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News intensity and volatility dynamics in large- and small-cap stocks: A non-gaussian SVAR approach

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ABSTRACT

This study examines the impact of news intensity on stock market volatility in the US, focusing on large-cap, mid-cap and small-cap firms. A structural vector autoregression model (SVAR) with non-Gaussian disturbances is employed to capture extreme events and sudden jumps. Results indicate a significant negative relationship between news intensity and volatility, which strengthens over longer horizons. The implied volatility index (VIX), as well as mid-cap and small-cap stock volatilities, exhibit stronger and more persistent responses to news shocks compared to large-cap stock volatility. These findings suggest that greater news flow can reduce uncertainty and speculative behavior, especially among smaller firms more sensitive to information shocks.

1. Introduction

Financial markets are highly sensitive to information flow, and new data are among the primary drivers of stock prices and market volatility (Nti et al., 2021). According to the efficient market hypothesis (EMH), stock prices adjust rapidly and efficiently to new information (Fama, 1991). However, in today's financial markets, the adjustment process has become more complex due to high-frequency trading, algorithmic responses, and the rapid dissemination of information through social media. This adjustment process, particularly in response to unexpected or surprise news, may lead to short-term increases in volatility (French and Roll, 1986). However, a higher intensity of publicly available news can reduce information asymmetry among market participants by broadly disseminating relevant data and discouraging speculative trading behavior (Diamond and Verrecchia, 1991). Nevertheless, some studies suggest that, especially in digital and social media environments, increased news intensity can amplify speculative behavior rather than suppress it, particularly among retail investors (Avioz et al., 2023; Yu et al., 2023).

Considering this dual nature of information flow, with its potential to increase volatility in the short term while promoting market stability over the long term, understanding the impact of news intensity on stock market dynamics has become increasingly important (Avioz et al., 2024). In an era marked by frequent information shocks and sudden market fluctuations, examining the relationship between news intensity and volatility provides valuable insights for investors and researchers, while offering guidance to policymakers committed to fostering more transparent, stable, and efficient financial markets.

News intensity can affect small-cap and large-cap stocks in different ways. Small-cap stocks typically suffer from higher information asymmetry, so increasing news flow may reduce uncertainty and results in lower volatility by filling informational gaps; however, in some cases, news may act as a surprise for small firms, temporarily increasing volatility (Durnev et al., 2003; Easley and O'Hara, 2004).

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In contrast, large-cap stocks tend to have more transparent and efficient information dissemination, and news intensity primarily leads to more efficient price adjustments, resulting in a more limited and short-lived impact on volatility (Fama and French, 1993). Furthermore, large-cap stocks are more liquid, allowing faster price adjustments with fewer abrupt jumps following news events, while low liquidity in small-cap stocks may cause sharper and more volatile reactions (Amihud and Mendelson, 1986; Chordia et al., 2005). From an investor profile perspective, small-cap stocks are often traded by individual investors, who may overreact to news, amplifying volatility, whereas large-cap stocks are mainly held by institutional investors, whose responses tend to be more rational and measurable (Barber and Odean, 2008; Jegadeesh and Titman, 1993).

Although empirical research supports the validity of the EMH, many studies continue to question this insight and debate the impact of factors such as information flow, news intensity, and news quality on financial markets (Yu et al., 2023).This study aims to investigate the impact of the news intensity index (USNI), measured using semantic fingerprints of news by Wu and Xu (2025), on the volatility of large-cap, mid-cap and small-cap firms in the United States financial markets, represented by the Standard & Poor's 500 (SP500), S&P 400 (SP400) and Russell 2000 (R2000) indices. Unlike traditional VAR models, a SVAR model with non-Gaussian disturbances is employed to better capture extreme events and sudden jumps (see e.g., Lanne et al., 2017). This approach more accurately models the fat tails and unexpected shocks in market movements, facilitating a deeper understanding of volatility dynamics. The study is expected to contribute to the discussion on the relationship between market fluctuations and changes in news intensity, the sensitivity of large, mid and small firms to information flow, and the effects of widespread public information dissemination on market uncertainty and speculative behavior.

To strengthen the identification strategy, we treat news intensity as an exogenous factor in the short term. Since most news is created and published by media independently of current market volatility, we assume that changes in news intensity directly affect market volatility, but not the other way around. This approach follows earlier studies that treat news flow as independent in the short term (Beber and Brandt, 2010; Tetlock, 2007). Although market volatility might affect news over longer periods, this is unlikely to happen within the same month, especially since we use monthly data. We acknowledge this possible feedback as a limitation.

2. Data and methodology

This study uses monthly data from 2002 to 2023, focusing on key financial indicators. The news intensity index (USNI) is constructed by Wu and Xu (2025) to capture the volume of news dissemination. Volatility measures include the VIX, the S&P 500 (SP500vol), the S&P 400 MidCap (SP400vol), and the Russell 2000 (R2000vol) indices.[1] VIX is a forward-looking volatility measure derived from option prices, reflecting market participants' expectations of future uncertainty. In contrast, SP500vol is a backward-looking measure calculated from historical price data, representing realized market volatility. Including both measures in this study allows for a comparative analysis of how news intensity impacts market expectations and actual price fluctuations. These data are obtained from Investing.com, and the realized volatilities of the indices are computed using the generalized autoregressive conditional heteroskedasticity (GARCH) method. In light of the statistical significance and the sum of parameters, some ARCH-GARCH structures are examined, leading to the conclusion that the GARCH (1,1) model is appropriate for producing both SP500vol and R2000vol.

The use of monthly data is primarily driven by the availability of the USNI index, which is constructed only at a monthly frequency. To maintain consistency, the volatility measures for large-cap, mid-cap, and small-cap indices have been aligned accordingly. While this approach may limit the capacity to capture short-term fluctuations or high-frequency volatility responses, monthly data are well-suited for examining long-term dynamics and structural patterns. We acknowledge that the potential smoothing of short-run volatility constitutes a limitation of this study. Nonetheless, given that the primary aim is to investigate long-term structural relationships, the monthly frequency is appropriate and has the potential to provide meaningful insights into the persistent effects of news intensity on financial market volatility.

SVAR with non-Gaussian distribution provides more efficient estimation of heavy-tailed distribution of error terms. Lanne et al. (2017) propose the maximum likelihood estimation to determine structural innovations of a VAR system that displays a student-t error distribution. The procedure follows a three-step estimation of the VAR parameter estimations, the log-likelihood function maximization through VAR estimations, and the optimization of scale and degrees of freedom parameters of the student-t distribution. The reduced form residuals from VAR estimation, $u_t(\widehat{k}) = y_t - \widehat{A_1}y_{t-1} - \dots - \widehat{A_p}y_{t-p}$, has a parameters vector of $\widehat{k}$ and lag-length of p. Then the log-likelihood function, which is conditional on estimated VAR parameters $\widehat{k}$, estimates distributional parameters of student-t density function θ, through

$$\log\mathscr{L}(\theta) = \log\mathscr{L}(\theta, \widehat{k}) = T^{-1}\sum_{t=1}^{T} l_t(\theta, \widehat{k}) \tag{1}$$

where $\theta = \theta(H, \sigma, df)$ captures the off-diagonal covariance matrix H, the scale σ and the degrees of freedom parameters df of student-t distribution. Lastly, the log-likelihood function substitutes θ with $\widehat{\theta}$ and is maximized to estimate k as:

[1] All variables are stationary at their levels according to the Augmented Dickey-Fuller test. Test results are available in Appendix Table A1.

Table 1
Estimation results.

	Model_VIX	Model_SP500	Model_SPMidCap	Model_R2000
Model Structure	[USNI, VIX]	[USNI, SP500vol]	[USNI, SPMidCapvol]	[USNI, R2000vol]
Sample size	253	253	253	253
Covid Dummy	0.113 ** (0.055)	0.150 ** (0.065)	0.27** (0.130)	0.386 *** (0.136)
USNI–>Volatility VAR Coefficient	−0.99 ** (0.52)	−1.150 ** (0.62)	0.186 (1.15)	−2.75 ** (1.26)
Portmeanteau Test for Autocorrelation	57.95 [0.15]	39.42 [0.80]	38.747 [0.91]	47.14 [0.50]
LR Test for identification	4.19 **	0.38	0.002	3.48
DF Test for Heavy Tails Impact of USNI shocks	10 (5.7)	9.1 (5.2)	8.3 (4.4)	9.8 (5.8)

*** $p<.01$
** $p<.05$ ~~*$p<.10$.~~ Square brackets indicate p-values, while parentheses represent standard errors.

Table 2
Forecast error variance decomposition for 60 months.

Horizon	Vix (%)	SP500vol (%)	SPMidCapvol (%)	R2000vol (%)
Initial (0)	0.12 %	0.30 %	0.00 %	0.32 %
1 month	1.11 %	0.20 %	0.01 %	1.80 %
2 months	2.58 %	0.14 %	0.31 %	2.24 %
6 months	2.87 %	0.31 %	0.56 %	2.60 %
1 year	2.86 %	0.33 %	0.90 %	2.61 %
2 years	2.77 %	0.33 %	1.22 %	2.62 %
5 years	2.74 %	0.32 %	1.31 %	2.62 %

$$\log\mathscr{L}\,(k) = \log\mathscr{L}\,(\widehat{\theta},k) = T^{-1}\sum_{t=1}^{T} l_t(\widehat{\theta},k) \tag{2}$$

3. Results

The SVAR model with non-Gaussian errors first estimates parameters with model diagnostics, then it provides a forecast error variance decomposition (FEVD) table for a 60-month horizon, bootstrapped impulse response functions (IRFs) with confidence bands, and a comparative historical decompostion (HD) analysis for volatility measures. Table 1 indicates initial evidence reporting that a one-period lagged deviation in USNI) significantly reduces stock market volatilities. Coefficients of the dummy variables capturing the COVID-19 period are significantly positive, implying increasing volatility during the pandemic. Furthermore, the degrees of freedom test of heavy tails of news intensity shocks on volatility measures confirms that considerable and extreme or rare events significantly exist, consistent with financial data specifications. Additionally, the estimated SVAR model is robust with respect to autocorrelation.

Table 2 presents how much USNI-related structural shocks contribute to the expected deviations in volatility measures. While the overall impact of a news intensity shock is low in the short run, its impact rises over longer periods, reaching its peak after 6 months. The news shocks are forecasted to be more responsible for the deviations of implied volatility (VIX) and small-cap index volatility (R2000vol) than large-cap index volatility (SP500vol). Moreover, the estimates indicate that news intensity shocks have a greater influence on mid-cap stock volatility compared to large-cap stocks, but less than that observed for small-cap stocks, highlighting a gradient of sensitivity across capitalization sizes.

Fig. 1 depicts the mean of responses of the volatility measures to the news intensity-related structural shocks after bootstrapping 1000 simulations. All IRFs converge to the steady state without high persistence and maintain stability. Fig. 1 shows that VIX and R2000vol respond negatively to the news shocks, while SP500vol behaves insignificantly. The initial impact of the news intensity shock is positive on historical realized volatilities; on the contrary, it is negative on market expectations of the volatility. In accordance with Table 3, VIX peaks at a significant 2.96 % negative response at the 2nd month, and the impact of news intensity shock disappears after 6 months. R2000vol initially responds positively but insignificantly, then the effect turns negative and peaks at the 2nd month with a 2.77 % reduction, which becomes insignificant after 4 months. Analogous to FEVD analysis, SP500vol shows consistently insignificant responses that fluctuate around zero. This suggests that news-related shocks explain only an insignificant portion of the deviations in SP500vol.

Fig. 1 and Table 3 reveal that VIX, as a forward-looking volatility indicator, reacts significantly and persistently to the news intensity shocks and responds to reduce uncertainty by processing new information. SP500vol and R2000vol, as realized or historical volatilities, respond less and exhibit more transitory responses. Since the large-cap index volatility, SP500vol, is already incorporated with the information, it is less sensitive to changes in news intensity. On the other hand, small-cap index volatility, R2000vol, is more

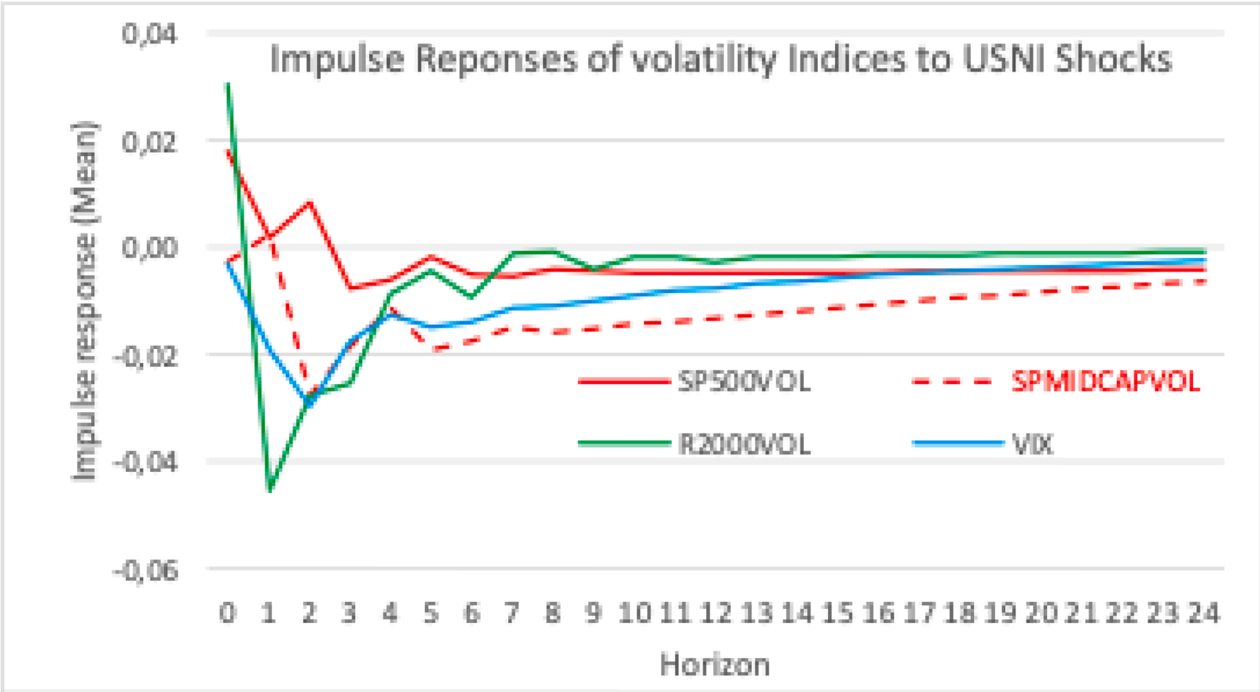

Fig. 1. The structural impulse responses from 1000 bootstrapped replications.

Table 3
The response of volatility measures to a one-standard-deviation USNI shock.

Horizon	VIX	SP500VOL	SPMidCapvol	R2000VOL
Initial (0)	−0.0030	0.0179	−0.0027	0.0307
	[−0.0104, 0.0044]	[0.0069, 0.0291]	[−0.0256, 0.0187]	[−0.0014, 0.0616]
1 month	−0.0189	0.0020	0.0027	−0.0453
	[−0.0299,−0.0078]	[−0.0137, 0.0178]	[−0.0263, 0.0333]	[−0.0712,−0.0210]
2 months	−0.0296	0.0083	−0.0274	−0.0276
	[−0.0421,−0.0175]	[−0.0105, 0.0265]	[−0.0564, 0.0025]	[−0.0533,−0.0027]
3 months	−0.0174	−0.0077	−0.0185	−0.0251
	[−0.0309,−0.0040]	[−0.0295, 0.0131]	[−0.0513, 0.0141]	[−0.0502, 0.0003]
4 months	−0.0125	−0.0061	−0.0112	−0.0084
	[−0.0225,−0.0024]	[−0.0250, 0.0108]	[−0.0352, 0.0135]	[−0.0235, 0.0072]
5 months	−0.0147	−0.0016	−0.0189	−0.0044
	[−0.0248,−0.0043]	[−0.0206, 0.0155]	[−0.0434, 0.0054]	[−0.0191, 0.0088]
6 months	−0.0137	−0.0050	−0.0175	−0.0090
	[−0.0245,−0.0024]	[−0.0245, 0.0138]	[−0.0435, 0.0054]	[−0.0213, 0.0045]
12 months	−0.0074	−0.0045	−0.0131	−0.0026
	[−0.0203, 0.0049]	[−0.0261, 0.0167]	[−0.0369, 0.0102]	[−0.0092, 0.0040]
24 months	−0.0025	−0.0040	−0.0063	−0.0008
	[−0.0139, 0.0080]	[−0.0248, 0.0161]	[−0.0196, 0.0064]	[−0.0038, 0.0021]

Notes: The impulse responses are based on 1000 bootstrapped simulations. Lower and upper 68 % confidence bands are presented in brackets. Structural shocks are identified through non-Gaussian maximum likelihood.

exposed to the dissemination of the information that reduces the uncertainty. Additionally, the results confirm that news intensity shocks reduce mid-cap stock volatility in the short term, but these effects dissipate after approximately four months, indicating a more transient impact compared to the other indices.

Fig. 2 visualizes the historical decomposition of the impact of news intensity shocks on the volatility measures over the observation period from 2002 to 2023. It reveals that there is a historical negative tendency between news intensity and volatility indices. The upsurges in volatilities follow the downward trend in news intensity during the observation period and vice versa. The HD results indicate that during both the great financial crisis in 2008–2009 and the 2011–2013 debt crisis in the Euro area, declining news intensity is accompanied by increasing stock market volatility. Among the volatility measures, VIX (red) responds the most, followed by R2000vol (blue), with SP500vol (green) showing the lowest reaction. Although different volatility measures exhibit distinct responses, they respond to the news intensity shocks in the same direction during approximately 60 % of the observations (152 out of 253). Additionally, in most occurrences (about 73–75 %), any given pair of volatility measures react in the same direction in response to news intensity shocks. Importantly, the historical decomposition shows that the net total impact of news intensity shocks on mid-cap stock volatility is greater than that on both SP500 and R2000 volatilities, emphasizing the significant role of mid-cap stocks in the transmission of news effects.

To ensure the robustness of our results, additional analyses involving Smooth Transition specifications (Lütkepohl and Netsunajev, 2017) were conducted and are presented in the Appendix. These robustness checks support the validity and consistency of the main findings.

4. Conclusion

This study examines the dynamic relationship between news intensity and stock market volatility for small-, mid-, and large-cap stocks in the U.S. using a SVAR model that accounts for non-Gaussian shocks. The findings reveal that higher news intensity generally contributes to a reduction in stock volatility over the long run, suggesting that increasing public information mitigates information asymmetry among market participants. This aligns with the EMH, which posits that stock prices quickly incorporate available information, thereby reducing volatility caused by uncertainty. However, the impact of news intensity on volatility is limited in the short term, especially for large-cap stocks, which tend to be more sensitive to unexpected news flow. The mid-cap stocks exhibit a response pattern that lies between those of large- and small-cap stocks, showing moderate sensitivity and timing of reaction. This heterogeneity highlights differences in how various market segments process and react to information. These results highlight the importance of information dissemination in stabilizing financial markets and provide insights for investors and policymakers aiming to understand volatility dynamics across different market segments.

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Ethics approval

This study does not involve human participants or animals and therefore did not require ethical approval.

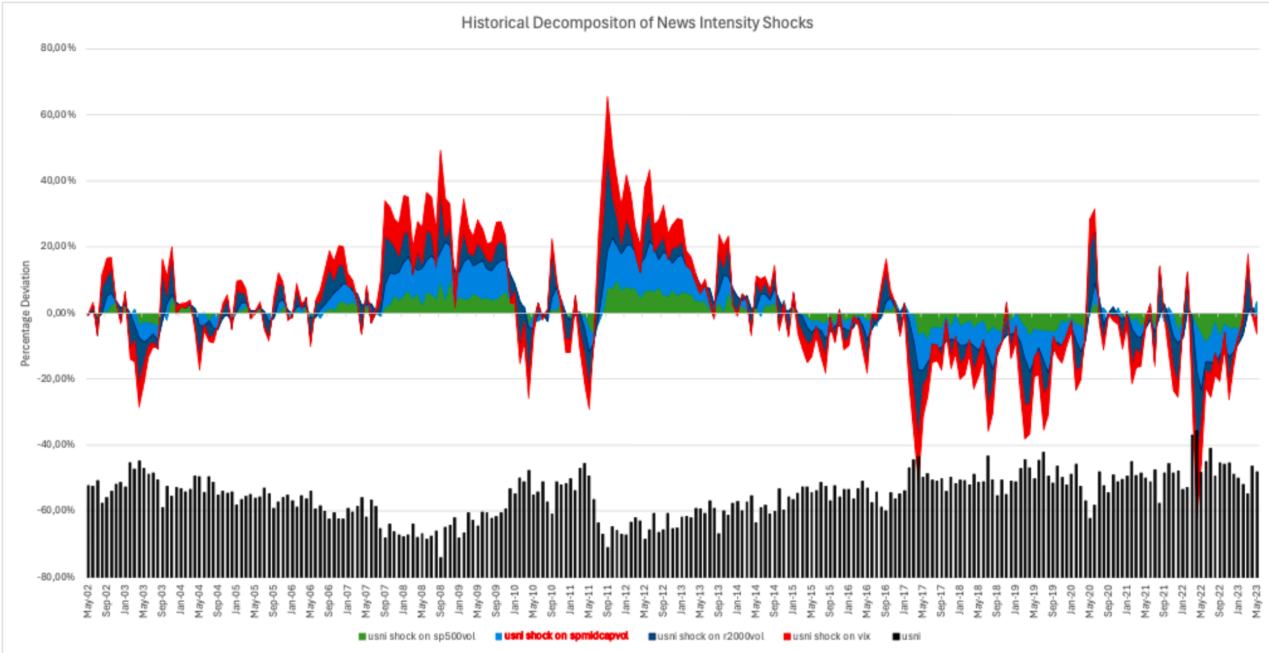

Fig. 2. Historical decomposition of USNI shocks on the volatility measures in percent deviations from the mean.

CRediT authorship contribution statement

Erhan Mugaloglu: Writing – review & editing, Writing – original draft, Methodology, Data curation. **Emrah Kocak:** Writing – review & editing, Writing – original draft, Supervision, Investigation, Conceptualization. **Umit Bulut:** Writing – review & editing, Writing – original draft, Methodology, Data curation.

Declaration of competing interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Appendix A

(Table A1)
(Table A2,Table A3)

Table A1
Unit-Root Test Analysis.

Variable	Type	TestStat	1pct	5pct	10pct
r2000vol	none	−4.46	−2.58	−1.95	−1.62
	drift	−9.647	−3.44	−2.87	−2.57
	trend	−9.67	−3.98	−3.42	−3.13
sp500vol	none	−2.246	−2.58	−1.95	−1.62
	drift	−3.759	−3.44	−2.87	−2.57
	trend	−3.757	−3.98	−3.42	−3.13
spmidcap400vol	none	−5.263	−2.58	−1.95	−1.62
	drift	−7.384	−3.44	−2.87	−2.57
	trend	−7.476	−3.98	−3.42	−3.13
usni	none	−0.028	−2.58	−1.95	−1.62
	drift	−3.751	−3.44	−2.87	−2.57
	trend	−4.364	−3.98	−3.42	−3.13
vix	none	−1.845	−2.58	−1.95	−1.62
	drift	−4.875	−3.44	−2.87	−2.57
	trend	−4.871	−3.98	−3.42	−3.13

Table A2
Smooth-Transition VAR Model Outputs.

Model	VIX Restricted	VIX Unrestricted	R2000VOL Restricted	R2000VOL Unrestricted	SP500VOL Restricted	SP500VOL Unrestricted
LogLikelihood	723.87	723.9	497.59	497.79	675.5	675.86
Transition_Point	76	76	76	76	176	176
Transition_Coefficient	2	2	1.5	1	2	2
Wald_Stat	0	0.06	0.01	0.41	0.49	1.16
Wald_p	0.99	0.81	0.94	0.52	0.48	0.28
B[1,1] (SE)	0.016 (0.001)	0.011 (0.008)	0.017 (0.001)	0.013 (0.006)	0.019 (0.001)	0.017 (0.003)
B[1,2] (SE)	0.000 (0.000)	0.012 (0.007)	0.000 (0.000)	0.010 (0.006)	0.000 (0.000)	0.008 (0.007)
B[2,1] (SE)	−0.013 (0.008)	−0.108 (0.053)	0.029 (0.020)	−0.193 (0.141)	0.014 (0.012)	−0.064 (0.071)
B[2,2] (SE)	0.133 (0.011)	0.080 (0.068)	0.320 (0.026)	0.254 (0.096)	0.189 (0.010)	0.179 (0.029)

Table A3
Forecast error variance decomposition for 60 months (Model: [USNI, VIX, SP500vol, R2000vol], recursive identification).

Horizon	Vix (%)	SP500vol (%)	R2000vol (%)
Initial (0)	0.02 %	0.87 %	0.97 %
1 month	0.79 %	0.46 %	1.53 %
2 months	2.33 %	0.45 %	1.77 %
6 months	2.66 %	0.33 %	2.15 %
1 year	3.07 %	0.31 %	2.18 %
2 years	3.75 %	0.64 %	2.20 %
5 years	4.50 %	1.15 %	2.25 %

(Fig. A1,Fig. A2,Fig. A3)

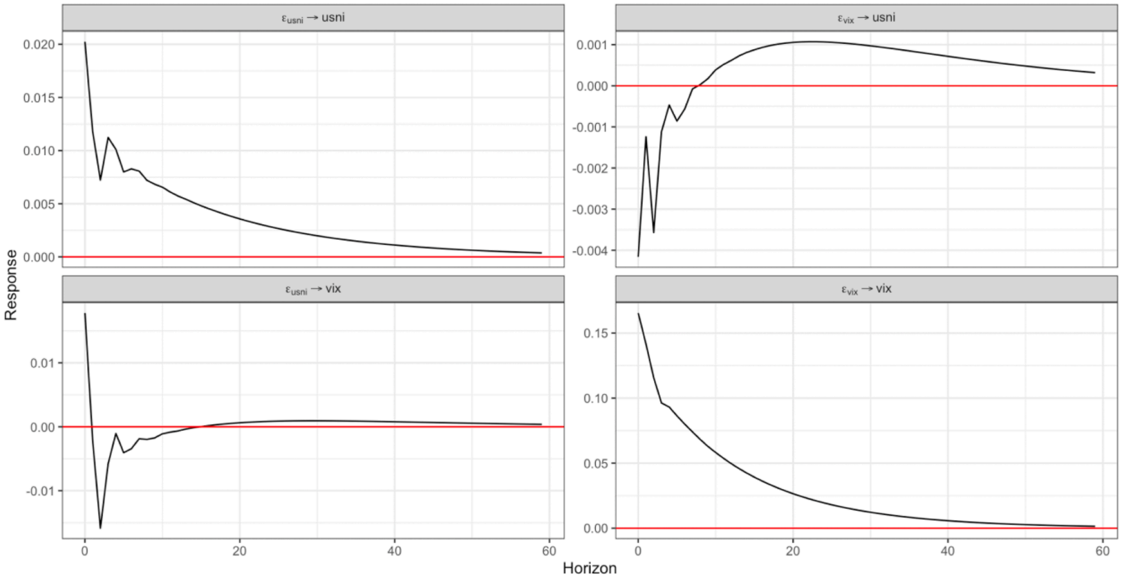

Fig. A1. Impulse responses of [USNI, VIX] structure without any zero restrictions.

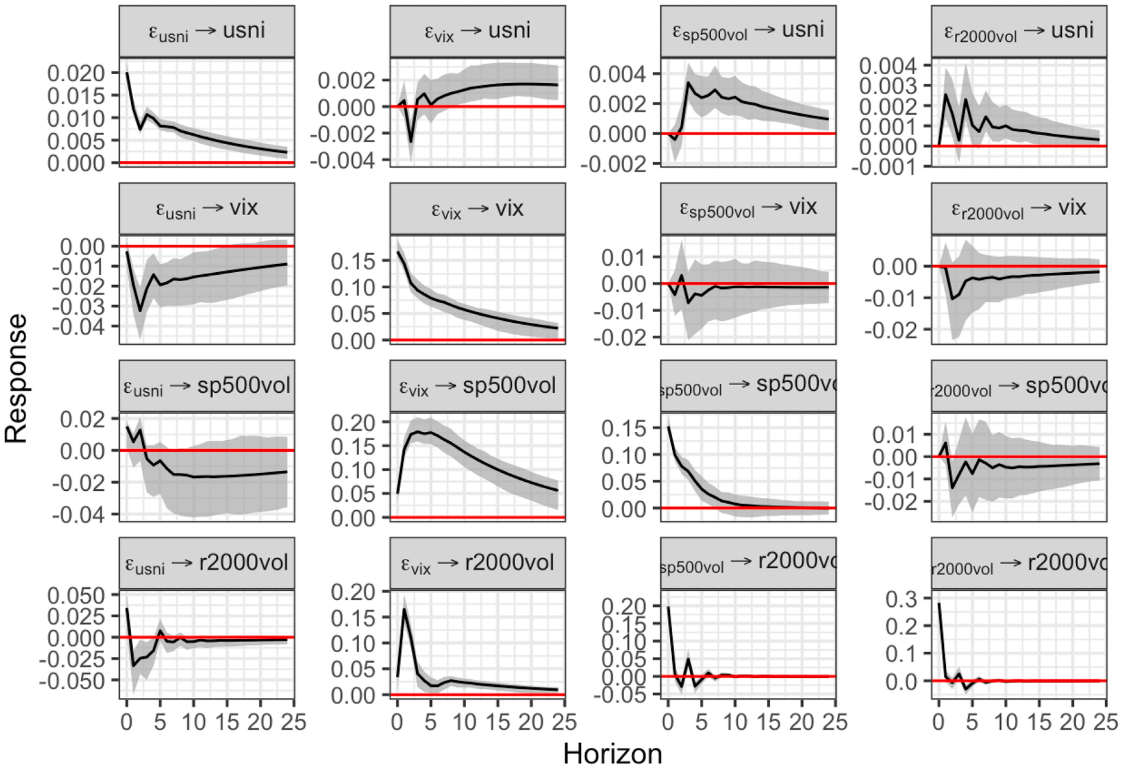

Fig. A2. IRF's Model [USNI, VIX, SP500vol, R2000vol].

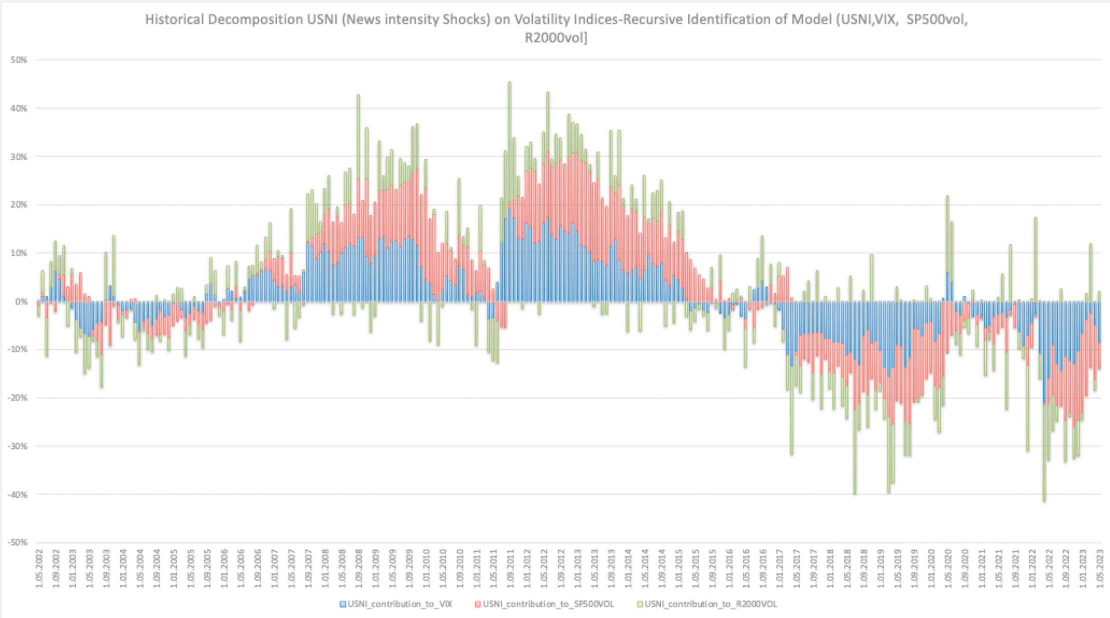

Fig A3. Historical Decomposition-Recursive Identification.

Data availability

Data will be made available on request.

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