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Modeling and Forecasting Market Dynamics around Geopolitical Shocks using Temporal Fusion Transformers

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CONTENT

1. BACKGROUND OF THE WORK AND ITS AIMS

1.1. Geopolitical shocks and their impact on financial markets

Geopolitical shocks, events such as wars, terrorist attacks, or sudden shifts in international relations have historically disrupted global political, economic, and financial systems. These shocks generate significant uncertainty, leading to sharp movements in financial markets (Baker et al., 2016; Bloom, 2009). Investors, faced with difficulty in valuing assets, often respond with rapid sell-offs and heightened risk aversion, resulting in elevated volatility (Fama & MacBeth, 1973). A key distinction exists between geopolitical risk (potential threats) and geopolitical shocks (realized events), with the latter triggering immediate market corrections (Caldara & Iacoviello, 2022).

Recent shocks, including the COVID-19 pandemic, Russia's invasion of Ukraine, and the Hamas attack on Israel have demonstrated how sudden disruptions produce global ripple effects across asset classes and economies. COVID-19 marked an unprecedented global crisis. Beginning in late 2019, it spread rapidly, prompting the World Health Organization to declare a global pandemic in March 2020. The virus disrupted supply chains, forced business closures, and caused mass unemployment (Fernandes, 2020). Stock markets collapsed, and the VIX, a key volatility index, spiked to 85.11, four times its average (CBOE, 2024). No previous health crisis caused comparable market disruption (Baker et al., 2020). Russia's full-scale invasion of Ukraine on February 24, 2022, triggered another surge in global financial volatility. Markets fell sharply, energy prices soared, and the VIX reached 39.00 (FRED, 2024e). The war disrupted European markets, raised concerns about energy security, and sparked sanctions, adding further uncertainty (Izzeldin et al., 2023). The October 7, 2023, Hamas attack on Israel escalated regional instability. The attack resulted in over 1,400 deaths and hundreds of hostages. Israel declared a state of war and began military operations in Gaza (Levy et al., 2024). Though the VIX rose only moderately, the event raised fears of broader regional conflict (Ugli, 2024). All three events triggered spikes in volatility—a key metric in asset pricing and risk management (Black & Scholes, 1973).

Volatility influences investment decisions, option pricing, and capital flows. High volatility often leads to reduced foreign investment and portfolio rebalancing. It also tends to cluster, with turbulent periods followed by more instability (Mandelbrot, 1963). Asymmetric volatility, where negative news causes larger spikes, complicates forecasting and underlines the importance of robust models like GARCH, which accommodate volatility clustering and leverage effects. Modeling volatility during geopolitical shocks is essential because such events trigger abrupt and significant changes in market dynamics, leading to heightened uncertainty and rapid shifts in asset prices.

Accurate volatility forecasts enable investors, policymakers, and risk managers to better assess and respond to systemic risk, helping to stabilize markets and prevent overreactions. Moreover, predictive models that capture volatility clustering and asymmetry offer valuable insights for optimizing portfolio strategies, setting appropriate risk limits, and enhancing decision-making during crisis periods.

1.2. Research scope

In this study, I have taken a detailed analysis of the effect of geopolitical shocks on market dynamics, as well as the possibilities for modeling and forecasting volatility in times of geopolitical shocks. To carry out the most comprehensive analysis possible, I examined many different aspects.

The first part of my investigation is concerned with identifying abnormal returns and abnormal volatility in times of geopolitical shocks. I was conducting a detailed event analysis for the period around the Russian attack on Ukraine and examined the reaction of the financial market to this shock in terms of returns and volatility. By analyzing sector-specific responses rather than aggregated indices, the study captures distinct behaviors across industries such as technology, healthcare, finance, and energy. Each sector reacts differently to macroeconomic changes, offering unique risk-return profiles (Elyasiani et al., 2020). For example, cyclical sectors like consumer discretionary are more responsive to economic shifts, while defensive sectors like healthcare remain relatively stable (Long & Plosser, 1987). Understanding these dynamics helps investors optimize returns through sector rotation and improved risk assessment (He et al., 2020; Sassetti & Tani, 2006). Sectoral analysis also reveals emerging trends, such as the rise of renewables or e-commerce impacts, and enhances benchmarking of individual stocks. The MSCI World Sector Indices, derived from the MSCI World Index, provide comprehensive coverage of large and mid-cap companies across 23 developed markets, representing around 85% of free float-adjusted market capitalization (MSCI, 2024a; 2024b). These indices are widely used as benchmarks by institutional investors and are transparent, regularly updated, and globally diversified. However, limitations include a strong U.S. weighting, underrepresentation of smaller yet influential firms, and exposure to currency risk.

The core aim was to assess how this major geopolitical shock affected the world's largest companies, particularly in terms of volatility—a key measure of uncertainty and investor disagreement. Volatility spikes often reflect divergent views on asset valuation, and large price swings indicate reactions to new information. The study applied the concepts of abnormal returns (Campbell & Lo, 1996; Fama, 1970) and abnormal volatility (Beaver, 1968; Brown & Warner, 1985) to measure sector-specific responses to the invasion. My concrete research questions are as follows:

- **Research Question 1:** Are there significant abnormal returns on the February 24, 2022 in the sectors of the MSCI World index, respectively?
- **Research Question 2:** Are there significant cumulative abnormal returns in the MSCI World index sectors up to 25 days after the February 24, 2022?
- **Research question 3:** Can significant abnormal volatility (-5,+5 days) around the Russian attack on Ukraine at February 24, 2022 in the MSCI market sectors be observed?

- **Research question 4:** Can a persistence in the abnormal volatility after February 24, 2022 in the MSCI market sectors be observed?
- **Research question 5:** Are there significant differences of the abnormal volatility between the MSCI market sectors?

The identification of abnormal returns and volatility is a fundamentally ex-post analysis and important for a retrospective assessment of the impact and duration of geopolitical shocks. From a practical point of view, for example that of an active market participant or a risk manager, the forward-looking aspect is more relevant, i.e. whether the evolution of market dynamics can be predicted. So, the second part of my study covers the modeling and forecasting of financial time series around geopolitical shocks. Particularly in turbulent times, action is often needed in the form of increasing hedges or adjusting the portfolios of market participants to adapt to the new situation and manage the risk of adverse effects. This always involves the best possible assessment of volatility. With my study, I wanted to provide insights for research and practice into which forecasting methods are best suited for modeling volatility on the one hand and out-of-sample forecasting on the other in phases of geopolitical shocks. I focused on the periods in which I observed a shock to the financial markets and analyze how different forecasting methods can predict periods of high volatility.

To do this, I evaluated different approaches for prediction, univariate and multivariate, as well as parametric and non-parametric approaches. The core model of my analysis is the state-of-the-art Temporal Fusion Transformer (TFT) for modeling and predicting time series. For my univariate parametric approach, and as a benchmark, I examined the frequently applied GARCH, EGARCH, and GJR-GARCH models in terms of their ability to explain and predict volatility for the most important financial instruments. From a practitioner's point of view, there is always a trade-off between model complexity and performance. Therefore, I also provided statistically significant differences in forecasting performance between model classes in my study.

In this context, I wanted to answer the following research questions:

- **Research Question 6:** Which GARCH-type model provides the best in-sample fit regarding the volatility of the analyzed financial instruments during the recent geopolitical shocks?
- **Research Question 7:** Which GARCH-type model provides the best out-of-sample forecasts regarding the volatility of the analyzed financial instruments during the recent geopolitical shocks?
- **Research Question 8:** Can the Temporal Fusion Transformer achieve better out-of-sample performance than the best performing GARCH-type model in times of geopolitical shocks?
- **Research Question 9:** Can the implementation of a regime-switching feature in the TFT increase the forecasting performance in times of geopolitical shocks?
- **Research Question 10:** Can a significantly better forecasting performance be achieved by optimizing the hyperparameters of the TFT than the performance averaged by a hyperparameter grid in times of geopolitical shocks?
- **Research Question 11:** Can a multivariate forecasting approach of the Temporal Fusion Transformer model achieve better results than a univariate approach of the TFT in times of geopolitical shocks?

To answer these questions, I used various modifications of the Temporal Fusion Transformer to predict the volatility of some of the most important financial instruments: the highly traded stock indices S&P 500, NASDAQ 100, Nikkei 225 and Hang Seng; Gold as the essential instrument for hedging against inflation and a long-term store of value; Brent Crude Oil as the most important source of energy; the 10 years Treasury Bond as the essential reference for fixed income, a benchmark for returns and the price of time; the exchange rate of Euro vs. US-Dollar as an indicator of the balance between the two most important currencies; and Bitcoin as an instrument with increasing market capitalization, high potential of growth and a hedge against inflation. For selected periods during the geopolitical shocks of COVID-19, the Russian attack on Ukraine and the Hamas attack on Israel, I examined how well the different methods could predict these phases of increased market volatility. Using a rolling window approach, I trained the model with data from the last 250 trading days and generate direct multi-step ahead forecasts for the next 10 trading days. Then I moved the window forward by one step. For the three periods of geopolitical shocks under consideration, I analyze around 60 steps of the window each.

1.3. Contribution to research and outline

Ensuring the robustness of results is essential in empirical studies. To achieve this, I analyzed nine financial assets across various markets—including stocks, commodities, bonds, currencies, and cryptocurrencies. This broad scope reduces sampling bias and enhances generalizability (Baltagi, 2008; Pesaran, 2015), while also enabling the identification of structural similarities or differences across markets. Though care must be taken with inter-variable correlations, this diverse dataset supports more resilient conclusions (Stock & Watson, 2012). Three major geopolitical shocks were analyzed: COVID-19, the Russian invasion of Ukraine, and the Hamas attack on Israel. These events differ in causes and macroeconomic impact, offering a rich basis for model testing. Evaluating multiple periods improves robustness by minimizing event-specific distortions and revealing model limitations or sensitivities (Giacomini & Rossi, 2010). Out-of-sample forecasts were used to assess predictive performance, helping mitigate overfitting risks and improve model selection (Welch & Goyal, 2008). I applied a rolling window method for training and testing forecasting models, generating multi-step forecasts (1–10 trading days ahead) to evaluate performance across different horizons. This cross-validation approach respects the time-series structure and enhances forecast reliability (Hyndman & Athanasopoulos, 2018). This work contributes to the growing field of volatility prediction amid increasing geopolitical uncertainty. As the global order transitions from unipolar to multipolar, the likelihood of disruptive geopolitical shocks rises, posing risks for portfolio management. Accurate volatility forecasts are critical for effective hedging, avoiding both over- and under-hedging. I began with an ex-post analysis of abnormal returns and volatility using MSCI World Sector Indices to show how sectors responded differently to the Russian invasion. This revealed not only the intensity of shocks but also the persistence and sector-specific impacts. Notably, some sectors benefitted during the turmoil.

To advance volatility prediction, I evaluated the Temporal Fusion Transformer (TFT), a neural network designed for time series forecasting. I tested univariate, multivariate, and regime-switching models, comparing their performance to traditional GARCH models. Given the limited literature on TFTs in the context of geopolitical shocks, this fills a notable research gap.

The thesis is structured as follows: Section 2 reviews related literature; Section 2 outlines methods and data; Section 3 covers the results of my research regarding the abnormal return analysis and the volatility forecasting by the Temporal Fusion Transformer Deep Learning network. Section 4 draws a conclusion, and sections 5 presents new scientific contributions. In section 6, I present my related publications.

2. MATERIAL AND METHODS

My research focused on two main areas. First, I analyzed abnormal market dynamics, specifically abnormal returns and volatility, around geopolitical shocks using MSCI World sector indices. I applied event study methodologies (Campbell & Lo, 1996; Fama, 1970) to evaluate stock sector responses to the Russian invasion of Ukraine. For abnormal volatility, I followed frameworks by Ahmed et al. (2020) and Beaver (1968). Second, I assessed the out-of-sample forecasting performance of the Temporal Fusion Transformer (TFT) during three geopolitical shocks: COVID-19, the Russian invasion, and the Hamas attack on Israel. Using a rolling window approach, I trained a

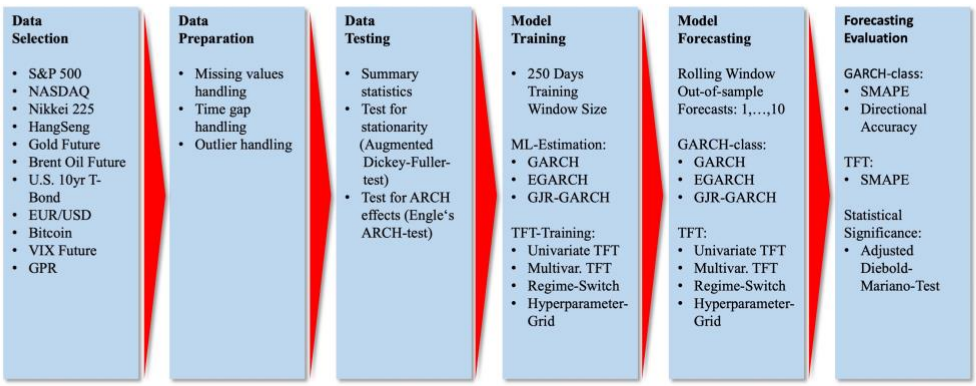

Figure 1: Research procedure for out-of-sample forecasting. Source: Own illustration using MS PowerPoint (2025).

multivariate TFT to forecast 1–10 day-ahead volatility for nine major financial instruments, including key stock indices (S&P 500, NASDAQ, Nikkei 225, Hang Seng), gold, Brent oil, 10-year Treasury bonds, EUR-USD, and Bitcoin. I incorporated the VIX futures and the Geopolitical Risk Index (GPR) as explanatory variables. I compared TFT's performance to GARCH, EGARCH, and GJR-GARCH models using SMAPE. I also tested univariate vs. multivariate approaches and evaluated a regime-switching version of TFT. Forecasts were repeated with varying hyperparameters (attention heads and hidden sizes) to assess robustness and improve prediction accuracy. The procedure is illustrated in Figure 1 and Figure 2.

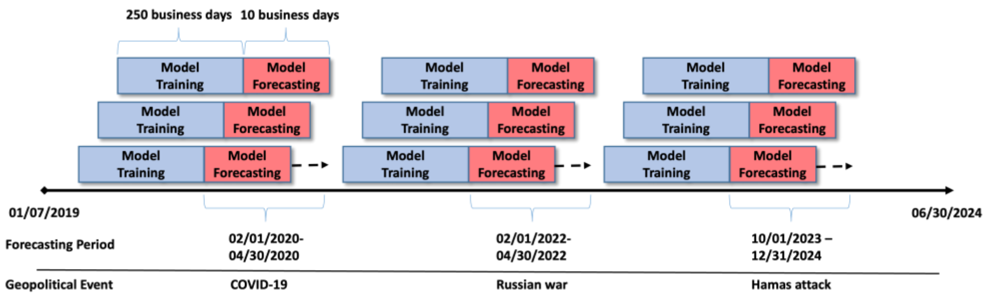

Figure 2: Rolling window approach for TFT out-of-sample forecasting. Source: Own illustration using MS PowerPoint (2025).

2.1. Applied methodology

There are several definitions of volatility: statistical volatility (Hull, 2022), conditional volatility (Bollerslev, 1986; Engle, 1982; Mandelbrot, 1963), which refers to the time-varying variance of returns, conditioned on past information, implied volatility which is the markets expectation of the future volatility of an asset, as inferred from the price of options (Black & Scholes, 1973), realized volatility, which is a non-parametric, ex-post measure of actual volatility, calculated using high-frequency intraday returns (Andersen et al., 2003) and historical volatility is the standard deviation of asset returns over a specified past window, without assuming time-variation (Poon & Granger, 2003). In our study, we used the statistical definition of Hull (2022) and the conditional volatility of Engle (1982). The classical definition assumes that returns r_t are random variables, and volatility captures their dispersion:

$$\sigma = \sqrt{Var(r_t)} = \sqrt{E[(r_t - \mu)^2]}$$

where r_t are log returns of a time series of a financial asset p_t and $\mu = E[r_t]$ is the expected value of r_t, for $t \in \{1, \dots, T\}$.

2.2. Abnormal Returns and Abnormal Volatility

To identify Abnormal Returns and Abnormal Volatility, I used the event study approach of Campbell & Lo (1996), Fama (1970) and MacKinley (1997) to analyze global stock market sector's reaction to the Russian attack. For the evaluation of abnormal volatility, I use the approach of Ahmed et al., (2020), Beaver (1968), Brown & Warner (1985), Landsman & Maydew (2002) and Prasad et al., (2021). In terms of formal notation, I followed Robus et al. (2024). The procedure of an event study using Abnormal volatility is based on estimating the model parameters within the pre-event phase and then using this model to make predictions for the event and post-event phase. Bialkowski et al., (2008) gave the notice that a one-step forecast does not produce an event-independent forecast. This problem can be solved by making the volatility forecast depends only on the information available before the event.

2.3. GARCH-Class Models

The Generalized Autoregressive Conditional Heteroscedasticity GARCH(p,q) process was introduced by Bollerslev (1986) to model the time-varying behavior of the variance. In addition to the ARCH model developed by Engle (1982), in which only the squared historical error terms are included to model the current variance, the GARCH model also consists of the historical variance. This was due to empirical observations that volatility shows persistence. The GARCH parameters determine the strength of the influence of the respective components. The EGARCH process was introduced by Nelson (1991) to model the leverage effect that occurs in many financial time series. The GJR-GARCH model of Glosten, Jagannathan, and Runkle (Glosten et al., 1993), which is also known as the threshold GARCH (T-GARCH) model, is proposed to capture the asymmetric behavior of volatility regarding good and bad news, and by allowing the current conditional variance has a different response to the past positive and negative returns, captured by the dummy variable D_t.

In my research, I used these three GARCH-type models in different parameter setups ($p = 1, \ldots, 5$ and $q = 1, \ldots, 5$). Thus, I evaluated the best-fitting GARCH type model from a set of 75 competing models. To estimate the GARCH(p,q) parameters, I used the approach of the maximum likelihood, regarding Bollerslev (1986), Bollerslev & Woodbridge (1992), and Nelson (1991).

2.4. The Temporal Fusion Transformer for volatility forecasting.

The Temporal Fusion Transformer (TFT) is a state-of-the-art deep learning architecture specifically developed for forecasting multivariate time series across multiple prediction horizons. Introduced by Lim et al. (2021), the TFT integrates key elements from LSTM networks, self-attention mechanisms, and interpretable model components, enabling it to model complex temporal dependencies while remaining transparent in its predictions (Figure 3). One of TFT's most valuable features is its ability to produce multi-horizon probabilistic forecasts using quantile regression, which not only provides point estimates but also generates prediction intervals, allowing for a more comprehensive representation of uncertainty. This makes the model particularly suited for applications in finance, energy, and other risk-sensitive fields. Moreover, the TFT is highly interpretable: its attention layers and feature importance scores allow users to identify which variables and time steps contributed most to a given forecast, supporting informed decision-making and model traceability. The architecture includes several innovative components. Variable Selection Networks (VSNs), powered by Gated Residual Networks (GRNs), dynamically assign weights to input features, filtering out noise and highlighting the most relevant variables. Static Covariate Encoders embed time-invariant inputs such as asset class or region, shaping model behavior throughout the network. The LSTM-based encoder-decoder architecture captures short- and medium-term dependencies, while known future inputs are integrated through the decoder. To capture long-range patterns, the multi-head attention mechanism learns to focus on different temporal segments, improving both accuracy and interpretability. The Temporal Fusion Decoder then combines outputs from the LSTM and attention layers, fusing them into a final representation that balances local and global patterns. Finally, the Quantile Prediction Layer generates forecasts at multiple quantile levels (e.g., 10%, 50%, 90%), offering a nuanced view of potential outcomes and supporting robust risk assessment.

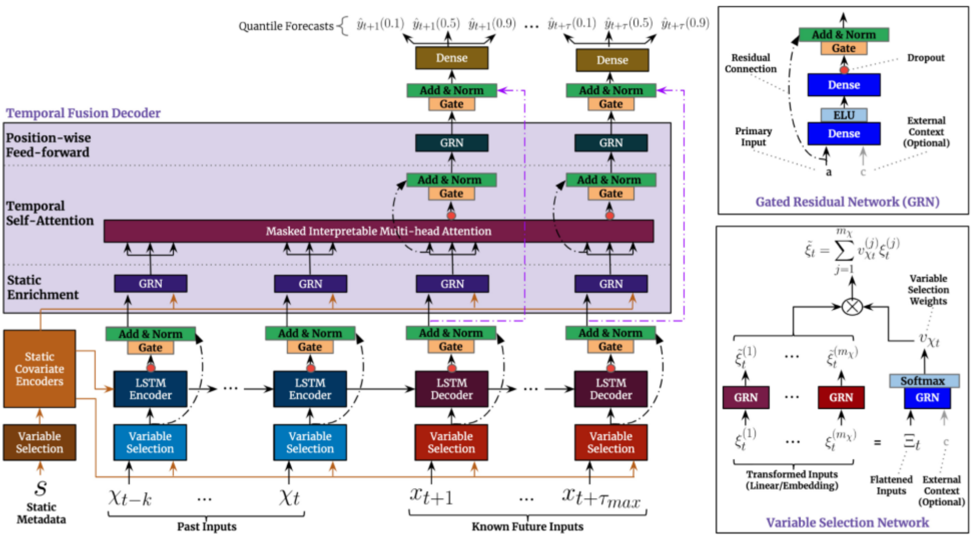

Figure 3: Temporal Fusion architecture. Source: Lim et al. (2021).

Table 1: Applied hyperparameter for Temporal Fusion Transformer training and forecasting

TFT Parameters	**Value**
Learning Rate	0.001
Dropout Rate	0.01
Minibatch Size	32
Attention Head	1, 4, 8
Hidden Size	16, 32, 64
Max. Epochs	100
Loss Metrics	MAE, MSE

Source: Own collection (2025).

This attribute is particularly relevant in the financial sector, where model decision traceability is essentially. Its ability to effectively model both short-term and long-term dependencies makes it a powerful tool for modern time series analysis tasks. To train the TFT, I used the combination of hyperparameters as shown in Table 1. In doing so, I based the hyperparameter selection by publications such as: Frank (2023); Hartanto & Gunawan (2024) and Lim et al. (2021).

Attributed to its flexibility, the Temporal Fusion Transformer (TFT) is particularly suited for modeling financial time series, which exhibit complex, non-linear dynamics such as short-term fluctuations, long-term dependencies, volatility clustering, regime shifts, and abrupt volatility spikes (Box et al., 2015; Engle & Bollerslev, 1986; Glosten et al., 1993). Short-term behaviors, including return autocorrelations, momentum effects, and market reactions, are captured via Gated Residual Networks (GRNs), LSTM encoders, and decoder self-attention. GRNs dynamically weight inputs at each time step, allowing selective focus on informative features as market conditions evolve (Farooq et al., 2024; Hartanto & Gunawan, 2024; Lim et al., 2021). For instance, during momentum phases, recent return indicators gain prominence while lagged inputs are down-weighted. The LSTM encoder learns temporal dependencies from recent data, detecting patterns such as price reversals or transient shocks. Decoder self-attention enhances forecast precision by integrating cross-horizon dependencies (Lim et al., 2021; Zhang et al., 2025).

Long-term structures, such as macroeconomic cycles or structural breaks, are addressed through temporal self-attention, static covariate encoders, and positional embeddings. Temporal attention assigns relevance to temporally distant events, enabling the model to capture lagged macro-financial dependencies, such as recurring effects of policy interventions. Static covariate encoders condition forecasts on fixed attributes (e.g., asset class, region), while positional embeddings help the model recognize calendar-based effects (Laborda & Zamanillo, 2023; Lim et al., 2021).

Volatility clustering, persistent variance over time (Engle, 1982), is effectively modeled through the interaction of LSTM, GRNs, and temporal attention. The LSTM internal state encodes recent volatility patterns, while GRNs modulate the importance of inputs such as rolling standard deviations and implied volatilities. Temporal attention enables recall of similar historical regimes beyond sequential memory constraints, enhancing the model's ability to learn the persistence and evolution of volatility (Bollerslev, 1986; Beck et al., 2025; Lim et al., 2021). In contrast, volatility spikes often result from exogenous shocks. TFT handles such discontinuities through its architectural adaptiveness. GRNs reweight inputs in response to abrupt changes, such as unanticipated macroeconomic data or sentiment shifts (Shen et al., 2025). LSTM components preserve short-term precursors to spikes, while temporal attention recalls historical analogs. Decoder self-attention refines the prediction trajectory, distinguishing between transient and regime-shifting events (Yang et al., 2025). Residual connections ensure stable transitions across market regimes.

Also, the TFT's quantile forecasting capabilities present significant advantages across financial applications. By estimating full conditional distributions, the model captures tail risks and non-linear behaviors central to financial risk management. In this context, accurate quantile forecasts enhance the estimation of Value-at-Risk and Expected Shortfall, enabling dynamic risk exposure adjustments in compliance with regulatory standards (Merlo et al., 2021; Petneház, 2021; Zha et al., 2024). For credit risk, TFT supports scenario-based estimation of default probabilities and losses. In portfolio management, TFT enables dynamic hedging and factor timing by incorporating tail-risk information. Its predictive capacity under stressed market conditions facilitates adaptive asset allocation and downside protection (Hartanto & Gunawan, 2024; Yang et al., 2025). Regulatory supervision also benefits, as TFT-based forecasts improve stress-test design and macroprudential oversight, aiding institutions and regulators in quantifying systemic vulnerabilities and determining capital adequacy with greater accuracy (Merlo et al., 2021; Storti & Wang, 2022; Taylor, 2019).

2.5. Forecasting Evaluation

Volatility forecasting has been addressed through various methods, including GARCH models, neural networks, and hybrid approaches.

Evaluating forecast performance is as critical as model choice. While traditional metrics like RMSE and MAE are widely used, Symmetric Mean Absolute Percentage Error (SMAPE) has gained prominence in financial econometrics due to its robustness and interpretability. Unlike MAPE, which becomes unstable near zero actual values, SMAPE normalizes forecast errors by the average of actual and predicted values, offering a bounded, symmetric metric (Goodwin & Lawton, 1999; Makridakis, 1993). This makes SMAPE especially suitable for evaluating volatility forecasts under heteroskedasticity or scale variation (Taylor, 2004). In my study, I focused on predicting financial volatility under geopolitical shocks using the Temporal Fusion Transformer (TFT). To evaluate model performance consistently and avoid contradictory results, I chose SMAPE as the sole forecast evaluation criterion. Using multiple FECs can lead to conflicting model rankings and inconsistent statistical inference (Diebold & Mariano, 1995; Hansen et al., 2011). Since my goal was to support portfolio adjustments and hedging decisions, percentage-based error measurement aligned best with practical objectives. SMAPE's bounded nature, symmetry, and scale robustness make it an effective and theoretically coherent choice for this analysis. To assess the statistical significance of the difference in performance between two forecasting models, we use the Diebold-Mariano test statistics (Diebold & Mariano, 1995). The goal hereby is, to assess whether to competing forecasting models have equal predictive accuracy. To account for possible heteroskedasticity and autocorrelation effects in the data, we adjust the Diebold-Mariano test statistics for the variance estimation, proposed by Newey & West (1987). For small samples, the DM test statistic can be biased, so, we adjust it by the approach of Harvey et al. (1997). The adjusted DM test (DM*) test statistics now follows a t-distribution.

2.6. Applied Datasets

2.6.1. MSCI World Sector Indices for Identification of Abnormal Returns and Abnormal Volatility

To analyze the market response, I combined the event and post-event phases (*t−5* to *t+25*) for MSCI World sector indices. As detailed in Robus et al. (2024), log-return data reveal near-zero average and median returns in the pre-event phase, sharp declines during the event, and positive returns in the post-event phase.

Table 2: MSCI World Sector Indices in research scope.

Index	ISIN	Abbreviation
MSCI World Index	MIWO00000PUS	MSCI
MSCI World Consumer Discretionary Index	MIWO0CD00PUS	CD
MSCI World Consumer Staples Index	MIWO0CS00PUS	CS
MSCI World Energy Index	MIWO0EN00PUS	EN
MSCI World Financials Index	MIWO0FN00PUS	FN
MSCI World Health Care Index	MIWO0HC00PUS	HC
MSCI World Industrial Index	MIWO0IN00PUS	IN
MSCI World Information Technology Index	MIWO0IT00PUS	IT
MSCI World Materials Index	MIWO0MT00PUS	MT
MSCI World Real Estate Index	MIWO0RE00PUS	RE
MSCI World Telecommunications Index	MIWO0TC00PUS	TC
MSCI World Utilities Index	MIWO0TC00PUS	UT

Source: Morgan Stanley Capital International (MSCI, 2024a, 2024b), Robus et al. (2024).

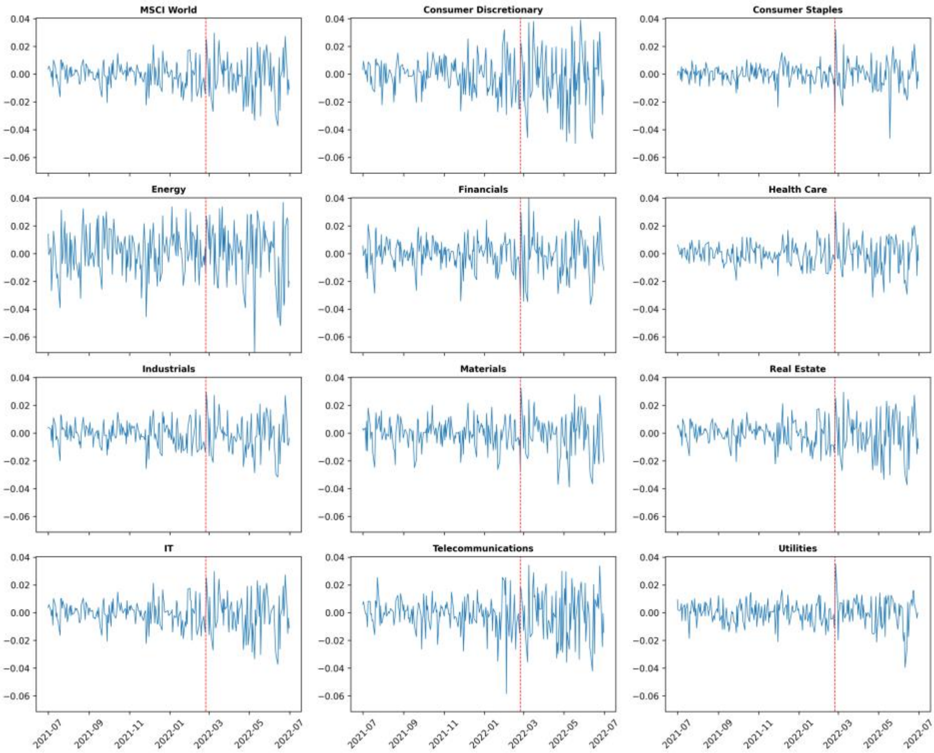

Figure 4: Log-returns for MSCI World Sector Indices (07/01/2021 – 06/30/2022). Dashed line marks the day of the Russian attack on Ukraine at February 24, 2022. Source: Own illustration using Python Matplotlib (2025).

The Russian invasion triggered immediate sell-offs, followed by sector-specific recoveries, indicating a reallocation driven by revised expectations regarding sectoral business models. The largest daily losses during the event phase were recorded in financials (−3.41%), consumer staples (−2.82%), materials (−2.64%), telecommunications (−2.63%), consumer discretionary (−2.51%), utilities (−1.97%), IT (−1.69%), real estate (−1.68%), industrials (−1.63%), energy (−1.46%), and health care (−1.25%). These figures highlight the varied impact across sectors and the dynamic market response to geopolitical uncertainty.

2.6.2. Dataset for Temporal Fusion Transformer Forecasting

This section will present and discuss the dataset, I used to evaluate the forecasting performance of the Temporal Fusion Transformer and the different GARCH-type models. I collected daily time series data on closing prices for selected financial instruments (Table 7). The used dataset contains 9 time series with closing prices from the January 7, 2019, to June 30, 2024 (Figure 4). Overall, I collected 1,388 business days for every financial instrument from Federal Reserve Bank of St. Louis (FRED): S&P500 (FRED, 2024a), NASDAQ 100 (FRED, 2024b), Nikkei 225 (FRED, 2024c), Gold (FRED, 2024d), Brent Crude Oil (FRED, 2024e), EUR-USD exchange rate (FRED, 2024f), 10-year Treasury Bond rate (FRED, 2024g) and Bitcoin (FRED, 2024h); and data for the Hang Seng stock index from Reuters database (Reuters, 2024) for historical data and calculated log-returns for the analysis.

Table 3. Financial instruments in scope for volatility forecasting analysis.

Financial Instrument	**ISIN**
S&P 500 Index	US78378X1072
NASDAQ 100 Index	US6311011026
Nikkei 225 Index	JP9010C00002
Hang Seng Index	HK0000004322
Gold	XC0009655157
Brent Crude Oil	XC0009677409
EUR/USD	EU0009652759
10yr. Treasury-Bond	US10YT
Bitcoin	CRYPT0000BTC

Source: FRED (2024a, 2024b, 2024c, 2024d, 2024e, 2024f, 2024g, 2024h), Reuters (2024).

I computed summary statistics for daily log-returns of each financial instrument for the entire dataset and selected periods: COVID-19, the Russian attack and the Hamas terrorist attack on Israel (Appendix). Furthermore, I collected historical data for the CBOE Volatility Index (VIX) (FRED, 2024i) and the Geopolitical Risk Index (2024), who was constructed by Caldara & Iacoviello (2022). Looking over the entire dataset, I found heavy daily losses: Bitcoin (-46.5%), 10-year Treasury Bond (-32.4%), Brent Crude Oil (-

28.0%), NASDAQ (-13.1%) and S&P 500 (-12.8%). But there were also profits. The maximum daily gains are led by the 10-year Treasury Bonds (+36.8%), followed by Brent Crude Oil (+27.4%) and Bitcoin: (+20.3%). I compared the periods of geopolitical shocks separately and found the following. The heaviest daily losses occurred during COVID-19 with average of daily losses across all financial instruments by -16.8%. It was -5.6% for the period of the Russian attack and -3.3% for the period of the Hamas terrorist attack on Israel. Bitcoin, Brent Crude Oil and Bonds suffered the most considerable daily losses in all three periods.

Comparing volatility using the standard deviation of daily returns between different periods, one can observe the following. The period of COVID-19 has the highest volatility, with an average standard deviation of daily returns of 4.6%. This is followed by the period of the Russian attack with 2.2% and then the period of the Hamas attack with 1.4%. Bitcoin, bonds, and oil have been found to have the highest volatility in all three periods of analyzed geopolitical events. Bonds were 11.8% during COVID-19, Brent Crude oil was 7.7% during the Russian attack, and Bitcoin was 2.8% during the Hamas attack. In the next step, I checked whether I need to perform further transformations on the time series before the analysis.

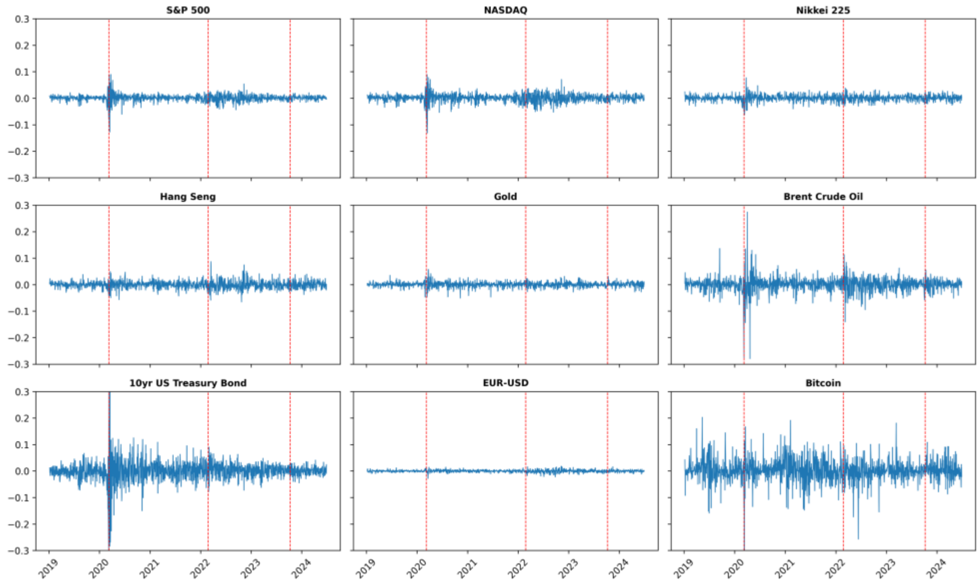

Figure 5: Daily log-returns for financial instruments in scope (01/07/2019 – 06/29/2024). Dashed lines mark geopolitical events: COVID-19 (03/09/20); Russian attack (02/24/22) and Hamas attack (10/08/23). Source: Own illustration using Python Matplotlib (2025).

This may be the case if a time series is not stationary. I tested this with the Augmented Dickey-Fuller test (Dickey & Fuller, 1979; Said & Dickey, 1984) and found that for all financial instruments, the null hypothesis, that a time series is not stationary, could rejected. In the last step, I wanted to test the feasibility of modeling volatility using GARCH models, i.e., whether the effects of heteroskedasticity can be observed in the time series. I use Engle's ARCH Lagrange Multiplier test (Engle, 1982). The null hypothesis assumes that there is no heteroscedasticity, whereby the parameters of an ARCH model are estimated using the data to be equal to zero. I could observe the following by applying Engle's ARCH test to the time series. The test could not be rejected for the EUR-USD exchange rate and Bitcoin but could rejected for all other financial instruments. This is an important indication that the current variance of the residuals of daily returns can be explained by the variance of the residuals of the past and provides the foundation for the further analysis. Furthermore, heteroscedasticity may also be present if the test is rejected. This may be because the time series under consideration has a high persistence in volatility. In this case, a GARCH model should be used for modeling. A second possibility is the presence of structural breaks that an ARCH model cannot sufficiently represent. In this case, the GJR-GARCH model shall be used.

3. RESULTS AND DISCUSSION

3.1. Abnormal Returns for MSCI World Sector Indices

This analysis examines abnormal returns (AR) in MSCI World sector indices surrounding the Russian invasion of Ukraine on February 24, 2022. Using an event window from $t-5$ to $t+5$, statistically significant ARs were most concentrated on the event day and immediately after. On 24 February, 7 of the 11 sector indices showed significant AR, while 5 remained significant on $t+1$. The effects largely diminished in subsequent days. Notably, the materials sector exhibited a significant AR even before the invasion. Average abnormal returns (AARs) show a significant market decline of −0.85% on the event day (t), followed by a +1.32% rebound on the day after $(t+1)$. This pattern suggests an initial reaction followed by selective corrective buying. "The strong U.S. weighting in the MSCI World Index may have also contributed to post-event recovery, as expectations shifted in favor of U.S.-based firms (Ali et al., 2023). Sector-level analysis reveals divergent responses. Significant negative ARs on the event day were recorded in consumer staples (−2.76%), financials (−3.01%), industrials (−0.87%), materials (−1.66%), and information technology (−2.53%)" (Robus et al., 2024). Conversely, real estate (+1.66%) and telecommunications (+2.00%) showed significant positive ARs. Consumer discretionary and energy sectors showed no significant responses. A cumulative abnormal return (CAR) analysis through t+25 highlights long-term impacts. Energy (+8.02%) and utilities (+7.29%) posted the strongest gains, likely due to anticipated supply disruptions and defensive capital reallocations. Financials suffered continued losses (CAR −5.50%), while healthcare (+4.12%) and real estate (+4.74%) saw substantial gains. The consumer discretionary sector underperformed (−2.94%), reflecting decreased demand for non-essential goods. Information technology (+2.44%) and materials (+3.02%) rebounded from initial losses, ending with positive CARs. Telecommunications and utilities also performed well over the long term, supported by stable cash flows and critical infrastructure roles. In sum, the Russian invasion triggered clear, sector-specific market reactions. Results confirm that geopolitical shocks like this one produce heterogeneous and lasting effects across global equity sectors, particularly in energy, finance, healthcare, and utilities. This supports the study's second research question on the sustained impact of geopolitical crises on financial markets. Overall, using the event study methodology, I have demonstrated that the Russian invasion had a clear and differentiated impact on sector-specific returns within the MSCI World Index. Notably, the energy, financials, healthcare, and utilities sectors exhibited significant cumulative abnormal returns by $t + 25$, suggesting that market participants revised their expectations for these sectors considering the geopolitical shock. These results confirm the second research question, indicating that the invasion had a sustained and heterogeneous influence across global equity markets.

3.2. Identification of Abnormal Volatility

3.2.1. Abnormal Volatility

This section presents findings on abnormal volatility (AVOLA) surrounding the Russian invasion of Ukraine on February 24, 2022. Using an event window from $t - 5$ to $t + 5$, volatility was measured relative to GARCH(1,1)-based forecasts. To reduce the influence of outliers, I computed a truncated mean (TMean), which excludes the minimum and maximum values per time point. Most AVOLA-TMean values exceeded 1, indicating realized volatility was generally higher than expected (Robus et al., in press). Notably, values spiked on $t - 2$ and $t - 1$, suggesting heightened anticipation of conflict, particularly after Russia's recognition of separatist regions and troop deployment on February 21, 2022. On the event day, AVOLA-TMean peaked at 8.99, and remained elevated on $t + 1$ (8.50), reflecting extreme market turbulence. Importantly, AVOLA captures volatility magnitude, not direction. While returns on the event day were largely negative, they reversed in many sectors by the following day, signaling market reassessment. By $t + 2$ to $t + 5$, AVOLA values normalized, suggesting reduced uncertainty. At the sector level, 8 out of 11 indices showed AVOLA > 1 on the event day. The highest values appeared in financials (57.46) and consumer staples (56.46).

Significant volatility was also observed in materials, utilities, telecom, IT, industrials, and real estate (Robus et al., in press). On $t+1$, abnormal volatility extended to all sectors, with 8 showing statistically significant results. Interpretations of sector behavior reflect varying investor expectations. Consumer discretionary stocks declined due to expected cuts in non-essential spending. Consumer staples faced uncertainty over Russian market losses. In contrast, energy showed muted volatility, possibly due to pre-existing adjustments and the sector's long-term, less speculative nature. Financials were affected by rising credit risk and reduced investment activity, while industrials saw spillover effects from lower capital demand. Healthcare volatility rose amid expectations of increased medical demand during crises. IT, with high debt and speculative valuations, suffered from investor flight to safety. Utilities and telecom gained attention due to their essential services and potential role in energy realignment. In summary, the Russian invasion triggered widespread abnormal volatility, especially on and after the event day. Sector responses varied, reflecting structural sensitivities and investor reallocation strategies, confirming the third research question on volatility behavior during geopolitical shocks (Robus et al., in press).

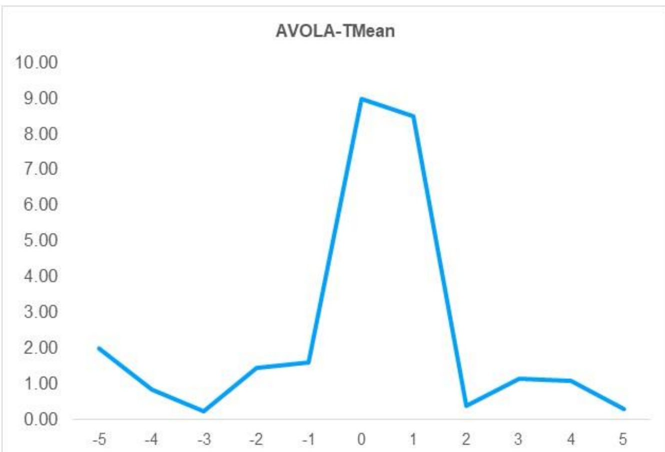

Figure 6: Trimmed mean for abnormal volatility (%) of MSCI Sector Indices around Russian invasion of Ukraine (02/17/22 – 03/03/22). Source: Robus et al. (in press).

3.2.2. Cumulated Abnormal Volatility

I now want to discuss the second question of this paper and examine whether the abnormal volatility remains persistent over a longer period after the event day. I do this by analyzing the cumulated abnormal volatility (CAVOLA). The idea here is that if the ratio of the sum of actual volatility and the sum of volatility predicted by GARCH(1,1) increases, abnormal volatility > 1 has occurred over the period. If this ratio does not change, the actual volatility corresponds to the forecast volatility. If the ratio is even lower, this means that the actual volatility over the period under review is lower than the forecast volatility. I start again with the analysis of the mean value. For reasons of consistency, I also used the TMean here. The results are illustrated in Figure 7. I have calculated cumulative abnormal volatility for t-1 (sum of AVOLA of the observations t-5 to t-1) as an initial value. This gives us also a benchmark for the abnormal volatility before the event day (Robus et al., in press).

I was able to observe the following for the CAVOLA-TMean. Starting from a value of 2.42 in t-1, it increases to 3.04 up to t+5. This is understandable, as although there are some sectors with increased abnormal volatility up to t-1, the majority can be observed in t and t+1, as shown in the previous analysis. What is surprising now is that the CAVOLA-TMean increases further to 3.24 by t+10 compared to t+5. This means that further abnormal volatility occurs in the time periods t+6 to t+10 and that there continue to be strong price fluctuations even days after the event day. In other words, the abnormal volatility is 20% higher than that around the event day. This also implies that there was a longer-term uncertainty regarding further developments among investors. From t+11 to t+20 one now see a decreasing values for CAVOLA-TMean (t+15: 3.01 and t+20: t+20). This suggests a calming of market participants, whose actions on the markets produce less volatility than the GARCH(1,1) model predicts. In the further observation period, one see that the CAVOLA-TMean of t+20 roughly corresponds to the CAVOLA of t+25. This means that the CAVOLA-TMean added from t+21 to t+25 is approximately one, which is the value where the actual volatility corresponds to the estimated volatility and has therefore returned to a long-term level. From a mean value perspective, I was thus able to show that the abnormal volatility was persistent up to the period t+10 and thus lasted longer than shortly after the event day. I will now look at the behavior of individual sectors. I observed the CAVOLA-TMean behavior just described for the following sectors: consumer staples, energy, health care, industrials, IT, materials and telecommunications (Robus et al., in press).

However, I also found different behavior in individual sectors. The persistence was particularly strong in the sectors: IT, telecommunications, health care, industrials and materials. In Financials, an already high CAVOLA value was observed at time t-1, followed by a sharp decline up to time t+5, after which CAVOLA rose again, as in other sectors. The zig-zag movement here up to t+25, suggests that the uncertainty in this sector will persist for longer or increase again after a certain time. One can see little persistence of abnormal volatility due to declining CAVOLA after t+5 at the real estate and utilities sector (Robus et al., in press). My analysis showed that abnormal volatility was persistent in many sectors until t+10. With these findings, I can confirm research question 4.

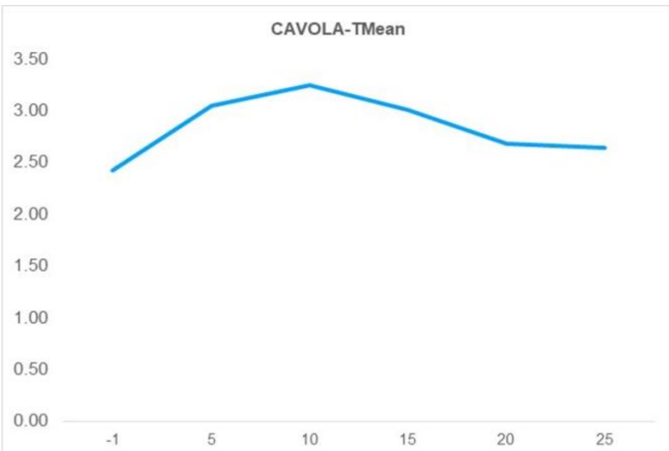

Figure 7: Trimmed mean cumulated abnormal volatility (CAVOLA-TMean) for MSCI Sector Indices around Russian invasion of Ukraine (02/17/22 – 03/31/22). Source: Robus et al. (in press).

3.3. Univariate Volatility Modeling and Forecasting of Financial Time Series during Geopolitical Shocks

3.3.1. In-Sample Analysis

This study evaluated the performance of various GARCH models in forecasting financial market volatility during three major geopolitical events: the COVID-19 pandemic, the Russian invasion of Ukraine, and the Hamas attack on Israel. Using high-frequency data over three distinct business-day periods, 75 different GARCH model configurations, 25 each from standard GARCH, EGARCH, and GJR-GARCH class, were applied to nine financial instruments. The model performance was assessed using the Akaike Information Criterion (AIC), and AIC weights were used to determine the likelihood of each model being the best fit to the volatility data. Across all instruments and periods, the EGARCH model consistently outperformed both GARCH and GJR-GARCH models. The Akaike weights indicated that EGARCH was, in nearly all cases, over 90% likely to be the best-fitting model. This performance advantage is largely due to EGARCH's ability to model the leverage effect, where negative returns cause disproportionately larger increases in volatility, common during sharp market downturns. The empirical data confirmed this: sharp daily losses during COVID-19 were followed by prolonged periods of elevated volatility, especially for the S&P 500, NASDAQ, Brent Crude Oil, and U.S. Treasury bonds. EGARCH models also tended to perform best when configured with higher-order lags, suggesting improved modeling of asymmetric responses and volatility persistence. These findings are supported by prior studies (e.g., Gharaibeh & Kharabsheh, 2023; Khan et al., 2023; Mitsas et al., 2022; Yildirim & Celik, 2020), which also found EGARCH superior in periods of geopolitical and structural volatility. Overall, the EGARCH model proves especially well-suited for capturing complex volatility dynamics during geopolitical crises. By showing that the EGARCH model achieved the best in-sample fit for the financial instruments in scope and periods of geopolitical shocks, I was able to answer my research question (Research Question 6).

3.3.2. Univariate Out-of-Sample Volatility Forecasting

This study evaluated the out-of-sample forecasting performance of GARCH models—standard GARCH, EGARCH, and GJR-GARCH—under geopolitical uncertainty across three major events: the COVID-19 pandemic, Russia's invasion of Ukraine, and the Hamas attack on Israel. Using a rolling-window approach based on 250 trading days, I generated 1- to 10-step-ahead forecasts for nine financial instruments. Forecast accuracy was assessed using the Symmetric Mean Absolute Percentage Error (SMAPE) and directional accuracy, with statistical significance tested via the Diebold-Mariano test. The EGARCH model consistently demonstrated the best point forecast performance. On average across all events and forecast horizons, EGARCH produced the lowest SMAPE for 51.85% of instruments. For short-term forecasts (1-step-ahead), EGARCH outperformed in 44.44% of cases, increasing to 51.85% at the 10-step horizon. GJR-GARCH followed closely, particularly excelling in 5-step-ahead forecasts. Simple GARCH models lagged in performance but occasionally performed best for specific instruments like Gold or the EUR/USD exchange rate. During the COVID-19 period, EGARCH provided the most accurate forecasts for over half the instruments, including NASDAQ, Bitcoin, and Brent Crude Oil. GJR-GARCH excelled with the S&P 500 and 10-year Treasury Bonds. In the Russian invasion period, EGARCH and GJR-GARCH were equally effective overall, while simple GARCH showed isolated success. EGARCH dominated long-horizon forecasts. During the Hamas conflict, EGARCH again delivered the best forecasts for most assets, particularly Gold, EUR/USD, and Bitcoin. GJR-GARCH performed well for the Hang Seng and NASDAQ, while simple GARCH models improved for select instruments.

In sum, EGARCH models consistently outperformed their counterparts, particularly in periods of heightened volatility and asymmetric return dynamics, confirming their robustness for forecasting under geopolitical stress. I also evaluated the directional forecasting accuracy of GARCH models during the three major geopolitical shocks. During the COVID-19 pandemic, the GJR-GARCH model achieved the highest directional accuracy across 66.67% of financial instruments for average 1- to 10-step-ahead forecasts, including indices like the S&P 500, Nikkei 225, and Hang Seng, as well as Gold, Oil, and EUR/USD. EGARCH performed best for NASDAQ, the 10-year Treasury Bond, and Bitcoin. For short-term (1-step-ahead) forecasts, GJR-GARCH again led with 77.78% accuracy, while EGARCH and the simple GARCH model performed well in select cases, particularly for Bitcoin and Gold. EGARCH dominated 5-step-ahead forecasts, leading for 55.56% of instruments. At the 10-step horizon, GJR-GARCH excelled again with 77.78% accuracy, followed by EGARCH at 55.56%. During the Russian invasion of Ukraine, GJR-GARCH led average directional accuracy (55.56%), especially for equities and Bitcoin. EGARCH followed with top results for Oil and the 10-year Treasury Bond. The simple GARCH model performed well only in isolated cases, such as Gold. For 1-step-ahead forecasts, simple GARCH surprisingly led in 66.67% of cases. At 5- and 10-step horizons, EGARCH and GJR-GARCH alternated in top performance, particularly for NASDAQ, EUR/USD, and Bitcoin. In the Hamas attack period, EGARCH and GJR-GARCH tied for best average directional accuracy (44.44%). EGARCH excelled at 10-step-ahead forecasts (66.67%), followed closely by GJR-GARCH (55.56%). Simple GARCH also showed improvements, especially for the Nikkei 225 and Treasury Bonds. Across all events, EGARCH and GJR-GARCH consistently offered robust directional forecasting across forecast horizons. This allowed me to answer the first part of my research question (Research Question 7).

3.4. Multivariate Volatility Modeling and Forecasting using the Temporal Fusion Transformer

Time series forecasting involves predicting future values based on past data and can be approached using either univariate or multivariate models. While univariate models (e.g., ARIMA) focus solely on the past values of a single variable, multivariate time series forecasting (MTSF) integrates multiple variables, capturing their interdependencies and offering improved predictive accuracy. GARCH models, vector autoregressive models, and machine learning techniques like the Temporal Fusion Transformer can be applied in both frameworks, with MTSF particularly beneficial in complex financial markets. Studies show MTSF enhances risk assessment, forecasting accuracy, and decision-making by including realized volatility, causal relationships, and multiple financial indicators. Overall, MTSF provides a more comprehensive and robust forecasting approach, especially when modeling the joint behavior of interconnected financial variables.

3.5. Multivariate direct multi-step out-of-sample Volatility Forecasting using the Temporal Fusion Transformer

This section presents the results of volatility forecasting using the Temporal Fusion Transformer (TFT) across three geopolitical shock periods: COVID-19, the Russian invasion of Ukraine, and the Hamas attack on Israel. I trained three TFT model variants: univariate, multivariate, and multivariate with regime-switching on nine financial instruments (e.g., S&P 500, Gold, Bitcoin), using a rolling window approach and 1- to 10-step-ahead direct forecasting. The models incorporated historical data and mutual spillover effects, with performance compared to traditional GARCH-type models using SMAPE and directional accuracy metrics. I also evaluated whether including a geopolitical shock indicator improved the TFT's predictive performance. Finally, I assessed whether specific TFT hyperparameter configurations outperformed the average, adding robustness to the forecasting results.

3.5.1. Analysis of multi-step out-of-sample forecasting performance

This study evaluates the forecasting accuracy of the Temporal Fusion Transformer (TFT) relative to GARCH-class models across three major geopolitical shock periods: the COVID-19 pandemic, the Russian invasion of Ukraine, and the Hamas attack on Israel. Each period presented unique volatility patterns, which allowed for a robust comparison across asset classes and forecast horizons. Using a rolling-window approach, I generated 1–10 day-ahead forecasts for nine financial instruments and evaluated accuracy using Symmetric Mean Absolute Percentage Error (SMAPE) and adjusted Diebold-Mariano tests. During the high volatility period of COVID-19 period, the TFT significantly outperformed GARCH models across nearly all financial instruments. For instance, in the case of the S&P 500, TFT achieved a SMAPE of 0.721 vs. 0.924 for EGARCH(3,4), with a statistically significant DM* value. Similar results were seen for NASDAQ, Nikkei 225, and Hang Seng, with TFT consistently better, especially for shorter horizons. For the Gold price, the difference was narrower, while the EUR-USD exchange rate was the only asset where GARCH outperformed TFT, likely due to its low volatility. Bitcoin, a highly volatile asset during this period, was forecasted far more accurately by the TFT. During the Russian invasion period, overall volatility was lower than during COVID-19 but still substantial. Again, TFT consistently outperformed GARCH models. For the NASDAQ, the TFT achieved a SMAPE of 0.449, while the best GARCH model was 0.651. The TFT showed particular strength in forecasting for equity indices and commodities like Brent Crude Oil, where it achieved 0.548 SMAPE vs. EGARCH(3,5) at 0.804. Even in the bond market, such as the 10-year US Treasury, TFT forecasts were more accurate (0.550) compared to GARCH (0.811). For FX and Bitcoin, the TFT also outperformed, except for gold, which remained a close call but still favored TFT. In the Hamas-Israel conflict, overall market volatility was lower compared to the previous periods, reflecting more localized geopolitical uncertainty. Nonetheless, the TFT again outperformed in most cases. For the S&P 500, it achieved a SMAPE of 0.856 vs. 1.736 for EGARCH(1,1). For NASDAQ and Nikkei 225, TFT achieved better results, though the performance gap narrowed. Interestingly, for gold, the TFT's advantage disappeared, SMAPE was 1.332 vs. 1.494 for GARCH, and the difference was not statistically significant. This may indicate TFT's limitations in predicting assets with complex or stable volatility dynamics. Brent Crude Oil and 10-year US bonds remained strongholds for the TFT, outperforming in all horizons.

Across all three periods, TFT consistently outperformed GARCH models for most financial instruments and forecast horizons. The short-horizon superiority of TFT was clear, particularly for 1–3 day forecasts, while GARCH models maintained more consistent performance across all horizons. TFT's ability to respond to fast market changes makes it particularly effective in periods of structural breaks or regime-switching volatility. By asset class, TFT excelled in equities and oil, while results for FX and crypto were more mixed. GARCH models were more competitive in lower-volatility environments like the EUR/USD exchange rate during COVID-19. For fixed income, the TFT performed exceptionally well during periods of high volatility and reversal, particularly in March 2020. In conclusion, the TFT offers a statistically and practically significant improvement in forecasting financial market volatility during geopolitical shocks. Its architecture, especially its capacity for multivariate input and attention mechanisms provides it with advantages in identifying and adapting to sudden shifts in volatility regimes. While GARCH models retain value for stable environments and longer-term forecasts, the TFT proves superior under most high-stress market conditions. This allowed me to answer my research question of whether the TFT can outperform the best GARCH-type model (Research Question 8).

3.5.2. Regime switching multi-step out-of-sample forecasting performance

This section analyzes the impact of implementing a regime-switching feature in the Temporal Fusion Transformer (RS-TFT) to improve volatility forecasting during geopolitical shocks. Volatility often spikes suddenly during such events and remains elevated, making forecasting especially challenging. Previously, the baseline TFT (BL-TFT) had no explicit indication of these high-volatility regimes, instead learning patterns implicitly. To test whether a regime indicator improves forecast accuracy, I labeled historical volatility values above the 75th percentile as “1” (high regime) and others as “0.” This regime-switching feature was then used as a covariate in the RS-TFT, indicating whether the latest known volatility observation was part of a high-volatility regime. This approach mimics regime probability logic in models such as the Markov-switching framework (Hamilton, 1988). For evaluation, both RS-TFT and BL-TFT models were trained using a rolling window (250 days) across nine financial instruments and three geopolitical events: COVID-19, the Russian invasion of Ukraine, and the Hamas attack on Israel.

Forecasting accuracy was assessed using SMAPE and tested using adjusted Diebold-Mariano statistics.

My results show consistent improvement with the RS-TFT. Across all assets and events, RS-TFT achieved an average SMAPE improvement of 4.53% over BL-TFT. The null hypothesis of equal predictive accuracy of RS-TFT and BL-TFT was rejected in 21 of 27 tests. The greatest improvements occurred during the Hamas attack period, despite its relatively moderate volatility. This suggests that RS-TFT helps prevent misforecasting elevated volatility in response to moderate shocks, where the baseline model might otherwise overreact. Asset-wise, RS-TFT provided the strongest and most consistent improvements for the S&P 500 (average SMAPE gain: 5.08%) and NASDAQ (5.91%), followed by Nikkei 225 (4.61%) and Hang Seng (5.00%). The greatest single gain (22.65%) was for the 9-step-ahead NASDAQ forecast during the Hamas attack. Gold showed the highest average improvement (9.04%), entirely driven by the Hamas period (25.85%), while effects were negligible during COVID-19 and the Russian invasion. Brent Crude Oil exhibited minimal improvement (1.37%), with the baseline model slightly outperforming in some cases. For 10-year US Treasuries, RS-TFT delivered steady improvements (avg. 4.37%) across all periods, with the largest gain during the Russian invasion. EUR-USD exchange rates saw modest but consistent gains (3.25%), and Bitcoin yielded mixed results: a decline during COVID-19 (-1.53%) but improvement during later periods (up to 6.09%).

The regime-switching feature had the greatest effect on medium-to-long-term horizons (e.g., $h = 6–10$), where standard autoregressive models struggle to capture structural changes. This supports the view that exogenous regime signals are more valuable when the temporal distance from known events increases. In summary, the RS-TFT enhances forecast performance during geopolitical shocks, particularly for equity indices and at longer horizons. Its ability to incorporate external regime signals makes it an effective tool for modeling volatility under structural market shifts. This analysis showed that the introduction of an additional explanatory variable (regime-switching feature) to identify high and low phases of volatility significantly improves the forecasting performance and thus answers my research question (Research Question 9).

3.5.3. Influence of hyperparameter optimization on the multi-step out-of-sample forecasting performance

An important task in adapting a neural network for a task is optimizing the hyperparameters Optimizing hyperparameters is a critical step in adapting neural networks like the Temporal Fusion Transformer (TFT) for forecasting financial time series, especially during volatile periods such as geopolitical shocks. Hyperparameters such as the number of attention heads and the hidden size are set before training and significantly affect model performance, generalization, and convergence. I conducted a grid search across key architectural hyperparameters (attention heads and hidden size) for three distinct periods: COVID-19, the Russian invasion of Ukraine, and the Hamas attack on Israel. Forecast accuracy was assessed using SMAPE, and statistical significance was tested by the Diebold-Mariano test statistics (Diebold & Mariano, 1995).

The attention head parameter determines how many parallel attention mechanisms the model uses. More attention heads allow the model to capture various dependencies across time, such as short-term movements and long-term market cycles. This helps in isolating noise, identifying volatility clusters, and modeling cross-asset correlations. Hidden size refers to the number of neurons per layer, controlling the model's representation capacity. Larger hidden sizes help detect complex patterns like regime shifts or structural breaks but can lead to overfitting if too large.

My results show a significant improvement by hyperparameter optimization. The average SMAPE gain across all financial instruments was 3.94% during COVID-19, 6.13% during the Hamas attack, and 2.81% during the Russian invasion. The best-performing models (BP-TFTs) most frequently used 8 attention heads (40.74%) and a hidden size of 32 (44.44%), indicating that a moderate model complexity offered the best trade-off between performance and generalization. At the asset level, the S&P 500 and EUR-USD consistently benefited from optimized hyperparameters across all periods. The NASDAQ, Nikkei 225, and Hang Seng showed significant improvements in most but not all periods. Brent Crude Oil and US Treasury bonds also exhibited consistent gains, though the optimal hyperparameter values varied more, reflecting changing data structure. Bitcoin showed mixed results, with significant improvement only during COVID-19.

The variability in performance across periods emphasizes the importance of tuning hyperparameters dynamically depending on market conditions. In conclusion, tuning architectural hyperparameters significantly enhances TFT performance. More attention heads improve the model's ability to extract multi-scale dependencies and filter noise, while a moderate hidden size enables the model to learn complex patterns without overfitting. These findings underscore the importance of aligning model architecture with the volatility structure of financial time series, particularly during regime changes induced by geopolitical shocks (Research Question 10).

3.5.4. The added value of a multivariate structured volatility forecasting approach

The Temporal Fusion Transformer (TFT) is well-suited for multivariate time series forecasting due to its architectural strengths. However, multivariate forecasting adds complexity, so it is important to assess whether this complexity results in improved performance over univariate models. To examine this, I compared a multivariate TFT model (BL-TFT) with a univariate TFT (UV-TFT) across nine financial assets—S&P 500, NASDAQ, Nikkei 225, Hang Seng, Gold, Brent Crude Oil, 10-year U.S. Treasury Bonds, EUR-USD exchange rate, and Bitcoin—during three periods of geopolitical shocks: the COVID-19 pandemic, the Russian invasion of Ukraine, and the Hamas attack on Israel. Each model was evaluated using a rolling-window approach, forecasting 1–10 days ahead. I measured accuracy using the Symmetric Mean Absolute Percentage Error (SMAPE) and tested significance using adjusted Diebold-Mariano test statistics. Out of 27 total evaluations (9 assets × 3 periods), the multivariate model outperformed the univariate model in 23 cases (82%), and the performance difference was statistically significant in 20 of those cases (87%). Multivariate models are particularly advantageous when assets are highly correlated, experience volatility spillovers, or respond to common exogenous factors, conditions prevalent during crises. During COVID-19, the multivariate model outperformed the univariate model for all assets with statistically significant results. During the Russian invasion, it outperformed in 7 out of 9 cases (6 statistically significant), and during the Hamas attack, in 6 out of 9 cases (5 statistically significant). These patterns correspond with volatility levels: highest during COVID-19, moderate during the Russian invasion, and lowest during the Hamas attack. At the asset level, the S&P 500 and NASDAQ were better forecasted by the multivariate model during COVID-19 and the Russian invasion but not during the Hamas attack, likely due to lower cross-asset correlations. For the Nikkei and Hang Seng indices, multivariate forecasts were superior during COVID-19 and the Hamas attack. For commodities, the multivariate model significantly outperformed for Gold and Brent Crude Oil during COVID-19 and the Russian invasion, and for Brent Crude Oil also during the Hamas attack. These results affirm that multivariate models are more robust during systemic shocks due to their ability to capture interdependencies and structural breaks. They also benefit from incorporating external indicators like the VIX or Geopolitical Risk Index. Univariate models, by contrast, treat each asset in isolation and miss key inter-market signals. In conclusion, the multivariate TFT provides more accurate and adaptive volatility forecasts under elevated geopolitical risk. Overall, the findings demonstrate that multivariate models offer a more robust and adaptive framework for volatility forecasting under conditions of elevated geopolitical risk (Research Question 11).

3.5.5. Model comparison between GARCH and Temporal Fusion Transformer

Generalized Autoregressive Conditional Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models have long been the standard for modeling time-varying volatility in asset returns. These parametric models capture volatility clustering by modeling conditional variance as a function of past residuals and variances, typically assuming stationarity and regularly spaced data. Extensions such as EGARCH and GJR-GARCH address asymmetries in volatility responses, notably the leverage effect. GARCH models are efficient, economically interpretable, and widely used for applications such as Value-at-Risk, option pricing, and financial stress testing. In contrast, the Temporal Fusion Transformer (TFT) represents a non-parametric deep learning approach to multi-horizon, multivariate forecasting. It integrates recurrent neural networks, attention mechanisms, and static covariate encoders in a sequence-to-sequence framework. Unlike GARCH, the TFT can model non-stationary, high-dimensional, and incomplete data without strong distributional assumptions. It distinguishes between observed, known, and static features, offering rich context-dependent learning. However, the TFT's flexibility comes at the cost of interpretability and computational efficiency. It is data-intensive, requires regularization, and demands significant computational resources for training.

While GARCH models are tailored specifically for volatility and deliver interpretable parameters, they struggle with irregular or missing data and are limited to univariate inputs unless extended. The TFT, meanwhile, handles multivariate data, volatility spillovers, and structural breaks more effectively, making it more robust in real-world, high-complexity settings. Overall, GARCH models are suitable for interpretable, efficient modeling of clean, stationary time series. The TFT is more appropriate for complex, nonlinear, multivariate datasets, particularly during systemic events or when forecasting is enhanced by incorporating exogenous variables. However, the TFT's advantages in flexibility and accuracy must be balanced against its reduced transparency and high computational cost.

4. CONCLUSION AND RECOMMENDATIONS

The world is experiencing repeated shocks that do not remain local in scope but have a global impact. These geopolitical shocks often arise from military conflicts, political unrest, or sudden changes in international relations and affect the most diverse facets of the social life, including economics and thus financial markets. Furthermore, geopolitical shocks impact the volatility of all assets, asset classes, sectors, and countries worldwide which in turn leads to changes in the behavior of international market players. It is obvious that these phases must be managed very cautiously by market participants and financial market supervisors to avoid devastating crashes. This dissertation has presented a comprehensive empirical investigation into the identification and forecasting of market dynamics under the influence of major geopolitical shocks. Using the latest geopolitical events: COVID-19 pandemic, Russia's invasion of Ukraine, and the Hamas attack on Israel as empirical object of research, the study evaluates abnormal returns, abnormal volatility, and forecasting performance using both traditional econometric and modern deep learning approaches. The empirical analysis spans four interconnected components. First, an event study on MSCI World Sector Indices reveals that geopolitical shocks trigger immediate negative abnormal returns in several sectors (e.g., energy, financials), while some sectors (e.g., healthcare, IT) show positive cumulative returns afterward. This heterogeneity underscores how investor sentiment and sector-specific risk assessments evolve during crises.

Second, volatility dynamics were explored using GARCH-based benchmarks. The results indicate significant and persistent abnormal volatility post-event, with spillover effects visible across sectors. This reflects increased uncertainty and shifting risk perceptions following shocks. Third, the performance of GARCH-type models (GARCH, EGARCH, GJR-GARCH) was benchmarked. EGARCH outperformed for point forecasts due to its asymmetry handling, while GJR-GARCH was superior for directional forecasting. This emphasizes the importance of aligning model choice with the use case (e.g., hedging vs. directional bets). Fourth, the study employed the Temporal Fusion Transformer (TFT) for direct, multi-step, multivariate forecasting. TFT consistently outperformed GARCH-class models across most instruments and forecast horizons. Its ability to process multivariate inputs, adapt to regime shifts, and incorporate exogenous variables led to substantial forecasting gains—particularly for short-term volatility. Enhancements such as a regime-switching feature (RS-TFT) and hyperparameter tuning further improved performance, especially during periods with subtle or complex volatility changes. Additionally, a comparison between univariate and multivariate TFT models showed that the multivariate version outperformed in 82% of cases, highlighting the value of modeling cross-asset relationships and incorporating variables like the VIX and Geopolitical Risk Index. The multivariate TFT's advantage was particularly pronounced during high-volatility regimes, confirming the importance of contagion and co-movement effects during systemic events.

From a practical standpoint, the research suggests that financial institutions should adopt adaptive, high-frequency forecasting tools like TFT for risk monitoring, capital allocation, and regulatory compliance, particularly in times of geopolitical unrest. TFT-based models can enhance early-warning systems, guide dynamic asset allocation, and improve derivatives pricing accuracy by better estimating short-term implied volatilities. While TFT models offer superior forecasting capabilities, they also require significant data, computational resources, and careful tuning. Therefore, the choice between GARCH and TFT should be context dependent. In highly regulated or resource-constrained environments, GARCH remains useful due to its simplicity and interpretability. However, for institutions operating in data-rich and rapidly evolving markets, incorporating TFT, either as a primary model or in a hybrid ensemble, offers significant performance advantages. In conclusion, the Temporal Fusion Transformer emerges as a powerful tool for forecasting volatility during geopolitical shocks. Its integration of attention mechanisms, multivariate capabilities, and adaptability to structural breaks positions it as a leading model for modern financial forecasting under uncertainty.

A hybrid modeling strategy, wherein TFT outputs serve as complementary signal generators or are used for benchmarking alongside conventional econometric models, represents a pragmatic approach to combining predictive strength with operational feasibility.

5. NEW SCIENTIFIC RESULTS

This dissertation presents several novel scientific contributions at the intersection of financial econometrics, time series forecasting, and machine learning by analyzing, modeling, and forecasting market dynamics during geopolitical shocks.

1. The research provided a volatility modeling and forecasting framework. Systematic testing of 75 GARCH-type models showed that EGARCH models consistently provided the best in-sample fit for volatility in three different periods of geopolitical shocks (Research Question 6). It was found that EGARCH models outperformed GARCH and GJR-GARCH-type models in point forecasts, while GJR-GARCH performed better in directional forecasts (Research Question 7).
2. Key methodological innovation is the application of the Temporal Fusion Transformer (TFT), a transformer-based deep learning network, for direct, multi-step, multivariate volatility forecasting. This research found that the TFT outperformed the best-performing GARCH-type model in almost all analyzed periods of geopolitical shocks and examined financial assets in the research scope (Research Question 8).
3. Further, this research could show that hyperparameter optimization of the Temporal Fusion Transformer significantly enhanced the forecasting performance, confirming that careful configuration and hybrid econometric deep learning approaches yield better forecasting outcomes (Research Question 10)
4. Finally, the improvement of a multivariate TFT setup was compared with a univariate TFT setup. The multivariate TFT approach provided superior short-term forecast accuracy, which was crucial during high-volatility episodes like March 2020 and the Russian invasion in 2022. This makes it particularly suitable for tactical risk management applications (Research Question 11).

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