Strength in Numbers? Assessing the Effectiveness of Large-Scale Drone Attacks in the Russia–Ukraine War

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Abstract

Placeholder

1 Introduction

The Russia-Ukraine war has demonstrated that drones are not only a central component of counterinsurgency but also of conventional warfare. Over the course of the war, Russia has increasingly relied on immense numbers of drones to barrage Ukrainian cities and overwhelm Ukraine's air defenses. This bombardment and a rapidly dwindling supply of Western-supplied defense munitions have forced Ukraine to innovate and develop first-person view (FPV) and even artificial intelligence (AI)-enabled drones to combat the overwhelming mass of Iranian and Russian-produced Shahed drones (Bondar 2025). Ukraine's technological advances and success in using drones to defend against a stronger adversary have demonstrated to Western militaries that cheap, mass-produced weapons can overpower more expensive ones, upon which powerful militaries like the United States have traditionally relied. At the same time, Russia's strategy of scaling up domestic production of Shahed drones and relying on these low-cost weapons to overwhelm Ukrainian defenses through cheap mass rather than expensive precision signals a shift in conventional military strategy (Albright, Burkhard, and Faragasso 2023; Jensen and Macias 2025). As a result, many countries are reconsidering their military strategies and shifting defense production towards more attritable weapons that can be massed against a target until defenses fail. For example, developing "attritable autonomous systems" is a cornerstone of the Replicator Initiative, a US Defense Department program aiming to deliver thousands of uncrewed aircraft like the LUCAS drone, a low-cost loitering munition reminiscent of the Shahed (Department of Defense 2024; Sayler 2024).

Calls within the Pentagon to shift to a strategy of affordable mass have been driven not only by the lessons learned in Ukraine but also by rising tensions with China and Washington's goal of preparing for conflict in the Indo-Pacific (House Armed Services Committee 2021; Sayler 2024). Although the United States possesses more advanced weapons, China has a significant advantage in the number of weapons and military personnel it commands (Department of Defense 2024). Ukraine's successes with drone warfare, as well as underwhelming US performance in DoD war-gaming, has undermined confidence in the US military's advantage and spurred this shift to attritable weapons (Sepinsky and Bae 2022; Insinna 2021).

However, little empirical research exists evaluating whether mass drone attacks are an effective military strategy. Although news organizations, think tanks, and federal defense agencies have written extensively on military strategy in the Russia-Ukraine war, almost none of this work includes quantitative analysis. This study provides the first regression-based analysis of whether mass drone attacks actually improve per-unit survival by modeling how the number of drones launched impacts the proportion that survives interception.

Understanding whether mass drone attacks increase survivability relaxes a strong assumption made by previous studies on airpower: that aerial attacks reach their intended targets. Prior studies on airpower in conventional war analyze air campaigns dominated by missiles and frequently prosecuted by one military superpower against a much weaker adversary (Byman and Waxman 2000; Stigler 2003; Harvey 2006; Lake 2009). However, the rise of drone warfare makes attrition warfare more likely, since the low cost of drones enables weaker adversaries to contest the airspace (Bremer and Grieco 2021). The inability of either party to establish air superiority suggests that aerial force is less guaranteed to hit its intended targets, in which case, prior findings about the role of airpower actually reflect the role of airpower *in air superiority settings,* and not in air campaigns more generally. If attrition warfare becomes more likely as advancements in drone technology continue to lower costs, the prior studies' findings may not be generalizable to modern conflicts.

Rather than focus on the coercive effects of airpower, this study seeks to understand under what conditions strikes even reach their intended targets: in other words, how does massing attacks affect weapon survivability? I estimate a beta-binomial regression to model how the number of drones launched by Russia affects the proportion that survive interception by Ukraine, using publicly available data published by Petro Ivaniuk, a Ukrainian researcher, and verified by the Center for Strategic and International Studies (CSIS) (Hollenbeck 2025; Atalan and Chavez n.d.). I find that mass does not improve drone survivability; surprisingly, launching more weapons in a single attack is associated with a lower proportion surviving interception, suggesting that Ukraine's defenses scale with attack size rather than succumbing to mass strikes. Not surprisingly, weapon type is the dominant predictor of survival, with ballistic missiles and Surface-to-Air Missiles (SAMs) surviving at rates above 85%. Changes in Russia's airpower strategies and Ukraine's air defenses, represented by discrete time periods in the model, produce large shifts in the probability of weapon survival; for example, Russia's adoption of saturation tactics in September 2024 initially increased survivability across all weapon types before degrading over time as Ukraine adopted increasingly advanced interception techniques. Geography is also a significant predictor of weapon survivability, with weapons launched from locations closer to Ukraine surviving at higher rates than those launched from distant sites.

2 Airpower as Coercion

In *Bombing to Win*, Pape (1996) argues that a "denial" strategy of using airpower to strike military targets, such as materiel, supply chains, and communication lines, effectively undermines an adversary's ability to wage war and translates to strategic success. In contrast, a "punishment" strategy that targets civilian infrastructure to erode public support is unlikely to coerce an adversary into changing its behavior (Pape 1996). While subsequent literature debates Pape's findings, much of it continues to suggest that airpower is most effective when it degrades an adversary's military rather than when it punishes civilians (Mueller 1998; Horowitz and Reiter 2001; Belkin et al. 2002; Allen and Martinez Machain 2020).

However, a capable adversary may intercept airstrikes and prevent the execution of a punishment or denial strategy. Studies that account for this possibility find that the success of an airpower campaign depends heavily on the adversary's ability to mount a defense. Byman and Waxman (2000) and Harvey (2006) both study Operation Allied Force, the NATO bombing campaign against Yugoslavia in 1999, and emphasize that Serbia's inability to counter-escalate militarily and failure to counter-coerce NATO strategically contributed significantly to the success of NATO's air campaign. Horowitz and Reiter (2001) move beyond the Kosovo conflict to test the role of military vulnerability in 53 cases of airpower coercion, and also find that coercion is more likely to be effective when the target's military vulnerability is higher. While these studies begin to consider how the disparity in military capabilities between two warring parties influences airpower effectiveness, they still implicitly assume that airpower, when applied, reaches its intended targets. This study provides a necessary insight into the causal pathway from airpower to coercive effects by modeling the tactical delivery of airpower, a precondition to coercive effects. The results demonstrate that a large attack does not guarantee a large number of successful strikes, suggesting that an adversary capable of intercepting strikes may altogether avoid the coercive effects of airpower.

Additionally, prior studies tend to measure adversarial capability at the campaign level rather than the operational level, potentially failing to account for how tactical interception of individual weapons reduces military vulnerability.[1] Like Horowitz and Reiter, most prior studies on airpower use small-N datasets of all instances of air campaigns (Pape 1996; Horowitz and Reiter 2001; Belkin et al. 2002; Allen 2007; Allen and Martinez Machain 2020). This paper extends prior quantitative studies by conducting a within-campaign analysis of weapon survivability in Russia's air campaign against Ukraine and leveraging a large-N dataset.

This study, therefore, fills a critical gap in the airpower literature by modeling the tactical delivery of airpower. I analyze the relationship between the number of weapons launched and the proportion that survive interception to determine whether large-scale attacks overwhelm defenses, in which case airpower reaches its intended targets and coercion is possible. If mass attacks overwhelm air defenses, larger attacks should increase the proportion of weapons that survive interception, implying the following hypothesis:

> *H1: As the number of weapons launched in an attack increases, the proportion of weapons surviving interception increases.*

This relationship logically precedes the causal link between airpower and coercion explored in prior studies; before airpower can coerce, strikes must reach their targets. Understanding whether mass translates to delivered airpower also sheds light on the role of adversarial capability, since an adversary's ability to intercept intended strikes and avoid the coercive effects of airpower likely explains some of the variation in the success of airpower campaigns.

The remainder of this paper proceeds as follows: Section 3 describes the data, including the construction of launch location and weather variables and the multiple imputation strategy for missing data. Section 4 presents the beta-binomial regression framework, model specifications, and theory-driven phase structure. Section 5 reports the results for both the

[1] Horowitz and Reiter use Pape's definition of military vulnerability, where the threat to loss of territorial control defines vulnerability.

all-weapon and drone-only models, including model diagnostics. Section 6 addresses possible limitations, and Section 7 concludes with a discussion of the implications for airpower strategy.

3 Data

This analysis examines Russian aerial attacks and Ukrainian interceptions; accordingly, ”survivability” refers to the probability that a Russian weapon evades Ukrainian interception. Modeling Russian weapon survivability rather than Ukrainian interception may seem counterintuitive, since most Western perspectives treat Russia as the adversary and model Ukrainian interception. However, I select Russian weapon survivability as the outcome for two reasons. First, this dataset reports only Ukrainian interceptions of Russian weapons, not Russian interceptions of Ukrainian weapons, limiting the analysis to viewing Russia as the offender and Russia as the defender. Nevertheless, Ukraine's publicly reported interception data is a more reliable and comprehensive source of weapon survivability than Russia's accounts (Plichta 2025, 45). Second, I model Russian weapon survivability rather than Ukrainian interception rates because this presents the most intuitive test of my hypothesis: the primary goal of increasing the size of an attack is to increase the number of strikes reaching an adversary, not to decrease the number of weapons intercepted (Department of the Army 2025, 5).

The dataset was created by Petro Ivaniuk, a Ukrainian researcher who manually compiled the data from official reports of the Air Force Command of the UA Armed Forces and the General Staff of the Armed Forces of Ukraine, published on social media such as Facebook and Telegram. The dataset has been cited several times by the Center for Strategic and International Studies (CSIS), which independently verified that the dataset matches the Ukrainian military's social media accounts detailing intercepted Russian drones (Hollenbeck et al. 2025; Atalan and Chavez n.d.; Jensen and Macias 2025).

The data contains all Russian drone and missile launches and Ukrainian interceptions from September 2022 to November 2025 and is aggregated by the type of weapon launched and the date and time of the attack. After excluding 212 frontline tactical drones (Kub, Lancet, Molníya) due to near-complete missing launch location data, the analysis sample contains 1,941 observations across four weapon categories: loitering munitions (Shahed-136/131, $n = 833$),[2] cruise missiles ($n = 635$), ballistic missiles ($n = 361$), and surface-to-air missiles ($n = 112$).[3]

Each observation records the number of weapons launched and the number intercepted by Ukraine. The number surviving interception is:

$$\text{survived}_i = \text{launched}_i - \text{intercepted}_i$$

The survival rate $p_i = \text{survived}_i/\text{launched}_i$ varies substantially across attacks. Figure 1 reveals a bimodal distribution: in most attacks, Ukraine intercepts either all or none of the weapons launched.

[2] Russia calls the Shahed-131 and Shahed-136 the 'Geran-1' and 'Geran-2', respectively (Emmett, Ball, and Jenzen-Jones n.d.). Russia initially relied on Iranian shipments of the Shahed drone before beginning domestic mass production of the 'Geran-2' at factories in the Alabuga SEZ (Albright, Burkhard, and Faragasso 2023). I use the name "Shahed" to remain consistent with the dataset, which does not differentiate Geran from Shahed drones.

[3] Attacks conducted with frontline tactical drones are structurally different than the attacks conducted with the other weapon types in the dataset: frontline tactical drones are close-proximity, frontline attrition weapons, whereas Shaheds, cruise missiles, ballistic missiles, and SAMs are long-range strike weapons that activate Ukraine's air defenses.

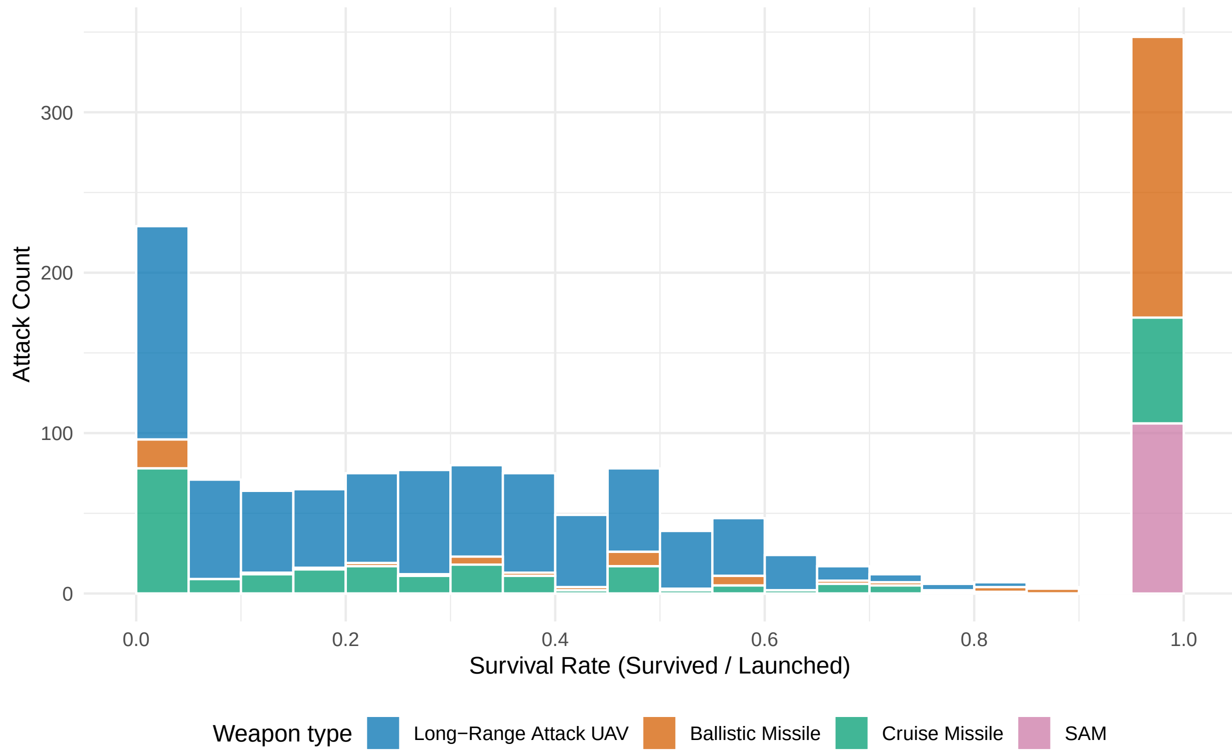

Figure 1: Distribution of weapon survival rates, colored by weapon type. The concentration at 0 (complete interception) and 1 (complete survival) motivates the beta-binomial specification.

In addition to the information on launch and interception totals, the data also include information on the launch and target locations. However, these variables present several challenges. First, both are inconsistently recorded at varying levels of specificity, ranging from the country, region, or administrative district level (oblast-level in Ukraine, federal subject-level in Russia). Country-level specificity is not useful as a control variable, and region-level coding specifies only broad directions, such as "North" and "South," which are not granular enough to serve as controls. Second, location information is frequently missing altogether from the data, particularly for the target variable. After excluding attacks conducted with frontline tactical drones, launch location information is available at the oblast/ federal subject level for approximately 77% of observations overall and 88% of Shahed attacks.

I supplement the launch location data with ERA5 Reanalysis weather data (temperature, wind speed, cloud cover) matched to the capital of each launch oblast/ federal subject, since variation in the weather within each administrative district is limited (Hersbach et al. 2023). This analysis contains modified Copernicus Climate Change Service information; neither the European Commission nor ECMWF is responsible for any use made of the Copernicus information or data it contains. Because some attacks originate from multiple recorded launch locations, I use mean weather conditions across all launch locations for each attack. Appendix G reports a diagnostic showing that each launch location's weather generally remains close to the attack-level mean. Weather is frequently included as a control variable in studies of drones because drone performance varies according to meteorological conditions (Johnston and Sarbahi 2016; Mahmood and Jetter 2023).

Missing data are handled via multiple imputation using Amelia II (100 imputations), with results pooled via Rubin's Rules (Honaker, King, and Blackwell 2011). Imputation overcomes missing data challenges related to missing launch location data, but not missing target location data; there are not enough observations with complete target location information to impute the missing observations. The imputation model includes all analysis variables; launch location dummies, weather, launched, and intercepted are imputed jointly to preserve cross-variable relationships.[4]

I estimate two primary models to explore the relationship between mass and survival. For each model, I estimate alternative specifications that vary the treatment of time (linear trend versus theory-driven phase dummies) and the inclusion of attack-size interactions. I select the preferred specifications using AIC and BIC and report full model-comparison results in Appendix J. For readability, I refer to the preferred all-weapon specification as Model 1 and the preferred Shahed-only specification as Model 2 throughout. Model 1 includes all weapon types and addresses the question: across all Russian aerial weapons, does launching larger

[4]Missingness diagnostic tests indicate that launch location missingness is associated with observed covariates including attack size, weapon type, and observed survival rates. All 100 imputations converged, and imputed means closely match observed means.

attacks improve weapon survivability? In addition to weapon type, this model includes interaction effects (the effect of attack size on weapon type), geography, weather, and time period shifts. Model 2 focuses on Shahed drones and provides a cleaner test of whether mass increases survivability for Shahed drones, the weapon around which Russia has developed its saturation doctrine (Jensen and Atalan 2025). Subsetting to Shaheds also enables the use of Shahed-specific phase breaks that reflect the drone-specific arms race between Russia and Ukraine as they compete to innovate in offensive and defensive drone capabilities.

Table 1: Model Specifications

	Full Model	**Long-Range Attack UAV Model**
Observations	1,484	808
Weapon Types	All long-range weapons	Long-Range Attack UAV category
Time Period	Sept 2022–Nov 2025	Sept 2022–Nov 2025
Weapons Launched	✓	✓
Night Attack	✓	✓
Weapon Type FE	✓	—
Launched × Weapon Type	✓	—
Launch Location FE	✓ (16 dummies)	✓ (7 dummies)
Weather at Launch	✓	✓
Phase Dummies	3 phases	3 UAV-model phases, days since Phase 3
Weapon Type Reference	Long-Range Attack UAV	—
Location Reference	Kursk	Krasnodar
Location Filtering	min_obs $\geq$ 25	min_obs $\geq$ 25
Imputation	Amelia (100 imputations)	Subset from full imputation

4 Research Design

The heterogeneity of the probability of survival motivates the Beta-Binomial rather than a standard binomial approach. Additionally, the concentration of observations at the 0% and 100% bounds, along with the variable and often small number of launches, make OLS inappropriate for three reasons: it treats all observations as equally informative regardless of attack size, it assumes constant error variance when the variance of proportions depends on both the mean and the number of trials, and it produces unbounded predictions for a response that is necessarily constrained to [0, 1] (McCullagh and Nelder 1989; Papke and Wooldridge 1996).

The outcome y_i is modeled using the Beta-Binomial:[5]

$$y_i \sim \text{Beta-Binomial}(\mu_i, \theta, M_i)$$

where y_i represents the count of drones surviving interception in attack i, M_i is the total number of drones launched in attack i, μ_i is the mean probability that a drone survives interception, and θ is the overdispersion parameter capturing the correlation between drones within the same attack. The parameter μ_i is modeled as a function of covariates including the number of drones launched by Russia, drone or weapon type, launch location, weather at launch location, and phase of the war. The overdispersion parameter θ accounts for the fact that drones launched in the same attack are not independent events.

Full covariate equations for both preferred specifications are reported in Appendix C.

I measure the efficacy of mass attacks using the number of weapons that survive interception because it indicates the extent to which the attacking or defending state has established or maintained air superiority, respectively. Achieving air superiority is one of the priorities of conventional military strategy, with the US Air Force defining it as a "degree of control of the air by one force that permits the conduct of its operations at a given time and place without prohibitive interference." (US Department of the Air Force 2023) Higher μ_i values correspond to Russia gaining control of the airspace, whereas lower μ_i values correspond to Ukraine retaining control.

I hypothesize that, as the number of drones launched by Russia increases, the number that survive interception will increase as a proportion of those launched. For example, when Russia launches a small attack of 5 drones, Ukraine may intercept 4 out of 5; however, when Russia launches a large attack of 100 drones, Ukraine may only intercept 20. This hypothesis

[5] Models are estimated using VGAM in R, with results pooled across 100 multiply-imputed datasets using Rubin's rules. Counterfactual predictions are based on 10,000 simulated coefficient draws.

is consistent with current US national security strategy (Hicks 2023; Sayler 2024).

Models are estimated using VGAM in R, pooled across 100 multiply-imputed datasets via Rubin's Rules, with 10,000 simulated coefficient draws for counterfactual predictions.

The unit of analysis is weapon type-day. Attacks are only observed when Russia launches an attack, meaning that this analysis asks whether scale improves per-unit survival given that Russia has launched an attack (in other words, this analysis does not model the probability of Russia launching an attack). Russia's decision to attack is likely endogenous to the probability of attack survivability; as Allen and Machain (2018) note, selection into airpower use is non-random and is driven by factors such as a state's military strength. As such, Russia likely conducts individual air attacks in instances where the attacks are more likely to hit their intended target, such as when meteorological conditions are favorable or from advantageous geographic positions. The weather and launch location variables absorb the observable dimensions of this concern.

Additionally, the phase dummies control for critical changes in Russia's ability to launch successful attacks and Ukraine's ability to defend that likely contribute to Russia's attack planning. The phase dummies are theory-driven structural breaks: for Model 1, *phase2* marks the Patriot system becoming operational (April 2023) and *phase3* marks Russian adoption of saturation tactics (September 1, 2024). For Model 2, *phase2* marks saturation tactics (September 2024) and *phase3* marks Ukraine's deployment of interceptor drones (March 2025), with an additional slope term capturing the progressive improvement in interception as the program scales.

5 Results

The overdispersion parameter ρ is significant in both specifications ($p < 0.001$), confirming that the beta-binomial is appropriate over the standard binomial.[6]

[6]Full pooled coefficient estimates for both models are reported in Appendix D.

5.1 Model 1: All Weapon Types

Weapon type is a dominant predictor of survivability in Model 1: SAMs and ballistic missiles have the highest survival rate, while Shaheds (reference category) are the most interceptable. Figure 2 shows the predicted survival probabilities for a single weapon launched during Phase 1 from the reference location.

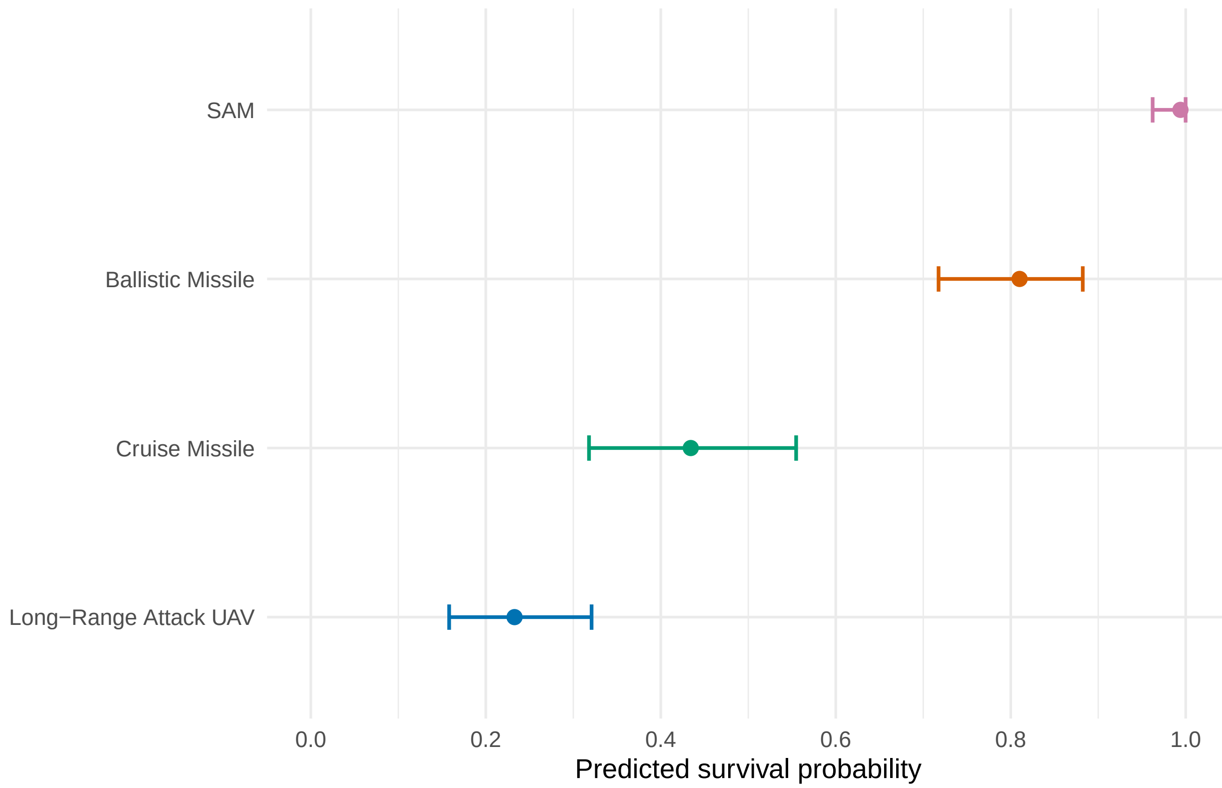

Figure 2: Predicted survival probability by weapon type (Model 1). SAMs and ballistic missiles are nearly impossible to intercept; loitering munitions are the most interceptable.

The interaction terms reveal that attack size effects differ by weapon type. For the reference category (Shaheds), attack size has no detectable effect (-0.0005, $p > 0.05$). This null result challenges the "mass overwhelms" narrative, which predicts that increasing the number of Shahed drones launched should increase survivability for the most interceptable weapon class. Even for ballistic missiles, each additional missile in a salvo reduces per-unit survival rate, possibly because larger salvos trigger concentrated defensive responses. For example, a single ballistic missile has approximately 85% predicted probability of survival, but a salvo of 10 reduces individual weapon survivability to approximately 50%, and a salvo of 26 (the observed maximum) to approximately 5%. Increasing the attack size for cruise missiles also decreases per-unit survivability. These findings demonstrate that the relationship between scale and effectiveness depends on the defender's baseline interception capability. For SAMs, however, larger barrages increase per-unit survival. Figure 3 shows these divergent effects.

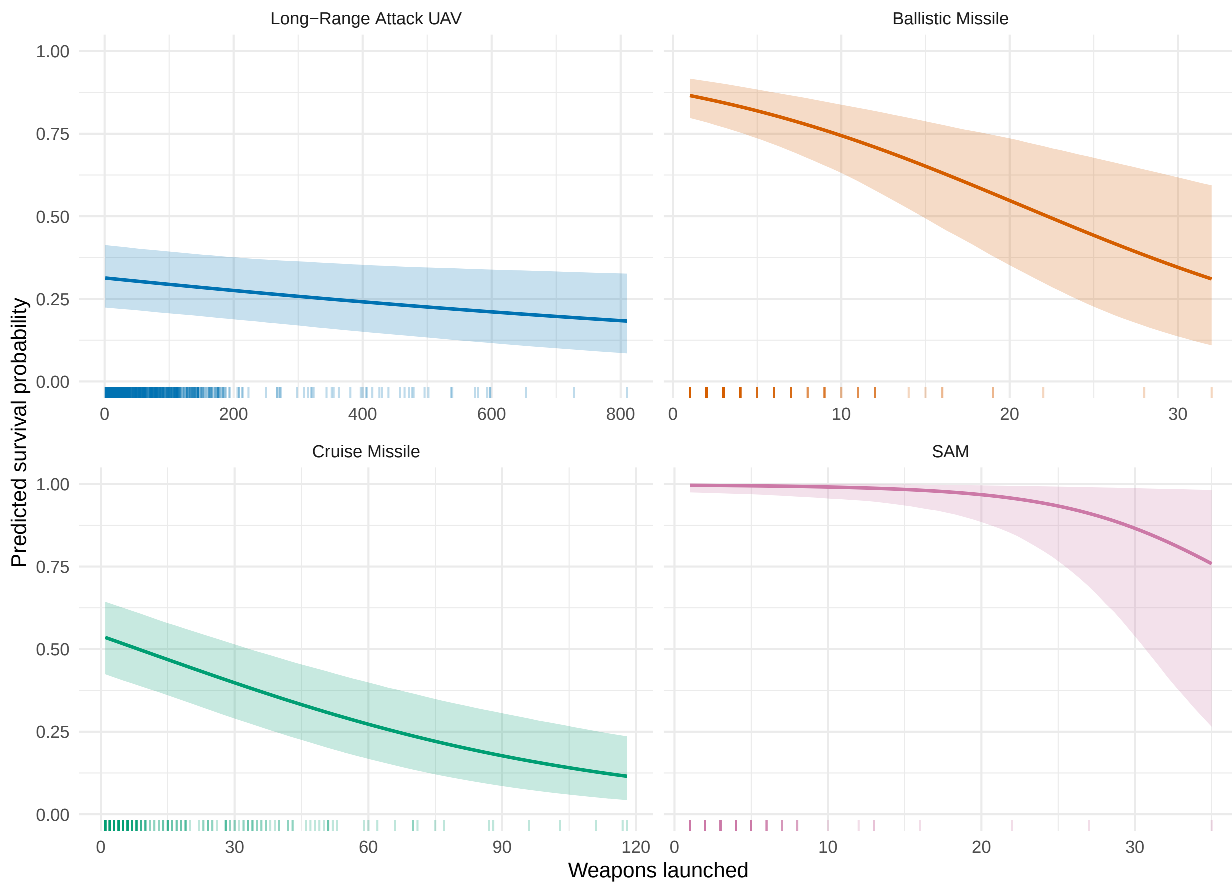

Figure 3: Effect of attack size on survival by weapon type (Model 1). Panels are scaled to each weapon type's observed attack-size range.

The Patriot phase dummy (Phase 2, April 2023), which represents Ukraine's acquisition of Patriot defense systems, is not significant (0.054, $p > 0.05$), indicating no detectable shift in interception rates following Patriot deployment (Congressional Research Service 2025).

Russia's adoption of saturation tactics and mass drone deployment (Phase 3, September 2024) is associated with an immediate and highly significant increase in survival (0.747, $p < 0.001$). Temperature is significant (-0.024, $p < 0.001$), suggesting that colder weather is associated with higher weapon survival.

Launch geography also matters. Figure 10 in Appendix F shows that attacks from Oryol and Rostov (close to Ukraine) have significantly higher survival, while attacks from Saratov and the Caspian Sea (distant launch points) have significantly lower survival, consistent with a flight-time mechanism (Albright and Faragasso 2025). This finding supports Lyall's (2015) finding that airpower effects are localized and Saunders and Souva's (2020) findings that air superiority varies spatially; Ukraine appears to achieve better air denial in areas further from the launch site where they have more time to react.

5.2 Model 2: Shahed Drones

Model 2 focuses exclusively on the Shahed-136/131. The attack size effect is now significant (-0.0008, $p < 0.05$) and indicates that larger Shahed attacks are associated with *lower* survivability, meaning that Ukraine intercepts larger attacks better than smaller attacks. This finding suggests that for Shaheds, Ukrainian defenses scale effectively with attack size. Importantly, this result directly contradicts my hypothesis and much of the ongoing research on the war in Ukraine that argues that mass overwhelms defenses (Jensen and Macias 2025; WarQuants 2025; Albright and Faragasso 2025).

This finding also adds important nuance to Pape's framework: if mass drone attacks fail to improve per-unit survivability, then the attacker becomes unable to achieve the *prerequisite* condition of delivering munitions on target necessary for either punishment or denial to operate as coercion.

However, Russia may accept this tradeoff because, even if the *rate* of survival decreases with larger attack sizes, the absolute number of drones surviving to hit their intended target may still increase. For example, a 25% survival rate in an attack of 1000 Shahed drones likely delivers greater effects than 75% of 100 in absolute terms. Current research suggests that this tradeoff is exactly the calculus Russia is making (Jensen and Macias 2025).

The phase structure also tells a clear narrative. Figure 4 shows the predicted Shahed survival probability over time. Phase 2 (saturation tactics adopted in September 2024, same as in Model 1) produces a massive jump in per-unit survivability, roughly tripling the odds of a Shahed surviving interception. Phase 3, which represents the first instance of Ukraine deploying interceptor drones against Shaheds (March 2025), initially corresponds to continued high survival rates, but the days_since_phase3 slope (-0.006, $p < 0.001$) reveals steady improvement as Ukraine's interceptor drone program progressively improves Ukraine's interception capability (FPRI 2026).

These phases provide support for Byman and Waxman's (2000) theory of counterescalation at the individual attack level of an airpower campaign; as Ukraine responds to Russia's escalation (saturation strategy) with a successful counterescalation (interceptor drones), the rate of survivability for Russia's Shaheds decreases.

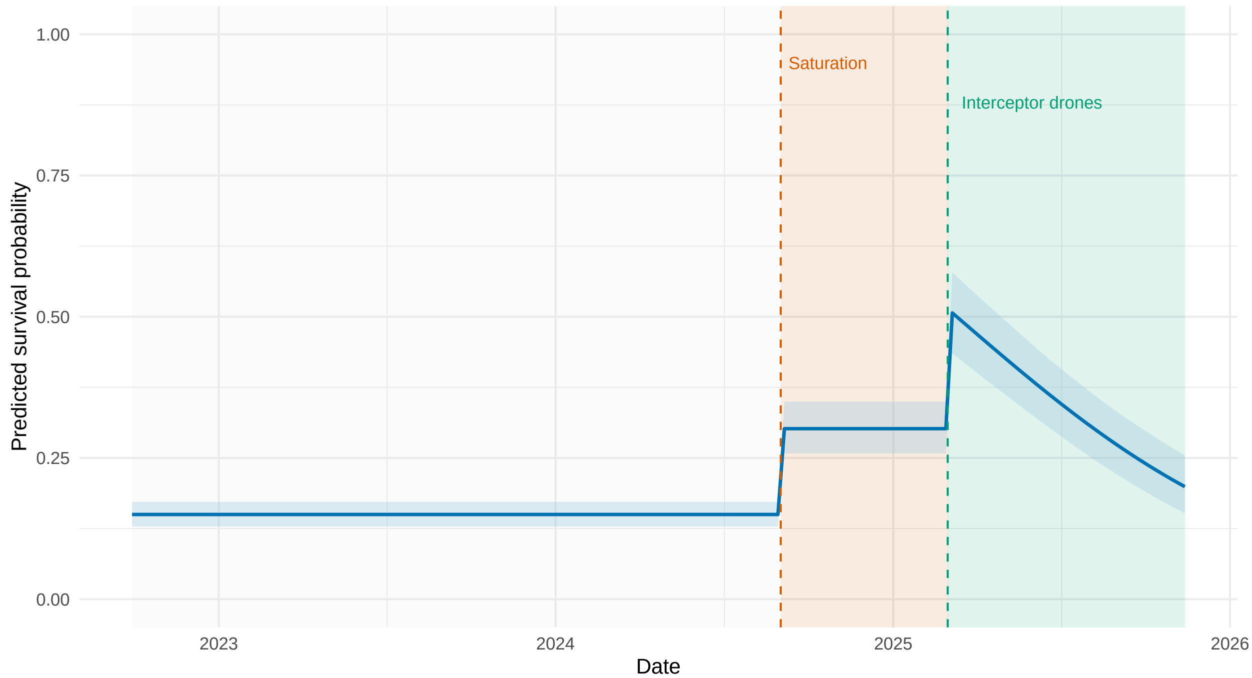

Figure 4: Predicted Shahed survival probability over time (Model 2). Vertical lines mark phase transitions.

Temperature, which was significant in a model with a linear time trend, loses significance once phase dummies are included (-0.007, $p > 0.05$). Phase 2 onset (September 2024) coincides with the start of the cold season in Ukraine and Russia, meaning temperature likely acted as a proxy for the saturation phase rather than a causal factor. Wind speed is also not a significant predictor of Shahed survivability. Cloud cover is the only weather variable with a significant effect in Model 2 (0.230, $p < 0.05$), though this result is not robust across all specifications.

Oryol is the only launch location significant across all Model 2 specifications (0.250, $p < 0.01$).

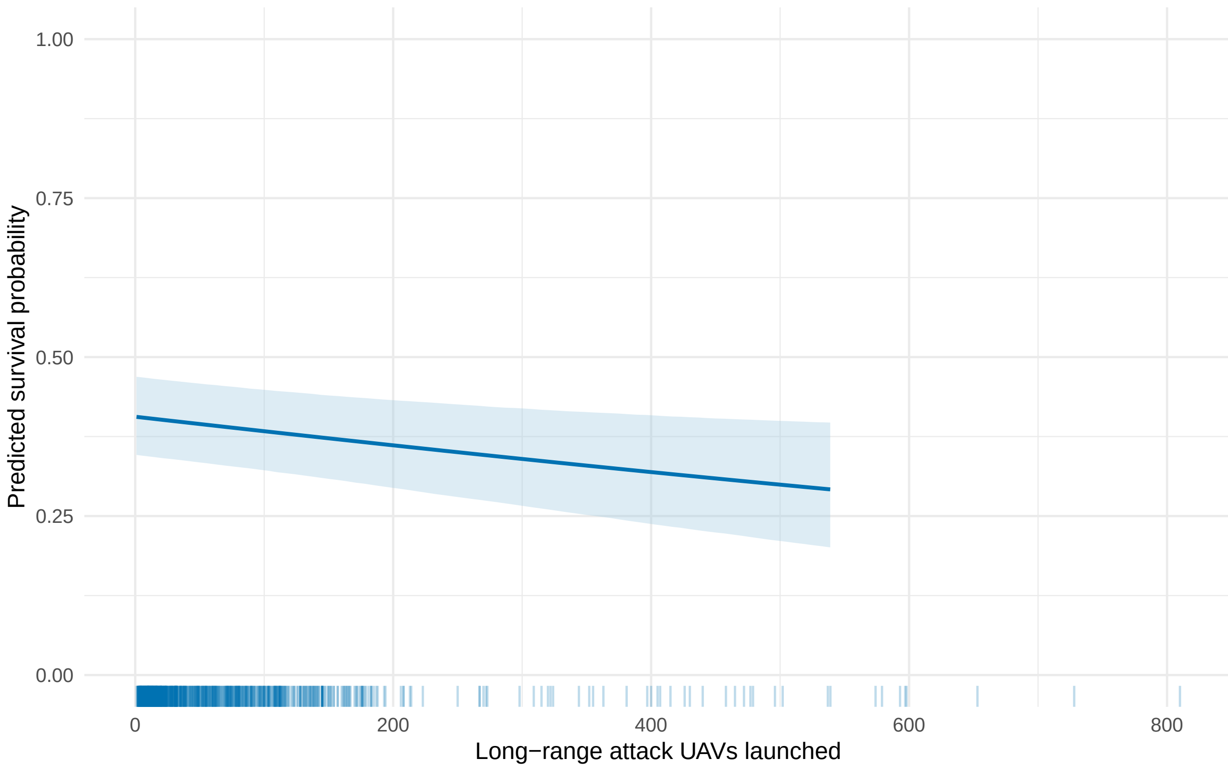

Figure 5: Effect of attack size on Shahed survival (Model 2).

5.3 Model Fit

Model selection via AIC/BIC favors the phase specifications over linear time trends for both models. Within Model 1, the interaction specification is preferred over main effects only. Full comparison tables for all specifications are reported in Appendix J. Figures 6 and 7 show binned randomized quantile residuals for the preferred specifications; residual means remain close to zero across fitted values and attack size, suggesting that the beta-binomial models do not systematically over- or under-predict survival for either small or large attacks. Q-Q plots are reported in Appendix E. I also run a series of robustness checks on the preferred models, first after including frontline tactical drones and second using complete cases rather than imputed data. The attack-size coefficients remain non-positive across these checks, supporting the main finding that mass does not overwhelm defenses; full results are reported in Appendices K and L.

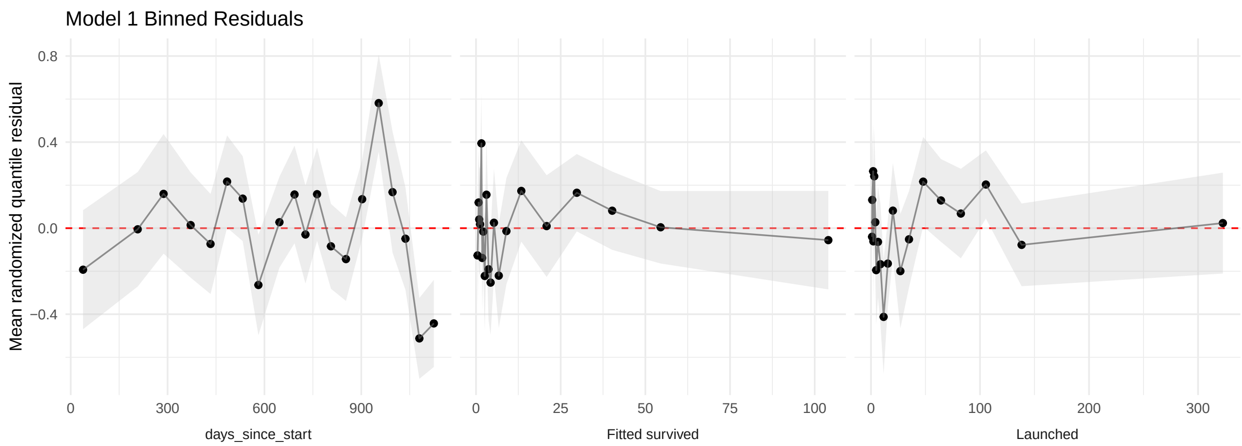

Figure 6: Binned quantile residuals for Model 1. Residual means remain close to zero across fitted values, attack size, and time.

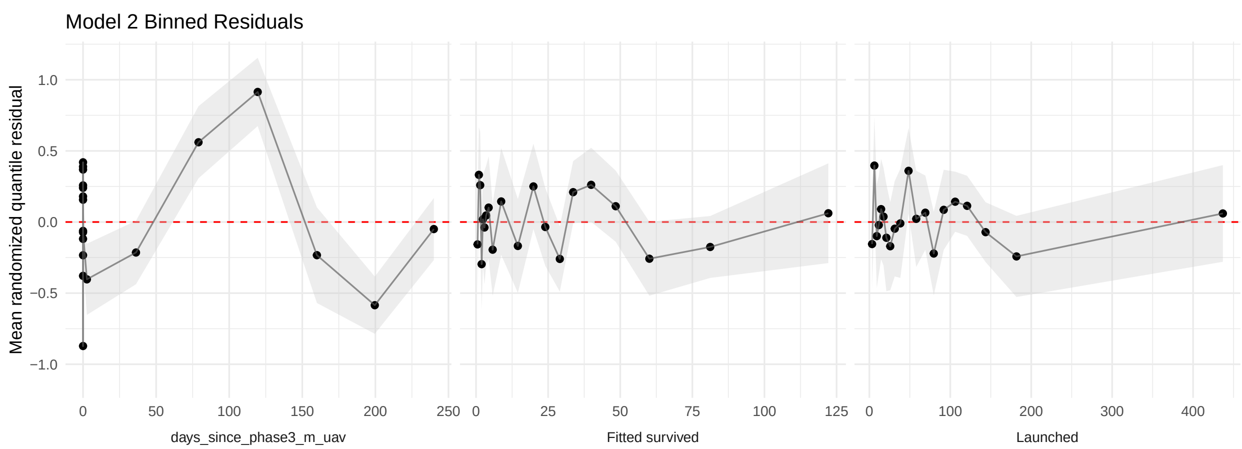

Figure 7: Binned quantile residuals for Model 2. Residual means remain close to zero across fitted values and attack size, with more variation over time.

6 Limitations

There are three main limitations to this analysis. First, conflict data are notoriously difficult to measure because the “fog of war” prevents accurate reporting (Sweet 2026). Additionally, relevant actors often have incentives to obfuscate data, either to hide evidence of violations of international law or for national security reasons. For example, consider US decisions to classify men aged 11 and over as "military-aged combatants" to avoid international condemnation over drone operations in Pakistan (Scahill and Staff of The Intercept 2016). While this analysis does not deal with casualties, my data on Ukrainian interceptions may be similarly influenced by the Ukrainian military's defense strategy. I expect their current defense strategy could bias the dataset toward either over-reporting or under-reporting interceptions.

In the instance of *over-reporting*, the Ukrainian military might be motivated to record higher numbers of interceptions than actually occur to convey capability and resolve to Western partners in the hope of receiving additional military aid. Recall that this dataset was created by scraping public-facing social media accounts such as Facebook and Telegram. Besides seeking to demonstrate success to Western policymakers and publics, the Ukrainian leadership may also want to reassure domestic audiences through evidence of Ukrainian successes on the battlefield. If this is the case, the data would understate the overall level of Russian weapon survivability, since overstating Ukrainian interceptions mechanically reduces the number of weapons coded as surviving.

To assess the sensitivity of the main result to reporting bias, I re-estimate Model 2 after systematically reducing reported interceptions. First, I incrementally reduce reported interceptions by 5-20% for only *large* attack sizes, defined as the 75th percentile of Shahed attack sizes; second, I reduce reported interceptions by the same proportion for *all* attack sizes. The results suggest that the main finding is robust to generalized over-reporting: when interceptions are reduced uniformly across all Shahed attacks, the launched coefficient remains negative and statistically significant even under a 20% reduction in reported interceptions. However, the result is more sensitive to differential over-reporting concentrated in large attacks, becoming statistically insignificant under a 5% reduction and reversing direction under larger reductions. This suggests that simple over-reporting does not bias the results; any over-reporting would need to be systematically correlated with attack size to explain the Model 2 result. Full results are reported in Appendix M.

In the instance of *under-reporting*, the Ukrainian military might be motivated by the same desire for additional Western military aid, but hope to achieve it by demonstrating need rather than capacity. While this strategy may have been effective during the Biden administration's tenure, it was much less likely to work following Trump's election in 2024. Trump is well-known for admiring strength in national leaders, and campaigned on skepticism of US involvement in and support of Europe generally. For these reasons, it is likely that, even if Ukraine under-reported interceptions earlier in the war, its incentives shifted toward demonstrating battlefield effectiveness as US support became more politically uncertain. Trump's election in 2024 coincided with Russia's implementation of drone-saturation tactics, so many of the dataset's observations come from 2024-2025. Under-reporting would bias the data in the opposite direction from over-reporting and overstate Russian weapon survivability, therefore making Ukrainian air defenses appear less effective than they actually are.

A second potential limitation is the possibility for an endogeneity problem with respect to the targets Russia chooses to attack. In my analysis, Russia's decision to launch weapons, especially Shahed drones, against specific locations is almost certainly influenced by military strategy. On the one hand, territory valuable to both Ukraine and Russia is likely both well-defended by Ukraine and prioritized by Russia, leading Russia to focus attacks on well-defended territory. This scenario creates an endogeneity problem because it means that the negative effect on survival of launching more drones may be an artifact of Russia concentrating large attacks on better-defended targets.

On the other hand, it is possible that Russia directs the majority of its attacks against poorly-defended Ukrainian positions based on intelligence about where Ukraine lacks air defenses. According to much of the reporting on the war, Russia uses Shahed drones to target Ukrainian civilians in cities; if the ultimate goal is undermining morale, there is no reason to think that Russia is necessarily targeting "valuable" locations in an attempt to gain territorial control. Furthermore, many of these attacks take place at night, during which time Ukrainian air defenses are weakened, suggesting that the results are unlikely to be solely a result of Russia concentrating attacks on well-defended targets.

Ideally, I would address this problem by controlling directly for target location. However, target information is not consistently observed (only 117 of the 833 Shahed observations used in Model 2 have any information on the target, and many of these observations only record the region of the country of the target). As a result, including target-location controls would require estimating the model on a highly selected subset of attacks and may introduce additional bias rather than solve the endogeneity problem. I therefore treat target selection as an important limitation and interpret the attack-size coefficient as a descriptive association rather than a causal estimate.

The third potential limitation is the reality that, even if the proportion of weapons surviving interception *decreases* relative to the number of weapons launched, the absolute number of weapons surviving may continue to *increase*. To return to the example from the beginning of the paper, consider that, if Ukraine intercepts 2 out of 5 drones in an attack, the interception rate is 40% and the absolute number surviving is 3. In an attack of 100 drones, even if the interception rate increases to 90%, 10 still survive. This increase in the number of surviving weapons might lend support to existing airpower literature, since it would suggest that states can still deliver airpower in the face of rapidly improving interception rates as long as they can continue to increase attack sizes.

However, the observed distribution of Shahed attack sizes shows that the very large attacks needed to produce high numbers of surviving drones are rare. The median Shahed attack consists of 39 drones; only 24 observations, or 2.9% of the dataset, involve 400 or more. Within the range of most of the observable data, increasing the number of Shahed drones launched in an attack only slightly increases even the total number of drones surviving interception.

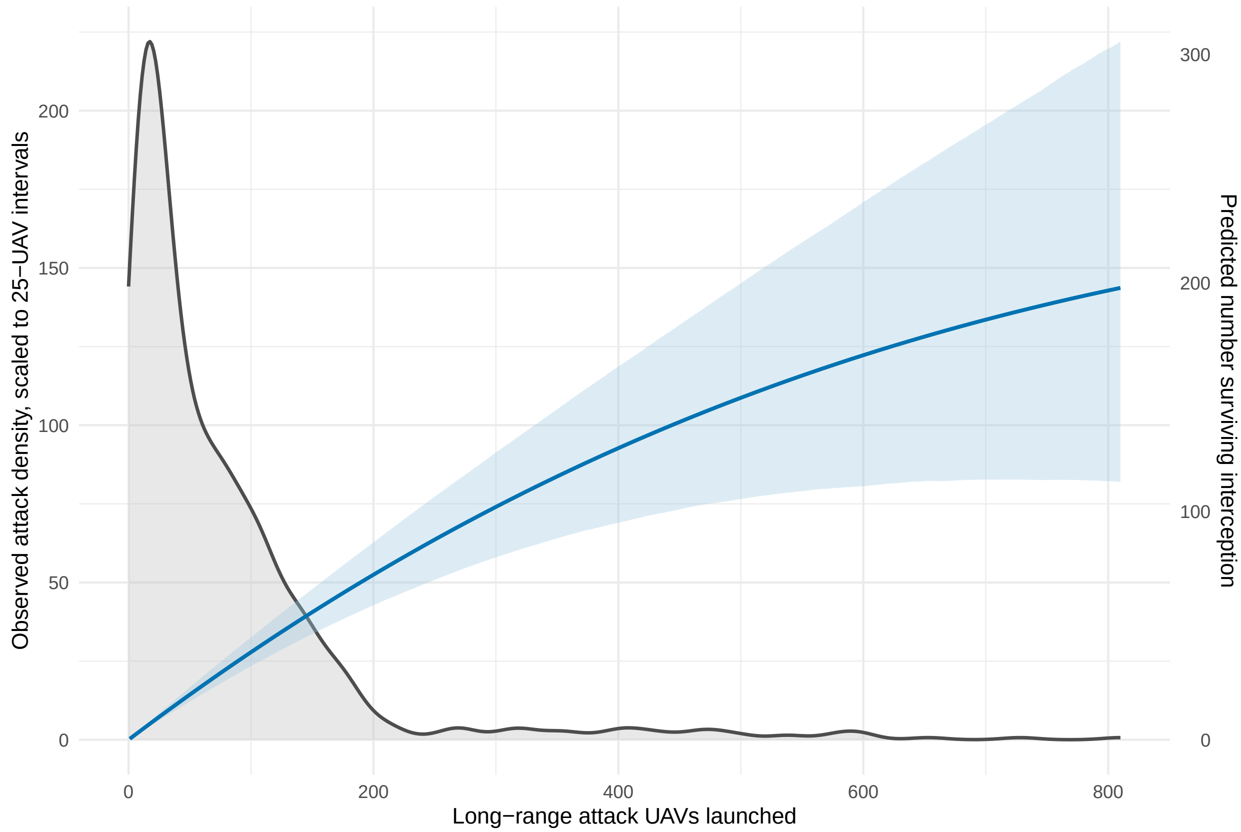

Figure 8: Predicted number of Shaheds surviving interception and observed attack-size density. Predicted values are from Model 2, holding launch location at the Krasnodar reference category and weather at observed means. The density curve is scaled to approximate the number of observed Shahed attacks in a 25-drone interval.

Nevertheless, the results do not show that mass attacks are incapable of producing damage in absolute terms. Instead, they show that mass does not improve per-unit survivability for Shahed drones. Russia may still deliver more aerial force by launching much larger attacks, but doing so requires moving into the tail of the observed attack-size distribution. There are also practical reasons to expect a ceiling on this strategy, including constraints on Shahed production capacity and the operational difficulty of coordinating large salvos.

7 Discussion and Conclusion

This analysis suggests that the marginal effect of scale on per-unit effectiveness is zero or negative for easily interceptable platforms like Shahed drones. Weapon survivability in individual attacks appears driven primarily by regime changes in defender capability, such as the acquisition of new air defense platforms and the adoption and learning of new interception techniques. Changes in the offense-defense balance occur as a result of strategic and technological innovations, not through quantity as current military strategy assumes.

These findings complicate the relationship between airpower and coercive effects established by Pape (1996, 1998) by demonstrating that the delivery of airpower is not guaranteed. Both punishment and denial strategies, therefore, have a potential delivery problem: launching more drones does not necessarily mean a higher proportion hit their intended targets. This finding also has implications for Posen (2003), who argues that US hegemony relies on control of the commons, including the airspace. Cheap, attritable Shahed drones initially provided Russia with the opportunity to contest Western air superiority established via more advanced air defense systems, but Ukraine's interceptor drones appear to have enabled Ukraine to regain some control of the air. The resulting equilibrium is dynamic and depends on adaptive counter-escalation (Byman and Waxman 2000).

The premise that mass overwhelms air defenses is not supported for platforms that are easily interceptable, like Shahed drones. Mass matters for hard-to-intercept weapons, such as SAMs, but for drones, investment in interception technology (which is also cheap and scalable) appears to negate the mass advantage.

This paper makes several substantive contributions: it is the first quantitative analysis of the delivery function, which provides critical insight into a prerequisite step in the relationship between airpower and coercive effects. Second, I also extend the airpower coercion literature and show that the relationship between attack scale and effectiveness is not monotonically positive, but depends on defensive capability as well as weapon type and geography. Third, these findings have direct implications for current US defense strategy.

The Replicator Initiative's assumption that affordable mass will overwhelm adversary defenses may not hold for platforms that are easily interceptable, suggesting that investment in scalable interception technology is at least as important as investment in mass production of attritable weapons. Future research should explore whether weapon type interactions, such as the effect of launching drones alongside missiles in coordinated salvos, alter the delivery function, and whether recent tactical developments such as low-altitude drone flight paths and new drone variants change the dynamics identified here.

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A Summary Statistics

Variable	N	Mean	Median	SD	Min	Max
Weapons Launched	1378	47.76	15	84.94	1	810
Weapons Destroyed	1469	29.95	10	61.19	0	747
Weapons Survived	1368	16.39	4	32.57	0	432
Temperature (°C)	1271	10.49	11.16	8.65	-19.53	30.91
Wind Speed (m/s)	1271	3.35	3	1.53	0.35	11.84
Cloud Cover (0–1)	1271	0.50	0.51	0.36	0	1

Table 2: Summary Statistics (Full Analysis Sample, $n = 1,484$ category-event observations)

B Missing-Data Diagnostics

Table 3: Missing-Data Diagnostic Tests for Launch Location Missingness

Sample	Outcome	Obs. Mean	Miss. Mean	t-test p	Logit Coef.	SE	Logit p
All weapons	Launched	51.914	12.788	< 0.001	-0.025	0.004	< 0.001
All weapons	Destroyed	34.164	8.620	< 0.001	-0.034	0.006	< 0.001
All weapons	Survival rate	0.455	0.466	0.616	0.081	0.243	0.739
Long-range attack UAV	Launched	85.689	19.164	< 0.001	-0.043	0.008	< 0.001
Long-range attack UAV	Destroyed	56.746	14.055	< 0.001	-0.069	0.013	< 0.001
Long-range attack UAV	Survival rate	0.285	0.183	< 0.001	-2.746	0.790	< 0.001

The dependent variable in the logistic regressions is an indicator for missing launch location. All t-tests are one-sided.

C Model Equations

For Model 1 (all weapons):

$$\begin{aligned}\text{logit}(\mu_i) = \beta_0 + \beta_1 \text{launched}_i + \boldsymbol{\gamma}' \text{WeaponType}_i + \boldsymbol{\delta}'(\text{launched}_i \times \text{WeaponType}_i) \\ + \boldsymbol{\lambda}' \text{Location}_i + \beta_T \text{temp}_i + \beta_W \text{wind}_i + \beta_C \text{cloud}_i \\ + \phi_2 \text{phase2}_i + \phi_3 \text{phase3}_i\end{aligned}$$

For Model 2 (Shahed only):

$$\begin{aligned}\text{logit}(\mu_i) = \beta_0 &+ \beta_1 \text{launched}_i + \boldsymbol{\lambda}' \text{Location}_i \\ &+ \beta_T \text{temp}_i + \beta_W \text{wind}_i + \beta_C \text{cloud}_i \\ &+ \phi_2 \text{phase2}_i + \phi_3 \text{phase3}_i + \phi_{3s} \text{days\_since\_phase3}_i\end{aligned}$$

D Full Regression Results

Table 4: Beta-Binomial Regression Results (Phase Specifications)

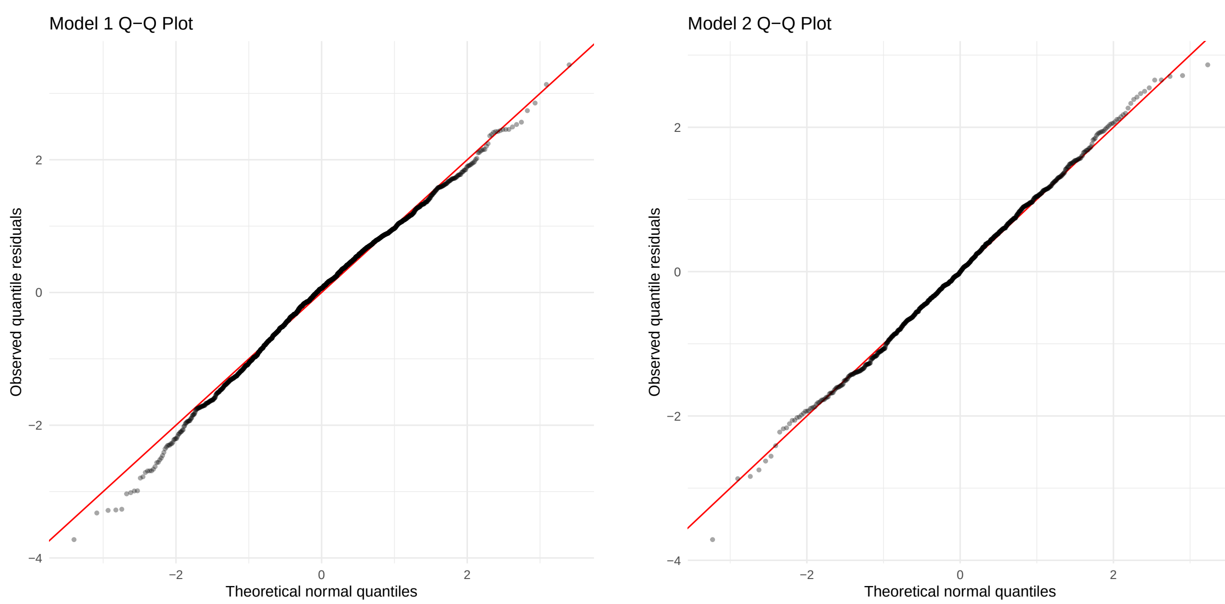
	Full Model		Long-Range Attack UAV Model	
Variable	Coef.	SE	Coef.	SE
Intercept (μ)	-1.0896***	0.2741	-1.0735***	0.2880
Intercept (ρ)	-1.6561***	0.0596	-2.0734***	0.0698
Launched	-0.0009*	0.0004	-0.0010*	0.0004
Night attack	0.0498	0.2043	-0.5468*	0.2485
Ballistic Missile	2.7726***	0.1858		
Cruise Missile	0.9577***	0.1370		
SAM	7.5128***	1.4873		
Launched × Ballistic	-0.0882***	0.0201		
Launched × Cruise	-0.0185***	0.0040		
Launched × SAM	-0.1481*	0.0627		
Belgorod	0.5507**	0.2002		
Bryansk	0.0220	0.0835	0.0424	0.0788
Crimea	0.1079	0.0700	-0.0300	0.0696
Donetsk	0.2224	0.3119		
Krasnodar	-0.1338	0.0864		
Kherson	0.3774	0.3649		
Oryol	0.2426**	0.0936	0.2399**	0.0870
Rostov	0.2636**	0.0873	0.0869	0.0901
Saratov	-0.6549***	0.1950		
Smolensk	-0.0454	0.1082	-0.1389	0.0956
Tambov	0.4221	0.3508		
Voronezh	0.2142	0.2068		
Zaporizhzhia	0.0888	0.2014		
Black Sea	0.1307	0.1596		
Caspian Sea	-0.1916	0.2270		
Sea of Azov	-0.1679	0.2532	0.0977	0.2768
Kursk			0.0886	0.0803
Mean Temperature	-0.0152***	0.0045	-0.0118*	0.0052

Table 4: Beta-Binomial Regression Results (continued)

Variable	Coef.	SE	Coef.	SE
Mean Wind Speed	-0.0038	0.0251	0.0033	0.0270
Mean Cloud Cover	0.1077	0.1160	0.1225	0.1238
Phase 2	-0.2896	0.1848	0.8990***	0.1107
Phase 3	0.7040***	0.0873	0.8958***	0.1239
Days Since Phase 3			-0.0057***	0.0006
N	1,484		808	
Imputations	100		100	

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Pooled across 100 imputations via Rubin's Rules with Barnard-Rubin degrees of freedom. Reference launch locations: Full Model, Kursk; Long-Range Attack UAV Model, Krasnodar. Full Model Phase 2: Patriot operational, Apr 2023; Phase 3: saturation tactics, Sep 2024. Long-Range Attack UAV Model Phase 2: saturation tactics, Sep 2024; Phase 3: interceptor drones, Mar 2025.

E Additional Diagnostic Plots



Model 1 *Model 2*

Figure 9: Q-Q plots of randomized quantile residuals for the preferred models.

F Launch Location Prediction Figures

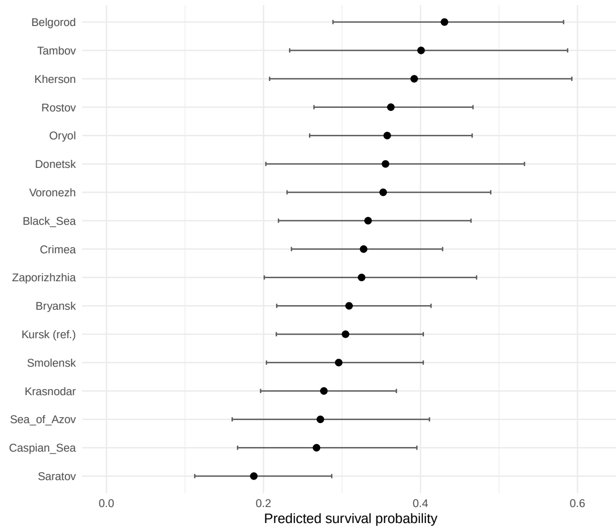


Figure 10: Predicted survival by launch location for loitering munitions (Model 1).

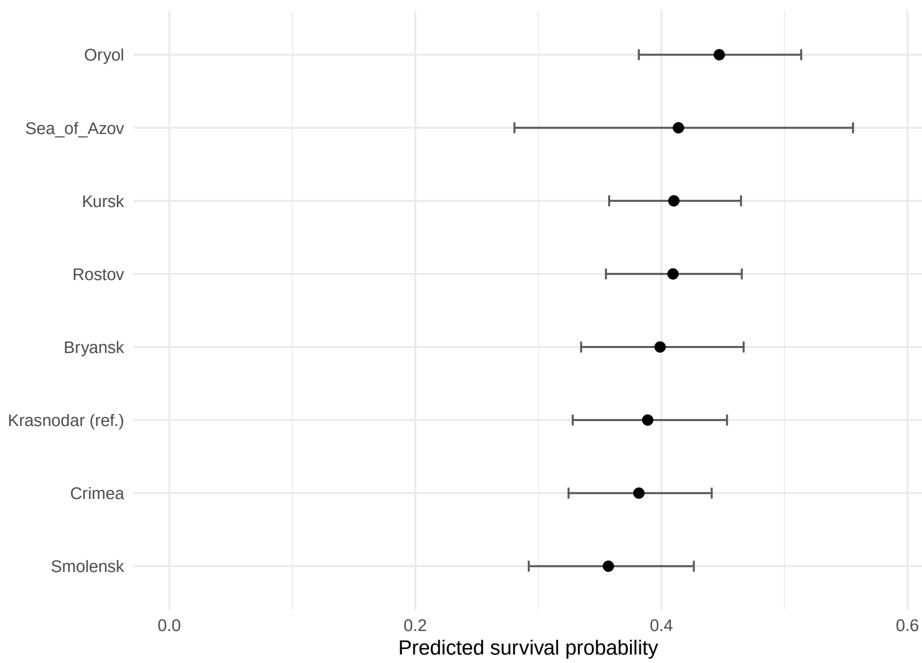


Figure 11: Predicted Shahed survival by launch location (Model 2).

G Launch Weather Averaging Diagnostic

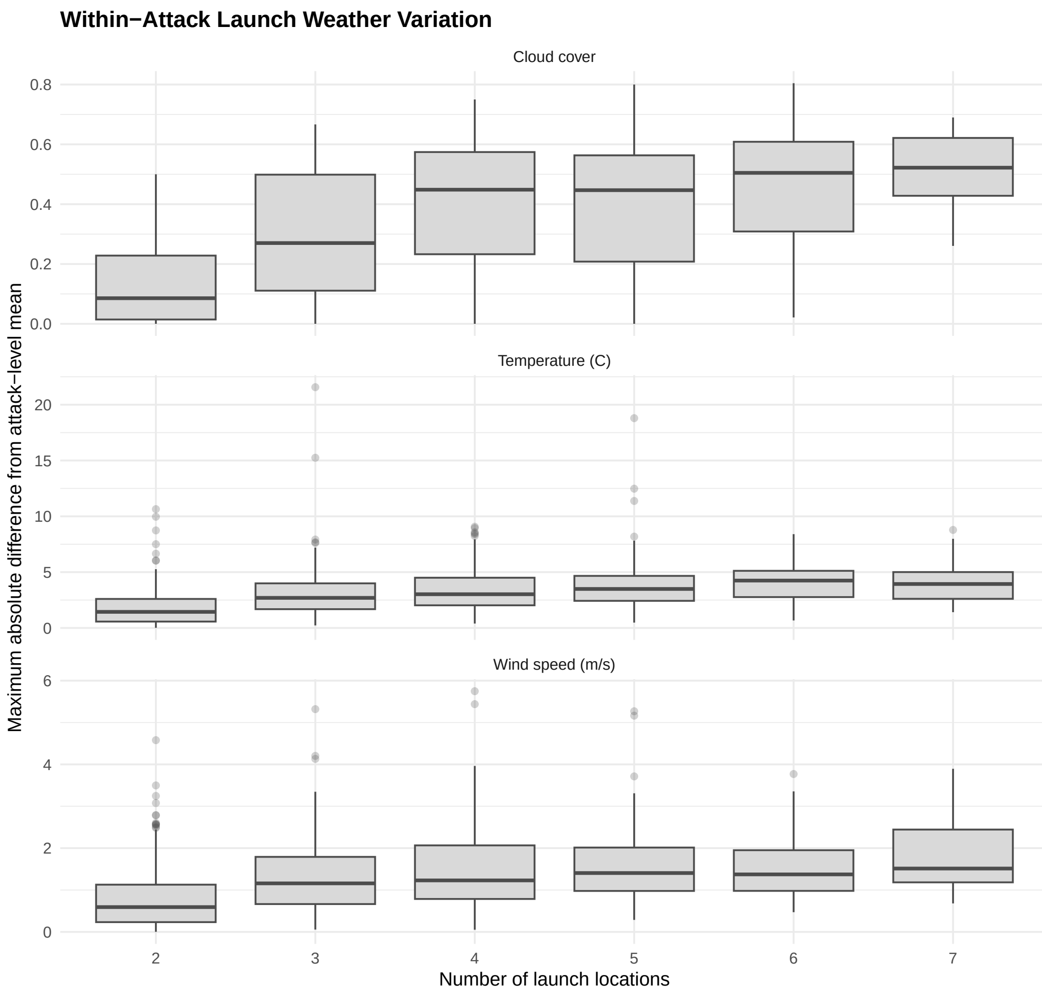


Figure 12: Maximum absolute difference between each attack-level mean weather value and its component launch-location weather values, by number of launch locations. Smaller values indicate that averaging across recorded launch locations does not substantially obscure within-attack weather variation.

H Attack Frequency

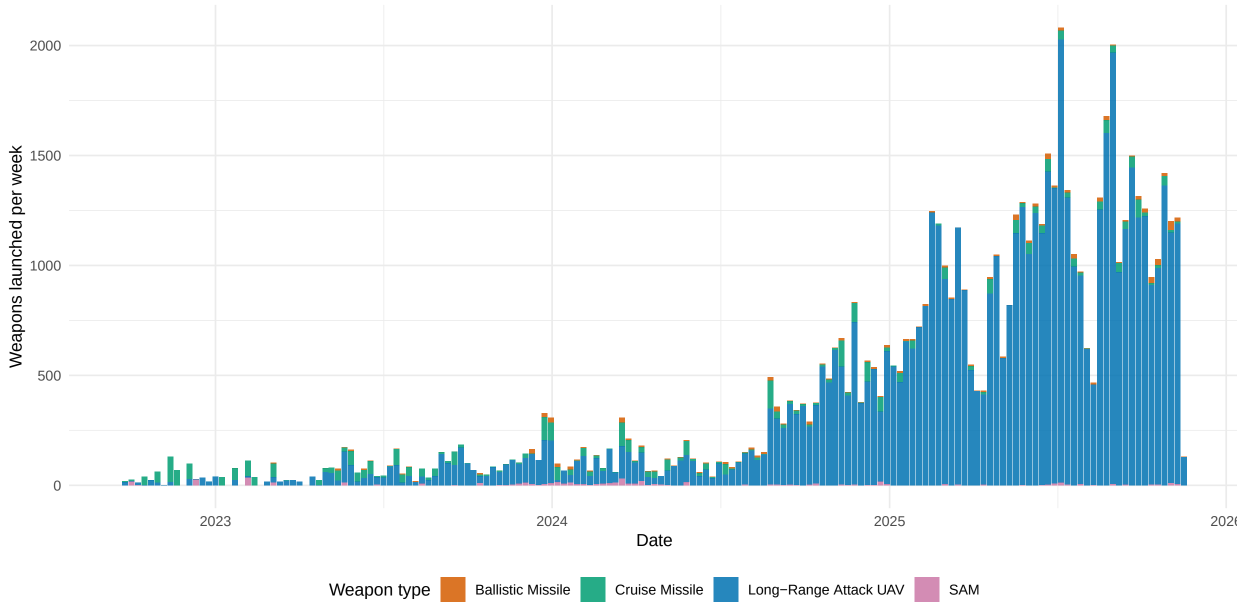


Figure 13: Weekly weapons launched by type.

I Weapon Type Classification

Category	Weapons Included
Loitering Munition	Shahed-136/131
Ballistic Missile	Iskander-M, KN-23, X-47 Kinzhal
Cruise Missile	X-101/X-555, Kalibr, Iskander-K, X-59, X-69, X-22, X-31, X-35, P-800 Oniks, 3M22 Zircon, Banderol, Unknown Missile
SAM (Ground Attack)	C-300, C-300/C-400, C-400
Excluded: Frontline Tactical	Kub, Lancet, Molniya

Table 5: Weapon Type Classification

J Model Selection

Table 6: Model Specification Comparison Using Multiply Imputed Data

Family	Specification	PPL AIC	PPL BIC	ΔPPL AIC	ΔPPL BIC	First AIC	First BIC	Mean AIC	Mean BIC	Selected
Full Model	m_full_inter_phase	7042.0	7206.4	0.0	0.0	6984.5	7148.9	7029.3	7193.7	✓
Full Model	m_full_nointer_phase	7098.2	7246.7	56.2	40.3	7047.8	7196.3	7087.5	7236.0	
Full Model	m_full_inter_linear	7092.7	7251.8	50.7	45.4	7034.9	7194.0	7080.9	7240.0	
Full Model	m_full_nointer_linear	7146.2	7289.3	104.1	82.9	7096.1	7239.3	7136.2	7279.4	
Long-Range Attack UAV Model	m_uav_core_phase	5162.5	5242.3	0.0	0.0	5131.7	5211.5	5158.7	5238.5	✓
Long-Range Attack UAV Model	m_uav_extended_phase	5164.9	5272.9	2.4	30.6	5131.5	5239.5	5154.2	5262.2	
Long-Range Attack UAV Model	m_uav_core_linear	5320.4	5390.8	157.9	148.5	5294.8	5365.2	5316.8	5387.3	
Long-Range Attack UAV Model	m_uav_extended_linear	5326.0	5424.6	163.5	182.3	5299.5	5398.1	5316.4	5415.0	

PPL evaluates the pooled coefficient vector on each completed dataset. First-imputation and mean completed-data criteria are reported as sensitivity comparisons. The selected model minimizes PPL BIC within each model family.

K Including Frontline Tactical Drones

Table 7: Robustness Results Including Frontline Tactical Drones

	Full Model		Long-Range Attack UAV Model	
Variable	Coef.	SE	Coef.	SE
Intercept (μ)	-1.0481***	0.2483	-0.9705***	0.2830
Overdispersion (ρ)	-1.6705***	0.0580	-2.0360***	0.0681
Launched	-0.0009*	0.0004	-0.0010**	0.0004
Night attack	0.0211	0.1880	-0.5949*	0.2387
Ballistic Missile	2.7563***	0.1981		
Cruise Missile	0.9641***	0.1395		
SAM	7.5234***	1.5907		
Frontline Tactical	1.1721	0.8064		
Launched × Ballistic	-0.0823***	0.0238		
Launched × Cruise	-0.0182***	0.0039		
Launched × SAM	-0.1481*	0.0641		
Launched × Frontline Tactical	0.0690	0.1064		
Oryol	0.2383*	0.0925	0.2405**	0.0885
Rostov	0.2635**	0.0869	0.0979	0.0944
Saratov	-0.6488***	0.1931		
Caspian Sea	-0.1811	0.2251		
Crimea	0.0991	0.0680	-0.0329	0.0695
Bryansk	0.0158	0.0828	0.0367	0.0801
Kursk			0.0929	0.0829
Smolensk	-0.0411	0.1076	-0.1243	0.0970
Black Sea	0.0999	0.1552	0.4965	0.3344
Sea of Azov	-0.1616	0.2657	0.1058	0.2880
Mean Temperature	-0.0155***	0.0045	-0.0123*	0.0053
Mean Wind Speed	-0.0084	0.0251	0.0004	0.0277
Mean Cloud Cover	0.1034	0.1107	0.1240	0.1217

Table 7: Robustness Results Including Frontline Tactical Drones (continued)

Variable	Coef.	SE	Coef.	SE
Phase 2	-0.2727	0.1785	0.8543***	0.1120
Phase 3	0.7039***	0.0870	0.8892***	0.1260
Days Since Phase 3			-0.0056***	0.0006
N	1,502		826	

Cells report coefficient and standard error. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The Long-Range Attack UAV model includes long-range attack UAVs plus frontline tactical drones.

L Complete Cases Without Imputation

Table 8: Robustness Results Without Imputation

	Full Model		Long-Range Attack UAV Model	
Variable	Coef.	SE	Coef.	SE
Intercept (μ)	-1.0793***	0.2905	-1.5060***	0.3198
Overdispersion (ρ)	-1.7953***	0.0583	-2.2162***	0.0667
Launched	-0.0011**	0.0004	-0.0009*	0.0004
Night attack	-0.0443	0.2217	-0.2243	0.2935
Ballistic Missile	3.1460***	0.2145		
Cruise Missile	0.9838***	0.1485		
SAM	19.4152	533.2816		
Frontline Tactical				
Launched × Ballistic	-0.0849***	0.0225		
Launched × Cruise	-0.0177***	0.0044		
Launched × SAM	-0.0003	51.0040		
Launched × Frontline Tactical				
Oryol	0.2791**	0.0885	0.2450**	0.0808
Rostov	0.2578**	0.0819	0.0557	0.0841
Saratov	-0.7254***	0.1880		
Caspian Sea	-0.2563	0.2288		
Crimea	0.1244	0.0661	-0.0402	0.0647
Bryansk	0.0186	0.0790	0.0442	0.0737
Kursk			0.1110	0.0753
Smolensk	-0.0393	0.1024	-0.1766*	0.0894
Black Sea	0.1997	0.1688		
Sea of Azov				
Mean Temperature	-0.0148***	0.0043	-0.0118*	0.0048
Mean Wind Speed	0.0011	0.0236	-0.0058	0.0249
Mean Cloud Cover	0.0995	0.1040	0.1009	0.1089
Phase 2	-0.3480	0.2539	1.0436***	0.1078
Phase 3	0.7623***	0.0881	0.9335***	0.1174
Days Since Phase 3			-0.0058***	0.0006
N	1,231		694	

Cells report coefficient and standard error. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Frontline tactical drones remain excluded; rows with missing model variables are dropped rather than imputed.

M Reporting-Error Sensitivity Analysis

Table 9: Reporting-Error Sensitivity Results for Model 2

Scenario	Correction	Affected Rows	Destroyed After	Coef.	SE
Large attacks only	0%	188	25,274	-0.0010*	0.0004
Large attacks only	5%	188	24,008	-0.0005	0.0004
Large attacks only	10%	188	22,745	-0.0001	0.0004
Large attacks only	15%	188	21,480	0.0002	0.0003
Large attacks only	20%	188	20,217	0.0005	0.0003
All Long-Range Attack UAV attacks	5%	749	38,163	-0.0008*	0.0003
All Long-Range Attack UAV attacks	10%	749	36,144	-0.0007*	0.0003
All Long-Range Attack UAV attacks	15%	749	34,121	-0.0006*	0.0003
All Long-Range Attack UAV attacks	20%	749	32,118	-0.0005*	0.0002

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Large attacks are Long-Range Attack UAV attacks with launched at or above the observed Long-Range Attack UAV 75th percentile. The 0% large-attack scenario is the uncorrected baseline.