Temperature Shocks and Health System Resilience: Evidence from the Supply Chain in Ghana*

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Abstract

This paper examines how extreme temperatures affect the operational capacity of a national health system by tracking facility-level demand for medical inputs in Ghana. We leverage a high-frequency panel of on-demand aerial deliveries to more than 2,700 facilities and link each facility's orders—volumes, emergency status, and product composition—to local monthly temperature exposure. Using a two-way fixed-effects approach, we show that heat spikes raise overall resupply demand and, importantly, increase the share of deliveries triggered by stockouts across all facility types. Mid- to high-tier facilities exhibit a contemporaneous rise in deliveries for critical patients. Product-level patterns indicate that heat primarily drives up demand for storable consumables such as fluids, while categories not directly heat-sensitive (e.g., family-planning supplies) remain flat. The total order counts tend to recede in the months after a heat shock, yet the stockout share persists—especially at higher-level facilities—consistent with inventories being drawn down by sustained caseloads and replenished via just-in-time resupply. We further document that consecutive months of extreme heat amplify stockout rates. Taken together, these results provide system-wide, facility-level evidence that temperature shocks transmit quickly through the supply chain, and shed light on the operational vulnerabilities of health systems under climate stress and the need to strengthen supply chain resilience as an adaptation strategy.

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1 Introduction

Climate change is reshaping the demand placed on health systems. Heatwaves, droughts, floods, and heavy rainfall are linked to excess mortality and morbidity (Vicedo-Cabrera et al., 2021; Abir et al., 2025; Campbell-Lendrum et al., 2023; Carleton et al., 2022), and strain the logistics that move medicines, vaccines, and blood to patients (Ebi et al., 2021). When extreme weather increases the incidence of heat-related illness, respiratory distress, vector-borne disease, or injuries, immediate pressure appears first as surges in requests for specific medical products and emergency deliveries, not only as downstream patient outcomes. Understanding this short-run, supply chain margin is essential for climate adaptation, as it is the margin that health ministries can anticipate, prepare for, and finance.

A large body of literature documents the links between adverse weather and health outcomes or spending, especially in low and middle-income countries (LMICs) where households face overlapping shocks and limited coping capacity (Abiona, 2017; Amondo et al., 2023; Freudenreich et al., 2022; Meierrieks, 2021; Ansah et al., 2021). Yet, most empirical work observes consequences after reaching patients (clinic visits, morbidity, mortality) or infers demand indirectly from administrative treatment records for a subset of drugs (Abir et al., 2025; Jhung et al., 2007; Klauber et al., 2021; Howe et al., 2008; Burchardt and Ameso, 2024; Gangwal et al., 2019; Demuyakor, 2020). We know far less about how weather shocks lead to increasing re-supply orders for medical inputs and the operational frictions that follow, including stockouts, emergency resupplies, and product-specific spikes. This gap in the literature limits the design of targeted preparedness policies (e.g., dynamic inventory rules, temperature-triggered routing, or pre-positioning of cold-chain items).

This paper addresses that gap by connecting extreme temperature exposure to facility-level demand for medical inputs using novel, granular logistics data. We assemble a panel of the full universe of resupply requests placed by more than 2,700 health facilities in Ghana to an aerial delivery network that has been operating in the country since 2019.[1] The data

[1] Access to this data has been granted under a data use agreement with Zipline, the company that

records at high frequency, each facility's order volume, whether the request was flagged as an emergency, and the composition of products delivered. Merged with monthly measures of local temperature shocks, this panel dataset allows us to estimate how heat affects health centers' demand for medical inputs, characterize which products drive the response, and quantify the persistence of stockout- and emergency-related deliveries over time. Moreover, by observing orders and deliveries directly, we measure climate-induced stress on the health system without the recall error that often affects survey data (Abir et al., 2025).

We implement a panel fixed-effects strategy to estimate the relationship between extreme temperature and health-system outcomes. Specifically, we compare facilities facing different realizations of abnormal temperature while controlling for facility fixed effects (capturing time-invariant differences), calendar-time seasonality, and intra-regional annual trends. To allow flexible, nonlinear responses, we model heterogeneity using equally spaced temperature bins. Standard errors are clustered at the facility level to account for serial correlation within facilities over time.

Our findings show that extreme temperatures meaningfully affect health-system functioning, complementing prior work on climate and health-system stress (Doh, 2024; Codjoe et al., 2020; Copeland et al., 2023; Howe et al., 2008; Wan et al., 2022; Aguilar-Gomez et al., 2025). We quantify the extent to which heat events increase total demand for medical supplies, raise the incidence of emergency deliveries, and trigger stockout-related resupplies. When temperatures spike, mid- to high-tier facilities exhibit a pronounced increase in requests for supplies used to treat ongoing emergencies. Product-level analyses align with previous clinical evidence: facilities in hotter-than-usual areas request more fluids (consistent with dehydration risk), while demand for supplies not directly tied to heat exposure—such as family-planning medications—remains unchanged. We also document dynamics: in the three months after extreme heat, overall order counts tend to fall back, yet the share of stockout-related deliveries persists—especially at higher-level facilities that treat more acute cases.

partnered with the Ghanaian government to provide this aerial-logistics service.

Our contribution is threefold. First, to the best of our knowledge, this paper provides the first system-wide, facility-level evidence linking extreme temperatures to demand for medical inputs, moving beyond patient outcomes and partial treatment records. Second, by exploiting plausibly exogenous temperature variation within a fixed-effects framework, we estimate the magnitude, composition, and timing of heat-induced surges in resupply and emergencies——evidence directly relevant for adaptive inventory management and last-mile routing under climate stress. Finally, by using granular, on-demand information we address recall error issues that are common with survey data. This enables us to document persistence and product specificity in shortages and to compare heterogeneous effects across tiers of a national health system. Taken together, our results underscore that strengthening supply-chain infrastructure is a core pillar of climate resilience and highlight the need to innovate distribution schemes that protect vulnerable populations and prevent widening health disparities.

The rest of the paper proceeds as follows. Section 3 describes the Ghanaian health system, the on-demand aerial logistics platform, and our data. Section 4 details the empirical strategy. Section 5 presents the results, and Section 6 discusses implications for policy and operations. Section 7 concludes.

2 Context

2.1 The Ghanaian Health System

Ghana's health system operates under the stewardship of the Ministry of Health (MoH), which is the policy-making and regulatory body for healthcare in the country (Saleh, 2012). Operational functions are largely delegated to the Ghana Health Service (GHS), an autonomous body charged with implementing national health policies and managing the bulk of public health service delivery in collaboration with five independent teaching hospitals.

The GHS is structured along both administrative and functional hierarchies. The administrative structure comprises national, regional and district levels, while the functional extends further down to sub-district and community levels. Each regional and district office of the GHS oversees corresponding health facilities, which include regional and district hospitals, health centers, and community-based health planning and services (CHPS). The system comprises over 1,800 health facilities at different levels of care, of which almost 50% are government-owned. The rest are privately-owned facilities (Saleh, 2012).

Health facilities in Ghana are tiered hierarchically, such that each is responsible for more severe and complicated health conditions. The system begins at the Community Health Planning and Services (CHPS) compounds, which are set up as the first line of care and are required to provide healthcare for minor illnesses and preventative care. If a patient presents with a more serious condition, they must be referred to a district health center (providing preventive and basic curative care), which can then be subsequently referred to a district or regional hospital (offering primary and emergency services as well as referrals), or to a teaching hospital, depending on the needs of the patient. In parallel, Ghana also maintains a diverse mix of private, quasi-governmental, and specialized hospitals to complement public service provision.

An important pillar of Ghana's healthcare delivery is the National Health Insurance Scheme (NHIS), launched in 2003 to provide financial risk protection and improve access to health services. The NHIS covers a broad set of services, including outpatient care, hospitalizations, maternity services, and treatment for common diseases. It is financed through a combination of payroll taxes, levies, and premiums, with exemptions in place for vulnerable populations such as children under 18, the elderly, and pregnant women. While the NHIS has substantially increased access to care, challenges remain. These include delays in provider reimbursement, fragmentation of service delivery, and coverage gaps for certain medications or specialized treatments, which can reduce its effectiveness and sustainability.

Another defining feature of Ghana's health governance is its ongoing decentralization process, aimed at transferring authority and resources to local governments and district health administrations. The reform's implementation has been uneven. While CHPS compounds embody the ethos of decentralized service delivery, their ability to meet local needs depends significantly on support from district assemblies and the broader health system infrastructure.

Taken together, Ghana's health system reflects a hybrid model of centralized policy-making and decentralized service delivery. While considerable progress has been made in expanding access and financial coverage, systemic constraints related to governance, financing, and logistics remain. These challenges are particularly salient in the context of external stressors such as climate-induced weather shocks, which can exacerbate service delivery disruptions and test the resilience of an already stretched system.

2.2 On-Demand Aerial Logistics System

Health supply logistics in Ghana are handled by a Centralized Medical Store (CMS), which distributes health supplies to ten Regional Medical Stores (RMS) for final delivery to health facilities in the country. These RMS facilities are responsible for further distribution to district medical stores (DMS), which in turn, deliver the supplies to their serviced health facilities every few months by car or motorcycle.

Parallel to this traditional last-mile distribution system, Ghana has an on-demand aerial logistics system to deliver essential medicines and emergency supplies promptly. This system is part of a public-private partnership with Zipline, a company that offers end-to-end aerial logistics for the delivery of vaccines and small health supplies in several low and middle-income countries.[2]

This logistics system is comprised of six distribution centers (DCs) located across different regions of the country, each of which has a warehouse, a call center, and a launching platform for launching Unmanned Aerial Vehicles (UAVs) with health supplies to health facilities.[3]

[2]Zipline first began its operations in Rwanda delivering blood in 2016, and since then, it has expanded to Ghana, Nigeria, Côte d'Ivoire, Kenya, Japan, and the United States.

[3]In the Fall of 2023, the company switched to a model of a centralized call center to align procedures

Most of the medical supplies distributed through this system are regularly sourced from the RMS and stored in the DCs to facilitate rapid response to requests. Supplies can be delivered to any health facility within a 90km radius from the distribution center, and facilities can make requests over phone, text, or WhatsApp.

Currently, this aerial system services more than 2,700 health facilities in the country, including CHPS, health centers, and district hospitals. Each type of health facility has a different list of supplies that can be requested through the system, which is determined by the complexity of the services it provides. For example, since CHPS are designed to focus on preventive treatments, they are not allowed to request blood or any other equipment to perform blood transfusions.

While the main appeal of this aerial system is the rapid speed of delivery during emergencies, health facilities often use it for scheduled replenishment of supplies or during stockouts. In fact, according to semi-structured interviews with health providers, reliability and preservation of product quality are other positive attributes of this system.[4] There are also several facilities that receive the majority of their supplies through this system during certain times of the year or even regularly, as drones can still deliver to places that are impossible to reach during flooding or with limited road infrastructure.

3 Data and Study Population

We put together a dataset of health facilities using data from two main sources. The administrative records of Ghana's aerial supply logistics and the MODIS Terra Satellite system from NASA. This dataset displays a panel structure with information at the facility-month level for the years 2019-2023. Health facilities are distinguished by type: CHPS, health center, and hospital.

regarding best practice when handling edge cases or complaints. This unique center is located in Omenako, where mobile and internet networks are reliable.

[4] These interviews were conducted in-person by the research team in March of 2024.

3.1 Data

Demand and delivery of medical supplies: We use administrative records from an aerial supply logistics system to construct measures of demand and delivery of medical supplies. This data was obtained through a data user agreement with Zipline, the private company that contracts with the national government to provide this service in the country, and it contains the universe of re-supply requests by all the health facilities it has served since the start of operations in 2019. For each request, we have information about the request's date and time, the name and GPS location of the facility that made the order, the type of facility, and the distribution center that was contacted. For fulfilled requests, we also have information on the time and duration of delivery, the type of supply and quantity requested, and whether the supplies were needed due to a current stockout or medical emergency.[5] To be consistent with the temperature measures, we aggregate this data at the facility-monthly level and for each pair, compute three main sets of outcomes: the total number of re-supply requests, the proportion of deliveries that were needed to manage a stockout or medical emergency at the health facility, and the proportion of deliveries by type of supply.

One of the main advantages of using data from this electronic on-demand delivery system as a source of re-supply requests is that it is less prone to the measurement error that arises with survey data due to incorrect recall or recording issues. Moreover, since we have information about the total number of re-supply requests regardless of whether they were fulfilled or not, this outcome constitutes a measure of total demand. In contrast, we interpret the outcomes on deliveries by type of supply and need as a lower bound on total demand, as this information refers only to fulfilled orders. Moreover, we recognize that the administrative records in our dataset only account for about 30% of the demand and deliveries of supplies for the total population in Ghana, given that the country counts with about 9,400 health facilities in total (as of 2022). Therefore, we acknowledge that our results account for a

[5]Some of the reasons why requests go unfulfilled include the stockout of region-specific supplies at Zipline's warehouse and lack of compliance with national restrictions about the type of products that can be requested by facilities that are not equipped to manage complex medical situations.

modest share of the complete supply-chain system.

We summarize the distribution of this data in Section 3.2.

Temperature: We calculate measures of maximum temperature data in the surrounding areas of each health facility using data from the MODIS Terra satellite from NASA, the GPS location of the health facilities, and administrative shapefiles of Ghana. The MODIS Terra satellite provides information on land surface temperature with a frequency of every one day at a pixel resolution 1000 meters. Thus, to make sure we had full geographic coverage, we created monthly composites of the data using around six images per month and facility's buffer zone. Our analysis uses a buffer zone of 25km around every health facility.[6]

3.2 Sample of Health Facilities

The study population in this analysis consists of 2,781 health facilities across 15 regions of the country. Of these, 49% are CHPS, 42% are health centers, and 5% are hospitals. Figure 1 displays the location of these facilities with the Regional Medical Stores and each of the six distribution centers (DCs) that are part of the aerial logistics system. These facilities are scattered around several regions of the country, and virtually all of them lie within the 90km operational radius of each DC. The median Euclidean distance between these facilities and their closest DC is roughly 60km, and half of the supplies requested through this aerial system have been delivered in under an hour (see Figure 2).

The aerial system managed by Zipline has received a total of almost 200,000 requests since its launch in Ghana. The median number of monthly requests by facility over the course of the dataset was 236, and most of them came from CHPS facilities, followed by health centers and then hospitals. Figure 3 shows the number of requests to each distribution center. Distribution centers 5 and 6 only became operational in 2021. The majority of the deliveries originate from GH3 and GH4, which are located in areas that may be more susceptible to infrastructure challenges. In contrast, GH1, despite being the distribution

[6]In future versions of this draft, we will examine the robustness of the results to different buffer sizes.

center closest to Accra, handles a comparatively smaller volume of deliveries.

Zipline's data also provides detailed information on delivery priority and on cases where deliveries were requested due to stockouts. As shown in Figure 4 stockouts occur most frequently at Health Centers and CHPS facilities, primarily due to shortages of vaccines. Around September 2022, other critical medical inputs, such as saline fluids used to treat dehydration from various diseases, also experienced notable stockouts. Supplies related to animal bites and mosquito-borne diseases, including anti-venom and anti-malarial medications, likewise showed nontrivial shortages. It is worth noting that the incidence of snake bites and malaria can increase following flooding, which boosts mosquito populations, as well as during periods of intensified agricultural activity — both of which are likely to rise in the aftermath of weather shocks.

The data also indicates whether a delivery is intended for a patient in critical condition, in which case the delivery is expedited. As shown in Figure 5, most critical patient requests originate from health centers, which are typically larger facilities receiving patients referred from CHPS. These urgent deliveries most often involve fluids or treatments for snake bites and mosquito-borne illnesses, such as anti-venom and anti-malarial medication.

Figure 6 displays the average and variance of the maximum temperature around each facility's buffer during the period of study, illustrating the variation in temperature across regions and across time.

4 Empirical Strategy

We conceptualize Zipline delivery data as the outcome of an equilibrium between demand for health services and supply of health services. On the demand side, health service use is shaped by factors that influence population health and wellbeing, such as socio-economic status, genetic predisposition to disease, and occupation. These factors can increase the likelihood of a health shock following a temperature shock, conditional on unobserved household characteristics (denoted by "U").

On the supply side, health service provision depends on all factors involved in treating a patient ("Hospital Functioning"). This includes: (1) facility-level capacity, such as the patient–doctor ratio, the seniority and expertise of staff, and the ability to prescribe or refer patients to higher-level facilities, and (2) the availability of medical supplies and medications, where Zipline plays a role in enabling timely delivery to health centers.

Weather shocks can plausibly affect either or both channels. We hypothesize, however, that higher average maximum temperatures will increase patient volume at health centers, straining the health system, whether it be from higher demand for services or lower capacity from the supply-side. This strain may increase the incidence of stockouts and, consequently, stockout-related deliveries by Zipline.

We also examine whether higher temperatures are associated with more critical patient deliveries. Due to the tiered structure of Ghana's health system, lower-level CHPS facilities rarely classify deliveries as critical, since such patients are usually referred to higher-level facilities. Any relationship between temperature shocks and critical deliveries is more likely to appear in higher-tiered facilities.

Prior evidence suggests that temperature shocks may increase deliveries of specific medical goods. Zipline's data identify the type of good delivered, enabling us to test this directly. For example, higher temperatures may increase demand for treatments related to respiratory distress, malaria, or snake bites, particularly during the planting season. In contrast, some goods, such as vaccines, or family planning supplies are unlikely to be temperature-sensitive in this way, making them useful for falsification tests.

We follow a specification similar to Aguilar-Gomez et al. (2025):

$$y_{iht} = \sum_{j=1}^{E} \gamma_j^t B_{jht} + \sum_{j=1}^{E} \gamma_j^{t-1} B_{jht-1} + \alpha_h + \alpha_m + \alpha_{ry} + \varepsilon_{dt} \tag{1}$$

where y is the outcome of the delivery request i made by facility d at time t. B_j^t and B_j^{t-1} are indicators for the jth bin of contemperaneous average maximum temperature and one month lagged average maximum temperature. To allow for heterogeneity in temperature effects, we utilize equally-spaced bins of three degrees Celsius, using the median bin of 31-34 degrees Celsius as the reference category. α_h are health facility fixed effects. α_m are month-of-year fixed effects to capture seasonality; and α_{ry} are region-by-year fixed effects to account for intra-regional annual trends. ε is an idiosyncratic error. Standard errors are clustered at the health facility level to account for potential correlation within facility across time.

5 Results

This section presents results along two main dimensions. The first focuses on supply chain logistics, measured by: (1) the number of re-supply requests, (2) the proportion of deliveries marked for critical patients, and (3) the proportion of deliveries triggered by stockouts at the health facility. The second examines delivery categories, specifically the proportion of deliveries consisting of: (1) respiratory-related medication, (2) family-planning-related medication, and (3) fluids. Respiratory-related medication includes treatments for asthma, allergies and tuberculosis. Family-planning-related supplies comprise products such as oral and external contraceptives, intrauterine devices (IUDs) and related medications. Fluids generally refer to saline solution and similar products used in a variety of medical contexts, including treatment for dehydration, fever or severe illness.

We expect some of these outcomes to be sensitive to extreme temperatures, while others can serve as a falsification test. We hypothesize that CHPS facilities should not experience a change in the proportion of critical deliveries, given their role in Ghana's tiered health system, where patients requiring critical care are referred to higher-level facilities. Similarly, we do not anticipate a strong relationship between extreme temperature and the use of contraceptives or other family-planning supplies.

In all figures and tables, we only show the contemporaneous effects of temperature, as in

Aguilar-Gomez et al. (2025) and to highlight the current stress caused by temperature on the health system. Figure 7 shows a coefficient plot of the results of our main specification (Equation 1), showing the effects of contemporaneous temperature bins. We estimated three models: (1) pooling all facilities, (2) CHPS facilities only, and (3) health centers and hospitals (HC/HSP) only.

For the total number of re-supply requests, we found that the lowest temperature bin had a negative effect on deliveries only for CHPS facilities. Compared to our reference of bin of $31-34°C$, there was no statistically significant effect until the highest temperature bin. In general, all facilities had 14 more deliveries as a result of extreme temperatures of more than $49°C$.

For the proportion of critical deliveries, there was no statistically significant effect for any facilities except the highest temperature bin, where health centers and hospitals saw an increased proportion of critical deliveries by 3.1%. This was not the case for CHPS facilities, which aligns with our expectations of how the Ghanaian health system works and are a statistically insignificant -.8%.

The proportion of stockout deliveries exhibited more heterogeneity. There was a clear trend downwards for temperature bins from $37°C$ until $46°C$. However, with higher temperature, there was a clear upward trend in the proportion of stockout deliveries for all types of health facilities. For all health facilities, the proportion of stockouts increased by 10%, with health centers and hospitals increasing by even more, 11.4%.

Moving now towards Figure 8, we tested the effects on the proportion of deliveries of respiratory-related medication, family planning medication and fluids. The proportion of family planning medication was not statistically significant for any temperature bin. In the case of respiratory-related medication, there was a statistically significant negative effect from health centers and hospitals for the highest temperature bin of -2%. For fluids, there was a large positive effect at the highest temperature bin for all facilities, but it was even higher for CHPS facilities at 19%.

6 Discussion

The results presented in Section 5 provide suggestive evidence that extreme temperatures exert a measurable and significant impact on the functioning of the health system. This is most clearly demonstrated by distinct patterns observed in the highest temperature bins, which differ markedly from those in lower temperature ranges. In fact, across nearly all model specifications, lower temperature bins show no statistically significant effects on the number of re-supply requests, the proportion of deliveries for critical patients, the prevalence of stockouts, or the types of goods delivered. This divergence underscores that it is not simply temperature variation, but specifically extreme heat events, that create measurable disruptions to health system operations.

The findings make it clear that the health system is not only affected but, in many cases, placed under considerable strain during periods of extreme heat. Importantly, the effects are not uniform across facility types, suggesting that institutional role and capacity shape vulnerability to climate stressors. For example, health centers and hospitals consistently show a higher proportion of deliveries designated for critical patients under extreme temperatures. Several plausible mechanisms could explain this pattern. One possibility is that extreme heat increases the incidence of acute medical conditions, such as severe dehydration, heat stroke, or respiratory distress, that require urgent intervention. This mechanism is supported by the results for CHPS facilities, where both the total number of deliveries and the share of fluid deliveries increase under extreme temperatures, reflecting a higher need for rapid response to dehydration and related conditions.

However, the pattern for health centers and hospitals is distinct. In these higher-tiered facilities, extreme heat does not lead to an overall increase in request volume but rather alters the composition of deliveries. This suggests that patient inflows to these facilities during extreme heat are more likely to involve acute, severe cases that require specialized treatment, rather than simply a greater number of patients. In other words, the stress on these facilities may be more qualitative (linked to the severity of cases) than quantitative.

Our use of this novel panel dataset of on-demand deliveries is critical for uncovering such dynamics. Without it, it would be difficult to obtain a real-time, granular view of how the Ghanaian health system responds to environmental stressors such as temperature shocks. This is particularly relevant in the context of low- and middle-income countries, where health supply logistics are frequently hindered by outdated infrastructure, fragmented supply chains, and limited resources for coordinated distribution. The results show that extreme heat consistently increases the proportion of stockout-related deliveries across all facility types. This finding indicates that under climate-induced stress, essential medical supplies are depleted more quickly, triggering an increased need for rapid replenishment.

A question that we are uniquely able to answer is the question of the dynamic nature of these deliveries. Previous work has commented on the ability of a health system to adjust after natural disasters (Suchman et al., 2018; Codjoe et al., 2020). More often than not, due to the nature of emergencies, data collection is not possible or not a priority. Particularly in the case of Ghana, others have written using ethnographic or qualitative work that floods and other extreme weather conditions can lead to severe shortages of medical supplies (Doh, 2024).

Our data allows us a high frequency view of how these shocks affect the stockouts and emergency deliveries, and we can quantify the time it takes for a health system to adjust after extreme weather events such as the temperature shocks we study in this paper. To explore this, we use a modified version of Equation 1:

$$y_{iht} = \sum_{j=1}^{E} \gamma_j^{t} B_{jht} + \sum_{j=1}^{E} \gamma_j^{t-1} B_{jht-1} \tag{2}$$

$$+ \sum_{j=1}^{E} \gamma_j^{t-2} B_{jht-2} + \sum_{j=1}^{E} \gamma_j^{t-3} B_{jht-3} \tag{3}$$

$$+\alpha_h + \alpha_m + \alpha_{ry} + \varepsilon_{dt} \tag{4}$$

where we now use three lags for each temperature bin. This specification allows us to see how each temperature bin's effect changes up to three months after the onset of the extreme shock.

Figure 9 shows the results of this regression. For ease of interpretation, we only show the lowest and the highest temperature bin. The lowest temperature bin can be interpreted as "business as usual" case where there is no stress on the health system due to temperature-related shocks. The rows of the figure show each outcome discussed in Figure 7 and the columns break the effects by each health facility type.

We find that deliveries flagged as "emergencies" show little systematic response to extreme temperatures, aside from the contemporaneous reaction at hospitals and health centers (Figure 7). By contrast, the main reaction shifts are on stockout-related deliveries and the total number of requests. Although total order volume declines over the subsequent three months (15–20 fewer requests per facility), the share of deliveries coded as stockouts rises at the time of the shock (about 12%), remains elevated one month later (about 3%), and for hospitals and health centers ticks up again three months after the shock (about 5%). Product-level patterns are consistent with this interpretation: facilities draw down storable consumables (e.g., fluids, antipyretics) more rapidly during heat episodes, while demand for items not directly heat-sensitive (e.g., family-planning medications) remains flat.

Taken together, these results suggest sustained pressure on facility inventories of routine, storable inputs, rather than large, heat-driven spikes in lifesaving emergency items (e.g., blood). We view this less as a blanket failure to adapt and more as evidence of an operational resilience indicator: facilities lean on Zipline for just-in-time replenishment when heat drives up caseloads. The persistence of stockout-coded deliveries at higher-tier facilities likely reflects constrained on-site buffer capacity for heat-sensitive consumables.

Alternatively, this persistence across time speaks to the inability of the health system to recover quickly after a temperature shock, which has implications for health policy. This is in contrast to settings in more developed economies where disaster relief agencies and existing infrastructure can pick up the slack during recovery (Howe et al., 2008) in days to weeks. This is even more critical as higher-level health facilities show more persistent stockout rates across time, where patients are often more critical and need more emergent care.

What is more troubling is the fact that more numerous onsets of extreme temperature can lead to larger effects on stockouts. We construct a variable on the number of consecutive months of extreme temperature shocks for a given health center and run the following regression:

$$y_{iht} = \beta CumExt_{ht} + \alpha_h + \alpha_m + \alpha_y + \varepsilon_{dt} \tag{5}$$

where $CumExt$ is a variable for the number of consecutive month of a temperature shock of more than 46 degrees Celsius. We also only use year fixed effects in this regression to avoid multicollinearity. We find that a larger number of consecutive shocks increase the proportion of stockout deliveries by 3%. This is shown in Table 1.

As temperatures rise and the onset of extreme temperature becomes more prevalent, without policy that creates more resilient health systems, delays in medication and treatment can cause large effects on health. Policy levers therefore could include calibrating buffer stocks for heat alerts, trigger-based reordering, and priority routing/pre-positioning during forecasted heat waves—measures that complement (rather than replace) the system's demonstrated use of rapid aerial resupply to absorb climate-induced demand surges.

7 Conclusion

In this paper, we use a novel panel dataset of the demand for medical supplies by health facilities to examine how temperature affects the operational capacity of the Ghanaian health system. We focus on three main outcomes: the total demand for supplies (as measured by the number of on-demand requests), the share of deliveries that are driven by stockouts, and the proportion of deliveries requested to treat ongoing medical emergencies. We find that high temperatures are associated with an increase in total re-supply needs and the proportion of stockout-driven deliveries. Additionally, emergency deliveries increased for health centers and hospitals.

We also analyze the deliveries by type of supplies and find that, consistent with the expectation that high temperatures can elevate the prevalence of severe dehydration, facilities in areas that experience extreme shocks request more re-supply of fluids. In contrast, the need for family planning medications does not change with extreme temperatures, which aligns with our hypothesis and serves as a falsification test.

Our analysis provides insights that can serve as an important indicator of how systems designed to facilitate the delivery of medical supplies, such as aerial supply logistics, may play a critical role in improving health system responsiveness during periods of heightened stress, including those linked to climate change.

Our work contributes to the literature by leveraging novel, granular data to show how a strongly hierarchical health system in an LMIC responds to weather-shock–induced stress, providing clear evidence that extreme temperatures can strain the operational capacity of health systems. This evidence highlights the urgent need to design more efficient allocation schemes for the provision of health supplies. Our findings have direct relevance for understanding health policy, service provision dynamics and logistics in low and middle-income countries, particularly in environments where infrastructure limitations and resource constraints amplify vulnerability to climate extremes.

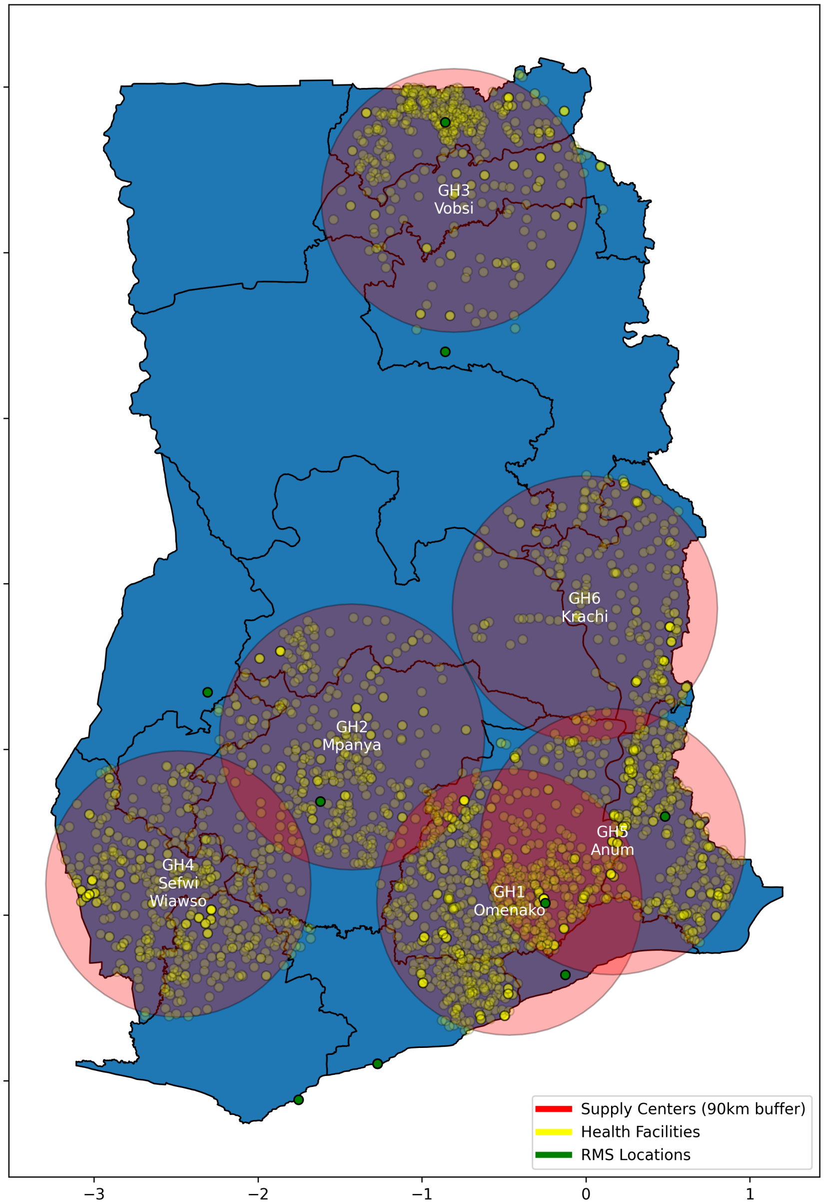
Future work could incorporate other types of weather shocks into the analysis, as different climatic events, such as flooding, drought, or dust storms, may have distinct effects on health system functioning. Another valuable direction would be to merge hospital records and direct measures of health service demand with our delivery data, allowing for a more comprehensive understanding of both the supply and demand sides of the health "market."

Finally, our findings have broader implications for the global conversation on climate adaptation and health system resilience. Extreme weather events are projected to increase in both frequency and intensity as the climate warms, placing mounting pressure on already stretched health systems in low and middle-income countries. The ability to maintain reliable, rapid delivery of essential medical supplies under these conditions is not merely a logistical challenge. Strengthening health supply chain infrastructure is a critical component of climate resilience and public health preparedness to prevent the widening of the existing health disparities and safeguard the well-being of vulnerable populations.

By presenting evidence that highlights potential vulnerabilities in health service delivery under extreme climate conditions, this work underscores the importance of considering mechanisms like innovative delivery technologies, in broader strategies to strengthen supply chain infrastructure. The patterns we identify can inform policymakers and development partners seeking to enhance logistical capacity, reduce health inequities, and safeguard vulnerable populations in an era of accelerating climate risk.

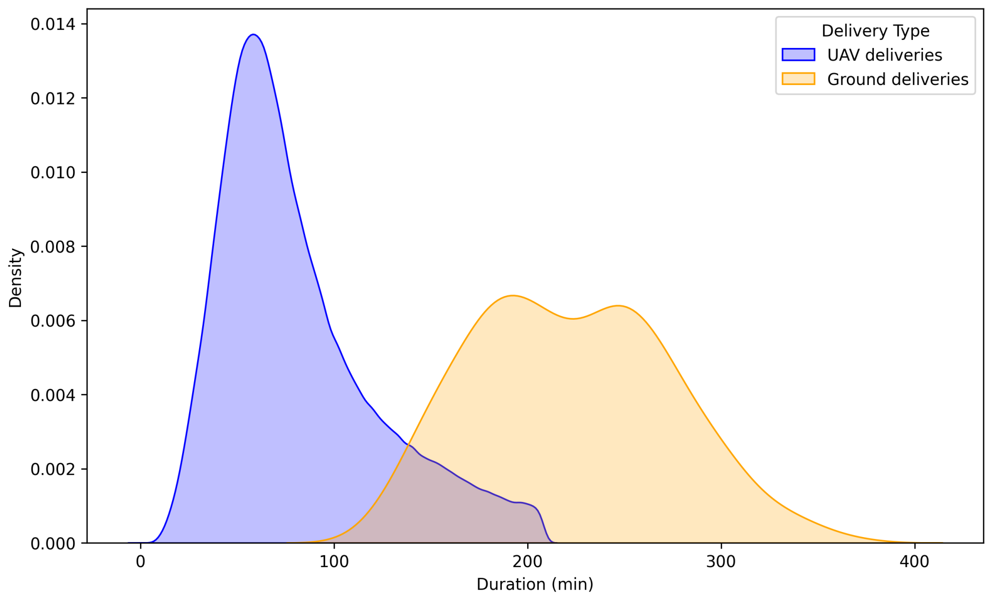
Figures and Tables

Figure 1: Distribution of Health Facilities by Aerial Supply Centers



Notes: Figure shows map of Ghana and the delivery radius of each Zipline distribution center in red. Yellow dots correspond to health centers that have received deliveries from Zipline. Green dots represents Regional Medical Stores.

Figure 2: UAV vs. Ground Delivery Duration to Health Centers



Notes: Figure shows normal kernel densities of delivery duration for Zipline UAV deliveries in purple and ground deliveries in yellow.

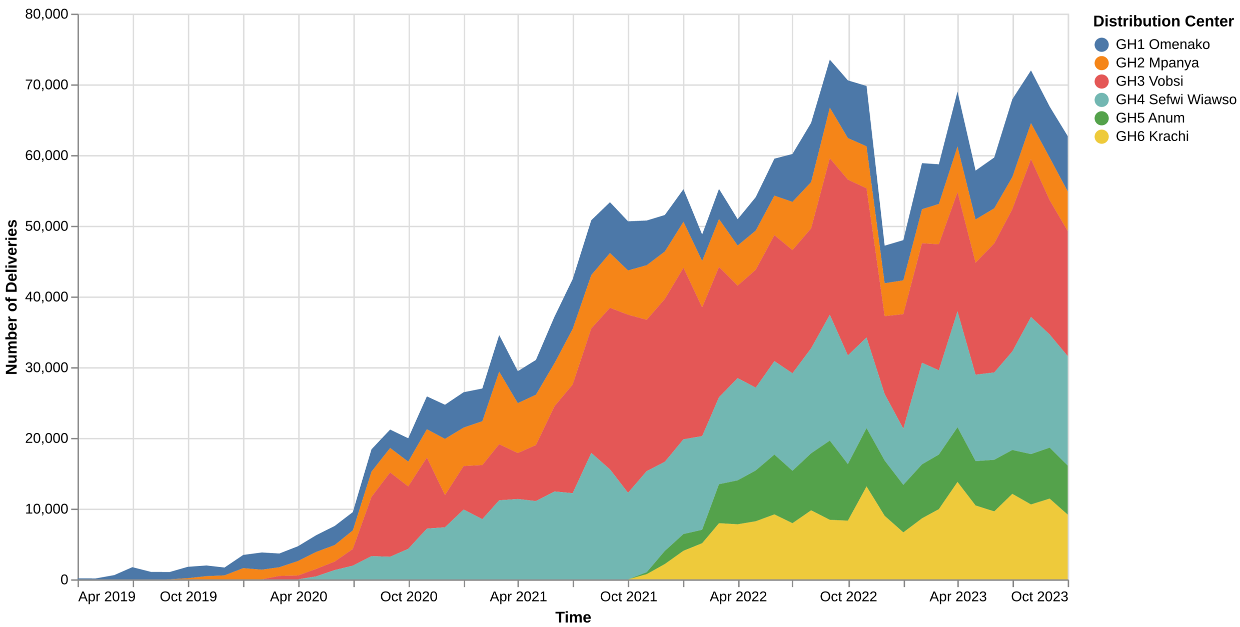
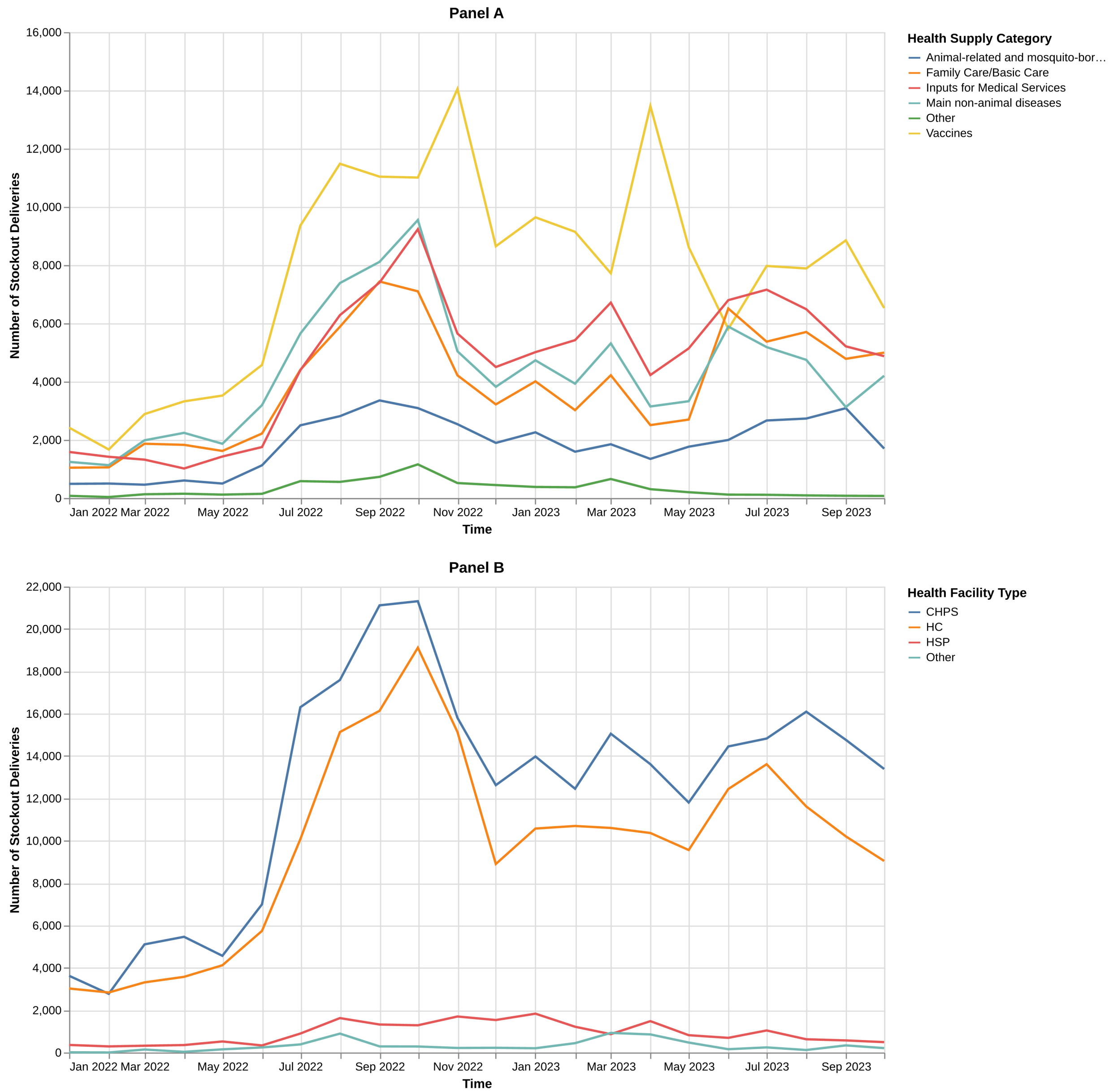


Figure 3: Zipline Deliveries by Distribution Center

Notes: Figure shows the number of Zipline deliveries by Zipline distribution center.

Figure 4: Stockouts by Health Center Type and Health Supply Type



Notes: Panel A of the figure shows the number of deliveries designated as stockouts for a health center, by the category of the supply being requested. Categories in legend were defined as composites of the following categories in the data: "Animal-related and mosquito-borne illnesses": {'Snake bite / rabies', 'Malaria'}, "Family Care/Basic Care": {'Family planning', 'Pregnancy', 'Pain management', 'Vitamins'}, "Inputs for Medical Services": {'Fluids', 'Tests and lab reactants', 'Disposable', 'ER and surgical supplies'}, "Main non-animal diseases": {'TB', 'HIV', 'Diabetes', 'Cardiovascular', 'Gastrointestinal', 'Allergy and cold', 'Antimicrobial', 'Cancer', 'MH and Neuro', 'Asthma'}, "Vaccines": {'Vaccine', 'Vaccine supplies', 'COVID Vaccine'}. Panel B shows the number of deliveries designated as stockouts, by the health facility type: community-based health planning and services (CHPS), Health Centers (HC) and Hospitals (HSP).

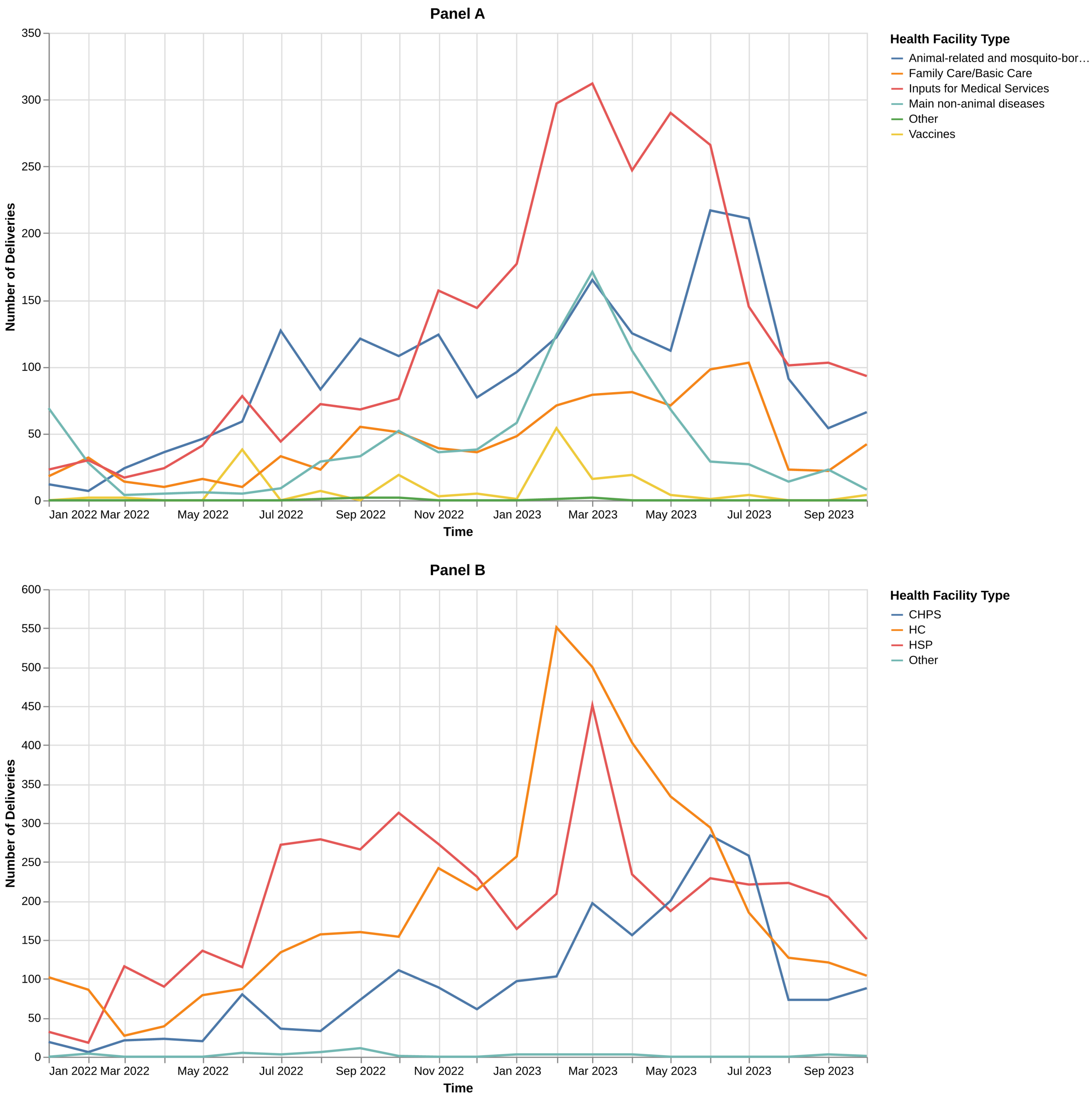


Figure 5: Critical Patient Deliveries by Health Center Type and Health Supply Type

Notes: Panel A of the figure shows the number of deliveries designated for critical patients (emergencies) for a health center, by the category of the supply being requested. Categories in legend were defined as composites of the following categories in the data: “Animal-related and mosquito-borne illnesses”: {’Snake bite / rabies’, ’Malaria’}, “Family Care/Basic Care”: {’Family planning’, ’Pregnancy’, ’Pain management’, ’Vitamins’}, “Inputs for Medical Services”: {’Fluids’, ’Tests and lab reactants’, ’Disposable’, ’ER and surgical supplies’}, “Main non-animal diseases”: {’TB’, ’HIV’, ’Diabetes’, ’Cardiovascular’, ’Gastrointestinal’, ’Allergy and cold’, ’Antimicrobial’, ’Cancer’, ’MH and Neuro’, ’Asthma’}, “Vaccines”: {’Vaccine’, ’Vaccine supplies’, ’COVID Vaccine’}. Panel B shows the number of deliveries designated for critical patients (emergencies), by the health facility type: community-based health planning and services (CHPS), Health Centers (HC) and Hospitals (HSP).

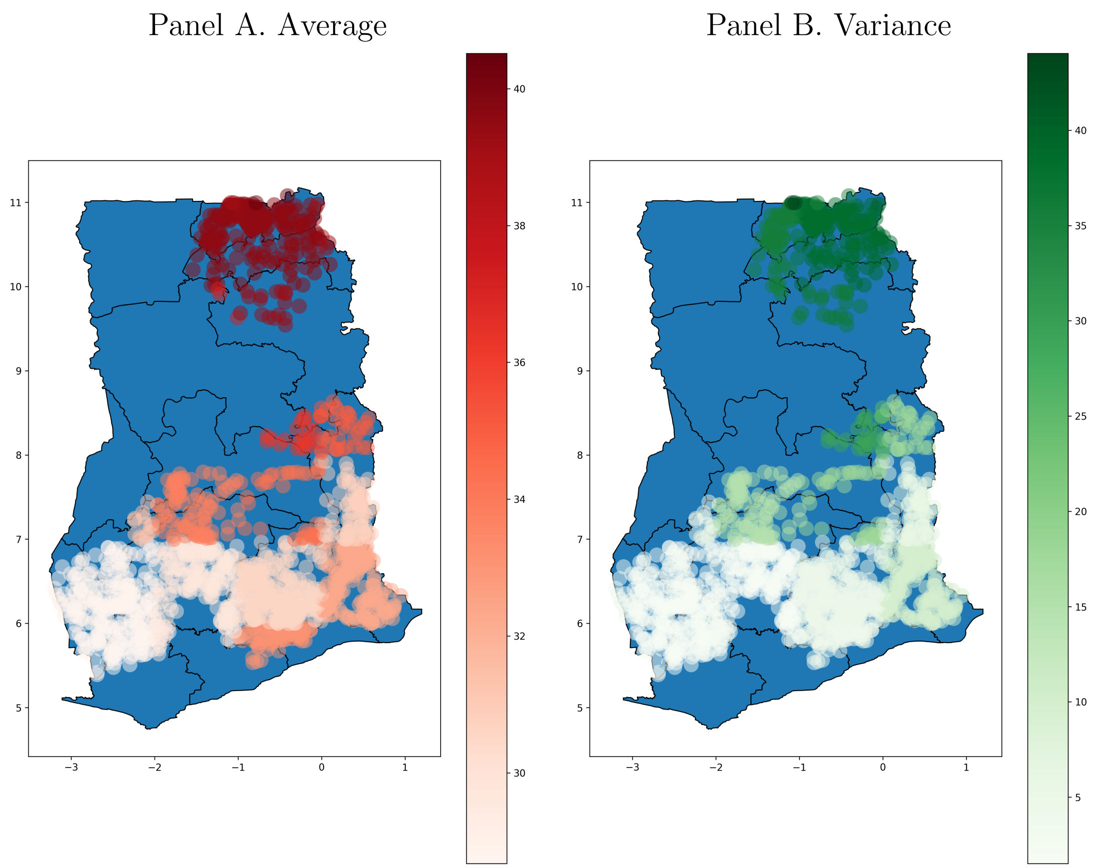


Figure 6: Distribution of maximum temperature Maximum Temperature Across All Months and Years

Notes: Panel A shows a map of Ghana with red-colored points denoting average of monthly average temperatures for each health center. Panel B shows a map of Ghana with green-colored points denoting the variance of monthly average temperatures for each health center.

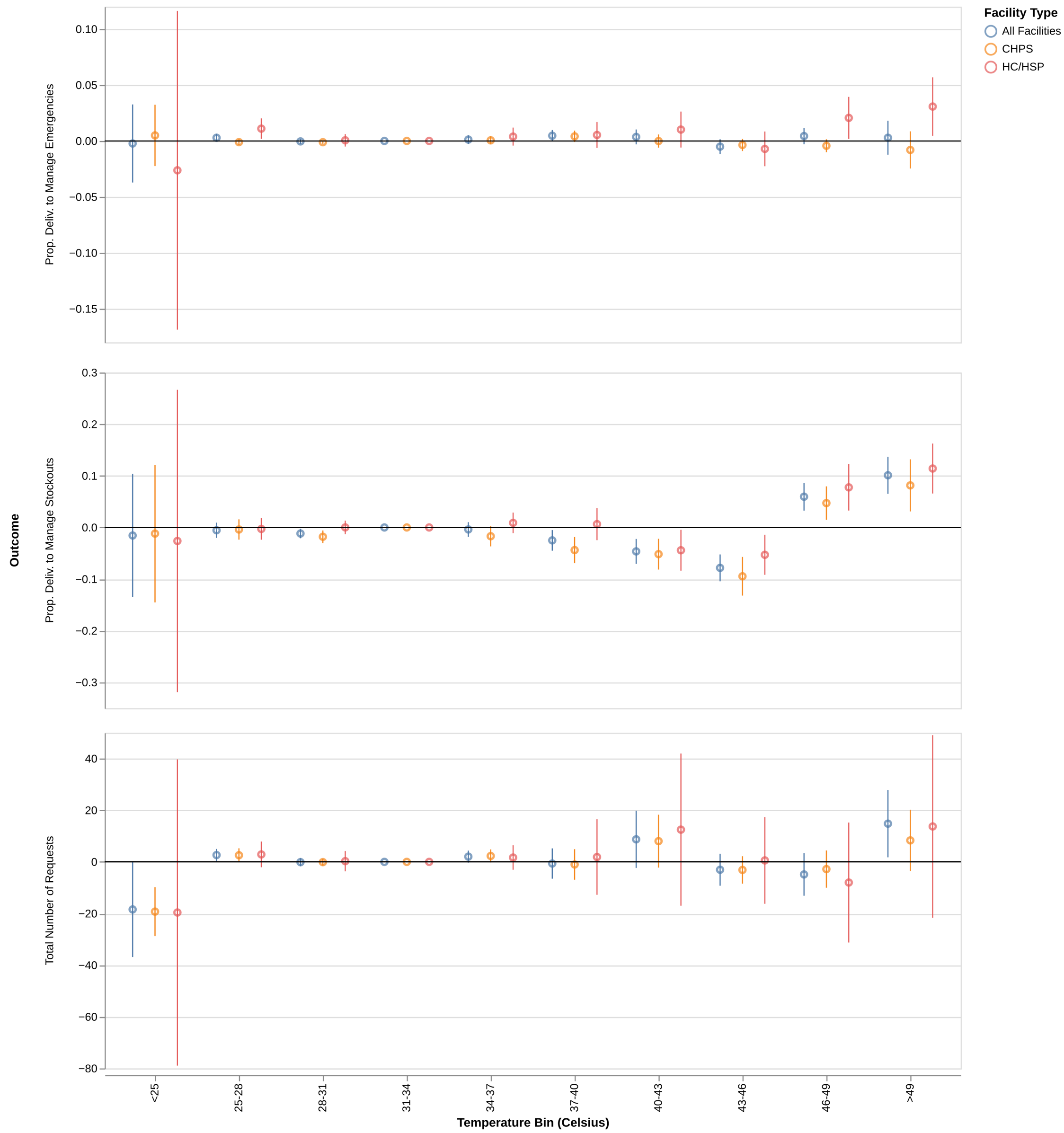
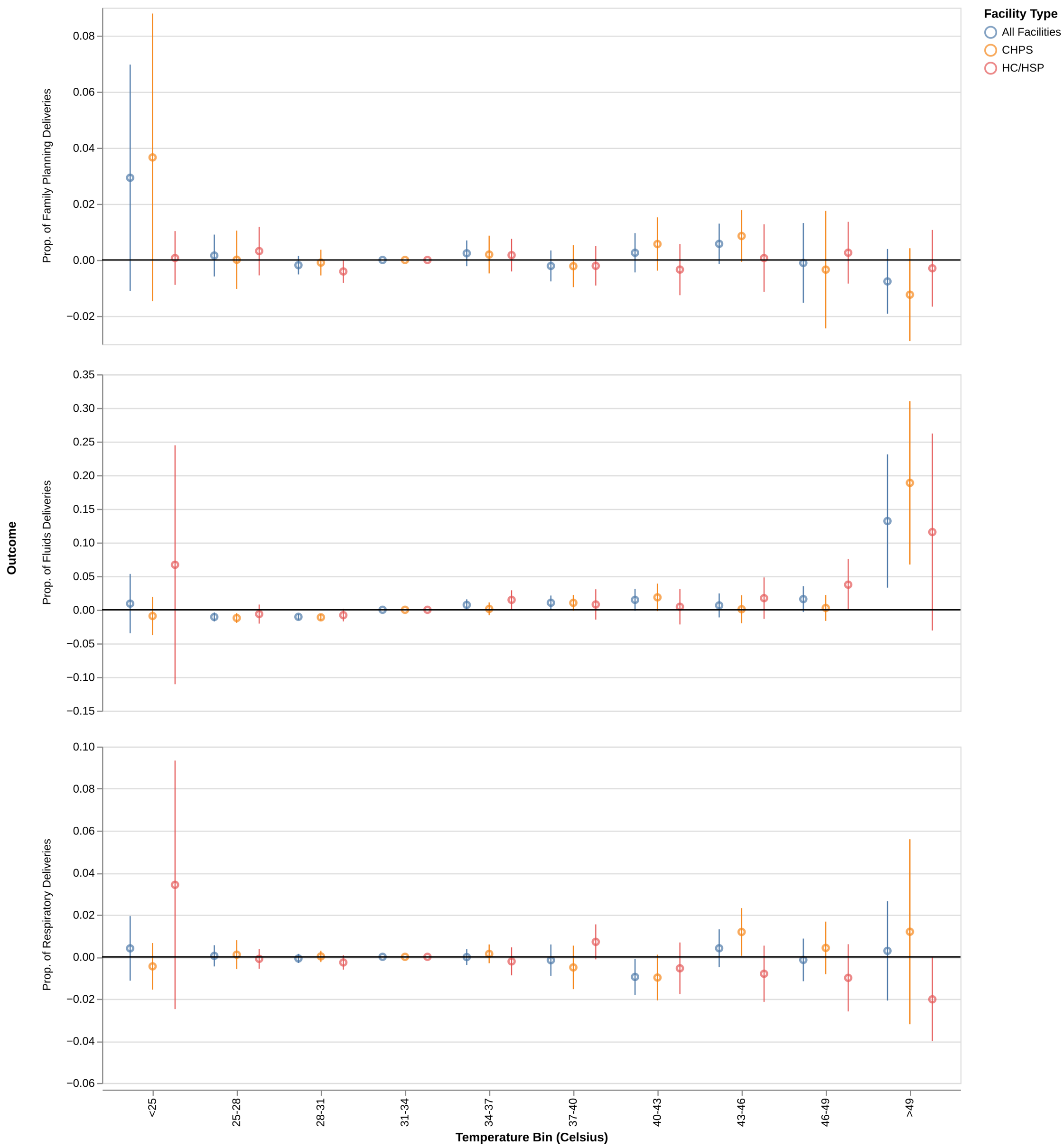


Figure 7: Number and Nature of Deliveries by Type of Facility

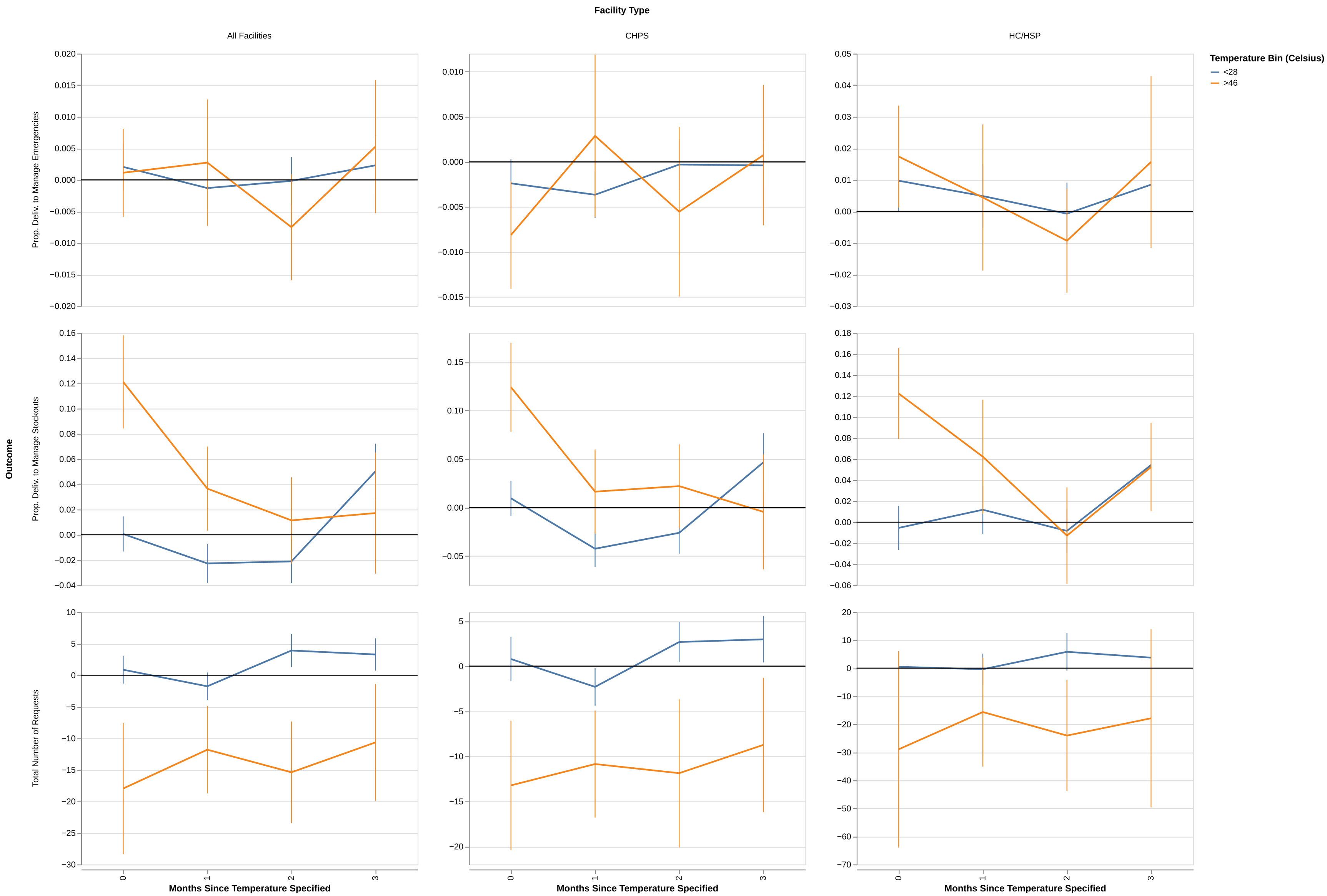
Notes: Figures shows a coefficient plot of contemperaneous effects of temperature bins for three outcomes: the total number of requests, the proportion of deliveries to manage stockouts, and the proportion of deliveries to manage emergencies. $31 - 34°C$ was used as the reference bin. Coefficients were estimated from the model in Equation 1 for each health facility type. Bars above and below coefficients denote 95% confidence intervals from clustered standard errors at the health facility level.

Figure 8: Deliveries by Type of Supply



Notes: Figures shows a coefficient plot of contemperaneous effects of temperature bins for three outcomes: the proportion of respiratory deliveries, the proportion of fluid deliveries, and the proportion of family planning deliveries. $31-34°C$ was used as the reference bin. Coefficients were estimated from the model in Equation 1 for each health facility type. Bars above and below coefficients denote 95% confidence intervals from clustered standard errors a the health facility level.

Figure 9: Lagged Temperature Shock for Number and Nature of Deliveries by Type of Facility



Notes: Figures shows a plot of lagged effects of low and extreme temperature bins for three outcomes: the total number of requests, the proportion of deliveries to manage stockouts, and the proportion of deliveries to manage emergencies. Coefficients were estimated from the model in Equation 1 for each health facility type. Bars above and below coefficients denote 95% confidence intervals from clustered standard errors at the health facility level. Rows show results for each outcomes, while columns show results for all facilities,

Table 1: Effect of Consecutive Extreme Temperatures on Stockout Rate

	Stockout Rate
Cumulative Extreme Temp.	0.0307***
	(0.0065)
Observations	23,291
R-squared	0.277

Clustered standard errors at the health center in parentheses.

Table shows the results of a regression based on the specification of Equation 5.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

A Regression Tables

	Prop. Deliv. to Manage Emergencies			Prop. Deliv. to Manage Stockouts			Total Number of Requests		
	All Facilities	CHPS	HC/HSP	All Facilities	CHPS	HC/HSP	All Facilities	CHPS	HC/HSP
<25	-0.002	0.005	-0.026	-0.016	-0.012	-0.026	-18.42*	-19.261***	-19.611
	(0.018)	(0.014)	(0.073)	(0.061)	(0.068)	(0.149)	(9.407)	(4.836)	(30.257)
25-28	0.003	-0.001	0.011**	-0.005	-0.004	-0.003	2.643**	2.574*	2.882
	(0.002)	(0.001)	(0.005)	(0.008)	(0.01)	(0.011)	(1.206)	(1.36)	(2.54)
28-31	-0.0	-0.001	0.001	-0.012**	-0.018***	0.0	-0.105	-0.103	0.275
	(0.001)	(0.001)	(0.003)	(0.005)	(0.006)	(0.007)	(0.813)	(0.664)	(2.011)
34-37	0.001	0.001	0.004	-0.004	-0.017*	0.009	2.034*	2.292*	1.675
	(0.002)	(0.002)	(0.004)	(0.007)	(0.01)	(0.01)	(1.184)	(1.296)	(2.412)
37-40	0.005*	0.004	0.005	-0.025**	-0.044***	0.006	-0.644	-1.012	1.882
	(0.003)	(0.003)	(0.006)	(0.01)	(0.013)	(0.016)	(2.997)	(3.017)	(7.458)
40-43	0.004	-0.0	0.01	-0.046***	-0.052***	-0.044**	8.723	8.031	12.481
	(0.003)	(0.003)	(0.008)	(0.012)	(0.015)	(0.02)	(5.65)	(5.231)	(15.031)
43-46	-0.005	-0.004	-0.007	-0.078***	-0.095***	-0.053***	-3.05	-3.121	0.566
	(0.003)	(0.003)	(0.008)	(0.013)	(0.019)	(0.02)	(3.159)	(2.705)	(8.57)
46-49	0.004	-0.004	0.021**	0.06***	0.047***	0.078***	-4.865	-2.801	-7.999
	(0.004)	(0.003)	(0.01)	(0.014)	(0.017)	(0.023)	(4.206)	(3.68)	(11.848)
>49	0.003	-0.008	0.031**	0.101***	0.081***	0.114***	14.806**	8.322	13.721
	(0.008)	(0.008)	(0.013)	(0.018)	(0.026)	(0.025)	(6.661)	(6.056)	(18.045)

Table 1: Regression Table of Main Specification on Logistics Outcomes

Notes: *$p < 0.10$ **$p < 0.05$ ***$p < 0.01$. Clustered standard errors at the health facility level in parentheses. Table shows results for contemperaneous effects of temperature bins for three outcomes: the total number of requests, the proportion of deliveries to manage stockouts, and the proportion of deliveries to manage emergencies. $31 - 34°C$ was used as the reference bin. Coefficients were estimated from the model in Equation 1 for each health facility type.

	Prop. of Family Planning Deliveries			Prop. of Fluids Deliveries			Prop. of Respiratory Deliveries		
	All Facilities	CHPS	HC/HSP	All Facilities	CHPS	HC/HSP	All Facilities	CHPS	HC/HSP
<25	0.029	0.037	0.001	0.009	-0.009	0.067	0.004	-0.005	0.034
	(0.021)	(0.026)	(0.005)	(0.022)	(0.015)	(0.091)	(0.008)	(0.006)	(0.03)
25-28	0.002	0.0	0.003	-0.011***	-0.012***	-0.006	0.0	0.001	-0.001
	(0.004)	(0.005)	(0.004)	(0.003)	(0.004)	(0.007)	(0.003)	(0.004)	(0.002)
28-31	-0.002	-0.001	-0.004**	-0.01***	-0.011***	-0.008*	-0.001	0.0	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.001)	(0.001)	(0.002)
34-37	0.002	0.002	0.002	0.007*	0.001	0.015**	-0.0	0.001	-0.002
	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)	(0.007)	(0.002)	(0.002)	(0.003)
37-40	-0.002	-0.002	-0.002	0.01*	0.01*	0.008	-0.002	-0.005	0.007*
	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)	(0.011)	(0.004)	(0.005)	(0.004)
40-43	0.003	0.006	-0.003	0.015*	0.018*	0.005	-0.01**	-0.01*	-0.005
	(0.004)	(0.005)	(0.005)	(0.008)	(0.01)	(0.013)	(0.004)	(0.006)	(0.006)
43-46	0.006	0.009*	0.001	0.007	0.001	0.017	0.004	0.012**	-0.008
	(0.004)	(0.005)	(0.006)	(0.009)	(0.011)	(0.016)	(0.005)	(0.006)	(0.007)
46-49	-0.001	-0.003	0.003	0.016	0.003	0.037*	-0.001	0.004	-0.01
	(0.007)	(0.011)	(0.006)	(0.01)	(0.01)	(0.02)	(0.005)	(0.006)	(0.008)
>49	-0.008	-0.012	-0.003	0.132***	0.189***	0.116	0.003	0.012	-0.02**
	(0.006)	(0.008)	(0.007)	(0.051)	(0.062)	(0.075)	(0.012)	(0.022)	(0.01)

Table 2: Regression Table of Main Specification on Types of Supplies

Notes: $*p < 0.10$ $**p < 0.05$ $***p < 0.01$. Clustered standard errors at the health facility level in parentheses. Table shows results for contemperaneous effects of temperature bins for three outcomes: the proportion of respiratory deliveries, the proportion of fluid deliveries, and the proportion of family planning deliveries. $31 - 34°C$ was used as the reference bin. Coefficients were estimated from the model in Equation 1 for each health facility type.

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