Twitter's daily happiness sentiment and the predictability of stock returns

Wanhai You , Yawei Guo , Cheng Peng

PII: S1544-6123(17)30019-3
DOI: 10.1016/j.frl.2017.07.018
Reference: FRL 752

To appear in: *Finance Research Letters*

Received date: 9 January 2017
Accepted date: 31 July 2017

Highlights

- We investigate the dynamic causal links between Twitter's happiness sentiment and stock returns.
- Quantile Granger non-causality approach is used to obtain a more complete picture of the causal relationship.
- The results indicate that the causal relations vary across different quantiles.
- Significance of causality from happiness sentiment to stock returns is mainly from high quantiles.
- The causal relationship from stock returns to happiness sentiment exist only in the tail area.

Twitter's daily happiness sentiment and the predictability of stock returns

Wanhai You[*a], Yawei Guo[b], Cheng Peng[b]

[a] *School of Economics and Management, Fuzhou university, Fuzhou, P R China*

[b] *Business School of Hunan university, Changsha, P R China*

Abstract

Using a novel investor sentiment proxy extracted from Twitter, this paper investigates whether investor sentiment as expressed in daily happiness has predictive power for stock returns in 10 international stock markets. To account for complex relationships between sentiment and stock returns, a Granger non-causality test in quantiles is used. Our empirical results indicate that the causal relations vary across different quantiles. We observe that the causal relationship from happiness sentiment to stock returns exist only in high quantiles interval. The causal relationship from stock returns to happiness sentiment exists only in the tail area.

Keywords: Investor sentiment; Daily happiness; Stock returns; Granger non-causality; Quantile regression

1. Introduction

Stock market is one of the most important parts of financial market nowadays. Stock market prediction has attracted much attention from both of academia and business. One of an important question is whether investor sentiment predicts stock returns. Rational risk-based asset pricing models argue that prices reflect the discounted value of expected future cash flows, even though some investors are not rational, their irrationalities are offset by arbitrageurs quickly. Instead, behavioral finance theory suggests the presence of noise traders in the stock market with correlated behavior and limits on arbitrage as conditions that can lead investor sentiment to influence asset prices (Shleifer and Summers, 1990; Hughen and McDonald, 2005; Baker and Wurgler, 2006). The notable work of De Long et al., (1990) models the influence of noise trading on equilibrium prices. Baker and Wurgler (2007) indicate that investor sentiment does have predictive power with respect to equity returns.

Several theoretical studies offer models establishing the nexus between investor sentiment and asset prices (Black, 1986; De Long et al., 1990). Investor sentiment predictive content in relation to the future market

[*] Corresponding author at: School of Economics and Management, Fuzhou University, 350116, China. Tel.: +86 18250166263; fax: +86 18250166263.
E-mail address: ywhfzu@163.com (W-H)

movements might act as an invaluable tool for the market participants in forming successful trading strategies (Baker and Wurgler, 2007). After that, a growing body of research has examined on the relationship between investor sentiment and asset prices (e.g., Schmeling, 2009; Dergiades, 2012; Kim and Kim, 2014; Huang et al., 2014; Siganos et al., 2014; Zhang et al., 2016). To empirically investigate this issue, various investor sentiment proxies, including the stock market-based proxies, the survey-based proxies, and the news and social media content-based proxies, have been employed.

Since the importance of this topic, there is increasing empirical literature to devote to the relationship between investor sentiment and stock returns (e.g., Brown and Cliff, 2004; Kling and Gao, 2008; Aloui et al., 2016). The results, however, are not uniform. Within the debate on the investor sentiment and stock returns nexus, the previous analysis is conducted mainly with the assumption that the relationship is linear. In reality, however, nonlinear is manifested in a relationship between most macro-variables. In finance variables, for example, nonlinear relationship may be caused by the fact that bullish and bearish markets behave differently. Dergiades (2012) argues that the results in many previous studies suffer from the assumption of linearity and then explores the Granger causality relationship between investor sentiment and stock returns from a non-linear perspective. Zhang et al., (2016) indicate that the distribution of stock returns and sentiment index are non-normal usually. To explore the heterogeneous relationships between sentiment and stock returns, the authors divide the sentiment index into quintiles. Chen et al., (2013) indicate that the relationship between investor sentiment and stock returns is more complex. To account for non-linear link, the authors explore panel threshold model to model the sentiment–industry returns' linkage.

To handle with this issue, the paper explores the nonlinear links between investor sentiment and stock returns using the Granger non-causality test in quantiles. This paper presents some new features that are not necessarily shared by existing studies. First, we investigate whether sentiment, released by social media, can indeed be used to predict the stock return in 10 international stock markets. The novel sentiment proxy, expressed as the daily happiness index extracted from Twitter, is used. To our knowledge, this index is used only once by Zhang et al., (2016). Second, we explore the causality link between sentiment and stock returns by using the Granger non-causality test in quantiles proposed by Chuang et al. (2009). There are two advantages to apply the quantile causality test compared to the classical causality tests. On the one hand, the classical causality tests based on the OLS framework is designed to explore the average causal relationship of the variables, and hence fail to capture the entire conditional distribution of sentiment and stock returns. However, heterogeneity is a usual characteristic of time-series variables and thus the classical methods may provide an incomplete description of the true causal relationship. In Granger non-causality test in quantile framework, we are able to capture existence or non-existence of causality at various market states (e.g., bear, i.e. lower quantiles, normal, i.e. median quantiles and bull, i.e. upper quantiles). On the other hand, a sample splitting procedure is usually required when investigating the response of stock returns to sentiment under various stock market situations. It is worth mentioning that segmenting the dependent variable into subsets according to its unconditional distribution and then running an OLS on these subsets is not an appropriate alternative to the quantile regression, due to severe sample selection problems (Koenker and Hallock, 2001). One can avoid this issue using quantile causality since it allows for testing causal relationships at any chosen conditional quantile level without pre-selecting some arbitrary sub-samples.

The remainder of this paper is organized as follows. Section 2 presents the data and methodology. Section 3 presents the results and Section 4 concludes the paper.

2. Data and methodology

2.1 Data

We explore the dynamic nonlinear causal relationships between investor sentiment and stock returns. Investor sentiment is measured by the daily happiness index extracted from Twitter. The daily happiness is collected from the website (http://hedonometer.org/index.html).This index is derived from the natural language processing technique using a random sampling of about 10% of all messages posted in Twitter. To quantify the happiness of the language, the Amazon's Mechanical Turk service is used to score the level of happiness of selected words appeared on Twitter, e.g., joy, successful, laughter, winning, excellent, and rainbow. Data for daily happiness include observations span the period 9st Sep, 2008 to 15th Nov, 2016, using daily frequency data. Stock prices have been obtained from Yahoo finance for 10 international stock markets, including USA (S&P 500), Canada (S&P/TSX), France (CAC 40), Germany (DAX), UK (FTSE 100), Hong Kong (Hang Seng), South Korea (KOSPI), Japan (Nikkei 225), Australia (S&P/ASX 200) and New Zealand (NZX 50 index). These countries or regions are chosen since almost all of these countries and region have large proportion of Twitter users. For comparison, other stock price indexes are converted into US dollars using the official exchange rate. Exchange rates for each currency are sourced from OANDA (www.oanda.com). Stock returns R_t are calculated by $\ln(P_t)-\ln(P_{t-1})$, where P_t is the close price at time *t*.

2.2 Granger non-causality test in quantiles

Following Granger (1969), the random variable x does not Granger cause the random variable *y* if

$$F_{y_t}(\eta|(\mathcal{Y},\mathcal{X})_{t-1}) = F_{y_t}(\eta|\mathcal{Y}_{t-1}), \quad \forall\, \eta \in \mathcal{R} \tag{1}$$

where $F_{y_t}(.|\mathcal{F})$ is the conditional distribution of y_t and $(\mathcal{Y},\mathcal{X})_{t-1}$ is theinformation set generated by y_t and x_t up to time *t*-1. That is, x_t does not Granger cause y_t if the past information of x_t does not alter the conditional distribution ofy_t. In the previous literature, it is common to test a necessary condition of Eq. (1) as follows

$$\mathbb{E}(y_t|(\mathcal{Y},\mathcal{X})_{t-1}) = \mathbb{E}(y_t|\mathcal{Y}_{t-1}), \tag{2}$$

where $\mathbb{E}(y_t|\mathcal{F})$ is the mean of $F_{y_t}(.|\mathcal{F})$. Here, x_t does not Granger cause y_t in mean if Eq. (2) holds. The hypothesis in Eq. (2) is usually tested by evaluating a linear model of $\mathbb{E}(y_t|(\mathcal{Y},\mathcal{X})_{t-1})$: α_0+$\sum_{k=1}^{p} \alpha_k\, y_{t-k} + \sum_{j=1}^{q} \beta_j\, x_{t-j}$. Testing Eq. (2) now amounts to testing $\beta_j = 0, j = 1,2,\dots,q$. However, failing to reject the null is compatible with non-causality in mean but says nothing about causality in other moments or other distribution characteristics. That is, failing to reject the necessary condition may not consistently reject Eq (1).

Given that a distribution can be completely determined by its quantiles, Granger non-causality in distribution can also be expressed in terms of conditional quantiles. To provide a complete understanding of the causal relationship between time series, Chuang et al. (2009) consider Granger non-causality test in quantiles. Let $Q_{y_t}(\tau|\mathcal{F})$ denotes the τ-th quantile of $F_{y_t}(.|\mathcal{F})$, thus Eq (1) equals

$$Q_{y_t}(\tau|(\mathcal{Y},\mathcal{X})_{t-1}) = Q_{y_t}(\tau|\mathcal{Y}_{t-1}), \qquad \forall\, \tau \in [a,b] \tag{3}$$

If Eq (3) holds, this indicates that x_t does not Granger cause y_t over the quantile interval [a, b]. To implement this test, the quantile regression method in Koenker and Bassett (1978) is used. The conditional quantile of y_t can be written as

$$Q_{y_t}(\tau|z_{t-1}) = \mathrm{w}(\tau) + \sum_{k=1}^{p} \alpha_k(\tau)\, y_{t-k} + \sum_{j=1}^{q} \beta_j\,(\tau) x_{t-j} = z'_{t-1}\theta(\tau), \tag{4}$$

where $z_{t-1} = \left(1, y'_{t-1,p}, x'_{t-1,q}\right)$; $y_{t-1,p} = \left(y_{t-1}, y_{t-2,\dots,}y_{t-p}\right)'$; $x_{t-1,q} = (x_{t-1}, x_{t-2,\dots,}x_{t-q})'$, $\theta(\tau) = (w(\tau), \alpha_1(\tau), \alpha_2(\tau), \dots, \alpha_p(\tau), \beta_1(\tau), \beta_2(\tau), \dots, \beta_q(\tau))'$. We can estimate Eq. (4) by minimizing asymmetrically weighted absolute deviations. Given a linear location-scale shift model for conditional quantiles, testing (3) amounts to testing H_0: $\beta(\tau) = 0,\ \forall\, \tau \in [a,b]$. Koenker and Machado (1999) and Chuang et al. (2009) suggest testing the entire process using a *sup-Wald* test. See Chuang et al. (2009) for a detailed description of the calculation of the statistics and the critical values.

3. Empirical results

Before implementing the Granger non-causality test, we test whether the variables used are stationary using Augmented Dickey–Fuller and Phillips-Perron approaches. The test equations for the series include both a constant and a trend. Table 1 indicates that we can reject the null of a unit root for all the series, indicating these series follow an I(0) process. To justify the motivation for a quantile-based analysis, Table 1 also presents the summary statistics for stock returns and happiness sentiment index. The variables are non-normal as suggested by the strong rejection of the null of normality under the Jarque-Bera statistic. The fact suggesting the presence of heavy tails provides an initial motivation to look at quantiles rather than a conditional mean based approach.

[Insert Table 1 about here]

For comparison, we first explore causal relationship between happiness sentiment and stock returns in mean framework using *F* test. We select the optimal lag truncation order by the Akaike Information Criterion (AIC). From Table 1 we can conclude that the variables are non-normal. Thus, we also report the results using a heteroskedasticity consistent (HC) variance-covariance matrix for the Granger test in Columns 3 and 5. As shown in Table 2, the *F*-statistics significantly reject the null of happiness sentiment does not Granger cause stock returns at the 10% level for Canada. Other cases, however, are not statistically significantly. The null hypothesis of stock return does not Granger cause happiness sentiment is rejected at the 5% level for UK. Overall, the Granger causality in mean indicates that there does not exist causal relationship between investor sentiment and stock returns for the most part. It is seen that happiness sentiment does not help to predict sock returns.

[Insert Table 2 about here]

The Granger non-causality in-mean framework indicates that there is no cause relationship between stock returns and sentiment. This raises the question of whether the dependence between these two variables exists at other levels (other than mean) of the conditional distribution of stock market returns or sentiment index. The Granger non-causality in mean test might overlook a significant relationship between sentiment and stock market returns. To answer this question, in the next section we apply the Granger non-causality in quantile to examine the dependence. In Granger non-causality test in quantile framework, we are able to capture existence or non-existence of causality at various market states.

To test the Granger non-causality relationship between happiness sentiment and stock returns, we consider the following quantile regression model

$$Q_{R_t}(\tau|\mathcal{X}_{t-1}) = \alpha_0(\tau) + \sum_{k=1}^{p} \alpha_k(\tau) R_{t-k} + \sum_{j=1}^{q} \beta_j(\tau) H_{t-j}, \quad (5)$$

$$Q_{H_t}(\tau|\mathcal{Y}_{t-1}) = \theta_0(\tau) + \sum_{k=1}^{p} \theta_k(\tau) H_{t-k} + \sum_{j=1}^{q} \varphi_j(\tau) R_{t-j}, \quad (6)$$

where R_t denotes stock return index; H_t denote investor sentiment proxy by Twitter's daily happiness index. *p* and q denote the lag length and we assume p=q in the paper. If the null hypothesis H$_0$: $\beta_1(\tau) = \cdots = \beta_q(\tau) = 0$ for quantile interval [a, b] is not rejected, we can say that happiness sentiment does not Granger cause stock returns at this quantile interval. If the null hypothesis H$_0$: $\varphi_1(\tau) = \cdots = \varphi_q(\tau) = 0$ for quantile interval [a, b] is not rejected, we can say that stock returns does not Granger cause sentiment at this quantile interval. We apply the Sup-Wald statistics to test the Granger non-causality for each quantile range. To conduct the Sup-Wald test, we select the optimal lag truncation order q^* by using a sequential lag selection method (Chuang et al., 2009). According to the following criteria, if the null hypothesis $\beta_q(\tau) = 0$ for $\tau \in [a, b]$ is not rejected but the null hypothesis $\beta_{q-1}(\tau) = 0$ for $\tau \in [a, b]$ is rejected. Then we set the optimal lag order as $q_* = q\text{-}1$ for the quantile interval$[a, b]$. If no test statistic is significant over that interval, then we choose q_*=1 as the optimal lag of order.

Before implementing the Granger non-causality in quantile, we first estimate Eq.(5) for various markets using quantile regression with $\tau =$ (0.05;0.06;...;0.95). Based on the select criteria, the optimal lag orders are 1 for all markets over the quantile interval [0.05, 0.95]. Fig.1 shows the QR estimates of $\beta_1(\tau)$ in the solid line and their 95% confidence intervals in the shaded area. The results indicate that the coefficient $\beta_1(\tau)$ varies with quantiles and exhibits an interesting pattern. In the case of CAC 40, DAX, Nikkei 225, KOSPI and NZX 50 INDEX, the magnitude of these estimates is relatively stable. The coefficients are not statistically significant at the 5% significant level for most of quantiles, especially for CAC 40 and DAX. We can conclude that there is no causality in quantile. In the case of other markets, the QR estimates are negative at lower quantiles and positive at upper quantiles. These estimates are, in general, significant at high quantiles. This shows that there is causality cause only at high quantile level.

[Insert Fig.1 about here]

To be sure, we apply sup-Wald test to check the joint significant. In this paper, we consider one large quantile interval [0.05, 0.95] and three small quantile intervals, namely [0.05, 0.2], [0.4, 0.6], and [0.8, 0.95]. As mentioned in previous section, the different quantile intervals for the returns might reflect different market states, e.g., low, medium and high quantile intervals are corresponding to the low, medium and high return states, respectively. Panel A of Table 3 reports the results of Granger non-causality in quanitle. For $\tau \in [0.05, 0.95]$, happiness sentiment Granger-cause S&P/ASX 200, S&P/TSX, FTSE 100, Hang Seng, and S&P 500 returns. Thus, lagged log daily happiness carries important information that is not contained in the past returns. That is, the result indicates that the amount of activity on social media is useful for predicting the stock market performance. However, happiness sentiment does not Granger-cause CAC 40, DAX, Nikkei 225, KOSPI, and NZX 50 returns for $\tau \in [0.05, 0.95]$. The result indicates that lagged daily happiness do not carries important information that is not contained in the past returns for these markets.

[Insert Table 3 about here]

The results correspond to quantile sub-intervals that indicate that the significant causality from happiness sentiment to stock returns for $\tau \in [0.05, 0.95]$ derives from upper levels of quantiles. For $\tau \in [0.05, 0.2]$, the results cannot reject the null hypothesis of sentiment does not Granger cause returns for all markets except S&P/TSX. Happiness sentiment does not Granger cause returns for all markets in the quantile interval $\tau \in [0.4, 0.6]$. That is, there is no causal relationship over the middle quantile intervals for all markets. In the case of S&P/ASX 200, S&P/TSX, FTSE 100, Hang Seng, and S&P 500, there is causal from happiness sentiment to stock returns over the high quantile interval [0.8, 0.95]. The result also holds for NZX 50. This implies that there is Granger causal from happiness sentiment to stock returns only for a high level of returns except S&P/TSX. This result justifies the assumption that investor sentiment is very likely to be a driving force on excess stock returns. This finding is similar to Ni et al., (2015). The authors conclude that investor sentiment has a larger impact on the stocks with higher returns, compared with the stocks with lower returns.

Panel B of Table 3 reports the test results for non-causality from returns index to happiness sentiment. In the case of S&P/ASX 200, S&P/TSX, FTSE 100, CAC 40, DAX, and KOSPI, the sup-Wald statistics for $\tau \in [0.05, 0.95]$ are significant at the 5% or 1% significant level. The result indicates that the stock market performance is useful for predicting the amount of activity on social media. Stock return does not Granger cause investor sentiment for all markets in the quantile interval $\tau \in [0.4, 0.6]$. Overall, we can conclude that there is causal from stock returns to happiness sentiment only for a high or low level of happiness sentiment for almost all of markets.

4. Concluding remarks

In this paper, we have explored the causal relationship between Twitter's daily happiness sentiment index and stock markets for 10 international markers from the perspective of quantile causality. A key advantage of Granger non-causality in quantile is in its ability to model economic relationships more richly than Granger non-causality in mean. Several interesting conclusions have been concluded. For the Granger causal from happiness sentiment to stock returns, the results show that there are significant differences at different points in the return distribution. In the case of S&P/ASX 200, S&P/TSX, FTSE 100, Hang Seng, and S&P 500, we conclude that happiness sentiment does not Granger cause stock returns. The results correspond to quantile sub-intervals indicate that the significant causality from happiness sentiment to stock returns for $\tau \in [0.05, 0.95]$ derives from upper levels of quantiles. For almost all of markets, there is causal from stock returns to happiness sentiment only for a high or low level of happiness sentiment. Regarding possible policy implications, investor sentiment has no effect on the stock market performance when the market in bear and normal phases. Different markets in the world take different approaches to cope with the effects of social media on stock market volatility.

Acknowledgements

The authors gratefully acknowledge the financial support from Fujian Social Science Planning Fund Program [grant number FJ2016C092]; the Hunan Provincial Innovation Foundation for Postgraduate [grant number CX2016B075].

References

Aloui, C., Hkiri, B., Lau, C. K. M., Yarovaya, L. (2016). Investors' sentiment and US Islamic and conventional indexes nexus: A time–frequency analysis. Finance Research Letters,19:54-59

Baker, M., Wurgler, J. (2006). Investor sentiment and the cross - section of stock returns. The Journal of Finance, 61 (4), 1645-1680

Baker, M., Wurgler, J. (2007). Investor sentiment in the stock market. The Journal of Economic Perspectives, 21 (2), 129-151

Black, F. (1986). Noise. The Journal of Finance, 41 (3), 528-543

Brown, G. W., Cliff, M. T. (2004). Investor sentiment and the near-term stock market. Journal of Empirical Finance, 11(1), 1-27

Chen, M. P., Chen, P. F., Lee, C. C. (2013). Asymmetric effects of investor sentiment on industry stock returns: Panel data evidence. Emerging Markets Review, 14, 35-54

Chuang, C. C., Kuan, C. M., Lin, H. Y. (2009). Causality in quantiles and dynamic stock return–volume relations. Journal of Banking & Finance, 33 (7), 1351-1360.

De Long, J. B., Shleifer, A., Summers, L. H., Waldmann, R. J. (1990). Noise trader risk in financial markets. Journal of Political Economy, 703-738

Dergiades, T. (2012). Do investors' sentiment dynamics affect stock returns? Evidence from the US economy. Economics Letters, 116 (3), 404-407

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. Econometrica: Journal of the Econometric Society, 424-438

Huang, D., Jiang, F., Tu, J., Zhou, G. (2014). Investor sentiment aligned: a powerful predictor of stock returns. Review of Financial Studies, doi:10.1093/rfs/hhu080

Hughen, J. C., McDonald, C. G. (2005). Who are the noise traders?.Journal of Financial Research, 28 (2), 281-298

Keynes, J.M., 1936. The General Theory of Employment, Interest, and Money. Macmillan, London

Kim, S. H., Kim, D. (2014). Investor sentiment from internet message postings and the predictability of stock returns. Journal of Economic Behavior & Organization, 107, 708-729

Kling, G., Gao, L. (2008). Chinese institutional investors' sentiment.Journal of International Financial Markets, Institutions and Money, 18 (4), 374-387

Koenker, R., Bassett Jr, G. (1978). Regression quantiles. Econometrica: Journal of the Econometric Society, 33-50.

Koenker, R., Hallock, K. (2001). Quantile regression: An introduction. Journal of Economic Perspectives, 15 (4), 43-56

Koenker, R., Machado, J. A. (1999). GMM inference when the number of moment conditions is large. Journal of Econometrics, 93 (2), 327-344

Ni, Z. X., Wang, D. Z., Xue, W. J. (2015). Investor sentiment and its nonlinear effect on stock returns—New evidence from the Chinese stock market based on panel quantile regression model. Economic Modelling, 50, 266-274

Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. Journal of Empirical Finance, 16 (3), 394-408

Shleifer, A., Summers, L. H. (1990). The noise trader approach to finance. The Journal of Economic Perspectives, 4 (2), 19-33

Siganos, A., Vagenas-Nanos, E., Verwijmeren, P. (2014). Facebook's daily sentiment and international stock markets. Journal of Economic Behavior & Organization, 107, 730-743

Zhang, W., Li, X., Shen, D., Teglio, A. (2016). Daily happiness and stock returns: Some international evidence. Physica A: Statistical Mechanics and its Applications,460, 201-209

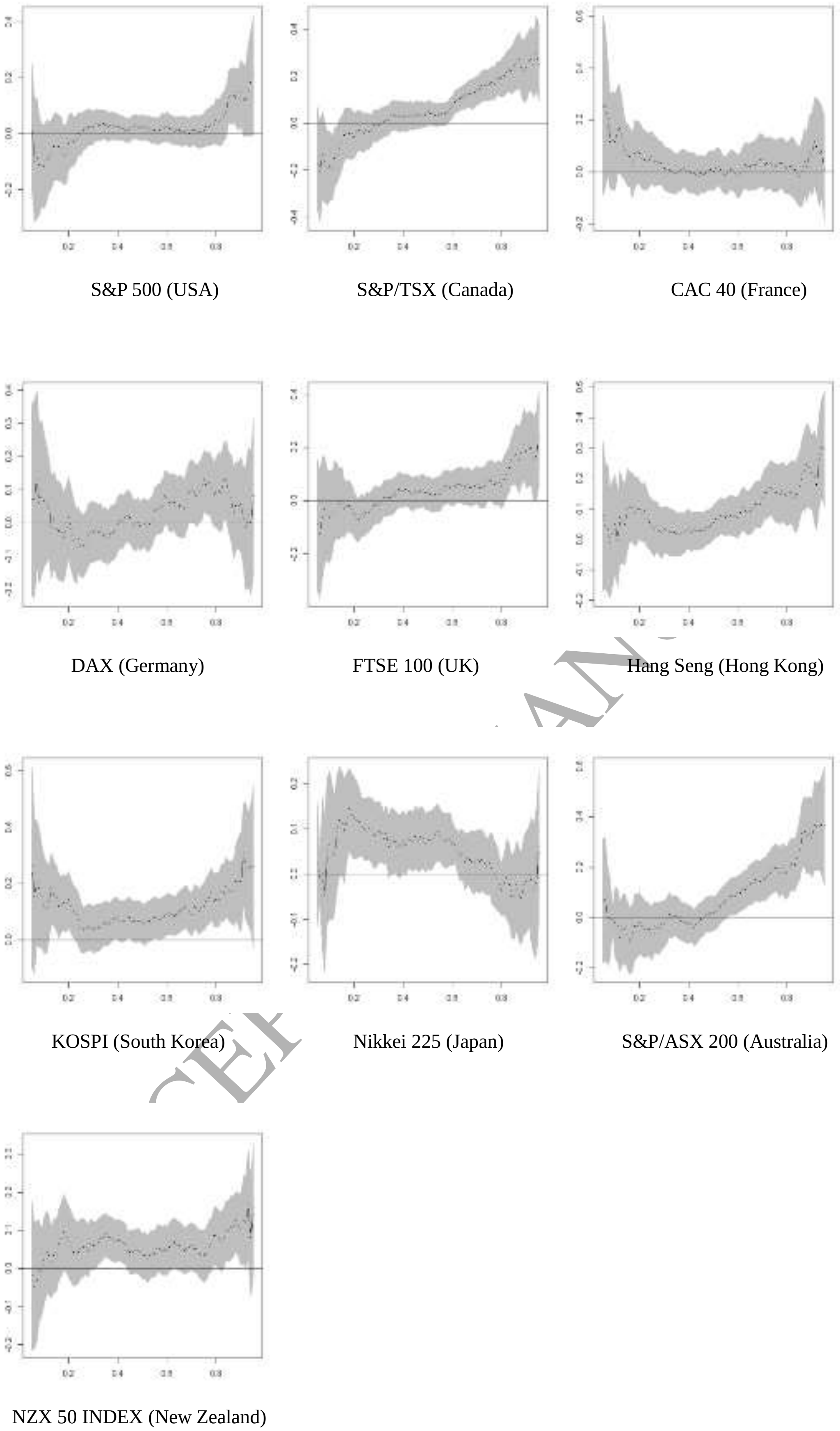

Fig. 1 QR estimates of the causal effects of happiness sentiment on stock returns

Table 1 Summary statistics

	N	mean	std	median	Kurtosis	JB stat	ADF	PP	min	max
S&P 500	2056	0.00028	0.01358	0.00059	10.63727	9758.7***	-12.441***	-50.313***	-0.0947	0.10957
						(0.0000)	(0.01)	(0.01)		
S&P TSX	2072	-0.00002	0.01471	0.00088	10.38345	9526.7***	-12.88***	-38.64***	-0.11627	0.11257
						(0.0000)	(0.01)	(0.01)		
CAC-40	2091	-0.0001	0.01772	0.00037	5.96992	3118.8***	-13.149***	-44.052***	-0.11208	0.11163
						(0.0000)	(0.01)	(0.01)		
DAX	2083	0.00013	0.01719	0.00058	4.97157	2161.3***	-12.768***	-42.335***	-0.09072	0.11192
						(0.0000)	(0.01)	(0.01)		
FTSE 100	2053	-0.00006	0.01514	0.00051	8.62238	6421.6***	-13.444***	-42.234***	-0.1086	0.10884
						(0.0000)	(0.01)	(0.01)		
Hang Seng	2044	0.00004	0.01588	0.0001	10.07779	8673.5***	-12.52***	-45.648***	-0.1358	0.13401
						(0.0000)	(0.01)	(0.01)		
KOSPI	2026	0.00012	0.0183	0.00073	20.81378	36754***	-12.098***	-40.678***	-0.19383	0.21172
						(0.0000)	(0.01)	(0.01)		
Nikkei 225	1996	0.00017	0.01447	0.00044	7.78064	5129.2***	-12.958***	-50.349***	-0.11023	0.10298
						(0.0000)	(0.01)	(0.01)		
S&P/ASX 200	2066	0.00000	0.01675	0.0004	5.77842	2979.2***	-12.8***	-41.76***	-0.12868	0.08542
						(0.0000)	(0.01)	(0.01)		
NZX 50 Index	1983	0.00038	0.01202	0.00094	5.12196	2249.9***	-11.324***	-37.734***	-0.07162	0.08842
						(0.0000)	(0.01)	(0.01)		
Happiness sentiment	2980	1.79669	0.00757	1.79767	3.06798	1314.7***	-3.9693**	-18.127***	1.76478	1.84949
						(0.0000)	(0.01051)	(0.01)		

P value in parentheses. The null hypothesis of Jarque-Bera test is normality.

*** Indicates statistical significance at 1% level.

** Indicates statistical significance at 5% level.

Table 2 Results for classical Granger no-causality between happiness sentiment and stock returns
HC: heteroskedasticity consistent.

Country or region	H_0: H_t does not Granger cause R_t		H_0: R_t does not Granger cause H_t	
	Homoskedastic	HC	Homoskedastic	HC
USA	1.26 (0.2474)	1.5487 (0.1158)	0.8817 (0.5496)	1.0265 (0.4178)
Canada	1.6386* (0.0815)	1.775* (0.0527)	1.6206* (0.0862)	1.5461 (0.1082)
France	0.9683 (0.4689)	0.9825 (0.4562)	1.687* (0.0778)	1.3691 (0.1880)
Germany	1.5185 (0.1175)	1.5294 (0.1137)	1.6376* (0.0817)	1.2216 (0.2661)
UK	0.8425 (0.5973)	1.0144 (0.4303)	2.5553*** (0.0032)	1.9508** (0.0292)
Hong Kong	0.8691 (0.5617)	0.8372 (0.5926)	0.5195 (0.8776)	0.6946 (0.7305)
South Korea	1.0519 (0.3965)	1.1997 (0.2857)	0.4679 (0.9115)	0.5723 (0.8379)
Japan	0.6095 (0.8071)	0.6794 (0.7446)	0.7193 (0.7071)	0.8236 (0.6059)
Australia	0.8395 (0.5904)	1.002 (0.439)	1.0589 (0.3907)	1.1447 (0.3241)
New Zealand	0.6131 (0.804)	0.6744 (0.7493)	0.9590 (0.4774)	1.0773 (0.3758)

*** Indicates statistical significance at 1% level.
** Indicates statistical significance at 5% level.
* Indicates statistical significance at 10% level.

Table 3 Test results for quantile causality between stock indices and investor sentiment.

Panel (A): investor sentiment → stock returns				
$\tau \in [a,b]$	[0.05,0.95]	[0.05,0.2]	[0.4,0.6]	[0.8,0.95]
USA	10.596** [1]	4.406 [1]	1.300 [1]	12.059***[1]
Canada	23.848***[1]	15.446***[1]	1.158 [1]	23.978***[1]
France	2.846 [1]	2.290 [1]	1.088 [1]	1.372 [1]
Germany	3.326 [1]	2.825 [1]	1.403 [1]	1.415 [1]
UK	11.731**[1]	5.602 [1]	0.477 [1]	12.805***[1]
Hong Kong	16.224***[1]	5.708 [1]	0.814 [1]	17.033***[1]
South Korea	5.752 [1]	1.162 [1]	0.534 [1]	5.819 [1]
Japan	3.387 [1]	2.121 [1]	1.811 [1]	0.735 [1]
Australia	12.368**[1]	5.616 [1]	2.188 [1]	13.624***[1]
New Zealand	7.780 [1]	5.836 [1]	0.624 [1]	7.780** [1]
Panel (B): stock returns → investor sentiment				
USA	5.907 [1]	37.242***[5]	1.246 [1]	5.907*** [1]
Canada	28.512***[4]	29.075***[4]	1.679 [1]	16.301** [3]
France	16.939** [3]	3.547 [1]	0.871 [1]	17.001***[3]
Germany	19.606** [4]	19.792***[4]	1.513 [1]	13.952** [3]
UK	24.784***[4]	17.061** [4]	0.522 [1]	16.171** [3]
Hong Kong	7.336 [1]	7.438** [1]	4.724 [1]	1.453 [1]
South Korea	54.510***[5]	57.649***[5]	1.178 [1]	10.734**[2]
Japan	2.286 [1]	36.325***[6]	0.655 [1]	2.407 [1]
Australia	15.847** [2]	7.837** [1]	1.729 [1]	15.944***[2]
New Zealand	2.604 [1]	2.604 [1]	1.305 [1]	9.949* [2]

Sup-Wald test statistics and the selected lag order (in square brackets) are reported.

$***$ Denotes significance at the 1% significance level.

$**$ Denotes significance at the 5% significance level.

$*$ Denotes significance at the 10% significance level.