Market Learning from Sequential Geopolitical Escalations: Evidence from Airline Stocks

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ABSTRACT

This study examines how financial markets respond to three sequential conflict escalations of increasing geographic scope: a local episode in Israel, a regional episode involving Iran, and a global episode involving the United States. Using a sequential event-study framework and a sample of 56 publicly traded airlines, we find that greater direct exposure to conflict-related regions is associated with larger immediate negative abnormal returns, primarily during the local episode. Across successive episodes, this pattern attenuates and partially reverses. Israeli airlines were eligible for government war-risk insurance from the outset, whereas eligibility for foreign airlines was extended only at the end of the regional episode. Markets took several months to fully incorporate the implications of domestic coverage, while the later extension of coverage appears to have been incorporated within days of the global episode. We find only partial support for a monotonic increase in market responses with escalation scope. Among airlines with pre-event Israeli operations, low-cost carriers experience larger losses than full-service carriers. Overall, the evidence indicates that exposure-based pricing is strongest during the initial local episode but weakens as the conflict broadens, with common geopolitical risk becoming increasingly salient relative to airline-specific exposure, a pattern consistent with investors incorporating prior experience and evolving policy responses.

Keywords: Geopolitical shocks; Market learning; Airline industry; Exposure-based pricing; War-risk insurance

JEL Classification Numbers: G10, G12, G14, G15, G22, H12, L90, L93

1. Introduction

How do financial markets learn from sequential geopolitical shocks? Do investors update risk assessments, or does each shock trigger a fresh response? These questions concern learning under uncertainty (Veronesi, 1999; Pastor & Veronesi, 2012, 2013): rational-learning models predict belief updating, whereas behavioral theories suggest that learning may be incomplete or shaped by salience and past experience (Malmendier & Nagel, 2011; Bordalo et al., 2019, 2022). Recent theory models geopolitical learning via Bayesian updating (Xing et al., 2026); we provide empirical evidence from market prices. Unlike prior work on repeated firm-level events or macroeconomic releases, we study an evolving geopolitical conflict whose scope and consequences change across successive episodes, allowing us to examine whether the pricing of firm-level exposure changes.

Geopolitical uncertainty is known to affect prices depending on firms' exposure (Boubaker et al., 2022; Zaremba et al., 2022; Klein, 2024; Wang et al., 2024; Karolyi, 2006; Caldara & Iacoviello, 2022; Tee et al., 2023; Chatziantoniou et al., 2025). Existing studies largely examine single events (e.g., Ren et al., 2026), leaving open whether investors revise the importance of exposure as risk escalates. The Middle East conflict beginning in 2023 offers a unique setting: three widening stages—local, regional, global—each with distinct economic consequences.

The airline industry is an ideal setting: economically critical (Tretheway & Markhvida, 2014; Zhang & Graham, 2020) yet highly sensitive to geopolitical shocks (Dube et al., 2021; Blampied & Mahadeo, 2024; Jin & Cairang, 2025; Cai et al., 2025; Costa et al., 2025; Sun et al., 2026), with heterogeneous responses across exposure, firm and country characteristics, and shock severity (Chen & Siems, 2004; Kollias et al., 2010; Eldor & Melnick, 2004; Drakos, 2004, 2010; Kaplanski & Levy, 2010; Kolaric & Schiereck, 2016; Arfaoui & Naoui, 2022). Kaplanski and Shenhar (2026, KS) benchmark the October 2023 episode; we treat it as the first realization of an evolving conflict and test whether markets subsequently revise their pricing of geopolitical exposure.

This study makes three contributions: (i) it examines how markets update the pricing of firm-level geopolitical exposure across realizations of an evolving conflict; (ii) richer cross-sectional classifications test whether priced-risk characteristics shift as the conflict expands from local to systemic; (iii) extending the sample through April 2026, it examines immediate market reactions and subsequent post-event dynamics. Government War Risk Insurance (GWRI) adds an institutional dimension.

The rest of the paper is organized as follows. Section 2 presents the data and hypotheses; Section 3 reports the main results; and Section 4 concludes.

2. Data and Hypotheses

The conflict unfolds in three successive episodes, with the following truces serving as benchmarks for recovery. According to KS, the 2023 Israel-Hamas local episode (LE) caused a 66% decline in passenger traffic to Israel and a 14.2% rise in jet fuel prices (JFP), disproportionately harming foreign carriers. GWRI was available to Israeli airlines from the outset, though markets took several months to incorporate its implications. Eligibility was extended to foreign airlines only at the end of the regional episode (RE). The direct Israel-Iran interstate confrontation RE on June 13–24, 2025, disrupted regional airspace and raised JFP by 16%. The global episode (GE), beginning in February 2026, drew in the U.S. and spilled into global aviation and energy markets, raising JFP by 80%.

While classifying LE and GE as escalations is straightforward, the RE also merits ex ante classification as a distinct escalation: it involved direct interstate combat with numerous casualties and large-scale damage on both sides, triggered Israel's largest reserve mobilization since 1973; the geopolitical risk index (GPRD) recorded its largest sample increase (Figure 1); JFP rose 16%; and the number of suspended flights more than doubled relative to LE. Because the duration was unknown ex ante, classifying it based on the realized 12-day duration would introduce hindsight bias, whereas our focus is on how investors assessed risk as information arrived.

Table 1 presents descriptive statistics for 56 publicly traded airlines, classified by Israeli carriers (ISR), non-Israeli carriers with Israeli operations (ISR-Op), and airlines without Israeli operations (NonISR-Op), as well as U.S. carriers, Middle East (ME) exposure (share of ME traffic), business model (full-service/low-cost carrier – FSC/LCC), and geographic origin.

We employ a sequential event study spanning 3/2023–4/2026. Abnormal returns (ARs) are computed using Fama-French's (2012) international three-factor model, with loadings estimated for 1/2018–2/2023. The small ISR warrants caution. It includes one pure-play airline and a second tourism-exposed firm. To address this, we conservatively exclude the latter from the panel regression. We also use the adjusted Patell (Kolari & Pynnönen, 2010) and BMP (Boehmer et al., 1991) tests on cumulative average ARs (CAARs), which account for event-induced volatility and cross-sectional dependence, complemented by panel regressions and bootstrap confidence intervals.

Our hypotheses capture heterogeneous airline responses and shifts in market reactions as the conflict evolves:

H1 (Exposure): Airlines with greater operational exposure experience more negative ARs immediately after each escalation. We further examine the subsequent 10–30 trading days to assess whether exposure-based differences persist or reverse as investors incorporate new information, including information on GWRI.

H2 (Escalation intensity): If investors respond mechanically rather than updating their interpretation of firm-level exposure, average market responses should become increasingly negative as the conflict escalates.

H3 (Market learning): Repeated escalations alter how markets price firms' exposure. We do not predict the direction but test whether the exposure-AR relationship remains stable or shifts as investors update their assessments. This updating may reflect learning from prior episodes and from GWRI's evolving scope. We interpret shifts as consistent with learning while controlling for GWRI periods, though the results may also reflect evolving institutional conditions.

H4 (Business model): Geopolitical shocks may affect LCCs and FSCs differently, given differences in cost structure, route networks, customer composition, operational flexibility, and institutional support. Because these factors may pull in opposite directions, the literature offers no clear prediction. We test whether markets distinguish LCCs from FSCs and whether this differentiation is stable or changes as the conflict evolves.

Together, H1–H4 disentangle (i) cross-sectional exposure effects within each escalation, (ii) changes in average market responses as geopolitical scope expands, and (iii) changes across successive events in the strength and persistence of exposure-based pricing.

3. Empirical Results

Figure 1 presents the main groups' full-sample CAARs, JFP, and GPRD. Following the LE, the main groups, particularly ISR, decline sharply; the pure-play carrier and its combination with the tourism-exposed firm (dashed) show similar patterns. Consistent with H1, ISR-Op shows more negative CAARs than NonISR-Op. Both recover by the first truce, but consistent with KS, ISR rebounds strongly while ISR-Op's gains reverse, indicating heterogeneous recovery and delayed incorporation of domestic GWRI.

The RE shows smaller, more uniform declines that reverse quickly, inconsistent with H2's predicted monotonic intensification and suggestive of muted exposure-based pricing. The GE produces broad-based uniform declines exceeding 20%, consistent with H2's aggregate prediction. Yet the muted RE response indicates that escalation effects do not increase smoothly with scope.

Figure 2 isolates escalations' CAARs with bootstrapped 95% confidence intervals. Following LE, the main groups in Figure 2(a) show negative CAARs. Thereafter, ISR remains depressed, while ISR-Op and NonISR-Op recover. A positive NonISR-Op/ISR-Op difference indicates larger immediate losses for more-exposed firms (H1). RE effects are weaker, with limited dispersion. GE generates large, uniform declines. Figure 2(b) shows similar patterns for ISR and U.S. airlines: strong LE losses but greater GE resilience. Differences between ISR/U.S. and other airlines are significantly positive locally but turn significantly negative globally. Figure 2(c) presents CAARs by ME exposure: high-exposure carriers incur larger local losses (H1) but improve thereafter. By the global episode, high- and medium-exposure carriers perform similarly and are less affected than low-exposure carriers. Both the reversal in ISR/U.S. relative standing and the convergence of high- and medium-exposure carriers globally are consistent with the extension of GWRI and with H3.

ISR-Op LCCs in Figure 2(d) perform worse across all episodes (H4). The FSC/LCC difference remains positive, indicating persistent business-model heterogeneity. Figure 2(e) shows that the NonISR-Op/ISR-Op difference, conditional on origin, is significantly positive after the LE (H1), diminishes regionally, and partially reverses globally, replicating the episode-dependent pattern across exposure groups. Overall, exposure's explanatory power is strongest locally, weakens regionally, and remains muted globally, consistent with H3 and potentially reflecting differences in conflict characteristics and evolving GWRI.

3.1. Statistical analysis

Table 2 reports average ARs for the 1–20 days before and after episodes. Post-LE ARs turn significantly negative, with ISR declining most sharply. Effects persist but attenuate over time. NonISR-Op declines are smaller but significant, ISR-Op intermediate, and LCCs larger.

RE effects are weaker and short-lived, beginning one day before the event, consistent with anticipation, and lasting about five days. GE is preceded by significant declines across all groups except ISR and produces the largest, most persistent impact. The adjusted Patell and BMP tests confirm significance ($P < 0.0001$). The growing pre-event response across episodes suggests that information about later escalations was incorporated progressively earlier.

3.2. Regression analysis

We next estimate the following panel regression:

$$AR_{i,t} = \gamma_0 + \sum_{e=1}^{3} \gamma_{1,e}\, D^{e}_{0-9,t} + \sum_{e=1}^{3}\sum_{g} \gamma_{2,g,e}\left(D^{e}_{0-9,t} \times G_{i,g}\right) + \sum_{e=1}^{3} \gamma_{3,e}\, D^{e}_{10-30,t} + \sum_{e=1}^{3}\sum_{g} \gamma_{4,g,e}\left(D^{e}_{10-30,t} \times G_{i,g}\right) + \sum_{k} \gamma_{5,k}\, Controls_{k,t} + \sum_{j=1}^{10} \gamma_{6,j}\, AR_{i,t-j} + \alpha_i + \varepsilon_{i,t}. \tag{1}$$

$AR_{i,t}$ is AR on stock i, day t. D^{e}_{0-9} and D^{e}_{10-30} are event-time dummies equal to one for the first 10 and subsequent 20 trading days after event $e \in \{LE, RE, GE\}$, and zero otherwise. $G_{i,g}$ is a group indicator defined relative to the omitted benchmark, NonISR-Op. Event-time coefficients capture within-firm changes, while interactions capture cross-sectional differences relative to NonISR-Op. Lagged $AR_{i,t-j}$ (j = 1…10) account for short-run autocorrelation. Firm fixed effects α_i control for unobserved time-invariant heterogeneity.

Table 3 reports regression estimates: Column (1) shows a large, significant post-local effect (–0.0066; t=–5.31), an insignificant regional effect, and a larger global decline (–0.0206; t=–3.93). ISR (–0.0328) and ISR-Op (–0.0050) interactions indicate stronger local effects that later diminish. This is economically meaningful: The baseline local and global effects imply compounded 10-day losses of approximately 6.4% and 19%, respectively; the ISR interaction implies an additional loss of approximately 27%. This attenuation is consistent with investors updating their assessment of exposure, although differences across episodes may also contribute.

Adding controls beyond the Fama-French factors for GPRD, JFP, and market returns (Column 2) reduces the effects by only 15%, with the global effect and the ISR/ISR-Op interactions essentially unchanged, suggesting that the findings are not driven by broad fuel-price or geopolitical-risk changes. Column (3) adds reversal dummies, showing a significant local rebound (0.0042; t=4.45), no significant regional effect, a weaker global adjustment (0.0062; t=1.86), and spillover to ISR-Op (0.0025; t=1.72).

Robustness checks (Columns 4–6) confirm stability both without fixed effects and with alternative Newey-West bandwidths. Column (7) adds controls for ISR/ISR-Op GWRI periods, the VIX, the 10-year minus 3-month Treasury spread, OECD unemployment, and industrial production. Results remain similar, with a larger regional post-event adjustment (0.0019; t=1.69), indicating that institutional/macro controls don't eliminate the post-event adjustment. Finally, NonISR-Op serves as the benchmark for global market conditions. Thus, ISR and ISR-Op's differential responses capture the incremental effect of conflict-related exposure beyond overall market movements.

Wald tests reject equality of coefficients between GE and earlier episodes (stronger global response). The ISR interaction differs between LE and later episodes, and ISR-Op differs between LE and GE, confirming that the pricing of exposure varies across episodes. Reversal-coefficient equality is rejected between LE and RE and at 10% between RE and GE. However, the local-vs-global baseline difference is insignificant. This likely reflects the composition of NonISR-Op: GWRI is largely irrelevant to the group as a whole, but it mixes carriers with negligible regional exposure alongside others with some exposure to regional disruption, so averaging across them may mask any group-level difference.

Table 4 assesses heterogeneity by U.S. origin, ME exposure, and business model. The LE shows significantly negative baseline effects, amplified for ISR, ME-exposed, and ISR-Op LCCs (H1). The RE yields smaller, insignificant effects, except for medium-exposed airlines, which show negative effects consistent with the market already pricing in domestic GWRI coverage for most high-exposure (ISR) carriers. The GE produces a negative effect that intensifies for NonISR-Op-LCC. A positive interaction for medium-exposed airlines is consistent with the market pricing the GWRI extension, which is most relevant to this group.

Post-event dynamics vary: a significant uniform reversal follows LE, whereas the global adjustment concentrates in U.S., ISR-Op-FSC, and NonISR-Op LCCs. For U.S. and ISR-Op-FSC carriers, this aligns with the GWRI extension and the market's experience with earlier policy responses. For NonISR-Op LCCs, by contrast, both the decline and the reversal are consistent with heightened exposure to exogenous factors (fuel costs, demand elasticity) that enter the regression with a single, sample-wide coefficient and may be incompletely absorbed by the LCC cost structure, rather than with conflict-specific learning.

Wald tests reject the null of equal baseline effects across global and earlier episodes. For ISR and high-exposure interactions, deviations are largest locally and fade thereafter, consistent with domestic GWRI coverage being priced in early; for medium exposure, by contrast, Local and Regional are indistinguishable, and the deviation emerges globally once the GWRI extension is priced in. The LE gap between highly and less-exposed carriers equals several months of an average airline's expected return; this gap narrows to near zero regionally before reappearing globally at a reduced magnitude, confirming that the shift is economically consequential.

4. Conclusion

Using airline stocks, this study examines how markets respond to three sequential, widening geopolitical episodes and tests four hypotheses. H1 (Exposure) is supported primarily during the local episode: greater exposure to Israel and the Middle East is associated with significantly larger immediate losses, but this differentiation weakens in subsequent episodes. H2 (Escalation intensity) is rejected: responses do not increase monotonically with escalation scope.

H3 (Market learning) receives evidence consistent with episode-dependent updating: exposure-based pricing is strongest locally, attenuates regionally, and remains muted globally. Consistent with the staggered rollout of GWRI coverage, highly ME-exposed airlines move from among the hardest-hit locally to comparatively less affected regionally, while carriers whose eligibility for GWRI was extended later show improvement during the global episode, converging toward the standing of highly exposed firms as common industry-wide risk gains weight relative to firm-specific exposure. We cannot rule out that these patterns also reflect differences in event characteristics and institutional developments, particularly the evolving GWRI. Post-event reversals follow the same trajectory: pronounced locally, absent regionally, and muted globally. H4 is supported: ISR-Op LCCs generally underperform FSCs, indicating persistent business-model heterogeneity.

The results are difficult to reconcile with a simple habituation story or with a gradual convergence toward sharper firm-level pricing. Instead, firm-specific exposure becomes less important as common geopolitical risk grows more salient, coinciding with investors' evolving incorporation of policy protection. These patterns carry broader implications: for investors, firm-level exposure may be most informative early in a recurring conflict but less reliable once industry-wide risk dominates; for risk managers, declining firm-level differentiation alongside rising aggregate losses suggests periodically reassessing route- and country-based hedges and supplementing them with market-wide hedges as risks broaden. For financial stability, regulators should treat firm-level exposure metrics as time-varying and episode-specific. Our framework may extend to other recurring correlated tail risks, such as climate disasters, cyberconflict, and pandemics, where the balance between idiosyncratic and systemic risk may evolve.

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Table 1. Descriptive statistics relating to airline companies

The table presents descriptive statistics for a sample of publicly traded airlines. Column (1) classifies firms as Israeli airlines (ISR), airlines with non-negligible Israeli operations (at least 0.5% of 2022 passenger traffic to or from Israel) (ISR-Op), or airlines without Israeli operations selected from the world's largest airlines (NonISR-Op). All firms are publicly traded, either directly or through a publicly traded parent company. Column (2) lists the airline's name. Columns (3)–(4) report the airline's geographic region and business model (blank cells indicate full-service carriers, FSC; low-cost carriers, LCC, are marked explicitly). Column (5) reports the airline's 2024 global revenue rank among the world's 50 largest airlines; airlines outside the top 50 occupy unlisted rank positions, while "/n" denotes a non-listed airline whose publicly traded parent company is ranked n. Column (6) reports the primary stock exchange; an asterisk (*) indicates that the airline is publicly traded through a tourism holding company. Column (7) reports total passengers carried in 2024. Column (8) identifies Israeli and U.S. airlines directly involved in the conflict. Column (9) classifies exposure to Middle East (ME) operations, defined as an airline's share of passenger traffic to and from the Middle East in 2022, immediately before the October 2023 conflict, relative to its total passenger traffic. Airlines are classified as high (H; >30%), medium (M; 10–30%), or low (L; ≤10%) exposure based on this measure.

(1) Group	(2) Company	(3) Region	(4) FSC/ LCC	(5) Global Rank	(6) Stock Exchange	(7) Passengers (million)	(8) Direct Involvement	(9) Exposure	(10) Israel Activity
ISR	El Al	Middle East		47	TASE	4.2	Y	H	1
	Israir A.	Middle East		—	TASE*	0.8	Y	H	5
ISR-Op	Delta A.L.	America		1	NYSE	171.4	Y	L	22
	Virgin Atl.			/1		4.4		L	29
	United	America		2	NASDAQ	144.3	Y	L	9
	American	America		3	NASDAQ	199.3	Y	L	16
	Lufthansa	Europe		4	XETRA	101.8		L	10
	Swiss Int.			/4		15.0		L	19
	Austrian.			/4		11.1		L	20
	Brussels			/4		6.8		L	28
	British Air.	Europe		5	LSE	94.7		L	23
	Iberia			/5		15.5		L	25
	A. France	Europe		7	Euronext	65.0		L	15
	KLM Royal			/7		25.8		L	34
	Tra. France		LCC	/7		18.3		H	14
	Transavia		LCC	/7		7.7		L	36
	Turkish	Middle East		12	BIST	71.8		M	4
	A. Canada	America		14	TMX	36.1		L	24
	Ryanair	Europe	LCC	15	Euronext	168.6		L	3
	EasyJet	Europe	LCC	21	LSE	69.7		L	6
	Wizz A.	Europe	LCC	31	LSE	51.1		M	2
	Pegasus	Middle East	LCC	49	BIST	26.9		M	7
	Aegean	Europe			Athens	12.5		L	11
NonISR-Op	Southwest	America	LCC	8	NYSE	126.6	Y	L	—
	China	Asia-Pacific		9	SSE	62.6		L	—
	Air China	Asia-Pacific		10	SSE	38.6		L	—
	China East.	Asia-Pacific		13	SSE	42.5		L	—
	Qantas	Asia-Pacific		16	ASX	21.8		L	—

(1) Group	(2) Company	(3) Region	(4) FSC/ LCC	(5) Global Rank	(6) Stock Exchange	(7) Passengers (million)	(8) Direct Involvement	(9) Exposure	(10) Israel Activity
	Singapore	Asia-Pacific		17	SGX	18.2		L	—
	All Nippon	Asia-Pacific		18	TSE	27.7		L	—
	LATAM	America		19	SantiagoX	62.4		L	—
	Korean	Asia-Pacific		20	KRX	19.1		L	—
	Cathay Pac.	Asia-Pacific		22	HKEX	22.8		L	—
	Japan	Asia-Pacific		23	TSE	19.5		L	—
	Alaska	America		24	NYSE	41.5	Y	L	—
	JetBlue	America	LCC	25	NASDAQ	39.6	Y	L	—
	IndiGo	Asia-Pacific	LCC	26	NSE	85.3		L	—
	Hainan	Asia-Pacific		27	SSE	21		L	—
	Jet2	Europe	LCC	28	LSE	15.5		L	—
	EVA	Asia-Pacific		29	TSE	11.3		L	—
	China A.	Asia-Pacific		30	TSE	9.6		L	—
	Asiana	Asia-Pacific		33	KRX	5.5		L	—
	Spring	Asia-Pacific	LCC	36	SSE	30		L	—
	Air New Z.	Asia-Pacific		40	NZX	12.3		L	—
	Frontier	America	LCC	43	NASDAQ	33.3	Y	L	—
	Copa H.	America		45	NYSE	13.8		L	—
	SkyWest	America		46	NASDAQ	40	Y	L	—
	Finnair	Europe		48	HEL	12		L	—
	Volaris	America	LCC	50	Mexbol	31.1		L	—
	Norwegian	Europe	LCC	—	OSE	26		L	—
	Air Arabia	Middle East	LCC	—	DFM	18		H	—
	Capital A	Asia-Pacific	LCC	—	KLSE	60		L	—
	Juneyao	Asia-Pacific		—	SSE	25		L	—
	A. Astana	Asia-Pacific		—	LSE	9		M	—
	Vietnam A	Asia-Pacific		—	HOSE	24		L	—
	Allegiant	America	LCC	—	NASDAQ	17	Y	L	—

Table 2. Average Abnormal Returns (ARs) around the local, regional, and global episode days
The table reports average ARs over event windows spanning 1 to 20 trading days before and after the local, regional, and global episodes. The sample is divided into Israeli airlines (ISR), airlines operating in Israel prior to the first event (ISR-Op), and airlines without operations in Israel (NonISR-Op). The latter two groups are further subdivided into full-service carriers (FSCs) and low-cost carriers (LCCs). U.S. denotes the nine U.S.-domiciled carriers directly involved in the conflict (spanning both ISR-Op and NonISR-Op). The ISR-Op event-study sample (N = 13) excludes airlines traded only through a parent company's stock (denoted '/n' in Table 1) and those with insufficient return history over the estimation window; Table 1 describes the full population of 21 ISR-Op airlines for completeness. ARs are calculated as specified in Figure 1. Statistical significance is assessed using the adjusted Patell and Boehmer-Masumeci-Poulsen (BMP) standardized cross-sectional tests, which evaluate the null hypothesis that ARs within the event window equal zero and account for cross-sectional dependence, event-induced volatility, and serial correlation. Significance levels are denoted by *, **, and ***, and by ^, ^^, and ^^^ for the adjusted Patell and BMP at 5%, 1%, and 0.1%, respectively.

				ISR-Op			NonISR-Op		
	Days	**ISR**	**U.S.**	**All**	**FSC**	**LCC**	**All**	**FSC**	**LCC**
N		2	9	13	9	4	33	22	11
Local	–20:–1	0.003	–0.002	–0.001	–0.002	0.001	–0.001	–0.001*^	–0.001
	–10:–1	0.001	0.004^	0.003	0.002	0.005	–0.000	–0.001	0.002
	–5:–1	0.007	0.005	0.006^^	0.005^	0.008^	0.003^^	0.001	0.006^^
	–1	–0.000	–0.013	–0.003	–0.005	0.002	0.001	0.000	0.002
	0	–0.203***^^^	–0.039***^^^	–0.053***^^^	–0.052***^^^	–0.057***^^^	–0.016***^^^	–0.008	–0.034***^^^
	0:4	–0.045***	–0.015***^^^	–0.015***^^^	–0.012***^^^	–0.021**^^	–0.004**^^^	–0.004*^^	–0.005^
	0:9	–0.031***^	–0.008***^^^	–0.011***^^^	–0.009***^^^	–0.015**^^^	–0.006***^^^	–0.006***^^^	–0.006**^^
	0:19	–0.013**	–0.006***^^^	–0.004*^^	–0.003*^	–0.005^	–0.002***^^	–0.002*^	–0.004*^
Regional	–20:–1	0.004	–0.004*^	–0.002	–0.001	–0.003	–0.000	0.000	–0.001
	–10:–1	0.002	–0.007**^^	–0.005*	–0.004^	–0.007	–0.003*^^^	–0.002	–0.004
	–5:–1	–0.003	–0.009**^	–0.008*^^	–0.008*^	–0.006	–0.002	–0.000	–0.006
	–1	–0.019	–0.023**^^	–0.030***^^^	–0.029***^^^	–0.031*^	–0.013**^^	–0.008***^^^	–0.024**^^
	0	0.006	–0.029***^^^	–0.022**^^	–0.021**^^	–0.023	–0.020***^^^	–0.016***^^^	–0.027**^^
	0:4	–0.005	–0.007	–0.012***^^^	–0.009*^^^	–0.017*^^^	–0.007***^^^	–0.005	–0.012***^^^
	0:9	0.000	–0.003	–0.002	–0.000	–0.006	–0.002	–0.001	–0.003
	0:19	–0.003	0.003	0.002	0.004*^	–0.004	–0.000	–0.000	–0.000
Global	–20:–1	–0.006	–0.001	–0.004**^^	–0.003	–0.007*^^	–0.000	–0.000	–0.001
	–10:–1	–0.006	–0.008**^	–0.006*^	–0.005	–0.008	–0.003	–0.001	–0.007*^^
	–5:–1	–0.014^^^	–0.012***^	–0.007*^	–0.007*	–0.007	–0.005	–0.001	–0.013***^^^
	–1	–0.002	–0.056***^^^	–0.048***^^^	–0.049***^^^	–0.045**^^	–0.017***^^^	–0.011***^^^	–0.029***^^^
	0	–0.039*^	–0.037***^^^	–0.053***^^^	–0.056***^^^	–0.047**^^	–0.043***^^^	–0.034***^^^	–0.059***^^^
	0:4	–0.005	–0.033***^^^	–0.029***^^^	–0.029***^^^	–0.029***^^^	–0.027***^^^	–0.023***^^^	–0.033***^^^
	0:9	–0.011	–0.022***^^^	–0.018***^^^	–0.018***^^^	–0.019***^^^	–0.018***^^^	–0.017***^^^	–0.022***^^^
	0:19	–0.005	–0.009***^^^	–0.009***^^^	–0.009***^^^	–0.011***^^^	–0.010***^^^	–0.010***^^^	–0.011***^^^

Table 3. Local, regional, and global e[pisodes regression analysis

Table 3 reports estimated coefficients and corresponding *t*-statistics (in parentheses) from the panel regression specified in Equation (1). The dependent variable is airline-stock ARs. The specification includes event-time indicators for the immediate (0–9 trading days) and reversal (10–30 trading days) windows following three geopolitical escalation episodes (local, regional, and global), along with interactions with indicators for Israeli carriers (ISR) and non-Israeli airlines operating in Israel (ISR-Op), relative to the benchmark group (NonISR-Op). Control variables include jet fuel prices (JFP), defined as the U.S. Gulf Coast kerosene spot price (U.S. Energy Information Administration); global equity market returns (Mrkt) from Kenneth French's data library; and the first difference in the geopolitical risk index (ΔGPRD) of Caldara and Iacoviello (2022). ISR and ISR-Op GWRI are dummy variables equal to one when government war-risk insurance is available for Israeli carriers and for all companies operating in Israel, respectively. The VIX is the CBOE volatility index for the S&P 500; 10Y minus 3M Rates is the difference between 10-year and 3-month U.S. government rates; Unemployment is the unemployment rate among OECD individuals aged 25 and older; and ΔIndustrial is the change in OECD industrial production. The baseline specifications include lagged ARs (up to 10 lags, not reported) and firm fixed effects. The sample covers March 2023 to April 2026. Standard errors are heteroskedasticity- and autocorrelation-consistent (HAC) and are estimated using a Newey-West estimator with a Bartlett kernel. Columns (1)–(6) present alternative specifications that vary the inclusion of fixed effects and the HAC bandwidth. The bottom panel reports Wald tests of coefficient equality across escalation episodes, based on Column (3). Negative (positive) *z*-statistics indicate that the left-hand episode coefficient is more negative (positive) than the right-hand episode coefficient. Statistical significance is denoted by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

Event	**Coefficient**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
	Intercept	0.0002	0.0039	0.0076***	0.0075***	0.0076***	0.0076***	0.0143*
		(0.57)	(1.63)	(3.06)	(3.05)	(2.96)	(3.26)	(1.76)
Local	D^{local}_{0-9}	–0.0066***	–0.0056***	–0.0045***	–0.0044***	–0.0045***	–0.0045***	–0.0050***
		(–5.31)	(–4.06)	(–3.23)	(–3.17)	(–2.59)	(–3.56)	(–3.19)
	$D^{local}_{0-9} \times ISR$	–0.0328***	–0.0330***	–0.0333***	–0.0298***	–0.0333***	–0.0333***	–0.0337***
		(–3.08)	(–3.11)	(–3.14)	(–2.82)	(–2.79)	(–3.31)	(–3.18)
	$D^{local}_{0-9} \times ISR\text{-}Op$	–0.0050**	–0.0050**	–0.0049**	–0.0053**	–0.0049*	–0.0049**	–0.0049**
		(–2.08)	(–2.09)	(–2.03)	(–2.24)	(–1.76)	(–2.10)	(–2.05)
Regional	$D^{regional}_{0-9}$	–0.0022	–0.0024	–0.0023	–0.0022	–0.0023	–0.0023	–0.0013
		(–0.67)	(–0.74)	(–0.73)	(–0.69)	(–0.70)	(–0.83)	(–0.42)
	$D^{regional}_{0-9} \times ISR$	–0.0015	–0.0015	–0.0017	0.0014	–0.0017	–0.0017	–0.0017
		(–0.35)	(–0.34)	(–0.40)	(0.33)	(–0.43)	(–0.47)	(–0.39)
	$D^{regional}_{0-9} \times ISR\text{-}Op$	–0.0006	–0.0006	–0.0004	–0.0009	–0.0004	–0.0004	–0.0005
		(–0.30)	(–0.31)	(–0.23)	(–0.46)	(–0.19)	(–0.26)	(–0.25)
Global	D^{global}_{0-9}	–0.0206***	–0.0192***	–0.0175***	–0.0172***	–0.0175***	–0.0175***	–0.0174***
		(–3.93)	(–3.66)	(–3.16)	(–3.10)	(–2.99)	(–3.52)	(–2.96)
	$D^{global}_{0-9} \times ISR$	–0.0015	–0.0016	–0.0018	0.0015	–0.0018	–0.0018	–0.0018
		(–0.29)	(–0.29)	(–0.33)	(0.29)	(–0.31)	(–0.38)	(–0.34)
	$D^{global}_{0-9} \times ISR\text{-}Op$	0.0008	0.0007	0.0009	0.0005	0.0009	0.0009	0.0009
		(0.46)	(0.45)	(0.55)	(0.29)	(0.52)	(0.65)	(0.54)
Local	D^{local}_{10-30}			0.0042***	0.0043***	0.0042***	0.0042***	0.0043***
				(4.45)	(4.49)	(2.90)	(4.55)	(3.56)
	$D^{local}_{10-30} \times ISR$			–0.0020	0.0013	–0.0020	–0.0020	–0.0021
				(–0.39)	(0.26)	(–0.34)	(–0.42)	(–0.41)
	$D^{local}_{10-30} \times ISR\text{-}Op$			0.0020	0.0015	0.0020	0.0020	0.0021

Event	Coefficient	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				(0.93)	(0.72)	(0.83)	(1.11)	(0.94)
Regional	$D_{10-30}^{regional}$			0.0004	0.0004	0.0004	0.0004	0.0019*
				(0.39)	(0.44)	(0.34)	(0.50)	(1.69)
	$D_{10-30}^{regional}$×*ISR*			–0.0071	–0.0037	–0.0071	–0.0071	–0.0072
				(–1.37)	(–0.74)	(–1.32)	(–1.40)	(–1.39)
	$D_{10-30}^{regional}$×*ISR-Op*			0.0016	0.0011	0.0016	0.0016	0.0016
				(1.39)	(1.03)	(1.26)	(1.32)	(1.41)
Global	D_{10-30}^{global}			0.0062*	0.0063*	0.0062*	0.0062**	0.0076*
				(1.86)	(1.89)	(1.93)	(2.07)	(1.89)
	D_{10-30}^{global}×*ISR*			0.0005	0.0037	0.0005	0.0005	0.0004
				(0.11)	(0.94)	(0.10)	(0.11)	(0.11)
	D_{10-30}^{global}×*ISR-Op*			0.0025*	0.0020	0.0025	0.0025*	0.0025*
				(1.72)	(1.43)	(1.48)	(1.79)	(1.74)
	JFP		–0.0015	–0.0032***	–0.0032***	–0.0032***	–0.0032***	–0.0049***
			(–1.53)	(–3.07)	(–3.06)	(–2.96)	(–3.30)	(–3.65)
	Mrkt		–0.0005	–0.0005	–0.0005	–0.0005	–0.0005	–0.0005
			(–0.67)	(–0.75)	(–0.75)	(–0.67)	(–0.79)	(–0.78)
	ΔGPRD		–0.0011*	–0.0011*	–0.0011*	–0.0011*	–0.0011*	–0.0011*
			(–1.75)	(–1.80)	(–1.80)	(–1.75)	(–1.83)	(–1.76)
	ISR GWRI							–0.0006
								(–0.71)
	ISR-Op GWRI							0.0014
								(1.18)
	VIX							0.0000
								(0.10)
	10Y minus 3M Rates							0.0792
								(1.00)
	Unemployment							–0.0007
								(–0.33)
	ΔIndustrial							–0.0020***
								(–3.47)
	Fixed effects	+	+	+	–	+	+	+
	Lag structure	6	6	6	6	4	8	6

Coefficient	H0:	$E_{local} = E_{regional}$	$E_{local} = E_{global}$	$E_{regional} = E_{global}$
$D_{0–9}$		0.62	2.33**	2.36**
$D_{0–9}$×*ISR*		–2.77***	–2.67***	0.00
$D_{0–9}$×*ISR-Op*		–1.47	–2.03**	–0.54
$D_{10–30}$		2.85***	–0.62	1.66*
$D_{10–30}$×*ISR*		0.71	–0.39	–1.18

$D_{10\text{–}30}\times$*ISR-Op*	0.17	–0.18	–0.49

Table 4. Airline characteristic regression analysis

The table reports estimated coefficients and corresponding *t*-statistics (in parentheses) from the panel regression specified in Equation (1). The dependent variable is airline-stock ARs. The specification includes event-time indicators for the immediate (0–9 trading days) and reversal (10–30 trading days) windows following three geopolitical escalation episodes (local, regional, and global), along with interactions with airline groups. Airline classifications include Israeli carriers (ISR), non-Israeli airlines operating in Israel (ISR-Op), U.S. airlines, ME operational exposure (high; >30%, Med; 10–30 operational exposure to the Middle East, defined as the share of 2022 passenger traffic to and from the Middle East relative to total passenger traffic), and business models (FSC and LCC). NonISR-Op and NonISR-Op FSC serve as omitted benchmark groups, where applicable. Controls, sample period, and AR construction follow Table 3. Firm fixed effects are included, and standard errors are heteroskedasticity- and autocorrelation-consistent, estimated using Newey-West. The bottom panel reports Wald tests of coefficient equality across episodes. Negative (positive) *z*-statistics indicate that the left-hand episode coefficient is more negative (positive) than the right-hand episode coefficient. Statistical significance is denoted by *, **, and ***, corresponding to the 10%, 5%, and 1% significance levels, respectively.

Event	**Coefficient**	**(1)**	**Coefficient**	**(2)**	**Coefficient**	**(3)**
	Intercept	0.0074***	*Intercept*	0.0074***	*Intercept*	0.0074***
		(3.01)		(3.01)		(3.02)
Local	D_{0-9}^{local}	–0.0048**	D_{0-9}^{local}	–0.0055***	D_{0-9}^{local}	–0.0045***
		(–2.42)		(–3.79)		(–4.14)
	$D_{0-9}^{local}\times ISR$	–0.0332***	$D_{0-9}^{local}\times High$	–0.0184***	$D_{0-9}^{local}\times ISR$	–0.0335***
		(–2.93)		(–2.58)		(–3.04)
	$D_{0-9}^{local}\times ISR\text{-}Op$	–0.0042	$D_{0-9}^{local}\times Med$	–0.0044*	$D_{0-9}^{local}\times ISR\text{-}Op\text{-}FSC$	–0.0032
		(–1.42)		(–1.88)		(–1.24)
	$D_{0-9}^{local}\times U.S.$	–0.0015			$D_{0-9}^{local}\times ISR\text{-}Op\text{-}LCC$	–0.0088***
		(–0.27)				(–2.70)
					$D_{0-9}^{local}\times NonISR\text{-}Op\text{-}LCC$	–0.0007
						(–0.38)
Regional	$D_{0-9}^{regional}$	–0.0021	$D_{0-9}^{regional}$	–0.0024	$D_{0-9}^{regional}$	–0.0019
		(–0.66)		(–0.68)		(–0.83)
	$D_{0-9}^{regional}\times ISR$	–0.0020	$D_{0-9}^{regional}\times High$	–0.0005	$D_{0-9}^{regional}\times ISR$	–0.0021
		(–0.49)		(–0.18)		(–0.55)
	$D_{0-9}^{regional}\times ISR\text{-}Op$	–0.0010	$D_{0-9}^{regional}\times Med$	–0.0039**	$D_{0-9}^{regional}\times ISR\text{-}Op\text{-}FSC$	0.0012
		(–0.32)		(–2.23)		(0.46)
	$D_{0-9}^{regional}\times U.S.$	–0.0023			$D_{0-9}^{regional}\times ISR\text{-}Op\text{-}LCC$	–0.0055
		(–0.81)				(–1.52)
					$D_{0-9}^{regional}\times NonISR\text{-}Op\text{-}LCC$	–0.0028
						(–0.89)
Global	D_{0-9}^{global}	–0.0160***	D_{0-9}^{global}	–0.0177***	D_{0-9}^{global}	–0.0164***
		(–2.62)		(–3.06)		(–2.98)
	$D_{0-9}^{global}\times ISR$	–0.0033	$D_{0-9}^{global}\times High$	–0.0021	$D_{0-9}^{global}\times ISR$	–0.0030
		(–0.57)		(–0.39)		(–0.54)
	$D_{0-9}^{global}\times ISR\text{-}Op$	–0.0010	$D_{0-9}^{global}\times Med$	0.0065***	$D_{0-9}^{global}\times ISR\text{-}Op\text{-}FSC$	–0.0000
		(–0.38)		(4.22)		(–0.01)
	$D_{0-9}^{global}\times U.S.$	–0.0052			$D_{0-9}^{global}\times ISR\text{-}Op\text{-}LCC$	–0.0010
		(–1.01)				(–0.46)

Event	Coefficient	(1)	Coefficient	(2)	Coefficient	(3)
					D_{0-9}^{global}×*NonISR-Op-LCC*	–0.0042***
						(–2.81)
Local	D_{10-30}^{local}	0.0051***	D_{10-30}^{local}	0.0046***	D_{10-30}^{local}	0.0045***
		(4.31)		(3.92)		(4.00)
	D_{10-30}^{local}×*ISR*	–0.0029	D_{10-30}^{local}×*High*	–0.0027	D_{10-30}^{local}×*ISR*	–0.0023
		(–0.64)		(–0.78)		(–0.46)
	D_{10-30}^{local}×*ISR-Op*	0.0023	D_{10-30}^{local}×*Med*	0.0013	D_{10-30}^{local}×*ISR-Op-FSC*	0.0011
		(0.96)		(0.70)		(0.42)
	D_{10-30}^{local}×*U.S.*	–0.0049			D_{10-30}^{local}×*ISR-Op-LCC*	0.0033
		(–1.50)				(1.06)
					D_{10-30}^{local}×*NonISR-Op-LCC*	–0.0017
						(–0.73)
Regional	$D_{10-30}^{regional}$	0.0003	$D_{10-30}^{regional}$	0.0005	$D_{10-30}^{regional}$	–0.0003
		(0.31)		(0.40)		(–0.25)
	$D_{10-30}^{regional}$×*ISR*	–0.0070	$D_{10-30}^{regional}$×*High*	–0.0027	$D_{10-30}^{regional}$×*ISR*	–0.0064
		(–1.43)		(–0.60)		(–1.20)
	$D_{10-30}^{regional}$×*ISR-Op*	0.0016	$D_{10-30}^{regional}$×*Med*	0.0019	$D_{10-30}^{regional}$×*ISR-Op-FSC*	0.0034
		(1.07)		(0.74)		(1.62)
	$D_{10-30}^{regional}$×*U.S.*	0.0006			$D_{10-30}^{regional}$×*ISR-Op-LCC*	–0.0002
		(0.15)				(–0.09)
					$D_{10-30}^{regional}$×*NonISR-Op-LCC*	0.0020
						(1.63)
Global	D_{10-30}^{global}	0.0048	D_{10-30}^{global}	0.0066**	D_{10-30}^{global}	0.0049
		(1.40)		(1.98)		(1.56)
	D_{10-30}^{global}×*ISR*	0.0017	D_{10-30}^{global}×*High*	0.0022	D_{10-30}^{global}×*ISR*	0.0016
		(0.42)		(0.64)		(0.39)
	D_{10-30}^{global}×*ISR-Op*	0.0025	D_{10-30}^{global}×*Med*	–0.0001	D_{10-30}^{global}×*ISR-Op-FSC*	0.0047**
		(1.39)		(–0.05)		(2.45)
	D_{10-30}^{global}×*U.S.*	0.0068**			D_{10-30}^{global}×*ISR-Op-LCC*	0.0011
		(2.36)				(0.47)
					D_{10-30}^{global}×*NonISR-Op-LCC*	0.0037***
						(3.08)
	JFuelPrice	–0.0031***	*JFuelPrice*	–0.0031***	*JFuelPrice*	–0.0031***
		(–3.02)		(–3.01)		(–3.02)
	Mrkt	–0.0005	*Mrkt*	–0.0005	*Mrkt*	–0.0005
		(–0.69)		(–0.69)		(–0.69)
	ΔGPRD	–0.0011*	*ΔGPRD*	–0.0011*	*ΔGPRD*	–0.0011*
		(–1.83)		(–1.83)		(–1.83)

Coefficient H0:	E_{local} = $E_{regional}$	E_{local} = E_{global}	$E_{regional}$ = E_{global}	E_{local} = $E_{regional}$	E_{local} = E_{global}	$E_{regional}$ = E_{global}	E_{local} = $E_{regional}$	E_{local} = E_{global}	$E_{regional}$ = E_{global}
$D_{0–9}$	–0.75	1.77*	2.03**	–0.85	2.08**	2.27**	–1.01	2.17**	2.42**
$D_{0–9}$×*ISR*	–2.60***	–2.35**	0.19				–2.70***	–2.49**	0.13
$D_{0–9}$×*ISR-Op*	–0.74	–0.83	–0.01						
$D_{0–9}$×*U.S.*	0.13	0.49	0.50						
$D_{0–9}$×*High*				–2.32**	–1.81*	0.26			
$D_{0–9}$×*Med*				–0.15	–4.02***	–4.69***			
$D_{0–9}$×*ISR-Op-FSC*							–1.23	–0.98	0.36
$D_{0–9}$×*ISR-Op-LCC*							–0.70	–2.01**	–1.05
$D_{0–9}$×*NonISR-Op-LCC*							0.57	1.46	0.39
$D_{10–30}$	3.20***	0.09	–1.26	2.27***	–0.63	1.67*	3.05***	–0.16	–1.54
$D_{10–30}$×*ISR*	0.63	–0.78	–1.39				0.58	–0.62	–1.21
$D_{10–30}$×*ISR-Op*	0.26	–0.07	–0.40						
$D_{10–30}$×*U.S.*	–1.09	–2.78***	–1.29						
$D_{10–30}$×*High*				0.01	–1.03	–0.87			
$D_{10–30}$×*Med*				–0.19	0.53	0.63			
$D_{10–30}$×*ISR-Op-FSC*							–0.70	–1.13	–0.47
$D_{10–30}$×*ISR-Op-LCC*							0.89	0.59	–0.39
$D_{10–30}$×*NonISR-Op-LCC*							–1.45	–2.15**	0.28

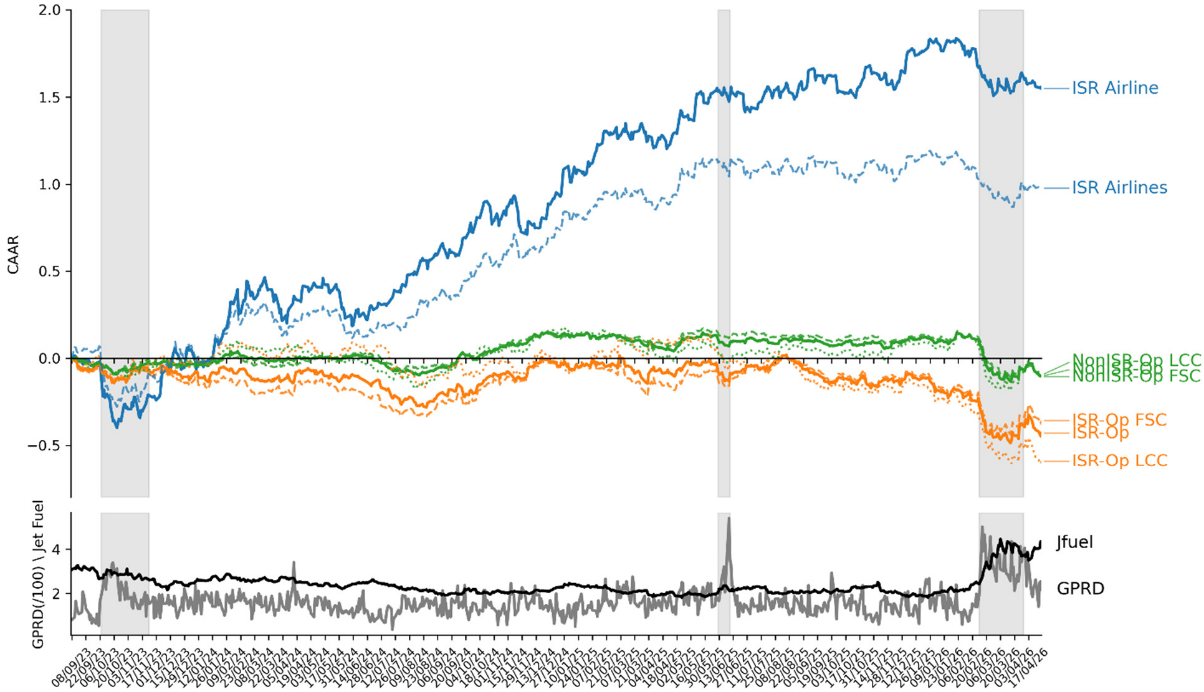
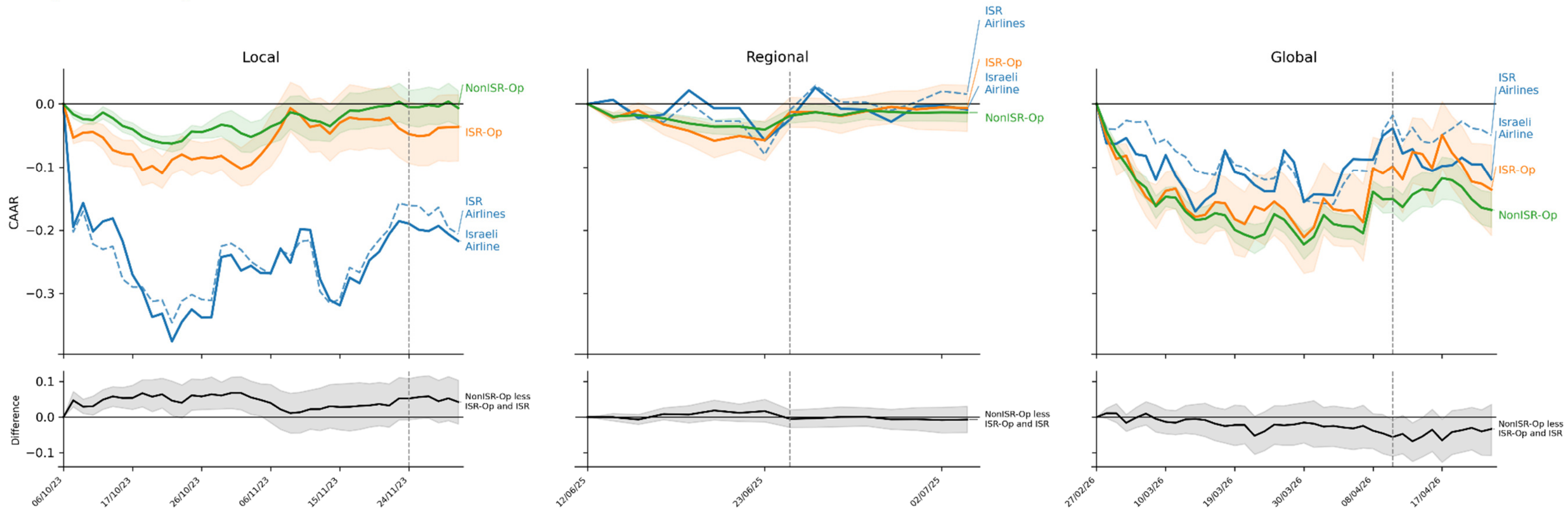
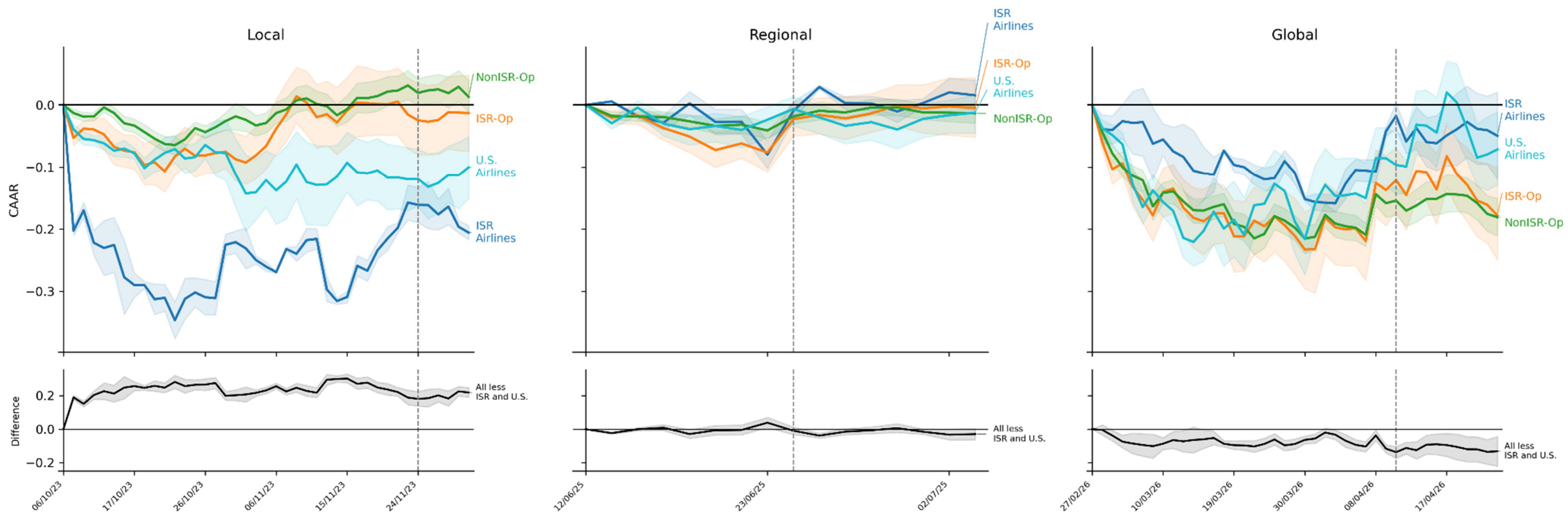


Fig. 1. Cumulative average abnormal returns (CAARs).
Figure 1 shows CAARs for the pure-play Israeli carrier, El Al (ISR); a second dashed series combining El Al and Israir, a carrier traded through a tourism holding company; non-Israeli airlines operating in Israel prior to the first event (ISR-Op); and airlines without operations in Israel (NonISR-Op) for the period September 2023–April 2026. Dashed and dotted lines further subdivide ISR-Op and NonISR-Op airlines into full-service carriers (FSCs) and low-cost carriers (LCCs). The lower panels show jet fuel prices (JFP) per gallon and the geopolitical risk index (GPRD). Gray-shaded areas denote the conflict-escalation local (October 2023), regional (June 2025), and global (February 2026) episodes, extending through the following truce. ARs are calculated as U.S.-dollar-denominated returns minus expected returns estimated using the Fama-French international three-factor model $AR_{i,t} = R_{i,t} - (\hat{\beta}_{M,i}RM_t + \hat{\beta}_{SMB,i}SMB_t + \hat{\beta}_{HML,i}HML_t)$.

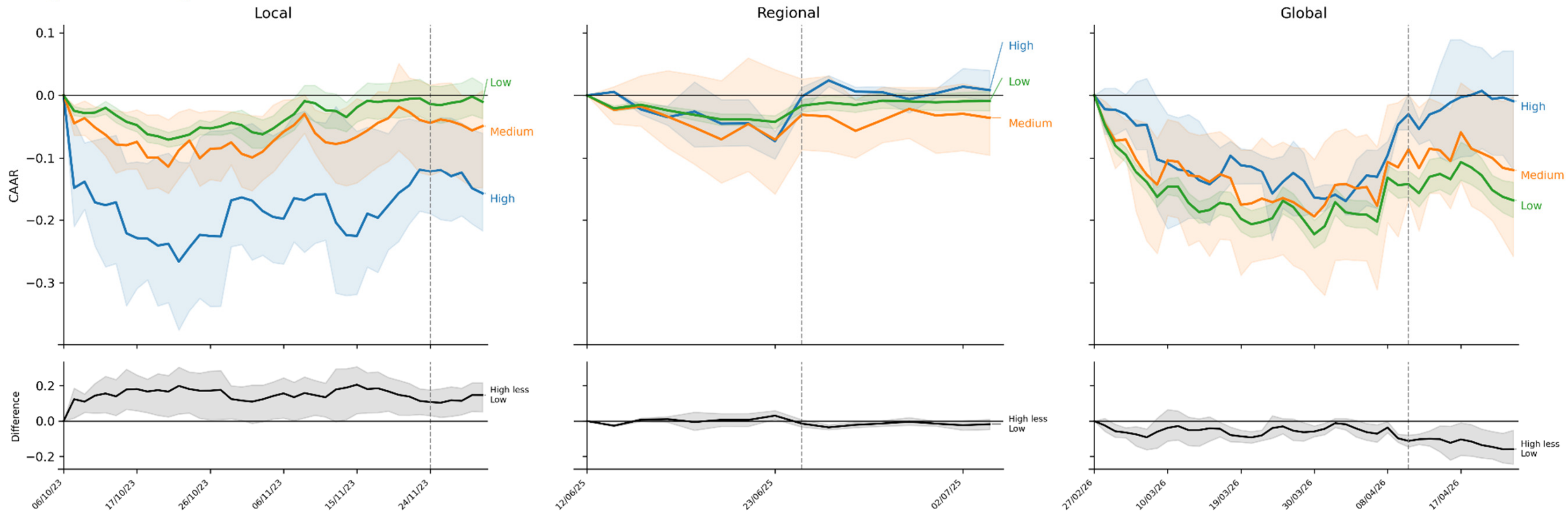
(a) Operational Exposure to Israel



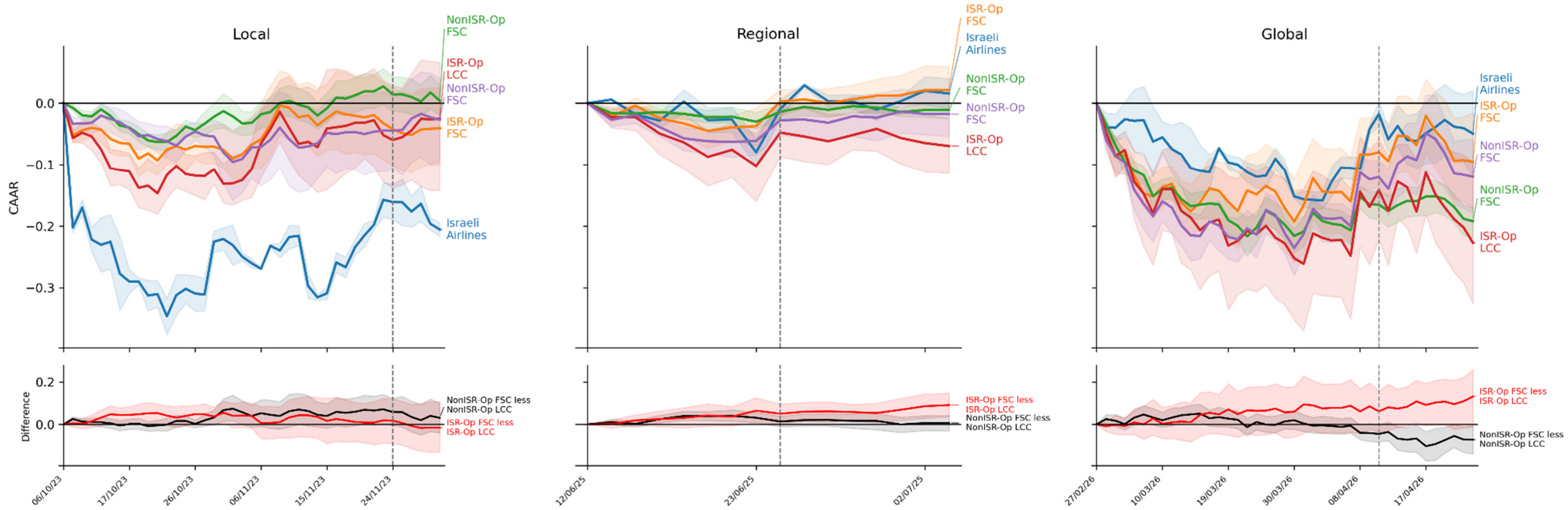
(b) Conflict Involvement



(c) Operational Exposure to Middle East



(d) FSC / LCC Business Model



(e) Region of Origin

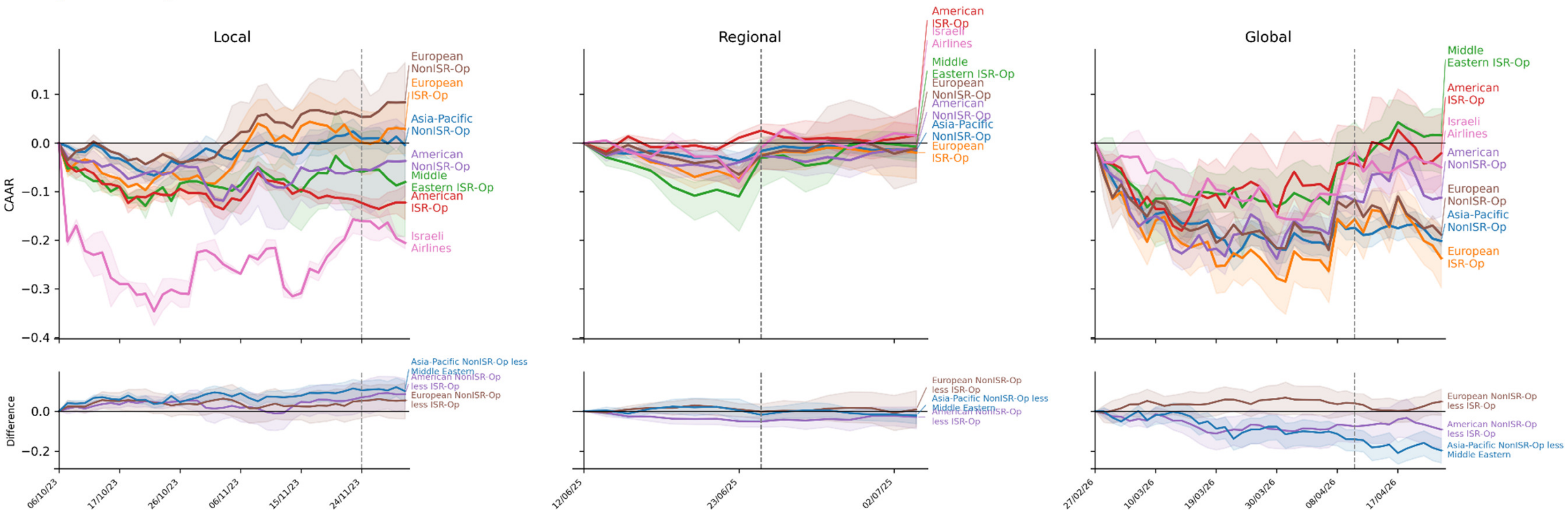


Fig. 2. Cumulative average abnormal returns (CAARs) by airline characteristics
Figure 2(a) displays CAARs following the local, regional, and global episodes for Israeli airlines (ISR), airlines operating in Israel before the first event (ISR-Op), and airlines without Israeli operations (NonISR-Op). The pure-play Israeli carrier and its combination with the second, tourism-exposed Israeli company (dashed line) show similar patterns. ARs are calculated as specified in Figure 1. Vertical dotted lines mark the first truce in each episode. The lower panel presents CAAR differences. Background shading denotes 95% confidence intervals estimated using a firm-level nonparametric bootstrap with 2,000 replications, preserving within-firm serial correlation. Bootstrap samples are drawn independently across groups, and confidence intervals are based on the empirical distribution of bootstrapped CAAR differences. Figure 2(b) separately identifies U.S. airlines, with lower panels showing differences between other airlines and the combined U.S. and ISR groups. Figure 2(c) presents airlines with high (H; >30%), medium (M; 10–30%), or low (L; ≤10%) operational exposure to the Middle East, defined as the share of 2022 passenger traffic to and from the Middle East relative to total passenger traffic. Figure 2(d) classifies airlines as ISR-Op FSCs, ISR-Op LCCs, NonISR-Op FSCs, and NonISR-Op LCCs. Figure 2(e) separates ISR-Op and NonISR-Op airlines by region of origin.