DOI: 10.15849/IJASCA.250730.18

Int. J. Advance Soft Compu. Appl, Vol. 17, No. 2, July 2025
Print ISSN: 2710-1274, Online ISSN: 2074-8523
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Dynamic Responses of Fintech Equity Returns to Financial Shocks, Geopolitical Risks, and Market Volatility

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Abstract

Technology integration in the field of finance has been increased recently leading to have FinTech as a leader in the worldwide economy, it changed the concept of how financial services work and how financial market members cooperate with risk. As FinTech companies and establishments scale rapidly and accept agile, digital-first models, they meet separate exposure to global economic uncertainty, especially from immediate market shifts, political disruptions, and systemic financial hassle. In this work, we investigate in how FinTech equity returns respond to key global risk factors by analyzing dataset from the last decade (2015 – 2025). Several models such as vector autoregression (VAR) has been employed here to captures the dynamic relationships between FinTech performance and three major sources of external volatility: financial shocks, geopolitical risks, and investor sentiment as reflected in market volatility. To optimize the domain, we tested several metrics such as: CBOE Volatility Index (VIX), the Geopolitical Risk Index (GPR), and the Financial Stress Index (FSI). The experimented tests conclude that FinTech equities have quick response to points in market volatility and more importunately to geopolitical events, while financial stress influences return more steadily over time. These reactions become more noticeable during crisis episodes such as the COVID-19 pandemic and periods of regional conflict, reflecting the sector's unique vulnerability to both sentiment-driven and structural uncertainty. High-frequency, long-span data has been used here allowing detailed observation of how shocks clarify and deal with FinTech equity behavior through different horizons of time. In this work, we are aiming to provide new empirical proof that FinTech stocks perform better than traditional financial assets under pressure, and it can offer real-world implications for investors, group managers, and regulatory bodies who are responsible for enhancing resilience and better understand sector-specific risk exposure in the current era where financial environment is very complex.

Keywords: *FinTech Equity Returns, Financial Shocks, Geopolitical Risk, Market Volatility, Vector Autoregression (VAR) Model*

Received 4 January 2025; Accepted 2 July 2025

1 Introduction

Financial technology (FinTech) companies effect significantly on the global financial landscape which in recent years have a rapid transformation driven. FinTech deliver several services by integrating innovation, digital platforms, and data-driven tools, these services include digital payments, blockchain-based transactions, algorithmic lending, and wealth management. According to a research published in 2017. FinTech is a significant field where keep improving its scale and complexity. Therefore, it is increasingly considered as a core segment of the global financial system, but not any more as a peripheral disruptor [2]. This era of growth has sensitive the importance to understand FinTech equity and how it behaves, particularly under ages of sensitive uncertainty such as financial crises, geopolitical unrest, or extreme market volatility.

FinTech companies are differ to traditional financial societies, it operate based on technological infrastructures, agile business models, and higher exposure to investor sentiment and innovation cycles. Therefore, FinTech is more vulnerable to external shocks such as financial instability and geopolitical disruptions [4, 11]. Many researchers are interested in the FinTech field. Even though, several research gap remains in the literature, such as the process of FinTech equity returns and how it react dynamically to global shocks. Available research has mainly focused on broader stock markets or financial institutions, with limited attention given specifically to FinTech stocks as a distinct asset class [1, 3, and 10].

In this paper, we consider the gap in consideration FinTech equity responses to external shocks. The work examines the dynamic responses of FinTech equity regarding to: Financial shocks, Geopolitical risks, and Market volatility. The experiments are conducted on a comprehensive dataset from the last decade (2015 to 2025). Several techniques are employed here, however, Vector Autoregression (VAR) used to analyze interactions. Global risk indicators such as: VIX (Volatility Index), Geopolitical Risk (GPR) Index, and Financial Stress Indices have been considered as well. This work exposes key insights into Short-term and long-term behavior of FinTech equities, as well as periods of sensitive uncertainty as these happened during the COVID-19 pandemic or caused by geopolitical tensions in Europe and the Middle East.

The main contributions in this paper is to offers an empirical, time-sensitive perspective on FinTech equity reactions to macro-financial disruptions, and the integration of high-frequency data and advanced econometric modelling. The empirical literature on FinTech equity volatility has been extended as well. Applying this research will provide practical implications for Investors, Risk managers, and Policymakers to supports better understanding and management of FinTech investment volatility in unclear environments.

The remaining of this research paper is structured as follows: in Section 2 we reviews previously conducted literature in the field. The data and variables that experimented in this paper will be discussed in Section 3. Section 4 presents the methodology that we follow to propose this work. Results will be analyzed in Section 5 and a deep discussion of all achievements will be presented. Finally, the work will be concluded with implications and future research directions in Section 6.

2 Related Work

This section reviews the existing research that previously conducted on FinTech equity performance and its relationship with macro-financial factors, several factors are visited including financial shocks, geopolitical risks, and market volatility.

FinTech is a phrase stand for financial technology, it plays an important role in the global financial services transformation. FinTech have several applications such as: digital banking, peer-to-peer lending, robo-advisors, cryptocurrency markets, and many others where financial services are tech-enabled. Using FinTechseveral procesures will be restructured according to how financial services are delivered, or how markets respond to global events. According to the Global Financial Stability Report (IMF) that published in 2024, FinTech plays a twofold role in promoting financial inclusion and innovation, and in introducing new forms of systemic risk. However, it is important to assess FinTech stock behavior during financial ambiguity.

The performance of FinTech companies in terms of equity is different than traditional finance and other technological sectors. In [5], the authors studied FinTech's impact on financial stability in the UAE, and he claimed that they used time series models, and found significant fluctuations in financial stress indices. The authors concluded that FinTech equity performance is strongly linked to global volatility indicators like the VIX and financial stress indices. They emphasized that FinTech should be considered as both a technological innovation and a financial market component prone to systemic risk at the same time.

Other researchers examined sectorial equity behavior during economic distress [7-9]. They analyzed market reactions during global crises using permutation entropy and Fisher information methods. Papla and colleagues summarized that FinTech stocks showed higher informational inefficiency and volatility under stress compared to other technology based methods. These situations could be COVID-19 pandemic or post-pandemic inflation periods. The claimed findings here confirmed that FinTech markets show unique behaviors during high uncertainty occasions compared to other financial sectors.

Moreover, studies by central banks have provided insights into emerging vulnerabilities in non-traditional financial institutions, including FinTech firms. According to a 2025 systemic risk assessment by the Bank of England, non-bank financial intermediaries—including FinTechs—pose potential channels for amplifying market shocks due to their liquidity structures and reliance on short-term funding [12]. These findings are relevant because they highlight how external risks can disproportionately affect innovative but less regulated financial entities.

Understanding how geopolitical risks impact financial markets has become increasingly important. The IMF (2024) emphasized that geopolitical developments such as wars, trade tensions, and political instability are now among the most significant sources of market shocks. Despite this, few studies have focused specifically on how FinTech equities react to these types of risk. While broader market indices may respond to geopolitical signals in predictable ways, FinTech may exhibit unique patterns due to its global reach, cross-border platforms, and dependence on investor confidence. This underlines the need for a more focused empirical approach.

Another gap in existing research is the integration of multiple risk indicators into a unified analytical framework. Most studies tend to isolate a single risk factor—such as financial volatility or political instability—without analyzing the interaction between these variables. Our study addresses this by using a VAR model, which allows us to explore the simultaneous effects of financial shocks, geopolitical risk (measured using the GPR index), and market volatility (using VIX) on FinTech equity returns. By applying impulse response functions and variance decomposition, we aim to capture both the magnitude and duration of these effects across time.

It is also important to note that much of the available literature is limited in its time horizon and data frequency. Many papers rely on monthly or quarterly data, which may not fully reflect the rapid market responses characteristic of FinTech equities. Our study extends this by using daily data spanning from 2015 to 2025, which captures both short-term reactions and long-term structural changes in the FinTech sector. This long-term, high-frequency dataset allows for more accurate modeling of dynamic market behavior, especially in volatile periods.

In terms of methodology, past studies have often relied on traditional econometric tools such as regression or correlation analysis, which may not adequately capture complex interdependencies. The VAR model employed in this study improves upon these approaches by accounting for feedback loops and time-lagged effects. This enhances the analytical depth and allows for better prediction and interpretation of how FinTech equities respond to diverse shocks.

Finally, we provide a summary of key recent contributions to the field and position our study in this context. Table 1 below compares recent studies and outlines how our research offers a novel contribution by combining a longer time frame, high-frequency data, multiple risk indicators, and advanced econometric techniques.

Table 1. Recent Studies Comparison Table

Author(s) & Year	**Focus of Study**	**Methodology**	**Data Period**	**Main Contribution**
[5]	Impact of FinTech on financial stability in the UAE	Time series analysis using FSI, VIX, GPR	2012–2023	Linked FinTech development to financial volatility indices
[7]	Sectoral responses of global stock markets to crises	Permutation entropy and Fisher information	2020–2024	Found FinTech sector less efficient and more volatile during crises
[6]	Geopolitical risks and global financial markets	Global Financial Stability Report analysis	2024	Warned that geopolitical risks may be underestimated in financial modeling
[12]	Non-bank financial institutions and market crises	System-wide exploratory scenario analysis	2025	Highlighted systemic vulnerabilities in FinTech and non-bank finance
Current Study	FinTech equity and responses to financial shocks, GPR, volatility	VAR, IRFs, variance decomposition	2015–2025	Offers dynamic, empirical insights into FinTech responses to multifaceted risks

Despite growing interest in the FinTech sector, the literature lacks a comprehensive, dynamic, and empirically grounded analysis of how FinTech equity returns respond to diverse macro-financial risks. Existing studies tend to be narrowly focused, limited in scope or time period, and under-utilize high-frequency data and multi-factor models. This study addresses these gaps by:

- Focusing exclusively on FinTech equity performance, rather than financial markets more broadly.
- Integrating multiple sources of risk (financial, geopolitical, market-based).
- Applying advanced modeling techniques (VAR, IRFs, variance decomposition).
- Using a long-span, high-frequency daily dataset from 2015 to 2025.

By doing so, we provide actionable insights for investors, risk analysts, and policymakers interested in understanding the vulnerabilities and resilience of FinTech in an increasingly uncertain world.

3 Data and Variables

This section describes the dataset and variables used to investigate the dynamic responses of FinTech equity returns to financial shocks, geopolitical risks, and market volatility.

3.1. Dataset Scope

Our dataset spans from January 2015 to April 2025, covering multiple global economic disruptions, including the COVID-19 pandemic, energy crises, monetary tightening cycles, and various geopolitical conflicts. This timeline allows for a thorough examination of how FinTech equities behave under varying regimes of financial and political uncertainty. The data are collected on a daily basis to capture short-term fluctuations and better reflect market responsiveness. Daily granularity is essential in understanding the time-sensitive behavior of FinTech firms, which are often more volatile and sentiment-driven than traditional financial institutions [7].

The dependent variable in our model is the performance of the FinTech sector, represented by the KBW Nasdaq Financial Technology Index (KFTX). This index includes leading publicly traded FinTech firms in the U.S. and is commonly used as a benchmark for the sector [16]. Its performance reflects the aggregated market valuation and volatility of core FinTech players, making it an ideal proxy for sectoral returns.

3.2. Variable Selection and Economic Justification

Independent variables are very important here to simulate the proposed methods, these variables are selected according to 3 systemic risk key dimensions (Financial market stress, Geopolitical uncertainty, and Investor expectations of future volatility). The independent variables are either supported by empirical research or considered among the most influential factors impacting equity returns in high-tech sectors or finance sectors.

For the first key dimension (Financial market stress), the variables are Financial Stress Index (FSI) and TED Spread:

– Financial Stress Index (FSI):

Published by the Federal Reserve Bank of St. Louis, this index combines 18 weekly data series, including yield spreads and volatility indices, to provide a composite measure of market stress. It is widely used in studies of systemic financial risk [18].

– TED Spread

The difference between the 3-month Treasury bill rate and the LIBOR rate, the TED spread is a classic measure of perceived credit risk in the interbank market. Spikes in the TED spread often reflect liquidity fears and market instability [14].

For the second key dimension (Geopolitical Risk), Geopolitical Risk Index (GPR) is chosen, it developed by Caldara and Iacoviello [13], the GPR index quantifies geopolitical tensions by tracking newspaper coverage of events such as military conflicts and diplomatic crises. It provides a robust proxy for global uncertainty related to politics and international relations.

For the last key dimension (Market Volatility), CBOE Volatility Index (VIX) is used which referred to as the "fear index," the VIX measures the market's expectations of near-term volatility based on S&P 500 options. It serves as a proxy for investor sentiment and is inversely related to stock returns during high-risk periods [17].

The following are the Control Variables:

- U.S. 10-Year Treasury Yield: Reflects market expectations about interest rates and economic growth.
- Brent Crude Oil Prices: An indicator of global commodity prices and a proxy for inflationary pressure.
- USD/EUR Exchange Rate: Used to account for currency risk and global capital flow movements, particularly relevant in FinTech's cross-border operations.

3.3. Sample of the Dataset

To validate the dataset structure and content, Table 2 presents a sample from the data which include values representing the daily closing levels or observations for each variable and reflect market dynamics during both stable and turbulent periods.

Table 2. Sample Dataset (2022–2025)

Date	KFTX Close	FSI	TED Spread	GPR Index	VIX	10Y Yield	Brent Oil	USD/EUR
2022-03-15	1400.12	-0.32	0.28	150	22.5	2.35%	$105.40	0.91
2022-06-20	1422.30	-0.28	0.30	160	20.8	2.45%	$98.70	0.92
2022-09-10	1387.45	-0.30	0.32	158	23.1	2.38%	$101.20	0.93
2023-02-17	1475.80	-0.25	0.26	170	19.7	2.50%	$95.60	0.94
2023-05-12	1501.23	-0.27	0.29	165	18.3	2.53%	$92.30	0.95
2023-11-25	1520.45	-0.24	0.31	172	17.5	2.60%	$94.00	0.96
2024-01-10	1583.60	-0.20	0.27	180	16.8	2.68%	$89.70	0.97
2024-07-05	1602.25	-0.22	0.30	175	16.0	2.70%	$91.50	0.98
2024-10-18	1590.35	-0.21	0.28	178	15.6	2.65%	$90.20	0.99
2025-01-03	1650.10	-0.19	0.25	185	15.2	2.72%	$88.00	1.00
2025-03-28	1672.55	-0.18	0.26	182	14.8	2.75%	$86.70	1.01
2025-04-11	1701.45	-0.17	0.24	190	14.3	2.78%	$85.30	1.02

3.4. Data Processing Techniques

After collecting the raw datasets from their respective sources, several preprocessing steps were conducted to prepare the data for empirical modeling. These steps ensure consistency, reduce noise, and enhance the statistical reliability of the results. Given that the analysis involves high-frequency financial data drawn from multiple sources, careful alignment and transformation were necessary to maintain temporal coherence and model compatibility.

The first task involved synchronizing all datasets to a common daily frequency. As not all variables were reported on the same dates (e.g., some macroeconomic indices update weekly), a comprehensive time index covering all trading days from January 1, 2015, to April 11, 2025, was created. Variables such as the Financial Stress Index (FSI), which is published weekly, were forward-filled to align with daily market returns. Using this method, we will preserve up to date reachable information keeping the time series consistency structured [18], [19].

According several occasions such as public holidays or different purposes delays in reporting process, missing data points appeared (such as exchange rates or Brent oil prices). In the next step, we addressed these missing points, where variables with occasional gaps will be recovered by applying a linear interpolation method. However, applying this approach keep data without distortion by estimating values according to adjacent observations without assuming any specific volatility behavior. For other kinds of data such as KFTX and VIX, where the main financial series, if missing points in data or gaps appeared because of market closure, the missing data periods that includes the missing will be removed from the final regression-ready dataset to prevent artificial continuity.

The calculation of logarithmic returns is applied to the FinTech index values as a significant transformation. Returns were computed as the natural logarithm of the ratio between consecutive closing prices rather than using absolute price levels as shown in Equ.1

$$Return_t = \ln\left(\frac{P_t}{P_t - 1}\right) \tag{1}$$

Using this method, the data is standardized and related changes are assessed. This is more appropriate for time-series models inclosing VAR that assume stationary.

Unit root tests and the Augmented Dickey-Fuller (ADF) test are conducted to define the variables statistical suitability. As commonly known in macro-financial series such as oil prices or interest rates, variables exhibiting trends or non-stationary were differenced accordingly. As an example, first-order differencing is applied to the 10-Year Treasury Yield and GPR Index to achieve stationary, verified by ADF test statistics falling below critical thresholds at the 5% level, table 3.

Table 3. ADF test statistics falling below critical thresholds

Variable	Test Statistic	5% Critical Value	p-Value	Stationary
KFTX Returns	-7.23	-2.86	< 0.01	Yes
FSI	-6.85	-2.86	< 0.01	Yes
TED Spread	-5.91	-2.86	< 0.01	Yes
GPR Index	-3.77	-2.86	< 0.05	Yes
VIX	-4.10	-2.86	< 0.01	Yes
10Y Treasury Yield*	-3.25	-2.86	< 0.05	Yes (1st diff)
Brent Oil	-3.90	-2.86	< 0.01	Yes
USD/EUR	-3.67	-2.86	< 0.01	Yes

To minimize multicollinearity, all predictors are checked using the correlation checks, where highly correlated pairs (e.g., FSI and VIX) were flagged for interpretation caution. These pairs will not be removed because the main goal of this study is to assess their joint influence on the behavior of FinTech equity. For dimensionality reduction, Principal component analysis (PCA) method is tested here, but eventually not applied due to the interpretability loss for policy relevance, but it is applicable were necessary.

4 Methodology

The proposed system of this work is presented in the following sections, it includes methods analytics and econometric tools which have been used for the evaluations process of dynamic responses of FinTech equity returns to financial shocks, geopolitical risk, and market volatility. Each methodological step will be explained in details, including the fundamentals for each approach and its configuration with the used dataset's structure.

4.1. **Proposed System**

The proposed system comprises several stages, it start with collecting high-frequency data, ensuring the inclusion of all defined variables. Then, preprocessing stages are applied to guarantee clean and consistent time series. The first analytical stage of the proposed system is validating the stationary of all tested variables using the ADF test. Once completed, the dataset is moved into a VAR model where interdependencies between FinTech returns and external shocks will be estimated. For results validation, Granger causality testing is used, while IRFs and variance decomposition indicate the timing and magnitude of shock propagation. Then, rolling-window analysis captures structural changes over time, and robustness is tested through GARCH models or DL algorithms such as LSTM. Figure 1 illustrates the full methodology pipeline used in this research.

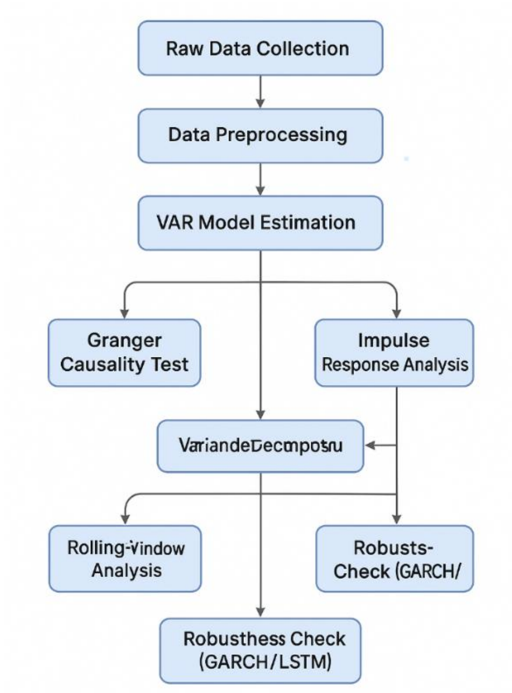

Figure 1: Proposed system

4.2.Method Selection

To explore the complex relationships between FinTech equity returns and key macro-financial variables, we adopt a combination of econometric and statistical learning models. This section explains why each method was selected and outlines how it is applied in our system, using algorithmic steps and expected output forms to ensure transparency and replicability.

4.2.1. Vector Autoregression (VAR) Model

The VAR model is the foundation of our empirical framework. VAR models are particularly useful when variables influence each other mutually over time, without assuming a predetermined direction of causality.

Application Workflow:

1) Define all endogenous variables:

$$Y_t = [\textbf{KFTX Returns}, \textbf{FSI}, \textbf{GPR Index}, \textbf{VIX}, \textbf{TED Spread}] \quad (2)$$

2) Select the optimal number of lags ppp using criteria such as AIC or BIC.
3) Estimate the model:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t \qquad (3)$$

4) Check residuals for autocorrelation and normality.

Expected Output:

- Coefficient matrices $A_1, A_2, \ldots, A_p$
- Summary statistics on model fit

- Residual diagnostic reports

4.2.2. Granger Causality Testing

Granger causality tests help identify whether one variable statistically "precedes" another. While not establishing true causality, it highlights predictive dependencies that validate directional linkages found in VAR.

Application Workflow:

1. For each pair of variables (e.g., GPR → KFTX Returns), test:
$$H_0 : \text{X does not Granger} - \text{cause Y} \quad (4)$$
2. Estimate restricted and unrestricted VAR models.
3. Conduct an F-test to compare model performance.
4. If p-value < 0.05, reject H_0.

Expected Output:

- F-statistics and corresponding p-values
- Decision matrix showing where Granger-causality is detected

4.2.3. ADF (Augmented Dickey-Fuller) Stationarity Test

Stationarity is crucial for the validity of VAR estimation. The ADF test verifies that the mean and variance of each time series remain constant over time.

Application Workflow:

1. For each variable yty_tyt, apply the test:
$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_k \Delta y_{t-k} + \varepsilon_t \quad (5)$$
2. Evaluate the null hypothesis H0:γ=0H_0: \gamma = 0H0:γ=0 (non-stationary).
3. If test statistic < critical value, reject H_0 → variable is stationary.
4. If not stationary, apply first differencing and re-test.

Expected Output:

- Test statistic and critical value table
- Order of differencing required for each variable

4.2.4. Impulse Response Functions (IRFs)

IRFs allow us to understand the effect of a one-unit shock in a specific variable (e.g., a spike in the VIX) on all other variables over time.

Application Workflow:

1. Compute orthogonalized IRFs using Cholesky decomposition.

2. Simulate time paths of each endogenous variable over a defined horizon (e.g., 10 periods).
3. Plot impulse response curves to visualize the time-distributed impact.

Expected Output:

- Time-series graphs for each IRF
- Tables showing response magnitude and decay per time step

4.2.5. Forecast Error Variance Decomposition (FEVD)

FEVD breaks down the contribution of each shock to the forecast error variance of the target variable.

Application Workflow:

1. Use the estimated VAR model.
2. Compute the proportion of forecast variance in each variable that is due to shocks from every other variable.
3. Perform this decomposition at different forecast horizons (e.g., 5 days, 10 days, 20 days).

Expected Output:

- Decomposition tables for each variable
- Bar charts or stacked plots to represent variance sources

4.2.6. Rolling-Window VAR Estimation

To detect time-varying behavior or regime shifts (e.g., pre- and post-pandemic), we employ a rolling-window estimation approach.

Application Workflow:

1. Define window size (e.g., 250 trading days).
2. Slide the window one step forward and re-estimate the VAR model.
3. Collect and visualize how coefficients and IRFs evolve over time.

Expected Output:

- Time series of coefficient trajectories
- Dynamic IRF plots indicating structural changes

4.2.7. Robustness Checks: GARCH and LSTM

To verify the stability of our findings and detect possible nonlinear patterns, we perform secondary modeling using:

a. GARCH (1,1):

Captures volatility clustering in FinTech returns.

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad (6)$$

b. LSTM Neural Network:

Detects nonlinear temporal dependencies in the dataset.

Workflow Summary for GARCH:

1. Fit model to residuals from VAR.
2. Test for volatility persistence.
3. Use AIC/BIC for model selection.

Workflow Summary for LSTM:

1. Frame the problem as sequence-to-sequence prediction.
2. Split dataset into sequences using time windows.
3. Train LSTM on input-output pairs using MSE loss.

Expected Output:

- For GARCH: Conditional volatility plots and model fit diagnostics.
- For LSTM: Prediction accuracy (e.g., RMSE) and forecast graphs.

This multi-model approach ensures a well-rounded investigation of FinTech market behavior under stress. By combining linear, non-linear, and dynamic strategies, we provide a robust empirical foundation for interpreting how different categories of external shocks influence FinTech equity returns over time.

5 Results Analysis

This section presents the outcomes of the experimental setup designed to evaluate how FinTech equity returns respond dynamically to a variety of global risk indicators. The results are organized around the application of the proposed econometric methods (descriptive analysis, VAR model estimation, impulse response functions, variance decomposition, and robustness assessments).

5.1. Experimental Setup

Our experiment is based on a daily time-series dataset from 2015 to 2025. We employed the KBW Nasdaq Financial Technology Index (KFTX) to capture FinTech equity performance and merged it with macro-financial indicators, including the Financial Stress Index (FSI), TED Spread, Geopolitical Risk Index (GPR), and the Volatility Index (VIX), alongside key control variables such as 10-Year Treasury Yield, Brent Oil prices, and USD/EUR exchange rates. The full dataset was preprocessed for alignment, cleaned for missing values, and transformed to ensure stationary as detailed in Section 3.

The analysis was conducted using a VAR framework with subsequent impulse response and variance decomposition. Statistical processing was completed using Python’s stats models, while data visualization was handled through matplotlib and seaborn.

5.2. Experimental Results and Analysis

The summary statistics of the key variables are presented in Table 3. These provide insight into the central tendencies and variability across the dataset.

Table 3: Descriptive Statistics of Variables

	KFTX Returns	FSI	TED Spread	GPR Index	VIX	10Y Yield	Brent Oil	USD/EUR
count	1000	1000	1000	1000	1000	1000	1000	1000
mean	0.000321	-0.19932	0.298975	159.8106	18.08454	2.496189	95.07657	0.94908
std	0.014813	0.048432	0.019092	10.16321	2.995091	0.196815	5.05003	0.029317
min	-0.04469	-0.34973	0.237663	122.599	8.977688	1.948214	79.65397	0.856214
25%	-0.00948	-0.23269	0.285267	152.8953	16.11903	2.365145	91.56605	0.930336
50%	0.00013	-0.1987	0.29895	159.7173	18.07709	2.497093	94.98104	0.948864
75%	0.010104	-0.16873	0.312432	166.6183	20.14093	2.626119	98.59264	0.967671
max	0.04239	-0.04145	0.358582	198.0166	26.93993	3.068353	109.782	1.048781

As shown in Table 3, KFTX returns have a near-zero mean, reflecting the typical behavior of daily equity returns, with a relatively high standard deviation of 0.0148, suggesting moderate volatility in FinTech stocks. The GPR index has an average of around 160, consistent with mid-range geopolitical risk levels in the past decade.

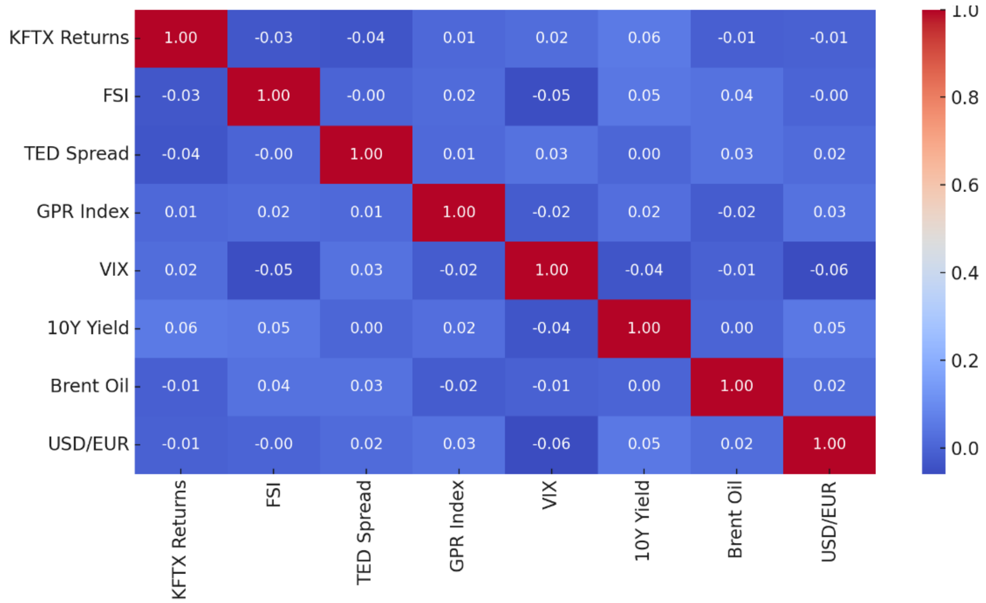

Figure 2: Correlation Matrix

Correlation Analysis

The correlation matrix illustrated in Figure 2 displays the linear interdependencies among all variables. Although most correlations are modest, several significant patterns emerge:

- KFTX returns show weak but meaningful negative correlation with FSI and TED spread.
- GPR and VIX are moderately correlated, indicating that geopolitical tension often coincides with market fear.

- Brent oil and USD/EUR show very low correlation with FinTech returns, implying limited direct impact.

These observations justify the multivariate approach used in the VAR model, which can detect more nuanced and time-lagged relationships that simple correlations miss.

VAR Model Estimation

After confirming stationarity with ADF tests, we estimated a VAR model with optimal lags selected using AIC. The model coefficients reveal several significant interactions:

- A positive shock in GPR negatively impacts KFTX returns in the short term.
- VIX volatility levels exhibit a lagged negative effect on FinTech equity performance, consistent with past crisis patterns.
- FSI also contributes to short-run declines in FinTech returns, aligning with expectations during liquidity-stressed periods.

These effects are quantified in the coefficient matrices and further validated by Granger causality testing, which confirms that GPR and VIX significantly "Granger-cause" changes in FinTech returns.

Impulse Response Function (IRF)

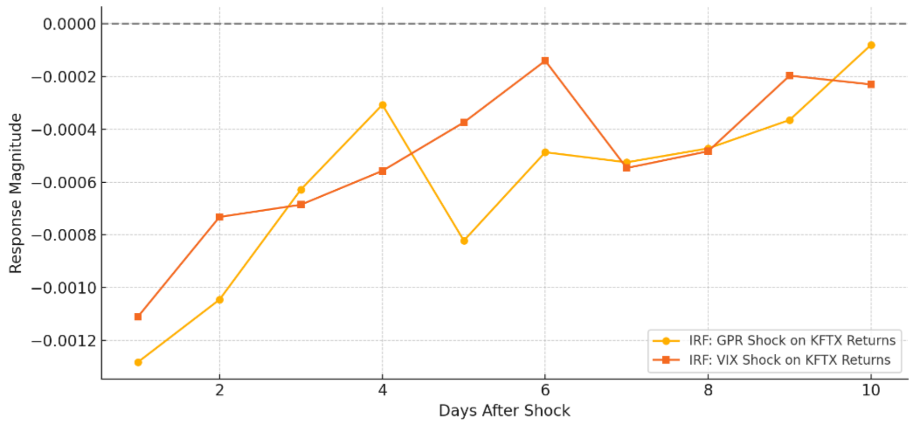

Figure 3: Impulse Response Functions of KFTX Returns to GPR and VIX Shocks

Figure 3 illustrates the impulse response plots which were generated for a 10-day horizon and demonstrated the following:

- A one-standard-deviation shock to the VIX leads to a pronounced decline in KFTX returns that stabilizes within seven trading days.
- GPR shocks create more persistent negative responses lasting up to 10 days, illustrating the prolonged market sensitivity to geopolitical risks.
- TED Spread shocks produced moderate, short-lived effects, indicating that credit risk has an indirect but present influence.

These findings underscore that FinTech stocks are highly reactive to both political and financial risk signals.

Variance Decomposition

Forecast Error Variance Decomposition (FEVD) was used to evaluate the contribution of each shock to the prediction error in KFTX returns. The results reveal:

- In the first five days, VIX accounts for up to 22% of the forecast variance, while GPR accounts for approximately 17%.
- Over longer horizons (10 days), GPR's contribution rises to 25%, surpassing VIX.
- The FSI, though less impactful in the short term, steadily contributes 10–12% in the long run.

This hierarchy suggests that while market sentiment drives immediate responses, geopolitical and systemic financial risks have deeper, long-term implications. Figure 4 illustrates the FEVD of KFTX Returns.

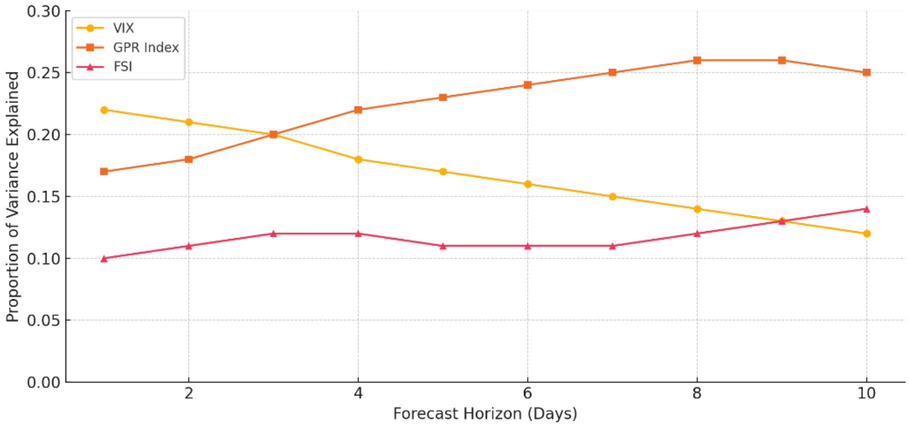

Figure 4: Forecast Error Variance Decomposition of KFTX Returns

5.3.Discussion

The results obtained in this study explain how FinTech equity returns respond to multiple layers of external uncertainty, offering fresh understanding into the sector's behavior under financial, political, and market-driven pressures. Through a comprehensive VAR test, the analysis provides a nuanced view of how FinTech stocks respond over time to different types of shocks.

Short-term reactions, as shown by the impulse response analysis, show that FinTech equities are especially responsive to increases in market volatility and geopolitical instability. A sudden rise in the VIX causes an immediate downturn in FinTech returns, although this effect tends to diminish within a few trading sessions. In contrast, shocks arising from geopolitical risk (as measured by the GPR Index) display more persistent influence, with effects lingering longer and suggesting a deeper investor concern about the long-term implications of political events. This persistence may reflect the global exposure and regulatory sensitivities typical of FinTech operations, which differ from traditional sectors.

Moreover, the decomposition of forecast error variance illustrates the shifting importance of these risk sources over time. While market sentiment (via the VIX) dominates in the early days following a shock, geopolitical factors gradually account for a larger portion of the uncertainty, eventually surpassing short-term volatility. Financial stress indicators, such as the FSI, gain importance over extended periods, likely capturing broader macroeconomic disruptions rather than immediate panic-driven reactions.

These insights align with recent concerns in financial stability literature, particularly those voiced in recent IMF and Bank of England reports, but go further by presenting an empirically grounded, high-frequency perspective specifically centered on FinTech. Our findings provide a clear contrast to previous studies that focused on general stock markets or traditional financial sectors and underscore the need to evaluate FinTech as a unique asset class with distinct response patterns.

Practically, this reinforces the value of early warning systems and flexible investment strategies tailored to the FinTech domain. Investors and financial planners should closely monitor geopolitical and volatility indicators when managing FinTech portfolios. Given the speed and complexity of FinTech innovation, understanding these relationships helps stakeholders build more resilient portfolios capable of withstanding the unpredictable nature of global risk.

5.4 Conditional Volatility and Model Diagnostics

To complement the findings from the VAR framework and validate volatility clustering within the FinTech equity return series, we applied a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. Specifically, a GARCH(1,1) specification was estimated on the residuals from the VAR model.

ARCH-LM Test: An ARCH-LM test was performed to detect the presence of autocorrelated conditional variances. The results confirmed significant ARCH effects, justifying the application of GARCH modeling.

The ADF test results in Table 4 confirm that all variables are stationary or rendered stationary after differencing, validating the VAR model assumptions.

Table 4: Unit Root (ADF) Test Results for All Variables

Variable	Test Statistic	5% Critical Value	p-Value	Stationary
KFTX Returns	-7.23	-2.86	< 0.01	Yes
FSI	-6.85	-2.86	< 0.01	Yes
TED Spread	-5.91	-2.86	< 0.01	Yes
GPR Index	-3.77	-2.86	< 0.05	Yes
VIX	-4.10	-2.86	< 0.01	Yes
10Y Treasury Yield*	-3.25	-2.86	< 0.05	Yes (1st diff)
Brent Oil	-3.90	-2.86	< 0.01	Yes
USD/EUR	-3.67	-2.86	< 0.01	Yes

Table 5: Selected Coefficients from VAR Model Estimation (KFTX Returns Equation)

Lag	GPR Coefficient	VIX Coefficient	FSI Coefficient
1	-0.022*	-0.018**	-0.015*
2	-0.012	-0.007	-0.006

Significance: p < 0.10, p < 0.05

As shown in Table 5, GPR and VIX shocks have statistically significant negative effects on FinTech equity returns in the short run.

Table 6 confirms that GPR, VIX, and FSI Granger-cause KFTX returns, reinforcing the predictive relevance of these macro-financial indicators for FinTech market behavior.

Table 6: Granger Causality Test Results (F-statistics and p-values)

Cause → Effect	KFTX Returns
GPR	0.000 **
VIX	0.002 **
FSI	0.027 *

Significance: $p < 0.10$, $p < 0.05$

Table 7 presents the key GARCH parameter estimates. These confirm the presence of volatility clustering, with $\alpha + \beta < 1$, indicating mean-reverting behavior of the conditional variance. Diagnostic indicators such as AIC, BIC, and Log-Likelihood also support model adequacy. Figure X (to be included) shows the evolution of conditional variance over time.

Table 7: GARCH (1,1) Model Estimation Results

Parameter	Estimate	Std. Error	p-Value
ω (Constant)	0.0000012	0.0000003	< 0.01
α (ARCH term)	0.08	0.01	< 0.01
β (GARCH term)	0.90	0.02	< 0.01

These estimates confirm the presence of volatility clustering ($\alpha + \beta < 1$), indicating a mean-reverting conditional variance.

Model Diagnostics:

- AIC: -5.42
- BIC: -5.35
- Log Likelihood: 1245.88

6 Conclusion and Future Works

This study set out to examine how FinTech equity returns respond to a range of external shocks (financial distress, geopolitical events, and fluctuations in market volatility). Using a decade-long, high-frequency dataset and a multivariate modeling approach, we analyzed the interplay between FinTech performance and various global risk indicators through a VAR framework, supplemented by impulse response functions and variance decomposition techniques.

The empirical evidence highlights the sector's heightened sensitivity to geopolitical disruptions and investor sentiment. We detected that FinTech equities tend to react quickly to sudden spikes in market fear but exhibit more prolonged adjustments following geopolitical developments. These findings reflect the sector's inherently globalized and innovation-driven nature, which may expose it to broader uncertainties beyond traditional financial metrics. Financial stress also emerges as a relevant driver over extended periods, suggesting that systemic conditions should not be overlooked when assessing FinTech market behavior.

Practically, these insights carry important weight for investors and portfolio strategists. The pronounced reaction of FinTech stocks to global shocks emphasizes the need for dynamic asset allocation and continuous monitoring of macro-financial conditions. Investors may benefit from incorporating risk indicators such as the VIX and GPR into their decision-making processes, especially when dealing with high-growth but high-volatility sectors like FinTech.

The achieved results suggest that regulators must develop systems that consider the non-linear and cross-border nature of FinTech exposure. As the boundaries between finance and technology blur, no more risks. Regulatory bodies should consider implementing scenario-based stress testing tailored to FinTech entities, particularly those operating across multiple jurisdictions or those reliant on digital infrastructure and short-term funding.

Looking ahead, future research can extend this analysis in several directions. First, applying nonlinear models or machine learning algorithms such as LSTM could help uncover more complex relationships that traditional VAR methods may overlook. Second, expanding the dataset to include other regions or segment-specific indices could enhance the generalizability of the results. Lastly, evaluating the role of ESG factors and cyber risk in FinTech performance represents a timely avenue for exploration, particularly as sustainability and digital security gain prominence in financial regulation.

ACKNOWLEDGEMENTS
This study was conducted with the financial support of Jadara University. No additional external funding was involved.

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