Assessing Efficacy of Mass Drone Attacks in the Russia-Ukraine War

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Abstract

Does launching more drones overwhelm air defenses? Current US defense strategy assumes that affordable mass will saturate adversary interception capability, yet little empirical evidence supports this claim. Using 1,941 observations of Russian drone and missile attacks against Ukraine from September 2022 to November 2025, I estimate beta-binomial regression models to test whether larger attacks increase per-unit weapon survivability. I find that mass does not improve per-unit survival for Shahed drones; launching more drones is associated with a *lower* proportion surviving interception, suggesting that Ukrainian defenses scale effectively with attack size. Weapon type is the dominant predictor of survivability, with ballistic missiles and SAMs surviving at rates above 85% while loitering munitions are routinely intercepted. Theory-driven phase breaks reveal that Russia's adoption of saturation tactics in September 2024 initially tripled Shahed survival odds, but Ukraine's deployment of interceptor drones in March 2025 has progressively restored interception capability. These findings complicate the airpower coercion literature by demonstrating that the physical delivery of airpower, which is a prerequisite for both punishment and denial strategies, is not guaranteed and does not scale linearly with the number of weapons launched.

1 Introduction

The Russia-Ukraine war is quickly becoming known as a drone war. Over the course of the war, Russia has increasingly relied on enormous numbers of Shahed drones to constantly barrage Ukrainian cities and overwhelm Ukraine's air defenses. This bombardment and a rapidly dwindling supply of Western-supplied defense munitions has 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. Ukraine's technological advances and success in using drones to defend against a stronger adversary has demonstrated to Western militaries that cheap, mass-produced weapons are capable of overpowering more expensive weapons, 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 in an effort to overwhelm Ukrainian defenses through cheap mass rather than expensive precision signals a change in conventional military strategy (Jensen 2025). As a result, many countries are reconsidering their own military strategies and consequently shifting defense production towards more attritable weapons that can be massed on 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 self-piloting ships and uncrewed aircraft as well as counter-drone systems (c-UAS) (Department of Defense 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 fears that China will invade Taiwan in 2027. Although the United States possesses more advanced weapons, China has a significant advantage over the United States in terms of the number of weapons and military personnel it commands (Department of Defense 2024). Ukraine's success with drones, in addition to underwhelming US performance in DoD wargaming, 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 published significant scholarship 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 per-unit survival 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 that were 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 means that attrition warfare is more likely, as weaker adversaries can more effectively contest the air space. The inability of either party to establish air superiority suggests that aerial force is less and 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. Much of the literature on airpower is organized around understanding under what conditions aerial force coerces an adversary, but, if strikes fail to reach their intended targets, then prior studies' findings about the effectiveness of punishment and denial strategies and the role of an adversary's capability 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 and how massing strikes affects weapon survivability. I estimate a beta-binomial to model how the number of drones launched by Russia impacts 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 International Studies (CSIS) (Hollenbeck 2025; Atalan and Chavez n.d.). I find that mass does not improve per-unit survivability for drones; 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 succumb 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 Russian weapon survival; for example, Russia's adoption of saturation tactics in September 2024 initially increased per-unit survivability across all weapon types before degrading over time as Ukraine adopted increasingly advanced interception techniques. Geography is a significant predictor of weapon survivability as well, with weapons launched from locations closer to Ukraine surviving at higher rates than those from distant sites.

2 Airpower as Coercion

In his foundational text *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 in an attempt to erode public support is unlikely to coerce an adversary to change their behavior (Pape 1996). Russia's Shahed campaign falls into the punishment strategy, as Russia has consistently sought to wear down civilian morale through persistent nightly drone attacks (Jensen 2025). Mueller (1998) argues that these punishment and denial categories are too binary and proposes a more rigorous classification scheme of airpower strategies. Under this new system, he finds that punishment can work under specific conditions (Mueller 1998). However, my results demonstrate that increasing the number of drones launched *lowers* survivability; the more drones Russia launches in a single attack, the more effectively Ukraine defends itself against that attack. Pape and Mueller's comparisons of airpower strategies assume successful application of airpower, but this study suggests that delivery of airpower can fail systematically. This finding suggests that the existing literature's conclusions about coercive effectiveness may be most applicable in settings of uncontested airspace.

Several studies do consider how an adversary's ability impacts airpower effectiveness, finding that success is highly dependent on an adversary's ability to mount a defense. However, these studies tend to measure adversarial capability at the campaign level rather than analyzing individual instances of air power application. 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 in their analysis of adversarial capability and use a multivariate probit to test the role of military vulnerability in 53 cases of airpower coercion. They operationalize military vulnerability on a scale of 1 to 5 depending on the disruption to military positions as a result of air strikes and find that coercion is more likely to be effective if the target's military vulnerability is higher.

While these studies begin to consider how the disparity in military capabilities between two warring parties influences air power effectiveness, they still make an implicit assumption in the causal pathway from airpower to coercive effects: that airpower, when applied, arrives at the intended targets, and that it scales linearly in accordance with escalation intention. This study provides a necessary insight into this causal chain by modeling the physical delivery of airpower, a prior step in the causal chain. The results of this study indicate that the delivery function is not linear, and an adversary capable of intercepting strikes may avoid the coercive effects of airpower. Prior understandings of adversary capability may have failed to account for how tactical interception of individual weapons reduces military vulnerability.

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.

Almost all of the literature on drone strikes examines drones in a counterterrorism or counterinsurgency context, in which the power dynamics between the warring parties differs significantly from those of interstate conflict. Nevertheless, these studies contribute to my analysis by establishing a methodological precedent. Drone strike literature, which emerged in the late 2000s and early 2010s following the "War on Terror" tends to use large-N datasets of drone strikes and terrorist attacks conducted within a single country, oftentimes Pakistan (Johnston and Sarbahi 2016; Mahmood and Jetter 2023; Lyall 2015). These prior studies also inform my model's relevant control variables. Several studies identify weather as an important control variable in drone strike analyses, since wind, temperature, and cloud cover all impact the ability to launch and control a drone, as well as drone effectiveness in successfully striking a target (Johnston and Sarbahi 2016; Mahmood and Jetter 2023).

Like the continuing debates around the effectiveness of coercive airpower in conventional war, the literature on drones is mixed as to whether strikes reduce terrorist and insurgent attacks or actually cause blowback. Some studies emphasize that drones are not as "precise" a weapon as previously assumed and that limited intelligence and poor weather conditions can contribute to inaccurate strikes and civilian harm (Bertolotti et al. 2021; Rigterink 2021). The 1990s witnessed a similar trend in which rapidly increasing accuracy and efficiency delivered by precision-guided missiles (PGMs) led many to criticize Pape and argue that the previously understood dynamics of airpower were no longer applicable (Pape 1998; Mueller 1998). This historical debate mirrors the modern-day revolutions in warfare in which drones promise to deliver "surgical precision" for low cost. However, Pape responded to critics by arguing that increasing accuracy and efficiency did not alter his main finding and punishment strategies remained less effective than denial, regardless of missile precision. My results extend this logic to mass: just as precision did not alter the fundamental dynamics of airpower, it appears unlikely that scale will either. The prevailing wisdom is that cheap drones enable strikes on targets in mass not previously witnessed in warfare; as a result, mass directed against military targets should effectively overwhelm an adversary's defenses and coerce change in behavior, while mass directed against civilian targets should prove so persistent that public morale collapses. Yet, launching more drones does not improve per-unit delivery. It is unlikely that mass, therefore, should meaningfully shift airpower strategy in favor of punishment strategy. If Pape is correct that punishment strategies are inherently less effective than denial, then, all things held equal, accuracy, efficiency, and mass directed at military targets rather than civilian infrastructure is still more likely to coerce an adversary.

This study fills a critical gap in the airpower literature by modeling the physical delivery of airpower and analyzing the relationship between the number of weapons launched and the proportion that survive interception. This relationship logically precedes the causal link between airpower and coercion explored in prior studies; before airpower can coerce through punishment or denial, weapons must physically arrive at 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 entirely 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 all-weapon and Shahed-only models, including model diagnostics. Section 6 concludes with a discussion of limitations and implications for airpower strategy.

3 Data

This analysis examines Russian aerial attacks and Ukrainian interception; accordingly, "survivability" refers to the probability that a Russian weapon evades Ukrainian interception. I adopt this orientation because Ukraine publicly reports interception data, making it the most reliable and comprehensive source available.

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, $n = 833$), cruise missiles ($n = 635$), ballistic missiles ($n = 361$), and surface-to-air missiles ($n = 112$).

Petro Ivaniuk, a Ukrainian researcher, created the dataset manually using official Ukrainian military reports published on social media accounts 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 2025; Atalan and Chavez n.d.).

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

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

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

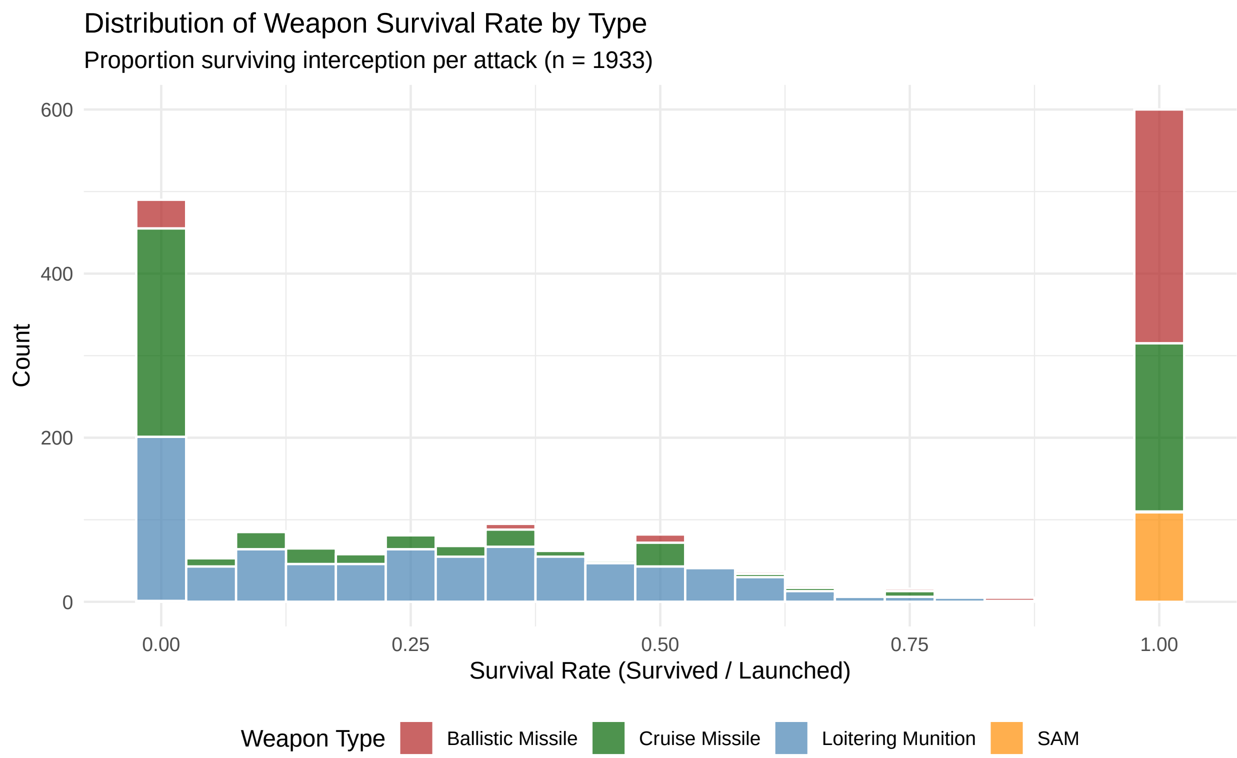

Figure 1: Distribution of weapon survival rates, colored by weapon type. The concentration at 0 (complete interception) and 1 (complete survival) motivates the beta-binomial specification.

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 the region-level coding only specifies directions such as "North" and "South," so it is unclear as to which exact locations these directions refer. 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. 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.

I supplement the launch location data with ERA5 Reanalysis weather data (temperature, wind speed, cloud cover) matched to the capital of each launch oblast, since variation in the weather within each administrative district is limited. Attacks may originate from multiple locations, so I use mean weather conditions across all launch locations for each attack; however, very few attacks are launched from more than one location, so I do not expect this averaging to substantively impact the results. 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. 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 destroyed are imputed jointly to preserve cross-variable relationships.[1]

I estimate two models to explore the relationship between mass and survival.[2] Model 1 includes all weapon types and addresses the question: across all Russian aerial weapons, does launching more improve per-unit survival? 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

[1] Missingness diagnostic tests indicate that launch location missingness is predicted by observed covariates including attack size and weapon type, and that attacks with missing location data tend to have lower survival rates. This suggests that complete-case analysis would overestimate survival. All 100 imputations converged, and imputed means closely match observed means. Full diagnostics are reported in the appendix.

[2] I estimate multiple specifications for each model, varying the time structure (linear trend vs. theory-driven phase dummies) and the inclusion of interaction terms. The preferred specifications, selected via AIC/BIC (see Section 4.3), are Model 1a-Phase and Model 2a-Phase. For readability, I refer to these as Model 1 and Model 2 throughout.

whether mass increases survivability for Shahed drones, which is the weapon Russia has developed its saturation doctrine around. Subsetting to Shaheds also enables the use of Shahed-specific phase breaks that reflect the drone-specific arms race occurring as Russia and Ukraine compete to innovate in offensive and defensive drone capabilities.

Table 1: Model Specifications

	Model 1 **All Weapons**	**Model 2** **Shahed Only**
Sample		
Observations	1,941	833
Weapon Types	All (4 categories)	Shahed-136/131 only
Time Period	Sept 2022–Nov 2025	Sept 2022–Nov 2025
Covariates		
Weapons Launched	✓	✓
Weapon Type FE	✓	—
Launched × Weapon Type	✓	—
Launch Location FE	✓(18 dummies)	✓(7 dummies)
Weather at Launch	✓	✓
Phase Dummies	phase2_m1, phase3_m1	phase2_m2, phase3_m2, days_since_phase3
Reference Categories		
Weapon Type	Loitering Munition	—
Location	Kursk	Krasnodar
Location Filtering	min_obs ≥ 25	min_obs ≥ 25
Imputation	Amelia (100 imp.)	Subset from full imp.

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:

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

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 date. The overdispersion parameter θ accounts for the fact that drones launched in the same attack are not independent events.

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):

$$\begin{aligned}
\text{logit}(\mu_i) = \beta_0 &+ \beta_1 \text{launched}_i + \boldsymbol{\lambda}' \text{Location}_i \\
&+ \beta_T \text{temp}_i + \beta_W \text{wind}_i + \beta_C \text{cloud}_i \\
&+ \phi_2 \text{phase2}_i + \phi_3 \text{phase3}_i + \phi_{3s} \text{days_since_phase3}_i
\end{aligned}$$

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."(U.S. 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 is consistent with current US national security strategy (Hicks 2023; Jensen 2025).

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_m1* marks the Patriot system becoming operational (April 19, 2023) and *phase3_m1* marks Russian adoption of saturation tactics (September 1, 2024). For Model 2, *phase2_m2* marks saturation tactics (September 1, 2024) and *phase3_m2* marks Ukraine's deployment of interceptor drones (March 1, 2025), with an additional slope term capturing the progressive improvement in interception as the program scales.

5 Results

Table 2 presents the pooled coefficients for both models. The overdispersion parameter ρ is highly significant in both specifications ($p < 0.001$), confirming that the beta-binomial is appropriate over the standard binomial.

Table 2: Beta-Binomial Regression Results

	Model 1 All Weapons		Model 2 Shahed Only	
Variable	Coef.	SE	Coef.	SE
Distribution Parameters				
Intercept (μ)	−1.446***	0.205	−1.958***	0.138
Overdispersion (ρ)	−1.448***	0.054	−2.140***	0.065
Attack Size				
Launched	−0.0005	0.0005	−0.0008*	0.0004
Weapon Type (Ref: Loitering Munition)				
Ballistic Missile	3.609***	0.203		
Cruise Missile	1.365***	0.120		
SAM	4.279***	1.071		
Launched × Weapon Type Interaction				
Launched × Ballistic	−0.191***	0.030		
Launched × Cruise	−0.020***	0.004		
Launched × SAM	0.829***	0.135		
Launch Location (Ref: Kursk / Krasnodar)				
Oryol	0.252*	0.101	0.250**	0.086
Rostov	0.258**	0.093	0.077	0.088
Saratov	−0.918***	0.198		
Caspian Sea	−0.575*	0.231		
Crimea	0.124	0.074	0.001	0.067

Table 2: Beta-Binomial Regression Results (continued)

Variable	Coef.	SE	Coef.	SE
Bryansk	0.013	0.091	0.052	0.078
Kursk			0.136	0.080
Smolensk	−0.081	0.120	−0.174	0.093
Black Sea	−0.225	0.158	−0.644	0.594
Sea of Azov	−0.110	0.243	−0.010	0.304
Other locations	(see appendix)			
Weather at Launch				
Mean Temperature	−0.024***	0.005	−0.007	0.005
Mean Wind Speed	−0.019	0.023	−0.028	0.025
Mean Cloud Cover	0.130	0.109	0.230*	0.116
Phase Dummies				
Phase 2	0.054	0.155	1.209***	0.109
Phase 3	0.747***	0.084	0.869***	0.119
Days Since Phase 3			−0.006***	0.001
Model Statistics				
AIC	7,549.0		4,941.3	
BIC	7,727.3		5,021.7	
N	1,941		833	

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Pooled across 100 imputations via Rubin's Rules.
Phase 2 (M1): Patriot operational, Apr 2023. Phase 3 (M1): Saturation tactics, Sep 2024.
Phase 2 (M2): Saturation tactics, Sep 2024. Phase 3 (M2): Interceptor drones, Mar 2025.

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.

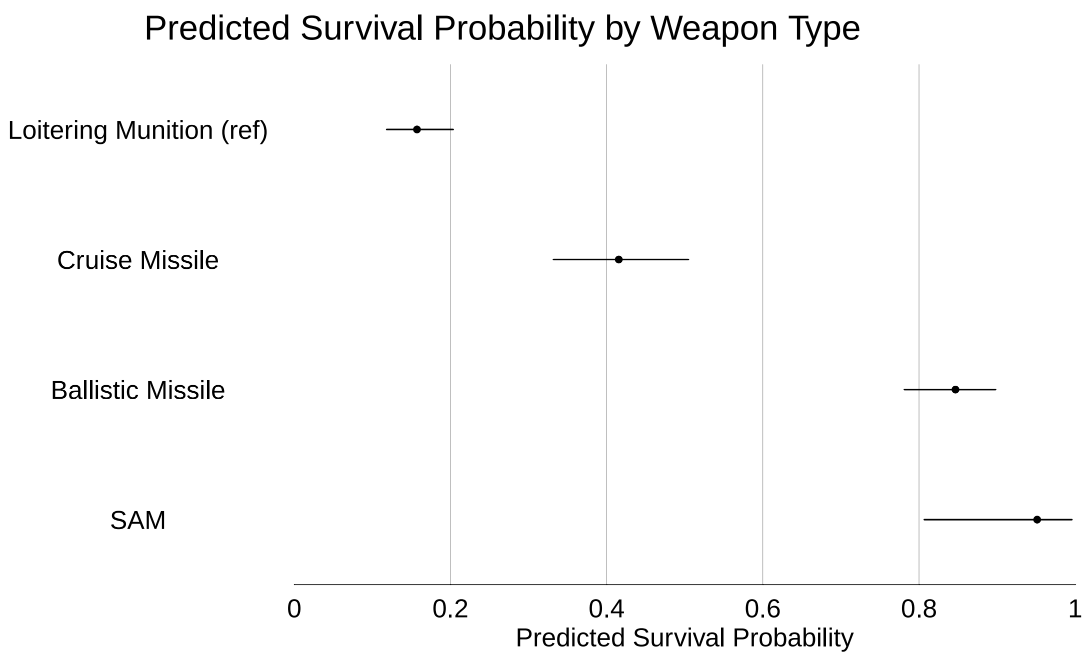

Figure 2: Predicted survival probability by weapon type (Model 1). SAMs and ballistic missiles are nearly impossible to intercept; loitering munitions are the most interceptable.

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 by 0.19 log-odds, possibly because larger salvos trigger concentrated defensive responses. For example, a single ballistic missile has approximately 85% predicted survival, but a salvo of 10 reduces individual weapon predicted survival 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.

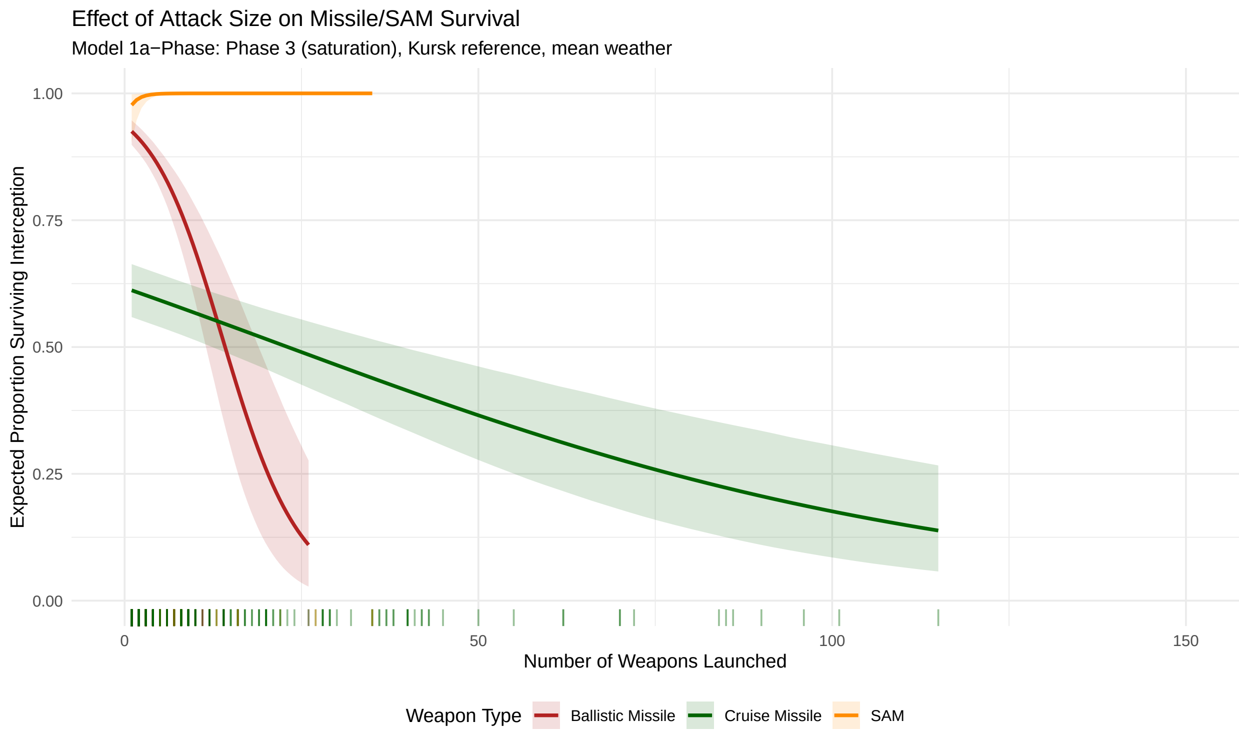

Figure 3: Effect of attack size on survival for ballistic missiles, cruise missiles, and SAMs.

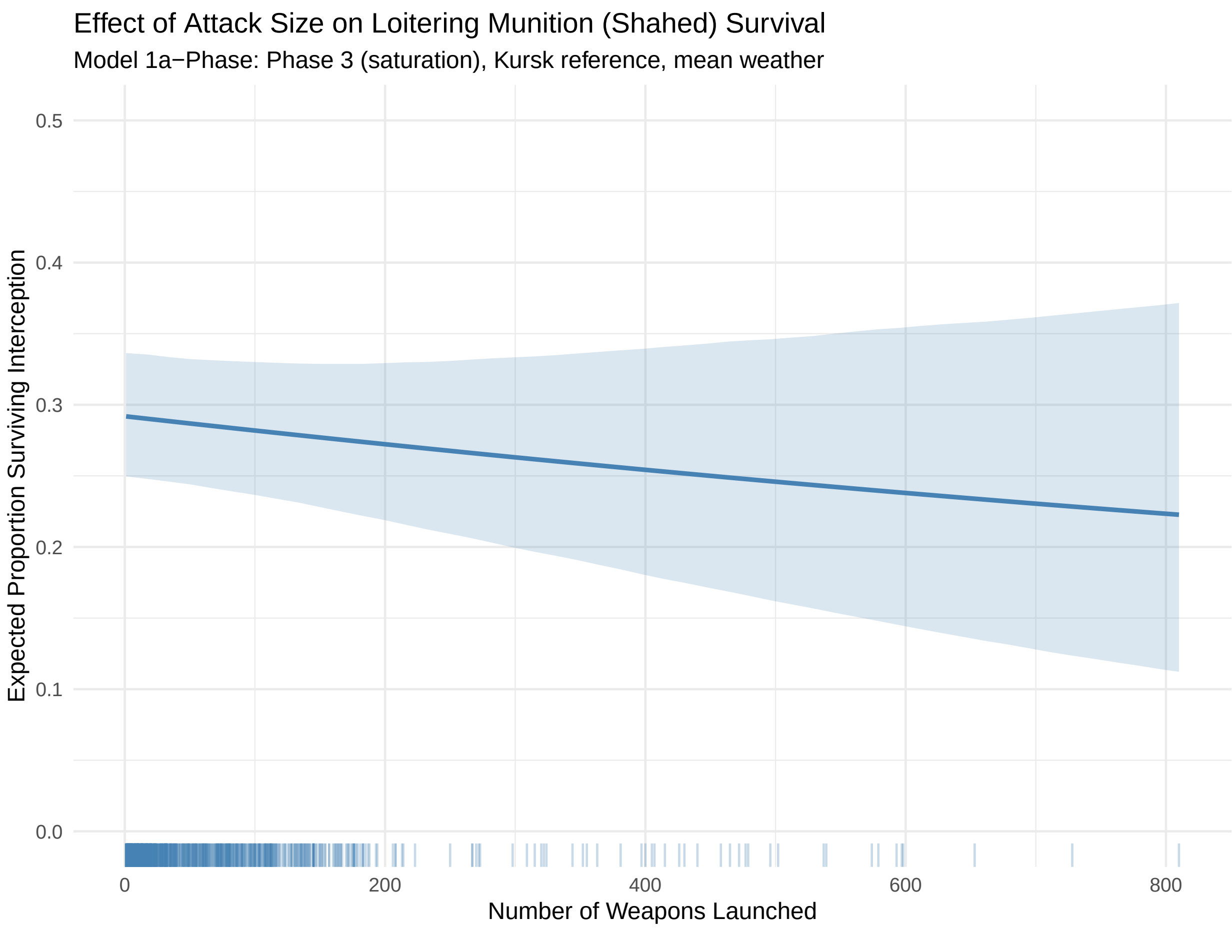

Figure 4: Effect of attack size on loitering munition (Shahed) survival. Y-axis scaled to 0–0.5.

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, $p < 0.001$) (Jensen 2025). Temperature is significant (-0.024, $p < 0.001$) and indicates that colder weather is associated with higher weapon survival.

Launch geography also matters. Figure 12 (Appendix) shows that attacks from Oryol and Rostov (closer 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 slightly *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 much of the ongoing research on the war in Ukraine that argues that mass overwhelms defenses (Jensen 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 at increasing rates 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 2025).

The phase structure also tells a clear narrative. Figure 5 shows the predicted Shahed survival probability over time. Phase 2 (saturation tactics, September 2024, same as in Model 1) produces a massive jump of 1.21 log-odds, 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 and other interception tactics), the rate of survivability for Russia's Shaheds decreases.

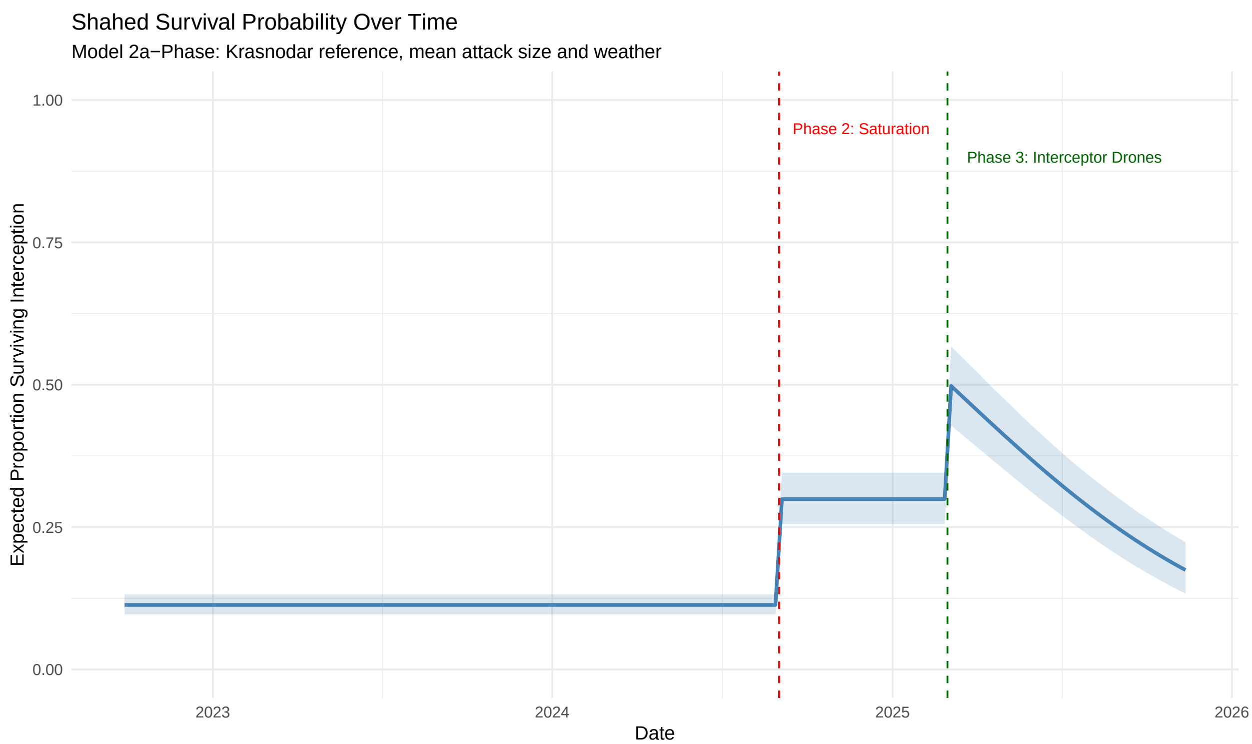

Figure 5: Predicted Shahed survival probability over time (Model 2). Vertical lines mark phase transitions.

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 marginally 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, $p < 0.01$).

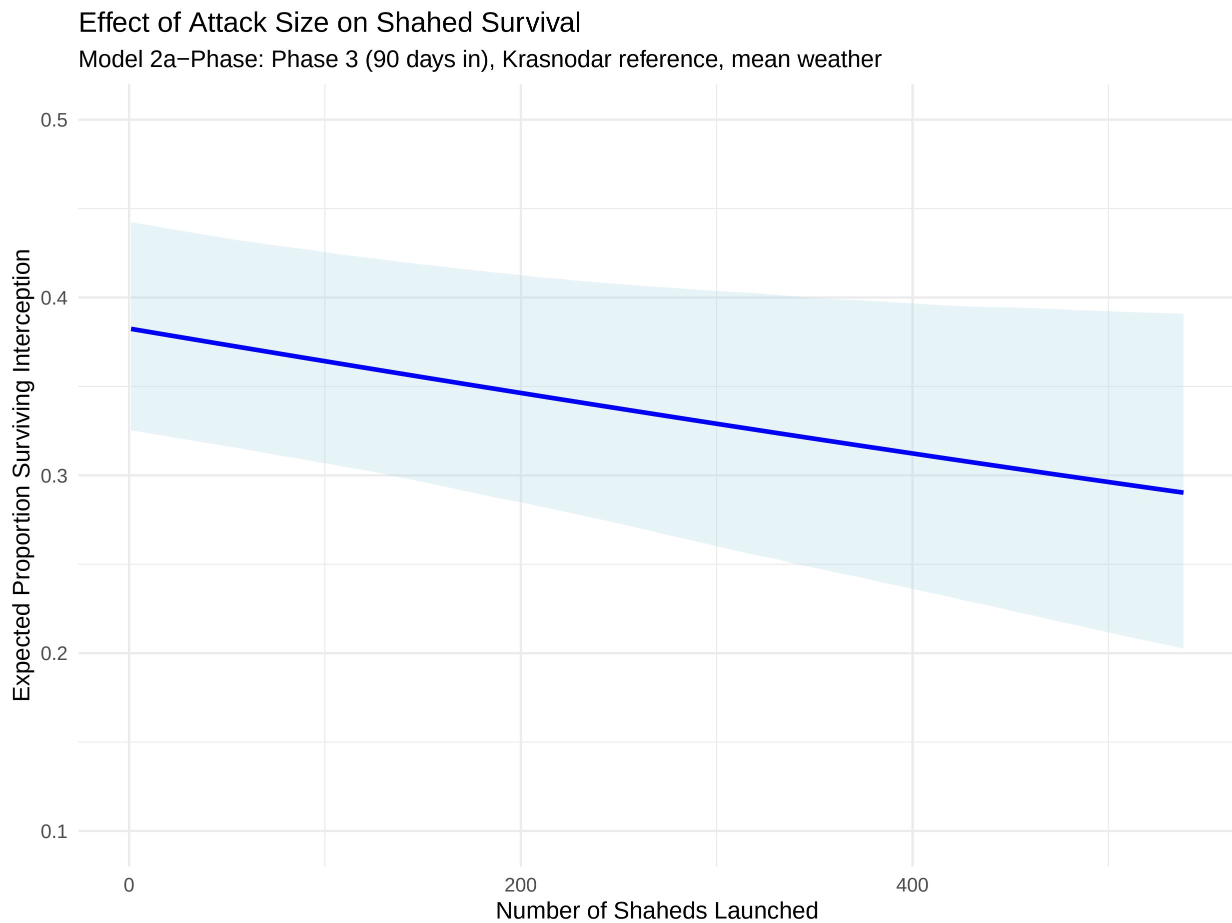

Figure 6: Effect of attack size on Shahed survival (Model 2).

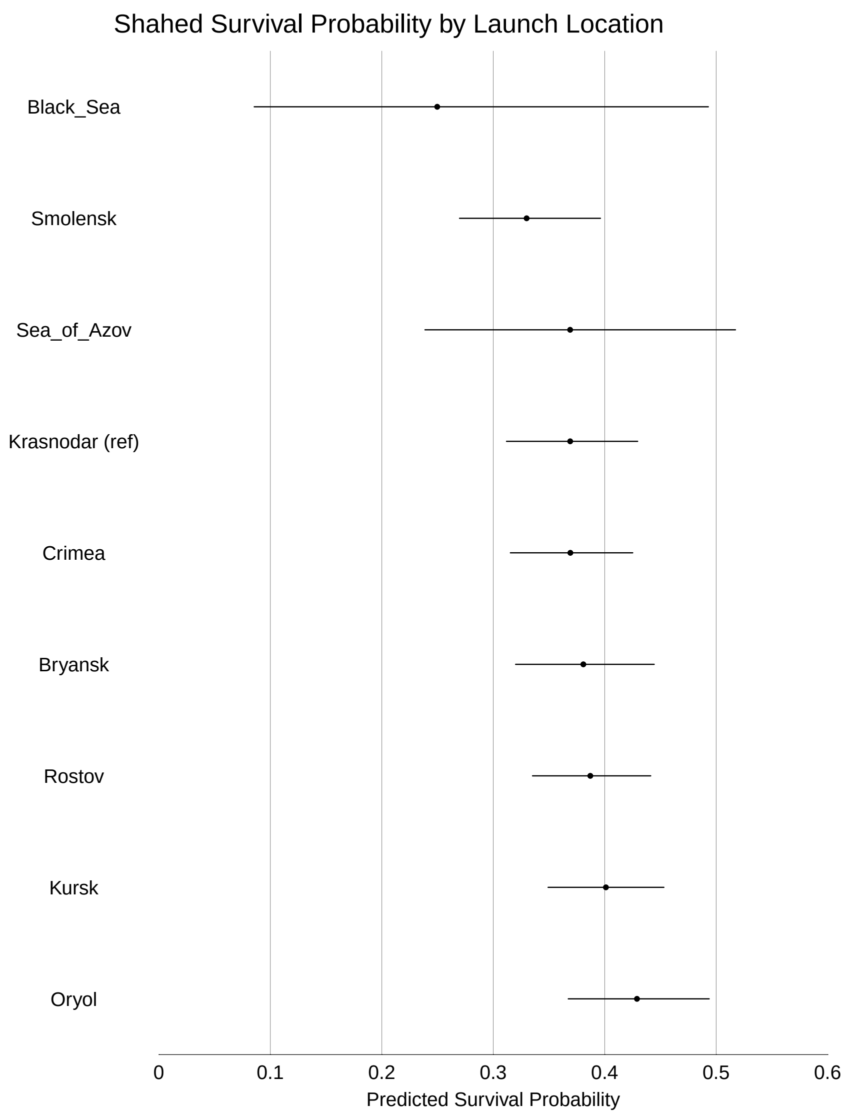

Figure 7: Predicted Shahed survival by launch location (Model 2).

5.3 Model Fit

Model selection via AIC/BIC favors the phase specifications over linear time trends for both models (Model 1: ΔAIC = 46; Model 2: ΔAIC = 178). Within Model 1, the interaction specification is preferred over main effects only. Randomized quantile residuals pass the Shapiro-Wilk normality test for both preferred models (Model 1a-Phase: $W = 0.999$, $p = 0.60$; Model 2a-Phase: $W = 1.000$, $p = 0.91$), indicating well-calibrated fit (Dunn & Smyth

1996, computed via glmxdiag). I estimate multiple specifications for each model, including linear time trends and theory-driven phase dummies, and with and without interaction terms. Model selection is based on AIC and BIC; full comparison tables for all specifications are reported in Appendix G. Randomized quantile residuals (Dunn and Smyth 1996) are used to assess model fit; Q-Q plots and binned residual plots for both preferred models are also reported in Appendix B.

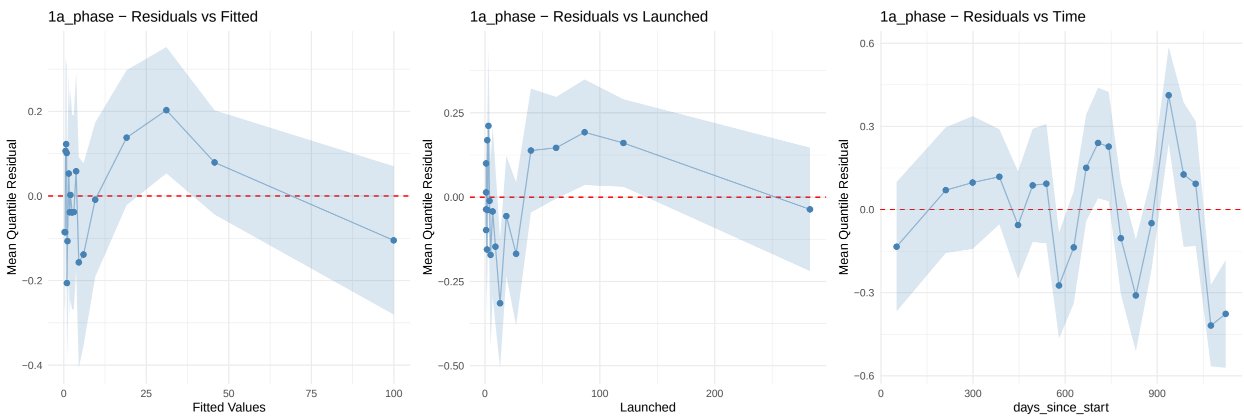

Figure 8: Binned quantile residuals for Model 1. Residual means hover near zero across fitted values, attack size, and time.

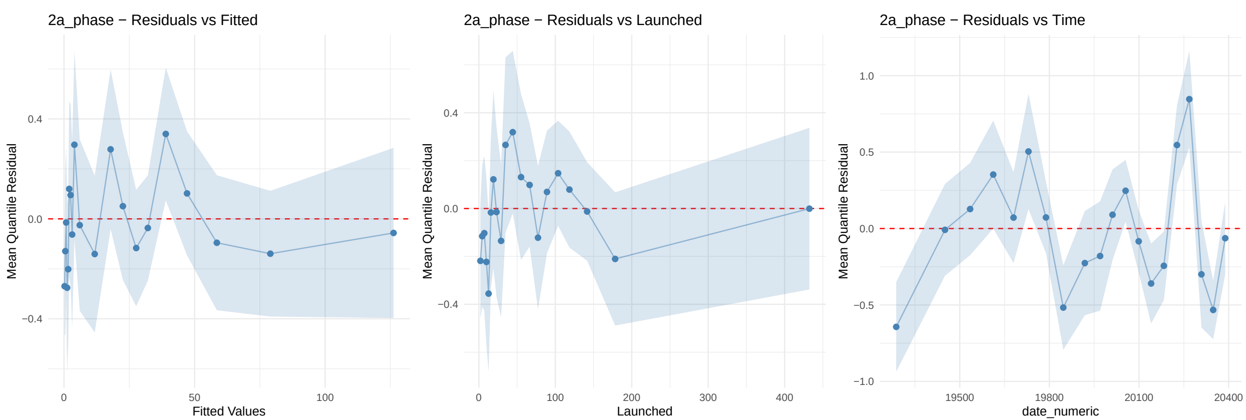

Figure 9: Binned quantile residuals for Model 2. Residual means hover near zero across fitted values, attack size, and time.

6 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) and Mueller (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 conveyed by 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 & Waxman, 2000).

The premise that mass overwhelms air defenses is not supported for platforms that are easily interceptible, 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	1,938	34.61	6.00	74.48	1	810
Weapons Destroyed	1,936	22.84	4.00	54.66	0	747
Weapons Survived	1,933	11.80	2.00	28.36	0	432
Temperature (°C)	1,502	9.68	10.31	8.50	−24.85	28.42
Wind Speed (m/s)	1,502	3.35	2.98	1.80	0.16	14.46
Cloud Cover (0–1)	1,502	0.50	0.51	0.37	0.00	1.00

Table 3: Summary Statistics (Full Dataset After Excluding Frontline Tactical, $n = 1{,}941$)

B Additional Diagnostic Plots

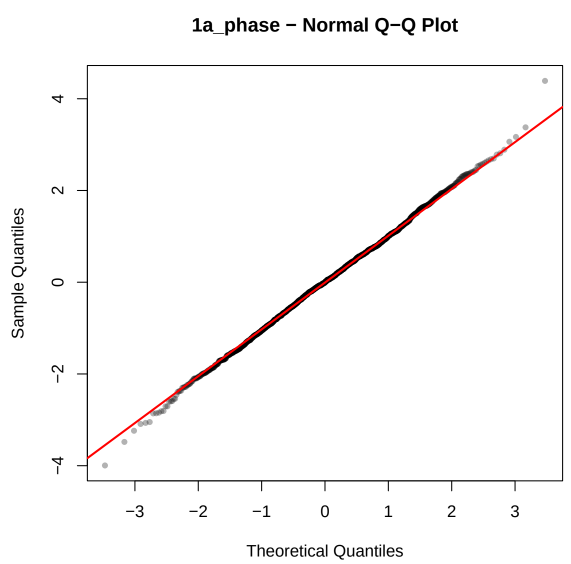

Figure 10: Q-Q plot of quantile residuals, Model 1.

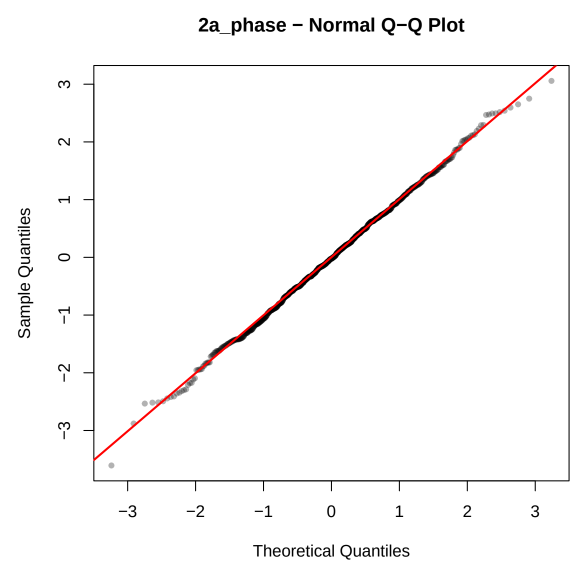

Figure 11: Q-Q plot of quantile residuals, Model 2.

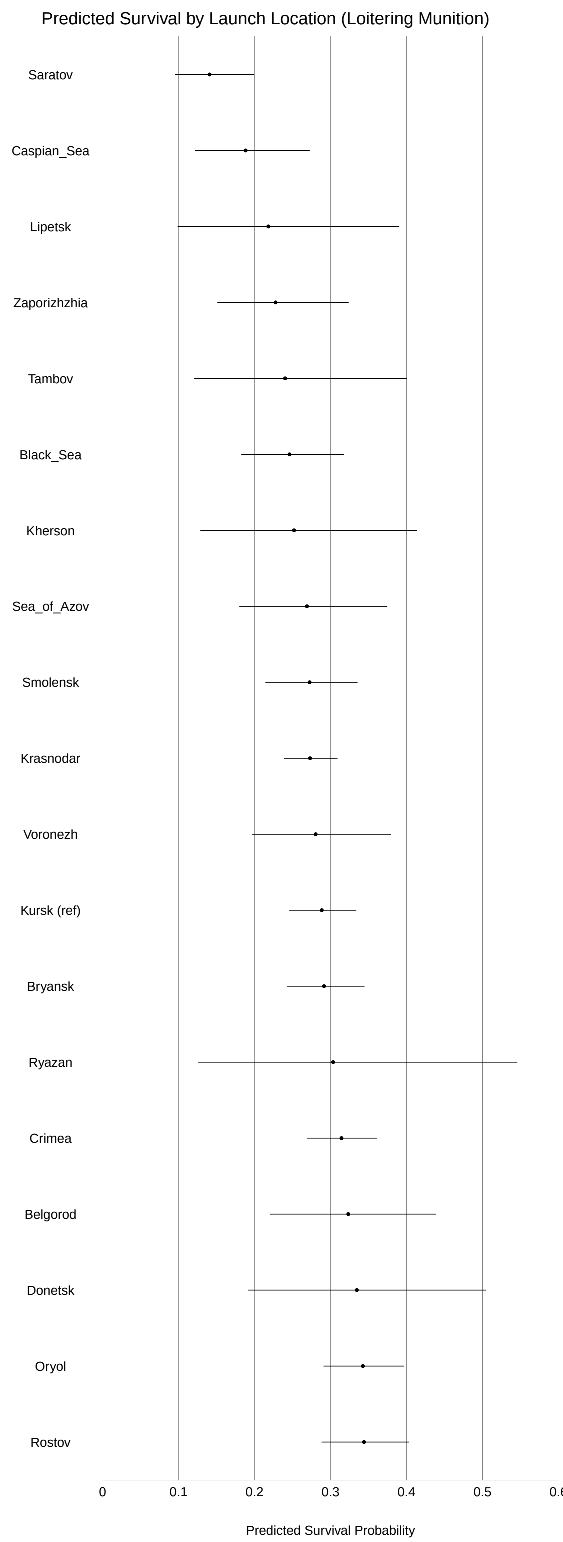

Figure 12: Predicted survival by launch location for loitering munitions (Model 1).

C Attack Frequency

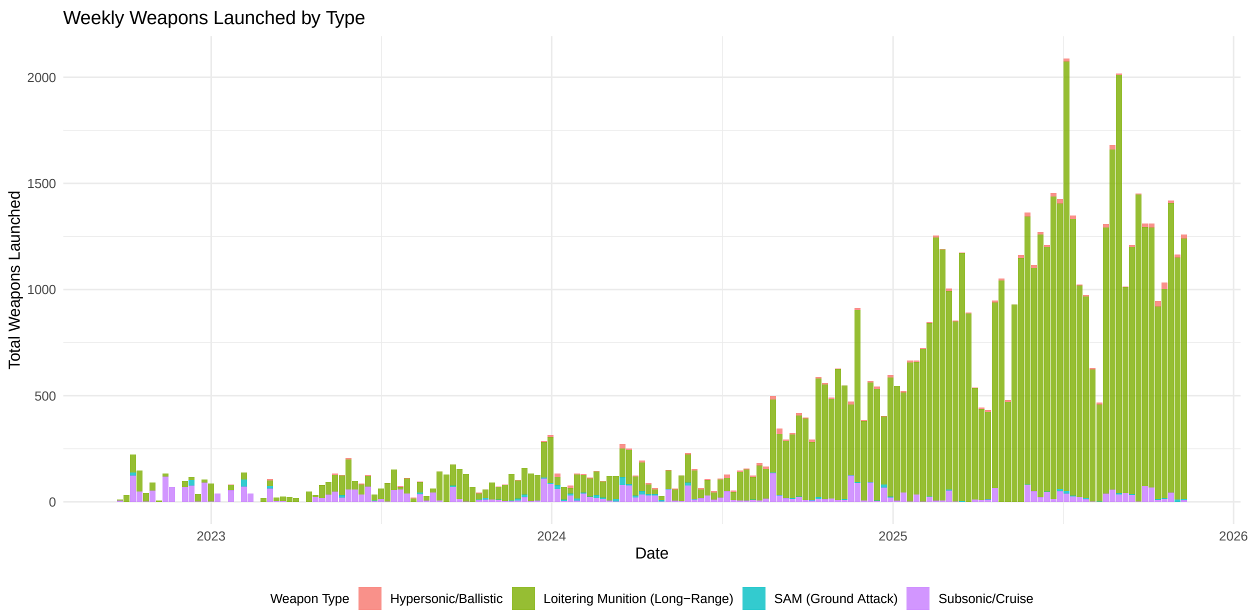

Figure 13: Weekly weapons launched by type.

D Effect of Temperature on Shahed Survival

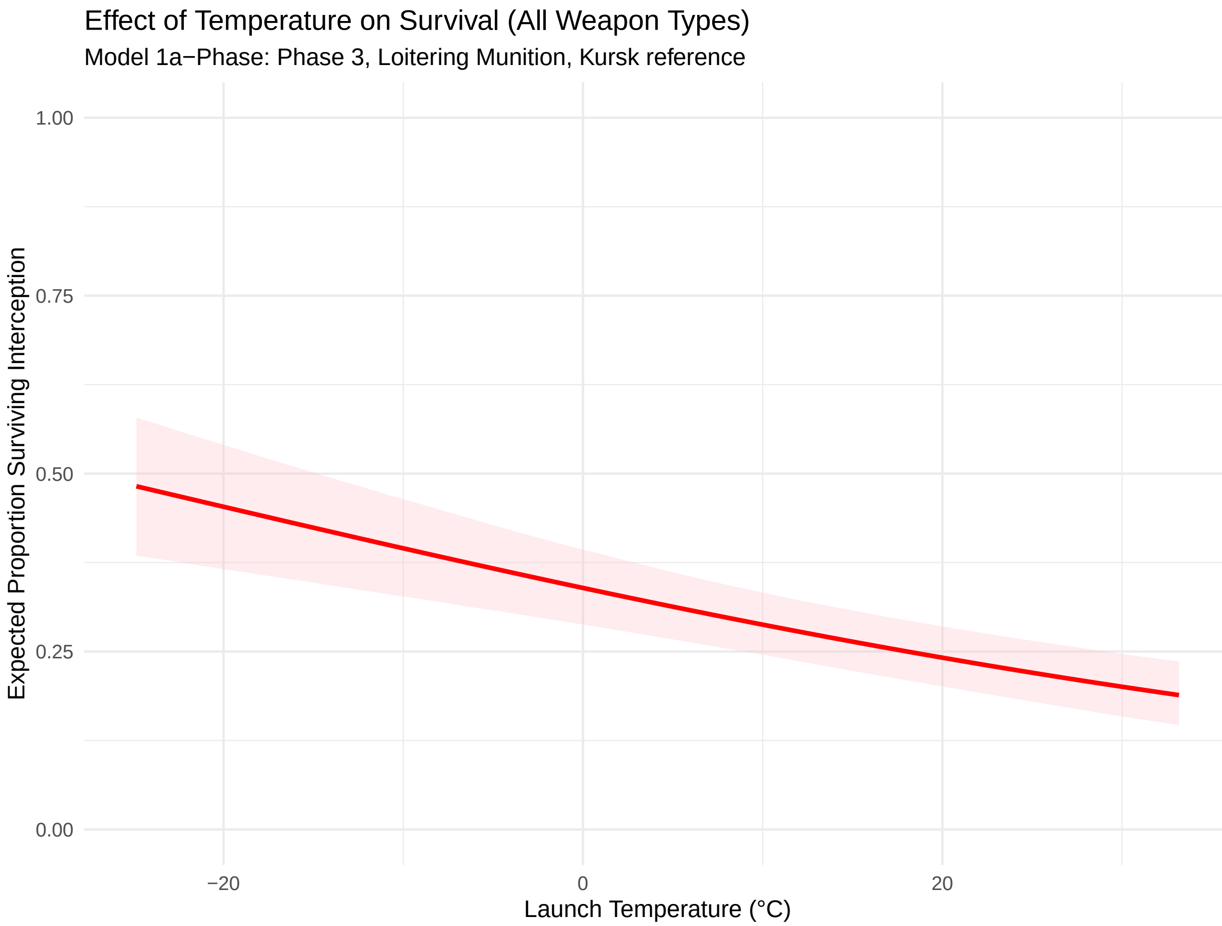

Figure 14: Effect of temperature on weapon survival (Model 1).

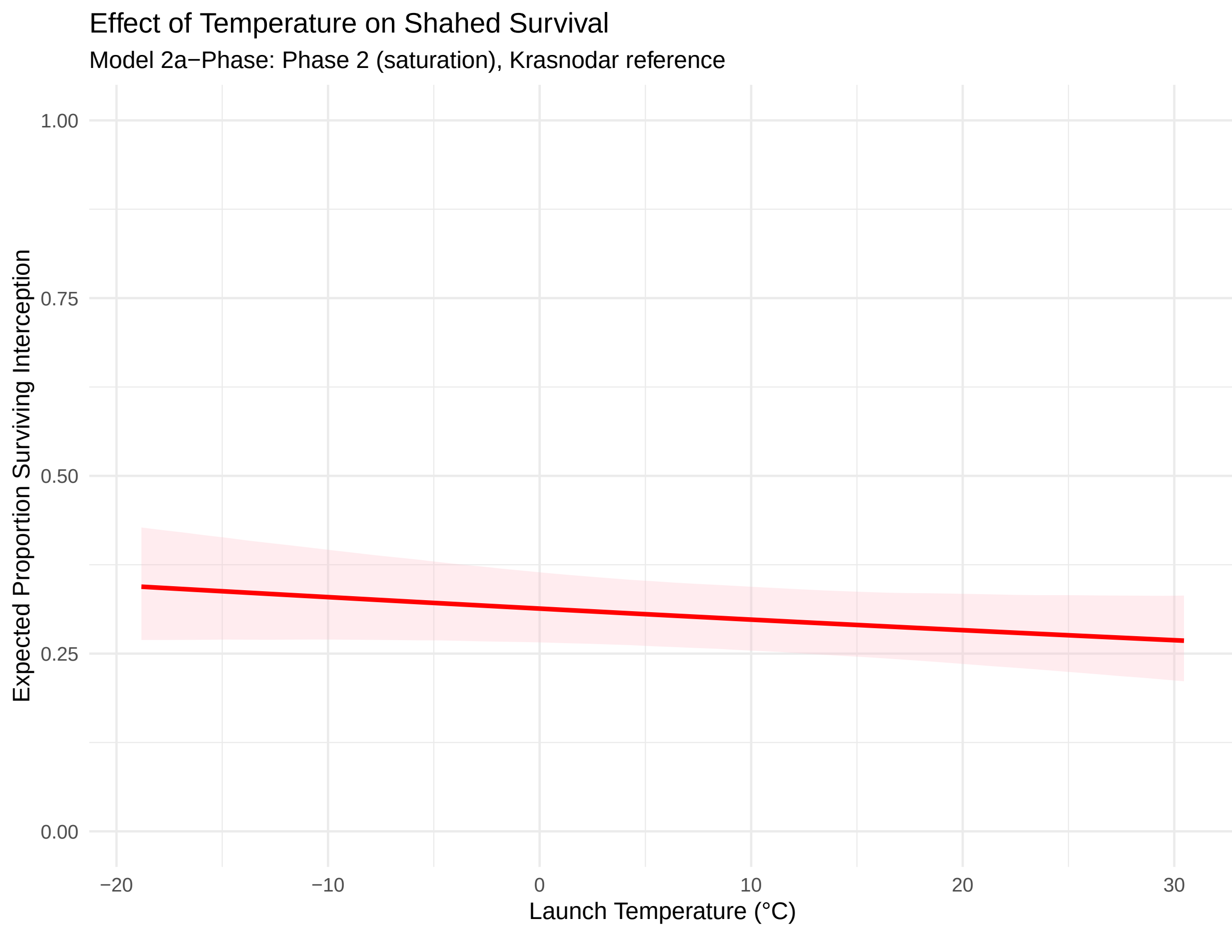

Figure 15: Effect of temperature on Shahed survival (Model 2). Temperature is not significant in the phase specification.

E Effect of Cloud Cover on Shahed Survival

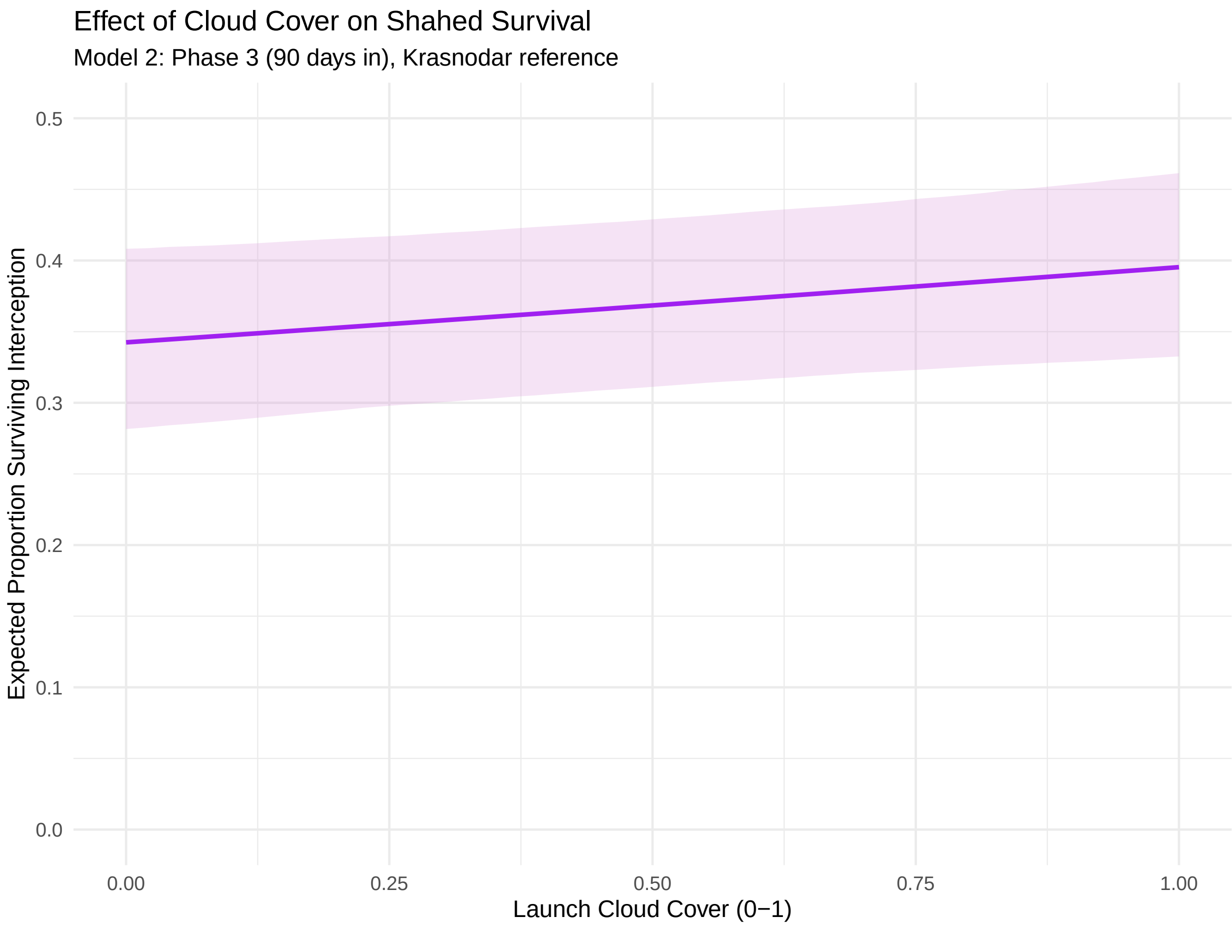

Figure 16: Effect of cloud cover on Shahed survival (Model 2). Y-axis scaled to 0–0.5. Cloud cover is marginally significant ($p < 0.05$) but not robust across all specifications.

F 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 4: Weapon Type Classification

G Model Selection

Specification	**AIC**	**BIC**	**RMSE**	**ΔAIC**	**ΔBIC**
Model 1: All Weapon Types					
1a-Phase: Interaction + Phases	**7,549.0**	**7,727.3**	**0.292**	**0**	**0**
1a: Interaction + Linear	7,595.0	7,767.7	0.296	46.0	40.4
1b-Phase: Main Effects + Phases	7,605.4	7,767.0	0.298	56.4	39.7
1b: Main Effects + Linear	7,646.0	7,802.0	0.300	97.0	74.7
Model 2: Shahed Only					
2a-Phase: Core Locations + Phases	**4,941.3**	**5,021.7**	**0.154**	**0**	**0**
2b-Phase: Extended Locations + Phases	4,945.9	5,054.6	0.154	4.6	32.9
2a: Core Locations + Linear	5,119.6	5,190.5	0.173	178.3	168.8
2b: Extended Locations + Linear	5,123.8	5,223.0	0.173	182.5	201.4

Table 5: Model Specification Comparison. Preferred specifications in bold. Phase specifications are decisively preferred over linear time trends by both AIC and BIC.