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Research article

Quantile connectedness between VIX and global stock markets☆

Buket Kirci Altinkeski [a], Sel Dibooglu [b,*], Emrah Ismail Cevik [c], Yunus Kilic [d], Mehmet Fatih Bugan [e]

[a] Halic University, Türkiye
[b] Craig School of Business, Missouri Western State University, USA
[c] Department of Economics, Tekirdag Namık Kemal University, Türkiye
[d] Department of Insurance, Akdeniz University, Türkiye
[e] Department of Public Finance, Gaziantep University, Türkiye

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ABSTRACT

This paper investigates the dynamics of the interactions between international stock returns and perceived volatility measured by the VIX index using quantile-on-quantile spillover analysis. Using weekly data from 1995 to 2023 and a comprehensive data set from developed and emerging stock markets, we investigate the relationship between the VIX and stock market returns accounting for time-varying relationships and cross-quantile relationships. Empirical results show that the indirectly related quantile total spillovers between the VIX and equity returns surpasses the directly related quantile total spillovers. High returns occur at low VIX levels and low returns at high VIX levels. The highest total spillovers across all stock markets occur at the highest quantile level for the VIX and the lowest quantile level for stock returns, for both developed and emerging markets. High connectedness between the VIX and stock market returns, particularly at extreme quantiles, suggests that investors should look at other investment vehicles for diversification during uncertain times.

1. Introduction

With the advent of globalization and increasing integration of national economies particularly through trade, investments, and financial flows, empirical studies on cross-country equity return correlations have gained significant traction due to their implication for international portfolio diversification. It is widely recognized that turbulent periods are characterized by amplified equity return volatilities and correlations on a worldwide scale (Mensi et al., 2023). The rise in interdependence among national economies has underscored the significance of international equity investments compared to investments in domestic markets. The liberalization of financial and capital markets has afforded investors new investment opportunities with portfolio diversification benefits by investing in foreign markets worldwide. However, the same globalization and international integration have reduced the advantages of diversification in emerging markets due to recent increases in the correlations between returns in broader emerging markets and developed markets (Bekaert et al., 2023). Investors looking to diversify their risk and maximize their returns by investing in international portfolios must carefully consider extant volatility in financial markets. The volatility in one market can simultaneously impact other markets, making it crucial for investors to analyze intermarket linkages, assess risks, and develop hedging strategies. The high volatility in financial markets often unsettles investors and discourages them from making investment decisions. Moreover, investors are concerned about the volatility in domestic markets and closely monitor volatility in global markets. This is particularly important as fluctuations in one market can have a contagion effect on other markets due to financial globalization (Mathur et al., 2002). Consequently, prudent investors must consider volatility in international financial markets when formulating their investment strategies (Gürsoy, 2020).

Volatility spillovers, as defined in the literature, refer to the short-term process by which volatility in one market affects volatility in other markets (So, 2001). Investors closely monitor this, and it plays a

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* Corresponding author.
E-mail addresses: buketkircialtinkeski@halic.edu.tr (B. Kirci Altinkeski), sdibooglu@missouriwestern.edu (S. Dibooglu), eicevik@nku.edu.tr (E.I. Cevik), yunuskilic@akdeniz.edu.tr (Y. Kilic), mfbugan@gantep.edu.tr (M.F. Bugan).

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significant role in shaping the investment choices of international investors. Investors typically adjust their decision-making based on various scenarios and market conditions (Shefrin & Belotti, 2007). A widely used indicator representing volatility in international markets is the volatility index created on the Chicago Board Options Exchange (CBOE), known as the Volatility Implied Index (VIX). This volatility index, also known as the fear gauge, is so named because it measures both upward and downward volatility perceived by the stock market. An elevated VIX signifies increased investor anxiety and market volatility, while a decreased VIX implies stronger market faith; as such, the VIX serves as a barometer for investors, and influences decision making. The VIX is influenced by macro and microeconomic factors and non-economic factors such as speculative activities, wars, and geopolitical tensions. Increased uncertainty and volatility in the VIX often stem from heightened speculative activity (Bildirici et al., 2022). When evaluating the global aspects of investments, one must consider the potential impact of the VIX index on fluctuations in stock returns across various markets.

Research on the VIX and stock markets can be motivated by behavioral finance, which focuses on how an investor processes information as well as issues that might influence a person's perception of risk in risky situations and investor sentiment. Since the VIX index is also referred to as a fear gauge, it warrants focusing on investor behavior and how it differs in calm times versus turbulent times. Many studies have approached the relationship between the VIX and stock markets from the behavioral finance perspective (Aharon, 2021; Akin & Akin, 2024; Bagchi, 2012; Zakamulin, 2016). Behavioral finance typically encompasses cognitive biases, emotions, and psychological factors that often significantly shape financial decisions and market outcomes (Shahani & Ahmed, 2022). Accordingly, investor sentiment is subject to fluctuations in mood, and these oscillations can cause temporary deviations in stock prices from their fundamental values (Zakamulin, 2016). Therefore, behavioral finance provides valuable insights into the factors driving fluctuations in the stock market and can assist market participants in making more informed and resilient investment decisions (Akin & Akin, 2024). There are also studies in the literature that relate the relationship between the VIX index and stock returns to risk aversion or the risk-return tradeoff (Chandra & Thenmozhi, 2015; Coudert & Gex, 2008; Kanas, 2013; Kownatzki, 2016). A negative economic outlook may increase risk aversion, as investors respond to the higher likelihood of diminished wealth situations by decreasing their propensity to take on risk (Scheicher, 2003). An escalation in risk aversion triggers an increase in all risk premia, consequently leading to a decline in asset prices throughout all financial markets (Coudert & Gex, 2008). Qadan et al. (2019) indicated that an increase in the VIX may reflect a rise in investors' risk aversion and could lead them to balance their portfolios by enhancing diversification. In some studies, the VIX index has been directly used as a proxy for investor sentiment (Smales, 2017; So & Lei, 2015). Investigating whether the VIX index serves as a fear gauge or an indicator of investor positive sentiment, Sarwar (2012a, 2012b) found that the VIX responds much more aggressively to negative changes in stock returns than positive changes of similar magnitude. This suggests that the VIX indicates investor fear rather than positive sentiment. Using the VIX index as an indicator of investor sentiment, Smales (2017) found a strong relationship between investor sentiment and stock returns. Cheuathonghua et al. (2019) noted that investor sentiment is stronger during financial crises than calm periods, revealing that even a small change in the VIX can significantly impact global markets under extreme market conditions.

The VIX index was constructed initially from options written on the S&P 100 index by the CBOE in 1993. In 2003, the methodology underlying the VIX index was modified and the index started to be based on the implied volatility of options written on the S&P 500 index (Prasad et al., 2022). To accelerate volatility trading and augment hedging prospects, the CBOE implemented VIX futures on March 26, 2004 (Frijns et al., 2016). The index is computed based on the differences between put and call options on stock prices (Fountain et al., 2008). The VIX represents forward-looking volatility, serving as an options market estimate of the expected volatility for the S&P 500 index expressed in percentage points over 30 days (Shu & Zhang, 2012). Investors set the index, which conveys consensus opinions about future stock market volatility, as a higher VIX conveys greater fear on the part of investors (Whaley, 2000). VIX futures witnessed a substantial surge in popularity, with daily trading volumes surpassing 200,000 contracts by 2014. Investors utilize VIX futures for hedging purposes due to the pronounced negative correlation between S&P 500 index returns and the VIX (Frijns et al., 2016). Notably, VIX futures have been demonstrated to be a considerably more cost-effective hedging instrument than S&P 500 index options (Szado, 2009).

The VIX index is widely recognized as having a significant impact on the performance of stock indices in emerging economies (Cheuathonghua et al., 2019). It is also closely monitored by central banks in various countries for policy formulation. When the VIX level is low, investors perceive low levels of risk. In contrast, a high VIX level indicates that investors perceive significant risk and expect sharp movements in the market in both directions. Consequently, increases in the VIX represent increases in overall market risk. Since the VIX conveys perceived risks in financial markets, regulators and policymakers monitor the VIX to assess systemic risk in financial systems. Hence, examining the dynamic interactions between the VIX and stock market indexes is important in terms of portfolio management and financial stability.

An increase in the VIX index is typically associated with a decrease in stock returns. Conversely, a decrease in the VIX index is related to an increase in stock returns, though this is not always the case. However, the VIX remains a vital indicator of stock performance and understanding under what condition the VIX is a useful predictor is paramount. Apart from serving as a valuable investment tool, the VIX can also be seen as an economic forecasting instrument due to its capacity to predict financial instability and broader, economy-wide severe downturns (Bildirici et al., 2023). Indeed, implied volatility, as measured by the VIX affects the pricing of risk in stock and bond markets and has implications for and serves as a predictor of real economic activity (Adrian et al., 2019).

The VIX index holds significant value since it offers a gauge of market risk and investor sentiment, thereby aiding in making informed investment choices. However, the relationship between the VIX and stock returns in general and the S&P 500 in particular is not consistently negative, necessitating a closer look at the relationship under different market conditions (Adrangi et al., 2019). Second, the relationship between the VIX index and stock returns may change over time. As such, one must use a methodology capable of examining the dynamic interactions between the VIX and stock returns under different stock market conditions and under different risk and investor sentiment perceptions with an allowance for a time-varying relationship. Finally, the relationship between the VIX and equity returns has been non-linear. Adrian et al. (2019) show that the relationship between the six-month cumulative U.S. equity market return and the six-month lag of the VIX is highly non-linear. Accordingly, increases in the VIX below the median are associated with a slight decline in equity returns; however, when the VIX is above the median in the intermediate range, expected stock returns go up. This relationship sharply reverses at extremely high levels of the VIX, with a rise in the VIX linked to a sharp decrease in stock returns. The latter observation at very high VIX values likely indicates the aftermath of severe financial crises, characterized by dismal stock performance and aggressive interest rate reductions following a decline in economic activity. Therefore, any study of the relationship between perceived volatility and equity returns must account for the non-linearities.

The primary objective of this study is to examine the relationship between the VIX and global stock markets in both time and quantile dimensions. First, we use the quantile-on-quantile spillover analysis developed by Gabauer and Stenfors (2024). This method enables us to investigate the relationships between variables directly and at reversely related quantile levels, which allows for examining the relationship under various market conditions. This is important as there is a documented non-linear and asymmetric relationship between the VIX index and stock returns (Adrian et al., 2019; Bekiros et al., 2017; Fu et al., 2016). As such, it is crucial to uncover the relationships between variables when the VIX is high (at high quantile levels) and stock returns are low (at low quantile levels) and vice versa. Our study contributes to the literature in several ways. First, it uses a comprehensive data set covering a sample of 20 developed and 20 emerging stock markets. Second, the relationship between the VIX and stock markets is analyzed based on both time-varying relationships and based on quantiles, which allows for non-linearity in the relationship. Hence, we study the relationship under different stock market conditions and under different risk and investor sentiment perceptions with an allowance for a time-varying relationship. This allows spillovers to vary over time and across quantiles, where the level of interconnectedness can be different. The issue is germane since our sample covers distinct events, such as the Euro launch and major worldwide crises. Third, providing a convincing explanation for the negative and asymmetric return-volatility relationship has posed significant challenges for financial economists (Bekiros et al., 2017). Our study intends to fill a gap by using a model that allows for an asymmetric relationship. Fourth, since the dataset spans 1995 to 2023, this period includes major events that led to significant increases in the VIX index, such as the 1997 Southeast Asian Financial Crisis, the 1998 Russian Crisis, the 2000 dotcom bubble, the 2001 Enron scandal, the 9/11 attacks, the 2001 Argentina and Turkey Crises, the 2003 Iraq War, the 2008 Global Financial Crisis, the 2011–12 European Debt Crisis, and the 2020 COVID-19 pandemic. Finally, to our knowledge, this study is the first to examine the relationship between the VIX and stock markets using the quantile-on-quantile spillover analysis.

The study's six sections are structured as follows. After the introduction, Section 2 reviews the relevant literature; Section 3 introduces the econometric methods; Section 4 presents the empirical results; Section 5 includes robustness checks and sensitivity analysis, and the final section concludes the paper.

2. Literature review

The stock market's expectation of volatility is based on S&P 500 index options, and the VIX index has been extensively studied in the finance and economics literature. Numerous studies have analyzed the mutual dependence between U.S. stock returns and the VIX; however, relatively few studies have examined the interaction between international stock market indices and the VIX index.

Volatility, which represents the simplest measure of risk or uncertainty, is a fundamental attribute employed to delineate and quantify fluctuations in asset prices (Shu & Chang, 2019). The implied volatility of option prices is often regarded as a reflection of investor views on the future market volatility of underlying assets. Option investors are generally perceived as more informed; implied volatility tends to outperform historical volatility in forecasting future realized volatility (Shu & Zhang, 2012). There is evidence to suggest a negative relationship between changes in the volatility index and changes in market index returns (Sarıtaş & Nazlıoğlu, 2019). Research by Shaikh and Padhi (2014), Fernandes et al. (2014), Kliger and Kudryavtsev (2013), Neng (2013), Hao and Zhang (2013), Esqueda et al. (2013), Sarwar (2012a, 2012b), Whaley (2009), Nossman and Wilhelmson (2009), Corrado and Miller (2005), Dash and Moran (2005), Whaley (2000) and Fleming et al. (1995) investigated the impact of the VIX Index on stock returns, finding that generally, higher VIX Index levels are linked to decreases in stock returns.

Korkmaz and Çevik (2009) used the GJR-GARCH and daily data from January 02, 2004 to March 17, 2009 to investigate the impact of the VIX on the stock markets of 15 emerging economies. The results indicate that adverse news in the market leads to a more pronounced increase in volatility. Specifically, the VIX index exerts influence on and elevates the volatility of the stock markets in Brazil, Argentina, Chile, Hungary, Peru, Turkey, Mexico, Poland, Thailand, Malaysia, and Indonesia. Kaya et al. (2014) constructed an ARDL model using monthly time series data from January 1999 to December 2013 to investigate the relationship between the VIX index and the stock markets in the OECD countries, finding a long-term relationship between the VIX index and stock markets. Sarwar and Khan (2017) tested the effects of the VIX index on stock returns in Latin America using daily data from January 06, 2003 to 90/30/2014 through multiple regression analysis and found the VIX index to have a significant and negative impact on the stock returns of Latin American countries throughout the sample. Using regressions and daily data from the Taiwanese stock market from January 01, 2007 to 12/31/2014, Huang and Wang (2017) examined the relationship between the VIX index and the stock returns and found evidence of a relationship between the VIX index and stock returns where changes in the VIX index influenced investor behavior. Ruan (2018) examined the relationship between market volatility (VIX index) and the stock market using dynamic Copula and ST-VCopula models. The empirical analysis focused on various countries' VIX index and stock markets. The findings from the analysis demonstrated a noteworthy influence of the VIX index on the interconnection among stock markets. Shu and Chang (2019) utilized daily data from 2004 to 2014 to analyze the relationship between three volatility indices and ten stock market indices, using a generalized VAR approach developed by Diebold and Yilmaz (2012). Empirical findings demonstrated a significant effect of volatility in explaining stock returns. Moreover, the study documented spillover effects in volatility indices, with the VIX as the primary transmitter and the implied volatility of the Korean stock market (VKOSPI) as the primary recipient of these transmissions. The results suggest that the VIX plays a leading role in international stock market movements.

Cheuathonghua et al. (2019) used daily data spanning 1998–2014 from 42 international emerging and developed markets. The authors examined how the VIX affects different aspects of market index activities, such as volatility, returns, and abnormal trading volume, especially during extreme financial crises and financial exuberance. They observed that the influence of the VIX spreads becomes significantly more noticeable during periods of extreme market turbulence and tends to have a spreading effect. Furthermore, their results indicated that the impact of the VIX is asymmetric, with a more substantial effect in bear markets, high volatility environments, and low trading volume markets. Additionally, the VIX spreads had a more significant impact on returns in developed markets, while they had a greater effect on volatility in emerging markets. Geographically, the influence of the VIX spreads was particularly prominent in Europe regarding returns and in Latin America regarding volatility. Adrangi et al. (2019) examined the response of four major equity markets (the U.S., the UK, France, and Germany) to structural breaks in the VIX index. Analyzing daily data from 2013 to 2018, they show equity market volatility in the U.S., the UK, France, and Germany reacted to structural shocks in the VIX from June 2013 to May 2016. However, in the aftermath of the Brexit vote, equity indices showed no response to VIX structural shocks, nor were they influenced by these shocks.

Alqahtani and Chevallier (2020) applied Engle's (2002) DCC-GARCH models to weekly data, aiming to forecast conditional correlations between Gulf Cooperation Council stock returns and three volatility indices: oil (OVX), gold (GVZ), and S&P 500 (VIX) markets. The results indicated that stock market returns exhibit negative correlations with each volatility measure, which are stronger during crisis episodes. Smales (2022) examined the connections between global stock markets using measures of market uncertainty. The study analyzed the linkages in financial market uncertainty among G7 countries using implicit volatility measures from January 2001 to December 2020. Using a sample of daily changes in G7 volatility measures, the uncertainty in the U.S. markets played a highly significant role in global stock market uncertainty in the sample.

Based on a concise examination of the available literature, it is clear that although negative associations have been identified between the VIX and various stock indices, no noticeable correlation has been established with specific indices. Our study has two key characteristics that set it apart from previous research. First, to the best of our knowledge, no prior investigation in the literature has explored the connection between the VIX index and stock markets across a comprehensive set of developed and emerging markets. Consequently, our study presents a fresh and innovative perspective on this subject. Second, our methodology accounts for spillovers that may occur over time and across different quantile levels. In a sense, our study offers a distinct analytical approach compared to other studies in the literature. It allows for a more detailed and precise examination of the relationship between the VIX index and stock markets over time and across various quantiles spanning nearly 30 years.

3. Quantile-on-quantile spillover analysis

We examine the dynamic relationship between the VIX and stock market returns by focusing on not only time-varying aspects but also various quantiles of the variables. Recently, Gabauer and Stenfors (2024) suggested a novel method dubbed quantile-on-quantile spillover analysis to investigate the transmission mechanism between a set of variables at various quantiles. This approach involves estimating the following Quantile Vector Autoregression (QVAR) models across different quantiles:

$$\boldsymbol{x}_t = \boldsymbol{\mu}(\boldsymbol{\tau}) + \sum_{j=1}^{p} \boldsymbol{B_j}(\boldsymbol{\tau})\boldsymbol{x}_{t-j} + \boldsymbol{u}_t(\boldsymbol{\tau}) \tag{1}$$

The variables $\boldsymbol{x}_t$ and $\boldsymbol{x}_{t-j}$ represent $K \times 1$ dimensional endogenous variables vectors, while $\boldsymbol{\tau}$ is a vector containing quantiles ranging between [0, 1]. The parameter p denotes the lag length of the QVAR model, $\boldsymbol{\mu}(\boldsymbol{\tau})$ represents a $K \times 1$ dimensional conditional mean vector, $\boldsymbol{B_j}(\boldsymbol{\tau})$ signifies a $K \times K$ dimensional QVAR coefficient matrix, and $\boldsymbol{u_t}$ is a $K\times 1$ dimensional error vector with a $K \times K$ dimensional variance-covariance matrix, $\boldsymbol{H}(\boldsymbol{\tau})$.

Calculating the generalized forecast error variance decomposition (GFEVD) suggested by Koop et al. (1996) depends on transforming the QVAR model into a Quantile VAR Moving Average model, $\boldsymbol{x_t} = \boldsymbol{\mu}(\tau) + \sum_{i=0}^{\infty}\mathbf{A}_i(\tau)\boldsymbol{u}_{t-i}(\tau)$. The F-step ahead GFEVD quantifies the impact of a shock in series j on series i, and is given by:

$$\varphi^{g}_{i\leftarrow j,\tau}(F) = \frac{\sum_{f=0}^{F-1}\left(\boldsymbol{e}_i'\mathbf{A}_f(\boldsymbol{\tau})\boldsymbol{H}(\boldsymbol{\tau})\boldsymbol{e}_j\right)^2}{H_{ii}(\boldsymbol{\tau})\sum_{f=0}^{F-1}\left(\boldsymbol{e}_i'\mathbf{A}_f(\boldsymbol{\tau})\boldsymbol{H}(\boldsymbol{\tau})\mathbf{A}_f(\boldsymbol{\tau})'\boldsymbol{e}_i\right)} \tag{2}$$

$$gSOT_{i\leftarrow j,\tau}(F) = \frac{\varphi^{g}_{i\leftarrow j,\tau}(F)}{\sum_{j=1}^{k}\varphi^{g}_{i\leftarrow j,\tau}(F)} \tag{3}$$

where $\boldsymbol{e_i}$ is a $K \times 1$ dimensional zero vector with unity in its ith position. The scaled GFEVD plays a central role in the spillover analysis and is used to calculate the total directional spillover TO (FROM) others. The TO total directional spillover reflects the influence series i exerts on all other series, while the total directional spillover FROM shows the combined impact of all series on series i. These spillover metrics can be computed as:

$$S^{gen,to}_{i\to\bullet,\tau} = \sum_{k=1,i\neq j}^{K} gSOT_{k\leftarrow i,\tau} \tag{4}$$

$$S^{gen,from}_{i\leftarrow\bullet,\tau} = \sum_{k=1,i\neq j}^{K} gSOT_{i\leftarrow k,\tau} \tag{5}$$

The NET total directional spillover for variables i can be calculated by subtracting the FROM the TO:

$$S^{gen,net}_{i,\tau} = S^{gen,to}_{i\to\bullet,\tau} - S^{gen,from}_{i\leftarrow\bullet,\tau} \tag{6}$$

When $S^{gen,net}_{i,\tau}$ is greater than 0 ($S^{gen,net}_{i,\tau}$ is less than 0), it signifies that variable i is exerting a greater (lesser) influence on all other variables compared to being influenced by them, thus indicating variable i as a net transmitter (receiver) of shocks. The adjusted total spillover index (TSI) can be calculated as follows:

$$TSI_\tau(F) = \frac{K}{K-1}\sum_{k=1}^{K} S^{gen,from}_{i\leftarrow\bullet,\tau} \equiv \frac{K}{K-1}\sum_{k=1}^{K} S^{gen,to}_{i\to\bullet,\tau} \tag{7}$$

This index shows the degree of network interconnectedness. An increase in the TSI implies higher connectedness.

4. Data and empirical results

This study investigates the relationship between the VIX and 40 stock markets (including 20 developed and 20 emerging countries[1]) using weekly data from January 1, 1995, to October 26, 2023, where the total number of observations is 1054. Weekly closing prices of stock market indices and the VIX were obtained from the Refinitiv Eikon database.[2] Stock market returns were calculated by taking the logarithmic first differences of stock market indexes. Table 1 presents the countries and their codes included in the sample.

Fig. 1 depicts the course of the VIX over the sample.[3] According to Fig. 1, it is evident that the VIX exhibited high levels between 1997 and 2003. This is expected as some noteworthy developments affected financial markets both in the U.S. and globally (such as the 1997 Southeast Asian Financial Crisis, 1998 Russian Crisis, 2000 dotcom bubble, 2001 Enron scandal, 9/11 attacks, 2001 Argentina and Turkey Crises, and the 2003 Iraq War). Due to the Global Financial Crisis, the VIX index started to rise in early 2007 and peaked in 2009, marking its highest level up to that point. Due to the European Debt Crisis, the VIX increased in 2011 and 2012. More recently, driven by the global COVID-19 pandemic, the VIX surged in 2020, reaching its all-time high.

Table 2 presents descriptive statistics for stock market returns in developed countries. The results show that the mean returns for all stock markets during the sample are positive except for Singapore. The Danish stock market has the highest mean returns, while the Singapore stock market has the lowest mean returns. Finland has the highest market volatility, as measured by standard deviations. The skewness and kurtosis values suggest that the distribution of the return series is left-skewed and leptokurtic. The Jarque-Bera normality test results indicate that the distribution of the return series is not normal. The ADF and PP unit root test results show that the return series are stationary.

Table 3 displays the descriptive statistics for the return series of emerging stock markets. The weekly mean returns of all countries, except for China, Jordan, and Thailand, are positive. Türkiye and Jordan stock markets provide the highest and lowest mean returns among emerging countries in the sample, respectively. The distribution of the return series is left-skewed, as indicated by the skewness values, and it exhibits an excessively fat tailed distribution according to the kurtosis values. The Jarque-Bera test results show the null hypothesis of normality is rejected at the 1% significance level for all series. All series are stationary per unit root test results.

[1] The country classifications are based on Morgan Stanley Capital International (MSCI).

[2] Utilizing daily stock indices from different continents poses an asynchronous data issue due to the varying trading hours of VIX and selected stock markets. As such, weekly data is more appropriate.

[3] The mean of VIX is 20.084, with a standard deviation of 8.168. The skewness and kurtosis are 2.079 and 10.809, respectively. Both the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests indicate stationarity in levels.

Table 1
List of countries.

Panel A: Market Development Classification			
Developed		Emerging	
Country	Code	Country	Code
Australia	AUS	Brazil	BRA
Austria	AUT	Argentina	ARG
Belgium	BEL	Chile	CHL
Canada	CAN	China	CHN
Denmark	DNK	Colombia	COL
Finland	FIN	Czechia	CZK
France	FRA	Egypt	EGY
Germany	DEU	Hungary	HUN
Ireland	IRL	India	IND
Italy	ITA	Indonesia	IDN
Japan	JPN	Jordan	JOR
Netherlands	NLD	Malaysia	MYS
New Zealand	NZL	Mexico	MEX
Portugal	PRT	Peru	PER
Singapore	SGP	Philippines	PHL
Spain	ESP	Poland	POL
Sweden	SWE	South Africa	ZAF
Switzerland	CHE	South Korea	KOR
United Kingdom	UK	Thailand	THA
USA	USA	Türkiye	TUR

Panel B: Regional Classification

North America	**Latin America**	**Europe**		**MENA**	**Asia Pacific**
Canada	Brazil	Austria	Italy	Egypt	Australia
Mexico	Argentina	Belgium	Netherlands	Jordan	China
USA	Chile	Czechia	Poland	South Africa	Japan
	Colombia	Denmark	Portugal		New Zealand
	Peru	Finland	Spain		India
		France	Sweden		Indonesia
		Germany	Switzerland		Malaysia
		Hungary	Türkiye		Philippines
		Ireland	UK		Singapore
					South Korea
					Thailand

We use the quantile-on-quantile spillover analysis explained above to examine the dynamic connectedness between the VIX and stock markets. We estimate the bivariate Quantile VAR model and select the optimal lag length using the Bayesian Schwarz Information Criterion. To capture the time-varying relationship between the variables, we use a rolling window where the window size is 252 weeks (1 year). Additionally, we chose a forecast horizon of 4 weeks (1 month) for variance decompositions. The results for developed stock markets are presented in Online Appendix A, Fig. 2A.

Note that results in Fig. 2A depict the average total spillover relationship obtained from different quantiles for the VIX and stock markets (such as $\tau_1 = 0.1, 0.2, \ldots, 0.9$ and $\tau_2 = 0.1, 0.2, \ldots, 0.9$), using the rolling window method. Consequently, the results represent the average of the dynamic relationships obtained from rolling windows. Moreover, the bottom left corner in each graph in Fig. 2A presents results for periods with a low VIX and stock returns, while the results in the top-right corner indicate periods when both the VIX and stock returns are high. These represent directly related quantile total spillovers. On the other hand, results in the top-left corner of Fig. 2A illustrate the dynamic relationship at quantile levels where the VIX is high and stock returns are low ($\tau_1 = 0.9$ and $\tau_2 = 0.1$), while the results in the top-right corner depict the dynamic results during periods where the VIX is low and stock returns are high ($\tau_1 = 0.1$ and $\tau_2 = 0.9$). These represent total spillovers from indirectly related quantiles. Note that the results in the middle of the graph represent the spillover analysis results at the median values for both variables. In addition, the intensity of the spillover effect is indicated by the shading of the cells: dark blue areas indicate high total spillovers, while white areas indicate low total spillovers.

The results of Fig. 2A reveal that the indirectly related quantile total spillovers between the VIX and developed stock market returns surpass the directly related quantile total spillovers. This suggests more asymmetric relationships between the VIX and stock returns than symmetric interactions. It also implies a more pronounced negative correlation between the variables: high returns occur during low VIX levels and low returns occur at high VIX levels. The highest total spillovers across all stock markets occur at the highest quantile level for the VIX and the lowest for stock returns ($\tau_1 = 0.9$ and $\tau_2 = 0.1$). Indeed, our results are consistent with those of Giot (2005), who found that negative stock index returns yield bigger changes in the VIX than positive returns. Moreover, the interconnectedness is also more pronounced at low VIX quantiles and high stock market return quantiles (southeast quadrant of the graph) and strongest at the southeast corner. However, the interconnectedness between the VIX and stock market returns reaches its peak during periods of elevated VIX levels and depressed stock returns, commonly associated with bearish market conditions. This observation aligns with a priori expectations; the VIX index, often referred to as a fear index, can be expected to exhibit heightened interaction with stock markets during financial market lows. Finally, high interconnectedness between stock returns and VIX levels occurs at unusually low and unusually high quantiles (0.1 VIX levels; 0.1 returns) and (0.9 VIX; 0.9 returns) even though these are not as pronounced as indirectly related

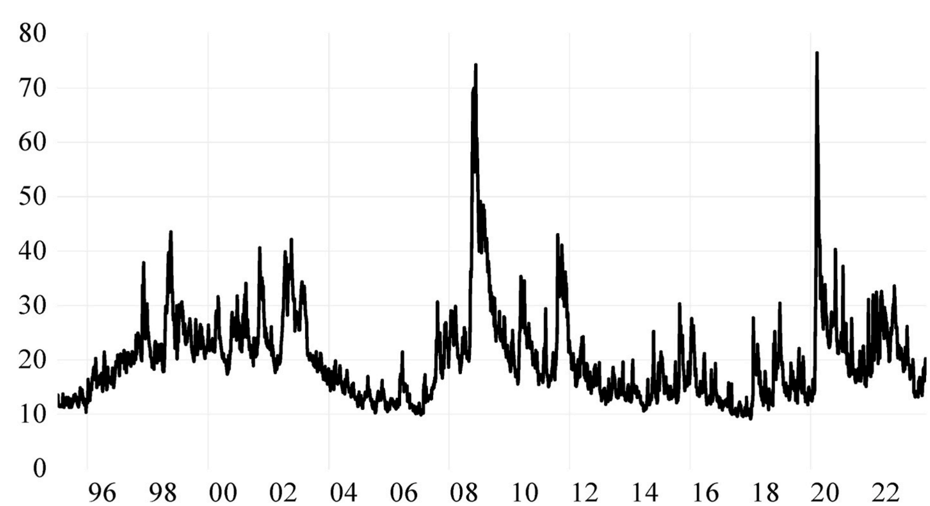

Fig. 1. Vix.

Table 2
Descriptive statistics for developed countries.

	AUS	AUT	BEL	CAN	CHE	DEU	DNK	ESP	FIN	FRA
Mean	0.080	0.023	0.038	0.104	0.093	0.072	0.203	0.086	0.091	0.092
Max	11.604	22.955	18.379	12.321	14.571	16.461	12.547	14.417	25.540	16.550
Min	−14.442	−33.827	−22.747	−19.124	−13.852	−22.338	−18.050	−18.341	−21.593	−21.193
Std. Dev.	2.061	3.467	2.948	2.292	2.384	3.048	2.637	3.128	4.204	2.893
Skewness	−0.698	−1.382	−0.829	−1.059	−0.600	−0.829	−0.636	−0.460	−0.536	−0.574
Kurtosis	7.206	14.438	11.400	10.598	8.035	8.708	6.780	5.992	7.524	8.907
J-B	1229.535	8671.282	4590.569	3896.123	1677.566	2212.766	996.336	613.569	1353.766	2267.781
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ADF	−39.377*	−8.436*	−15.886*	−13.176*	−41.793*	−41.396*	−15.134*	−15.49*	−13.818*	−20.046*
PP	−39.484*	−39.73*	−39.901*	−38.644*	−41.807*	−41.341*	−40.145*	−41.324*	−41.628*	−43.288*
	IRL	**ITA**	**JPN**	**NLD**	**NZL**	**PRT**	**SGP**	**SWE**	**UK**	**USA**
Mean	0.013	0.032	0.019	0.103	0.025	0.009	−0.005	0.138	0.055	0.151
Max	17.294	12.087	15.542	18.030	7.564	10.927	17.597	13.772	13.344	10.775
Min	−26.541	−20.456	−20.482	−16.944	−12.765	−18.727	−14.989	−16.911	−14.964	−16.748
Std. Dev.	3.427	3.156	2.834	2.892	2.142	2.883	2.742	3.116	2.298	2.364
Skewness	−0.807	−0.558	−0.333	−0.604	−0.329	−0.674	−0.160	−0.539	−0.529	−0.888
Kurtosis	9.618	6.401	6.547	7.734	5.355	6.777	6.968	6.297	8.173	8.287
J-B	2905.971	802.399	815.927	1494.44	374.366	1007.071	992.631	753.451	1746.138	1947.895
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ADF	−6.776*	−19.973*	−7.645*	−19.439*	−9.527*	−40.547*	−8.667*	−14.718*	−16.138*	−40.429*
PP	−41.92*	−39.73*	−41.314*	−42.343*	−40.494*	−40.553*	−37.072*	−41.878*	−42.271*	−40.538*

Note: J-B is Jarque-Bera normality test. * indicates stationarity at 1% significance level.

Table 3
Descriptive statistics for emerging countries.

	ARG	BRA	CHL	CHN	COL	CZK	EGY	HUN	IDN	IND
Mean	0.161	0.159	0.047	−0.025	0.158	0.07	0.233	0.204	0.152	0.169
Max	26.244	30.445	12.795	21.603	19.179	13.661	20.524	21.902	22.101	16.63
Min	−44.862	−26.58	−31.755	−19.561	−41.62	−23.56	−24.108	−25.657	−23.119	−19.913
Std. Dev.	5.372	3.959	2.837	4.262	3.656	3.171	3.951	4.035	3.956	3.349
Skewness	−0.59	−0.644	−1.318	−0.305	−1.051	−0.744	−0.373	−0.742	−0.3	−0.439
Kurtosis	8.561	11.53	17.393	6.032	18.477	7.906	6.694	9.264	8.539	6.569
J-B	2025.517	4663.889	13418.36	599.404	15287.61	1647.408	889.994	2596.578	1945.456	846.752
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ADF	−36.709*	−10.836*	−17.737*	−20.104*	−36.56*	−19.496*	−8.812*	−15.089*	−13.975*	−11.725*
PP	−36.749*	−42.053*	−38.308*	−39.167*	−36.572*	−39.871*	−36.52*	−38.797*	−37.88*	−38.228*
	JOR	**KOR**	**MEX**	**MYS**	**PER**	**PHL**	**POL**	**THA**	**TUR**	**ZAF**
Mean	−0.040	0.087	0.190	0.008	0.127	0.018	0.057	−0.018	0.490	0.134
Max	14.442	18.522	13.657	27.385	20.535	16.341	15.837	25.93	24.555	12.587
Min	−46.171	−19.198	−20.388	−15.371	−26.383	−17.294	−21.605	−21.999	−30.988	−27.655
Std. Dev.	2.768	3.688	2.971	2.849	4.084	3.239	3.596	3.927	5.248	2.783
Skewness	−3.024	−0.175	−0.247	0.594	−0.395	−0.232	−0.293	0.266	−0.268	−0.927
Kurtosis	57.819	6.413	6.394	15.793	6.875	5.988	5.985	7.956	6.458	11.54
J-B	190609.9	737.743	737.342	10344.39	980.29	572.829	579.879	1556.8	767.519	4785.234
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ADF	−26.843*	−7.958*	−12.507*	−9.935*	−12.949*	−20.647*	−9.699*	−19.065*	−13.288*	−10.43*
PP	−40.331*	−40.256*	−39.296*	−38.307*	−39.389*	−38.919*	−38.007*	−38.577*	−38.968*	−41.768*

Note: J-B is Jarque-Bera normality test. * indicates stationarity at 1% significance level.

quantiles.

The analysis reveals varying levels of related and indirectly related quantile total spillovers between the VIX and various stock market returns. The highest total spillovers are observed between the VIX and the New Zealand stock market ($\tau_1 = 0.9$ and $\tau_2 = 0.9$), while the lowest total spillover is found between the VIX and the Portuguese stock market ($\tau_1 = 0.3$ and $\tau_2 = 0.2$). Conversely, the highest total spillover index for indirectly related quantiles occurs between the VIX and the U.S. stock market ($\tau_1 = 0.9$ and $\tau_2 = 0.1$).

The results for the average dynamic *net spillover* analysis for developed stock markets are given in Online Appendix A, Fig. 3A. In the figure, blue cells denote quantiles where the VIX is a net spillover transmitter, while brown cells represent quantiles where the VIX is a net receiver of spillovers. It is evident that the VIX is a net spillover receiver at extremely high and meager stock returns. More specifically, unusually low and high stock returns (0.1 and 0.9 quantiles) influence general perceived market volatility as measured by the VIX at all quantiles except very low and very high volatility episodes. However, there is a variation where unusually low and unusually high stock market returns affect the VIX. In Austria, Spain, New Zealand, and Singapore extreme stock returns affect the middle quantiles of the VIX, whereas in the rest of the sample, extreme stock returns exert influence on the middle and upper middle quantiles of the VIX. Conversely, the VIX seems to be a net spillover provider under a wide range of stock market return conditions. Specifically, extremely low and high VIX quantiles provide spillovers to stock market returns with no exceptions.

The results from the dynamic total spillover analysis for emerging markets are illustrated in Online Appendix A, Fig. 4A. A close look at the results reveals that the highest spillover index values are concentrated in the cells at each graph's top-left corner. This suggests that spillovers between the VIX and stock returns peak when the VIX registers its highest levels and stocks markets are in extreme bear market territory. Conversely, notable total spillover indices are observed in the cells positioned at the bottom-right corner of the graphs, indicating that indirectly related quantile spillovers outweigh directly related quantile spillovers. Among all emerging markets, the highest total spillovers are observed between the VIX and the Mexican stock market, while the lowest total spillover is recorded between the VIX and the Jordanian stock market. Notably, the Jordanian stock market exhibits the lowest total spillovers across all quantile levels as compared to other stock markets.

The results from the dynamic *net spillover* analysis for emerging stock markets are given in Online Appendix A, Fig. 5A. A comparison with the findings obtained for developed stock markets in Fig. 3A reveals a notable distinction: emerging stock markets exhibit a limited number of net spillover providers. Specifically, the VIX is a net spillover receiver at extreme stock market return episodes (0.1 and 0.9 quantile levels) and within the 0.5 to 0.8 quantile range for the VIX. Conversely, the VIX is a net spillover provider at other quantile levels. Notably, at the 0.9 quantile level for the VIX, it emerges as a significant net spillover provider to all stock markets. These results underscore that while the VIX generally acts as a spillover provider across emerging stock markets, the spillover effect's magnitude peaks at extreme VIX values. This is not surprising in that emerging stock market developments have less impact on the VIX than developed markets. Note also that the interconnectedness profiles of emerging European economies such as Poland, Hungary, Czechia are similar to developed markets, perhaps due to their higher income levels and closer integration with the Eurozone.

The results from the spillover analysis can be summarized as follows.

- There is an asymmetric relationship between the VIX and stock returns, with total spillover being higher during periods when the VIX is high and stock returns are low. This indicates that the VIX is more responsive to extreme changes in market returns, consistent with rising portfolio insurance premiums during periods of high market anxiety and turbulence (Sarwar, 2012a, 2012b).
- The integration between the VIX and developed stock markets is significantly higher compared to emerging stock markets. The total spillover between the VIX and developed stock markets is greater than that with emerging markets. As suggested by Magner et al. (2021) and Ozcan (2021), the VIX can influence the synchronization of stock market returns across different regions and asset classes, where an increase in the VIX leads to greater perceived uncertainty, causing returns to move similarly.
- Outside of the U.S., the stock markets that exhibit the highest spillover with the VIX are those of Canada, Germany, France, and the UK. The high level of interconnectedness between these countries' stock markets and the VIX can be attributed to the similarities in their business cycles with that of the U.S.
- Compared to other developed countries, the interconnectedness between the VIX and Japan is lower. This finding is consistent with Bekiros et al. (2017), who attribute this to the ownership structure of firms listed on the Japanese stock market and the lack of liquidity.
- The relationship between European stock markets and the VIX generally exhibits a homogeneous structure, showing little variability across countries.
- The connection between the VIX and Asia–Pacific countries is typically low. A similar result is observed for countries in the MENA region. Specifically, the total spillover between the Jordan stock market and the VIX is the lowest compared to other countries. This finding aligns with expectations, as the Jordan stock market is classified as a frontier market, with low integration with other stock markets and relatively low trading volume.
- There is a high level of connectedness between North American countries and the VIX. South American stock markets are more connected to the VIX among emerging countries. Overall, the patterns observed suggest that financial or bilateral linkage/integration may be playing a role in connectedness.

Online Appendix A, Fig. 6A and 7A present the averaged directly related and reversely related dynamic total spillover index results. The figures reveal a consistent pattern: the reverse-related average total spillover index is greater than the directly related average total spillover index over the sample and across countries. This observation underscores a robust asymmetric relationship between the VIX and stock returns, characterized by stronger spillover effects in the reverse direction (e.g., low VIX and high returns and vice versa). This implies that extremely low levels in one series are associated with extremely high developments in the other series and are consistent with higher asymmetric linkages between the VIX and stock returns. Overall, our empirical results indicate that there is not only heterogeneity in the return-volatility relationship across countries but there is also regional heterogeneity.

5. Robustness checks

To examine the robustness of our empirical findings, we conduct robustness and sensitivity analysis. Firstly, we applied the cross-quantilogram analysis suggested by Han et al. (2016) to explore the predictability relationship between the VIX and stock markets across various quantile levels. This involved calculating cross-correlations between the VIX and each stock market and assessing the statistical significance of these correlations using the Ljung-Box Q statistic.

Online Appendix B presents the results of the cross-quantilogram analysis for selected countries that exhibit the highest correlation with the VIX.[4] According to the results in Fig. 1B, there is a significant asymmetric feedback relationship between the VIX and stock returns of developed countries. This is because bidirectional predictability is observed at extreme quantiles, while generally a unidirectional predictability relationship can be observed at median values. In contrast, an analysis of the outcomes for developing nations reveals a prevailing unidirectional correlation at various quantile levels. This correlation indicates that the causality direction is from the VIX towards stock markets at low stock return levels, while it shifts towards stock returns from the VIX at median and higher return levels. In conclusion, the cross-quantilogram results are consistent with the findings of the quantile-on-quantile spillover analysis in that both methods indicate a high degree of connectedness between the VIX and developed stock markets at extreme quantile levels.

Finally, a sensitivity analysis is conducted for the quantile-on-quantile spillover analysis. The spillover analysis is repeated with a rolling window size of 504 (two years) and a forecast horizon of four weeks. The results for the selected countries are shown in Online Appendix B, Fig. 3B. Accordingly, the findings in Fig. 3B are similar to the results in Fig. 2A and 4A.

6. Conclusions

In this paper, we investigate the dynamics of the interactions between international stock returns and perceived volatility measured by the VIX index using the quantile-on-quantile spillover analysis. The VIX's dynamic interactions with stock returns across quantiles and over time provide valuable insights for investment strategies, risk management, and financial market stability. Using weekly data from 1995 to 2023 and a comprehensive data set from 20 developed and 20 emerging stock markets, we investigate the relationship between the VIX and stock market returns, accounting for time-varying and cross-quantile relationships.

Empirical results show that the indirectly related quantile total spillovers between the VIX and equity returns surpass the directly related quantile total spillovers. This suggests a higher degree of asymmetric relationships between the VIX and stock returns compared

[4] The cross-quantilogram analysis results for all countries are shown in Online Appendix B, Fig. 2B.

to symmetric interactions. High returns occur at low VIX levels and low returns at high VIX levels. The highest total spillovers across all stock markets occur at the highest quantile level for the VIX and the lowest for stock returns for developed and emerging markets. The net spillover analysis shows that the VIX seems to be a net spillover receiver at extremely high and extremely low stock returns. More specifically, unusually low and high stock returns (0.1 and 0.9 quantiles) influence generally perceived market volatility as measured by the VIX at all quantiles except very low and very high volatility episodes. On the other hand, the VIX seems to be a net spillover provider under a wide range of stock market return conditions. Specifically, extremely low and high VIX quantiles provide spillovers to stock market returns with no exceptions. Our results are broadly in line with Khalfaoui et al. (2023) where the connectedness structure is such that the VIX and returns act as net transmitters and receivers of shocks under various market conditions.

Comparing developed markets to emerging markets, results show a relatively stronger relationship between developed stock returns and the VIX than those suggested by emerging markets. The non-uniform connectedness profiles across emerging markets suggest that investors can look at country-specific information to formulate their portfolios. For instance, since the highest total spillovers in developed markets occur between the VIX and the New Zealand stock market, it can be recommended that investors pay attention to the New Zealand market during periods of rising VIX. Conversely, as the lowest total spillover is observed between the VIX and the Portuguese stock market, investors might consider focusing on the Portuguese market during periods of a high VIX. In emerging markets, investors should avoid the Mexican market during periods of a rising VIX, while shifting focus to the Jordanian market might be a prudent strategy. Finally, given that implicit volatility indices generate stock market synchronization and high connectedness between the VIX and stock market returns, particularly at extreme quantiles of their distribution, investors should look at other investment vehicles such as treasuries, gold and precious metal funds, commodities, and the U.S. dollar during increased uncertainty, as they may afford diversification benefits.

Given that the VIX index is closely monitored by policymakers and regulators to evaluate the potential risks within financial systems, the outcomes of this study could also prove advantageous for policymakers. By identifying the correlation between the VIX index and stock markets, governments can seize opportunities to implement measures safeguarding small investors and directing capital towards appropriate assets. Additionally, these findings could prove valuable for central banks in their policymaking efforts and in maintaining financial stability. Furthermore, the VIX index can be an important forecasting tool; as such, it may also indicate the economy's overall course. In future research, scholars may delve into the asymmetric relationship between the VIX index and stock markets by exploring its connection with specific subcategories of behavioral finance, such as overreaction and herd behavior.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bir.2024.07.006.

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