Civil Response to Government Alerts Declines During Russian Invasion of Ukraine

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War is the cause of tremendous human suffering. To reduce such harm, governments have developed tools to alert civilians of imminent threats. Whether these systems are effective remains largely unknown. We study the introduction of an innovative smartphone application that notifies civilians of impending military operations developed in coordination with the Ukrainian government after the Russian invasion. We leverage quasi-experimental variation in the timing of more than 3,000 alerts to study the sheltering behavior of persons using high frequency geolocation pings tied to 17 million mobile devices, 60\% of the connected population in Ukraine. We find that civilians respond sharply to alerts overall, quickly seeking shelter. These rapid post-alert changes in population movement attenuate over time, in a manner that cannot be explained by sheltering underground or calibration to the signal quality of alerts. Responsiveness is weakest when civilians have been living under an extended state of emergency, consistent with the presence of an alert fatigue effect. Our results suggest 8-15\% of civilian casualties observed during the later periods of the conflict could have been avoided with sustained public responsiveness to government alerts.
Introduction

Interstate military disputes, especially those that unfold in densely populated urban areas, disrupt civilian life, undermining human welfare and reducing economic activity. In an attempt to reduce civilian casualties and promote freedom of movement, governments often engage in extensive messaging about where and when potential attacks may occur. Governments of 40 countries, representing at least 58% of the global population, have developed these messaging systems to address persistent threats to physical security (Figure 1). By informing the public during conflict, governments and aligned private actors may thwart harm.

Despite the importance of alert systems and their extensive use in states under conflict, there is no evidence to date on whether and under what conditions these alerts impact public behavior. Although it is intuitive to expect civilians to take immediate, costly action in response to alerts of imminent harm, it is not clear how quickly they respond to these messages, and indeed, whether they do so at all (1). This evidence gap is largely due to our inability to reliably measure how people’s movements shift in the moments following notification of imminent threats. Yet public response to this type of high-frequency, localized messaging remains a first-order concern for public policy (2). In order to minimize harm while enabling continued economic and social activity during conflict, public actors need a mechanism for transmitting information that shapes mobility and enables the public to seek shelter and calibrate their movements with respect to the militarized environment.

Study overview

We provide the first credible estimates of behavioral change in response to government alerts about imminent risk. We study these dynamics in Ukraine following the February 2022 invasion by Russian forces. After the incursion of military forces into urban areas, the Ukrainian government coordinated and developed a smartphone application for transmitting public alerts.
about impending Russian military operations. These messages were then re-circulated via a collection of mobile device applications as well as through social media platforms (e.g., Telegram). We compile these messages about location and minute-in-day risks to quantify the information available to civilians. We combine the location and timing of these messages with high-frequency, spatially disaggregated data on device mobility. This pairing of messages and mobility enables us to study whether mobility changes discontinuously as alerts are transmitted to mobile devices. This quasi-experimental approach provides credible estimates of costly, real-world responses to alerts during conflict.

Relying on estimates from more than 3,000 local, device-by-minute event studies, we document five core findings: (i) civilians, on average, respond sharply to alerts, rapidly increasing their movement patterns as they flee imminent harm; (ii) these rapid post-alert changes in civilian movement attenuate substantially as the war progresses; (iii) post-alert changes in vertical movement suggest widespread use of underground shelters, which attenuates with time; (iv) public responsiveness attenuates even when civilians are exposed to higher quality information; (v) post-alert movement patterns more rapidly attenuate when the local population has been living under an extended ‘state of alarm’ (high duration of recent bombardment alerts). Taken together, these results are consistent with the presence of an alert fatigue effect.

To quantify the consequences of diminished public responsiveness to government messages, we conduct a series of counterfactual exercises to bound the number of excess civilian casualties sustained during the later periods of the conflict. Linking the mobility response to a novel source of information on civilian harm, we find that mobility early on significantly reduced the number of civilian casualty events, and diminished responsiveness led to a large number of plausibly avoidable civilian deaths. Our bounding exercises suggest between 8-15% of civilian casualties could have been avoided if post-alert responsiveness had remained the same over time. These figures suggest that government messaging can be a powerful tool to minimize harm during
war, but public engagement with these alerts is essential.

**Literature and contribution**

This research addresses a number of prominent, open questions in the social sciences. Prior work has considered how civilians respond to weather shocks and natural disasters (3), localized economic shocks (4), and political crises (5). Other work has considered how civilians’ decisions to flee are shaped by exposure to violence during war (6, 7). Less focus has been paid to how population displacement during a period of heightened uncertainty can be shaped by an information operation run by a government actor (8).

Moreover, research on informational nudges typically focuses on low-cost, low-stakes settings, where behavioral change may have a marginal effect on worker productivity (9), utilization of public services (10), or engagement with politics (11). We focus on a case where acquiring and disseminating information to the public is relatively high-cost and where the public’s response to the informational nudge is typically very high-stakes. Where research has focused on high-risk settings, this work has focused almost exclusively on downstream behavioral proxies or on a narrow geographic context. This research fills this gap by directly studying the behavioral outcome of interest—whether and how much civilians evade danger—and in a country-scale, repeated quasi-experimental setting.

This research also addresses a prominent gap in our understanding of decisions under risk. Prior work has found that risk profiles remain largely stable over time (12), with exogenous shocks typically triggering an increase in risk aversion (13). Research on these topics is typically limited by the use of lab-based measures of low-stakes and/or hypothetical decision-making. These measures are also difficult to track over time and may not have much transferability to high-stakes decisions under risk. Our study speaks directly to these gaps in design and setting, enabling us to study device-by-minute variation in responsiveness over time and in
response to a multitude of informational shocks over time. Unlike prior work, we find that responsiveness attenuates over time, even after we account for an alternative mechanism through which civilians can substitute risk or exposure to higher quality information (that civilians are likely to know is higher quality). Moreover, a gap in responsiveness quickly emerges over time between subjects exposed to longer (versus shorter) emergency alert duration. This broadly suggests that risk profiles do not demonstrate a tendency towards risk aversion in a high-stakes setting. Instead, our results are consistent with cognitive fatigue generating negative externalities: increasingly risky decisions under uncertainty.

**Conceptual framework**

We anticipate, all else equal, civilians will respond to warnings about an imminent threat by seeking shelter. In our primary design, this will involve evading harm through rapid movement. This overall effect may vary over time, as the conflict environment becomes less (or more) dynamic. There are three plausible mechanisms that could explain why escaping harm through evasion (population movement) might attenuate over time. First, civilians may have quickly adapted to the threat environment, seeking shelter underground rather than fleeing above ground. Second, attenuation in responsiveness could be due to a calibration of whether signals from the government are informative (i.e., government messages in a given area may be undermined by a high false positive rate). Third, attenuation could be due to *alert fatigue* (alternatively, normalization to risk), which is likely accelerated by the duration that civilians spend on persistent ‘states of emergency’ (longer duration alerts). We evaluate these arguments empirically using a combination of high frequency alerts and population mobility information, observed over time.
Results

Evading harm through movement We begin by studying whether and how civilians respond to bombardment alerts. This is shown in Figure 3 for the pooled sample between March and September 2022. Across our various outcomes and across periods, the pre-alert indicators help to validate that movement patterns were not significantly shifting prior to the threat notification being sent. This suggests that civilians were not acting in anticipation of a future threat prior to the alert, evidence in favor of the credibility of our identification strategy. After the alert is sent, we find a large, consistently positive effect of notification on overall movement as well as speed. Post-alert civilians move quickly to avoid the potential military operation that prompted the government notification.

Attenuation over time We test whether these overall effects, pooled across the entire conflict, may vary heterogeneously across periods. We have split the conflict into three phases: the first two months of recorded alert activity; the second two months, when Russian forces had settled into certain areas and were in engaging in regular activities; and a final phase, when Russian forces had largely reached stasis or were losing ground in certain regions. These are the three response profiles in Figure 4, where increasing warmth of color corresponds to a later stage of the war. Notice that the public was most responsive to alerts in the first two periods of the conflict. However, the post-alert response has significantly diminished, suggesting limited post-alert civilian sheltering via distance traveled.

Sheltering underground We investigate whether the attenuation in civilian movement after alerts reflects adaptation—increasing use of on-site or nearby bomb shelters, by leveraging the spatial telemetry of cellphone devices. Using these signals in space (Z dimension), we can es-

1We discuss sample composition changes in Supporting Information.
timate vertical population movement. We anticipate that civilians engaging in post-alert flight will also take advantage of underground infrastructure to avoid potential bombardment risks. We reproduce the event study specification shown above, switching the outcome of interest from distance traveled to vertical movement via discernible changes in altitude. These results are shown in Figure 5. Notice that there are significant reductions in altitude post-alert for the earliest period of the conflict. This is consistent with seeking shelter underground. However, the estimated effects following the alert attenuate to roughly zero during the later stages of the conflict. This indicates that the public was not adapting to the bombardment risks by substituting spatial flight for sheltering below ground. Instead, our results suggest civilians were similarly less likely to engage in efforts to avoid bombardment overall after the alerts were circulated.

**Calibrating signal quality** Another central mechanism that could explain attenuation is public calibration to information quality. Messages transmitted by the government vary in quality, as measured by the extent to which an anticipated military operation materializes in a particular location at a specific time during which there was an alert sent to the public through the application. Since conflict events are salient, we anticipate civilians are aware of and respond to conflict. In another study, we test this conjecture and find a robust association between retrospective self-reports of communal violence exposure and local violent events (as measured through the VIINA platform) during the sample period in Ukraine. If civilians learn over time that signal quality varies dynamically, they may adjust their behavior accordingly. In particular, we would expect to see less attenuation in responsiveness among devices receiving other higher quality signals (lower false positive rates) if this change in behavior is driven by calibration. We test this conjecture using trends in local false positive rates in 14, 7, and 3 day windows prior to the alert of interest. Following our other tests, we split this parameter at the median, and compare the period-by-period change in responsiveness across populations with higher and
lower quality signals. These results are shown in Figure 6. We find no evidence of diminished attenuation among populations exposed to higher quality information. Instead, the trend in attenuation remains similar across high and low quality signals. These results are also stable if we use alternative windows (see Figures SI-4 and SI-5).

**Alert fatigue** We evaluate whether the duration of alert exposure influences public responsiveness. To measure alert duration, we take advantage of information about when alerts are active (start and end time) as well as when alerts occur within a moving window of fixed width (21 days). We then split the sample of notification alerts based on whether the alert occurs during a period of high (above median) alarm exposure or not. Subsequently, we visualize how the public responds to bombardment alerts during various conflict periods, allowing our estimated effects of notification to vary with recent trends in the duration of time under alarm. These results are introduced in Figure 7. Notice in the upper left panel that high and low duration estimates overlap significantly, suggesting that increased movement patterns after alert notifications were consistent early in the conflict. However, as the conflict reaches the later phases, in the middle and right panels, the total movement response declines and it declines disproportionately for individuals that have been exposed to an intense information pressure to seek shelter. These effects are also consistent if we use cumulative duration of exposure, rather than recent trends in exposure, indicating that alerts with longer lengths may undermine the public’s responsiveness to government messages.

**Excess deaths due to shift in responsiveness** We next turn our attention to estimating excess deaths due to non-responsiveness. In particular, we consider the counterfactual where post-alert movement remains consistent over time at the level we observe during the first phase of the conflict. If civilians moved, on average, as much as they did during this initial phase, how
many civilian casualties could have been avoided? Additional details on the methodology used for calculating excess death is provided in Supporting Information. We present three excess death estimates in the time series (Figure 8). We do this to help bound the figures we present across various plausible counterfactual estimates. First, we incorporate day-specific measures of post-alert mobility as well as day-specific weights that help us adjust the casualties-per-event calculation. Second, we adjust our measure of post-alert mobility using trends in movement observed between the first and third periods (but keeping our casualty weights consistent). This approach is most similar to the split sample approach in our main design. Third, we combine the trends in movement with trends in event severity, which allows us to smooth our spikes in casualties-per-event due to a sudden but temporary shift in weapon lethality. The time series of excess deaths is shown in Figure 8. The first and second approaches bound the excess death estimates between 8% and 15%. The third approach is 12%.

**Discussion**

We provide credible quantitative evidence of the effectiveness of messaging about imminent risk during conflict. Combining granular data on population movement and high-frequency, localized alerts about imminent threats, we find that civilians respond sharply to these alerts, moving significantly in the minutes following notifications. These rapid shifts in mobility decline as the war continues, consistent with public fatigue. We corroborate these findings by leveraging elevation signals, which indicate the public did not adjust to a sharp attenuation in observable movement by seeking shelter underground. Attenuation also could not be explained by calibration to the quality of information. This attenuation in movement, however, is marginally greater among individuals exposed to longer alerts that kept the Ukrainian public in affected areas under protracted states of alarm. Our counterfactual exercise suggests 8 to 15% of civilian casualties could have been avoided if public responsiveness remained as high throughout the conflict as it
was during the initial phase. Understanding why the public’s engagement changed so quickly
during a high stakes conflict has significant implications for prior work.

Taken together, these results clarify whether and how civilians respond to government mes-
saging during conflict, with relevance to how future information campaigns can improve welfare
by thwarting public exposure to violence during militarized disputes.

Materials and Methods

Mobile Device Movement Anonymized device-level location data is obtained from location
data provider Veraset\(^2\). The data consists of “pings”, which are timestamped GPS locations
shared by the device with a mobile app. Veraset aggregates and cleans such data, obtained from
thousands of so-called “Software-Development Kits” (SDK), which are packages of tools that
provide the infrastructure for many mobile applications. Location data from the same device but
different SDKs can be combined by relying on the anonymized device ID, which is a unique
string associated with a particular mobile device and can only be changed through a factory
reset.

As a result, the data provide insights into the movement of a substantial share of Ukrainian
mobile devices: after cleaning the data and filtering it on a period and regions of interest, we
obtain around 500 million unique pings, corresponding to around 17 million unique devices.
With a population of 44 million and smartphone penetration of 63%, this corresponds to around
60% of Ukrainian mobile devices. The cleaning and filtering steps applied are as follows. First,
we restrict the sample to pings observed between January 1 and September 30, 2022. To im-
prove data quality, we remove so-called “jumpy” pings, which result from distortions in the
GPS signal, by filtering out pings where the device moved from one location to the next at a
speed faster than 300 km/h. We also remove pings with a horizontal accuracy (the radius of
\(^2\)https://www.veraset.com/
the margin of error of the device’s location) of more than 150 meters. Finally, we only retain pings in those regions for which we have air raids data (see below for more details). The sample scale of devices remains consistent with changes in the relocation patterns of Ukrainian citizens during the sample period as reported by the United Nations High Commissioner for Refugees (UNHCR). We find similar distances traveled per device by day throughout the sample period, with a temporary increase during August 2022.

**Air Raid Alerts** Data on the start and end times of region-wide air raid alerts was scraped from the Telegram channel of the popular mobile app Air Alert Ukraine by Volodymyr Agafonkin³ and published online. The Air Alert app was developed by Ukrainian software development company stfalcon⁴ and Ukrainian security company Ajax Systems⁵ with support from the Ukrainian Ministry of Digital Transformation. Users can select regions of interest and receive loud alert warnings informing them of the beginning and end of a civil defense alert in the region. Importantly, the app does not collect geolocation data, which means activation of the alert should not bias the geolocation signals received from the Veraset data. Moreover, it is only possible to activate alerts for one region at a time, so we can reasonably expect users in Ukraine to tune into the alerts for their region of residence. The app creators claim the app is the only one of its type that supports critical alerts, where notifications are delivered even when a smartphone is in silent or sleep mode. The type of alerts the app delivers fall under civil defense alerts and includes airstrike warnings, chemical attacks, impending technological catastrophes, etc. Between February and September 2022, the app had been downloaded around 5.5 million times in Ukraine. Not all regions have scraped alert data available: Figure 2 shows the regions for which there is air alert data.

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³https://agafonkin.com/
⁴https://stfalcon.com/
⁵https://ajax.systems/
**Violent Event Data** We leverage violent event data from two sources. The primary source is the Violent Incident Information from News Articles (VIINA) \(^{14}\). The platform tracks violence in Ukraine using a multitude of source streams, including domestic sources in Ukraine, Russia, as well as open source intelligence reports gathered from social media. The balance of source locations and types is used to establish cross-source coverage, addressing potential sources of reporting bias. The data is processed in near-real-time using natural language processing. Our measures of combat activity and events involving civilian casualties are drawn from the platform’s recurrent neural network (RNN) classification of events. To calculate the damage multiplier used in our excess deaths exercise, we rely on information from the Armed Conflict Location and Event Data Project (ACLED), which combines supervised and unsupervised collection and processing techniques \(^{15}\). Although this source lacks the source coverage and cross validation of VIINA, ACLED includes information on the estimated number of casualties associated with each recorded event.

**Geospatial Data** We match the alert regions from the Air Alert app to official administrative regions in Ukraine from 2015 at the oblast (region), raion (district), and city levels \(^{16}\), the result of which is shown in Figure 2. Similarly, we intersect the mobile device pings with these administrative regions to deduce which alert a device is exposed to.

**Research Design**

To assess civilian response to air raid alerts, we estimate the following event study specification for a window of 30 minutes around each alert,

\[
Response_{it} = \sum_{t=t_0-10}^{t_0+30} \delta_t + \varepsilon_{it}, \tag{1}
\]
where $i$ indicates a unique mobile device; $t$ is a minute of the hour (e.g. 5:00pm to 5:01pm); $Response_{it}$ is a measure of device $i$'s movement in minute $t$, where our main measure is the total distance the device moved between subsequent pings; $\delta_t$ is a dummy variable for being in minute $t$; the sum iterates over all such dummies from 10 minutes before to 30 minutes after the alert; and $\varepsilon_{it}$ is an error term. We allow for the panel to be unbalanced (i.e., not every device has a ping in every minute in the window), but require there to be at least one ping in each minute, or else we drop the corresponding alert. This results in a total of 3,119 estimated versions of Equation 1. To illustrate the results of our event studies in a digestible format, we plot the central tendency of the ten minutes before the alert, the minute of the alert notification, and the subsequent thirty minutes. Additional details about split-period and split-sample estimates are provided in Supporting Information.
Fig. 1. Countries with activity alert platforms

Note: figure depicts the number and distribution of countries with persistent physical security alert platforms. These platforms include sirens, cell tower emulators, and mobile device applications. Data compiled from publicly available media, open source materials, and government documents detailing the platforms.
Fig. 2. Air Alerts by Day and Region

Note: figure depicts the number of distinct air alerts that were broadcast on the Air Alert Ukraine app in a given region on a given day. An alert that spans multiple days is counted on each of the days.
**Fig. 3. Strong overall public response to bombardment alerts**

*Notes:* figure shows pooled estimates of air alert event studies between March and September 2022. Figure documents changes in distance traveled (sum) across time (minutes relative to treatment) for the 61 minute window centered around the minute of the air alert notification. The vertical line separates the pre-period trends from the post-treatment effects.

**Fig. 4. Strong public response to alerts declines as war progresses**

*Notes:* figure shows pooled estimates of air alert event studies between March and September 2022. Figure shows changes in distance traveled (sum) across time (minutes relative to treatment) for the 61 minute window centered around the minute of the air alert notification. The vertical line separates the pre-period trends from the post-treatment effects. Periods are indicated by various colors.
**Fig. 5.** Altitude response suggests decline in movement not due to increased sheltering underground

*Notes:* figure shows pooled estimates of air alert event studies between March and September 2022. Figure shows changes in altitude (e.g., movement up/down within buildings) across time (minutes relative to treatment) for the 61 minute window centered around the minute of the air alert notification. The vertical line orients separates the pre-period trends from the post-treatment effects. Periods of conflict are designated using various colors. Effects are shown in level changes.

**Fig. 6.** Attenuation in responsiveness to alerts present even among population exposed to high quality information about risk

*Notes:* figures show period-specific estimates of air alert event studies between March and September 2022. *Left* shows changes in distance traveled (sum) across time (minutes relative to treatment) for the 61 minute window centered around the minute of the air alert notification. The vertical line orients separates the pre-period trends from the post-treatment effects. Effects are shown in meters. Samples are split at the median of false alerts using a 14-day bandwidth (additional results demonstrate robustness). Results are shown for March/April. *Middle* shows changes in distance traveled during May/June. *Right* shows changes in distance traveled between July and September.
Fig. 7. Increased exposure to alerts associated with decreased response

Notes: figures show period-specific estimates of air alert event studies between March and September 2022. Left shows changes in distance traveled (sum) across time (minutes relative to treatment) for the 61 minute window centered around the minute of the air alert notification. The vertical line orients separates the pre-period trends from the post-treatment effects. Effects are shown in meters. Samples are split at the median of alert exposure (duration of alerts within regions and time periods) calculated as a 21-day moving average. Results are shown for March/April. Middle shows changes in distance traveled during May/June. Right shows changes in distance traveled between July and September.
Fig. 8. Calculation of excess death suggests potentially large losses due to public non-responsiveness to government messages.

Notes: figure shows estimates of excess death between May and September 2022. Counterfactual movement is calculated as the deviation between the current period (day of sample) and the first phase of the conflict.
References


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Supplementary materials

Ethics Statement

The mobile device data does not contain uniquely identifying information regarding device users. The unique vector of information that binds location information across collection platforms is an anonymized device identifier that cannot, without significant effort, be modified by the user. This identifier, however, cannot be linked with certainty to any identifying administrative data. Conducting the study did not involve direct interaction with or manipulation of human subjects.

Supplemental Methods

Estimation of event studies

The main estimation strategy an event study specification for a window of 30 minutes around each alert,

\[ \text{Response}_{it} = \sum_{t=t_0-10}^{t_0+30} \delta_t + \varepsilon_{it}, \]

where \( i \) indicates a unique mobile device; \( t \) is a minute of the hour (e.g. 5pm to 5:01pm); \( \text{Response}_{it} \) is a measure of device \( i \)'s movement in minute \( t \), where our main measure is the total distance the device moved between subsequent pings; \( \delta_t \) is a dummy variable for being in minute \( t \); the sum iterates over all such dummies from 10 minutes before to 30 minutes after the alert; and \( \varepsilon_{it} \) is an error term. We allow for the panel to be unbalanced (i.e., not every device has a ping in every minute in the window), but require there to be at least one ping in each minute, or else we drop the corresponding alert. This results in a total of 3,119 estimated versions of Equation 1. To illustrate the results of our event studies in a digestible format, we plot the central tendency and local polynomial fit of the ten minutes before the alert, the minute
of the alert notification, and the subsequent thirty minutes.

In the split-period results, we show the local polynomial fit of mobility over time leads and lags by splitting the pool of event studies based on when the alert occurs.

In the elevation results, we show results for a slight revision of Equation 1 (repeated above as Equation 2):

\[ elevation_{it} = \sum_{t=t_0-10}^{t_0+30} \delta_t + \varepsilon_{it}, \]

where \( i \) indicates a unique mobile device; \( t \) is a minute of the hour (e.g., 5pm to 5:01pm); \( elevation_{it} \) is a measure of device \( i \)'s movement in the \( Z \) dimension (vertical movement) in minute \( t \), where our main measure is the total distance the device moved between subsequent pings; \( \delta_t \) is a dummy variable for being in minute \( t \); the sum iterates over all such dummies from 10 minutes before to 30 minutes after the alert; and \( \varepsilon_{it} \) is an error term.

In the split-period specification with signal quality and, separately, alert duration, we show the local polynomial fit of mobility over time leads and lags by splitting the pool of event studies based on when the alert occurs and the median of the parameter. In Figure 6, we split by the median of false positive rates observed in the prior 14 day window. In Figure 7, we split by the median of alert duration.

**Sample composition**

It is possible that attenuation in responsiveness could be due to an endogenous shift in the sample of devices over time (selective exit or entry). Specifically, if the set of devices that exits the sample early are risk averse and respond at a higher rate on average (i.e., greater movement per alert), then attenuation might be a mechanical feature of sample change over time. As we discuss in the main text, changes in the sample scale mirror changes in population relocation.
documented by UNHCR. Additional details are here: https://bit.ly/3zwZ4ee. Dis-
tances traveled are also consistent over time with only a slight increase in travel per device-day in August 2022.

Although endogenous exit and entry in this setting are difficult dynamics to address, we repeat the split-period event study design above using the set of devices observed in all periods and compare the elasticity of attenuation. Below is a formal definition:

$$\text{elasticity of attenuation} = \frac{\bar{r}_{\text{restrict}}}{\bar{r}_{\text{all}}} \frac{r_{1}^{\text{restrict}}}{r_{1}^{\text{all}}},$$

(4)

where $\bar{r}$ is the average post-alert response per period across the two samples ($all$ is the full sample; $restrict$ is the set of devices present in all periods).

If attenuation is due to sample composition changes, we would expect an elasticity much larger than one (significantly less attenuation among the restricted sample). If attenuation is the same or increases among the restricted sample, we would expect an elasticity of one or below one. We find an elasticity below one ($\frac{.2717}{.3957} = .69$), suggesting that there is significant attenuation between periods even among this strict sample of devices.

**Counterfactual estimation of excess death due to diminished responsiveness**

To estimate excess deaths due to the shift in responsiveness, we need to consider several parameters:

- $\beta_b$ captures the correlation between sheltering (movement) and civilian harm. $b$ indicates the benchmark sample, which in our setting is the first period of the conflict.

- $\gamma_t$ captures the damage multiplier—the calculated ratio of civilian casualties to civilian casualty events. This scaling weight is designed by $t$, to allow the ratio to change dynamically to reflect changes in military tactics and weaponry.
• $\Delta t$ indicates the change in movement relative to the benchmark period.

• $\text{alerts}_t$ count of alerts period day $t$.

The counterfactual is then calculated as the sum of day-specific products, as in:

$$\text{excess deaths} = \sum_{t=0, \max(t \in p=3)} \beta_b \times \gamma_t \times \Delta t \times \text{alerts}_t. \tag{5}$$

Now we turn to parameter estimation in Equation 5. We recover $\beta_b$ from the following specification:

$$\text{civcas}_{it}^{\text{events}} = \beta_b \text{sheltering}_{it} + \theta \text{military}_{it}^{\text{events}}. \tag{6}$$

Where $\text{sheltering}_{it}$ is the observed movement patterns observed in response to the alert in location $i$ at time $t$, $\text{civcas}_{it}^{\text{events}}$ captures the count of civilian casualty events recorded during a short reporting period after the alert that are plausibly occurred during the alert window itself as well as military operations (events) that occurred during the same window. The quantity of interest is $\beta_b$. We find a robust negative correlation between movement and civilian casualty events during the initial phase of the conflict (-0.0674, $p < .01$, in kilometer terms). So $\beta_b = -0.0674$ (in KM). We then use ACLED data to calculate $\gamma_t$, which enables us to specify a scalar that converts estimated events to casualties.

We implement three approaches to bound our estimates:

1. We incorporate day-specific measures of post-alert mobility as well as day-specific weights that help us adjust the casualties-per-event calculation. This approach allows $\gamma_t$ and $\Delta t$ to be derived directly from the raw casualty and movement data.

2. We adjust our measure of post-alert mobility using trends in movement observed between the first and third periods (but keeping our casualty weights consistent). This approach is most similar to the split sample approach in our main design. To be clear, $\Delta t$ is calculated
as linear trend fit across the medians of the first and third periods while $\gamma_t$ is derived directly from the raw casualty data.

3. We combine the trends in movement with trends in event severity, which allows us to smooth our spikes in casualties-per-event due to a sudden but temporary shift in weapon lethality. This allows us to smooth $\gamma_t$, using a moving average, and leverage a trend for $\Delta t$. 
Supplemental Results

**Fig. SI-1.** Strong overall public response to bombardment alerts, alternative transformation

*Notes:* figure show pooled estimates of air alert event studies between March and September 2022. Figure documents changes in distance traveled (sum) across time (minutes relative to treatment) for the 61 minute window centered around the minute of the air alert notification, with an inverse hyperbolic sine transformation. The vertical line separates the pre-period trends from the post-treatment effects.
Fig. SI-2. Strong public response to alerts declines as war progresses, alternative transformation

*Notes:* figure shows pooled estimates of air alert event studies between March and September 2022. Figure shows changes in distance traveled (sum) across time (minutes relative to treatment) for the 61 minute window centered around the minute of the air alert notification, with an inverse hyperbolic sine transformation. The vertical line separates the pre-period trends from the post-treatment effects. Periods are indicated by various colors.

Fig. SI-3. Altitude response suggests decline in movement not due to increased sheltering underground, alternative transformation

*Notes:* figure shows pooled estimates of air alert event studies between March and September 2022. Figure shows changes in altitude (e.g., movement up/down within buildings) across time (minutes relative to treatment) for the 61 minute window centered around the minute of the air alert notification, with an inverse hyperbolic sine transformation. The vertical line orients separates the pre-period trends from the post-treatment effects. Periods of conflict are designated using various colors. Effects are shown in level changes.
**Fig. SI-4.** Attenuation in responsiveness to alerts present even among population exposed to high quality information about risk, 7-day bandwidth

*Notes:* figures show period-specific estimates of air alert event studies between March and September 2022. *Left* shows changes in distance traveled (sum) across time (minutes relative to treatment) for the 61 minute window centered around the minute of the air alert notification. The vertical line orients separates the pre-period trends from the post-treatment effects. Effects are shown in meters. Samples are split at the median of false alerts using a 7-day bandwidth. Results are shown for March/April. *Middle* shows changes in distance traveled during May/June. *Right* shows changes in distance traveled between July and September.

**Fig. SI-5.** Attenuation in responsiveness to alerts present even among population exposed to high quality information about risk, 3-day bandwidth

*Notes:* figures show period-specific estimates of air alert event studies between March and September 2022. *Left* shows changes in distance traveled (sum) across time (minutes relative to treatment) for the 61 minute window centered around the minute of the air alert notification. The vertical line orients separates the pre-period trends from the post-treatment effects. Effects are shown in meters. Samples are split at the median of false alerts using a 3-day bandwidth. Results are shown for March/April. *Middle* shows changes in distance traveled during May/June. *Right* shows changes in distance traveled between July and September.
Fig. SI-6. Increased exposure to alerts associated with decreased response, cumulative duration

Notes: figures show period-specific estimates of air alert event studies between March and September 2022. Left shows changes in distance traveled (sum) across time (minutes relative to treatment) for the 61 minute window centered around the minute of the air alert notification. The vertical line orients separates the pre-period trends from the post-treatment effects. Effects are shown in meters. Samples are split at the median of alert exposure (duration of alerts within regions and time periods) calculated as cumulative duration since the start of the conflict. Results are shown for March/April. Middle shows changes in distance traveled during May/June. Right shows changes in distance traveled between July and September.