Research in International Business and Finance 54 (2020) 101298

Contents lists available at ScienceDirect

Research in International Business and Finance

journal homepage: www.elsevier.com/locate/ribaf

Can happiness predict future volatility in stock markets?

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ARTICLE INFO

JEL classification:
Twitter based happiness index
VIX index
Linear and nonlinear causality
Investor sentiment

Keywords:
G12
G14

ABSTRACT

In this paper, we use the Twitter based happiness index as a proxy for investor sentiment in order to examine whether happiness influences future market volatility of country VIX indexes. Our sample includes the major stock markets of the USA, Canada, UK, Germany, France, Netherlands, Switzerland, Japan, China, Hong Kong, India, Brazil, South Korea, and South Africa. Using linear and nonlinear causality tests, we find that Twitter happiness significantly causes the future volatility of the sample countries. The robustness checks show no divergence from our primary findings and provide strong evidence of a nonlinear relationship between investor sentiment and future stock market volatility.

1. Introduction

Conventional finance theory suggests that asset prices are determined by fundamental value; hence, psychological and behavioural factors are ignored in asset pricing. For instance, rational risk based stock pricing models maintain that asset prices mirror the discounted value of future expected cash flows, and even though a few investors might be irrational, arbitrageurs quickly offset their irrationality. In contrast, dramatic crashes in global stock exchanges (for example, the Global Financial Crisis of 2007 − 08, European Debt Crisis of 2011 − 12, and Chinese Financial Crisis of 2015) highlight how traditional asset pricing theories fail to explain such abnormal circumstances in stock markets. Meanwhile, a growing body of literature based on behavioural finance theories argues for the role of psychological factors in financial markets. Moreover, behavioural theories suggest that the presence of noise traders in capital markets with homogenous behaviour and restrictions on arbitrage are conditions that cause investor sentiment to affect stock prices (Shleifer and Summers, 1990; Hughen & McDonald, 2005; Baker and Wurgler, 2006). Baker and Wurgler (2007) argue that investor sentiment contains functional predictive content about stock returns.

While several theoretical and empirical studies examine the impact of investor sentiment on stock returns and volatility (Black, 1986; De Long et al., 1990; Baker et al., 2012; Frugier, 2016; Li et al., 2017a), investor sentiment is not directly observable, and the challenge of finding appropriate proxies for investor sentiment remains. Studies use three categories of proxy to measure investor sentiment. The first is stock market based proxies, such as variation in discounts of closed-end funds (Lee et al., 1991), bid-ask spreads, turnover (Baker & Stein, 2004), dividend premium, proportion of equity in new issues, average first-day stock returns on

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https://doi.org/10.1016/j.ribaf.2020.101298
Received 3 December 2019; Received in revised form 6 July 2020; Accepted 16 July 2020
Available online 17 July 2020
0275-5319/

IPOs (Baker and Wurgler, 2006, 2007.) and portfolio allocation share of equity against fixed income and cash securities (Edelen et al., 2010). The second stream is survey based proxies, including investor intelligence as proposed by the American Association of Individual Investors (Lee et al., 2002), the UBS/Gallup survey (Qiu and Welch, 2006), the Conference Board's consumer confidence (Lemmon and Portniaguina, 2006) and investor sentiment by animusX (Lux, 2011). Although these traditional measures of investor sentiment provide some useful insight into the relationship between investor sentiment and asset prices, both have their disadvantages; for example the market based proxies have many confounding factors, and the survey based proxies cannot guarantee response quality. Finally, the development of the internet and social media offers the opportunity to use people's proactive searching and posting information to formulate new proxies of investor sentiment. These news and social media proxies include content from the Wall Street Journal (Tetlock, 2007), Yahoo Finance (Kim and Kim, 2014), Google Trends (Da et al., 2015), Facebook (Siganos et al., 2014), Google Insights (Joseph et al., 2011) and Twitter (Bollen et al., 2011).

As a proxy of investor sentiment, Twitter offers a great opportunity to enhance understanding of the complex dynamics of financial markets. Twitter is one of the largest social media platforms, with around 330 million active users, and the stock market is among the most discussed topics. Various stakeholders, such as individual investors, institutional investors, financial analysts, regulators, and news agencies, tweet information related to the stock market which includes commentaries, rumours, and suggestions. As millions of users post tweets, they depict the market sentiment and collective wisdom of various stakeholders. Many studies have examined the relationship between Twitter content and stock market performance and found a significant impact of Twitter on financial markets (Sul et al., 2017; Piñeiro-Chousa et al., 2018; Shen et al., 2019).

In particular, the Twitter based happiness index is widely used as a proxy of investor sentiment. For a sample of international markets, Zhang et al. (2016) show that Twitter happiness strongly influences returns and intra-day volatility of the stock index, while You et al. (2017) find a causal relationship between the Twitter based happiness index and stock returns for ten international markets. Other studies suggests a bi-directional relationship between the Twitter based happiness index and stock market variables (Li et al., 2017b), and a contemporaneous long-term association between the Twitter based happiness index and industry indexes (Zhao, 2020)[1] . However, to the best of our knowledge, no empirical studies have examined the association between the Twitter based happiness index and implied volatility indexes. Given that little, if anything, is known about the direct link between the Twitter based happiness index and implied volatility, our study fills this gap by providing empirical evidence of whether happiness influences stock market volatility, using forward-looking VIX indexes to reflect the volatility of the underlying stock markets. We rely on forward-looking volatility indexes instead of historical volatility since, nowadays, VIX indexes are considered the main indicator of investor fear (Badshah, 2018). Naturally, our study is linked to the literature that discusses the relationship between investor sentiment originating from social media and stock market dynamics. The main contribution of our study is an investigation of the role of a new online proxy of investor happiness in predicting future volatility in stock markets. The findings of the study hold important implications for international investors and portfolio managers, since understanding the link between happiness and future volatility could help in making optimal portfolio decisions.

Following the argument that the link between investor sentiment and volatility could be mis-specified by ignoring nonlinearity (Bekiros et al., 2016) and given that the distribution of stock returns and sentiment indexes is not usually normal (Zhang et al., 2016), we examine the causality between Twitter happiness and future volatility using linear and nonlinear causality tests. We also provide international evidence of the underlying relationship, as our sample markets are the USA, Canada, UK, Germany, France, Netherlands, Switzerland, Japan, China, Hong Kong, India, Brazil, South Korea, and South Africa.

Theoretically, noisy signals such as investor sentiment cause systematic risk and affect stock prices by causing deviation from their fundamental values resulting in higher market volatility (De Long et al., 1990). In addition, the rise in misperception due to noise trading induces excessive price uncertainty. Given that volatility serves as a crucial link between investor sentiment and stock returns, and investor sentiment serves as a significant driver of stock market volatility (Lee et al., 2002; Stambaugh et al., 2012), our findings show how Twitter happiness predicts future market volatility at a broader market level. The findings imply that the Twitter based happiness index, which mirrors the collective behaviour of millions of users, contains effective information to predict future stock market volatility. Moreover, optimism is strongly related to future volatility in the markets.

The remainder of this short note is structured as follows: Section 2 outlines the data and econometric methodology; Section 3 provides the empirical findings; and Section 4 concludes.

2. Data and econometric methodology

We collect Twitter based happiness index data from http://hedonometer.org/index.html, which is generated from the Twitter Gardenhose feed database of over 50 million twitter posts. The index is formulated from nearly 10,000 sentiment-related words in randomly selected twitter posts in the database. We take the data for country stock markets implied volatility (VIX) indexes from Thomson Reuters Datastream. We study the period 16th March 2011 to 27th June 2019 due to data availability. Table A2 in the appendix reports the summary statistics of the Twitter based happiness index and country VIX indexes. The statistics for the sample period reveal that among country fear indexes, the Brazilian market has the highest mean value of implied volatility, whereas the lowest average volatility is found for the UK. The results of the skewness, kurtosis, and Jarque-Bera tests exhibit non-normality for all series. The results of the augmented Dicky-Fuller (ADF) test with structural break show all the series to be stationary, which satisfies the requirement of VAR model estimation. We report the results of the Brock, Dechert, and Scheinkman (BDS) test of linearity in

[1] We provide a summary of the literature on the topic in Table A1 in the appendix.

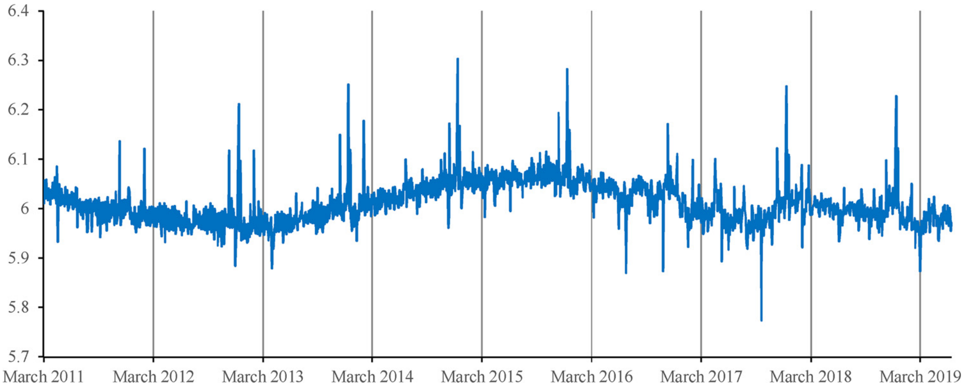

Fig. 1. Time-series graph of the Twitter based happiness index.

Table A3 in the appendix. The significant values of the BDS statistics support the nonlinearity of all the variables in our model. The findings of the ADF tests with structural break and BDS tests reinforce our use of nonlinear causalities.

Fig. 1 illustrates the evolution of the happiness index for the whole period, and shows that events around the globe impact it significantly. For instance, adverse events such as the terrorist attack in Paris, tsunami in Japan, or mass shooting in Las Vegas cause a decrease in the happiness index, and there is an opposite effect for positive news (https://hedonometer.org/timeseries/en_all/). The pattern reinforces the notion of the Twitter based happiness index as a fitting proxy for investor sentiment.

In order to investigate the dynamic association between the Twitter based happiness index and stock market volatility, we log-transform all series and estimate the vector auto-regressive (VAR) model. The basic VAR model setup employed in the study is:

$$Y_t = c + \sum_{j=1}^{k} B_j Y_{t-j} + \mu_t \tag{1}$$

where Y_t is a vector that contains n variables, c is a constant, and μ_t is a vector of the error correction terms in the model. The lag length is selected using the Schwarz information criterion. In order to determine the causal link, we use linear Granger causality (Granger, 1969) and the nonlinear causality test of Diks and Panchenko (2006). A brief description of the methodology is presented in Appendix A1. The bivariate model for the linear Granger causality test is:

$$\begin{aligned} Y_{1t} &= \beta_{10} + \beta_{11} Y_{1t-1} + \ldots + \beta_{1k} Y_{1t-k} + \alpha_{11} Y_{2t-1} + \ldots + \alpha_{1k} Y_{2t-k} + \mu_{1t} \\ Y_{2t} &= \beta_{20} + \beta_{21} Y_{2t-1} + \ldots + \beta_{2k} Y_{2t-k} + \alpha_{21} Y_{1t-1} + \ldots + \alpha_{2k} Y_{1t-k} + \mu_{2t} \end{aligned} \tag{2}$$

In Eq. (2) the lag length for the test is determined the Schwarz information criterion. In order to reduce the risk of over rejection of the null hypothesis, we use the non-parametric test of Diks and Panchenko (2006). As a robustness check, we apply the Taylor and artificial neural network (ANN) based causality models proposed by Péguin-Feissolle and Teräsvirta (1999) and later Péguin-Feissolle et al. (2013).[2]

3. Empirical findings

Table 1 reports the VAR coefficients, where the VAR model explains the relationship between the Twitter happiness index and country implied volatility indexes. The lag length for the model is selected using the Schwarz information criterion. We see from the estimates that the country fear indexes for the USA, Brazil, Netherlands, Switzerland, India, China, Hong Kong, and Japan, the previous day happiness index has a significant influence on the next day implied volatility indexes. The findings suggest that the higher the happiness, the higher the next day implied volatility. Optimistic online sentiments are associated with high future volatility in the aggregate market. The findings are in accord with Zhang et al. (2016) who find a higher level of happiness to be associated with higher volatility. Interestingly, most of the markets where the influence of the Twitter based happiness index on future volatility is significant are also the most volatile markets in the sample (for example Brazil, China, and Japan). The findings somewhat corroborate earlier evidence that suggests that the skewness of returns and volatility tend to be higher for the happiest subgroup (Zhang et al., 2016; Shen et al., 2018).

In the rest of the sample markets, namely Canada, UK, Germany, France, South Africa, and South Korea, Twitter happiness has no significant impact on next-day volatility. However, despite insignificant results for a few market indexes, the coefficients are consistently positive for the first lag. These results again highlight the positive link between happiness and fear in the stock markets. There is a consistently negative impact of the happiness index on the country volatility indexes at the fifth lag, indicating that positive investor sentiment does not persist over time. The findings are the same as many studies which show a negative relationship between investor sentiment and stock markets (Siganos et al., 2014; Lao et al., 2018; Shen et al., 2019). The findings show that the relationship between Twitter happiness and implied volatility reverses over time.

[2] We skip the details of Taylor and ANN based causality tests due to space considerations but refer the reader to the original paper.

Table 1
VAR model estimations.

	USA	CAN	BRA	UK	GER	NET	FRA	SWI	SAF	IND	CHN	HKG	SKR	JPN
HAP_{-1}	0.913**	0.591	0.742***	0.272	0.720**	0.868***	−0.253	0.848***	0.034	0.535**	0.777***	0.739***	0.603**	0.738***
	(0.361)	(0.424)	(0.232)	(0.370)	(0.286)	(0.320)	(0.512)	(0.271)	(0.139)	(0.235)	(0.240)	(0.261)	(0.285)	(0.286)
HAP_{-2}	−0.357	0.306	−0.319	0.525	0.168	0.074	1.186**	−0.015	−0.013	0.125	−0.291	−0.006	0.029	0.038
	(0.406)	(0.475)	(0.260)	(0.415)	(0.322)	(0.360)	(0.574)	(0.305)	(0.156)	(0.264)	(0.270)	(0.294)	(0.320)	(0.321)
HAP_{-3}	0.228	−0.046	0.206	0.150	0.192	0.579	0.231	0.472	0.155	−0.457*	−0.021	0.105	−0.443	−0.600*
	(0.405)	(0.474)	(0.260)	(0.414)	(0.321)	(0.360)	(0.574)	(0.305)	(0.155)	(0.264)	(0.269)	(0.294)	(0.320)	(0.321)
HAP_{-4}	0.251	0.444	0.283	−0.183	−0.164	−0.306	−0.441	−0.297	−0.046	0.014	0.285	0.081	0.206	0.768**
	(0.406)	(0.475)	(0.260)	(0.415)	(0.322)	(0.360)	(0.575)	(0.305)	(0.155)	(0.264)	(0.270)	(0.294)	(0.320)	(0.321)
HAP_{-5}	−0.792**	−0.781*	−0.364	−0.330	−0.421	−0.601*	−0.141	−0.501*	0.060	−0.131	−0.359	−0.613**	−0.392	−0.689**
	(0.361)	(0.424)	(0.232)	(0.370)	(0.286)	(0.321)	(0.513)	(0.272)	(0.139)	(0.235)	(0.240)	(0.261)	(0.285)	(0.286)

Note: The table reports VAR estimation results; HAP (Twitter based happiness index), USA (United States), CAN (Canada), BRA (Brazil), UK (United Kingdom), GER (Germany), NET (Netherlands), FRA (France), SWI (Switzerland), SAF (South Africa), IND (India), CHN (China), HKG (Hong Kong), SKR (South Korea), and JPN (Japan). Standard errors are presented in (). *, **, and *** represent significance at 10 %, 5 %, and 1 %, respectively.

Table 2
Granger casualty test results for linear and nonlinear models.

Null Hypothesis	Linear GC (Granger, 1969) Stat	Nonlinear GC (Diks and Panchenko, 2006) Stat
HAP ↦ USA	9.897*	1.873**
HAP ↦ CAN	8.056	1.256
HAP ↦ BRA	17.724***	2.203**
HAP ↦ UK	7.215	1.755**
HAP ↦ GER	15.386***	1.436*
HAP ↦ NET	20.733***	1.514*
HAP ↦ FRA	8.363	1.744**
HAP ↦ SWE	22.122***	2.200**
HAP ↦ SFA	3.714	1.772**
HAP ↦ IND	9.905*	1.578*
HAP ↦ CHN	14.264**	1.035
HAP ↦ HKG	14.669**	1.564*
HAP ↦ SKR	13.923**	1.628*
HAP ↦ JPN	15.584***	2.026**

Note: The table reports linear and nonlinear causality results; HAP (Twitter based happiness index), USA (United States), CAN (Canada), BRA (Brazil), UK (United Kingdom), GER (Germany), NET (Netherlands), FRA (France), SWI (Switzerland), SAF (South Africa), IND (India), CHN (China), HKG (Hong Kong), SKR (South Korea), and JPN (Japan). The symbol "↦" represents the null hypothesis of Granger non-causality. *, **, and *** represent significance at 10 %, 5 %, and 1 %, respectively.

Table 2 reports the results for the linear (Granger, 1969) and nonlinear (Diks and Panchenko, 2006) Granger causality tests. The findings of both linear and nonlinear Granger causality tests confirm that the Twitter based happiness index significantly influences the country VIX indexes. In the case of linear Granger causality test, the null hypothesis is rejected for ten sample countries, indicating that the Twitter based happiness index causes the implied volatility index. The results indicate that changes in investor sentiment lead to significant changes in the future volatility of the stock markets. Social media activity has important implications for the implied volatility of stock markets, and it can be implied from the findings that today's investor sentiment is reflected in next day's market volatility. The findings can again be linked to earlier evidence that highlights the causal effects of Twitter happiness on various assets. Li et al. (2017) show a positive bi-directional relationship between the daily Twitter based happiness index and range based volatility of the stock market, and a similar relationship is documented for other financial markets; for instance, Shen et al. (2019) find a positive influence of Twitter happiness on the realized volatility of Bitcoin.

The findings of the nonlinear Granger causality test also show a causal relationship between happiness and implied volatility. The findings reinforce the notion of investor sentiment as a leading indicator of future volatility in stock markets. The Twitter based happiness index contains useful predictive information about the future volatility of stock markets. The null hypothesis is rejected for thirteen of the sample stock markets. Only Canada shows no significant relationship between the Twitter based happiness index and the volatility index. The findings imply that our results are not compromised by the linearity assumption, since the nonlinear tests confirm our earlier conclusions. The findings have important implications for market participants relating to risk management and market efficiency. Our findings imply that investors should carefully monitor the information content of the Twitter based happiness index to make timely investment decisions and shield against future volatility. Following the volatility feedback hypothesis, investors can use the information content of the Twitter based happiness index to generate higher returns on their portfolios. Finally, policy makers should recognize the effects of happiness on stock market efficiency and formulate polices to reduce the negative effects of social media content on stock markets.

In order to ensure the robustness of our results, we employ additional nonlinear (Taylor and ANN based) causality tests proposed by Péguin-Feissolle and Teräsvirta (1999) and report the results in Table 3. The results are almost the same as our previous results, and support the finding that the Twitter based happiness index has a significant impact on the country VIX index. The null hypothesis is rejected for all sample markets, excluding Canada, by both types of test. The results once again indicate the predictive capability of the Twitter based happiness index for future stock market volatility. Overall, the findings show causality from Twitter happiness to implied volatility for almost all sample markets. Therefore, we can summarize our findings that the Twitter based happiness index significantly predicts implied stock market volatility, and confirm the existence of a significant nonlinear relationship between the Twitter based happiness index and implied volatility, which is confirmed using a battery of nonlinear causality tests.

4. Conclusions

Social media platforms have a significant influence on asset prices, and therefore we investigate the predictive power of Twitter happiness for the future volatility of international stock markets. Using linear and nonlinear causality tests, we find that the Twitter based happiness index, as a proxy for investor happiness, is a useful predictor of future stock market volatility. In general, our findings highlight a significant dependence between online sentiment and the implied volatility of stock markets. Our findings are consistent across various approaches and provide useful insights for investment decisions and portfolio management. The robustness

Table 3
Causality test results for nonlinear causality model.

Null Hypothesis	Nonlinear Causality Models Taylor Stat	ANN Stat
HAP ↦ USA	79.107***	3.068**
HAP ↦ CAN	2.538	2.332*
HAP ↦ BRA	97.019***	10.828***
HAP ↦ UK	65.382***	5.358***
HAP ↦ GER	112.742***	15.661***
HAP ↦ NET	125.294***	13.513***
HAP ↦ FRA	39.085***	2.928*
HAP ↦ SWE	108.156***	12.532***
HAP ↦ SFA	31.382***	5.192***
HAP ↦ IND	74.285***	5.862***
HAP ↦ CHN	81.283***	8.450***
HAP ↦ HKG	100.548***	5.588***
HAP ↦ SKR	71.354***	2.433*
HAP ↦ JPN	55.072***	4.851***

Note: The table reports additional nonlinear causality results; HAP (Twitter based happiness index), USA (United States), CAN (Canada), BRA (Brazil), UK (United Kingdom), GER (Germany), NET (Netherlands), FRA (France), SWI (Switzerland), SAF (South Africa), IND (India), CHN (China), HKG (Hong Kong), SKR (South Korea), and JPN (Japan). The symbol "↦" represents the null hypothesis of Granger non-causality. *, **, and *** represents significance at 10 %, 5 %, and 1 %, respectively.

results illustrate no divergence from our primary findings and provide strong evidence of a nonlinear relationship between investor sentiment and future volatility in the stock market. From the perspective of investors, the findings highlight the relevance of behavioural theories for portfolio decisions and how investors can use such information to adjust investment strategies. Portfolios managed considering the information contained in the Twitter based happiness index can outperform traditional passively managed portfolios (buy and hold strategy) in terms of risk and return. The findings also shed light on the influence of variations in happiness on the risk aversion of investors in stock markets. Although our sample does not include emerging markets because of data availability constraints, understanding the relationship between happiness and implied volatility in emerging markets may have important implications for investors regarding risk management and portfolio diversification.

However, our findings should be interpreted with caution as various other factors impact happiness and implied volatility. While we document the causal relationship between Twitter happiness and implied volatility, much less is known about the mechanics that drive this underlying relationship. We leave this for future research to investigate.

CRediT authorship contribution statement

Muhammad Abubakr Naeem: Writing - review & editing, Conceptualization, Methodology, Software, Formal analysis. **Saqib Farid:** Writing - original draft. **Faruk Balli:** Writing - review & editing, Supervision. **Syed Jawad Hussain Shahzad:** Writing - review & editing, Supervision.

Appendix A

A1 Nonlinear causality test of Diks and Panchenko (2006)

In order to reduce the risk of over rejection of the null hypothesis, we use the non-parametric test of Diks and Panchenko (2006).

Take two stationary time series (A_t, B_t). In this case, A_t Granger causes B_t if the past and current values of (A_t) hold additional information regarding future values of (B_t), which is not related to the past and current values of (B_t). Now suppose delay vectors as $A_t^{lx} = (A_{t-l+1}, \ldots, A_t)$ and $B_t^{lx} = (B_{t-l+1}, \ldots, B_t)$. The null hypothesis stipulates that previous values of A_t^{lx} containing no functional information about B_{t+1} can be written as follows:

$$H_0\colon B_{t+1} \mid (A_t^{l_x}; B_t^{l_y}) \sim B_{t+1} \mid B_t^{l_y} \tag{A.1}$$

In Eq. (A.1), l_x and l_y represent past values of A and B and '~' indicates equivalence in the underlying distribution. Now considering $C_t = B_{t+1}$ and dropping the lags and time index in Eq. (A.1), the conditional distribution of C is represented as $(A, B) = A, B$, which is the same as that of C given as $B = b$ following the null hypothesis. Thus, Eq. (A.1) can be written as joint distributions with a joint probability function $f_{A,B,C} = (a, b, c)$ that satisfies the following condition, which shows A and C are conditionally independent on $B = b$ for each fixed value of B.

Table A1
Summary of studies of the influence of Twitter content on stock markets.

Reference	Study Period	Method	Summary
Bollen et al. (2011)	2008	Granger causality analysis & self-organizing fuzzy neural network	Predictions of DJIA closing values can be significantly improved by the inclusion of specific public mood dimension data derived from Twitter.
Sul et al. (2017)	2011 – 13	Regression	Sentiment in tweets about a specific firm from investors has a significant impact on the stock returns of the next day.
Zhang et al. (2016)	2008 – 15	Granger causality tests	Happiness has explanatory power for index return and range based volatility.
You et al. (2017)	2008 – 16	Quantile Granger non-causality	The causal relationship from stock returns to happiness exist only in the tail area.
Shen et al. (2017)	2008 – 15	Event study	Findings show that the skewness around the highest happiness days is significantly larger than the skewness around the lowest happiness days.
Piñeiro-Chousa et al. (2018)		Granger causality tests ARIMA	Investor sentiment and gold returns predict S&P500 index returns.
Zhao et al. (2020)	2011 – 19	Granger causality tests	Findings show that index returns vary tremendously across quantile happiness subgroups, and the subgroup return differences are strongly significant at 1% levels.

$$\frac{f_{A,B,C}(a,b,c)}{f_B(b)} = \frac{f_{A,B}(a,b)}{f_B(b)}\frac{f_{B,C}(b,c)}{f_B(b)} \tag{A.2}$$

Following Diks and Panchenko (2006), the reformulated null hypothesis can be written as:

$$q = E\left[f_{A,B,C}(A,B,C)f_B(B) - f_{A,B}(A,B)f_{B,C}(B,C)\right] \tag{A.3}$$

In Eq. (A.3) $\widehat{f}_W(W_i)$ denotes the local density estimator of d_w. The variate random vectors W and W_i are defined as:

$$\widehat{f}_W(W_i) = (2\varepsilon)^{-d_W}(n-1)^{-1}\sum_{j,j\neq 1} I_{ij}^W \tag{A.4}$$

In Eq. (A.4) $I_{ij}^W = I(\|W_i - W_j\| < \varepsilon_n)$ is the indicator function, ε_n is the bandwidth depending upon the sample size n. Given this estimator, the test statistic is a scaled version of q in Eq. (A.3).

$$T_n(\varepsilon) = \frac{(n-1)}{n(n-2)}\sum_i \left(\widehat{f}_{A,B,C}(A_i,B_i,C_i)\widehat{f}_B(B_i) - \widehat{f}_{A,B}(A_i,B_i)\widehat{f}_{B,C}(B_i,C_i)\right) \tag{A.5}$$

Further, for $l_x = l_y = 1$ if $\varepsilon_n = Cn^{-\beta}$ for a positive constant C and $\beta \in (\frac{1}{4}, \frac{1}{3})$, Diks and Panchenko (2006) show that, under strong mixing, the statistic is:

$$\sqrt{n}\frac{(T_n(\varepsilon_n) - q)}{S_n} \overset{d}{\to} N(0,1) \tag{A.6}$$

In Eq. (A.6) $\overset{d}{\to}$ represents convergence in the distribution, and S_n denotes the asymptote of $T_n(.)$.

Table A2
Descriptive statistics.

	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	ADF	Break
USA	16.260	48.000	9.140	5.465	2.022	8.226	−7.678***	8/12/2011
CAN	15.757	36.710	3.970	4.581	1.413	5.154	−6.828***	20/04/2011
BRA	33.174	72.830	16.670	8.535	0.987	4.119	−5.743***	13/10/2014
UK	15.720	43.610	6.194	5.323	1.853	7.374	−7.671***	15/06/2012
GER	20.145	50.740	10.980	6.375	1.714	6.754	−6.259***	15/06/2012
NET	17.677	47.250	9.192	6.039	1.548	5.666	−6.391***	16/06/2016
FRA	19.591	55.594	0.429	6.434	1.383	5.611	−7.076***	15/06/2012
SWI	15.935	44.467	8.810	4.738	2.202	9.737	−6.846***	12/09/2011
SAF	18.933	34.070	10.610	3.684	0.821	3.788	−4.429**	4/10/2011
IND	17.579	37.700	10.450	4.727	1.255	4.522	−6.801***	15/05/2014
CHN	25.709	63.420	15.090	6.805	1.664	6.838	−6.280***	23/11/2011
HKG	19.366	51.970	11.360	5.612	1.690	6.697	−5.704***	20/04/2011
SKR	15.917	50.110	9.720	5.301	2.584	11.606	−5.712***	23/11/2011
JPN	22.423	69.750	12.190	6.044	1.347	7.065	−9.883***	24/06/2016
HAP	6.008	6.303	5.774	0.043	0.960	7.277	−18.497***	21/04/2011

Note: Std. Dev. represents the standard deviation, and the ADF test indicates the augmented Dicky-Fuller test with break-point. The sample period is 16th March 2011 to 27th June 2019. **, and *** indicate significance at 5 % and 1 %, respectively.

Table A3
BDS test of nonlinearity.

m	USA	CAN	BRA	UK	GER	NET	FRA	SWI	SAF	IND	CHN	HKG	SKR	JPN
2	13.563***	10.766***	9.708***	11.444***	11.153***	12.175***	10.520***	12.826***	5.697***	9.773***	13.289***	13.565***	17.168***	13.297***
3	19.089***	14.459***	12.217***	14.434***	14.068***	15.525***	13.341***	15.775***	7.194***	13.138***	16.662***	18.318***	20.959***	17.148***
4	23.392***	17.349***	14.000***	16.572***	16.963***	18.428***	16.300***	17.945***	7.905***	15.195***	18.760***	21.099***	23.140***	20.329***
5	27.214***	19.865***	15.846***	19.037***	19.809***	21.178***	18.995***	20.061***	7.890***	16.936***	20.575***	24.059***	25.452***	23.202***
6	31.442***	22.240***	18.629***	21.955***	23.464***	24.982***	22.339***	22.508***	7.907***	18.655***	22.939***	27.709***	27.852***	26.131***

Note: The entries indicate the z-statistics BDS test based on the residuals of the VAR model of stock market volatility with the Happiness Index (HAP). m denotes the embedding dimension of the BDS test.
*** indicate significance at 1 %.

Appendix B. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ribaf.2020.101298.

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