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Sentiment and Financial Market Connectedness: The Role of Investor Happiness

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Abstract

We examine the relationship between investor sentiment and connectedness patterns across global stock markets within a quantile-on-quantile framework. Our findings show that investor happiness, built on Twitter feed data as a proxy for investor sentiment, has a significant effect on both the return and volatility spillovers across major global stock markets. While the sentiment effect is found to be relatively stronger on volatility spillovers, we observe that the relationship between sentiment and connectedness is asymmetric for return and volatility connectedness and displays quantile specific patterns with distinctly different effects observed for sentiment shocks. The findings suggest that both investors and policy makers should be particularly vigilant against sentiment shocks, in either direction, as these shocks can have significant risk effects, contributing to volatility spillovers globally.

Keywords: Advanced Equity Markets, Returns and Volatility, TVP-VAR, Dynamic Connectedness, Investor Happiness, Quantile-on-Quantile Regression.

JEL codes: C22, C32, G10.

1 Introduction

The role of investor sentiment as a driver of return dynamics in financial markets is well-established in the literature. In the asset pricing literature, a number of studies including Baker and Wurgler (2006), Frazzini and Lamont (2008) and Antoniou et al. (2013) establish a link between investor sentiment and market anomalies like size, value and momentum, while other studies link investor sentiment to herding and speculative behavior in financial markets (e.g. Lemmon and Ni, 2011; Blasco et al., 2012). Given the evidence that links macroeconomic fundamentals to the happiness of nations (e.g. Di Tella et al., 2013), one can argue that the sentiment effect of economic fundamentals spills over to financial markets via two distinct channels that drive (i) corporate investment and consumer spending decisions in the real economy and consequently, asset valuations; and (ii) changes in risk appetite and tendency to over/under-react to information, which in turn, affect investors' trading behavior. Considering the latter channel, the sentiment effect can be expected to spill over to multiple markets given the level of globalization in capital markets, either via cross-border capital flows or information spillovers across markets. Indeed, the empirical evidence links investor sentiment to feedback trading, suggesting that sentiment can partially explain autocorrelation patterns in financial returns as well as correlated trading behavior across different markets (e.g. Kurov, 2008; Chau et al., 2011). Clearly, such a spillover effect has not only investment implications as it can hurt the effectiveness of global diversification strategies, but also means that policy makers will have to be prepared for the potentially unfavorable spillover effects of sentiment changes across the global financial markets.

This paper contributes to the literature from a new perspective by examining the effect of investor sentiment on the return and volatility connectedness of financial markets via the time-varying parameter vector autoregressive (TVP-VAR) model-based connectedness framework of Antonakakis and Gabauer (2017). More specifically, we use the TVP-VAR framework to compute the time-varying total connectedness index (TCI) which measures the network of interconnectedness among ten advanced stock markets including Australia, Canada, France, Germany, Hong Kong, Japan, New Zealand, South Korea, the United Kingdom (UK), and the United States (US). This approach combines the widely-used connectedness approach of Diebold and Yilmaz (2012, 2014) with the TVP-VAR framework of Koop and Korobilis (2014) and hence overcomes the drawbacks of the generally used rolling-window VAR methodology of Diebold and Yilmaz (2012, 2014) as it bypasses the need to arbitrarily set the rolling window-size, which, in turn leads to loss of observations and it is not sensitive to outliers in the data.

As a second novelty, we utilize a social media based investor happiness index built on Twitter feed data as a proxy for investor sentiment. Given that investor sentiment is not directly measurable or observable, traditionally, two routes have been taken to measure investor sentiment (see Bathia and Bredin, 2013 and Bathia et al., 2016 for more details). One approach captures investor sentiment by various market-based measures considered as proxies for investor sentiment (Baker and Wurgler, 2006; 2007), while the second approach focuses on survey based indices (e.g. Da et al., 2015).[1] More recently, following the work of Da et al. (2015), a third approach has originated, extracting metrics of investor sentiment from news and contents of social media (e.g. Garcia, 2013; Zhang et al., 2016, 2018; You et al., 2017). Da et al. (2015) argue that their method and the internet-based measures of investor sentiment are generally more transparent relative to the other alternatives that adopt market and survey-based approaches. This is because the market-based method captures the equilibrium outcome of many economic forces other than investor sentiment, while the survey-based method is more likely to be prone to measurement errors as it inquires about attitudes. Another disadvantage of these traditional approaches to capture investor sentiment is that they tend to produce

[1] Da et al. (2015) propose an investor-sentiment index using daily Internet search data from millions of households in the U.S. by focusing on particular ‘economic’ keywords that reflect investors’ sentiment towards economic developments.

metrics at lower (monthly or quarterly) frequencies. In our study, we use an investor sentiment proxy based on Twitter feeds that is available at daily frequency, thus allowing us to capture the dynamic effect of sentiment on connectedness patterns in financial markets. Another advantage of the happiness index used in our study is that it is global in nature, given the dominance of Twitter users in the ten countries serving as major players in the world financial system, thus allowing us to capture investor sentiment at a broader level. Needless to say, the happiness index has been successfully employed in analyzing the predictability of returns and volatility of international equity markets (see for example, Zhang et al. 2016, 2018, You et al. 2017, Reboredo and Ugolini 2018).

The empirical analysis to examine the link between investor happiness and return/volatility spillovers across financial markets via the total connectedness index (TCI) is based on the quantile-on-quantile (QQ) approach recently developed by Sim and Zhou (2015). The QQ model, as a generalization of the standard quantile regression, is a combination of the quantile regression and nonparametric estimation frameworks, allowing us to examine how the conditional quantiles of the total connectedness index relate to the quantiles of the happiness index. The QQ approach, unlike quantile regressions, provides us a more comprehensive insight as we can analyze the response of the entire conditional distribution of TCIs simultaneously to various levels of investor sentiment (as captured by the quantiles of the happiness index). To the best of our knowledge, this is the first paper to employ the QQ framework to examine the relationship between investor sentiment and return/volatility connectedness of financial markets based on the TVP-VAR framework.

Our findings establish a significant link between investor sentiment and the connectedness of global stock markets. While the sentiment effect is asymmetric for return and volatility spillovers, we show that sentiment shocks, measured by the extreme quantiles of the investor happiness index, generally have distinct effects on connectedness patterns. The inferences from the quantile-based model suggest that behavioral factors may be playing a role in the effect of investor sentiment on the spillover patterns across financial markets. The findings open a new avenue for future research to look into the economic and behavioral drivers of sentiment shocks, which in turn, affect financial market connectedness. The remainder of the paper is organized as follows: Section 2 outlines the basics of the TVP-VAR model used to obtain the time-varying connectedness index for stock market returns and volatility as well as the QQ model to relate TCIs to investor sentiment. Section 3 presents the data and empirical results and Section 4 concludes the paper.

2 Methodology

2.1 The TVP-VAR Model

As mentioned earlier, we measure the return and volatility spillovers across the stock markets in the sample via the total connectedness indices (TCI) obtained from the full-fledged time-varying parameter vector autoregressive (TVP-VAR) model of Antonakakis and Gabauer (2017). In particular, the model specification of Antonakakis et al. (2018) with a lag length of order one, as suggested by the Bayesian information criterion (BIC), is used. Thus, the estimated TVP-VAR model (for either returns or volatility of the ten stock markets) is formulated as

$$\boldsymbol{z}_t = \boldsymbol{B}_t \boldsymbol{z}_{t-1} + \boldsymbol{u}_t \qquad \boldsymbol{u}_t \sim N(\mathbf{0}, \boldsymbol{S}_t) \tag{1}$$

$$vec(\boldsymbol{B}_t) = vec(\boldsymbol{B}_{t-1}) + \boldsymbol{v}_t \qquad \boldsymbol{v}_t \sim N(\mathbf{0}, \boldsymbol{R}_t), \tag{2}$$

and transformed to its TVP-VMA representation by $\boldsymbol{z}_t = \sum_{i=1}^{p} \boldsymbol{B}_{it} \boldsymbol{z}_{t-i} + \boldsymbol{u}_t = \sum_{j=0}^{\infty} \boldsymbol{A}_{jt} \boldsymbol{u}_{t-j}$, where $\boldsymbol{z}_t$, $\boldsymbol{z}_{t-1}$ and $\boldsymbol{u}_t$ are $k \times 1$ dimensional vectors and $\boldsymbol{A}_t$, $\boldsymbol{B}_t$ and $\boldsymbol{S}_t$ are $k \times k$ dimensional matrices. Finally, $vec(\boldsymbol{B}_t)$ and $\boldsymbol{v}_t$ represent $k^2 \times 1$ dimensional vectors with $\boldsymbol{R}_t$ defined as a $k^2 \times k^2$ dimensional matrix.

Based upon $\boldsymbol{A}_t$ and $\boldsymbol{S}_t$, we next compute the H-step ahead (scaled) generalized forecast error variance decomposition (GFEVD) of Koop et al. (1996) and Pesaran and Shin (1998). Wiesen et al. (2018) argue that the GFEVD, which is completely invariant of the variable ordering, should be preferred over the orthorgonalized forecast error variance decomposition in case no theoretical framework that allows to identify the error structure is available. The GFEVD ($\tilde{\phi}^{g}_{ij,t}(H)$) is interpreted as the influence variable j has on variable i in terms of its forecast error variance share and can be mathematically formulated as

$$\phi^{g}_{ij,t}(H) = \frac{S^{-1}_{ii,t}\sum_{t=1}^{H-1}(\boldsymbol{\iota}'_i\boldsymbol{A}_t\boldsymbol{S}_t\boldsymbol{\iota}_j)^2}{\sum_{j=1}^{k}\sum_{t=1}^{H-1}(\boldsymbol{\iota}_i\boldsymbol{A}_t\boldsymbol{S}_t\boldsymbol{A}'_t\boldsymbol{\iota}_i)} \qquad \tilde{\phi}^{g}_{ij,t}(H) = \frac{\phi^{g}_{ij,t}(H)}{\sum_{j=1}^{k}\phi^{g}_{ij,t}(H)},$$

with $\sum_{j=1}^{k}\tilde{\phi}^{g}_{ij,t}(H) = 1$, $\sum_{i,j=1}^{k}\tilde{\phi}^{g}_{ij,t}(H) = k$ and $\boldsymbol{\iota}_j$ corresponds to a selection vector with unity on the jth position and zero otherwise.

Finally, the (corrected) TCI – which ranges between zero and unity (Chatziantoniou and Gabauer, 2019) – is computed as

$$C^{g}_{t}(H) = \frac{1}{k-1}\sum_{j=1}^{k} 1 - \tilde{\phi}^{g}_{ii,t}(H). \tag{3}$$

This measure can be interpreted as the average impact one variable has on all others (or all others have on one variable). Thus, a low (high) value for the TCI implies that a shock in one variable has on average a low (high) effect on all other variables and so the market risk is low (high).

2.2 Quantile-on-Quantile (QQ) Model

After obtaining the TCI series from the TVP-VAR model, we next use the QQ approach to examine the relationship between the return/volatility connectedness of the equity markets in the sample and investor sentiment proxied by the investor happiness index. The QQ model is built on the following nonparametric quantile regression framework, specific to our case

$$TCI_t = \beta^{\theta}(Sentiment_t) + u^{\theta}_t \tag{4}$$

where TCI_t and $Sentiment_t$ are the total connectedness index of stock returns or volatilities and the investor sentiment index in period t respectively, θ is the θ-th quantile of the conditional distribution of the TCI and u_t^θ is a quantile error term whose conditional θ-th quantile is equal to zero. In this framework, the term $\beta^\theta(\cdot)$ is assumed to be an unknown functional form, which is to be determined from the data.

The standard quantile regression model in equation (4) allows the effect of investor sentiment index to vary across the different quantiles of the TCI of stock returns (or volatilities); however, this model is unable to capture the dependence in its entirety as the term $\beta^\theta(\cdot)$ is indexed on the TCI quantile θ only and not the investor sentiment quantile. Therefore, in order to get a comprehensive insight on the effect of sentiment on financial market connectedness, we focus on the relationship between the θ-th quantile of the TCI and the τ-th quantile of the sentiment, denoted by P^τ. This is done by examining equation (4) in the neighborhood of P^τ via a local linear regression. As $\beta^\theta(\cdot)$ is unknown, this function is approximated through a first-order Taylor expansion around a quantile P^τ, such that

$$\beta^\theta(P_t) \approx \beta^\theta(P^\tau) + \beta^{\theta'}(P^\tau)(P_t - P^\tau) \tag{5}$$

where $\beta^{\theta'}$ is the partial derivative of $\beta^\theta(P_t)$ with respect to P (also called the marginal effect or response) and is similar in interpretation to the coefficient (slope) in a linear regression model. Next, renaming $\beta^\theta(P^\tau)$ and $\beta^{\theta'}(P^\tau)$ as $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)$ respectively, we rewrite equation (5) as

$$\beta^\theta(P_t) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(P_t - P^\tau). \tag{6}$$

Next, substituting equation (6) in equation (4), we obtain

$$S_t = \underbrace{\beta_0(\theta,\tau) + \beta_1(\theta,\tau)(P_t - P^\tau)}_{(*)} + u_t^\theta \tag{7}$$

where the term $(*)$ is the θ-th conditional quantile of the TCI. Unlike the standard conditional quantile function, equation (7) captures the overall dependence structure between the θ-th quantile of TCI and the τ-th quantile of sentiment as the parameters β_0 and β_1 are doubly indexed in θ and τ. In the estimation of equation (7), $\hat{P}_t$ and $\hat{P}^\tau$, respectively and the local linear regression estimates of the parameters $\hat{\beta}_0$ and $\hat{\beta}_1$ are obtained by solving:

$$\min_{b_0,b_1} = \sum_{i=1}^{n} \rho_\theta \left[S_t - \hat{\beta} - \hat{\beta}_1(\hat{P}_t - \hat{P}^\tau)\right] K\left(\frac{F_n(\hat{P}_t - \tau)}{h}\right) \tag{8}$$

where $\rho(u)$ is the quantile loss function, defined as $\rho(u) = u(\theta - I(u < 0))$ and I is the indicator function. $K(\cdot)$ denotes the kernel function and h is the bandwidth parameter of the kernel. Because of its computational simplicity and efficiency, the Gaussian kernel is used to weight the observations in the neighborhood of P^τ. Specifically, in our analysis, these weights are inversely related to the distance between the empirical distribution function of $\hat{P}_t$, denoted by $F_n(\hat{P}_t) = \frac{1}{n}\sum_{k=1}^{n} I(\hat{P}_k < \hat{P}_t)$, and the value of the distribution function that corresponds with the quantile P^τ, denoted by τ. The bandwidth parameter h is selected using the cross-validation regression approach with a local linear regression.

3 Data and Empirical Findings

3.1 Data

Given the shortcomings associated with the market- and survey-based approaches to measure investment sentiment discussed earlier, we utilize the daily happiness index, obtained from Hedonometer.org, as our proxy for investor sentiment.[2] The raw daily happiness scores are derived from a natural language processing technique based on a random sampling of about 10% (50 million) of all messages posted in Twitter's Gardenhose feed. To quantify the happiness of the atoms of language, Hedonometer.org merge the 5,000 most frequent words from a collection of four corpora: Google Books, New York Times articles, Music Lyrics and Twitter

[2]The data is available for download from: https://hedonometer.org/api.html.

messages, resulting in a composite set of roughly 10,000 unique words. Then, using Amazon's Mechanical Turk service, Hedonometer.org scores each of these words on a nine point scale of happiness, with 1 corresponding to "sad" and 9 to "happy". Words in messages written in English (containing roughly 100 million words per day) are assigned a happiness score based on the average happiness score of the words contained in the messages. In our application, we convert the happiness index into its natural logarithmic values.

In the case of stock market data, we focus on ten developed stock markets including Australia (S&P/ASX 200), Canada (S&P/TSX), France (CAC 40), Germany (DAX), Hong Kong (Hang Seng), Japan (Nikkei 225), New Zealand (NZX 50), South Korea (KOSPI), the UK (FTSE 100) and the US (S&P 500). The decision to focus on these advanced economies is driven by the fact that these countries have a large number of Twitter users which aligns with the use of the happiness index based on Twitter feed data. The capital market data are derived from from Yahoo Finance available free for download at: http://finance.yahoo.com, and includes the opening, high, low and the closing prices for the aggregate stock market index for each country. The log-returns are computed based on the closing price of each of the index, while the range-based estimate of volatility (Garman and Klass, 1980) is computed as $\frac{1}{2}hl_{i,t}^2 - (2 \times ln(2) - 1)oc_{i,t}^2$, where $hl_{i,t}$ is the difference in natural logarithms of the highest and lowest prices of index i on day t, and $oc_{i,t}$ is the difference in natural logarithms of the opening and closing prices of index i on day t. The empirical analysis covers the daily period of 11th September, 2008 to 22nd November, 2019, with the start and end dates being purely driven by the availability of the happiness index.

3.2 Empirical Findings

Figure 1 presents the plots for the estimated TCI series that measure return and volatility connectedness of the equity markets in the sample as well as the happiness index. We generally observe greater time-variation in volatility spillovers across financial markets compared to return spillovers with notable upswings in mid-2011 when the Arab Spring started to roil global markets. Another notable upturn in connectedness patterns occurs later in 2015 during the Chinese stock market crash that was a severe correction due to the decline in the Chinese economic activity with far reaching effects across global economies (Ahmed and Huo, 2019). The happiness index, on the other hand, displays a rather variable pattern over time with notable upswings generally during the turn of the year which coincides with the holiday period in Western nations, while several large downturns are also observed around mid-2009 when Michael Jackson died, in mid-2016 during the terror attack in Orlando and mass shooting of Dallas police officers and later in 2019 when mass shootings happened in Texas and Ohio. Clearly, these events result in significant mood changes among the public which can in turn affect their behavior in financial markets.[3]

As a preliminary check, we first estimated standard ordinary least squares (OLS) regressions to examine the response of the TCIs to the investor happiness index. The standard linear regressions yield the conditional mean-based estimates of 0.3931 and -0.5884, for return and volatility spillovers, respectively, with both coefficients significant at the highest level of significance. Therefore, the preliminary checks provide the initial evidence of a significant investor sentiment effect on connectedness patterns in financial markets. While connectedness of returns are found to increase with the perception of happiness among investors, we find that the opposite holds true for volatility. It can be argued that the positive effect of sentiment on return connectedness is due to a rise in risk appetite driven by favorable future expectations, which in turn, enhances cross-border capital flows, leading to a rise in the connectedness of financial market returns. The negative effect on volatility spillovers, on the other hand, can be a manifestation of the well-documented leverage effect which refers to the empirical evidence that

[3]For example, studies including Hirshleifer and Shumway (2003) and Yuan et al. (2006) relate stock returns to investors' mood driven by weather conditions or lunar phases, respectively.

establishes a link between asset returns and volatility (e.g. Christie 1982). Nevertheless, the preliminary results support a significant sentiment effect on the spillover effects across financial markets.

While the OLS results are informative, they fail to provide the complete picture for the relationship conditional on the normal and extreme states of TCI and the investor sentiment index and the QQ approach discussed earlier allows us to assess those relationships at the quantile level. Figures 2 and 3 present the QQ model results that relate the TCIs of the returns and volatilities respectively with the happiness index. Specifically, we plot the estimates of the impact of the various quantiles of the happiness index on the quantiles of the TCIs, i.e., $\beta_1(\theta, tau)$, described in equation (6). As explained earlier, these estimates are similar to the slope term in a linear regression model, reflecting the sensitivity of the TCIs to investor sentiment. However, given that $\beta_1(\theta, tau)$ is doubly indexed in θ and τ, the estimates reported in the figures measure the relationship between the θ-th quantile of TCIs and the τ-th quantile of the happiness index. The plots are color-coded in such a way that the color represents the degree of sensitivity (red indicating higher sensitivity), with the TCI quantiles placed on the y-axis and the sentiment quantiles on the x-axis.

We observe that, while the results are generally consistent with the findings obtained from the OLS regressions, the relationship between sentiment and connectedness displays quantile specific patterns in terms of the strength of the sentiment effect to the extent that the sign of the effect can change direction at extreme quantiles. In the case of return spillovers presented in Figure 2, we observe that investor happiness generally contributes positively to the connectedness of stock market returns with relatively more consistent effects at central quantiles of happiness, corresponding to normal market states. Interestingly, however, we observe that the relationship turns negative at extremely low and high sentiment values, suggesting that sentiment shocks in either direction negatively affect return connectedness, possibly as investors display greater heterogeneity in how they process new information that drives the sentiment shock. Consistent with the findings from OLS regression, we observe in Figure 3, that the opposite is the case for volatility connectedness. While the results are generally stronger (in terms of size of the sentiment effect) in the case volatility connectedness compared to that for returns, we observe that sentiment shocks in either direction positively affect volatility spillovers across financial markets. The sentiment effect is found to be more robust at the high quantiles of sentiment, suggesting that positive sentiment shocks positively contribute to risk spillovers, while the positive effect of sentiment is limited only low quantiles of TCI when sentiment is low. Overall, our findings establish a strong link between investor sentiment and connectedness patterns across global financial markets, while the sentiment effect is asymmetric for return and volatility spillovers. These findings suggest that both investors and policy makers should be particularly vigilant against sentiment shocks, in either direction, as these shocks can have significant risk effects, contirbuting to volatility spillover effects globally.

4 Conclusion

This paper contributes to the literature on the effect of investor sentiment on return dynamics in financial markets by examining the relationship between investor happiness and return/volatility spillovers across global stock markets. Utilizing the TVP-VAR based connectedness model of Antonakakis and Gabauer (2017) within a quantile-on-quantile framework recently developed by Sim and Zhou (2015), we show that investor happiness, built on Twitter feed data as a proxy for investor sentiment, has a significant effect on the return and volatility connectedness of ten major global stock markets. While the sentiment effect is found to be relatively stronger on volatility spillovers, we observe that the relationship between sentiment and connectedness displays quantile specific patterns with sentiment shocks at extreme quantiles of the happiness index having distinctly different effects. We also show that the sentiment effect is asymmetric for return and volatility spillovers such that when connectedness of returns (volatilities) and sentiment is either extremely low or high, the effect of happiness on connectedness of returns (volatilities) is negative (positive).

We argue that the asymmetry in the effect of sentiment on connectedness patters for returns and volatility can be partially explained by the well-documented leverage effect in stock markets. However, the quantile based evidence indicating distinct patterns at extreme high/low sentiment quantiles suggest that behavioral drivers may also be playing a role in how sentiment shocks contribute to volatility spillovers across global markets. An interesting research question for future research is the role of economic and behavioral factors as a driver of sentiment shocks and if certain type of events or uncetainty factors have a relatively larger contribution to large swings in investor sentiment.

References

Ahmed A. D., Huo, A. (2019). Impacts of China's crash on Asia-Pacific financial integration: Volatility interdependence, information transmission and market co-movement. Economic Modelling 79, 28-46.

Antonakakis, N. and Gabauer, D. (2017). Refined Measures Of Dynamic Connectedness Based On TVP-VAR. MPRA Paper 78282, University Library of Munich, Germany.

Antonakakis, N., Gabauer, D., Gupta, R., and Plakandaras, V. (2018). Dynamic Connectedness Of Uncertainty Across Developed Economies: A Time-Varying Approach. Economics Letters, 166, 63–75.

Antoniou, C., Doukas, J. A., Subrahmanyam, A. (2013). Cognitive Dissonance, Sentiment, and Momentum. The Journal of Financial and Quantitative Analysis 48 (1), 245−275.

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

Baker, M., and Wurgler, J. (2007). Investor sentiment in the stock market. Journal of Economic Perspectives 21, 129−152.

Bathia, D., and Bredin, D. (2013). An examination of investor sentiment effect in G7 stock market returns. European Journal of Finance 19, 909−937.

Bathia, D., Bredin, D., and Nitzsche, D. (2016). International sentiment spillovers in equity returns. International Journal of Finance and Economics 21, 332−359.

Blasco, N., Corredor, P., Ferreruela. S. (2012).Market sentiment: A key factor of investors' imitative behaviour. Accounting and Finance 52 (3), 663−689.

Chatziantoniou, I., and Gabauer, D. (2019). EMU-Risk Synchronisation and Financial Fragility Through the Prism of Dynamic Connectedness. Working Papers in Economics & Finance 2019-07, University of Portsmouth, Portsmouth Business School, Economics and Finance Subject Group.

Chau, F., Deesomsak, R., Lau M.C.K. (2011). Investor sentiment and feedback trading: Evidence from the exchange-traded fund markets International Review of Financial Analysis 20 (5), 292−305.

Christie, A. A. (1982). The stochastic behavior of common stock variances: Value, leverage and interest rate effects. Journal of Financial Economics 10, 407−432.

Da, Z., Engelberg, J., Gao, P. 2015. The Sum of All FEARS Investor Sentiment and Asset Prices. Review of Financial Studies 28, 1−32.

Diebold, F. X. and Yılmaz, K. (2012). Better To Give Than To Receive: Predictive Directional Measurement Of Volatility Spillovers. International Journal of Forecasting, 28(1), 57–66.

Diebold, F. X. and Yılmaz, K. (2014). On The Network Topology Of Variance Decompositions: Measuring The Connectedness Of Financial Firms. Journal of Econometrics, 182(1), 119–134.

Di Tella, R., MacCulloch, R. J., Oswald, A. J. (2013). The macroeconomics of happiness.The Review of Economics and Statistics 85(4), 809–827.

Frazzini, A., Lamont, A. O. (2008). Dumb money: Mutual fund flows and the cross section of stock returns. Journal of Financial Economics, 88, 299–322.

García, D. (2013). Sentiment during recessions. Journal of Finance 68, 1267−1300.

Garman, M.B., and Klass, M.J. (1980). On the estimation of security price volatilities from historical data. Journal of Business, 53, 67–78.

Hirshleifer D., Shumway T. (2003). Good day sunshine: Stock returns and the weather J. Finance, 58 (3) (2003), 1009−1032.

Kim, B., Suh, S. 2018. Sentiment-based momentum strategy. International Review of Financial Analysis 58, 52−68.

Koop, G. and Korobilis, D. (2014). A New Index Of Financial Conditions. European Economic Review, 71, 101–116.

Koop, G., Pesaran, M.H., and Potter, S.M. (1996). Impulse Response Analysis In Nonlinear Multivariate Models. Journal of Econometrics, 74(1), 119–147.

Kurov, A. (2008). Investor sentiment, trading behavior and informational efficiency in index futures markets. Financial Review, 43, 107–127.

Lemmon, M., Ni, S. X. (2011). The effects of investor sentiment on speculative trading and prices of stock and index options. SSRN working paper.

Pesaran, H.H. and Shin, Y. (1998). Generalized Impulse Response Analysis in Linear Multivariate Models. Economics Letters, 58(1), 17–29.

Reboredo, J.C., and Ugolini, A. (2018). The impact of Twitter sentiment on renewable energy stocks. Energy Economics 76, 153−169.

Sim, N., and Zhou, H. (2015). Oil prices, US stock return, and the dependence between their quantiles. Journal of Banking and Finance, 55, 1–8.

Wiesen, T.F., Beaumont, P.M., Norrbin, S.C., and Srivastava, A. (2018). Are Generalized Spillover Indices Overstating Connectedness? Economics Letters, 173, 131–134.

You, W., Guo, Y., and Cheng, P. (2017). Twitter's daily happiness sentiment and the predictability of stock returns. Finance Research Letters 23, 58−64.

Yuan K., Zheng L., Zhu Q. (2006). Are investors moonstruck? Lunar phases and stock returns J. Empir. Finance, 13 (1), 1−23.

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

Zhang, W., Wang, P., Li, X., and Shen, D. (2018). Twitter's daily happiness sentiment and international stock returns: Evidence from linear and nonlinear causality tests. Journal of Behavioral and Experimental Finance, 18, 50−53.

Figure 1: Time series plots

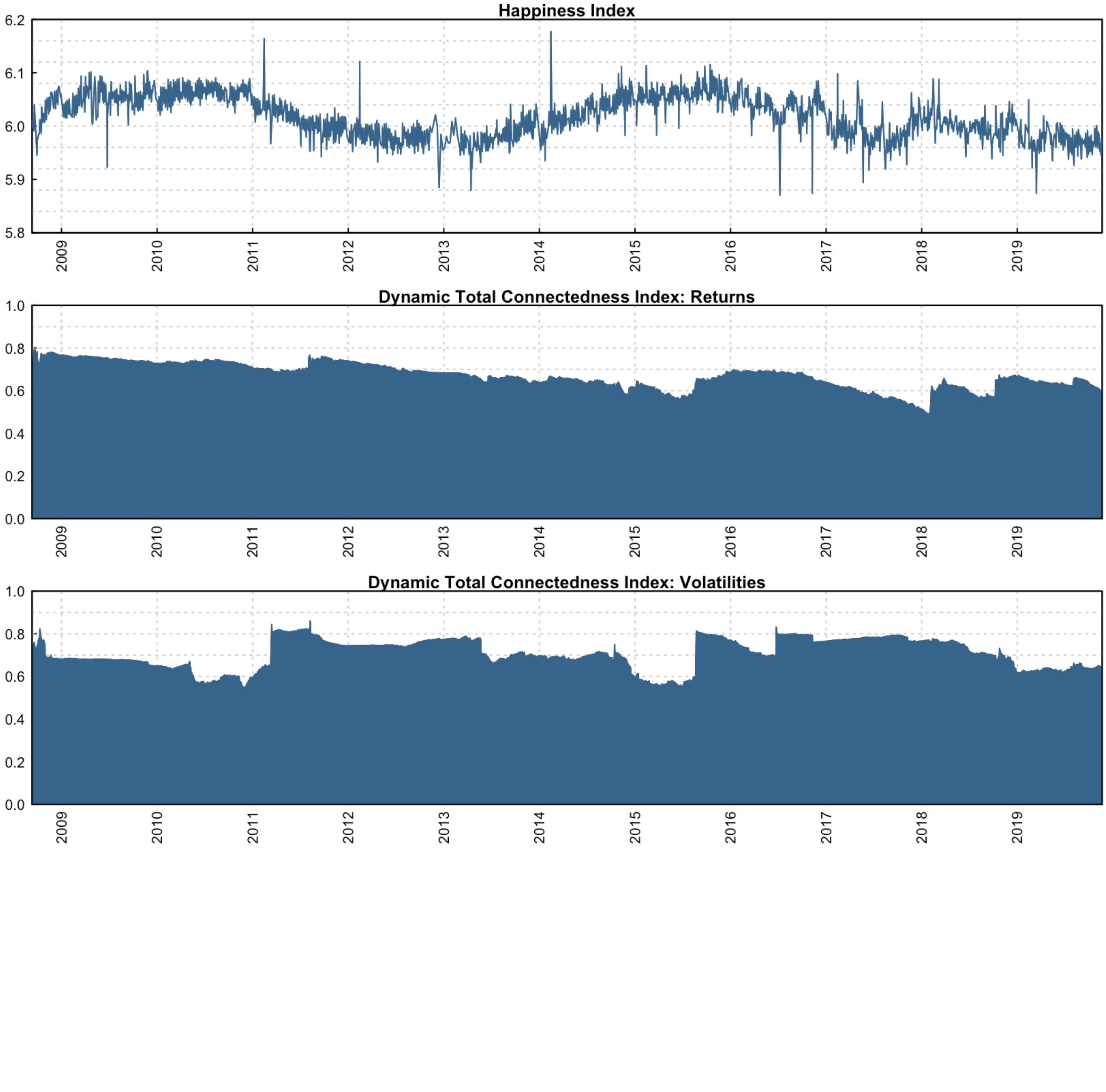

Figure 2: Quantile slope estimates for return connectedness

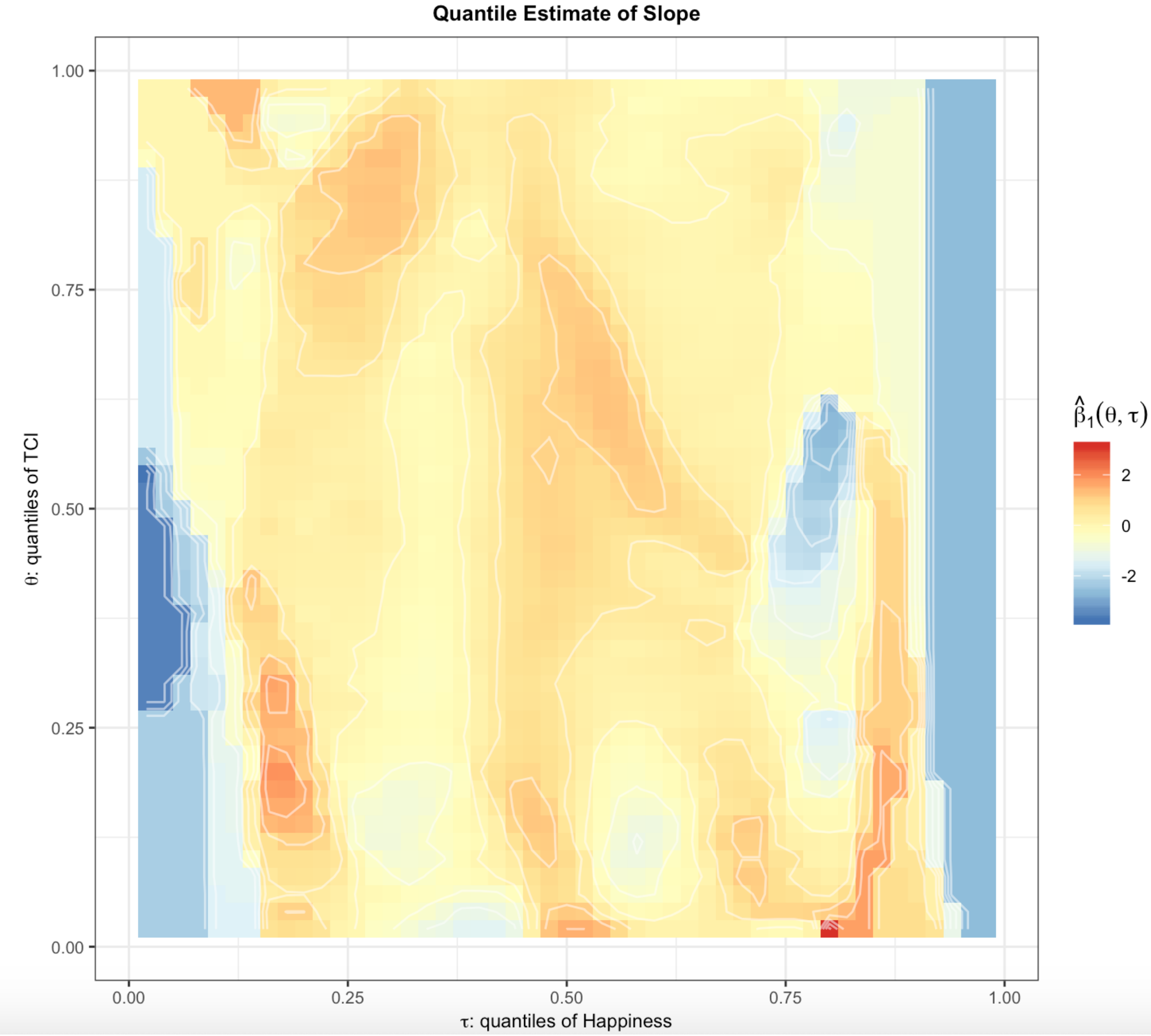

Figure 3: Quantile slope estimates for volatility connectedness