Expectations of War and Peace: Evidence from Ukraine's GDP-Warrant

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Abstract

How are expectations of economic recovery formed during wartime? I study this question using Ukraine's GDP-linked warrant, a sovereign security whose payouts depend directly on the country's economic growth, together with a news-based War – Peace index built from global media coverage over 2018 – 2025. After Russia's 2022 invasion, the warrant's returns became largely disconnected from emerging-market and global bond conditions. I find that ordinary day-to-day changes in conflict news have little reliable effect on returns, while news shocks above an estimated threshold produce significantly larger repricing. These shocks coincide with approximately 23.8% higher conditional volatility, which decays with a half-life of about four to five trading days. The volatility response is asymmetric: escalating shocks raise volatility, while comparable de-escalation shocks do not. The results suggest that during conflict, expectations of recovery are revised mainly through discrete geopolitical catalysts rather than continuous news.

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1. Introduction

How investors form expectations about a country's economic recovery shapes its borrowing costs, its access to financing, and its policy choices. Yet it is unclear how those expectations are updated during an active war. This study seeks to gain a deeper understanding of how investors actively price future economic growth during the Russia – Ukraine War. Following the Annexation of Crimea, the Ukrainian government issued a financial instrument, a warrant, that is linked to the country's GDP. This warrant's payout directly coincides with the country's economic growth figures, that is, if real GDP grows more than 3% a year and nominal GDP is above 125.4 billion USD. Below these thresholds the warrant pays nothing. Since issue, the warrant served as a claim on the country's future growth expectations. When Russia invaded Ukraine in February of 2022, this warrant became a near-pure bet on the war outcome and Ukraine's post-war economic recovery.

War has been known to have severe economic consequences on the financial health of a country. It reduces economic growth (Collier, 1999; Abadie and Gardeazabal, 2003; Cerra and Saxena, 2008), disrupts public trade and global markets (Glick and Taylor, 2010), and public investment collapses (Benmelech and Monteiro, 2025; Imai and Weinstein, 2000). Wars and geopolitical shocks can cause treasury yields to fall (Rigobon and Sack, 2005), get priced into bond markets (Frey and Kucher, 2000) and increase the risk of default on sovereign credit (Demiralay et al., 2024).

Previous researchers have already published work on this specific Ukrainian warrant and other similar financial instruments from other countries. Igan et al. (2021) analyzed the premia on state-contingent debt instruments, focusing on GDP-linked warrants from Ukraine, Greece, and Argentina. More broadly, Federle et al. (2026) examined how wars and military threats affect sovereign bond markets, and Rexer et al. (2022) examined how sovereign bond markets price the onset of violent conflicts. My study aims to contribute to the literature by analyzing the reconstruction and expected economic recovery in the time of conflict using GDP-linked financial instruments to gauge investor sentiment.

This study uses daily closing price data on XS1303929894, the International Securities Identification Number (ISIN) for Ukraine's USD-denominated GDP-linked security, issued by the Ministry of Finance of Ukraine. Using data compiled from GDELT, this study creates a

news-based index similar to the Geopolitical Risk Index (GPR), by Caldara and Iacoviello (2022), and Economic Policy Uncertainty Index (EPU), by Baker et al. (2016). By measuring specific escalating and de-escalating words covered in the media, this study creates a net War – Peace index to monitor the escalation and de-escalation of the Russia – Ukraine War. This allows me to systematically measure how this warrant is affected by peace summits or continuing conflict. I first test whether the warrant priced Ukraine's recovery separately from broader bond markets by comparing its returns with emerging-market sovereign bonds (VWOB) and a Central and Eastern European government bond index. I further examine how escalating and de-escalating news affect the warrant's value, using a threshold regression that separates ordinary daily news from unusually large news shocks. I then use an EGARCH model to test whether these shocks also change the warrant's volatility, and whether escalation and de-escalation news affect that volatility differently. Finally, a market implied long run GDP model is created to back out investors' expectations of future annual GDP growth.

I find that during periods of heightened war and geopolitical conflict, a country's market-implied economic growth expectations can become increasingly idiosyncratic relative to global and surrounding regional conditions. In this environment, growth expectations are not systematically revised in response to continuous day-to-day conflict news but instead respond primarily to large catalyst-driven information shocks. These shocks provide substantially greater explanatory power for warrant returns and are associated with an approximately 23.8% increase in conditional volatility, with a volatility half-life of roughly four to five trading days. This creates temporary volatility regimes in which investor expectations of future economic recovery are sharply repriced. Additional findings indicate that escalation and de-escalation are priced asymmetrically: escalation shocks significantly increase volatility, while comparable de-escalation shocks produce no statistically reliable volatility response. Together, the results suggest that investor expectations are revised primarily through discrete, high-magnitude geopolitical catalysts rather than continuous changes in the daily news environment.

The remainder of this paper is structured as follows: Section 2 describes the data and methodology used, Section 3 presents empirical results, and Section 4 concludes.

2. Data and Methodology

Asset Selection

To measure the impact of the economic effects of the Russia – Ukraine War on the financial health of Ukraine, a specific public Ukrainian warrant is used to see how fluctuations in this asset might impact the perception of the conflict, the ISIN registration being XS1303929894, and the ticker symbol being UKRAIN 0 05/31/41 REGS. Originally issued in 2015, during Ukraine's debt restructuring after The Russian Occupation of Crimea in February 2014, this financial instrument is directly tied to the GDP of Ukraine. Payouts must meet two conditions before funds can be transferred to investors, Ukraine's nominal GDP must remain above 125.4 billion in USD and real GDP growth must exceed 3% in a year. If both obligations are not met the warrant fails to pay out. The warrant made only one payment over its life. Reference year 2019, with real GDP growth of 3.2%, produced a payment of USD 12.58 per USD 1,000 notional on 31st May 2021. Reference year 2023 growth of 5.3% triggered a claim of approximately USD 665 million due in June 2025, but Ukraine imposed a moratorium on GDP-warrant payments effective 27th August 2024, and the claim was not settled. This warrant was exchanged in December 2025 into new Series C Bonds due 2032, with new interest rates starting at 4% and scaling to 7.25%, after the Ukrainian Ministry of Finance achieved a 99.06% investor participation in the exchange. Although this asset no longer exists, its historical price movements allow researchers to quantify shifting investor sentiment regarding Ukraine's long-term economic viability, wartime resilience, and post-war reconstruction prospects.

<Insert Figure 1>

Data Sources

To obtain data on the GDP-warrant data was used from Cbonds. Cbonds is a global financial market data provider that specializes in fixed-income securities and tracks over 1 million bonds across over 190 countries.[1] Data for this instrument spans from May 9th, 2016, to December 22nd, 2025, when it was ultimately transitioned into a Series C Bond. Control variable data for VWOB, the Vanguard Emerging Markets Government Bond ETF, was obtained via

[1] Cbonds. (2026). *About the platform*. https://cbonds.com/about/

Yahoo Finance and for CEE 10-year treasury bond index, data was obtained via Stooq. A popular free financial data platform.

War – Peace Index Construction

To systematically identify the escalation and de-escalation of the Russia – Ukraine War, a news related coverage index was created to measure the intensity of the conflict. Following the methodology first created by Baker et al. (2016) to measure economic uncertainty and following other similar news related indexes like the Caldara and Iacoviello (2022) GPR index and Caldara et al. (2020) Trade Policy Uncertainty (TPU) index, my War – Peace index measures how frequent war and peace terminology is being used in popular media outlets. The index's first filters geographically by using articles mentioning both Ukraine (or Kyiv) and Russia and then counts how many war-related terms (e.g., invasion, shelling, offensive) and peace-related terms (e.g., ceasefire, negotiations, truce), then normalized by total GDELT-monitored articles that day, yielding a war share and a peace share.[2] A direction value was created, using the formula:

$$\text{Direction}_t = (\text{Peace}_t - \text{War}_t) / (\text{Peace}_t + \text{War}_t)$$

This creates a range from -1 (coverage entirely war-focused) to +1 (coverage entirely peace-focused). The value registers -0.844 on the day of the invasion in February 2022, and -0.176, +0.346, and +0.455 on the days of the March 2022 Istanbul negotiations and the 2025 Alaska and Geneva talks, consistent with known developments in the conflict.[3]

A salience value was also created to measure the overall news intensity about the Russia – Ukraine War. This index was created using the formula:

$$\text{Salience}_t = (\text{Peace}_t + \text{War}_t) / \text{Total_News}_t$$

If salience is high on a given day, it means Russia – Ukraine War coverage takes up a large share of all monitored news. It does not say whether the coverage is peaceful or warlike, just how prominent the conflict is. On the day of invasion salience measured 14.24%, showing high global

[2] Peace related terms: ceasefire, peace talks, peace deal, truce, armistice, negotiations. War related terms: invasion, offensive, shelling, airstrikes, bombardment, mobilization, escalation. Specific code is provided in the GitHub.
[3] On May 15, 2025, the day prior to when the Istanbul talks took place, direction registered 0.527.

media attention. Following the invasion on the 28th of February, salience reached 16.9%, when first negotiations began, having one of the highest recordings in the entire index.

To measure how strongly the overall news environment is tilted towards peace or war and the intensity of that coverage, both the direction and salience values are used to create a signed intensity measure with the formula:

$$\text{Signed_Intensity}_t = \text{Salience}_t \times \text{Direction}_t$$

On the day of invasion signed intensity reached -0.1201, an extremely high directional signal showing elevated war escalation. While the day after the 2025 Alaska Summit, signed intensity reached its highest measured value of +0.04204. Both value being consistent with developments in the conflict.

<Insert Figure 2>

Control Variables

To measure the relationship between the Ukrainian GDP warrant and other variables, this analysis uses OLS regressions to determine how outside forces impact the warrant. To control these outside forces, two control variables are selected to measure different effects. Ticker VWOB, the Vanguard Emerging Markets Government Bond ETF, was chosen to account for emerging market sovereign bond risk. This measures the relationship of the Ukrainian GDP warrant against other similar assets from similar emerging markets. Data for this ETF is procured through Yahoo Finance.

The other variable this study measures against is CEE risk. Since no specific CEE bond index exists, to control this, a basket of 10-year government bond data is compiled into an equally weighted index from the top five largest countries from this region, by GDP size. This index has bonds from Poland, Romania, Czech Republic, Hungary, and Slovakia. All five countries proximity to Ukraine allows this study to measure the geopolitical risk associated with being close to the Russia – Ukraine Conflict and surrounding CEE region.

Multiple OLS regressions are run on both control variables. Additional pre-invasion testing is conducted to measure the before and aftereffects of the control variables as well as full-time period tests. The data windows for the analysis range start at the GDP-warrants earliest

available historic price date of May 9th, 2016, and concludes on December 22nd, 2025. February 24th, 2022, is used to separate the before and after analysis, as it's the day Russia invaded Ukraine. Simple daily changes or delta in percentage are used to measure relationships in both yields and price path, for yield (Daily Yield = $Yield_t - Yield_{t-1}$) and for daily return (Daily return = $(Price_t - Price_{t-1}) / Price_{t-1}$). Pre-and post-invasion data samples aren't symmetrical, with pre-invasion data spanning 1,389 days (May 9th, 2016 - February 23rd, 2022) and post-invasion data spanning 848 days (February 24th, 2022 - December 22nd, 2025).

3. Empirical Results

The empirical results sections proceed in multiple stages. First, my analysis uses an ordinary least squares model (OLS) to determine a relationship between the Ukrainian-GDP warrant and worldwide emerging markets' government bonds and Central and Eastern European government bonds. Additional regression tests are conducted to determine the relationship between escalating and de-escalating news. Next, an EGARCH model is used to determine whether escalating news coverage raises volatility more than de-escalating news, to measure the symmetry of reaction and how long the reactions persist. Lastly, a market-implied GDP growth gauge is backed out of the warrant's price.

Control Variables OLS Models

This analysis uses ordinary least squares as an attempt to identify the impact of emerging markets and Central and Eastern European risk. Regressions are separated by time horizon, with regressions on the full period (May 9th, 2016 – December 22nd, 2025), regressions on pre-invasion (May 9th, 2016 – February 23rd, 2022) and post-invasion (February 24th, 2022 – December 22nd, 2025).

For emerging market risk, the model is specified as follows:

$$R_t = \alpha + \beta \cdot V_t + \varepsilon_t \quad (1)$$

Where R_t is the warrant's daily return on day t, α is the intercept and the warrant's average return when VWOB is flat, β is the slope coefficient and measures how much the warrant moves per 1% move in VWOB, V_t is VWOB's daily return, ε_t is the error term. The model for Central and Eastern European risk is specified as follows:

$$R_t = \alpha + \beta \cdot \Delta Y_t + \varepsilon_t \quad (2)$$

Where R_t, α, and ε_t stay consistent with the previous interpretation, while β is how much the warrant moves per 1% move in the CEE index, and ΔY_t is the daily change in the equally weighted CEE index. Estimated coefficients are shown in table 1.

<Insert Table 1>

With both controls being significant, VWOB is positive across all three periods at less than the 1% level and CEE being negative and statistically significant at the 1% level. R^2 for VWOB showed the biggest change in relationship going from 0.098 pre-invasion to 0.010 post invasion, while β remained nearly unchanged (1.195 to 1.128).[4] Showing, before the war, the warrant functioned similarly to an emerging market bond; after, war specific factors began to dominate its pricing and emerging market credit became a minor factor.

Central and Eastern Europe exposure is kept constant throughout the full period and post-invasion period with a R^2 of .011, while pre-invasion R^2 was slightly higher at 0.012, which explains very little of the surrounding region's risk exposure on the warrant. Suggesting that the warrant's price was more reliant on the global credit conditions, not on regional Central and Eastern European credit conditions.

Across all specifications, R^2 values return low figures (1-10%). These controls explain only a small fraction of the warrant's daily variation. Meaning the instrument is relatively idiosyncratic to regional credit instruments while only slightly affected by global credit conditions, during the pre-invasion time period, while post-invasion becomes even less reliant on global credit conditions. Suggesting other factors having greater influences on the warrant's price.

News Index Regressions

Using an ordinary least square model, in an attempt to measure the relationship between the War – Peace index and the Ukrainian GDP-warrant, this analysis uses the previously created

[4] Rising yields correspond to falling bond prices; a positive change in the CEE-5 index therefore reflects deteriorating regional credit conditions. The negative coefficient thus indicates that worsening regional risk is associated with declining warrant prices, economically the same directional relationship as the positive VWOB coefficient, expressed in the opposite sign convention because ΔY is a yield change rather than a price return.

signed intensity value to measure the warrant's return based on both direction and total media coverage of the Russia – Ukraine War. This model also follows the full-period, pre-invasion and post-invasion framework identified in the last section, except starting on January 1st, 2018, due to data limitations. The model is as specified:

$$R_t = \alpha + \beta \cdot \Delta SI_t + \varepsilon_t \quad (3)$$

Where R_t is the warrant's daily price return on day t, α is the intercept and the warrant's average return when signed intensity is flat, β is the slope coefficient and measures how much the warrant moves per 1% move in signed intensity, SI is signed intensity on day t and, and ε_t is the error term. Estimated coefficients are shown in table 2.

<Insert Table 2>

With full-period and post-invasion results being statistically significant ($P<0.1$), and pre-invasion results failing to reach statistically significant, due to limited War and Peace data, analysis on this discussion focuses on full and post periods and should be taken with caution, due to the limited significance. Both full-period and post-invasion explain variation in the warrant's daily return. With full-period R^2 being 0.0274 and post-invasion 0.0334. Intuitively this makes sense and has economic significance, as increases in peace related news coverage tends to increase the warrant's price and war-oriented news coverage decreases the warrant's price. Overall, the results suggest that changes in the Russia – Ukraine Conflict explains only a modest share of daily return variation, and the coefficient is consistent with the warrant's underlying exposure to Ukraine's future economic performance.

Since the GDP-warrant is sensitive to fluctuations in the War – Peace Index, an additional threshold model is used to measure the same sensitivity, to identify how differently the warrant reacts when Ukraine news shocks become unusually large. To do this, a two-regime threshold regression is used, with the formulas:

$$R_t = \alpha + \beta_L \Delta SI_t + \varepsilon_t, \quad |\Delta SI_t| \leq c \quad (4)$$

$$R_t = \alpha + \beta_H \Delta SI_t + \varepsilon_t, \quad |\Delta SI_t| > c \quad (5)$$

Where R_t is the warrant's daily return, ΔSI_t is the daily signed intensity change, c is the estimated threshold, β_L is the slope when $|\Delta SI_t|$ is at or below the threshold, β_H is the slope when $|\Delta SI_t|$ exceeds the threshold, and ε_t is the error term.

< Insert Table 3>

The threshold regression identifies a nonlinear relationship between changes in signed news intensity and GDP-warrant returns. In the post-invasion sample, the estimated threshold is $|\Delta SI_t| = 0.00437$, meaning the warrant appears to respond differently once a news shock's magnitude exceeds this level. A bootstrap test confirms the threshold itself is statistically warranted ($p = 0.003$), rejecting the null of no threshold effect at the 1% level. Below the threshold ($n = 860$), the estimated slope is negative and not statistically significant ($\beta = -3.026$, HAC $p = 0.147$), indicating no reliable relationship between ordinary day-to-day news fluctuations and warrant returns. Above the threshold ($n = 100$), the slope is positive and significant ($\beta = 3.713$, HAC $p = 0.0098$). The difference between the two regimes itself is significant ($\Delta\beta = 6.739$, HAC $p = 0.0084$), confirming a genuine shift in sensitivity rather than noise across two similarly behaved subsamples. The threshold specification also meaningfully improves model fit relative to the linear model, raising R^2 from .0334 to 0.0639 in the post-invasion sample. Because the threshold is defined on the absolute value of the shock, the positive above-threshold slope implies that large de-escalation shocks ($\Delta SIt > 0$) are associated with higher warrant returns, while large escalation shocks ($\Delta SIt < 0$) are associated with correspondingly lower returns, while shocks of ordinary size in either direction produce little measurable price response.

Economically, the results suggest that the warrant does not respond proportionally to every marginal change in news. Ordinary changes in the news environment appear to have little systematic effect, while sufficiently large escalation or de-escalation shocks trigger a much stronger repricing response. An insignificant below-threshold coefficient does not imply that ordinary news has little to zero effect on pricing, only that the model does not detect a statistically reliable systematic response at that scale.

EGARCH Volatility Testing

Having identified that elevated war news coverage decreases the GDP-warrant's return, increased peace related news increases the warrant's return, and identifying and measuring a threshold that produces greater price movement, this section uses an EGARCH model to test whether escalation and de-escalation shocks affect the conditional volatility of the warrant, independent of their effect on direction and magnitude of returns. This section aims to measure the symmetry of war and peace related news, whether crossing the previously identified threshold is associated with increased volatility, and whether such volatility persists beyond the shock day itself. An AR (1)-EGARCH (1,1) model with exogenous news regressors and Student-t innovations is estimated, specified as follows:

$$\text{Mean equation: } R_t = \mu + \varphi R_{t-1} + \varepsilon_t,\ \varepsilon_t = \sigma_t z_t \quad (6)$$

$$\text{EGARCH: } \log(\sigma_t^2) = \omega + \beta \log(\sigma_{t-1}^2) + \alpha\,(|z_{t-1}| - E|z|) + \gamma z_{t-1} + \delta_P \cdot \text{PeaceShock}_t + \delta_W \cdot \text{WarShock}_t \quad (7)$$

Where Rt is the warrant's daily return, μ is the average return, φ captures short-run return autocorrelation, and εt is the return innovation, decomposed into a conditional volatility term σ_t and a standardized shock z_t. In the variance equation, ω is the baseline log-variance, β is the persistence of volatility from one day to the next, α captures how strongly the magnitude of the prior day's shock affects today's volatility, and γ is the asymmetry term, allowing negative and positive return shocks to affect volatility differently. PeaceShock_t and WarShock_t isolate the positive and negative components of the daily signed-intensity change, defined as $\text{PeaceShock}_t = \max(\Delta SIt, 0)$ and $\text{WarShock}_t = \max(-\Delta SIt, 0)$, so that δ_P and δ_W measure the separate effects of de-escalation and escalation shocks on conditional volatility. A Student-t error distribution is used in place of a normal distribution to account for the warrant's heavy-tailed return behavior.

<Insert Figure 3>

<Insert Table 4>

To connect this model to the threshold-regression results, the same estimated threshold c used in the return-threshold model is reused here to define an extreme-news state, $\text{Extreme}_t = 1$ if

$|\Delta SI_t| > c$ and 0 otherwise, which is added to the variance equation to test whether crossing the threshold identifies a distinct volatility regime rather than only a distinct return regime.

The results support an asymmetric picture of how news affects warrant risk. Escalation shocks are associated with significantly higher conditional volatility in both full-period and post-invasion samples ($\delta W = 0.081$, $p<0.0001$ full-period; $\delta W = 0.062$, $p=0.025$ post-invasion). While de-escalation shocks show no statistically significant reliable volatility effect in either period (δP $p=0.763$ full-period, $p=0.637$ post-invasion). This asymmetry means the warrant's risk profile responds to bad news but not to comparably sized good news.

Using the threshold indicator identified in the previous section, crossing the threshold creates a meaningfully higher volatility state. The extreme shock coefficient is significant in both periods ($p<0.001$ full-period, $p<0.01$ post-invasion), and translating the post-invasion coefficient into a volatility multiplier via $\exp(\delta/2)$ implies conditional volatility approximately 23.8% higher on days when the news shock exceeds the threshold, holding other EGARCH dynamics constant. This effect is not purely contemporaneous: A lagged extreme-shock indicator is also significant when entered on its own ($p=0.015$), though it loses significance once the contemporaneous indicator is included ($p=0.775$), indicating the volatility response is primarily same-day.

The model also finds a significant asymmetric response to the warrant's own return shocks, independent of news variables: γ is negative in all specifications but only marginally significant in most ($\gamma=-0.319$, $p=0.088$ full-period; $\gamma=-0.108$, $p=0.091$ post-invasion; significant at 5% only in the post-invasion threshold model, $\gamma=-0.118$, $p=0.046$), consistent with the standard EGARCH finding that negative price shocks generate a larger volatility response than positive shocks of equal size. Volatility persistence is high in both periods ($\beta\approx0.86$), implying a volatility half-life of roughly 4.2-4.8 trading days. Diagnostic tests on the standardized residuals show no meaningful remaining ARCH effects, and the threshold-augmented EGARCH specification improves fit over the baseline model on both AIC and BIC, indicating that the extreme news state carries genuine explanatory power rather than adding unwarranted complexity.

The EGARCH results extend the threshold-regression findings from returns to risk: large geopolitical shocks, particularly escalation shocks, place the warrant into a measurably higher-

volatility regime that decays with a half-life of roughly four to five days, while ordinary news flow and de-escalation shocks produce no comparable volatility effect.

Robustness Check

Due to large, outsized returns and major news coverage in the first several days following Russia's invasion in Ukraine, additional testing is conducted to account for this abnormal period. This robustness section will focus on the signed intensity OLS regression, the EGARCH model and the threshold model. All variables remain consistent with an adjusted testing window of March 2nd, 2022, to December 22nd, 2025, instead of the original window at the beginning of the invasion. This section specifically focuses on the post-invasion period.

<Insert Table 5>

Previous OLS regression data on signed intensity resulted in an R^2 of 0.0334, with results being statistically significant (P<0.01, HAC P<0.1). Adjusting to the new specified window results in a substantially weaker relationship: results are no longer statistically significant (P=0.153, HAC P=0.480), and R^2 fall to 0.0021. This indicates that the linear relationship between the news index and warrant returns is concentrated within the initial invasion window (February 24th – March 1st, 2022), rather than being a consistent explanatory variable of returns.

<Insert Table 6>

Similar testing is conducted using the EGARCH model, examining both the escalation and de-escalation asymmetry and the extreme-shock threshold specification. In the original post-invasion sample, escalating shocks were significantly associated with higher conditional volatility (P<0.05), while de-escalating shocks showed no statistical significance (P=0.637). Adjusting to the new specified window, this result is essentially unchanged, with escalation remaining significant (P<0.05) and de-escalation remaining insignificant (P=0.875), indicating volatility asymmetry is not driven by the initial invasion period.

The extreme shock threshold specification shows the same pattern. In the original sample, crossing the estimated news shock threshold was associated with significant increase in conditional volatility (P<0.01), corresponding to an increase in volatility of 23.8%. Adjusting to the new specified windows, this effect remains significant (P<0.01) and conditional volatility

increasing by approximately 19.5%, with a slightly lower threshold of 0.00423 from 0.00437. Additionally, in the previous time period, crossing the threshold nearly doubled explanatory power, from an R^2 of 0.0334 to 0.0639. Using the adjusted time period R^2 increases from 0.0021 to 0.02. Although a lower number than before, crossing the threshold increases R^2 by tenfold. These results show that the threshold model is supported by the adjusted time period, with robustness checks validating that warrant's returns are associated with large magnitudes of information.

While previous sections analyze the full post-invasion time period, adjusting the time period of analysis confirms what was previously found. Daily escalating and de-escalating news has little explanatory power on the GDP-warrant's returns, and the collapse in R^2 furthermore suggests that the warrant is dependent on large media shocks. While EGARCH and threshold results are broadly consistent, escalating shocks remain significant and unchanged while de-escalating shocks do not, and crossing the threshold remains significant at the 1% level, with volatility increasing. This pattern supports the paper's central interpretation. The evidence supports magnitude-dependent repricing and asymmetric volatility response, not a stable linear relationship between news sentiment and returns.

Summary

To summarize, my empirical tests have examined the relationship between the Ukrainian GDP-warrant and similar emerging markets government debt, both globally and the surround Central and Eastern European region and the effects of escalation and de-escalation of the Russia – Ukraine War. In seeking to analyze investor expectations through the warrant's behavior, this study finds evidence that when media shocks are decomposed by magnitude, fluctuations in war and peace coverage show a limited reliable relationship with the warrant's returns, while shocks that exceed an estimated threshold produce a significant and economically large repricing response. Testing using the EGARCH model also shows crossing an estimated threshold is associated with meaningfully larger volatility and that this volatility decays with a half-life of roughly four to five days. Providing evidence that, the Ukrainian GDP-warrant is priced by discrete, large-magnitude information rather than continuous daily coverage, effectively creating temporary geopolitical pricing regimes.

Pre- and post-invasion testing shows substantially reduced explanatory power from global emerging market credit conditions for the warrant, suggesting that country-specific factors became increasingly important to the warrant's return and the financial environment became more idiosyncratic. This is in-line with the existing literature in this topic (Ren et al., 2023; Soliman and Le Saout, 2024; Boutchkova et al., 2012).

Additional testing also reveals escalating and de-escalating news on the conflict price the warrant asymmetrically. Escalation shocks significantly raise conditional volatility, while comparable de-escalation shocks do not. The asymmetric response is consistent with the broader volatility literature showing adverse information can generate a stronger volatility response than favorable information (Nelson, 1991; Engle and Ng, 1993; Glosten et al., 1993), as well as more recent evidence documenting asymmetric financial-market responses to geopolitical risk (Qin et al., 2020; Bossman et al., 2023; Choi, 2024).

Application

The structure of the Ukrainian GDP-warrant allows the warrant's price to recover an implied GDP being priced by investors. Rather than treating the warrant's price movements only as changes of the financial asset, the warrant can be expressed in terms of the implied economic conditions underlying its payout structure. This produces a market-implied GDP growth expectation gauge that translates changes in price into an economically interpretable measure.

The warrant's payout eligibility has to meet two conditions: nominal GDP has to be above 125.4 billion USD, and real GDP growth must exceed 3% in a year, both conditions have to be met simultaneously in a single year. Since nominal GDP has far exceeded the requirement, the condition has been non-binding since 2018, leaving growth as the hurdle as an operative constraint. Payments reflect a 15% participation rate on growth between 3% and 4% and a 40% participation rate on growth above 4% (Cabinet of Ministers of Ukraine, 2015). The instrument's payment and expected payment show this directly. Reference year 2019, with growth of 3.2%, paid 1.26% of par; reference year 2023, with a growth of 5.3%, triggered a claim of 20.5% of par. A 2.1 percentage point difference in growth produced a sixteen-fold difference in payment.

This analysis expresses the warrant's price as the discounted present value of its future contractual payments, allowing to recover the level of economic growth consistent with the

warrant's observed valuation. Expected future cash flows are calculated by using the warrant's nonlinear payout structure to the assumed distribution of annual real GDP growth. The model accounts for the probability and magnitude of growth exceeding the 3% threshold, allowing expected payments to vary with both mean GDP growth and its standard deviation. These expected cash flows are then discounted to the present value to determine the warrant's theoretical price. Rather than specifying the future GDP growth and calculating the corresponding theoretical warrant price, the model reverses this relationship. Using observed market prices, the contractual payout structure, assumptions regarding the distribution of future GDP growth and discount rates, the model numerically solves for the mean annual real GDP growth rate that equates the theoretical and observed prices. Resulting in a measure representing a model-implied long-run growth equivalent. The model is specified as follows:

$$P_t = \sum_y \frac{E_t[CF_{y(\mu_t,\sigma)}]}{(1+r_t)^{\tau_y}} \quad (8)$$

Where P_t is the observed warrant price at time t, E_t is the expected conditional on information at time t, CF_y is the contractual cash flow associated with reference year y, μ_t is the model-implied mean annual real GDP growth rate, σ is the assumed annual GDP growth standard deviation using 3% for an emerging country by the International Monetary Fund (2007) and assuming a normal distribution, τ_y is the years remaining until the associated payment date, and r_t is discount rate using the estimated 6.65% risk premium from Igan et al. (2021) and three-month U.S. Treasury bill rate data from the Federal Reserve.

<Insert Figure 4>

The implied GDP growth gauge reveals substantial changes in growth-equivalent valuation throughout the sample period. Prior to Russia's full-scale invasion, the gauge reached its highest estimated value of approximately 2.04% in March 2018, before declining to 0.38% on February 23rd, 2022. Following the invasion the measure fell to −0.76%, a decline of 1.14 percentage points in a single trading session, and reached a wartime low of −1.51% on March 4th, 2022. By May 29th, 2025, the gauge had recovered to 0.69%. Estimates before 2019 are affected by the contract's USD 125.4 billion nominal GDP floor, which creates a discontinuity in the model price, and observations after May 30th, 2025 are not interpreted, as Ukraine withheld the payment for reference year 2023 and the price subsequently reflected the pending exchange into

Series C Bonds. Estimated growth should not be used as a direct forecast for future economic performance. Credit risk, liquidity conditions, and restructuring expectations may also influence the warrant's observed valuation.

4. Conclusion

War and geopolitical events can have major influences on the economic state of a country. Following a conflict, financial recovery can be very difficult to determine. This study sets out to determine investors' future expectations of economic recovery following a war, using a publicly traded sovereign GDP instrument. Understanding the impact of future expectations of growth is particularly important given the significance it plays in investment decision making, financial policy and government legislation.

This study's empirical results demonstrate that war plays an important role in changing the financial landscape of a country and affects how future expectations of economic growth are repriced. After war breaks out, a country's state becomes more idiosyncratic and daily conflict shows little effect on economic expectations, while larger events caused by catalysts show increased effect on future economic expectations. These same events coincide with a same-day jump in volatility that decays with a half-life of about four to five days, creating temporary geopolitical pricing regimes. Additional findings show investors react asymmetrically to de-escalating and escalating news, with escalation raising volatility while de-escalation does not.

Several limitations apply. The warrant is illiquid and has a limited sample size and is no longer publicly traded. The model-implied growth estimates are sensitive to assumptions regarding the distribution of future GDP growth, discount rates, sovereign risk premium, and contractual payment restrictions. Because nonpayment risk, liquidity effects, and restructuring expectations are not independently identified, the recovered growth parameters should be interpreted as model-conditional valuation equivalents rather than direct forecasts of economic performance. Further research could include analyzing different assets such as Ukraine's conventional Eurobonds or extend the research to state-contingent instruments issued by other emerging countries. Additional testing is required to determine if these results are universal across all conflicts.

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Figure 1: Ukrainian GDP-Warrant Price Series



Figure 2: Signed Intensity

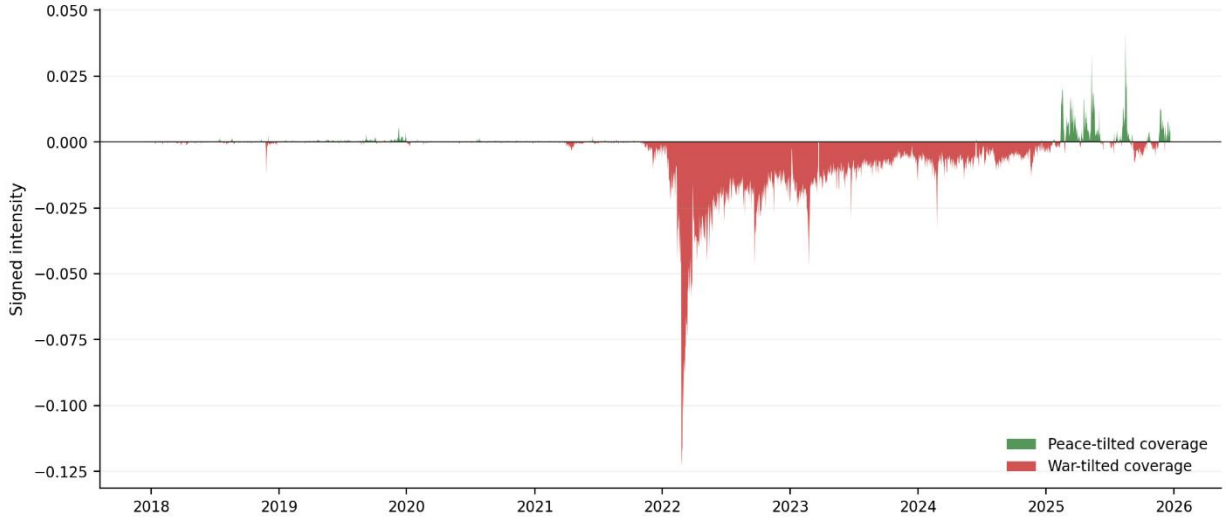


Figure 3: EGARCH Conditional Volatility

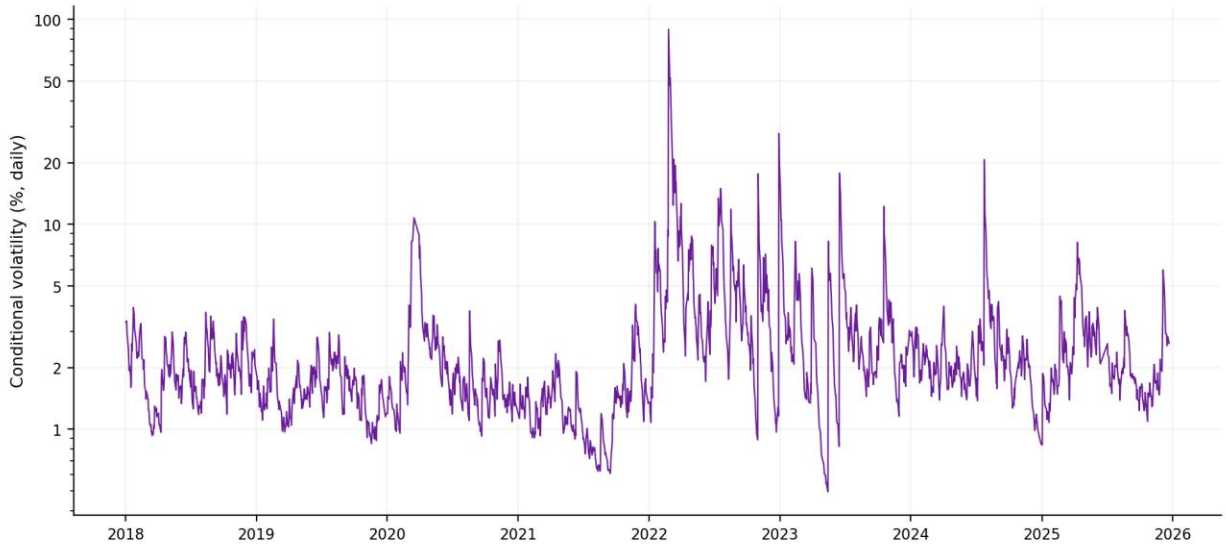


Figure 4: Model-Implied Long-Run Real GDP Growth

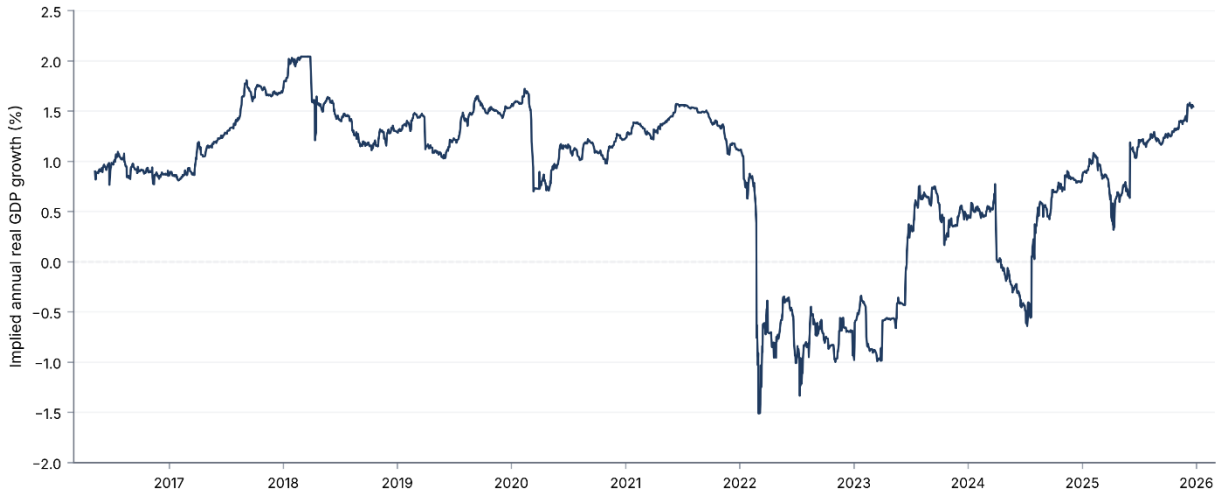


Table 1: Control Variable OLS Regressions

	R_warrant Full period	**R_warrant Pre-invasion**	**R_warrant Post-invasion**	**R_warrant Full period**	**R_warrant Pre-invasion**	**R_warrant Post-invasion**
Constant	0.001	0.001	0.003	0.001	0.001	0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
V (VWOB return)	1.165***	1.195***	1.128***			
	(0.163)	(0.098)	(0.364)			
ΔY (CEE-5)				−0.103***	−0.075***	−0.114***
				(0.021)	(0.018)	(0.037)
Adj. R^2	0.023	0.098	0.010	0.011	0.012	0.011
F-Statistic	51.20	147.56	9.59	24.90	17.09	9.62
Durbin-Watson	2.41	1.87	2.40	2.37	1.77	2.39
N	2,178	1,357	821	2,067	1,283	784

Note: OLS regressions of daily Ukrainian GDP-warrant returns on two sovereign-credit controls. V is the daily return on the Vanguard Emerging Markets Government Bond ETF (VWOB); ΔY is the daily change in an equally weighted CEE-5 10-year government bond index (Poland, Romania, Czech Republic, Hungary, Slovakia). Samples are split at 24th February 2022. Standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 2: News Index OLS Regression

	R_warrant Full period	**R_warrant Pre-invasion**	**R_warrant Post-invasion**
Constant	0.001	0.000	0.001
	(0.001)	(0.001)	(0.002)
β (Δ Signed Intensity)	2.531*	0.868	2.616*
	(1.505)	(0.938)	(1.570)
OLS p-value	<0.001	0.304	<0.001
HAC p-value	0.093	0.354	0.096
R^2	0.0274	0.0010	0.0334
Adj. R^2	0.0269	0.0001	0.0324
F-Statistic	56.15	1.06	33.08
N	1,993	1,033	960

Note: OLS regressions of daily warrant returns on the daily change in the War–Peace Signed Intensity Index, where positive values indicate a shift toward peace coverage and negative values a shift toward war coverage. Samples are split at 24th February 2022. Standard errors in parentheses; HAC p-values use Newey–West inference with five lags. Stars follow HAC inference. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 3: Two-Regime Threshold Model

	R_warrant Full period	**R_warrant Pre-invasion**	**R_warrant Post-invasion**
Estimated threshold c	0.00316	0.00022	0.00437
β_l (below threshold)	−2.148	−11.265	−3.026
	(0.268)	(0.136)	(0.147)
β_h (above threshold)	3.082**	0.978	3.713***
	(0.036)	(0.286)	(0.010)
$\Delta\beta$ ($\beta_h - \beta_l$)	5.230**	12.243*	6.739***
	(0.027)	(0.096)	(0.008)
Observations below c	1,792	615	860
Observations above c	201	418	100
Linear-model R^2	0.0274	0.0010	0.0334
Threshold-model R^2	0.0386	0.0029	0.0639
N	1,993	1,033	960

Note: Two-regime threshold regressions of daily warrant returns on ΔSI. Observations with |ΔSI| at or below the estimated threshold c are assigned to the below-threshold regime with slope β_L; those above take slope β_H. The threshold is selected by grid search minimizing the sum of squared residuals over the 10th–90th percentile of |ΔSI|. Δβ tests whether the two slopes differ. HAC p-values in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 4: EGARCH Models

	Panel A: News shock asymmetry		*Panel B: Threshold state*	
	Full period	**Post-invasion**	**Full period**	**Post-invasion**
Mean equation				
μ	−0.000	−0.000	−0.000	−0.000
	(0.506)	(1.000)	(0.396)	(1.000)
φ	0.077***	0.026	0.075***	0.023
	(0.000)	(0.341)	(0.000)	(0.400)
Variance equation				
ω	−0.791***	−1.069***	−0.814***	−1.000***
	(0.000)	(0.000)	(0.000)	(0.000)
α	1.945**	0.931***	1.995**	0.872***
	(0.037)	(0.000)	(0.037)	(0.000)
β	0.865***	0.849***	0.860***	0.861***
	(0.000)	(0.000)	(0.000)	(0.000)
γ	−0.319*	−0.108*	−0.346*	−0.118**
	(0.088)	(0.091)	(0.081)	(0.046)
δ_P (PeaceShock)	0.006	-0.013		
	(0.763)	(0.637)		
δ_W (WarShock)	0.081***	0.062**		
	(0.000)	(0.025)		
δ_E (Extreme state)			0.454***	0.427***
			(0.000)	(0.003)
Implied volatility increase			25.5%	23.8%
Volatility half-life (days)	4.8	4.2	4.6	4.6
Student-t d.f.	2.03	2.15	2.03	2.16
AIC	−11,313.5	−4,900.5	−11,312.3	−4,906.9
BIC	−11,263.2	−4,856.7	−11,267.5	−4,867.9
N	1,993	960	1,993	960

Note: This table reports AR(1)-EGARCH(1,1) estimates of conditional volatility in daily Ukraine GDP-warrant returns. Panel A tests asymmetric volatility responses to peace and war news shocks, while Panel B tests whether news changes exceeding the estimated threshold create an extreme-volatility state. αmeasures shock sensitivity, βvolatility persistence, and γreturn-shock asymmetry. δ_P, δ_W, and $\delta_E$measure the effects of peace shocks, war shocks, and extreme news states, respectively. Values in parentheses are p-values. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 5: Return Models Excluding Initial Invasion Window

	News index OLS		*Threshold model*	
	Baseline	**Adjusted**	**Baseline**	**Adjusted**
β (Δ Signed Intensity)	2.616*	0.794		
	(1.570)	(1.124)		
OLS p-value	<0.001	0.153		
HAC p-value	0.096	0.480		
Estimated threshold c			0.00437	0.00423
β_l (below threshold)			−3.026	−3.110
			(0.147)	(0.153)
β_h (above threshold)			3.713***	2.135*
			(0.010)	(0.075)
$\Delta\beta$ ($\beta_h - \beta_l$)			6.739***	5.245**
			(0.008)	(0.035)
Observations above c			100	103
R^2	0.0334	0.0021	0.0639	0.0203
N	960	956	960	956

Note: This table reports robustness tests excluding February 24th–March 1st, 2022. "Baseline" uses the original post-invasion sample, while "Adjusted" begins March 2nd, 2022. The OLS model estimates the relationship between warrant returns and changes in Signed Intensity. The threshold model separates ordinary and extreme news shocks using estimated cutoff c, with $\beta_L$and $\beta_H$measuring responses below and above the threshold. Values in parentheses are standard errors or HAC p-values as reported. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 6: EGARCH Models Excluding Initial Invasion Window

	Panel A: News shock asymmetry		*Panel B: Threshold state*	
	Baseline	**Adjusted**	**Baseline**	**Adjusted**
Variance equation				
α	0.931***	1.045***	0.872***	1.008***
	(0.000)	(0.000)	(0.000)	(0.000)
β	0.849***	0.864***	0.861***	0.875***
	(0.000)	(0.000)	(0.000)	(0.000)
γ	−0.108*	−0.156**	−0.118**	−0.172**
	(0.091)	(0.044)	(0.046)	(0.016)
δ_P (PeaceShock)	-0.013	-0.004		
	(0.637)	(0.875)		
δ_W (WarShock)	0.062**	0.058**		
	(0.025)	(0.032)		
δ_E (Extreme state)			0.427***	0.356***
			(0.003)	(0.008)
Implied volatility increase			23.8%	19.5%
Volatility half-life (days)	4.2	4.7	4.6	5.2
Student-t d.f.	2.15	2.11	2.16	2.11
AIC	−4,900.5	−4,907.6	−4,906.9	−4,912.1
BIC	−4,856.7	−4,863.8	−4,867.9	−4,873.2
N	960	956	960	956

Note: This table reports EGARCH robustness tests excluding February 24th–March 1st, 2022. "Baseline" uses the original post-invasion sample and "Adjusted" begins March 2nd, 2022. Panel A tests separate volatility effects from peace and war shocks, while Panel B tests the effect of entering an extreme-news state. αmeasures shock sensitivity, βvolatility persistence, and γasymmetry. Values in parentheses are p-values. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.