Financial market connectedness: The role of investors' 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 has a significant effect on both the return and volatility spillovers across global stock markets. While the sentiment effect is found to be relatively strong on volatility spillovers, we observe that the relationship between sentiment and connectedness is asymmetric for return and volatility connectedness. 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: Equity Markets, Investor Happiness, TVP-VAR, Dynamic Connectedness, Quantile-on-Quantile Approach.

JEL codes: C22, C32, G10.

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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. Tella et al., 2003), 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 global markets (e.g. Kurov, 2008; Chau et al., 2011).[1] 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 et al. (2020). More specifically, we use this 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).

As a second novelty, we utilize a social media based investor happiness index built on

[1]Several other studies link price cascades and feedback trading to investor sentiment, particularly in the context of herding behavior (Da et al., 2015; Liao et al., 2011; Blasco et al., 2018, , among others). Ferreira and Kallinterakis (2006) further argue that collective behavioural patterns can potentially lead to feedback trading, mispricing and excess volatility.

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; 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).[2] More recently, 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 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 – allows us to examine how the conditional quantiles of the TCI relate to the quantiles of the happiness index. Henc, this methodology provides us with more comprehensive insights as we can analyze the response of the entire conditional distribution of TCIs simultaneously to various levels of investor sentiment. To the best of our knowledge, this is the first paper that employs the QQ framework to examine

[2] 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.

the relationship between investor sentiment and return/volatility connectedness of financial markets.

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 TVP-VAR based connectedness measures

As mentioned earlier, we measure the return and volatility spillovers across global stock markets via the TCI series obtained from the TVP-VAR based connectedness approach of Antonakakis et al. (2020). This framework improves the seminal work of Diebold and Yilmaz (2012); Diebold and Yılmaz (2014) in multiple ways, as (i) it is less sensitive to outliers, (ii) the time-variation of the parameters is estimated more accurately, (iii) it avoids the loss of observations and (iv) no arbitrarily chosen rolling-window size is required. In particular, we choose a TVP-VAR specification with a lag length of order one – as suggested by the Bayesian information criterion (BIC) – which can be outlined as follows:

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

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

where $\boldsymbol{z}_t$ and $\boldsymbol{u}_t$ are $k \times 1$ dimensional endogenous variables and error term vectors respectively. $\boldsymbol{B}_t$ and $\boldsymbol{S}_t$ illustrate $k \times k$ dimensional time-varying VAR coefficient and variance-covariances matrices, and $vec(\boldsymbol{B}_t)$ and $\boldsymbol{v}_t$ represent $k^2 \times 1$ dimensional vectors with $\boldsymbol{R}_t$ defined as a $k^2 \times k^2$ dimensional variance-covariance matrix. Calculating the connectedness measures requires to transform the TP-VAR to its TVP-VMA representation which can be done by the following equation: $\boldsymbol{z}_t = \sum_{i=1}^{p} \boldsymbol{B}_{it} \boldsymbol{z}_{t-i} + \boldsymbol{u}_t = \sum_{j=0}^{\infty} \boldsymbol{A}_{jt} \boldsymbol{u}_{t-j}$, where $\boldsymbol{A}_t$ demonstrates a $k \times k$ dimensional time-varying VMA coefficient matrix.

Next, we compute the H-step ahead (scaled) generalized forecast error variance decomposition (GFEVD) of Koop et al. (1996) and Pesaran and Shin (1998) which can be mathematically formulated as:

$$\phi^g_{ij,t}(H) = \frac{S^{-1}_{ii,t} \sum_{t=1}^{H-1} (\boldsymbol{\iota}'_i \boldsymbol{A}_t \boldsymbol{S}_t \boldsymbol{\iota}_j)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} (\boldsymbol{\iota}_i \boldsymbol{A}_t \boldsymbol{S}_t \boldsymbol{A}'_t \boldsymbol{\iota}_i)} \qquad \tilde{\phi}^g_{ij,t}(H) = \frac{\phi^g_{ij,t}(H)}{\sum_{j=1}^{k} \phi^g_{ij,t}(H)}, \tag{3}$$

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, 2021; Gabauer, 2021) – is computed as

$$C^g_t(H) = \frac{1}{k-1} \sum_{j=1}^{k} 1 - \tilde{\phi}^g_{ii,t}(H). \tag{4}$$

This measure can be interpreted as the degree of interconnectedness and hence market risk. A low (high) TCI value implies that a shock in one variable has on average a low (high) effect on all other variables and hence represent low (high) market interconnectedness.

2.2 Quantile-on-Quantile (QQ) Model

After obtaining the TCI series, we employ the QQ approach to examine the relationship between the equity market return/volatility connectedness and the investor happiness index. The QQ model is built upon the following nonparametric quantile regression framework:

$$TCI_t = \beta^\theta(Sentiment_t) + u^\theta_t \tag{5}$$

where TCI_t and $Sentiment_t$ are the market interconnectedness of 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^θ_t is a quantile error term whose conditional θ-th quantile is equal to zero.

The standard quantile regression model in equation (5) 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, 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 (5) 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

$$\beta^{\theta}(P_t) \approx \beta^{\theta}(P^{\tau}) + \beta^{\theta'}(P^{\tau})(P_t - P^{\tau}) \tag{6}$$

where $\beta^{\theta'}$ is the partial derivative of $\beta^{\theta}(P_t)$ with respect to P and is similar in interpretation to the coefficient 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 (6) as

$$\beta^{\theta}(P_t) \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(P_t - P^{\tau}). \tag{7}$$

By substituting equation (7) in equation (5), we obtain:

$$S_t = \underbrace{\beta_0(\theta, \tau) + \beta_1(\theta, \tau)(P_t - P^{\tau})}_{(*)} + u_t^{\theta} \tag{8}$$

where the term $(*)$ is the θ-th conditional quantile of the TCI. Unlike the standard conditional quantile function, equation (8) 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 (8), $\hat{P}_t$, $\hat{P}^{\tau}$, $\hat{\beta}_0$ and $\hat{\beta}_1$ are obtained by solving:

$$\min_{b_0, b_1} = \sum_{i=1}^{n} \rho_{\theta} \left[S_t - \hat{\beta} - \hat{\beta}_1(\hat{P}_t - \hat{P}^{\tau}) \right] K \left(\frac{F_n(\hat{P}_t - \tau)}{h} \right) \tag{9}$$

where $\rho(u)$ is the quantile loss function, defined as $\rho(u) = u(\theta - I(u < 0))$. I and K denote the indicator and the kernel function, respectively and h is the bandwidth parameter of the kernel which is selected using the cross-validation regression approach with a local linear regression. Because of its computational simplicity and efficiency, the Gaussian kernel is used to weight the observations in the neighborhood of P^{τ}.

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 as proxy for investor sentiment.[3] 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

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

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 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".

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 retieved from Yahoo Finance over the 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. The log-returns are computed based on the closing price of each of the index, while the volatility is computed following the well-known range-based estimate of Garman and Klass (1980). This transformation has been used as the authors have shown that the retrieved series can be considered as normally distributed whereas other volatility measures are often non-normally distributed and exhibit fat tails which challenge multiple econometric techniques. Moreover, note, we also followed Zhang et al. (2016) in this regard in using the range-based estimator of volatility, which is indeed a model-free estimate of the latent process of volatility, and hence is not conditional on the specific type of volatility models, like the GARCH-family models generally used to compute volatility of a series in daily data.

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 during the Great Financial Crisis, 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.

[INSERT FIGURE 1 AROUND HERE.]

As a preliminary check, we first estimated a standard linear regression model to examine the response of the TCIs to the investor happiness index. The linear model yields slope estimates of 0.3931 and -0.5884, for return and volatility spillovers, respectively, both highly significant at the 0.1% significance level. These results provide us with the initial evidence on the role of investor sentiment over financial market spillovers. 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 establishes a link between asset returns and volatility (e.g. Christie, 1982).

While those 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. As discussed earlier, the QQ approach allows us to assess those relationships at the quantile level. Figures 2-3 present the QQ model results that relate the happiness index with the TCI series. While the results are generally consistent with the findings obtained from the linear regressions, the relationship between sentiment and market risk is found to display 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, 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.

Further analyzing the asymmetric effect of investor sentiment on return connectedness, however, we observe that distinguishing the positive and negative changes in investor sentiment does not yield any additional insight as positive and negative investor sentiment changes largely mimic the right and left tails of the initial plot where we do not differentiate between positive and negative sentiment changes. The only noteworthy deviation, however, seems to be the pronounced effect between low TCI and high investor happiness values, associating low market risk with high values of investor happiness.

[INSERT FIGURE 2 AROUND HERE.]

In the case of volatility connectedness, however, consistent with the findings from the linear regression, we observe in Figure 3, that sentiment has largely a negative effect on volatility connectedness. While the results are generally stronger for volatility than return connectedness, 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 to low quantiles of TCI when sentiment is low.

[INSERT FIGURE 3 AROUND HERE.]

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, contributing to volatility spillover effects globally. Also the asymmetric analysis of investor sentiment on volatility connectedness has led to a similar pattern, while the linkage is not as strong as for the overall analysis.

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 et al. (2020) within the quantile-on-quantile framework of Sim and Zhou (2015), we show that investor happiness has a significant effect on the return and volatility connectedness of the ten most important global stock markets. While the sentiment effect is found to be relatively strong 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.

The findings have significant implications for global investors in terms of diversification benefits from allocating funds across markets as sentiment changes can significantly impact correlated market behavior, thus potentially hurting diversification benefits. Furthermore, policy makers can use signals from sentiment changes in global markets in order to take precautions in domestic markets to avoid correlated market fluctuations and/or tail risks. In future studies, it would be interesting to extend our findings to additional measures of spillovers and examine sentiment related effects on the net total or pairwise directional connectedness (Adekoya and Oliyide, 2020).

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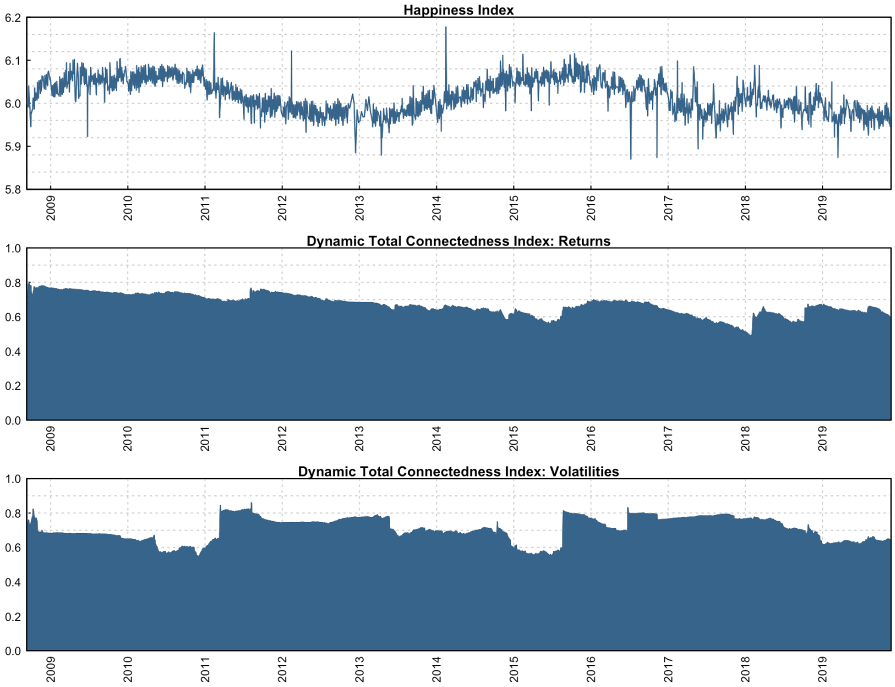
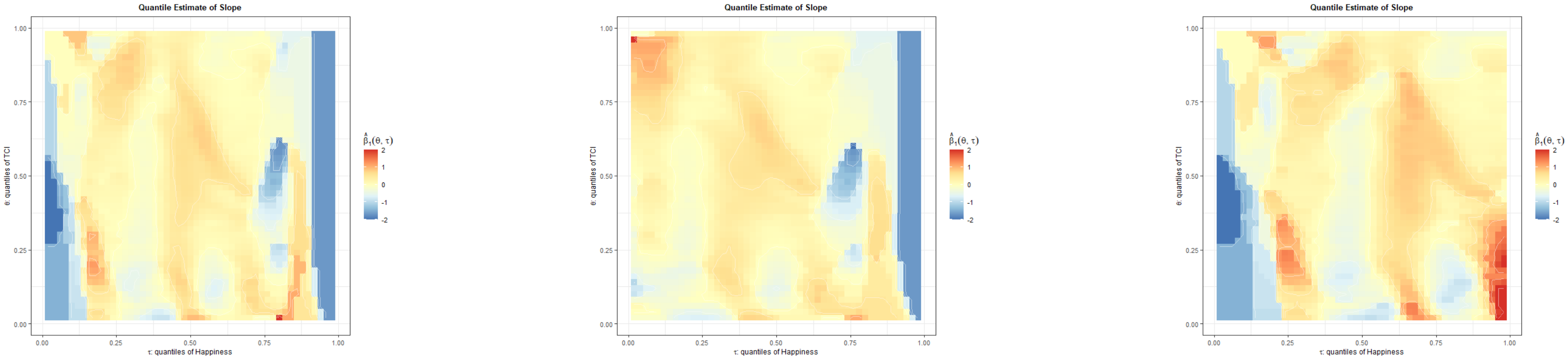
Figure 1: Time series plots



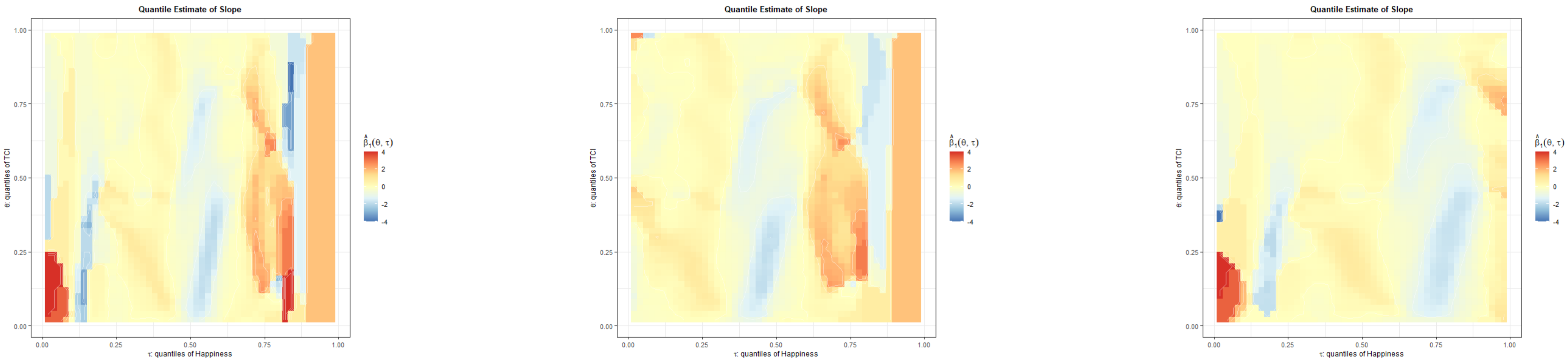
Notes: This figure presents the time series plots for the happiness index and the TCI indexes for return and volatility connectedness.

Figure 2: Quantile slope estimates for return connectedness



Notes: The first plot illustrates the link between investor happiness and return connectedness. The second and third plots demonstrate the link between positive and negative changes in investor happiness, respectively, and return connectedness.

Figure 3: Quantile slope estimates for volatility connectedness



Notes: The first plot illustrates the link between investor happiness and volatility connectedness. The second and third plots demonstrate the link between positive and negative changes in investor happiness, respectively, and volatility connectedness.