Twitter's Happiness Index and G7 Stock Markets: A Quantile Connectedness Approach

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This paper provides empirical evidence on spillover effects from G7 stock market indices returns and Twitter's happiness sentiment index using connectedness measures based on quantile vector autoregressions for data spanning from 2009 to 2023. The analysis, based on quantile connectedness, highlights important differences in spillovers across quantiles. In general, total dynamic connectedness is greater at low and high quantiles throughout the whole period, with the noticeable exception of the Covid-19 pandemic period, where connectedness is strong at all quantiles. Further, it is found that Twitter's happiness is a substantial net receiver of spillovers from stock returns at low and high quantiles, whereas the effect is mild at the median and conditional mean. Finally, the study offers evidence that stock returns and Twitter's happiness are more connected following adverse shocks.

Keywords: Happiness, Investor sentiment, Returns connectedness, Spillover effects, Quantile VAR

Introduction

A substantial body of literature has explored the connection between sentiment and economic choices. Advocates of behavioral economics and finance theories have forcefully argued that the traditional approach based on the utility-maximizing economic agent cannot fully explain the observed irrational behavior in markets, and sentiment has emerged as a possible explanation for the observed deviations from rational behavior. Sentiment can be broadly defined as beliefs about the future state of the world that are not justified by the fundamentals or the available evidence; therefore, individuals may make decisions under the influence of temporary moods. Several scholars have studied the relationship between individual mood and actual choices in experimental settings (Arkes et al., 1988; Isen & Patrick, 1983; Nygren et al., 1996) and in real-world situations (Delis & Mylonidis, 2015; Kliger & Levy, 2003).

Lane (2017) comprehensively reviewed the relationship between happiness and economic choices. Since a question concerning happiness or wellbeing is included in many country-level surveys, several papers have investigated the relationship between happiness and economic variables. The first scholar to address this issue was Easterlin (1974), who analyzed the influences and effects on the wellbeing of income, unemployment, education, and health with his happiness paradox. Later, Blanchflower and Oswald (2004) cast some doubts and analyzed life satisfaction in various countries, showing how a higher income leads to greater happiness at first, but later, as individuals get used to it, the level of wellbeing remains

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constant. Further studies have been carried out in various European countries thanks to the Eurobarometer surveys by Inglehart (1990), relating happiness to macroeconomic factors such as unemployment (Clark & Oswald, 1994; Frey and Stutzer, 2002), inflation (Di Tella et al., 2001), institutional and political conditions. All these variables report a negative correlation with happiness, especially for unemployment, where Clark and Oswald (1994) concluded that "joblessness depresses wellbeing more than any other single characteristic, including important negative ones such as divorce and separation".

Apergis et al. (2019) conducted a study using microdata from five European countries to examine the impact of happiness on portfolio choices. Their findings indicated that individuals with higher levels of happiness are more likely to take on greater financial risks, such as allocating a larger portion of their portfolios to risky assets. Overall, it seems reasonable to conclude that an individual's level of happiness may influence their risk attitudes and perceptions, subsequently impacting their financial decision-making processes. This literature indicates that positive (negative) moods make investors more (less) willing to bear more risk.

Goodell et al. (2023) reviewed the literature on emotions and finance, connecting emotions to specific stock market anomalies. While happiness relates to the single individual, mass sentiment or mass happiness can have an impact on economic variables. Olson (2006) stated that the aggregation of individual positive moods into social positive moods or trends reduces the individual's perception of risk while increasing the perception of gains.

Social media serve as natural collectors and amplifiers of individual moods. The Happiness Index on Twitter, developed by Dodds et al. (2011), provides an effective method for aggregating individual happiness into a collective measure of daily happiness. This allows us to correlate a time series of happiness with any economic time series observed at a daily frequency. Using Amazon's Mechanical Turk service, the researchers assessed 10,000 words on a scale from 1 to 9 for their happiness value. These words are among the 10,000 most frequently used in Google Books, *New York Times* articles, music lyrics, and Twitter messages. For a 10% random sample of the 500 million messages posted daily on Twitter, the researchers calculated the average happiness score based on approximately 200 million words each day. The result is a time series of Twitter's happiness index (THI), covering the period from September 9, 2008 to May 26, 2023. This paper investigates whether and to what extent Twitter's Happiness Index relates to G7 stock market returns. Adopting the quantile connectedness approach, the paper's main contribution is the investigation of static and dynamic spillover effects across the entire distribution of stock returns and happiness.

The rest of the paper is organized as follows: the next section provides a brief literature review of the relationship between THI and financial markets. The subsequent section explains the empirical methodology and describes the data used in the analysis, followed by the main empirical findings. The last section offers conclusion.

Literature Review

A comprehensive literature review on how Twitter's happiness affects financial markets is provided in Kyriazis (2023), to which the study refers for a more detailed account. Zhang et al.

(2016) investigated the relationship between THI and stock returns in 11 stock markets. They divided the distribution of the happiness index into quantiles and provided evidence of a contemporaneous correlation between stock returns and the lower and upper quantiles of happiness. Further, they offered evidence of Granger causality from happiness to stock returns for most stock market indices and no evidence of causality was found working in the opposite direction. These findings indicate a potential impact of sentiment on predicting stock market returns through social media. Using Quantile Vector Autoregressions (QVAR), You et al. (2017) studied whether Twitter's happiness helps predict stock returns considering quantile Granger-causality tests, i.e., considering Granger-causality at various quantiles of the distribution of stock returns and happiness, and not simply at the conditional mean, therefore providing a more detailed account of the causality relationship between sentiment and stock returns. They found that happiness Granger-causes stock returns but only for the right tail of the distribution of returns, i.e., causality from happiness to stock returns occurs only for high returns. On the other hand, when studying Granger causality from stock returns to happiness, they could reject the null hypothesis of non-causality at lower and upper quantiles. They concluded that stock returns significantly impact low or high levels of happiness.

Following the Granger causality test approach, Naeem et al. (2020) analyzed whether Twitter's happiness index Granger-causes volatility in major stock markets. According to their results, based on linear and nonlinear Granger causality tests (at the conditional mean), happiness Granger-causes stock market volatility for most countries.

An analysis of the link between happiness and gold prices has been carried out by Byström (2020). He found that when looking at the unconditional moments, there is virtually no correlation between Twitter's happiness index and the price of gold. However, considering the correlation between gold prices and Twitter's happiness for different thresholds of the distribution of happiness, he found that gold prices and happiness are positively (negatively) correlated with happiness in the left (right) tail of the distribution.

Adopting a quantile regression framework and including a substantial set of control variables, Lee and Chen (2020) studied the linkage between Twitter's happiness and ETF returns and ETF abnormal returns. They found a positive impact of happiness on ETF returns at high quantiles and a positive impact on ETF abnormal returns at all quantiles. Lee and Chen (2020) also included country-level happiness data from the World Happiness Report, which includes both observed wellbeing indicators, such as GDP per capita and life expectancy, and self-reported measures of life satisfaction, such as corruption perception and confidence in the government. After including these alternative indicators of happiness, they found that previous results for Twitter's sentiment index still hold.

Self-reported happiness available in cross-sectional datasets has also been studied as a possible determinant of risky behavior. Using data from the Dutch Household Survey and weather (unexpected sunshine) as an instrumental variable for happiness, Guven (2012) found that happier people tend to save more and attach more importance to savings for the future. Considering data from the Dutch Household Survey and the German Socioeconomic Panel and using weather (unexpected sunshine) as an instrumental variable for happiness, Guven and Hoxha (2014) found that happiness has a negative impact on stocks and bond holdings and that, further, it adversely affects the propensity to invest in shares. Counterintuitively, happier people tend to participate less and to invest less in shares.

Bouri et al. (2021) examined the role of Twitter's happiness in the volatility of several cryptocurrencies. They used a DCC-GARCH model to estimate the conditional volatilities and, in the same spirit of the generalized impulse response function used by Diebold and Yilmaz (2012), they considered the variance impulse response function to assess the impact of a shock on conditional volatility. Once the total connectedness index (TCI) has been computed, they set up a quantile-on-quantile regression model to relate α^{th} quantile of total connectedness to the β^{th} quantile of the distribution of Twitter's happiness. They found a sizeable impact of sentiment on TCI at low quantiles of the distribution of happiness and an increasing impact starting from median happiness up to the third quantile, a sharp drop thereafter up to significantly higher quantiles where the relationship is strong. Overall, cryptocurrency volatility and happiness exhibit strong connectedness at very high quantiles of happiness and for quantiles less than the median.

Data and Methodology

Quantile Connectedness

The seminal papers by Diebold and Yilmaz (2009 and 2012) on the measurement of volatility spillovers have spurred substantial empirical literature on spillovers and connectedness among financial assets. Ando et al. (2022) extended their approach by considering QVAR, which introduces the idea of quantile connectedness. Following Chatziantoniou et al. (2021), this methodology is briefly reviewed next.

Let x_t be a $k \times 1$ vector of stationary time series, the stock market index returns, and the log difference of happiness. For each quantile $\tau \in (0, 1)$, the dynamics of x_t as a QVAR or order p are modeled as follows

$$x_t = \Phi_1(\tau)x_{t-1} + \ldots + \Phi_p(\tau)x_{t-p} + u_t(\tau) \qquad \ldots(1)$$

where $\Phi_j(\tau)$ is a $k \times k$ matrix of coefficients for the j^{th} lag of the vector autoregression for the quantile of order τ and $u_t(\tau)$ is a vector of zero mean error terms of size $k \times 1$ with $k \times k$ variance-covariance matrix $\Sigma(\tau)$. Let $A_i(\tau)$ for $i = 1, \ldots,$ be the coefficient matrices of the infinite MA representation, so that $x_t = \Phi_1(\tau)x_{t-1} + \ldots + \Phi_p(\tau)x_{t-p} + u_t(\tau) = \sum_{i=0}^{\infty} A_i(\tau)u_{t-i}(\tau)$, where $A_0(\tau)$ is the identity matrix.

For each quantile τ, the H-step-ahead generalized forecast error variance decomposition matrix has a generic element given by

$$\theta_{ij}^{g}(H)=\frac{\sum(\tau)_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i' A_h(\tau)\Sigma(\tau)e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' A_h(\tau)\Sigma(\tau)\, A_h'(\tau)e_i\right)} \qquad \dots(2)$$

where e_i is the selection vector (hereafter, to simplify notation, the quantile index τ is used where no confusion arises). Since the row sum of the matrix is not equal to 1, each θ_{ij}^{g} is normalized as follows:

$$\tilde{\theta}_{ij}^{g}(H)=\frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{k}\theta_{ij}^{g}(H)} \qquad \dots(3)$$

As a result of the normalization, we have $\sum_{j=1}^{k}\tilde{\theta}_{ij}^{g}(H)=1$ and $\sum_{i,j=1}^{k}\tilde{\theta}_{ij}^{g}(H)=k$ (Diebold & Yilmaz, 2012). Directional spillover (FROM and TO) can then be computed as follows. The directional spillover received by variable *i* FROM all other variables *j* is given by

$$S_{i\leftarrow j}^{g}(H)=\sum_{j=1;j\neq i}^{k}\tilde{\theta}_{ij}^{g}(H) \qquad \dots(4)$$

and the directional spillover transmitted by asset *i* TO all other assets *j* is

$$S_{i\rightarrow j}^{g}(H)=\sum_{j=1;j\neq i}^{k}\tilde{\theta}_{ij}^{g}(H) \qquad \dots(5)$$

Finally, net spillovers can be directly obtained as $S_i^g(H)=S_{i\rightarrow j}^{g}(H)-S_{i\leftarrow j}^{g}(H)$. The total spillover or TCI is given by

$$TCI(H)=\sum_{i,j=1;i\neq j}^{N}\tilde{\theta}_{ij}^{g}(H) \qquad \dots(6)$$

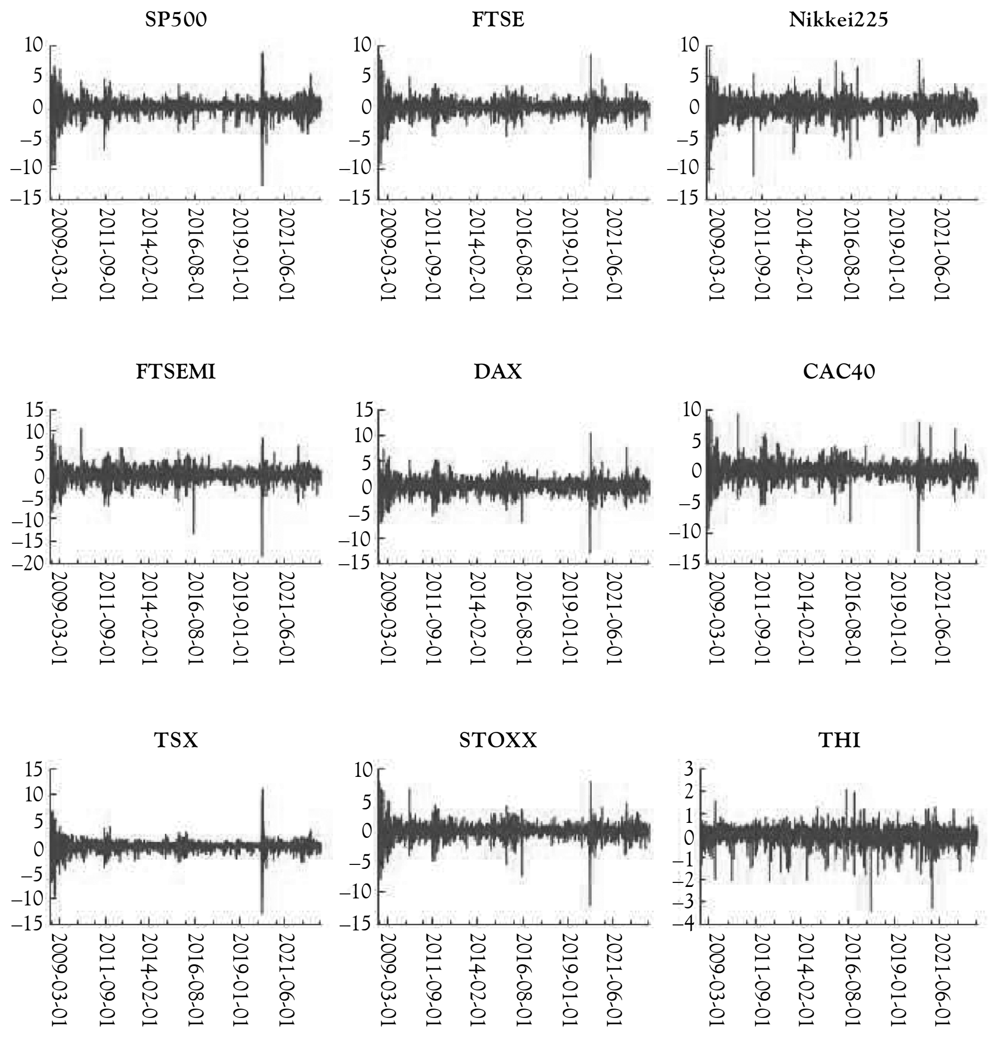
The adjusted TCI (Adj-TCI), which takes values in [0,1], proposed by Chatziantoniou and Gabauer (2021), is simply *Adj-TCI (H)=TCI(H)/(N – 1)*.

Data

In this paper, we consider daily stock market indices for G7 countries, namely the US (S&P500), the UK (FTSE 100), Canada (S&P/TSX), Japan (Nikkei225), Germany (DAX), France (CAC40), Italy (FTSEMIB), and the European Union (STOXX600). Daily data are downloaded from https://finance.yahoo.com/. The sample spans from September 9, 2008 to May 26, 2023. Daily data for THI are obtained from https://hedonometer.org/. The daily happiness data is regressed on the day-of-the-week and Holiday dummies (Thanksgiving, Christmas Eve, Christmas Day, New Year's Eve, New Year's Day, and Easter) and the residuals are used in the empirical analysis. Returns are computed as the first difference of the log of stock market indices. Similarly, the change in the log of the THI index is also computed.

Figure 1 shows the time series of stock index returns for the countries in the sample and for happiness. A period of sustained turbulence characterizes the beginning of the sample following the Lehman Brothers' failure of September 2008, with more episodes of turbulence occurring around the outbreak of the Covid-19 pandemic.

Figure 1: Stock Market Index Returns and Log-Difference of Happiness



Summary statistics are reported in Table 1. As expected, returns have zero mean, and all series, including *THI*, exhibit negative unconditional asymmetry and large excess kurtosis, implying a longer left tail and fat tails, particularly for the Canadian stock market index. The Jarque-Bera test indicates significant deviations from a Gaussian distribution. Additionally, the Ljung-Box test strongly suggests the presence of autocorrelation in both the levels and the squares of stock market index returns. The autocorrelation in the squares is particularly attributed to the volatility clusters observed in the sample. All these features are typically found in financial time series, which are shared by *THI* as well.

Table 1: Summary Descriptive Statistics on Stock Market Index Returns and Log-Difference of Happiness, 2008-09-23/2023-06-08

Variable	Mean	SD	Skewness	Kurtosis	Jarque-Bera	Ljung-Box	Ljung-Box2
SP500	0.023122	1.3245	–1.0120	11.877	17,563.23	201.658	4,793.491
FTSE	–0.010464	1.1809	–0.72078	11.180	15,376.283	117.24	2,993.138
Nikkei225	0.0003774	1.4764	–0.79489	8.1187	8,281.324	98.631	2,681.979
FTSEMI	0.0037272	1.6859	–0.86031	9.9590	12,359.156	52.467	649.778
DAX	0.0071974	1.4026	–0.56256	7.1542	6,346.246	76.831	1,758.945
CAC40	0.0088357	1.4392	–0.47532	8.3688	8,583.728	91.46	1,872.269
TSX	0.0047815	1.1651	–1.4127	22.194	60,568.043	154.444	4,009.564
STOXX	0.0029610	1.2292	–0.78197	9.5661	11,368.582	87.249	2,174.061
THI	–0.0027530	0.37921	–1.2764	8.4641	9,457.141	164.54	49.744

Unit root tests for non-stationarity for each time series are reported in Table 2. Test results for unit root tests, namely by the augmented Dickey-Fuller (ADF) test by Dickey and Fuller (1979), the $Z(\rho)$ and $Z(t)$ tests by Phillips and Perron (1988) and the DF-GLS test by Elliott et al. (1996) are reported in columns (1)-(4). The last column contains the KPSS stationarity test by Kwiatkowski et al. (1992), with automatic bandwidth selection and Bartlett kernel. Critical values at a 5% level are reported in the last row. Overall, unit root tests strongly reject the null hypothesis of non-stationarity for the returns series and happiness, and consistently, the KPSS test does not reject the null hypothesis of stationarity at a 5% level. These results suggest that the log difference of THI and stock index returns are stationary and can be used in the following connectedness analysis.

Table 2: Unit Root and Stationarity Tests					
Variable	**ADF**	**Z(ρ)**	**Z(t)**	**DF-GLS**	**KPSS**
SP500	–15.909	–3,358.943	–61.039	–6.233	0.351
FTSE	–17.19	–2,789.768	–53.272	–3.746	0.343
Nikkei225	–16.379	–3,178.194	–56.519	–8.536	0.148
FTSEMI	–16.217	–2,975.86	–55.445	–6.316	0.119
DAX	–15.441	–2,887.049	–52.497	–7.799	0.109
CAC40	–17.186	–2,865.43	–54.24	–8.037	0.148
TSX	–16.404	–3,024.521	–55.481	–2.488	0.141
STOXX	–16.317	–2,786.997	–52.351	–4.488	0.156
THI	–16.979	–3,002.964	–62.026	–3.373	1.322
5% Critical Values	–2.860	–14.10	–2.860	–2.832	1.574

Results and Discussion

In the empirical analysis, a QVAR of order 1, a 10-day forecast horizon (i.e., $H = 20$ days), and, in the dynamic analysis, a rolling window of size 200 are considered. The analysis is carried out using the software R and the R-package "Connectedness Approach" by Gabauer (2025).

Table 3a contains the spillovers among stock index returns. THI is computed as in Diebold & Yilmaz (2012), and Table 3b shows the spillovers at the median ($\tau = 0.5$). The own-variance share of shocks can be read off the main diagonal of the table. At the same time, off-diagonal entries represent an estimate of the contribution to the forecast error variance of the i^{th} variable coming from the j^{th} variable. For instance, considering Table 3a, only 8.79% of the forecast error variance of the FTSE index comes from shocks in the SP500 index. The row sums, excluding the main diagonal cell, are reported in the last column, and they represent the contributions to the forecast error variance of the i^{th} stock index returns coming from other variables in the model. The results indicate that the contribution of each stock index return to its forecast error variance is (much) lower than the contribution from other stock indices, i.e., spillovers from others are larger than the own contribution. For example, 80.39% of the forecast variance error of the FTSE index comes from innovations in other stock indices (with a minimal contribution coming from THI).

On the other hand, the row labeled "TO" contains the contribution of the column variable to the forecast variance error to others. Apart from the Nikkei index, contributions

Table 3a: Static Spillovers at the Conditional Mean

	SP500	FTSE	Nikkei225	FTSEMIB	DAX	CAC	TSX	STOXX	THI	FROM
SP500	25.81	10.82	1.68	9.30	11.42	11.11	17.86	11.88	0.12	74.19
FTSE	8.79	19.61	2.39	12.59	14.38	15.70	9.76	16.73	0.05	80.39
Nikkei225	10.54	9.31	31.92	8.17	9.52	10.18	9.28	10.94	0.12	68.08
FTSEMIB	7.76	13.37	1.82	20.83	15.42	16.69	7.73	16.34	0.04	79.17
DAX	8.95	14.00	2.05	14.13	19.10	16.65	8.16	16.92	0.03	80.90
CAC	8.35	14.76	2.27	14.75	16.07	18.41	8.24	17.11	0.04	81.59
TSX	17.51	12.01	2.15	9.22	10.49	10.99	25.38	12.05	0.19	74.62
STOXX	8.82	15.30	2.45	14.04	15.88	16.64	8.90	17.91	0.05	82.09
THI	0.41	0.30	0.25	0.22	0.18	0.20	0.62	0.32	97.51	2.49
TO	71.14	89.87	15.07	82.43	93.36	98.16	70.55	102.29	0.65	623.51
Incl. Own	96.96	109.48	46.99	103.26	112.45	116.56	95.94	120.20	98.16	Adj-TCI/TCI
Net	−3.04	9.48	−53.01	3.26	12.45	16.56	−4.06	20.20	−1.84	77.94/69.28

Table 3b: Static Spillovers in the Median Quantile VAR ($\tau = 0.5$)

	SP500	FTSE	Nikkei225	FTSEMIB	DAX	CAC	TSX	STOXX	THI	FROM
SP500	28.94	9.86	1.86	9.04	10.43	10.70	17.08	11.42	0.67	71.06
FTSE	8.74	22.10	2.08	11.99	14.15	15.30	8.41	16.71	0.53	77.90
Nikkei225	11.08	7.86	34.35	7.93	9.17	9.94	8.63	10.05	0.98	65.65
FTSEMIB	7.65	12.32	1.67	23.02	15.11	16.61	6.81	16.31	0.50	76.98
DAX	8.47	13.26	1.95	13.67	20.50	17.11	6.98	17.68	0.38	79.50
CAC	8.24	13.74	2.16	14.45	16.45	19.69	7.17	17.70	0.40	80.31
TSX	17.67	10.24	2.14	8.53	9.40	10.12	30.31	10.95	0.63	69.69
STOXX	8.79	14.54	2.18	13.74	16.43	17.14	7.67	19.12	0.41	80.88
THI	1.39	1.33	1.33	1.57	1.35	1.43	1.46	1.53	88.60	11.40
TO	72.02	83.15	15.37	80.95	92.49	98.35	64.21	102.35	4.50	613.39
Incl. Own	100.96	105.25	49.72	103.96	112.99	118.04	94.53	121.47	93.09	Adj-TCI/TCI
Net	0.96	5.25	–50.28	3.96	12.99	18.04	–5.47	21.47	–6.91	76.67/68.15

to others are sizeable, ranging from 70% (TSX) to more than 102% (STOXX). From and to contributions are negligible for THI, with just 2.5% of the forecast variance error of THI coming from shocks to stock indices returns.

The difference between "directional from others" and "directional to others" gives the so-called "net volatility spillovers." A variable is a net receiver (transmitter) of shocks when its impact on others is smaller (larger) than the influence of all others. Nikkei225 stock index is a large net receiver of shocks. THI is a net receiver, too, but again, the magnitude of the effect is negligible. Conversely, STOXX is a net transmitter of shocks.

The TCI indicates that almost 70% of the returns forecast error variance comes from spillovers. The percentage rises to almost 80%, considering the adjusted TCI index. However, THI generates few of these spillover effects. Overall, spillovers computed at the conditional mean suggest that Twitter's happiness index is little connected with G7 stock index returns.

A similar result is obtained in Table 3b, where spillovers are computed at the conditional median ($\tau = 0.5$). The qualitative picture is almost unchanged; however, the directional spillover from stock index returns to THI is four times as large as in the classical settings, and the directional spillover to others is about 7 times as large. THI still has quite a low interconnectedness with stock index returns, even though the influence of THI increases.

The picture is substantially different when we look at the fifth and the ninety-fifth conditional quantile, as in Tables 3c and 3d. It is noticed that at the fifth conditional quantile, Table 3c, 83.13% of the forecast variance error of THI comes from shocks to stock market indices, and contributions from shocks to THI to stock market indices are as high as 69.15%. The spillover effect is similar if we consider the ninety-fifth quantile, Table 3d, where 80.47% of the forecast error variance of THI comes from shocks to stock market indices, and contributions of shocks to THI to stock market indices are as high as 64.73%. The magnitude of the from and to spillovers of stock indices returns and THI is comparable. Hence, connectedness varies with the quantile.

A detailed picture of Total Connectedness over a finer set of quantiles can be obtained from Figure 2, where TCI at different quantiles and the TCI at the conditional mean are graphed. Connectedness is U-shaped across quantiles, taking greater values at the lower and higher quantiles and a minimum at the median. Further, total connectedness at the conditional mean is very close to TCI at the median.

The strength and the direction of the connectedness among the various stock indices and THI can be better appreciated by considering the graph of the network of spillovers at the median, and the ninety-fifth and fifth quantiles, as in Figure 3. At the median, THI and Nikkei225 are net receivers even though there are noticeable differences: THI is a light net receiver from each stock market while, on the other hand, Nikkei225 turns out to be a very strong net receiver with SP500, STOXX, DAX, and CAC the most important transmitters. The story is quite different at extreme quantiles, where THI is the most important net receiver. These findings indicate that spillovers to THI are more significant than those from Twitter's happiness at extreme quantiles. This suggests that happiness may be more responsive

Table 3c: Static Spillovers at the Fifth Conditional Quantile ($\tau = 0.05$)

	SP500	FTSE	Nikkei225	FTSEMIB	DAX	CAC	TSX	STOXX	THI	FROM
SP500	14.25	10.68	9.76	10.65	10.99	10.90	12.27	11.56	8.95	85.75
FTSE	11.37	12.61	9.64	11.24	11.63	11.65	11.18	12.37	8.32	87.39
Nikkei225	11.59	10.45	13.64	10.57	10.92	10.77	11.24	11.42	9.39	86.36
FTSEMIB	11.07	11.10	9.43	13.01	11.79	11.90	10.79	12.36	8.55	86.99
DAX	11.09	11.27	9.52	11.53	12.74	12.02	10.75	12.61	8.47	87.26
CAC	11.08	11.36	9.44	11.73	12.09	12.58	10.83	12.67	8.21	87.42
TSX	12.41	10.85	9.83	10.76	11.03	10.91	13.73	11.53	8.95	86.27
STOXX	11.35	11.46	9.50	11.54	11.98	12.01	10.86	12.99	8.32	87.01
THI	10.74	9.99	10.37	10.27	10.30	10.05	10.72	10.69	16.87	83.13
TO	90.71	87.16	77.50	88.29	90.71	90.21	88.64	95.22	69.15	777.58
Incl. Own	104.96	99.77	91.13	101.30	103.46	102.79	102.37	108.21	86.02	Adj-TCI/TCI
Net	4.96	–0.23	–8.87	1.30	3.46	2.79	2.37	8.21	–13.98	97.20/86.40

Table 3d: Static Spillovers at the Ninety-Fifth Conditional Quantile ($\tau = 0.95$)

	SP500	FTSE	Nikkei225	FTSEMIB	DAX	CAC	TSX	STOXX	THI	FROM
SP500	14.92	11.03	9.12	10.86	11.37	11.17	12.35	11.19	7.99	85.08
FTSE	11.22	13.58	9.03	11.50	11.98	11.94	10.66	12.07	8.03	86.42
Nikkei225	11.42	10.63	14.46	10.70	11.01	10.89	10.87	10.81	9.20	85.54
FTSEMIB	10.97	11.70	8.90	13.77	12.14	12.28	10.30	12.16	7.79	86.23
DAX	11.12	11.66	8.96	11.79	13.45	12.40	10.45	12.34	7.83	86.55
CAC	11.12	11.84	8.83	11.92	12.52	13.15	10.41	12.48	7.72	86.85
TSX	13.01	11.08	9.24	10.74	11.15	10.97	14.71	10.98	8.12	85.29
STOXX	11.15	11.96	8.88	11.84	12.55	12.48	10.56	12.90	7.69	87.10
THI	10.33	9.91	10.32	9.93	10.19	9.89	10.17	9.73	19.53	80.47
TO	90.34	89.81	73.28	89.27	92.91	92.02	85.77	91.77	64.37	769.54
Incl. Own	105.26	103.39	87.75	103.04	106.36	105.17	100.47	104.67	83.89	Adj.-TCI/TCI
Net	5.26	3.39	–12.25	3.04	6.36	5.17	0.47	4.67	–16.11	96.19/85.50

Figure 2: TCI at Different Quantiles and Conditional Mean

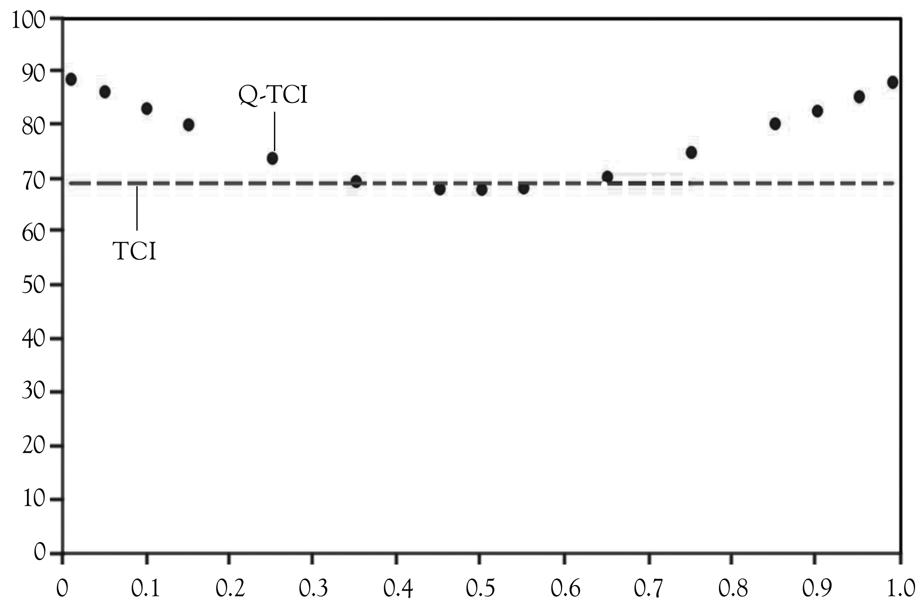
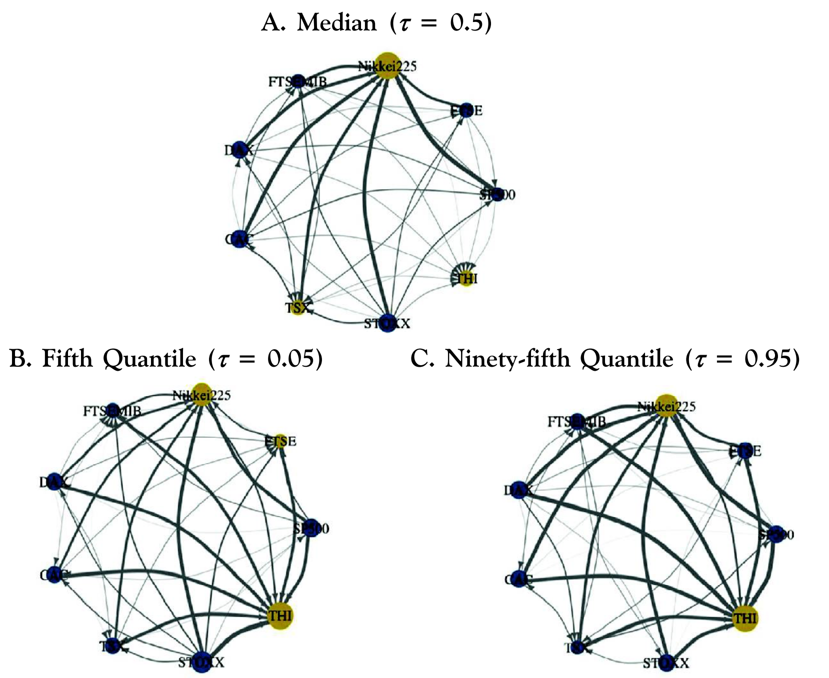


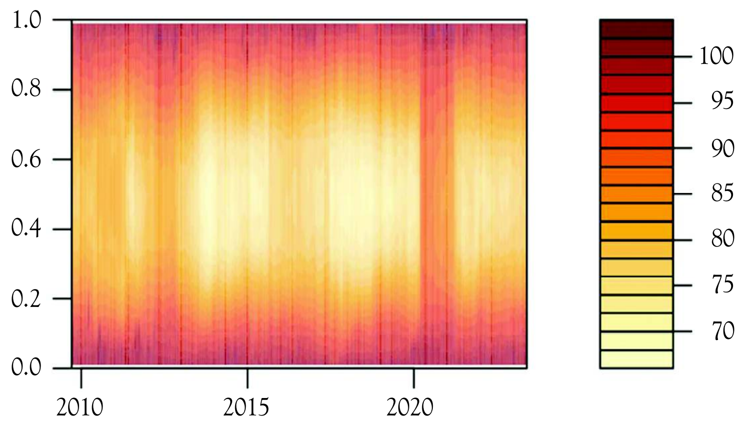
Figure 3: Networks of Net Pairwise Directional Connectedness at Various Quantiles



to shocks to stock market returns when these shocks occur in the lower or upper tail of the conditional distribution.

Total dynamic connectedness at different quantiles, using a rolling window of size 200 for a forecast horizon of 10 days, is represented as a heatmap in Figure 4, where warmer colors indicate tighter connectedness. The heatmap clarifies that connectedness is stronger for negative and positive changes in the distribution of returns and happiness, say above the 90% quantile and below the 10% one. Further, greater connectedness at all quantiles has been observed up to 2013, especially during the Covid-19 pandemic.

Figure 4: Quantile Total Dynamic Connectedness



Dynamic net connectedness for each variable is graphed in Figures 5a and 5b. The most striking result concerns the Nikkei225 index, a net receiver of shocks throughout the whole sample period. In general, happiness is also a net receiver, particularly at quantiles lower than 20% and greater than 80%, whereas, during the Covid-19 pandemic, happiness has been a net receiver at all quantiles. Finally, European stock indices, particularly the CAC and DAX indices, are mild net transmitters of spillover effects. It is worth noticing that during the Covid-19 pandemic, the net transmitter role of the STOXX index was weakened, mirroring the increased role of Twitter's happiness as a net receiver.

Following Ando et al. (2022), in Figure 6, we graph the relative tail dependence (RTD), a measure of the differential behavior of left and right total connectedness indices. RTD is computed as the difference between total connectedness at the 95th and 5th quantiles, with positive (negative) values indicating stronger connectedness in the right (left) tail. RTD fluctuates over time between positive and negative values, with prolonged periods of stronger connectedness in the left tail alternating with shorter and more volatile clusters of greater dependence in the right tail. This suggests that stock indices and happiness sentiment are more connected during adverse shocks. The average and the median RTD are both equal to –1% and about 61% of the RTDs are negative, indicating a prevalence of stronger

Figure 5a: Quantile Dynamic Net Directional Connectedness – Stock I

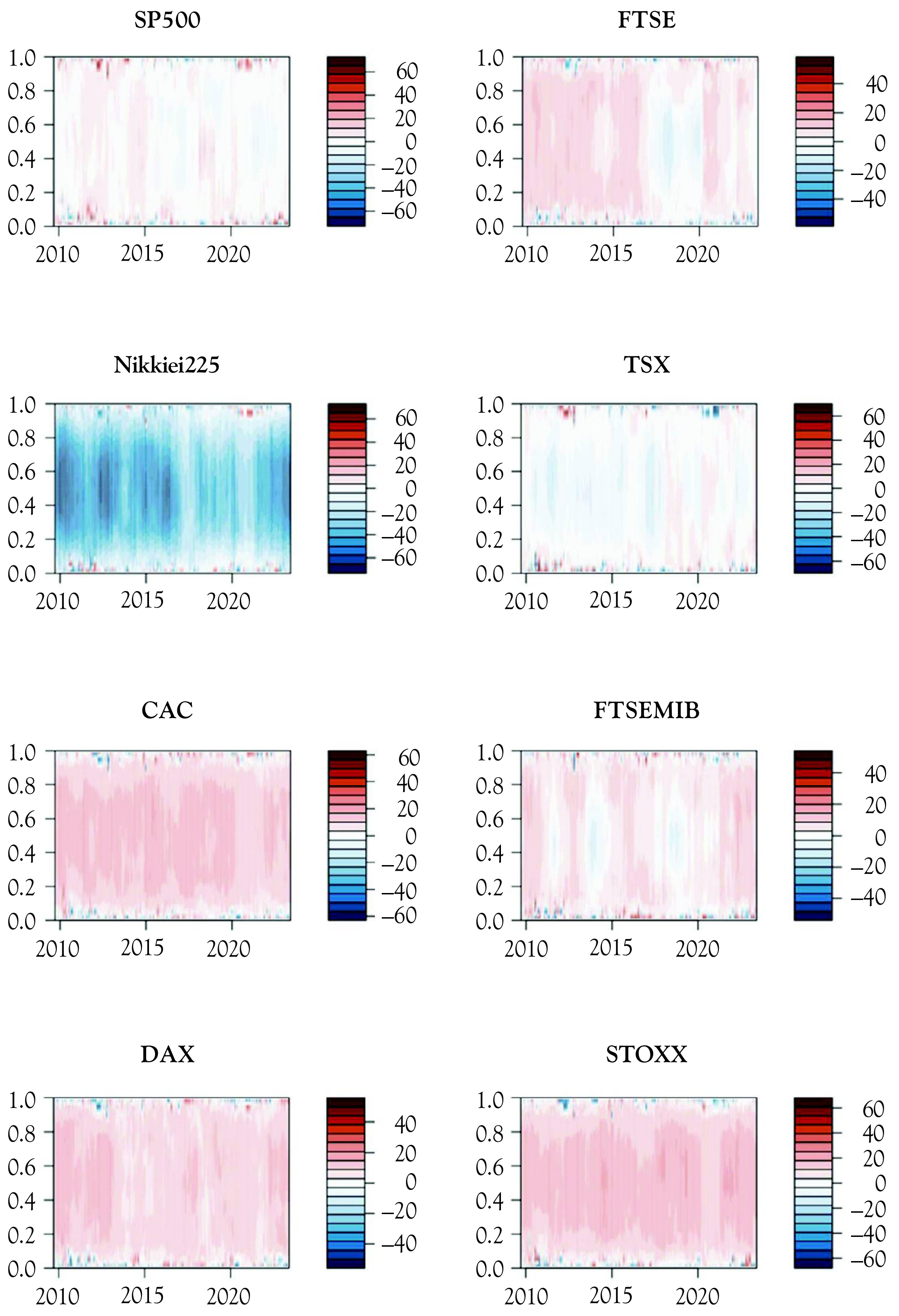


Figure 5b: Quantile Dynamic Net Directional Connectedness – Twitter's Happiness

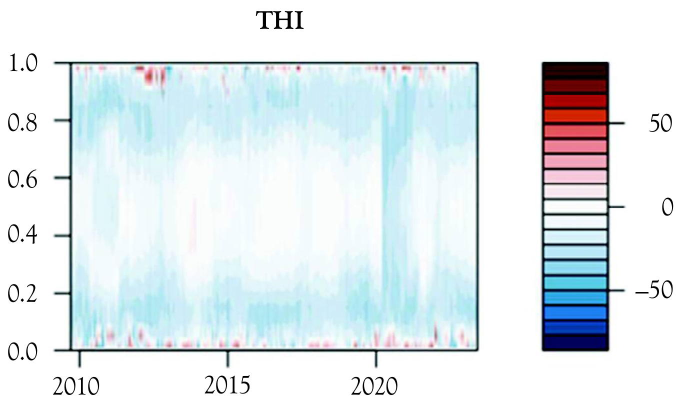
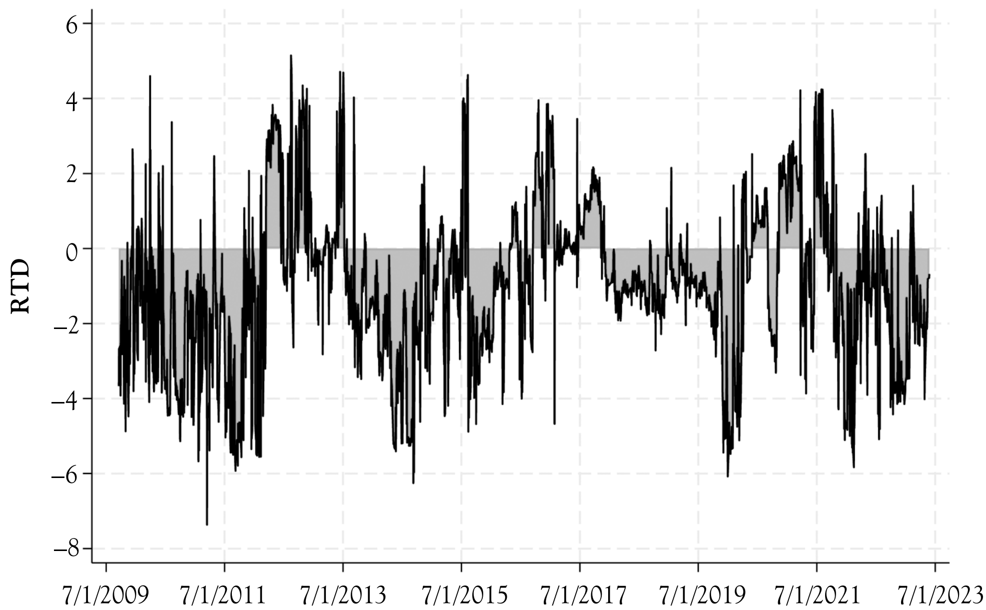


Figure 6: Relative Tail Dependence ($TCI_{0.95} - TCI_{0.05}$)



connectedness in the left tail. The maximum RTD is given by 5.14%, and the minimum equals –7.36%, so the magnitude of left-tail connectedness is greater, too.

Conclusion

This paper has investigated the existence and extent of spillover effects from stock returns in G7 countries and Twitter's happiness sentiment and vice versa. The quantile connectedness approach of the analysis has shed light on the complex relationship between stock returns and happiness sentiment. At the standard conditional mean, little spillover effects were found, and at the median, as well. Connectedness is not constant across quantiles, but, on the contrary, it is more significant at low and high quantiles, highlighting the importance of looking at the whole set of quantiles of the conditional distribution. Over the sample period, happiness has been a net receiver from innovations to stock returns, and more so during the outbreak of the Covid-19 pandemic. Additionally, happiness sentiment reacts more significantly at the fifth and ninety-fifth quantiles, particularly to extreme positive shocks. Thus, according to the results, happiness is a net receiver of spillovers from stock markets, suggesting a net directional link going from innovation in the stock markets to happiness sentiment and not vice versa. ⅄

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