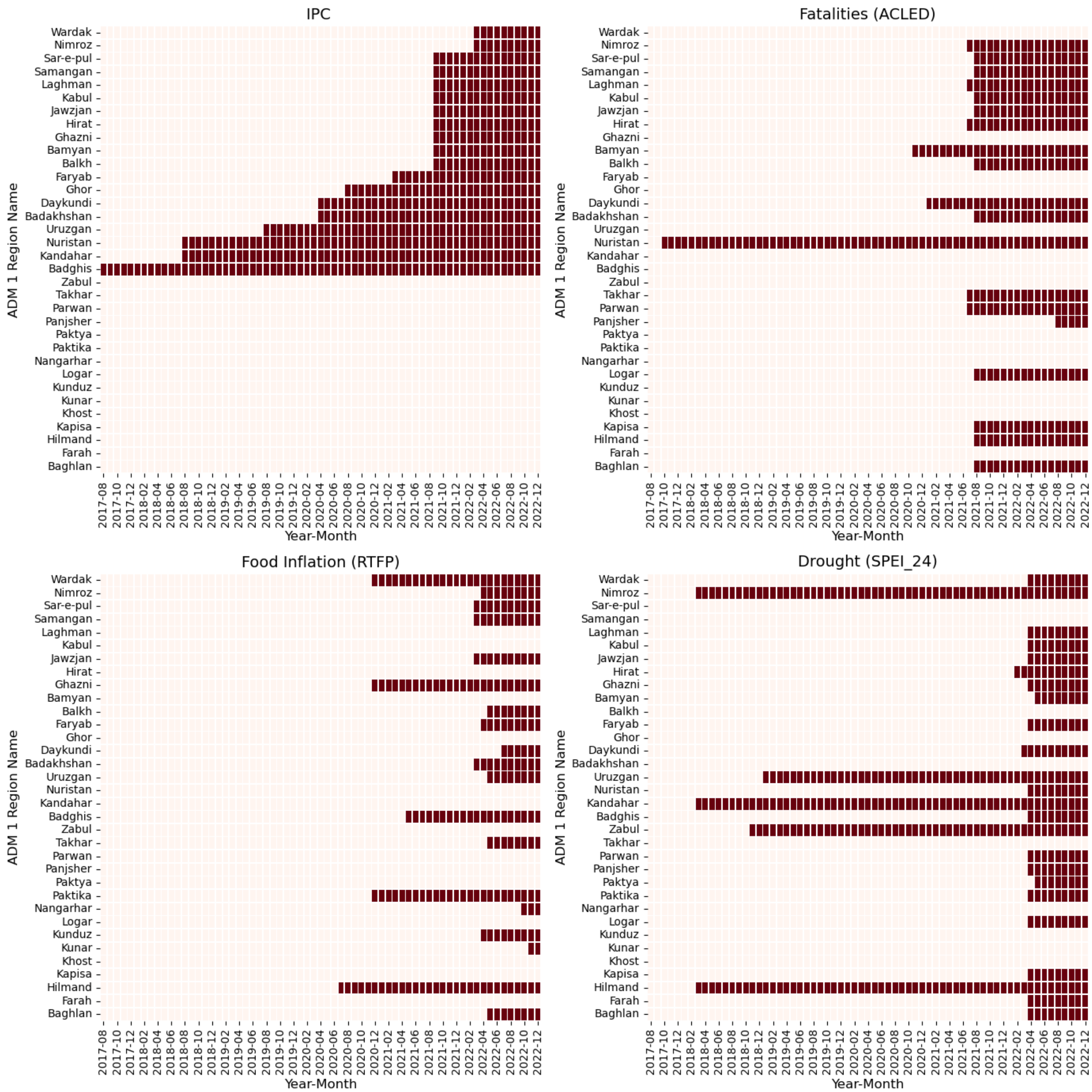
Note: This figure presents the average immediate (0–2 month) treatment effects of humanitarian aid in response to Phase 4 food insecurity escalations, estimated using the Callaway and Sant'Anna (2021) approach with three covariates: fatalities, food price inflation, and drought (SPEI-24). The effects 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

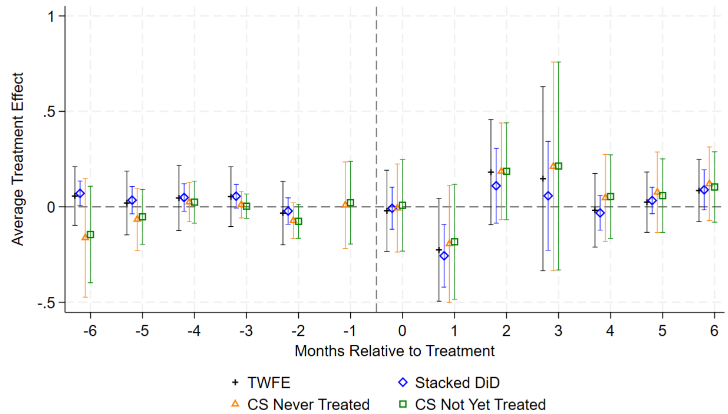
Figure 18: **Treatment Status Defined by IPC and Other Extreme Events (2017 to 2022)**



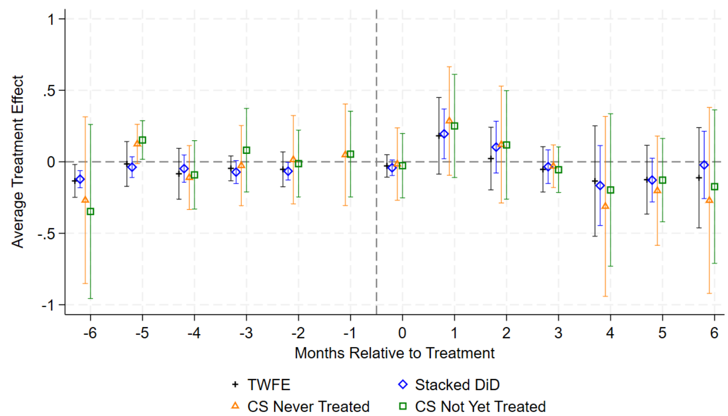
Note: This figure presents the treatment status of extreme events across four indicators, documenting occurrences from 2017 to 2022. The top-left panel shows IPC Phase 4 escalations, indicating Food Emergencies. Extreme events for the remaining indicators are defined as follows: food price inflation 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)**

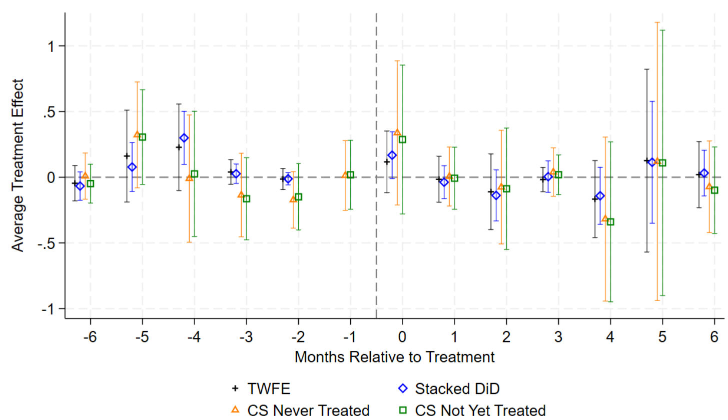
(a) Fatalities



(b) Food Inflation



(c) Drought



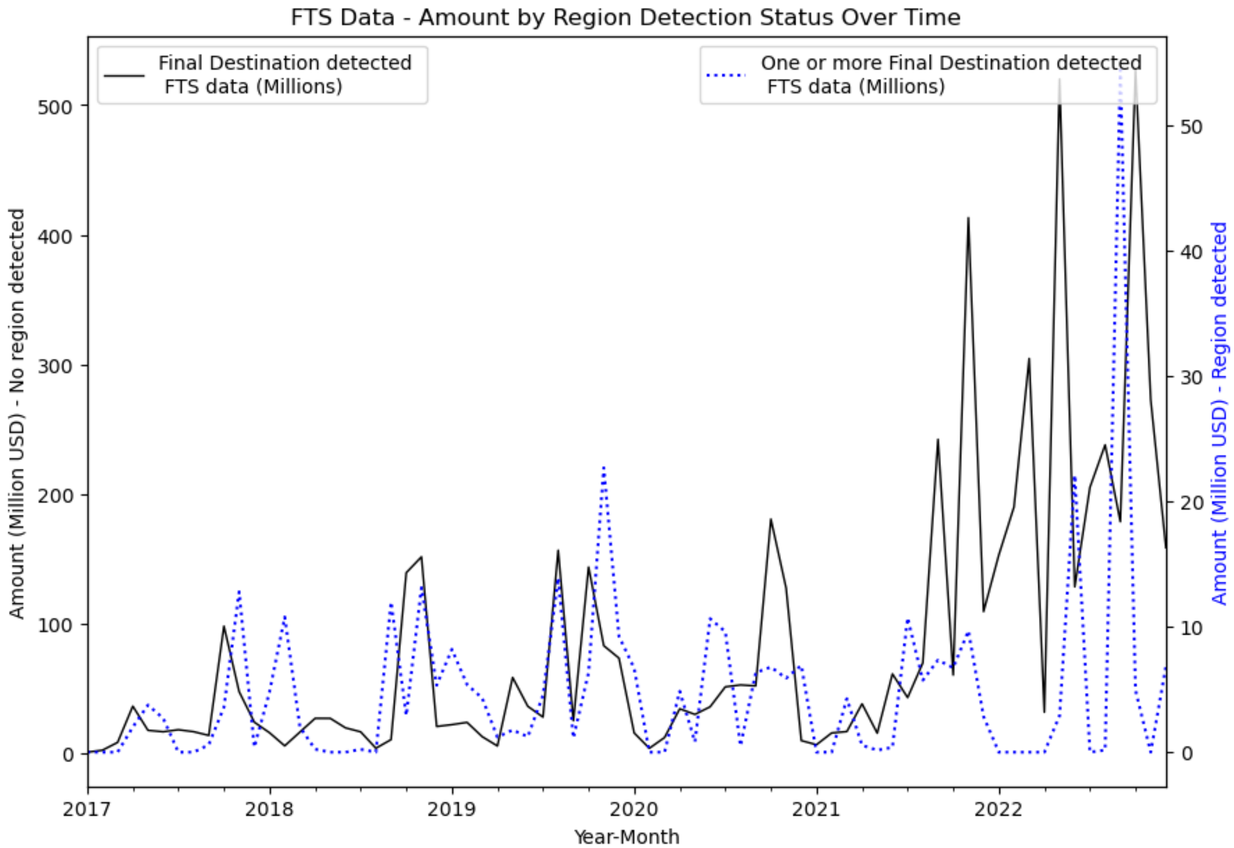
Note: This figure presents the event study of the average treatment effect over months relative to treatment for three indicators: extreme fatalities from political violence (top), food inflation (middle), and drought (bottom). Each plot displays the estimated average treatment effects derived from various 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)**



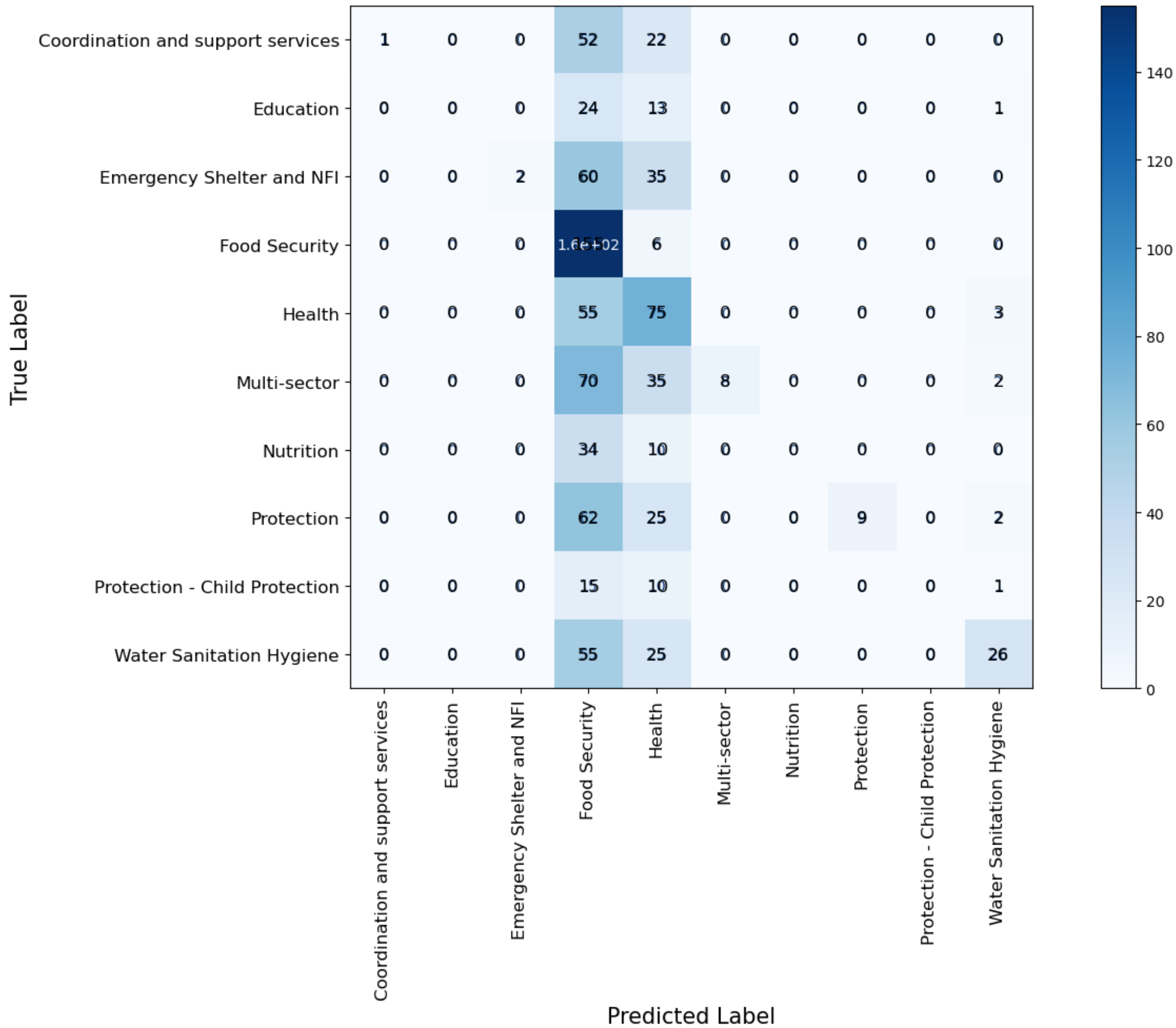
Note: This figure displays the trend in humanitarian aid amounts recorded in the Financial Tracking Service (FTS) from 2017 to 2022, distinguished by final ADM1 destination detection status. The solid black line represents aid amounts with no specific final destination region detected, while the dotted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

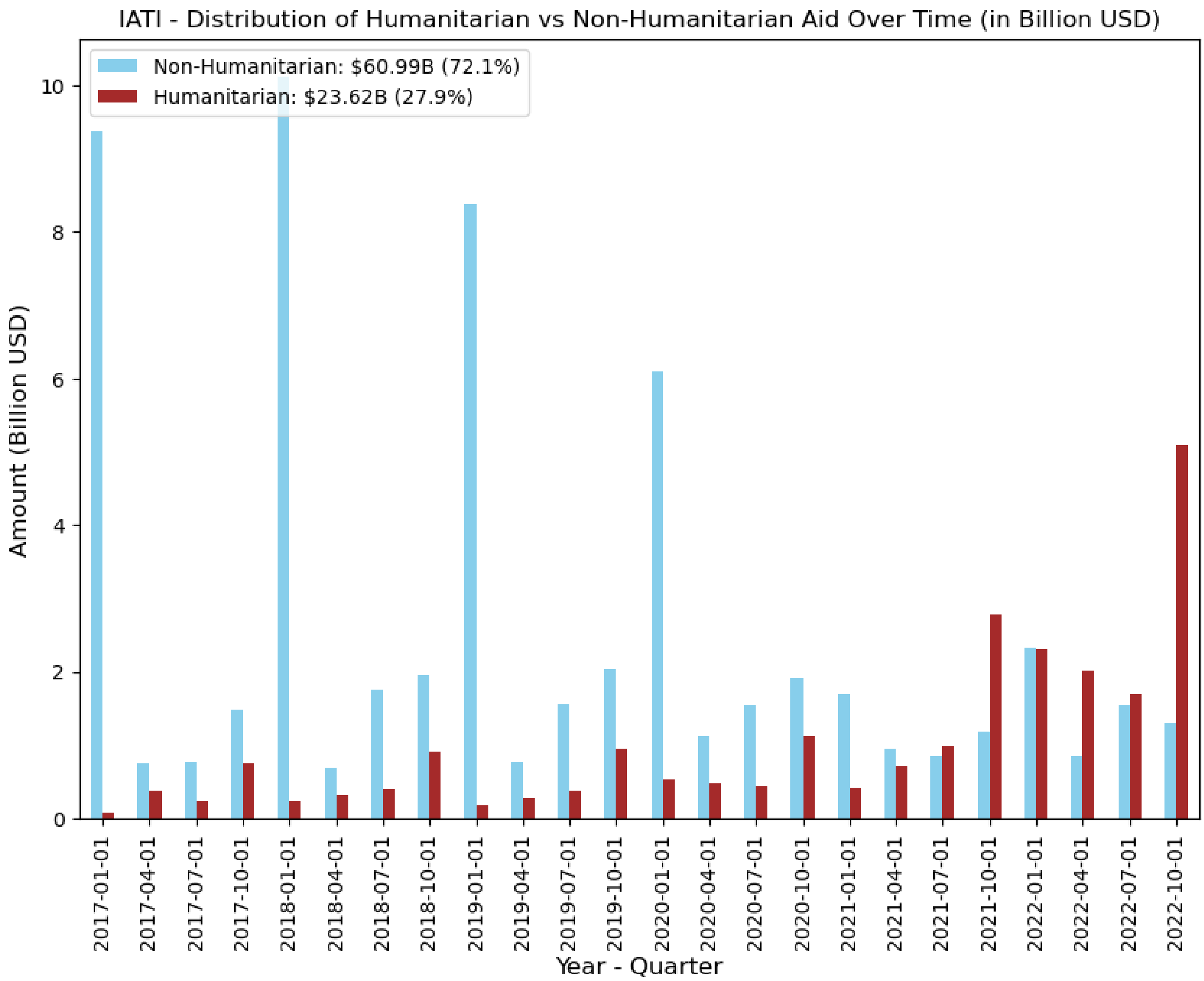
Note: This table presents the performance of an NLP model in predicting keywords for humanitarian aid transactions based on description text. The table includes precision, recall, and F1-scores for each aid category. Although the model shows high recall for "Food Security," meaning it rarely misses true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

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



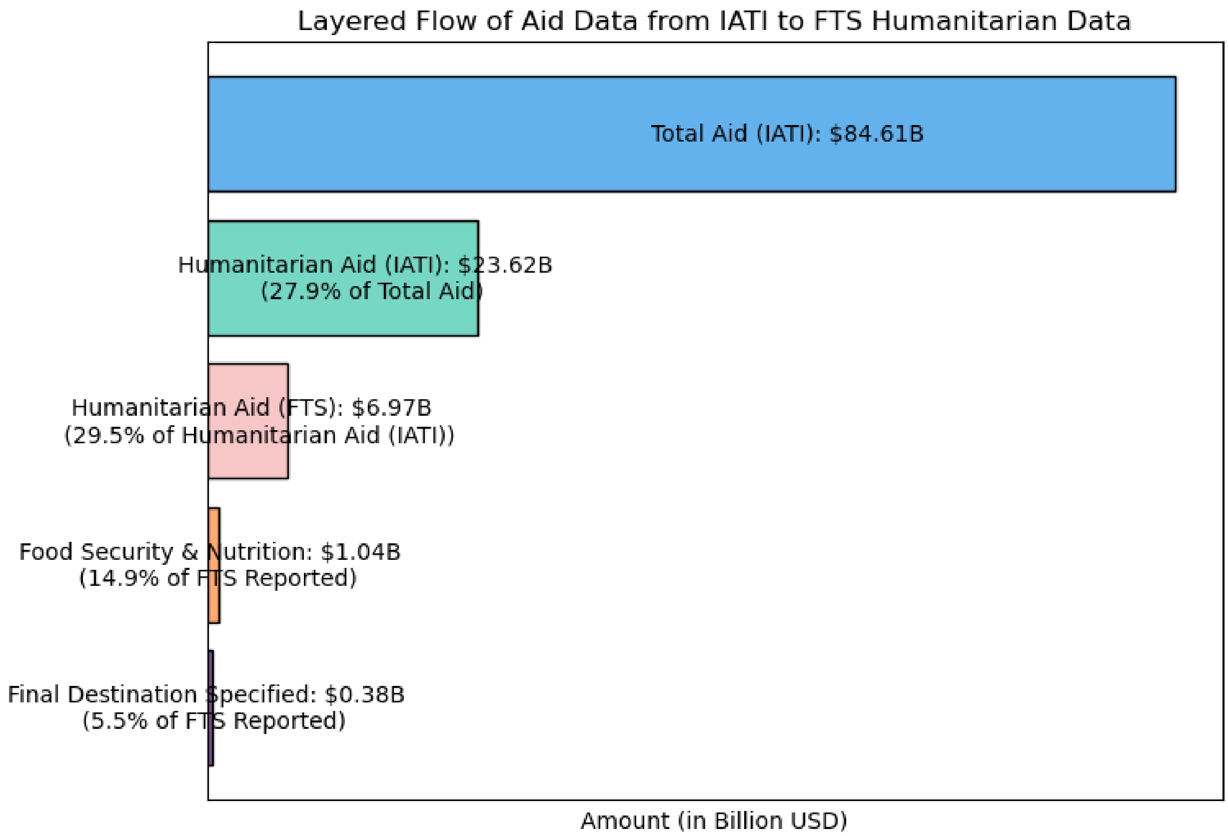
Note: The confusion matrix shows the performance of the classification model across various humanitarian aid categories. The model demonstrates high accuracy for the **Food Security** category, with 160 correct predictions. However, other categories frequently misclassify into **Food Security**, likely due to overlapping terminology in transaction descriptions or a high frequency of "Food Security" labels in the training set. Categories like **Coordination and Support Services**, **Emergency Shelter and NFI**, and **Water Sanitation Hygiene** are commonly misassigned to "Food Security," while less common categories, such as **Education** and **Protection - Child Protection**, show low classification accuracy. This pattern suggests a need for refining the training dataset or adjusting the model to reduce bias toward frequently occurring categories and improve differentiation for underrepresented categories. ◁ Back

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



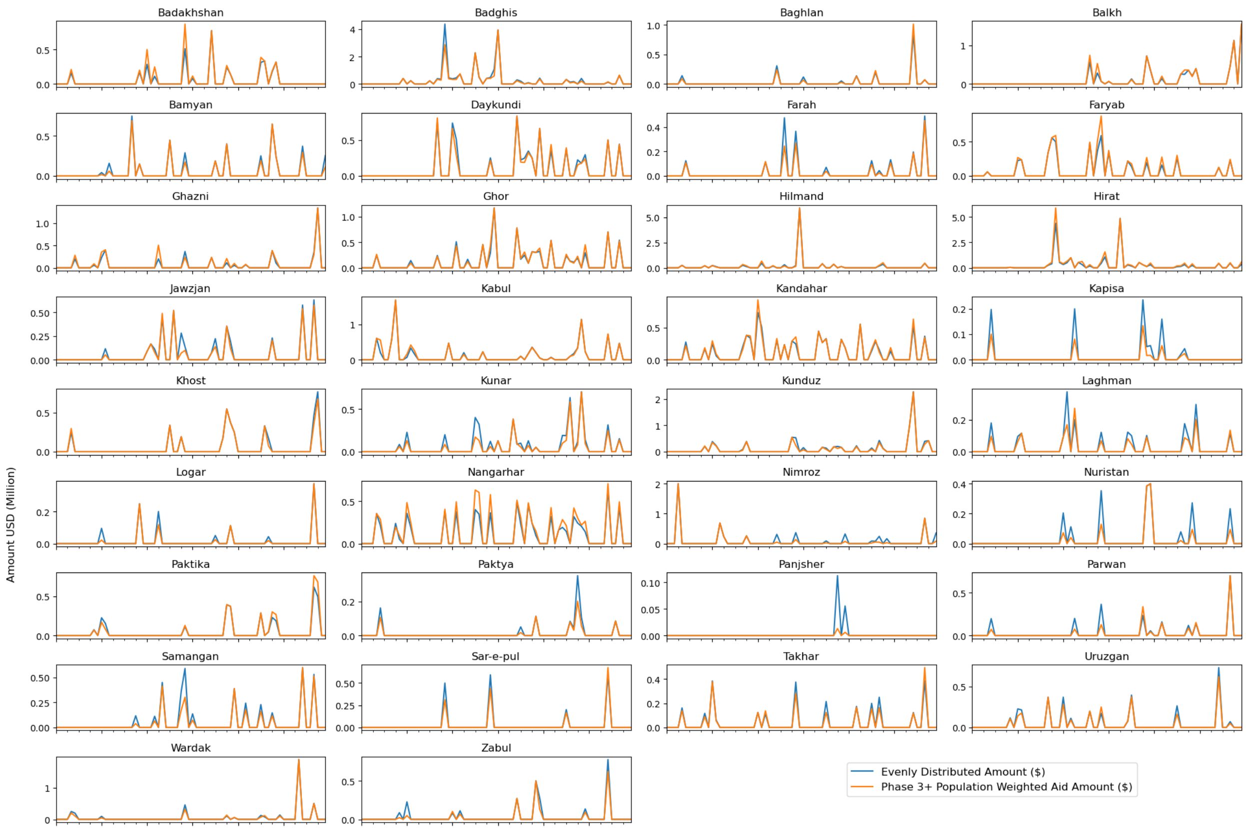
Note: This figure illustrates the trend in international aid distribution in Afghanistan, as tracked by the International Aid Transparency Initiative (IATI) from 2017 to 2022, differentiating between humanitarian and non-humanitarian aid. ◃ Back ◃ Appendix Back

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