Investor Sentiment and Market Volatility Nexus around the Globe: Term-structure, Transmission Networks, and Market Hierarchies

Jitender Soni[a,*], Pramod Kumar Naik[a]

[a]Indian Institute of Technology Madras, Chennai, 600036, TN, India

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ABSTRACT

This paper examines the term structure and dynamic transmission network of investor sentiment and market volatility across four global market segments (world, developed, emerging, and frontier) and six major regional equity markets. Using daily data from January 2010 to December 2025, we first estimate multi-horizon sentiment–return interaction models to investigate how aggregate and decomposed investor sentiment influences market volatility across alternative investment horizons. We then employ a Time-Varying Parameter Vector Autoregression (TVP-VAR) connectedness framework to analyze the evolving transmission of sentiment-driven volatility across global markets. The results reveal a pronounced horizon-dependent relationship between investor sentiment and market volatility. Investor sentiment reduces short-horizon volatility, but this stabilizing effect gradually weakens and becomes positive in several markets over longer investment horizons. Decomposing sentiment into bullish and bearish components further reveals significant asymmetric effects. The TVP-VAR analysis shows that developed markets act as the primary transmitters of sentiment-induced volatility shocks, while emerging and frontier markets mainly function as shock receivers. The QVAR framework confirms these findings across different market conditions. Overall, the study provides new evidence on the term structure of sentiment-driven volatility and its dynamic cross-market transmission, offering valuable insights for both market participants and policy makers.

1. Introduction

Research on the nexus between investor sentiment and equity market volatility has gained considerable attention and expanded significantly in recent years. In this paper, we consider investor sentiment and equity market volatility jointly to examine their relationship over a multi-horizon framework and dynamic transmission mechanism across global and regional markets. The motivation for analyzing sentiment and volatility jointly arises from their intrinsic interdependence, both within the individual market and across the international financial systems. Market volatility remains one of the most persistent and extensively studied phenomena in financial markets, playing a central role in contemporary finance research. Alongside, investor sentiment is widely recognized as a key behavioral factor influencing market volatility (Wang et al., 2006; Baker and Wurgler, 2007; Baker et al., 2012; Brown and Cliff, 2005), while heightened volatility may also reinforce shifts in investor sentiment (Baker and Wurgler, 2007; Verma and Soydemir, 2009; Da et al., 2015).

The behavioral finance literature established that investors characterized by overconfidence and excessive optimism often engage in aggressive trading activity, potentially generating synchronized market behavior and a herding effect that temporarily suppresses volatility (Barberis et al., 1998; Baker and Wurgler, 2006; Odean, 1998; Barber and Odean, 2001; Hirshleifer and Hong Teoh, 2003; Chiang et al., 2010; Sias, 2004). On the other hand, fear and pessimism may trigger disorderly selling pressures, thereby amplifying market fluctuations (Black, 1986; Barberis et al., 1998; Verma and Verma, 2007; Baker and Wurgler, 2007; Da et al., 2015; Shiller, 2000). Such behavioral responses reflect the influence of irrational trading decisions on asset price dynamics. However, the impact of irrational sentiment on volatility is unlikely to remain constant across different investment horizons. In the short term, a common optimistic sentiment may reduce price dispersion through coordinated trading and herding behavior, thereby lowering volatility (Naik and Soni, 2026). In contrast, over longer horizons, accumulated mispricing arising from excessive optimism may require correction, resulting in increased volatility as asset prices adjust toward their fundamental values (Yang and Gao, 2014; He et al., 2020). Therefore, identifying the term structure of sentiment-driven volatility is crucial for understanding how behavioral forces contribute to both temporary market calm and subsequent episodes of volatility in equity markets.

Secondly, given the well-established evidence that global financial markets are highly interconnected, sentiment shocks originating in one market can rapidly transmit to others through channels such as cross-border capital flows, investor portfolio rebalancing, and information spillovers (Diebold and Yilmaz, 2009; Baker et al., 2012; Bekaert et al., 2002; Baker et al., 2012; Bekaert et al., 2014; Forbes and Rigobon, 2002). However, the existing literature has largely examined investor sentiment as a predictor of asset returns or as a determinant of market-specific volatility. The possibility that irrational sentiment itself may represent a transmissible behavioral shock remains relatively unexplored. Investor

*Corresponding author

jsoni8600@gmail.com, hs23d021@smail.iitm.ac.in (J. Soni); pramod.iitm.ac.in (P.K. Naik)

https://www.linkedin.com/in/jitender-soni-phd/ (J. Soni); https://hss.iitm.ac.in/pramod-kumar-naik/ (P.K. Naik)

ORCID(s): 0009-0006-7771-7650 (J. Soni); 0000-0002-2806-874X (P.K. Naik)

sentiment may therefore spread across markets not only through its direct impact on asset prices but also as a behavioral mechanism that reshapes investors' expectations, risk perceptions, and trading decisions in interconnected markets. Examining the transmission of such behavioral shocks across the global equity network represents a distinct analytical challenge compared with conventional studies of return or volatility spillovers. As it shall require modeling sentiment and volatility as jointly endogenous variables within a dynamic interconnected system.

Furthermore, substantial cross-country differences in investor composition may influence both the magnitude of the sentiment–volatility relationship and the direction and intensity of behavioral shock transmission. For instance, Reuters reported that retail investors accounted for approximately 20–25% of trading activity in US equity markets in 2025, with their participation increasing to nearly 35% in April. In contrast, the 2016 annual report of the Shanghai Stock Exchange indicated that individual investors contributed around 85% of daily trading volume in China (Jones et al., 2025). Consistent with these structural differences, Chen et al. (2007) show that Chinese retail investors trade more frequently and aggressively than their US counterparts. Such variations in market participant composition imply that the influence of sentiment on volatility, as well as the direction and strength of behavioral contagion, may differ substantially across markets. Therefore, the structure of a market's investor base may determine not only the extent to which sentiment affects domestic volatility but also its role as a transmitter or receiver of behavioral shocks within the global financial network.

We aim to address these issues by examining the sentiment–volatility nexus and its cross-market transmission within a global framework. To achieve this objective, the analysis is conducted at both the *global* and *regional* levels using daily data from ten MSCI equity indices, representing four global market classifications (World, Developed, Emerging, and Frontier Markets) and six regional classifications (North America, Latin America, Europe, Middle East and Africa, Asia, and Pacific). This selection enables our study to draw inferences through both the market development status and geographical region lenses. Collectively, these indices cover 75 equity markets represented by MSCI.

We begin by examining the term structure of the sentiment effect on realized volatility by modeling a sentiment–return interaction model within a multi-horizon framework, following the state-dependent amplification mechanism proposed by He et al. (2020). Subsequently, we employ the Time-Varying Parameter Vector Autoregression (TVP-VAR) connectedness framework of Antonakakis et al. (2020) to trace the behavioral shock transmission network and identify the market classifications that serve as persistent transmitters and receivers of investor sentiment and market volatility shocks.

The study contributes to the expanding behavioral finance literature in several important ways. *First*, we extend the existing literature by providing evidence on the term structure of investor sentiment effects on realized volatility across global equity markets. Distinct from existing studies, such as Kumari and Mahakud (2015) and Kim and Ryu (2021), which examine limited investment horizons or individual markets, our study captures the dynamic evolution of sentiment-induced volatility effects across four global and six regional market classifications simultaneously, thereby providing insights into how the behavioral consequences of investor sentiment unfold over time. *Second*, we model investor sentiment and volatility as endogenous variables within a TVP-VAR framework, enabling us to examine how sentiment operates not only as a local determinant of volatility but also as a transmitted behavioral shock that propagates across the global equity market network. *Third*, the use of MSCI indices, as they are standardized according to market development classifications, enhances comparability across different market segments, while the use of daily technical indicators provides a high-frequency measure of investor psychology and market sentiment dynamics.

The remainder of the paper is structured in the following layout. Section 2 reviews the relevant literature. Section 3 describes the data and variable construction. Section 4 outlines the methodology. Section 5 presents and discusses the empirical results. Robustness of the results is checked in Section 6. Section 7 concludes with implications of the study.

2. Review of Literature

The literature examining the relationship between investor sentiment and financial market volatility has expanded substantially over the past three decades. This field has progressed from early theoretical frameworks on noise trading to a wide-ranging empirical body of research covering diverse markets, asset classes, and methodological approaches. In this section, we review the relevant literature aligned with the objectives of the present study. Accordingly, the literature review is structured around four interconnected strands of existing research: (i) the measurement of investor sentiment across global equity markets; (ii) the influence of sentiment on market conditions and financial stability; (iii) cross-market spillovers and transmission mechanisms; and (iv) the dynamic relationship between sentiment and volatility across developed and emerging equity markets.

Quantifying Investor Sentiment as variable

Investor sentiment broadly refers to investors' expectations about future returns and risks that are not fully explained by market fundamentals but are instead shaped by noise, emotions, and psychological biases. In this context, investor sentiment captures the collective optimism or pessimism of market participants regarding future market conditions. Behavioral finance literature emphasizes that this non-fundamental component of investor expectations can contribute to excessive volatility, persistent mispricing, and deviations from fundamental values (Baker and Wurgler, 2006; De Long et al., 1990).

Since investor sentiment is not directly observable, researchers have developed two broad approaches to its measurement: the bottom-up and top-down approaches. The bottom-up approach is primarily survey-based and measures sentiment by directly capturing investors' expectations and perceptions. Although this method provides a conceptually intuitive measure of sentiment, its availability is generally limited to lower frequencies, thereby restricting its suitability for analysing daily financial market dynamics.

The Top-down approach, formalized by Baker and Wurgler (2006, 2007), derives sentiment from market-based indicators that reflect aggregate investor behaviour. These indicators include closed-end fund discounts, IPO volume and initial returns, the equity share of new issues, and trading turnover, which collectively capture prevailing market sentiment. Typically, these proxies are regressed against market and macroeconomic fundamentals, and the residual component is interpreted as the irrational sentiment component associated with behavioural biases. The residual-based sentiment index has subsequently been widely adopted in empirical studies across different financial markets (Baker and Wurgler, 2006; Wang et al., 2006; Verma and Soydemir, 2009; Dash and Mahakud, 2012; Kumari and Mahakud, 2015; Naik and Padhi, 2016; Dash and Maitra, 2019; Yadav and Naik, 2024).

However, most of the Baker–Wurgler sentiment proxies are not available at a daily frequency, limiting their application in high-frequency financial market analysis. Consequently, recent studies have increasingly employed market-based technical indicators, such as the Relative Strength Index, Psychological Line Index, trading volume, adjusted turnover, and advance–decline ratio, which capture investor psychology, trading intensity, and market breadth on a daily basis (Yang and Zhou, 2015; Ryu et al., 2017; Kim and Ryu, 2021; Naik and Soni, 2026)

Investor Sentiment and Market Volatility

Investigating the relationship between investor sentiment and equity market volatility has been an intriguing area of inquiry within behavioral finance over recent decades. Early contributions by Brown and Cliff (2004), Baker and Wurgler (2006, 2007), Wang et al. (2006), and Verma and Verma (2007) established a positive association between contemporaneous sentiment and subsequent volatility, suggesting that collective investor irrationality can sow the seeds of future price instability. More recent studies, including Xie et al. (2023) and Gao et al. (2022), document similar evidence for the Chinese equity market. In the Indian context, several studies have reported a significant relationship between investor sentiment and market volatility (Dash and Mahakud, 2012; Kumari and Mahakud, 2015; Naik and Padhi, 2016; Haritha and Rishad, 2020; Chakraborty and Subramaniam, 2020; Naik and Soni, 2026). Specifically, Kumari and Mahakud (2015) demonstrate that sentiment possesses predictive power for realized volatility over shorter horizons, although evidence from studies such as Corsi (2009) indicates that this predictive ability may weaken as the measurement horizon extends. More recently, Naik and Soni (2026) examine the term structure of the sentiment–volatility relationship, highlighting the importance of considering investment horizons in understanding behavioral effects.

However, aggregate sentiment indices typically capture only the overall optimism or pessimism prevailing in the market and may mask the possibility that positive and negative sentiment states generate asymmetric consequences. Extending the De Long et al. (1990) noise-trader framework, He et al. (2020) develop an asymmetric setting in which optimistic sentiment stabilizes returns through the *Friedman effect*, whereas pessimistic sentiment increases volatility through the *create-space effect*. Subsequent evidence from Naik and Soni (2026) for the Indian market and Mili et al. (2024) during the COVID-19 period further supports this asymmetric mechanism, demonstrating that negative sentiment shocks induce larger and more persistent volatility responses than comparable positive shocks.

The state-dependent nature of the sentiment–volatility nexus is further documented by Yang and Copeland (2014) for UK equity markets and Bahloul and Bouri (2016) for US futures markets. These studies show that the impact of sentiment on volatility depends on prevailing market conditions, particularly the direction of contemporaneous returns. Such state dependence provides the behavioral foundation for incorporating an interaction term into the baseline framework of the present study.

Despite these advances, the existing literature has not examined the complete term structure of sentiment effects while simultaneously accounting for multiple investment horizons, decomposed sentiment components, and state-dependent transmission mechanisms within a global cross-market framework. The present study addresses this gap by mapping the broader behavioral dynamics of global investors across different market environments.

Cross-Market Sentiment Spillovers

The global, local, and contagion effects of investor sentiment were first examined systematically by Baker et al. (2012) for Canada, France, Germany, Japan, UK, and US markets. Liu et al. (2023) subsequently construct aggregate spillover indices across ten countries (the U.S., China, Japan, the U.K., Germany, Australia, South Korea, Spain, Brazil, and Mexico) over 2003–2020. Bathia et al. (2016) examine the transmission of US sentiment to G7 returns using a VAR framework. These studies confirm that sentiment is not a unique phenomenon limited to only a few markets. But the coverage is selective and leans towards developed segments.

The Sentiment shocks originating in one market rarely remain localized. Baker et al. (2012) describe sentiment as contagious, spreading quickly across borders through a few key channels. From an economic-theory lens, the first is capital mobility, as institutional investors shift funds internationally in response to changing sentiment, carrying optimism or pessimism with them (Broner et al., 2006; Forbes and Warnock, 2011; Bekaert et al., 2013). The second works through portfolio rebalancing, in which a price move in one market changes investors' risk exposure, pushing them to adjust holdings elsewhere to keep portfolios balanced (Markowitz, 1952; Kyle and Xiong, 2001; Kodres and Pritsker, 2002). Finally, when information is incomplete, sentiment itself becomes a signal (Diebold and Yilmaz, 2009; Barberis et al., 1998; Baker et al., 2012). Investors in one market read price movements and trading activity elsewhere as a clue for what to expect next.

Bekaert et al. (2014) address these channels and transmission devices as *wake-up call effect*, and argue that contagion is amplified by globalization. High-frequency information flows and the increasing dominance of algorithmic and institutional trading accelerate the synchronization of market reactions. From a behavioral finance perspective, herd behavior and correlated beliefs further strengthen this transmission mechanism, causing local sentiment shocks to evolve into broader global sentiment waves. These theoretical channels imply that investor sentiment is not merely a domestic behavioral construct but a transnational force capable of shaping global market dynamics.

However, the existing literature has predominantly examined investor sentiment as a predictor of returns and volatility rather than as a transmissible behavioral shock that propagates alongside volatility innovations. Furthermore, cross-market investigations have largely focused on developed economies, leaving an important unresolved question: which markets absorb and transmit these behavioral shocks once they propagate through the global financial system? To address these gaps, this study incorporates investor sentiment indices and volatility measures as jointly endogenous variables within a TVP-VAR framework, thereby conceptualizing irrational sentiment not merely as an explanatory factor for returns, but as a behavioral shock that both responds to and contributes to the evolution of volatility dynamics across markets.

Developed versus Emerging Equity Markets

A persistent finding in the international finance literature is that emerging and frontier equity markets behave differently from their developed counterparts. This is directly relevant to sentiment dynamics and our study. Bekaert and Harvey (1997) document that emerging market returns are more volatile and more sensitive to local conditions. In emerging markets, volatility display greater persistence and sharper episodic spikes than the faster mean-reverting patterns of developed markets. These structural differences partly reflect thinner investor bases, less developed derivatives markets, and greater dependence on cross-border capital flows. And all of these distinctions arguably increase vulnerability to externally originating behavioral shocks.

Some prior research confirms that sentiment effects are stronger in markets with high retail investor participation and limited institutional presence, consistent with the noise-trader mechanism (Schmeling, 2009; Zouaoui et al., 2011). Studies of individual emerging markets like India (Naik and Padhi, 2016; Haritha and Rishad, 2020; Yadav and Naik, 2024), China (He et al., 2020; Xie et al., 2023), South Africa (Rupande et al., 2019), and South Korea (Ryu et al., 2017) collectively show that irrational sentiment exerts a significant and asymmetric influence on both returns and volatility, with effects typically stronger than those in developed markets. However, these studies adopt a single-market or bilateral perspective and do not address the structural question of whether emerging markets are net importers of behavioral shocks from the global system.

The present study extends beyond the conventional single-market perspective by conceptualizing investor sentiment as a macro-financial phenomenon and examining the dynamics of irrational investor mood at both global and regional levels. Rather than treating markets as isolated entities, we view different market development tiers as interconnected behavioral systems within which sentiment and volatility shocks can propagate. Accordingly, this study provides a systematic comparative assessment of sentiment–volatility interactions across the entire market development spectrum and investigates whether the transmitter–receiver structures identified in the broader connectedness literature for returns and volatility also characterize the cross-market transmission of behavioral sentiment shocks.

3. Data and Variables

3.1. Data

Our dataset comprises four global (world, developed, emerging, and frontier) and six regional (North America, Latin America, Europe, Europe - Middle East - Africa, Asia, and Pacific) equity market indices, with the sample period extending from January 1, 2010, to December 31, 2025. This results in approximately 4,150 daily observations for each index. The data are obtained from the Bloomberg Terminal and MSCI Index Factsheets. Python and Microsoft Excel are employed for data preprocessing, management, and visualization, while RStudio, Stata, and EViews are utilized for statistical and econometric analyses.

The selected sample period encompasses a broad range of sentiment-relevant market anomalies and major global economic and financial events. Specifically, the period captures the post-global financial crisis (GFC) recovery phase (2010–2012), the Eurozone Debt Crisis and the US Taper Tantrum (2013), the Chinese equity market crash and Brexit referendum (2015–2016), the COVID-19 pandemic shock (2020), the global inflation surge and monetary policy tightening cycle (2021–2022), the Russia–Ukraine conflict (2022), and the subsequent phase of elevated geopolitical and trade-policy uncertainty during 2024–2025. These episodes differ substantially in their underlying sources, transmission mechanisms, and market responses, potentially generating heterogeneous patterns of investor sentiment spillovers and volatility transmission across equity markets. Accordingly, the 2010–2025 sample period provides an appropriate empirical setting for examining dynamic connectedness within and across structurally distinct market regimes.

The *Morgan Stanley Capital International* (MSCI), classifies the global equity markets into *Developed*, *Emerging*, *Frontier*, and *Standalone Markets* based on economic development, market size and liquidity, and accessibility

Table 1
Selected MSCI Equity Indices

MSCI Index (Abbreviation)	Markets Covered	Constituents	MCap ($ Mil)
All Country World Index (WLD)	47 Developed+Emerging	2,517	93,122,804.78
World Index (DM)	23 Developed	1,320	82,893,361.39
Emerging Markets Index (EM)	24 Emerging	1,197	10,229,443.38
Frontier Markets Index (FM)	28 Frontier	247	191,403.79
North America Index (NA)	2 Developed	627	62,437,313.09
Latin America Index (LA)	5 Emerging	86	749,967.07
Europe Index (EU)	15 Developed	403	13,615,348.80
Europe-Middle East-Africa Index (EMEA)	11 Emerging	145	1,234,881.86
Asia Index (AS)	8 Emerging	966	8,244,594.45
Pacific Index (PC)	5 Developed	275	6,617,863.89

Source: MSCI Index Factsheets as of December 31, 2025

to international investors. The methodology is designed to capture approximately 85% of the free-float-adjusted market capitalization of each market through large- and mid-cap securities within a consistent and globally comparable framework.

Unlike country-specific benchmarks such as the NIFTY 50, S&P 500, Nikkei 225, and FTSE 100, MSCI indices provide broader and more comparable cross-market coverage by applying uniform criteria for security selection, classification, weighting, and rebalancing across countries. This consistency makes MSCI indices particularly suitable for examining international patterns of investor sentiment and volatility spillovers.

Building on this classification framework, our study investigates the sentiment–volatility relationship from an aggregate macro-financial perspective by treating each MSCI market category as a representative indicator of a broader stage of equity market development. Accordingly, the analysis incorporates four global-level and six regional MSCI indices, with all index values denominated in US dollars to ensure cross-market comparability.

Our study investigates the sentiment–volatility relationship from an aggregate macro-level perspective. We treat each MSCI classification as a representative measure of a broader stage of equity market development. Accordingly, the analysis incorporates four global-level and six regional MSCI indices, with all index values expressed in USD. Table 1 provides a detailed list of indices examined in the study.

3.2. Variables

We use three types of variables for our analysis: i) *sentiment proxies*, from which the irrational sentiment index is constructed; ii) *market fundamentals*, used to purge rationally driven variation from those proxies; and iii) *realized volatility* measures, which serve as the dependent variable in the term-structure analysis and endogenous series in the TVP-VAR connectedness framework. A detailed description of all three is provided in Table 2.

As discussed in Section 2, the existing literature employs either bottom-up or top-down approaches to construct investor sentiment measures, depending on the objectives and context of the study. In this study, we adopt a top-down sentiment measurement approach, broadly following the framework proposed by Baker and Wurgler (2006). This approach has been extensively utilized in investor sentiment research over the past two decades (Wang et al., 2006; Qiang and Shu-e, 2009; Kumari and Mahakud, 2015; Naik and Padhi, 2016; Haritha and Rishad, 2020). However, most market-based sentiment proxies developed under this framework are available only at monthly frequencies, which limits their applicability in high-frequency analyses. Since our study employs daily data, we construct a comparable sentiment measure using market-based technical indicators that are available at the daily frequency. Specifically, we incorporate the Relative Strength Index (RSI), Psychological Line Index (PSY), Trading Volume (VOL), Average Turnover Rate (ATR), and the advance–decline line, following prior studies such as (Yang and Zhou, 2015; Ryu et al., 2017; Kim and Ryu, 2021; Naik and Soni, 2026).

The index-based fundamental variables—including lagged returns, log market capitalization, dividend yield, P/E ratio, forward P/E, and price-to-book ratio—capture key dimensions of market fundamentals, such as momentum, market size, expected cash flows, and valuation conditions, which may contribute to rational fluctuations in observed sentiment proxies (Baker and Stein, 2004; Fama and French, 1993; Campbell and Shiller, 1988b,a; La Porta, 1996). Accordingly, these variables are incorporated as control factors to separate the fundamental-driven component of sentiment from its non-fundamental or irrational component, thereby allowing us to obtain a cleaner measure of investor sentiment.

Realized (historical) volatility measures over six rolling horizons (V10–V360) serve as the dependent variables in the term-structure regression models and as the endogenous volatility indicator in the TVP-VAR framework. Each volatility series is computed by Bloomberg as the annualized standard deviation of daily logarithmic returns over the corresponding lookback window N:

$$V_t^N = \sqrt{\frac{252}{N-1} \times \sum_{n=0}^{N-1} \left(\ln\left(\frac{I_{t-n}}{I_{t-n-1}}\right) - \frac{1}{N} \sum_{m=0}^{N-1} \ln\left(\frac{I_{t-m}}{I_{t-m-1}}\right) \right)^2} \tag{1}$$

where I_{t-n} and I_{t-n-1} are consecutive daily index levels, and the scalar 252 annualizes the variance. The six measures correspond to $N \in \{10, 30, 60, 90, 180, 360\}$.

4. Methodology

As mentioned earlier, our study examines the impact of investor sentiment on global and regional equity market volatility across different time horizons, as well as the transmission of sentiment and volatility shocks across markets. To achieve this objective, we proceed in the following four stages.

4.1. Irrational Sentiment

We employ five sentiment proxies in our studies as shown in Table 1 (Panel A). These variables are assumed to capture the overall daily raw sentiment prevailing in the market for each equity index. However, raw sentiment proxies may contain both

Table 2
List of Variables

Category	Variable	Definition / Formula	Key References
Panel A: Sentiment Proxies (daily; at level; Bloomberg)			
Implicit market-based sentiment proxies (top-down)	Relative Strength Index	$RSI_t = 100 \times RS_t / (1 + RS_t)$, where RS_t is the 14-day ratio of average gains to average losses (Chong et al., 2014). Values > 50 indicate gains dominating; ≥ 70 overbought; ≤ 30 oversold.	Yang and Zhou (2015); Ryu et al. (2017)
	Psychological Line Index	$PSY_t = (T^u/T) \times 100$, where T^u is the number of index price up-closes over a 12-day window T. Values ≥ 75 (≤ 25) signal optimism (pessimism).	Yang and Zhou (2015); Ryu et al. (2017); Kim and Ryu (2021); Mili et al. (2024)
	Adjusted Turnover Rate	$ATR_t = \frac{R_t}{\lvert R_t \rvert} \times \frac{\text{Traded Value}_t}{\text{Market Cap}_t}$, where R_t is the daily return. Sign-adjusts turnover by market direction to capture trading intensity relative to price movements. Traded value replaces volume due to data constraints.	Yang and Zhou (2015); Ryu et al. (2017)
	Log Trading Volume	$VOL_t = \ln(\text{Trading Volume}_t)$. Log-transformation reduces skewness; volume reflects the level of market participation and noise-trading activity.	Baker and Stein (2004)
	Advance-Decline Line	Daily net change in the cumulative difference between advancing and declining index constituents. Captures market-breadth dynamics absent from price-based proxies. The ADL is used in place of the advance-decline ratio due to data availability at the MSCI index level.	Brown and Cliff (2004); Kumari and Mahakud (2015); Naik and Soni (2026)
Panel B: Equity Market Fundamentals (lagged one day; Bloomberg & MSCI Factsheets)			
Rational controls for irrational sentiment extraction	**Return**	Lagged daily log return: $\ln(P_t/P_{t-1})$. Controls for the momentum feedback through which past returns rationally reinforce sentiment.	Baker and Stein (2004); Baker and Wurgler (2006)
	LogMCAP	Lagged log of free-float market capitalization: $\ln\left(\sum_i P_{i,t} \times S_{i,t}^{\text{float}}\right)$. Controls for size-related fundamental effects.	Fama and French (1993); Ryu et al. (2017)
	DivYld	Aggregate dividend yield: D_t/P_t. Captures fundamental cash-flow expectations and rational discount-rate variation.	Campbell and Shiller (1988b)
	PER	Price-to-earnings ratio: $\text{Price}_t/\text{Earnings}_t$ (aggregate weighted-average across index constituents). Reflects current-earnings valuation and information-driven pricing.	Campbell and Shiller (1988a)
	PE_Fwd	Forward P/E: $\text{Price}_t/\text{Expected Earnings}_{t+1}$. Forward-looking valuation controlling for analysts' rational earnings expectations.	La Porta (1996)
	PBR	Price-to-book ratio: $\text{Market Value}_t/\text{Book Value}_t$ (free-float-weighted aggregate reported by MSCI). Captures accounting-based valuation and structural risk premia.	Fama and French (1993)
Panel C: Realized Volatility (Bloomberg; annualized %)			
Rolling window (historical) volatility	**V10, V30** Short horizon	Annualized std. dev. of daily log returns over the past 10 and 30 trading days (see Eq. 1). Sensitive to immediate shocks, liquidity events, and news arrival.	Naik and Soni (2026)
	V60, V90 Medium horizon	Lookback windows of 60 and 90 trading days. Capture sustained repricing of risk following macroeconomic developments.	Naik and Soni (2026)
	V180, V360 Long horizon	Lookback windows of 180 and 360 trading days. Reflect structural, persistent volatility states associated with business-cycle fluctuations and macro-financial regime shifts.	Bekaert and Harvey (1997)

Source: Author's own work

rational and irrational components. The rational component reflects investors' responses to information related to the fundamental characteristics of a stock, index, or market as a whole. In contrast, the irrational component arises from behavioral biases, heuristics, and non-fundamental influences, consistent with the perspectives of behavioral finance and economics.

Since our study focuses on the irrational component of investor sentiment, following Baker and Wurgler (2006) and Verma and Soydemir (2009), we isolate the irrational sentiment component by removing the variation in each proxy that can be explained by market fundamentals. Specifically, each underlying index-related implicit sentiment proxy is regressed on a set of key index fundamentals at lag $(t-1)$, as reported in Table 1 (Panel B). Accordingly, letting $x_{j,t}$ denote the j-th sentiment proxy at time t, where $j \in \{RSI, PSY, ATR, VOL, ADL\}$, we isolate the irrational component by running the following regression for each proxy:

$$x_{j,t} = \alpha_{j,0} + \sum_{k=1}^{K} \beta_{j,k}\, \text{Funda}_k + \varepsilon_{j,t} \tag{2}$$

where, α is a proxy-specific constant, β are the estimated coefficients, and $\varepsilon_{j,t}$ is the error term. The vector of fundamentals is given by:

$$\text{Funda}_k = \big(Return_{t-1}, LogMCAP_{t-1}, DivYld_{t-1}, PER_{t-1}, PE^{Fwd}_{t-1}, PBR_{t-1}\big)$$

The residuals from Equation (2), $\hat{\varepsilon}_{j,t}$, are purged of rationally driven variation and are therefore interpreted as the irrational sentiment proxies (Verma and Soydemir, 2009).

$$X_{i,t} = \hat{\varepsilon}_{i,t} \tag{3}$$

These residuals are interpreted as orthogonalized irrational sentiment proxies ($X_{i,t}$) and are subsequently used to construct the composite sentiment index and for further empirical analysis.

4.2. Sentiment Index with Principal Component Analysis

Having obtained the orthogonalized (irrational) sentiment proxies $X_{i,t}$ ($\hat{\varepsilon}_{i,t}$) for each implicit proxy $i \in \{$ADL, ATR, VOL,

Table 3
PCA Results for Global and Regional Equity Markets

Market	Eigenvalue	Variance (%)
WLD	2.20824	44.16
DM	2.32932	46.59
EM	2.01460	40.29
FM	2.23988	44.80
NA	2.28111	45.62
LA	2.22465	44.49
EU	2.21958	44.39
EMEA	2.25341	45.07
AS	2.22177	44.44
PC	2.24403	44.88

Source: Author's own work

PSY, RSI} from Eq. (2), we construct a composite irrational investor sentiment index using Principal Component Analysis (PCA) for all MSCI indices. PCA is a widely used approach in the investor sentiment literature and popularized by Baker and Wurgler (2006). By concentrating the maximum information content into a smaller number of components, PCA identifies the underlying latent structure within the data, making it particularly suitable for constructing composite indices. This process combines multiple behavioral and market-based indicators into a single representative measure. PCA reduces the dimensionality of these proxies into a single composite index while maximizing the proportion of explained variance, thereby minimizing the need for arbitrary weighting of individual sentiment measures (Baker and Wurgler, 2006).

The first principal components obtained using PCA for all global and regional equity indices are quite significant and account for approximately 45% of the total variance in the five-sentiment proxy data set. Hence, following the thumb rule, we retain only the first principal component (Comp1) to construct the sentiment index across all MSCI equity indices. Using the Stata `predict` command, the composite irrational investor sentiment index ($SENTI_t$) is constructed as the score on:

$$SENTI_t = \sum_{i=1}^{5} v_{i,1} X_{i,t} \tag{4}$$

where $v_{i,1}$ denotes the factor loading (eigenvector $\mathbf{v}_1$) of the i-th standardized proxy on the first principal component (Comp1). A higher (positive) value of $SENTI_t$ reflects greater irrational bullish sentiment, while lower (negative) values reflect irrational bearish sentiment, consistent with the interpretation in Baker and Wurgler (2006) and Verma and Soydemir (2009).

Table 3 reports the PCA estimates obtained from STATA, providing Eigenvalues and Variance Contribution coefficients for Principal Component 1 (Comp1) of all five implicit market sentiment proxies for each MSCI equity index.

4.3. Sentiment-Volatility Nexus

We examine the relationship between investor sentiment and market volatility in two complementary steps, as discussed below. Together, the two methods allow us to assess both the magnitude and the direction of the term structure and asymmetry in the sentiment-volatility relationship across the globe. The models are estimated for each market $i \in$ {WLD, DM, EM, FM, NA, LA, EU, EMEA, AS, PC} and each horizon $N \in \{10, 30, 60, 90, 180, 360\}$, yielding 60 regressions each for global and regional classifications.

Aggregate Sentiment Effects

To examine the relationship between aggregate irrational investor sentiment and market volatility, we estimate the following model:

$$V_t^N = \alpha + \beta_1\, \mathrm{SENTI}_t + \beta_2\, R_t + \beta_3 \left(\mathrm{SENTI}_t \times R_t\right) + \varepsilon_t \tag{5}$$

where, V_t^N is the N-day rolling realized volatility (Eq. (1)) for a respective market at time t; SENTI_t is the composite irrational sentiment index with positive (negative) values reflecting bullish (bearish) mood; R_t is the contemporaneous daily log return; and ε_t is the error term.

The sentiment index (SENTI_t) is a contemporaneous, real-time measure. On day t, it captures the aggregate irrational mood of the market, where positive values indicate bullish conditions, negative values indicate bearish conditions. It has no memory of prior days and it is a snapshot of the prevailing market psychology. The realized volatility measure (V_t^N) is a backward-looking rolling measure. On day t, it records the annualized standard deviation of daily log returns over the N trading days ending at t.

In Eq. (5), β_3 captures how the sentiment-volatility association is amplified or dampened depending on the concurrent return direction (market state). The return term $\beta_2 \cdot R_t$ accounts for the fundamental price movement entering the window on day t, since today's return is one of the N constituent observations of V_t^N. It represents the rational, information-driven component of any contemporaneous change in the rolling measure. Our focus is $\beta_1 \cdot \mathrm{SENTI}_t$, that represent the sentiment-associated increment. The portion of the current rolling volatility level linked to today's irrational market mood, conditional on both the window's historical level and today's fundamental return. In this sense, β_1 approximates the *sentiment-specific* component of realized volatility, the excess variation associated with irrational market mood beyond what mechanical window persistence and fundamental price movements already explain.

It should be noted that this regression identifies contemporaneous association, not causal direction, documenting the association and its term structure, which is a well-established empirical exercise in the sentiment literature (Wang et al., 2006; Kumari and Mahakud, 2015; He et al., 2020). The contemporaneous sentiment-return interaction term is included because the sentiment-volatility association is not constant across market states. He et al. (2020) formally show that optimistic sentiment behaves differently under rising markets than under falling ones, and pessimistic sentiment amplifies volatility through a mechanism conditioned on the prevailing return environment.

Sentiment Decomposition

The baseline interaction model, as shown in Eq. (5), treats aggregate irrational sentiment symmetrically. The same coefficient governs both bullish and bearish episodes. Therefore, as an extension, we decompose the sentiment index into positive and negative components following Naik and Padhi (2016) and Naik and Soni (2026). This allows us to assess whether the two sentiment states carry additional information about the direction and magnitude of the volatility association. The extended regression specification is:

$$V_t^N = \alpha + \beta_1^{+}\, SENTI_t^{+} + \beta_1^{-}\, SENTI_t^{-} + \beta_2\, R_t + \varepsilon_t \tag{6}$$

where, $SENTI_t^+ = ((SENTI_t)^2 \times D_t)$ and $SENTI_t^- = ((SENTI_t)^2 \times (1-D_t))$. D_t denotes a dummy variable that equates to 1 when the investor sentiment index ($SENTI_t$) is positive and 0 when it is negative. Both decomposed series enter the model with positive signs, so β_1^+ and β_1^- are directly comparable in magnitude. A finding of $\beta_1^- > \beta_1^+$ constitutes the evidence of asymmetry, which is that bearish irrational sentiment is more strongly associated with volatility than an equivalent magnitude of bullish irrational sentiment.

4.4. TVP-VAR Connectedness Framework

To examine the dynamic transmission of investor sentiment and realized volatility across global and regional equity market segments, we employ the Time-Varying Parameter Vector Autoregression (TVP-VAR) connectedness framework of Antonakakis et al. (2020), which extends the generalized forecast error variance decomposition (GFEVD) approach of Diebold and Yilmaz (2012, 2014) to a time-varying setting. The RStudio `ConnectednessApproach` package is used to run the model. TVP-VAR(1) model specification is as follows.

TVP-VAR Model

Let $\mathbf{y}_t = (y_{1t}, y_{2t}, \dots, y_{kt})'$ be a $k \times 1$ vector of endogenous variables at time t, comprising the sentiment indices and realized volatility series for each market classification. The TVP-VAR(p) model, with $p = 1$ for parsimony, is given by

$$\begin{aligned} \mathbf{y}_t &= \mathbf{c}_t + \mathbf{B}_{1,t}\,\mathbf{y}_{t-1} + \boldsymbol{\varepsilon}_t, \qquad \boldsymbol{\varepsilon}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{S}_t), \\ \boldsymbol{\beta}_t &= \boldsymbol{\beta}_{t-1} + \mathbf{u}_t, \qquad \mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}) \end{aligned} \tag{7}$$

where $\mathbf{B}_{1,t}$ is the time-varying $k \times k$ coefficient matrix, $\mathbf{S}_t$ is the time-varying error covariance matrix, $\boldsymbol{\beta}_t = \mathrm{vec}([\mathbf{c}_t, \mathbf{B}_{1,t}]')$ evolves as a driftless random walk, and $\mathbf{S}_t$ is updated via an exponentially weighted moving average (EWMA) with forgetting factor $\kappa = 0.96$. This formulation avoids the arbitrary window selection of rolling-window VAR estimators while preserving full-sample information at each point in time.

Generalized Forecast Error Variance Decomposition

Connectedness measures are derived from the H-step-ahead GFEVD of Koop et al. (1996) and Pesaran and Shin (1998), which is preferred over the Cholesky-based FEVD because it is invariant to variable ordering. The normalized GFEVD element $\tilde{\varphi}_{ij,t}^{(H)}$ gives the share of the forecast error variance of variable i attributable to shocks in variable j at time t:

$$\tilde{\varphi}_{ij,t}^{(H)} = \frac{s_{jj,t}^{-1} \sum_{h=0}^{H-1} \left(\mathbf{e}_i' \mathbf{A}_{h,t} \mathbf{S}_t \mathbf{e}_j\right)^2}{\sum_{h=0}^{H-1} \mathbf{e}_i' \mathbf{A}_{h,t} \mathbf{S}_t \mathbf{A}_{h,t}' \mathbf{e}_i}, \qquad \sum_{j=1}^{k} \tilde{\varphi}_{ij,t}^{(H)} = 1 \tag{8}$$

where $\mathbf{e}_i$ is a selection vector and $s_{jj,t}$ is the (j,j) element of $\mathbf{S}_t$. We set $H = 10$ to capture short- to medium-run spillovers.

Connectedness Measures

From $\tilde{\boldsymbol{\Phi}}_t^{(H)} = [\tilde{\varphi}_{ij,t}^{(H)}]$, we construct the total connectedness index (TCI), directional spillovers transmitted (TO) and received (FROM), and the net position (NET) at each t:

$$\begin{aligned} \mathrm{TCI}_t^{(H)} &= 1 - \frac{1}{k}\sum_{i=1}^{k} \tilde{\varphi}_{ii,t}^{(H)}, \qquad C_{i\to\bullet,t}^{(H)} = \frac{1}{k}\sum_{\substack{j=1\\ j\neq i}}^{k} \tilde{\varphi}_{ji,t}^{(H)}, \\ C_{\bullet\to i,t}^{(H)} &= \frac{1}{k}\sum_{\substack{j=1\\ j\neq i}}^{k} \tilde{\varphi}_{ij,t}^{(H)}, \qquad C_{i,t}^{\mathrm{NET},(H)} = C_{i\to\bullet,t}^{(H)} - C_{\bullet\to i,t}^{(H)} \end{aligned} \tag{9}$$

where TCI captures system-wide interdependence, and a positive (negative) $C_{i,t}^{\mathrm{NET}}$ identifies market i as a net transmitter (receiver) of shocks.

5. Empirical Results and Discussion

5.1. Descriptive Statistics and Trends

Tables 4 and 5 report the descriptive statistics, ADF unit-root test results, and pairwise correlation coefficients for the global and regional sentiment and volatility series, respectively. All series are stationary at levels, validating their direct use in both the regression and TVP-VAR frameworks.

It is important to keep in mind the distinct nature of the two variables when interpreting the descriptive statistics. The sentiment index represents a real-time daily measure, where a positive value on day t reflects a bullish aggregate market sentiment, whereas a negative value indicates bearish market conditions. On the other hand, V10 volatility series (only V10 is reported for brevity) is a backward-looking rolling measure that captures the magnitude of index price fluctuations over the previous ten trading days ending at t, reported as an annualized percentage. Since both variables are measured contemporaneously, a negative unconditional correlation suggests that periods of greater optimism are generally associated with lower recent price volatility. This serves as an initial indication of the noise-trader stabilization mechanism proposed by (De Long et al., 1990) for our study.

At the global level, the correlation coefficient of 0.96 between World (WLD) and Developed markets (DM) sentiment confirms that global sentiment cycles are largely driven by developed-market investor sentiment. Emerging markets (EM) sentiment correlates moderately with WLD (0.65) and DM (0.53). Frontier markets (FM) sentiment shows the lowest cross-market correlations (0.38–0.40), reflecting the relatively thin and less integrated nature of such markets in the global sentiment dynamics. On the volatility side, EM has the highest mean (14.25), consistent with greater persistence and extreme episodic spiking in emerging-market price variation, as documented by Bekaert and Harvey (1997). FM volatility is the lowest on average (8.03) but registers the widest tail spikes, driven by illiquidity rather than sustained instability. Unconditional sentiment-volatility correlations are uniformly negative across all global pairs (−0.09 to −0.22).

At the regional level, North America (NA) co-moves most closely with Europe (EU) ($r = 0.59$), reflecting tight financial linkages among the two clusters of the largest developed equity markets worldwide. Asia (AS) and Pacific (PC) display the lowest cross-regional correlations, possibly indicating partial decoupling of East Asian market mood from Western cycles.

On the volatility front, Latin America (LA) stands out with the highest mean (21.49). Its sample maximum of 160.26, registered during the March 2020 COVID-19 shock, is the largest V10 value in the entire dataset. March 2020 spikes are a concrete illustration of how sharply a short-horizon rolling measure spikes when a burst of extreme price variation enters a ten-day window. NA (14.23) and

Table 4
Descriptive Statistics, Stationarity and Correlation Matrix — Global

Panel A: Descriptive Statistics and Stationarity Test

Variable	Mean	Std. Dev.	Min	Max	ADF Stat.	p-value	Stationarity
WLD_SENTI	0.00732	1.43755	-6.37783	5.0789	-11.66	0.00	I(0)
DM_SENTI	0.01174	1.43815	-6.01037	4.6265	-11.25	0.00	I(0)
EM_SENTI	0.00856	1.49825	-6.26785	4.77576	-10.63	0.00	I(0)
FM_SENTI	0.02243	1.44026	-5.44715	6.50706	-9.46	0.00	I(0)
WLD_V10	11.98329	8.01772	2.00	101.6	-6.74	0.00	I(0)
DM_V10	12.43112	8.48012	2.16	107.51	-6.68	0.00	I(0)
EM_V10	14.24728	7.17936	3.54	76.89	-7.1	0.00	I(0)
FM_V10	8.02907	5.01962	1.59	72.41	-8.51	0.00	I(0)

Panel B: Correlation Matrix

	WLD_SENTI	DM_SENTI	EM_SENTI	FM_SENTI	WLD_V10	DM_V10	EM_V10	FM_V10
WLD_SENTI	1.00							
DM_SENTI	0.96055	1.00						
EM_SENTI	0.65335	0.52777	1.00					
FM_SENTI	0.40054	0.37570	0.39336	1.00				
WLD_V10	-0.18173	-0.21967	-0.09857	-0.22734	1.00			
DM_V10	-0.18033	-0.21872	-0.09398	-0.21864	0.99739	1.00		
EM_V10	-0.15683	-0.18926	-0.10496	-0.22601	0.83007	0.80339	1.00	
FM_V10	-0.14149	-0.15740	-0.09889	-0.20213	0.64708	0.64327	0.58168	1.00

Source: Author's own work

Table 5
Descriptive Statistics, Stationarity and Correlation Matrix — Regional

Panel A: Descriptive Statistics and Stationarity Test

Variable	Mean	Std. Dev.	Min	Max	ADF Stat.	p-value	Stationarity
NA_SENTI	0.01997	1.46398	-5.22396	3.54059	-9.59000	0.00	I(0)
LA_SENTI	0.01909	1.49131	-5.38336	4.30752	-10.52000	0.00	I(0)
EU_SENTI	-0.01104	1.37851	-4.79002	3.29940	-11.11000	0.00	I(0)
EMEA_SENTI	-0.00191	1.44204	-4.29092	4.74363	-11.84000	0.00	I(0)
AS_SENTI	-0.00905	1.51699	-6.35922	4.90625	-10.46000	0.00	I(0)
PC_SENTI	-0.00681	1.46962	-5.18944	3.68244	-11.08000	0.00	I(0)
NA_V10	14.22641	10.20878	2.34000	127.82000	-7.73000	0.00	I(0)
LA_V10	21.48968	11.57399	3.50000	160.26000	-8.29000	0.00	I(0)
EU_V10	16.27223	9.54436	2.72500	96.31040	-6.20000	0.00	I(0)
EMEA_V10	17.70888	9.81655	1.55860	85.48230	-6.94000	0.00	I(0)
AS_V10	15.35166	7.48472	3.33180	75.12830	-7.50000	0.00	I(0)
PC_V10	14.72887	7.33807	2.24920	77.78270	-8.39000	0.00	I(0)

Panel B: Correlation Matrix

	NA_SENTI	LA_SENTI	EU_SENTI	EMEA_SENTI	AS_SENTI	PC_SENTI	NA_V10	LA_V10	EU_V10	EMEA_V10	AS_V10	PC_V10
NA_SENTI	1.0000											
LA_SENTI	0.4619	1.0000										
EU_SENTI	0.5948	0.5118	1.0000									
EMEA_SENTI	0.4402	0.5794	0.6372	1.0000								
AS_SENTI	0.3327	0.3929	0.4528	0.5192	1.0000							
PC_SENTI	0.3466	0.3352	0.4619	0.4245	0.5671	1.0000						
NA_V10	-0.2341	-0.0558	-0.1980	-0.1353	-0.1310	-0.2008	1.0000					
LA_V10	-0.1653	-0.0867	-0.1712	-0.0873	-0.1321	-0.1818	0.7528	1.0000				
EU_V10	-0.1700	-0.0539	-0.1611	-0.1108	-0.1098	-0.1685	0.7713	0.6642	1.0000			
EMEA_V10	-0.1524	-0.0890	-0.1637	-0.0991	-0.1279	-0.1719	0.6162	0.6690	0.7805	1.0000		
AS_V10	-0.1432	-0.0478	-0.1388	-0.1033	-0.1008	-0.1610	0.7237	0.6108	0.7165	0.6395	1.0000	
PC_V10	-0.1186	-0.0153	-0.1079	-0.0348	-0.0682	-0.1350	0.6327	0.5017	0.6271	0.5405	0.6884	1.0000

Source: Author's own work

PC (14.73) are the calmest on average, reporting the stability of developed equity markets. Regional sentiment-volatility correlations (−0.02 to −0.23) reinforce the same short-run stabilization pattern observed at the global level.

Figs. 1–2 and Figs. 3–4 plot the full-sample trajectories of sentiment and volatility dynamics for global and regional segments, respectively. The sentiment series shows clear directional swings around the major disruption episodes (the 2013 Taper Tantrum, the 2015 Chinese market crash, the 2016 Brexit referendum, the March 2020 COVID-19 collapse, etc.), each of which corresponds to a discrete spike in the V10 plots. The simultaneous collapse of sentiment and surge in ten-day rolling volatility during these episodes reflects the tight temporal alignment between real-time market mood and short-horizon realized price variations.

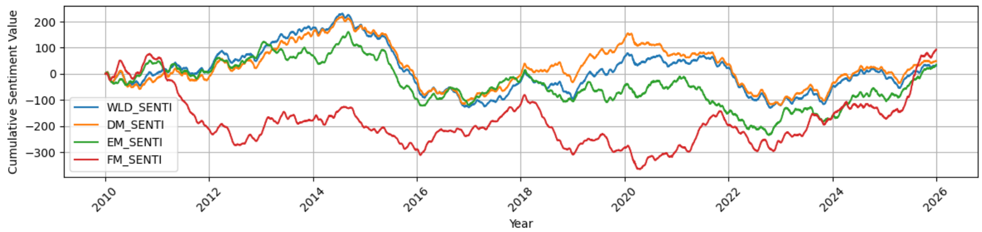


Figure 1: Global Sentiment Trends

Source: Author's own work

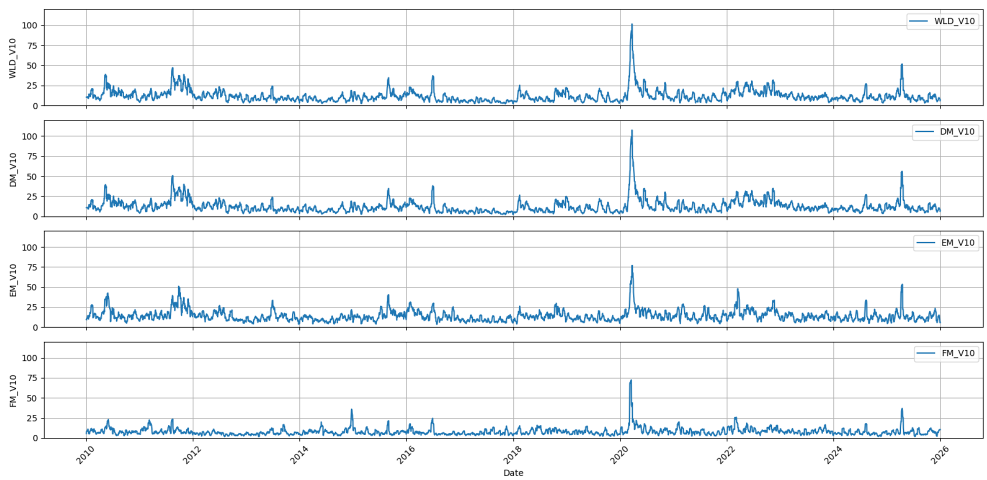


Figure 2: Global Volatility Dynamics

Source: Author's own work

5.2. Sentiment–Volatility Nexus

The results from sentiment-return-volatility interaction model (Eq. 5) are reported in Table 6, and the $\hat{\beta}_1$ coefficients for SENTI are plotted in Figure 5. The coefficient moves through three distinct phases across the term structure, and the results can be discussed as short-horizon compression, medium-horizon adjustment, and long-horizon reversal in several markets.

Short Horizon (V10–V30)

The coefficient of SENTI at the 10-day (V10) horizon is negative and highly significant across all ten markets, indicating that periods of heightened irrational optimism (pessimism) are associated with lower (higher) rolling volatility at the shortest horizon examined. According to De Long et al. (1990), collectively bullish

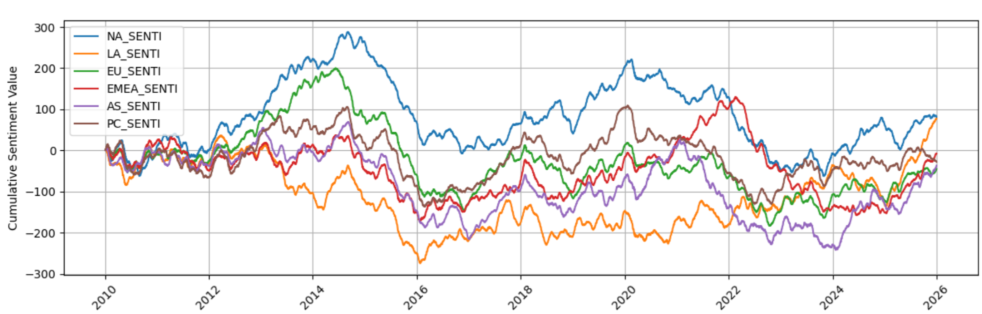


Figure 3: Regional Sentiment Trends

Source: Author's own work

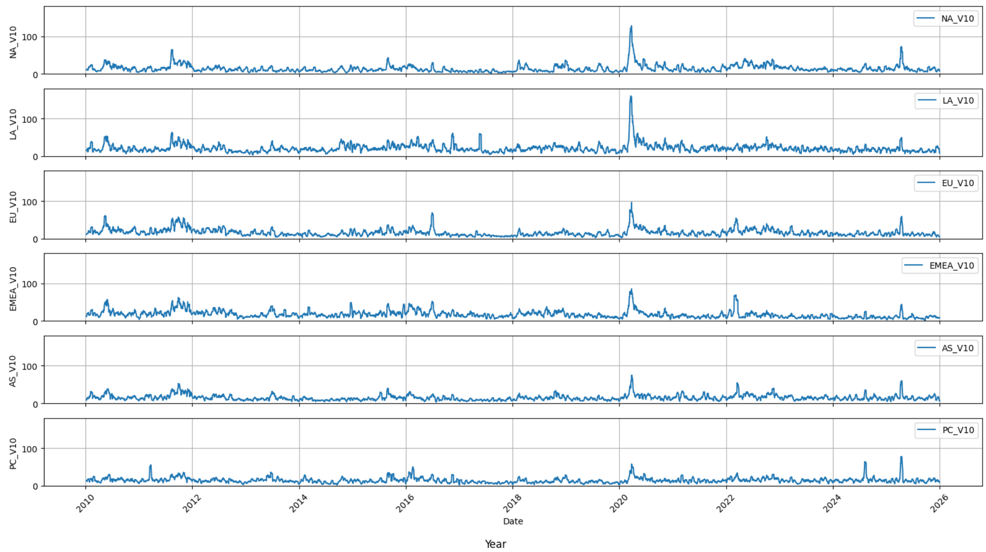


Figure 4: Regional Volatility Dynamics

Source: Author's own work

sentiment induces coordinated buying behavior, thereby compressing return variance over short horizons. He et al. (2020) refer to this synchronization mechanism as the *Friedman effect*. The magnitude of this short-horizon compression differs markedly across markets: North America (−2.649), Developed Markets (−2.120), and Europe (−1.954) exhibit the strongest compression, while Emerging Markets (−1.147) and Frontier Markets (−0.902) show comparatively weaker, though still highly significant, effects. This pattern is consistent with benchmark-driven institutional rebalancing in developed markets, generating more synchronized trading activity than the relatively noisier and less coordinated retail herding that characterizes emerging and frontier markets. Notably, for Frontier Markets, the coefficient is negative and significant at V10, suggesting that sentiment-driven synchronization operates even in less liquid markets once volatility persistence is not separately absorbed. But the magnitude of the impact is weakest for FM amongst all market segments. The interaction term SENTI×R attains its largest magnitude in NA and FM at V10, implying that prevailing market conditions reinforce, rather than substitute for, the behavioral channel in these markets, consistent with the state-dependent amplification mechanism proposed by He et al. (2020).

By V30, the compression effect weakens substantially and loses statistical significance in six of the ten markets (EM, FM, LA, EU, EMEA, AS, PC), while remaining significant in WLD, DM, and NA. This rapid attrition between V10 and V30 indicates that the short-horizon compression effect is highly concentrated at the very shortest measurement window, and dissipates faster than previously suggested once the model is not conditioned on lagged volatility.

Medium Horizon (V60–V90)

At the medium horizons (V60 and V90), the coefficient of SENTI is statistically indistinguishable from zero across nearly all markets, with the exception of Developed Markets (DM), which retain a significant negative coefficient through V60 and V90, and North America (NA), which remains significant through V60 and V90. Asia (AS) is a notable departure from the broader pattern: its coefficient turns positive and marginally significant at V90, foreshadowing the sign reversal that becomes more pronounced at longer horizons. These findings are broadly consistent with the existing literature, which documents the transitory nature of sentiment effects and their tendency to weaken over longer horizons (Naik and Soni, 2026; Kim and Ryu, 2021; Li, 2021). The persistence of a significant negative coefficient in DM and NA at medium horizons, where most other markets have already lost significance, suggests that institutional trading strategies such as momentum investing and benchmark tracking prolong sentiment effects in the most developed market segments (Bekaert and Harvey, 1997). The SENTI×R interaction term remains positive and significant across all markets at V60 and V90, though its magnitude declines steadily from the peak observed at V10, indicating that the state-dependent amplification effect weakens but does not disappear as sentiment observations become more temporally separated from the corresponding return realizations.

Long Horizon (V180–V360)

At long horizons, the SENTI coefficient loses statistical significance in the majority of markets, consistent with a broad-based dissipation of the sentiment–volatility relationship as the measurement window lengthens. North America again stands out as the most persistent case, retaining a negative, albeit no longer significant, coefficient through V360, consistent with a slower and more orderly mean reversion of investor psychology in the most institutionalized market in the sample. The most striking exception to the broader pattern of dissipation is Europe (EU), where the coefficient reverses sign and becomes significantly positive at V360. The sentiment-correction cycle proposed by Baker and Wurgler (2007) offers a plausible interpretation: the 360-day volatility window encompasses not only the initial phase of sentiment-induced compression but also a subsequent correction and unwinding process, such that periods of elevated annual volatility coincide with contemporaneously optimistic sentiment readings. While several other markets (EM, LA, EMEA, FM, PC) display a similar sign flip toward positive territory at V360, none of these reversals

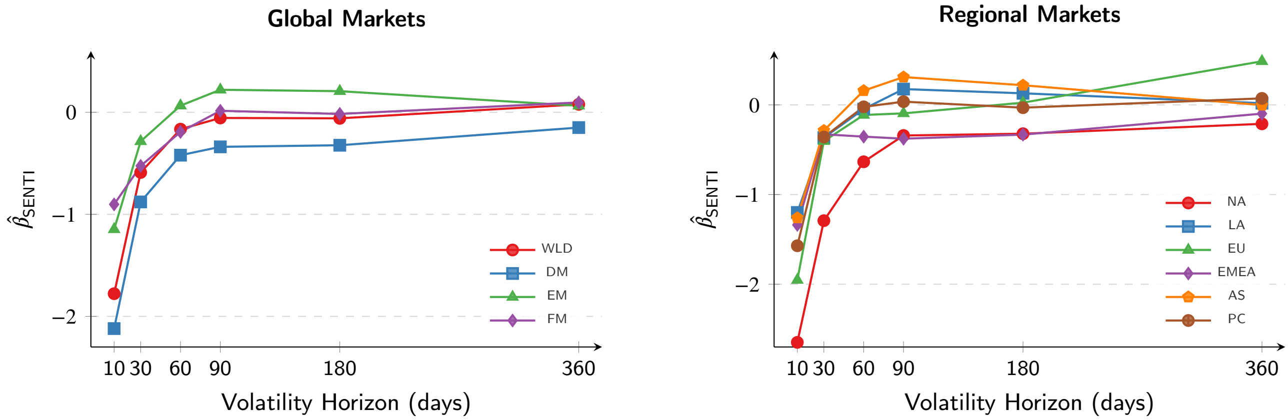


Figure 5: Term Structure of Sentiment Effects on Volatility

Source: Author's own work

attain statistical significance, indicating that the V360 reversal documented here is a robust feature specific to Europe rather than a generalized phenomenon across the sample. By contrast, DM and EMEA retain negative (though insignificant) point estimates at V360, suggesting that mispricing corrections in these markets, where they occur, are not strong enough to flip the net sign of the annual sentiment–volatility relationship.

5.3. Asymmetric Effects of Positive and Negative Sentiment

The results of the asymmetric effect analysis, reported in Table 7, broadly corroborate the short-horizon compression documented in Section 5.2, while revealing a more nuanced asymmetry than the aggregate specification alone can capture. In North America (NA) and Developed Markets (DM), the effect of irrational optimism/positive sentiment (β_1^+) is either statistically insignificant or, in the case of NA at V30 and EU at V10, negative and significant. This finding indicates that bullish sentiment is associated with *lower* short-horizon volatility in these markets, the opposite of what the positive-sign restriction in Eq. (6) would predict. By contrast, the coefficient on pessimistic sentiment (β_1^-) is positive and highly significant across nearly all horizons for NA, DM, EU, EMEA, and PC, with NA showing the largest short-horizon response. The net asymmetry measure, $\Delta\hat{\beta} = \beta_1^+ - \beta_1^-$, is therefore strongly negative at short horizons across these markets, confirming that developed and developed-adjacent markets are considerably more sensitive to irrational pessimism than to irrational optimism, and that this asymmetry is concentrated almost entirely in the V10–V30 window.

In the case of the Emerging Markets segment (EM, LA, AS), the panel reveals a qualitatively different pattern from the developed-market story above. At short horizons (V10), β_1^- dominates β_1^+ just as in developed markets. For instance, EM shows $\beta_1^+ = -0.123$ (insignificant) against $\beta_1^- = 0.752^{***}$, and LA shows $\beta_1^+ = 0.112$ (insignificant) against $\beta_1^- = 1.294^{***}$. However, by the medium horizon (V60–V90) this ordering reverses: β_1^+ becomes positive and significant while β_1^- loses significance, most clearly in EM ($\beta_1^+ = 0.267^{***}$ vs. $\beta_1^- = 0.034$ at V90) and AS ($\beta_1^+ = 0.398^{***}$ vs. $\beta_1^- = 0.054$ at V90). This medium-horizon reversal of the asymmetry (bullish sentiment overtaking bearish sentiment as the dominant driver of volatility) is a distinctive feature of the emerging-market segment not present in DM, NA, or EU, and may reflect the more retail-dominated, momentum-prone character of trading in these markets, where optimism can fuel sustained speculative buying pressure that builds volatility gradually rather than compressing it immediately (Bekaert and Harvey, 1997; De Long et al., 1990).

The net asymmetry measure ($\Delta\hat{\beta}$) accordingly switches sign across the term structure for EM and AS, moving from negative at V10 to positive by V60–V90, before both coefficients lose significance at the longest horizons (V180, V360), consistent with the broader long-horizon dissipation documented in Section 5.2. Figure 6 illustrates this evolution directly: the crossing point between the $SENTI^+$ and $SENTI^-$ lines occurs visibly earlier and more sharply in EM and AS than in any developed-market panel, where $SENTI^-$ remains above $SENTI^+$ across nearly the entire horizon range.

Taken together, the results from Eq. (6) confirm that the aggregate sentiment specification in the main analysis masks two distinct asymmetric patterns rather than one uniform asymmetry. In developed markets (DM, NA, EU, PC), pessimistic sentiment dominates optimistic sentiment throughout the short-to-medium horizon, consistent with the "create-space effect" of He et al. (2020) and the conventional view that pessimistic irrational sentiment carries greater market-moving weight than equivalent optimism. In emerging markets (EM, AS), this ordering is confined to the shortest horizon and is overturned at medium horizons, where optimistic sentiment becomes the more economically meaningful driver of volatility – a finding that qualifies, rather than contradicts, the broader asymmetry hypothesis.

5.4. Sentiment Spillover and Volatility Transmission

Tables 8 and 9 report the full-sample average connectedness matrices from the TVP-VAR model estimated over the eight-variable global system (four sentiment indices and four V10 series) and the twelve-variable regional system (six sentiment indices and six V10 series), respectively. Figures 7 to 12 present the corresponding network diagrams, Total Connectedness Index (TCI), and net directional connectedness (NET) profiles.

It should be noted that the directional TO and FROM measures capture shock transmission, that is, the propagation of behavioral

Table 6
Term-structure of Sentiment effects on Volatility

Global Markets

	Const	SENTI	R	(SENTI×R)	Adj. R^2
WLD					
V10	10.1243***	−1.7778***	3.3622***	1.9877***	0.2886
	(39.02)	(−8.24)	(9.03)	(12.16)	
V30	11.3991***	−0.5897***	1.8067***	1.3456***	0.1417
	(40.38)	(−2.99)	(5.38)	(10.16)	
V60	12.0929***	−0.1656	1.1564***	0.9683***	0.0826
	(40.61)	(−0.92)	(4.29)	(8.33)	
V90	12.4798***	−0.0557	0.8795***	0.7771***	0.0594
	(42.48)	(−0.31)	(3.69)	(7.01)	
V180	13.1771***	−0.0594	0.6438***	0.4982***	0.0328
	(48.45)	(−0.34)	(3.00)	(5.75)	
V360	14.0597***	0.0776	0.2981	0.2967***	0.0142
	(54.86)	(0.44)	(1.57)	(4.13)	
DM					
V10	10.4519***	−2.1199***	3.8458***	2.0530***	0.3080
	(37.99)	(−9.35)	(9.80)	(9.51)	
V30	11.7536***	−0.8786***	2.2254***	1.3872***	0.1490
	(40.58)	(−4.19)	(6.41)	(10.12)	
V60	12.4791***	−0.4204**	1.5168***	0.9985***	0.0851
	(40.60)	(−2.19)	(5.40)	(9.19)	
V90	12.8906***	−0.3387*	1.2432***	0.7940***	0.0606
	(42.24)	(−1.78)	(4.90)	(8.03)	
V180	13.6248***	−0.3231*	0.9506***	0.4995***	0.0343
	(47.71)	(−1.72)	(4.26)	(6.80)	
V360	14.5173***	−0.1499	0.5613***	0.2948***	0.0141
	(54.22)	(−0.83)	(2.98)	(4.91)	
EM					
V10	12.8404***	−1.1471***	1.9464***	1.2928***	0.1514
	(46.76)	(−4.85)	(5.07)	(8.16)	
V30	14.0811***	−0.2847	0.8613***	0.8279***	0.0753
	(53.35)	(−1.47)	(3.07)	(8.43)	
V60	14.6345***	0.0650	0.4067*	0.5870***	0.0469
	(57.45)	(0.36)	(1.80)	(8.57)	
V90	14.9366***	0.2205	0.1844	0.4661***	0.0375
	(62.17)	(1.30)	(0.92)	(7.81)	
V180	15.5037***	0.2068	0.0737	0.2798***	0.0219
	(73.24)	(1.46)	(0.48)	(6.92)	
V360	16.2940***	0.0639	0.1101	0.1441***	0.0052
	(77.41)	(0.40)	(0.67)	(3.51)	
FM					
V10	7.3119***	−0.9024***	1.5177***	1.3918***	0.1508
	(44.06)	(−5.78)	(4.03)	(5.32)	
V30	8.2365***	−0.5256***	1.0214***	0.7757***	0.0586
	(42.58)	(−3.71)	(3.38)	(5.17)	
V60	8.6807***	−0.1928	0.6286***	0.5362***	0.0268
	(47.11)	(−1.59)	(2.59)	(5.29)	
V90	8.9285***	0.0147	0.3040	0.4020***	0.0173
	(49.78)	(0.12)	(1.43)	(5.29)	
V180	9.3550***	−0.0163	0.2350	0.2329***	0.0072
	(59.31)	(−0.17)	(1.33)	(4.40)	
V360	9.9037***	0.0965	0.1323	0.1888***	0.0066
	(62.26)	(0.81)	(0.74)	(3.58)	

Regional Markets

	Const	SENTI	R	(SENTI×R)	Adj. R^2
NA					
V10	11.4042***	−2.6486***	4.6250***	2.4388***	0.3544
	(33.11)	(−12.93)	(13.20)	(7.78)	
V30	12.9579***	−1.2914***	2.8764***	1.6416***	0.1831
	(39.31)	(−5.83)	(7.79)	(8.36)	
V60	13.9044***	−0.6348***	1.9056***	1.1807***	0.1025
	(39.40)	(−3.09)	(6.86)	(8.45)	
V90	14.4557***	−0.3417*	1.4028***	0.9384***	0.0701
	(41.10)	(−1.70)	(5.80)	(7.67)	
V180	15.4297***	−0.3218	1.0111***	0.5691***	0.0371
	(46.73)	(−1.53)	(4.50)	(6.73)	
V360	16.5539***	−0.2117	0.6222***	0.3165***	0.0143
	(52.33)	(−1.03)	(3.15)	(5.46)	
LA					
V10	18.7410***	−1.1998***	1.5162***	1.7020***	0.2148
	(43.83)	(−3.51)	(4.18)	(6.04)	
V30	20.6705***	−0.3659	0.8055***	1.0208***	0.1029
	(53.80)	(−1.34)	(2.92)	(6.39)	
V60	21.5060***	−0.0468	0.5950**	0.7673***	0.0685
	(59.31)	(−0.17)	(2.00)	(6.28)	
V90	22.0639***	0.1760	0.3618	0.5982***	0.0481
	(59.88)	(0.69)	(1.42)	(5.86)	
V180	22.9582***	0.1289	0.2750	0.3892***	0.0278
	(66.37)	(0.59)	(1.48)	(5.38)	
V360	24.3044***	0.0187	0.2051	0.2051***	0.0084
	(69.98)	(0.07)	(1.16)	(4.01)	
EU					
V10	14.1970***	−1.9535***	2.8444***	1.7750***	0.2091
	(41.56)	(−6.29)	(7.24)	(13.86)	
V30	15.5731***	−0.4045	1.2826***	1.1977***	0.1007
	(42.58)	(−1.46)	(4.22)	(10.20)	
V60	16.2389***	−0.1129	0.8933***	0.9408***	0.0715
	(45.20)	(−0.45)	(3.53)	(8.04)	
V90	16.6532***	−0.0949	0.7406***	0.7774***	0.0547
	(47.36)	(−0.39)	(3.26)	(7.16)	
V180	17.3726***	0.0245	0.4698**	0.5498***	0.0349
	(53.23)	(0.11)	(2.38)	(5.89)	
V360	18.3517***	0.4860**	−0.0256	0.4095***	0.0268
	(59.31)	(2.15)	(−0.14)	(4.12)	
EMEA					
V10	15.5757***	−1.3384***	1.8190***	1.6560***	0.1668
	(42.71)	(−4.48)	(5.57)	(11.09)	
V30	17.0654***	−0.3283	0.8639***	1.1287***	0.0956
	(45.30)	(−1.27)	(3.32)	(10.25)	
V60	17.7773***	−0.3543	0.8223***	0.8854***	0.0716
	(48.19)	(−1.35)	(3.58)	(10.64)	
V90	18.2261***	−0.3776	0.7459***	0.7277***	0.0555
	(50.12)	(−1.47)	(3.48)	(10.19)	
V180	19.1222***	−0.3319	0.5832***	0.4871***	0.0348
	(58.36)	(−1.57)	(3.38)	(8.04)	
V360	20.3281***	−0.0979	0.3348**	0.3256***	0.0167
	(66.29)	(−0.47)	(1.97)	(5.61)	
AS					
V10	13.8267***	−1.2602***	1.9874***	1.2243***	0.1487
	(47.80)	(−5.45)	(5.67)	(10.76)	
V30	15.0037***	−0.2864	0.7917***	0.7992***	0.0757
	(52.99)	(−1.55)	(3.31)	(10.47)	
V60	15.5215***	0.1585	0.2502	0.5892***	0.0514
	(57.76)	(0.88)	(1.20)	(9.67)	
V90	15.8000***	0.3100*	0.0442	0.4850***	0.0445
	(62.39)	(1.73)	(0.23)	(8.32)	
V180	16.3236***	0.2190	0.0216	0.3178***	0.0275
	(72.23)	(1.44)	(0.14)	(7.34)	
V360	17.0673***	−0.0026	0.1552	0.1876***	0.0084
	(76.59)	(−0.02)	(0.93)	(4.31)	
PC					
V10	13.2662***	−1.5711***	2.6441***	1.2993***	0.1640
	(50.44)	(−5.90)	(6.62)	(9.65)	
V30	14.4848***	−0.3594	0.9984***	0.7402***	0.0588
	(52.02)	(−1.52)	(3.49)	(10.61)	
V60	15.0229***	−0.0221	0.4801**	0.4936***	0.0315
	(57.44)	(−0.11)	(2.21)	(9.42)	
V90	15.3388***	0.0357	0.3430*	0.3559***	0.0206
	(63.05)	(0.20)	(1.87)	(7.71)	
V180	15.8322***	−0.0314	0.2478*	0.1922***	0.0097
	(80.49)	(−0.23)	(1.78)	(4.45)	
V360	16.3559***	0.0723	0.0638	0.0862**	0.0026
	(91.95)	(0.51)	(0.46)	(2.42)	

Notes: OLS with HAC standard errors (Newey–West bandwidth = 10). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. t-statistics in parentheses. Sample: 1 January 2010 – 31 December 2025..

Source: Author's own work

Table 7
Asymmetric Effects of Positive and Negative Sentiment

Global Markets

	Const	$SENTI^+$	$SENTI^-$	R	Adj.R^2	$\Delta\hat{\beta}$
WLD						
V10	10.4432***	0.0627	1.2332***	1.9705***	0.0996	−1.1705
	(19.24)	(0.13)	(5.47)	(3.41)		
V30	11.5823***	0.3730	0.6021***	0.8575**	0.0364	−0.2292
	(31.43)	(1.48)	(4.10)	(2.13)		
V60	12.2611***	0.3931**	0.3044***	0.4283	0.0177	0.0887
	(35.93)	(2.32)	(2.92)	(1.41)		
V90	12.6182***	0.3594**	0.2069**	0.2781	0.0128	0.1525
	(39.56)	(2.57)	(2.37)	(1.06)		
V180	13.3176***	0.1758	0.1306*	0.2735	0.0053	0.0452
	(46.19)	(1.58)	(1.74)	(1.28)		
V360	14.1264***	0.1414	0.0623	0.1438	0.0027	0.0790
	(53.63)	(1.63)	(0.73)	(0.78)		
DM						
V10	11.0665***	−0.2819	1.3128***	2.3772***	0.1135	−1.5947
	(21.51)	(-0.65)	(5.59)	(4.20)		
V30	12.1592***	0.0970	0.6786***	1.2398***	0.0375	−0.5816
	(31.53)	(0.39)	(4.42)	(3.00)		
V60	12.8532***	0.1407	0.3667***	0.7636**	0.0139	−0.2259
	(34.88)	(0.78)	(3.40)	(2.41)		
V90	13.2174***	0.1020	0.2748***	0.6172**	0.0088	−0.1728
	(37.59)	(0.66)	(3.05)	(2.26)		
V180	13.9346***	−0.0552	0.1754**	0.5309**	0.0048	−0.2305
	(43.68)	(-0.42)	(2.32)	(2.44)		
V360	14.7101***	−0.0436	0.1025	0.3620**	0.0020	−0.1462
	(51.48)	(-0.41)	(1.23)	(2.00)		
EM						
V10	13.4828***	−0.1229	0.7524***	1.2604***	0.0429	−0.8753
	(42.08)	(-0.91)	(4.14)	(3.40)		
V30	14.5024***	0.1070	0.3047**	0.4615*	0.0110	−0.1977
	(48.94)	(1.00)	(2.45)	(1.78)		
V60	14.9100***	0.2116**	0.1125	0.1242	0.0072	0.0991
	(53.62)	(2.13)	(1.23)	(0.61)		
V90	15.1146***	0.2669***	0.0341	−0.0368	0.0101	0.2328
	(59.29)	(2.63)	(0.43)	(-0.21)		
V180	15.6200***	0.1895**	−0.0141	−0.0588	0.0075	0.2036
	(69.54)	(2.51)	(-0.23)	(-0.45)		
V360	16.3909***	0.0476	0.0068	0.0653	0.0004	0.0408
	(73.02)	(0.75)	(0.09)	(0.47)		
FM						
V10	7.4624***	0.0257	0.5248***	−0.1550	0.0619	−0.4991
	(35.15)	(0.13)	(4.89)	(-0.16)		
V30	8.3622***	−0.0129	0.2793***	0.0655	0.0200	−0.2922
	(35.94)	(-0.12)	(3.32)	(0.12)		
V60	8.7861***	0.0372	0.1310**	0.0220	0.0047	−0.0938
	(40.38)	(0.48)	(2.12)	(0.06)		
V90	8.9294***	0.1386**	0.0647	−0.1364	0.0071	0.0740
	(43.68)	(2.15)	(1.18)	(-0.52)		
V180	9.4120***	0.0482	0.0150	−0.0588	0.0005	0.0332
	(51.75)	(1.10)	(0.34)	(-0.33)		
V360	9.8648***	0.1001*	0.0340	0.0126	0.0042	0.0661
	(59.42)	(1.70)	(0.69)	(0.09)		

Regional Markets

	Const	$SENTI^+$	$SENTI^-$	R	Adj.R^2	$\Delta\hat{\beta}$
NA						
V10	12.8535***	−0.9573***	1.7468***	3.2111***	0.1433	−2.7041
	(31.32)	(-4.90)	(6.93)	(6.91)		
V30	13.8786***	−0.3258**	0.9859***	1.9044***	0.0534	−1.3117
	(33.75)	(-2.08)	(6.10)	(4.92)		
V60	14.6598***	−0.1253	0.5547***	1.1732***	0.0194	−0.6800
	(34.16)	(-0.87)	(4.89)	(4.08)		
V90	15.0619***	−0.0178	0.3761***	0.8240***	0.0099	−0.3939
	(36.25)	(-0.13)	(3.84)	(3.34)		
V180	15.8843***	−0.1056	0.2289**	0.6058***	0.0056	−0.3345
	(42.42)	(-0.83)	(2.40)	(2.81)		
V360	16.7512***	−0.0482	0.1638*	0.4194**	0.0030	−0.2120
	(49.08)	(-0.37)	(1.73)	(2.26)		
LA						
V10	19.8994***	0.1121	1.2943***	0.8309*	0.0423	−1.1821
	(28.95)	(0.24)	(3.39)	(1.91)		
V30	21.4549***	0.2208	0.5523**	0.3382	0.0116	−0.3315
	(41.61)	(0.87)	(2.37)	(1.20)		
V60	22.0616***	0.2817	0.3370*	0.2585	0.0076	−0.0553
	(50.41)	(1.53)	(1.72)	(0.90)		
V90	22.6078***	0.2564	0.1316	0.1034	0.0037	0.1248
	(52.83)	(1.61)	(0.79)	(0.43)		
V180	23.3086***	0.1767	0.0795	0.1050	0.0025	0.0973
	(61.53)	(1.39)	(0.65)	(0.60)		
V360	24.5038***	0.0361	0.0836	0.1554	0.0004	−0.0475
	(67.21)	(0.30)	(0.59)	(0.95)		
EU						
V10	15.3790***	−0.6163***	1.2562***	1.8775***	0.0712	−1.8725
	(36.92)	(-3.21)	(5.37)	(4.44)		
V30	16.3003***	0.0976	0.5165***	0.6990**	0.0146	−0.4189
	(38.91)	(0.56)	(3.25)	(2.36)		
V60	16.8328***	0.2078	0.2842**	0.3836	0.0064	−0.0764
	(42.44)	(1.28)	(2.35)	(1.61)		
V90	17.1967***	0.1723	0.1863*	0.2581	0.0032	−0.0140
	(45.23)	(1.08)	(1.70)	(1.23)		
V180	17.7929***	0.1653	0.0653	0.0989	0.0013	0.1000
	(52.41)	(1.13)	(0.69)	(0.57)		
V360	18.5795***	0.3939***	−0.0818	−0.2228	0.0077	0.4757
	(60.44)	(2.79)	(-0.77)	(-1.40)		
EMEA						
V10	16.8946***	−0.2063	0.9411***	0.9848***	0.0317	−1.1474
	(39.82)	(-1.20)	(4.88)	(2.58)		
V30	17.9980***	0.1116	0.3860***	0.3253	0.0070	−0.2744
	(41.79)	(0.73)	(2.92)	(1.25)		
V60	18.3097***	0.1544	0.4251***	0.4049*	0.0111	−0.2707
	(45.00)	(1.09)	(3.44)	(1.90)		
V90	18.6368***	0.1248	0.3756***	0.3620*	0.0095	−0.2508
	(47.58)	(0.93)	(3.20)	(1.92)		
V180	19.4020***	0.0452	0.2811***	0.3197**	0.0066	−0.2359
	(54.63)	(0.39)	(3.11)	(2.27)		
V360	20.4581***	0.1086	0.1702*	0.1868	0.0036	−0.0616
	(63.78)	(0.99)	(1.79)	(1.34)		
AS						
V10	14.4594***	−0.1335	0.7996***	1.3812***	0.0476	−0.9331
	(43.73)	(-1.23)	(5.19)	(4.12)		
V30	15.3622***	0.1681*	0.3346***	0.4360*	0.0150	−0.1665
	(48.65)	(1.70)	(3.26)	(1.95)		
V60	15.7275***	0.3226***	0.1146	−0.0105	0.0135	0.2080
	(53.97)	(3.34)	(1.44)	(-0.06)		
V90	15.8740***	0.3980***	0.0539	−0.1698	0.0208	0.3441
	(59.21)	(3.72)	(0.80)	(-1.01)		
V180	16.3536***	0.2725***	0.0400	−0.1067	0.0139	0.2326
	(68.56)	(3.40)	(0.75)	(-0.86)		
V360	17.0453***	0.0939	0.1169	0.1416	0.0047	−0.0230
	(70.74)	(1.48)	(1.40)	(1.00)		
PC						
V10	14.3626***	−0.5878***	0.7594***	1.9235***	0.0643	−1.3471
	(46.25)	(-4.89)	(4.95)	(5.20)		
V30	15.0575***	−0.0716	0.2578***	0.6710***	0.0096	−0.3294
	(50.59)	(-0.53)	(2.67)	(2.73)		
V60	15.4349***	0.0514	0.0644	0.2467	0.0016	−0.0130
	(55.45)	(0.46)	(0.86)	(1.35)		
V90	15.6544***	0.0719	0.0023	0.1337	0.0015	0.0696
	(60.52)	(0.70)	(0.03)	(0.87)		
V180	16.0826***	−0.0192	−0.0180	0.0998	0.0004	−0.0012
	(78.03)	(-0.24)	(-0.35)	(0.88)		
V360	16.4424***	0.0459	−0.0315	0.0082	0.0008	0.0774
	(92.34)	(0.60)	(-0.56)	(0.07)		

Notes: t-statistics are reported in parentheses below each coefficient, computed using HAC-robust standard errors (Bartlett kernel, Newey-West bandwidth = 10). ***, **, and * denote significance at the 1%, 5%, and 10% levels. Sample: 1 January 2010–31 December 2025. OLS estimation. $\Delta\hat{\beta} = \beta_1^+ - \beta_1^-$ measures net sentiment asymmetry.

Source: Author's own work

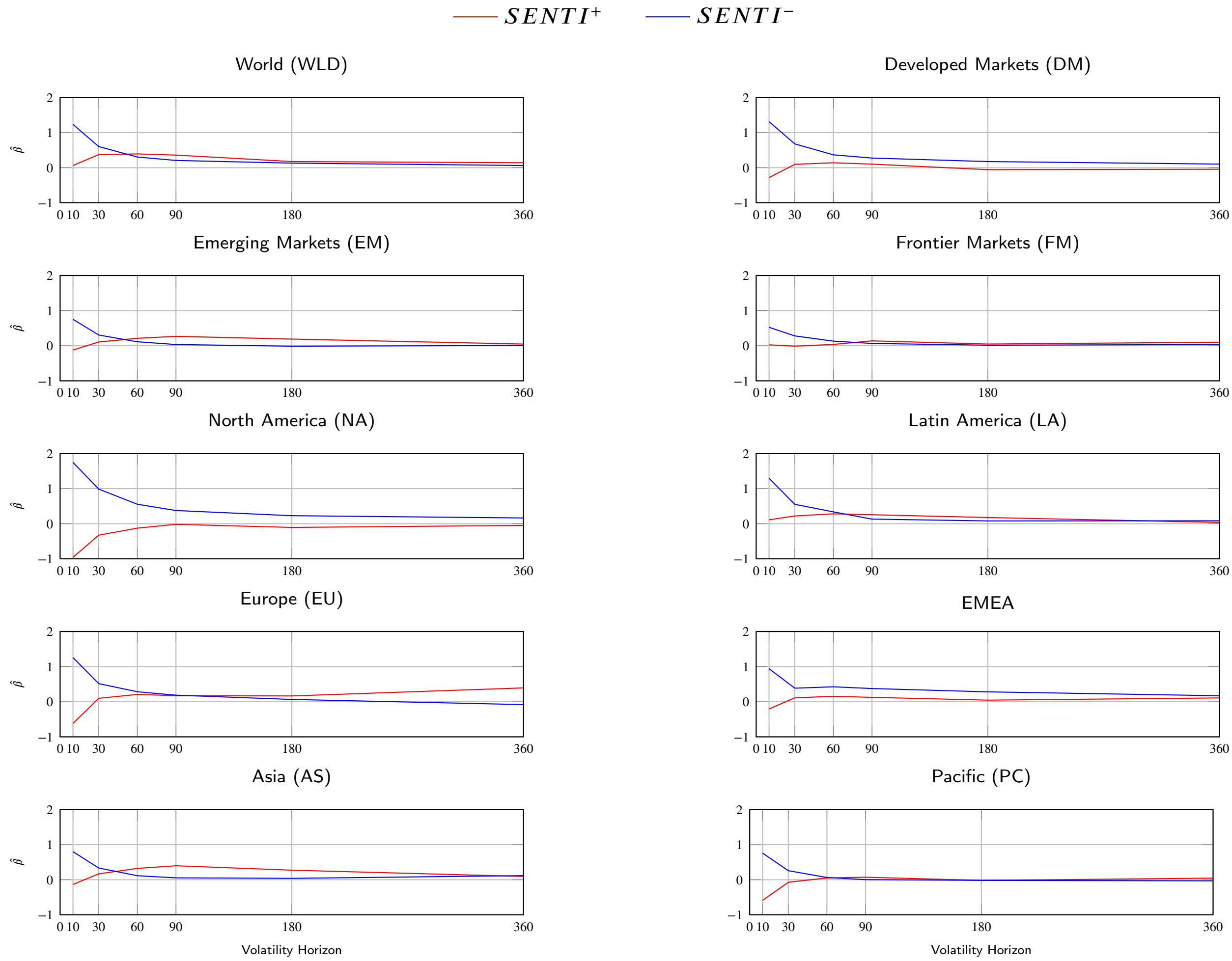


Figure 6: Asymmetric Effects of Positive and Negative Sentiment

Source: Author's own work

impulses across markets. In contrast, a market's persistent NET transmitter or receiver status over the full sample reflects structural dominance, an enduring characteristic of the global equity market hierarchy rather than a temporary intensification during crisis episodes. Distinguishing between these concepts is important because conflating them can lead to misleading interpretations. A market that briefly strengthens its transmitter role during a crisis is exhibiting shock transmission, whereas a market that consistently maintains positive NET connectedness throughout 2010–2025, irrespective of crisis periods, demonstrates structural dominance. The evidence presented below shows that developed markets exhibit both features, while emerging and frontier markets remain persistently subordinate.

The global system exhibits a TCI of 52.75% on average, indicating that, approximately, half of the forecast error variance across all eight variables is attributable to cross-variable shocks. WLD_SENTI (TO = 85.36%) and DM_SENTI (TO = 76.66%) are the most influential transmitters of behavioral shocks, followed by WLD_V10 (70.60%) and DM_V10 (66.51%). This pattern confirms that the developed market dynamics are primary drivers of both sentiment and volatility spillovers within the global system. FM_SENTI (26.73%) and FM_V10 (22.85%) transmit the least, consistent with frontier markets' limited financial integration and their correspondingly weak role as generators of irrational sentiment impulses for the broader global system. In terms of net connectedness, WLD_SENTI (+23.65) and DM_SENTI (+17.05) are the strongest net transmitters, while EM_V10 (−26.52) is the largest net receiver in the entire system.

The regional system exhibits a TCI of 56.64%, slightly above the global figure. EU_SENTI (TO = 83.71%) and NA_SENTI (TO = 81.28%) are the dominant transmitters of behavioral shocks. Asian and Pacific sentiments transmit the least (47.10% and 35.27%), consistent with their lower cross-regional sentiment correlations documented in Table 5. The NET row reveals a clean structural divide along development lines: NA and EU are uniformly net exporters of behavioral shocks, while AS and PC are net importers. This divide is not attributable to differences in financial market size alone. It also reflects the composition of the investor base. North American and European equity markets are dominated by institutional investors, such as pension funds, mutual funds, and ETFs benchmarked to global indices, whose correlated rebalancing directly propagates the behavioral state of developed-market investors into the capital flows that determine asset prices in emerging markets. When developed-market institutional sentiment

Table 8
Connectedness Measures – Global Sentiment and Volatility

	WLD_SENTI	DM_SENTI	EM_SENTI	FM_SENTI	WLD_V10	DM_V10	EM_V10	FM_V10	FROM
WLD_SENTI	38.29	35.29	15.46	5.51	1.63	1.60	1.00	1.22	61.71
DM_SENTI	37.26	40.39	10.67	4.91	2.07	2.05	1.14	1.51	59.61
EM_SENTI	23.19	16.38	48.83	7.39	0.93	0.88	1.30	1.09	51.17
FM_SENTI	10.84	9.89	8.92	61.61	2.37	2.21	1.88	2.29	38.39
WLD_V10	4.14	4.44	2.23	2.08	36.11	36.45	9.47	5.07	63.89
DM_V10	4.31	4.66	2.24	2.07	36.34	37.87	7.55	4.95	62.13
EM_V10	3.45	3.59	2.79	2.03	20.50	17.12	43.81	6.71	56.19
FM_V10	2.17	2.41	1.27	2.74	6.76	6.19	7.34	71.13	28.87
TO	85.36	76.66	43.58	26.73	70.60	66.51	29.68	22.85	421.96
Inc.Own	123.65	117.05	92.41	88.34	106.71	104.37	73.48	93.98	cTCI/TCI
NET	23.65	17.05	-7.59	-11.66	6.71	4.37	-26.52	-6.02	60.28/52.75
NPT	7.00	6.00	5.00	2.00	3.00	4.00	1.00	0.00	

Notes: Diagonal elements represent own-variable contributions; off-diagonal elements capture spillover effects. FROM denotes total directional spillovers received. cTCI and TCI refer to the corrected and standard Total Connectedness Index, respectively.

Source: Author's own work

Table 9
Connectedness Matrix – Regional Sentiment and Volatility

	NA_SENTI	LA_SENTI	EU_SENTI	AS_SENTI	PC_SENTI	EMEA_SENTI	NA_V10	LA_V10	EU_V10	AS_V10	PC_V10	EMEA_V10	FROM
NA_SENTI	48.57	12.24	14.69	4.26	3.33	8.58	2.76	1.71	1.28	0.86	0.79	0.92	51.43
LA_SENTI	11.36	47.25	11.74	6.57	3.82	14.18	0.75	1.07	0.88	0.68	0.75	0.94	52.75
EU_SENTI	14.99	12.09	39.53	6.09	4.81	15.44	1.68	1.23	1.04	1.18	1.03	0.87	60.47
AS_SENTI	9.55	11.73	10.18	40.18	9.02	12.84	1.25	1.26	0.93	1.23	1.00	0.83	59.82
PC_SENTI	14.34	9.96	12.70	9.85	36.57	9.49	1.46	1.35	1.30	1.03	0.92	1.04	63.43
EMEA_SENTI	8.95	14.94	15.54	9.72	5.10	39.80	1.47	0.98	0.93	0.79	0.92	0.85	60.20
NA_V10	6.83	2.97	4.32	2.04	1.97	3.44	48.83	9.49	9.78	2.66	1.89	5.77	51.17
LA_V10	2.62	2.48	2.42	1.50	1.20	2.14	11.80	50.55	9.02	3.12	2.71	10.44	49.45
EU_V10	3.72	2.80	3.83	1.77	1.70	2.70	13.56	8.87	38.70	3.41	3.35	15.60	61.30
AS_V10	2.90	2.44	2.87	1.87	1.29	2.39	10.31	8.55	8.84	40.45	7.71	10.37	59.55
PC_V10	3.61	2.10	3.10	2.01	1.67	2.27	10.10	5.36	8.25	8.59	44.83	8.11	55.17
EMEA_V10	2.41	2.00	2.32	1.41	1.35	2.17	7.76	10.87	15.25	5.44	4.01	45.02	54.98
TO	81.28	75.75	83.71	47.10	35.27	75.65	62.92	50.73	57.50	28.99	25.07	55.75	679.72
Inc.Own	129.85	123.00	123.24	87.28	71.84	115.45	111.75	101.28	96.20	69.44	69.90	100.77	cTCI/TCI
NET	29.85	23.00	23.24	-12.72	-28.16	15.45	11.75	1.28	-3.80	-30.56	-30.10	0.77	61.79/56.64
NPT	10.00	11.00	9.00	7.00	5.00	8.00	5.00	4.00	3.00	1.00	0.00	3.00	

Notes: Diagonal elements represent own-variable contributions; off-diagonal elements capture spillover effects. FROM denotes total directional spillovers received.

Source: Author's own work

shifts, the resulting portfolio adjustments impose that behavioral impulse on markets whose own investor bases have limited capacity to absorb or offset it.

Latin America (+23.00) is the notable exception among emerging regional markets, acting as a net transmitter of behavioral shocks despite its emerging-market classification. This exception arguably reflects the structural role of commodity price dynamics in shaping LA investor sentiment. Oil, metals, and agricultural exports constitute the fundamental backbone of Latin American equity markets. The sentiment cycles driven by commodity price movements (which are themselves anchored to global demand conditions originating in developed economies) are transmitted to other emerging markets through commodity-linked risk-appetite spillovers. LA sentiment, therefore, functions as a conduit through which global commodity sentiment enters the broader emerging-market network, explaining its anomalously high TO measure. In the volatility block, NA_V10 (+11.75) is the only unambiguous net transmitter, while AS_V10 (−30.56) and PC_V10 (−30.10) record the largest net-receiver values in the regional system, underscoring that short-horizon price dispersion in Asia-Pacific markets is the terminal destination of behavioral shocks generated elsewhere.

Interestingly, and probably the most novel finding from our analysis, the findings point to a clear behavioral hierarchy in the global equity markets, with Western developed markets emerging as the primary sources of behavioral shock transmission. In contrast, markets across the Global South (particularly in South Asian economies) predominantly act as net recipients of these shocks. Interestingly, several emerging markets that are more integrated with developed Western markets in terms of proximity, either function as secondary transmitters or occupy relatively neutral positions within the spillover network. This pattern suggests that behavioral shock transmission is influenced not only by the level of market development but also by geography, proximity of economic integration, and investor composition. Taken together, the results

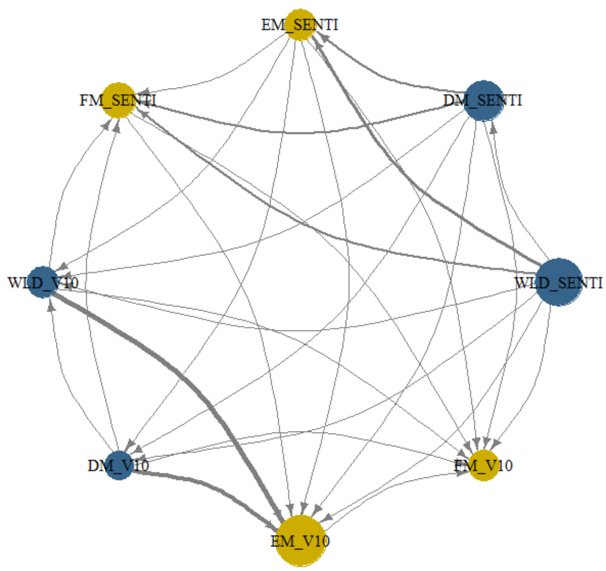


Figure 7: Global Sentiment–Volatility Spillover Network

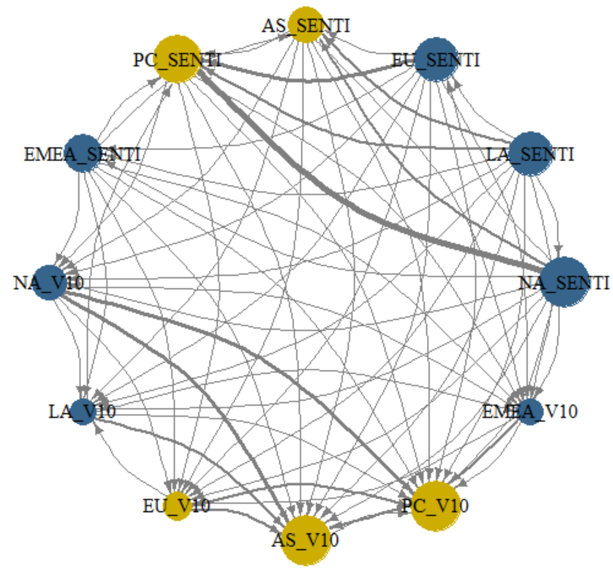


Figure 8: Regional Sentiment–Volatility Spillover Network

Source: Author's own work

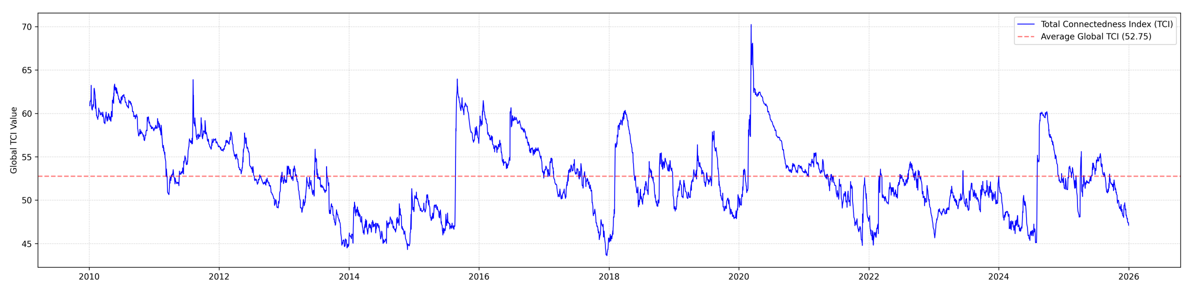


Figure 9: Global Total Connectedness Index (TCI)

Source: Author's own work

indicate that both regional linkages and the demographic characteristics of market participants play important roles in shaping how behavioral shocks propagate across international equity markets.

The time-varying TCI, reported in Figure 9 and 10, confirms that the degree of behavioral interconnection is not constant across time. Both systems spike sharply during major stress episodes, most prominently during the COVID-19 shock of March 2020. It is that

Figure 10: Regional Total Connectedness Index (TCI)

Source: Author's own work

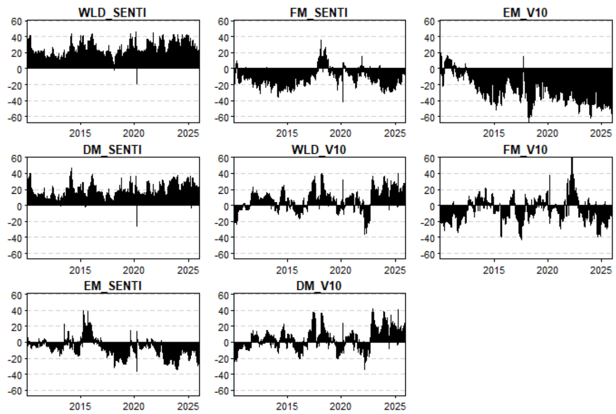


Figure 11: Global NET Connectedness Index

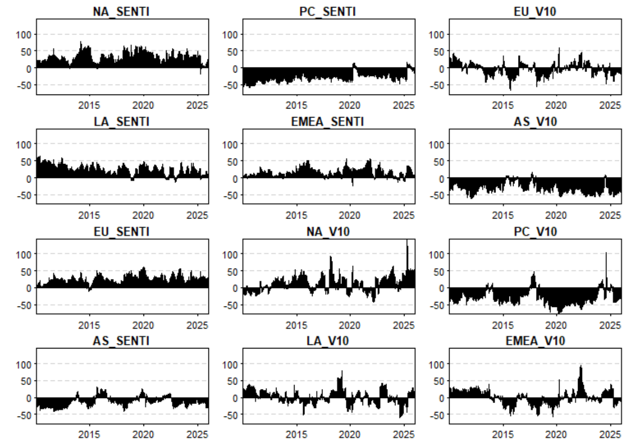


Figure 12: Regional NET Connectedness Index

Source: Author's own work

very crisis when sentiment and volatility dynamics across all market tiers converge almost simultaneously, a pattern that reflects the psychological synchronization produced by a common global fear signal, eliminating the idiosyncratic variation in investor mood that ordinarily keeps cross-market connectedness at moderate levels. The 2013 Taper Tantrum and the 2015–16 Chinese market correction also register as local maxima in both TCI series, though with considerably smaller amplitudes. Critically, the net directional plots confirm that the WLD/DM-transmitter and EM/FM-receiver roles are persistent structural features of the global network throughout the full 2010–2025 sample, not artefacts of crisis-period averaging. The hierarchy is visible in calm periods and in turbulent ones alike. Crises amplify the degree of transmission but do not create the directional asymmetry, that asymmetry is embedded in the architecture of global equity markets.

6. Robustness Checks

The TVP-VAR model is more suited to identifying when the system becomes more connected (event-driven variation). To identify whether bad-market and good-market states transmit shocks differently (tail asymmetry), and to verify the robustness of the baseline TVP-VAR connectedness results, we employ the Quantile VAR (QVAR) of White et al. (2015) and Chatziantoniou et al. (2021) as a complementary framework. Whereas the TVP-VAR (Section 4.4) allows model parameters to evolve over time t via forgetting factors, the QVAR conditions on the quantile $\tau \in (0,1)$ of the joint distribution of variable $\mathbf{y}_t$, yielding a static but distributional characterization of connectedness. This allows the transmission mechanism between investor sentiment and volatility variables to vary across bearish, normal, and bullish market states.

For brevity, we restrict this analysis to six MSCI regional indices (NA, LA, EU, EMEA, AS, PC). The QVAR model is estimated at five quantiles, $\tau \in \{0.05, 0.25, 0.50, 0.75, 0.95\}$, representing extreme downside conditions, lower-tail stress regimes, median market states, upper-tail expansion regimes, and extreme bullish conditions, respectively. Connectedness measures are computed via the generalized forecast error variance decomposition (GFEVD) over a 10-step-ahead forecast horizon. The quantile connectedness analysis serves two important purposes. *Firstly*, it verifies whether the spillover hierarchy observed in TVP-VAR framework remains stable across the heterogeneous market conditions or not. *Secondly*, it identifies whether or not the sentiment- or volatility-driven spillovers dominate during extreme market regimes. We deploy the QVAR(1) model, with the specification reported in Appendix C.

Table 10 reports the quantile landmarks of each selected series over the full sample (Jan 2010–Dec 2025). The results in Figure 13 reveal a nonlinear U-shaped evolution of total connectedness across quantiles. Total connectedness remains substantially higher during lower-tail and upper-tail market conditions (85% at $\tau = 0.05$ and 84% at $\tau = 0.95$), while spillover intensity declines sharply around the median quantile (48%). This pattern indicates that cross-market spillovers intensify considerably during periods of financial distress and speculative market expansion. Whereas the relatively stable market conditions exhibit weaker interdependence or shock transmissions across markets.

Figure 14 visually summarizes the asymmetric transmission patterns and dominance across quantiles by reporting NET connectedness measures. American, European, African, and adjacent markets (NA, LA, EU, EMEA) predominantly act as net transmitters of sentiment shocks at lower and median quantiles. However, these variables reverse their roles and become net receivers under extreme upper-tail conditions. This reversal suggests that sentiment-driven spillovers weaken during highly optimistic market regimes, indicating that bearish sentiment shocks are less likely to spill over. This coincides with the earlier findings of strong dominance of negative sentiment not only in the term structure but also in cross-market transmissions from west to east.

In contrast, volatility variables become substantially more dominant at higher quantiles for NA, LA, EU, and EMEA markets. In particular, NA_V10, EU_V10, and EMEA_V10 emerge as strong net transmitters under upper-tail market conditions, indicating that volatility shocks increasingly dominate global spillover transmission during speculative and high-volatility regimes. Asia-Pacific variables exhibit persistent net receiver characteristics across most quantiles. Among them, PC_SENTI displays the largest negative NET connectedness values, reaching approximately −40% at the median quantile.

Table 10
Quantile Landmarks for Regional Sentiment and Volatility Series

Quantile	NA_SENTI	LA_SENTI	EU_SENTI	AS_SENTI	PC_SENTI	EMEA_SENTI	NA_V10	LA_V10	EU_V10	AS_V10	PC_V10	EMEA_V10
$\tau = 0.05$	−2.63	−2.41	−2.42	−2.50	−2.56	−2.45	4.95	10.24	6.36	7.29	6.30	7.17
$\tau = 0.25$	−1.02	−1.13	−0.98	−1.12	−1.03	−1.03	8.09	15.11	9.97	10.38	10.25	11.23
$\tau = 0.50$	0.23	0.09	0.15	0.06	0.08	0.08	11.82	19.14	13.98	13.86	13.51	15.55
$\tau = 0.75$	1.15	1.15	1.04	1.11	1.12	1.08	17.48	25.33	19.66	18.01	17.38	21.20
$\tau = 0.95$	2.07	2.37	1.99	2.32	2.22	2.23	30.84	38.72	32.97	28.99	27.63	36.66

Source: Author's own work

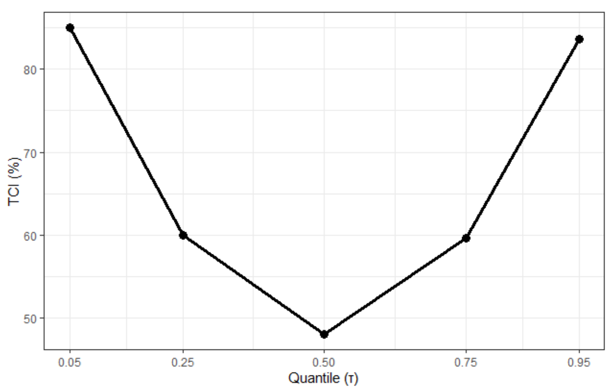


Figure 13: Total Connectedness Index (TCI) Across Quantiles

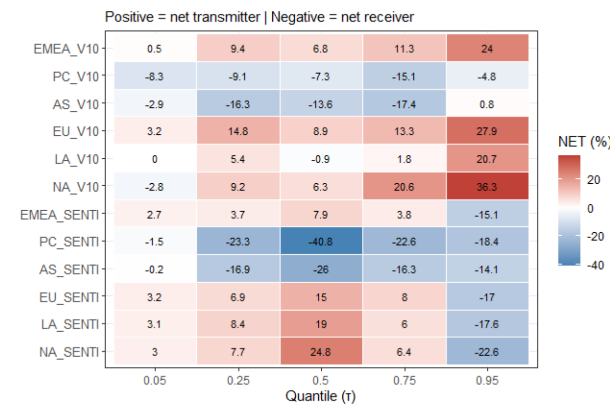


Figure 14: NET Connectedness Heatmap Across Quantiles

Source: Author's own work

The directional TO connectedness profiles indicate that sentiment variables generally exhibit declining spillover intensity from lower-tail to median quantiles before partially recovering at upper-tail levels. By contrast, volatility variables display a sharp increase in directional spillovers at higher quantiles, particularly for North American and European volatility indices. Figure 15 illustrates these nonlinear directional connectedness patterns separately for sentiment and volatility variables.

Overall, the quantile connectedness analysis strongly validates the robustness of the baseline TVP-VAR findings. The dominance of developed market variables as primary transmitters remains broadly intact across quantiles, while Asia-Pacific markets consistently behave as net receivers of shocks. More importantly, the quantile framework reveals substantial nonlinearities that cannot be captured through conventional mean-based connectedness models. The evidence clearly demonstrates that volatility spillovers dominate during upper-tail market conditions, whereas sentiment-driven spillovers are relatively stronger during normal and lower-tail regimes. The results, therefore, confirm that the global sentiment–volatility transmission mechanism is highly asymmetric, regime-dependent, and strongly amplified during extreme market conditions.

7. Conclusion

This study investigates how irrational investor sentiment shapes equity market volatility across alternative investment horizons and how sentiment-induced behavioral shocks propagate through the global equity market hierarchy. The key findings of the analysis are summarized as follows.

First, we find that irrational investor sentiment generates a distinct *behavioral term structure* in equity market volatility. At short investment horizons (V10–V30), sentiment exhibits a negative and statistically significant association with contemporaneous realized volatility across most markets. This pattern is consistent with a herding-induced compression of price dispersion: periods of elevated irrational optimism encourage coordinated directional trading, reducing the heterogeneity of investor beliefs that normally contributes to price fluctuations. As prices become temporarily anchored around a shared optimistic valuation, realized volatility within short rolling windows declines. This finding is consistent with the *Friedman stabilization effect* operating at the aggregate market level.

As the investment horizon lengthens to V60 and V90, the effect of sentiment gradually weakens and converges toward zero as fundamental factors increasingly dominate the price formation process. This adjustment occurs more rapidly in emerging markets, where sentiment-driven episodes tend to be intense but short-lived, whereas it proceeds more slowly in developed markets, where institutional trading can sustain sentiment effects over longer periods. At the longest horizon (V360), the relationship reverses sign in several markets—most notably in EM, LA, and EU. This reversal arises because the 360-day backward-looking window incorporates the heightened volatility associated with the correction phase that follows periods of sentiment-induced overvaluation. The turbulent unwinding of accumulated mispricing becomes embedded in the historical variance measured by the long rolling window, generating a positive association between current optimistic sentiment and the realized volatility of the preceding year.

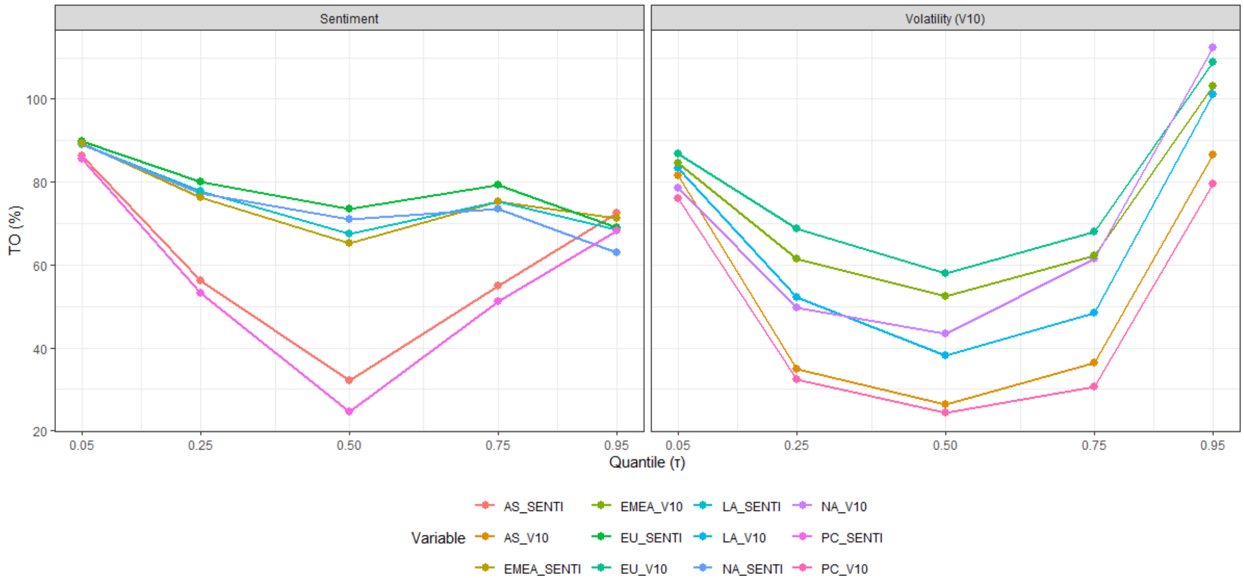


Figure 15: Directional TO Connectedness Across Quantiles

Source: Author's own work

Importantly, this sign reversal is absent in North America and the aggregate developed market index (DM) at the annual horizon. Their deeper institutional arbitrage capacity appears to prevent mispricing from accumulating to levels that produce substantial correction-phase volatility. North America is the only region in which the negative sentiment–volatility relationship remains statistically significant at both V180 and V360, reflecting the most disciplined and persistent mean reversion of investor psychology in the sample. By contrast, frontier markets exhibit statistically insignificant SENTI coefficients across all horizons, suggesting that the noise-trader stabilization mechanism requires a minimum degree of coordinated trading activity to generate either a measurable compression of realized volatility or a subsequent correction-driven increase in long-horizon variance.

Second, we find that irrational investor sentiment is not merely a local driver of volatility but also a *transmittable behavioral impulse* whose cross-market propagation follows a persistent structural hierarchy. In the global system, WLD_SENTI and DM_SENTI emerge as the dominant transmitters of behavioral shocks, whereas EM_V10 is the largest net receiver. This finding implies that short-horizon realized volatility in emerging markets is driven primarily by irrational sentiment innovations originating in developed markets rather than by endogenous shifts in local investor psychology.

A similar pattern is observed in the regional system. NA_SENTI and EU_SENTI are the leading transmitters of behavioral shocks, while AS_V10 and PC_V10 absorb the largest shares of externally generated sentiment impulses. Importantly, this directional asymmetry is structural rather than crisis-specific. The transmitter–receiver hierarchy persists throughout the entire 2010–2025 sample and is evident during both tranquil and turbulent periods, with crisis episodes intensifying the magnitude of transmission but not creating the underlying asymmetry.

This behavioral architecture reflects differences in investor composition across market tiers. In developed markets, institutional investors benchmarked to global indices engage in highly correlated portfolio rebalancing, transmitting the prevailing behavioral state of developed-market participants directly into the capital flows and price dynamics of emerging markets. When investor sentiment in North America or Europe shifts, the resulting portfolio adjustments impose these behavioral impulses on markets whose investor bases possess limited capacity to absorb or offset them. Consequently, emerging and frontier markets act as net importers of behavioral shocks, not because local investor psychology is unimportant, but because externally transmitted behavioral forces dominate local sentiment in shaping short-horizon realized volatility. Latin America constitutes a notable exception among emerging regions, acting as a net transmitter of behavioral shocks. This role likely reflects the region's strong dependence on commodity price cycles, which are structurally linked to demand conditions in developed economies and generate sentiment dynamics that spill over to other emerging regions through commodity-related risk appetite channels.

Third, the QVAR robustness analysis reveals that the transmission mechanism is *regime-dependent* in a behaviorally meaningful way. Total connectedness exhibits a pronounced U-shaped pattern across quantiles, reaching approximately 85% in the lower tail and 84% in the upper tail, while declining to around 48% at the median quantile. During distress regimes, fear and loss aversion act as pervasive common factors across all market tiers, reducing idiosyncratic differences in investor psychology and generating near-complete behavioral synchronization.

By contrast, during speculative regimes, the elevated connectedness arises from a fundamentally different mechanism. In these periods, volatility variables emerge as the dominant transmitters, whereas sentiment variables assume a less prominent role. This regime-dependent shift in transmission leadership suggests that irrational sentiment shocks dominate the network during fear-driven episodes, while the realized volatility consequences of earlier optimism become the primary sources of spillovers during greed-driven periods. This finding provides novel evidence that the fear–greed asymmetry documented in single-market studies also characterizes the propagation of behavioral shocks across the global equity market network.

These findings carry important implications for behavioral finance research, investment practice, and macroprudential policy.

From a research perspective, the documented behavioral term structure—comprising herding-induced stabilization at short horizons, gradual attenuation as fundamentals reassert themselves, and correction-driven reversal at longer horizons—establishes a set of empirical regularities that rational pricing models cannot readily accommodate. Moreover, the persistent transmitter–receiver hierarchy, which is shaped by institutional composition and the architecture of global capital flows rather than by market size alone, identifies investor base heterogeneity as a fundamental determinant of behavioral shock propagation and highlights an important avenue for future cross-country sentiment research.

For investment practitioners, the results indicate that irrational sentiment measures are most valuable as short-horizon volatility indicators. Their predictive content declines rapidly beyond a 30-day horizon and may even become contrarian at annual horizons, particularly in markets with limited arbitrage capacity. Furthermore, because emerging-market volatility is substantially imported from developed-market sentiment, effective short-term risk management for internationally diversified portfolios requires monitoring irrational sentiment conditions in developed markets—not merely domestic sentiment indicators—as an early warning signal of turbulence in emerging markets.

From a macroprudential perspective, the persistence of the behavioral hierarchy and its amplification during periods of market stress suggest that domestic policy instruments alone are insufficient to contain externally transmitted behavioral shocks in emerging and frontier markets. Accordingly, coordinated international monitoring of institutional sentiment dynamics in developed markets, including ETF flow patterns and benchmark-driven portfolio positioning, should complement country-specific macroprudential frameworks.

Future research could extend the present analysis in the following two directions. Incorporating text-based and social-media-derived sentiment measures alongside the technical proxies employed in this study would provide complementary evidence on whether the behavioral term structure and transmission hierarchy persist across fundamentally different measures of irrational investor psychology. Extending the analysis to country- or sector-level MSCI indices would uncover within-group heterogeneity that aggregate market classifications necessarily conceal and provide finer-grained evidence on the institutional environments and investor compositions that generate the strongest behavioral shock-transmission effects.

Appendix A.

Supplementary Evidence on the Joint study of Sentiment and Volatility

From a behavioral finance perspective, investor sentiment and volatility are inherently interconnected and exhibit bidirectional feedback. Therefore, to preliminarily assess the suitability of a joint SENTI–V10 system, we estimate separate TVP-VAR connectedness systems for sentiment-only and volatility-only variables. The purpose is not to test robustness, but rather to verify whether each variable independently contains sufficient spillover information to warrant joint modeling. If both independent systems exhibit meaningful and economically interpretable connectedness structures, this provides *ex-ante* support for estimating the baseline joint framework.

Table A.1
Global-Level Connectedness Comparison

(a) Sentiment-only

	WLD_SENTI	DM_SENTI	EM_SENTI	FM_SENTI	FROM
WLD_SENTI	40.31	37.26	15.92	6.51	59.69
DM_SENTI	39.70	43.17	11.08	6.05	56.83
EM_SENTI	24.17	17.16	50.66	8.02	49.34
FM_SENTI	12.80	12.11	9.33	65.76	34.24
TO	76.67	66.53	36.34	20.57	200.11
Inc.Own	116.98	109.70	87.00	86.33	cTCI/TCI
NET	16.98	9.70	-13.00	-13.67	66.70/50.03
NPT	3.00	2.00	1.00	0.00	

(b) Volatility-only

	WLD_V10	DM_V10	EM_V10	FM_V10	FROM
WLD_V10	41.38	41.73	10.75	6.14	58.62
DM_V10	41.82	43.51	8.64	6.02	56.49
EM_V10	23.41	19.62	48.94	8.02	51.06
FM_V10	8.29	7.65	8.16	75.90	24.10
TO	73.52	69.00	27.56	20.19	190.27
Inc.Own	114.90	112.51	76.50	96.09	cTCI/TCI
NET	14.90	12.51	-23.50	-3.91	63.42/47.57
NPT	3.00	2.00	1.00	0.00	

Table A.2
Regional-Level Connectedness Comparison

(a) Sentiment-only

	NA_SENTI	LA_SENTI	EU_SENTI	EMEA_SENTI	AS_SENTI	PC_SENTI	FROM
NA_SENTI	53.15	12.50	16.22	9.38	4.84	3.91	46.85
LA_SENTI	11.30	50.30	12.16	14.90	7.15	4.18	49.70
EU_SENTI	16.69	12.74	41.94	16.28	6.76	5.60	58.06
EMEA_SENTI	9.81	15.99	16.25	42.57	10.04	5.33	57.43
AS_SENTI	10.79	12.80	11.30	13.45	42.15	9.51	57.85
PC_SENTI	15.77	10.89	14.44	10.08	10.62	38.20	61.80
TO	64.37	64.93	70.37	64.10	39.41	28.53	331.70
NET	17.52	15.23	12.31	6.67	-18.45	-33.28	cTCI/TCI
Inc.Own	117.52	115.23	112.31	106.67	81.55	66.72	66.34/55.28
NPT	4.00	5.00	2.00	3.00	1.00	0.00	

(b) Volatility-only

	NA_V10	LA_V10	EU_V10	EMEA_V10	AS_V10	PC_V10	FROM
NA_V10	61.11	12.51	12.81	7.57	3.52	2.48	38.89
LA_V10	13.46	57.11	10.76	11.94	3.74	2.99	42.89
EU_V10	16.59	11.02	45.99	18.49	4.00	3.91	54.01
EMEA_V10	9.09	12.63	17.32	50.18	6.29	4.50	49.82
AS_V10	11.75	9.95	10.60	11.86	46.79	9.05	53.21
PC_V10	12.05	6.59	10.07	9.68	10.04	51.58	48.42
TO	62.94	52.69	61.56	59.54	27.58	22.93	287.24
NET	24.05	9.80	7.54	9.72	-25.63	-25.48	cTCI/TCI
Inc.Own	124.05	109.80	107.54	109.72	74.37	74.52	57.45/47.87
NPT	5.00	4.00	2.00	3.00	1.00	0.00	

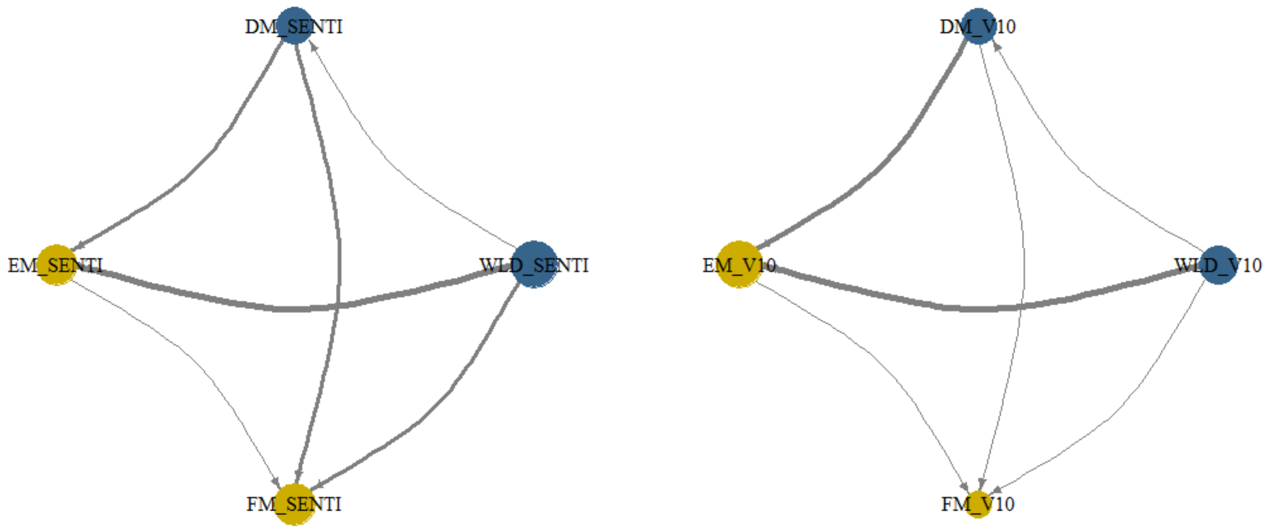
joint framework.

Table A.1 compares the static connectedness matrices for the sentiment-only and volatility-only global systems. The sentiment-only system reports an average TCI of 50.03%, while the volatility-only system reports 47.57%. This suggests that behavioral spillovers dominate volatility spillovers at the global level. The network in Fig. A.1 structures reveal that developed markets remain dominant net transmitters in both systems, whereas emerging and frontier markets act as net receivers.

Table A.2 compares the regional sentiment-only and volatility-only connectedness systems. The regional sentiment-only system reports a higher TCI (55.28%) than the volatility-only system (47.87%), suggesting stronger behavioral interconnectedness across regional blocs. The regional network structure in Fig. A.2 shows that North America and Europe act as dominant transmitters, while Asia and Pacific remain major receivers.

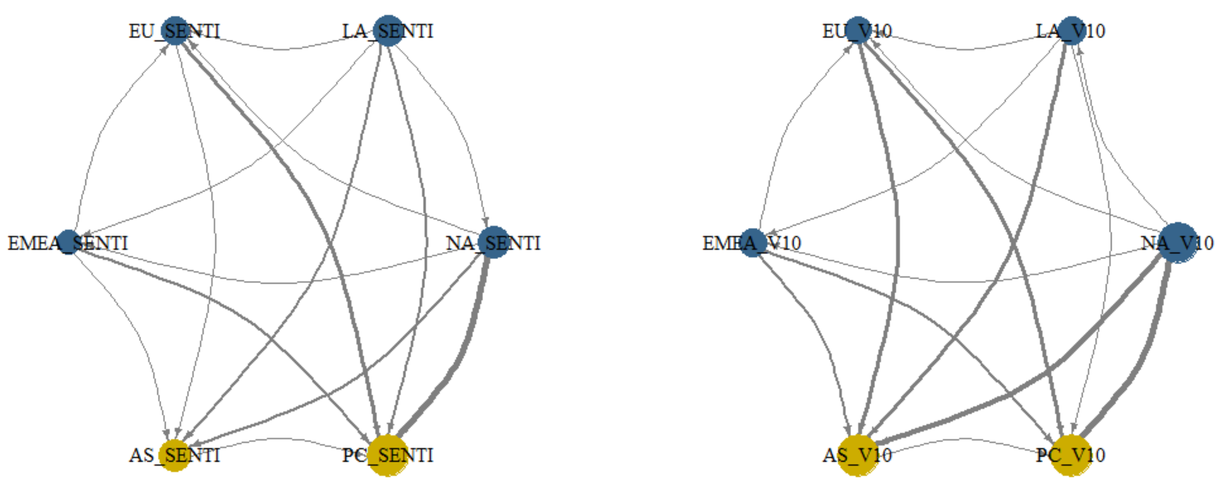
The separate sentiment-only and volatility-only systems confirm that both behavioral and risk channels independently generate economically meaningful spillovers across markets. Sentiment connectedness is consistently stronger than volatility connectedness in both the global and regional systems, indicating that behavioral transmission plays a more dominant role in shaping market interconnectedness. These findings provide preliminary empirical support for the baseline joint TVP-VAR specification, as it enables a more comprehensive assessment of how behavioral expectations and market risk interact in transmitting shocks across financial markets.

Appendix B.



(a) Sentiment Network (b) Volatility Network

Figure A.1: Global-Level Spillover Network Comparison



(a) Sentiment Network (b) Volatility Network

Figure A.2: Regional-Level Spillover Network Comparison

Conditional Volatility via EGARCH(1,1) and Its Spillover Transmission

A natural concern with our baseline specification is that realized volatility is constructed using rolling look-back windows beginning at 10 trading days (V10). This imposes a fixed, backward-looking measurement window rather than allowing volatility to evolve endogenously from the return process itself. To address this concern, we construct an alternative volatility series for each market using the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model. We use this conditional volatility series, rather than realized volatility, as the input to our TVP-VAR connectedness framework.

We proceed in two stages. In the first stage, for each market, we estimate an EGARCH(1,1) model in which the explanatory role of investor sentiment is channeled exclusively through the conditional variance equation, where it enters as an exogenous regressor estimated jointly with the model's own persistence and asymmetry terms by maximum likelihood, an approach pioneered by Lee et al. (2002) and subsequently adopted by Verma and Verma (2007), Bahloul and Bouri (2016), and Naik and Soni (2026). The mean and variance equations are specified as:

$$R_t = a + b_1 R_{t-1} + \epsilon_t \tag{B.1}$$

$$\log(\sigma_t^2) = \omega + \beta \log(\sigma_{t-1}^2) + \alpha \left(\left| \frac{\epsilon_{t-1}}{\sigma_{t-1}} \right| \right) + \gamma \left(\frac{\epsilon_{t-1}}{\sigma_{t-1}} \right) + \delta \,\mathrm{SENTI}_t \tag{B.2}$$

$$Volatility_t = \sqrt{\log(\sigma_t^2)} \tag{B.3}$$

Table B.1
EGARCH(1,1) Model Estimations Across Global and Regional Markets

Market	ω	β	α	γ	δ (SENTI)
WLD	-0.1748***	0.9595***	0.1968***	-0.1282***	-0.0116***
	(-16.4000)	(292.4276)	(16.3572)	(-15.2689)	(-3.7677)
DM	-0.2008***	0.9457***	0.2243***	-0.1167***	-0.0268***
	(-17.3612)	(243.2028)	(16.8166)	(-13.6978)	(-7.8526)
EM	-0.1067***	0.9668***	0.1296***	-0.1320***	0.0086***
	(-11.0356)	(247.6184)	(11.0510)	(-12.3104)	(2.9990)
FM	-0.2768***	0.9204***	0.2428***	-0.0528***	-0.0268***
	(-14.1114)	(118.6066)	(14.6811)	(-5.0700)	(-6.7925)
NA	-0.2432***	0.9020***	0.2788***	-0.0833***	-0.0696***
	(-19.2998)	(168.4570)	(18.4391)	(-7.4398)	(-15.4029)
LA	-0.0814***	0.9702***	0.1319***	-0.0786***	-0.0016
	(-9.9721)	(252.1220)	(12.7797)	(-7.1745)	(-0.5441)
EU	-0.1090***	0.9737***	0.1447***	-0.1181***	-0.0003
	(-15.0400)	(381.5991)	(15.4386)	(-12.6946)	(-0.1141)
EMEA	-0.0830***	0.9816***	0.1140***	-0.1229***	0.0100***
	(-9.7540)	(447.8560)	(10.7826)	(-12.1193)	(3.7623)
AS	-0.0941***	0.9723***	0.1206***	-0.1113***	0.0061**
	(-10.8664)	(291.5525)	(11.0388)	(-10.1171)	(2.1319)
PC	-0.1346***	0.9512***	0.1643***	-0.0765***	-0.0178***
	(-14.4128)	(171.8356)	(14.6730)	(-6.9874)	(-4.3330)

Note: z-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Source: Author's own work

In Eq. (B.2), β captures the persistence of conditional volatility, α captures the magnitude effect of return shocks, γ captures the asymmetric (leverage) response to positive versus negative shocks, and δ captures the direct effect of investor sentiment on conditional volatility, uncontaminated by any sentiment-driven variation already absorbed through the mean equation.

Table B.1 reports these EGARCH(1,1) estimates for each market. The leverage term γ_i is negative and significant across all global and regional markets, confirming the standard EGARCH asymmetry whereby negative return shocks raise future conditional volatility more than positive shocks of equal magnitude. The sentiment coefficient δ_i is negative and significant in WLD, DM, FM, NA, and PC, corroborating the short-horizon compression result reported for V10 in Section 5.2, but turns positive and significant in EM, EMEA, and AS (all are emerging market segments), while remaining statistically insignificant in LA and EU. This heterogeneity in sign and magnitude mirrors the cross-market asymmetries already documented there.

In the second stage, we extract the fitted conditional volatility variance series $\hat{\sigma}_t^2$ from each market's EGARCH(1,1) estimation, re-estimate them to standard deviations, and substitute it for realized volatility (V10) in the TVP-VAR connectedness framework specified in Section 4.4, holding the lag order, forecast horizon, and rolling specification unchanged from the baseline.

Since $\hat{\sigma}_t^2$ is itself partly shaped by sentiment through δ, this exercise answers a more demanding question than simply whether sentiment shapes volatility within a given market. The real question is whether sentiment-*conditioned* volatility still shows the same directional transmission pattern, with developed markets as net transmitters and emerging or frontier markets as net receivers, once volatility is stripped of its rolling-window construction and instead derived endogenously from each market's own return-shock process.

Table B.2 reports the resulting static connectedness matrix for the global system using *sentiment-driven EGARCH-volatility* in place of V10. The total connectedness index of 50.77% is broadly comparable to the V10-based volatility-only system reported in main empirical finings in Table 8 (52.75%) and preliminary test results of Table A.1 (47.57%). Developed markets and the world index remain the dominant net transmitters, while emerging markets and frontier markets remain net receivers, preserving the same directional hierarchy observed under the V10 specification.

Table B.3 reports the resulting static connectedness matrix for the regional system using *sentiment-driven EGARCH-volatility* in place of V10. North America emerges as the dominant net transmitter, while Asia and Pacific remain the dominant net receivers, consistent with the regional hierarchy documented under both the sentiment-only and volatility-only systems in Appendix A.

The total connectedness index (54.38%) sits between the regional sentiment-only (55.28%) and volatility-only (47.87%) systems, indicating that EGARCH-derived volatility transmits a level of regional connectedness broadly consistent with the baseline measures.

The transmitter-receiver hierarchy documented in our baseline TVP-VAR analysis (Section 5.4) is preserved under EGARCH-volatility, both globally and regionally. This confirms that the directional architecture of global sentiment-driven volatility transmission is not an artifact of the realized-volatility construction, but a structural feature of how behavioral shocks propagate through markets of differing development tiers, regardless of how conditional volatility itself is measured.

Appendix C.

Quantile VAR (QVAR) Model Specifications

The QVAR(1) replaces the time-varying coefficient matrix $\mathbf{A}_t$ in Equation (7) with a quantile-specific coefficient matrix $\mathbf{A}(\tau)$, estimated *equation-by-equation* via quantile regression rather than the Kalman filter recursion of Eq. (7):

$$\begin{gathered} Q_{\mathbf{y}_t}\left(\tau \mid \mathcal{F}_{t-1}\right) = \boldsymbol{\mu}(\tau) + \mathbf{A}(\tau)\,\mathbf{y}_{t-1}, \\ \hat{\boldsymbol{\beta}}_i(\tau) = \arg\min_{\beta} \sum_{t=1}^{T} \rho_\tau\left(y_{i,t} - \mathbf{x}_{t-1}'\boldsymbol{\beta}\right) \end{gathered} \tag{C.1}$$

where $Q_{\mathbf{y}_t}(\tau \mid \mathcal{F}_{t-1})$ denotes the τ-th conditional quantile of $\mathbf{y}_t$ given the information set $\mathcal{F}_{t-1}$; $\boldsymbol{\mu}(\tau)$ and $\mathbf{A}(\tau)$ are quantile-specific intercept and autoregressive coefficient matrices; $\mathbf{x}_{t-1} = (1,\, \mathbf{y}_{t-1}')'$; and $\rho_\tau(u) = u\left(\tau - \mathbf{1}_{\{u<0\}}\right)$ is the asymmetric check (tick) loss function solved for each variable i. The quantile residuals $\hat{\boldsymbol{\varepsilon}}_t(\tau) = \mathbf{y}_t - Q_{\mathbf{y}_t}(\tau \mid \mathcal{F}_{t-1})$ yield a quantile-specific covariance matrix $\boldsymbol{\Sigma}(\tau)$, which replaces the time-varying $\boldsymbol{\Sigma}_t$ of TVP-VAR setup.

The Wold representation, GFEVD, and connectedness measures follow the same structure as TVP-VAR setup, with the time subscript t replaced by the quantile index τ, and the Kalman-filtered estimates $(\mathbf{A}_t,\, \boldsymbol{\Sigma}_t)$ replaced by their quantile-regression counterparts $(\mathbf{A}(\tau),\, \boldsymbol{\Sigma}(\tau))$, so that $\boldsymbol{\Psi}_h(\tau) = \mathbf{A}(\tau)^h$ and the GFEVD entries become $\phi_{ij}^{g}(H,\tau)$. The resulting total connectedness index (TCI), directional spillovers transmitted (TO) and received (FROM), and net position (NET) at quantile τ are:

$$C_i^{\leftarrow}(H,\tau) = \sum_{\substack{j=1 \\ j\neq i}}^{k} \phi_{ij}^{g}(H,\tau) \tag{C.2}$$

$$C_i^{\rightarrow}(H,\tau) = \sum_{\substack{j=1 \\ j\neq i}}^{k} \phi_{ji}^{g}(H,\tau) \tag{C.3}$$

$$C_i^{\mathrm{NET}}(H,\tau) = C_i^{\rightarrow}(H,\tau) - C_i^{\leftarrow}(H,\tau) \tag{C.4}$$

Table B.2
Volatility Connectedness Table (TVP-VAR) — Global Markets (EGARCH-Volatility)

	WLD_Volatility	**DM_Volatility**	**EM_Volatility**	**FM_Volatility**	**FROM**
WLD_Volatility	40.25	41.93	12.12	5.70	59.75
DM_Volatility	40.20	44.36	9.75	5.68	55.64
EM_Volatility	25.59	21.94	44.10	8.36	55.90
FM_Volatility	10.98	10.90	9.90	68.22	31.78
TO	76.77	74.77	31.77	19.75	203.06
Inc.Own	117.02	119.14	75.87	87.97	cTCI/TCI
NET	17.02	19.14	-24.13	-12.03	67.69/50.77
NPT	2.00	3.00	1.00	0.00	

Source: Author's own work

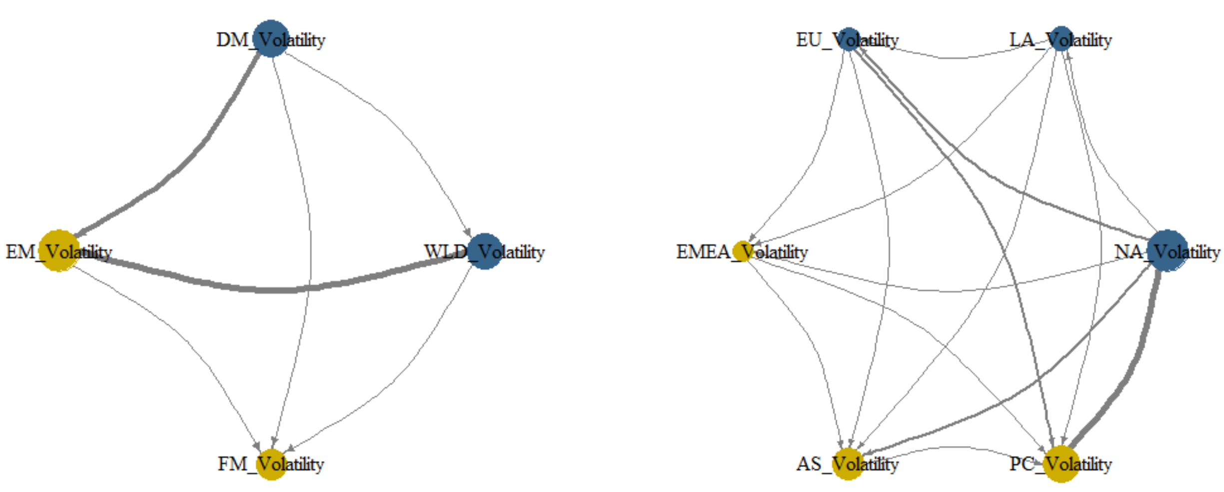
Table B.3
TVP-VAR Connectedness Matrix — Regional Markets (EGARCH-Volatility)

	NA_Volatility	LA_Volatility	EU_Volatility	EMEA_Volatility	AS_Volatility	PC_Volatility	FROM
NA_Volatility	66.79	10.19	10.87	5.39	3.96	2.80	33.21
LA_Volatility	16.64	52.03	11.19	11.61	5.02	3.51	47.97
EU_Volatility	20.54	13.11	39.00	16.61	5.81	4.94	61.00
EMEA_Volatility	10.62	14.88	17.45	43.45	8.53	5.07	56.55
AS_Volatility	14.51	10.48	13.36	13.50	38.01	10.14	61.99
PC_Volatility	22.79	8.97	13.88	9.09	10.80	34.48	65.52
TO	85.09	57.64	66.74	56.21	34.12	26.46	326.25
Inc.Own	151.88	109.67	105.74	99.65	72.13	60.94	cTCI/TCI
NET	51.88	9.67	5.74	-0.35	-27.87	-39.06	65.25/54.38
NPT	5.00	4.00	3.00	2.00	1.00	0.00	

Source: Author's own work

$$\mathrm{TCI}(H,\tau) = \frac{1}{k}\sum_{\substack{i,j=1 \\ i\neq j}}^{k} \phi_{ij}^{g}(H,\tau) \tag{C.5}$$

The key distinction from the TVP-VAR is that these measures are *unconditional on time* but *conditional on the distributional state* τ: a TCI markedly higher at the tails ($\tau \in \{0.05, 0.95\}$) than at the median ($\tau = 0.50$) signals tail-driven contagion that the TVP-VAR cannot detect. We estimate the QVAR(1) at $\tau \in \{0.05, 0.25, 0.50, 0.75, 0.95\}$ with $k = 12$ and $H = 10$, consistent with the TVP-VAR specification.



(a) Global-Level Network (b) Regional-Level Network

Figure B.1: Global vs. Regional Spillover Network (EGARCH-Volatility)

Source: Author's own work

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the author(s) used Grammarly, Claude, and ChatGPT to check the grammar and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

CRediT authorship contribution statement

Jitender Soni: Conceptualization, Software, Visualization, Formal analysis, Data Curation, Writing - Original Draft. **Pramod Kumar Naik:** Conceptualization, Methodology, Supervision, Validation, Writing - Review & Editing.

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