Investor sentiment connectedness: Evidence from Linear and Nonlinear Causality Approaches#

AVIRAL KUMAR TIWARI[1], DEVEN BATHIA[2], ELIE BOURI[3] and RANGAN GUPTA[4]

[1]Rajagiri Business School, Rajagiri Valley Campus, Kakkanad, Kochi 682039, Kerala, India

E-mail Address: aviral.eco@gmail.com

[2]School of Business and Management, Queen Mary University of London, Mile End Road, London E1 4NS, UK

E-mail Address: d.bathia@qmul.ac.uk

[3]Corresponding author. School of Business, Lebanese American University, Lebanon.

E-mail Address: elie.elbouri@lau.edu.lb

[4]Department of Economics, University of Pretoria, Hatfield, Pretoria 0002, South Africa

E-mail Address: rangan.gupta@up.ac.za

Abstract

This paper provides a novel perspective in determining the Granger causality of sentiment across the US, Latin America, Eurozone, Japan and Asia (excluding Japan), based on monthly data covering the period of January 2003 to November 2017. Using a survey-based sentiment index of 'sentix', our results suggest strong evidence of nonlinearity and structural breaks making the use of linear causality models unreliable. Using a kernel-based multivariate nonlinear causality test, we find that causality runs from Eurozone to the US, Asia, and Japan, with Japan also causing the Eurozone sentiment, and Latin America causing Japanese sentiment. Interestingly, when we apply rolling estimations to detect time-varying causality for the cases of Eurozone and US, Eurozone and Asia, Eurozone and Japan, and Latin America and Japan, the results suggest evidence of bi-directional spillovers during certain months of the recent global financial crisis, and thereafter. Overall, our findings indicate that the sentiment of Japan, Asia, and the US are related quite strongly with that of the Eurozone, as well as the sentiment of Japan and Latin America.

Keywords: Sentiment spillovers; Linear and Nonlinear Causality; US; Latin America; Eurozone; Asia.
JEL Codes: C32, G40.

We would like to thank two anonymous referee for many helpful comments. However, any remaining errors are solely ours.

1. Introduction

"Bull markets are born on *pessimism*, grow on *scepticism*, mature on *optimism* and die on *euphoria*" (Sir John Templeton)

The above quote simply embeds the state of affairs of the global financial markets due to investors' behaviour. Such a view held by a legendary investor about financial markets shows that investors don't ignore their prevailing sentiment levels in financial markets when making investment decisions. Words like 'pessimism', 'scepticism', 'optimism', and 'euphoria' reflect the *sentiment* of investors at varying levels, and have become standard lexicon in the popular press in recent years to explain the performance of financial markets. Precisely, 'investor sentiment' represents investors' optimism and pessimism about future returns. According to Brown and Cliff (2004), it represents the expectations of market participants relative to a norm: a bullish (bearish) investor expects returns to be above (below) average, whatever average may be. Notably, the rise of globalization has made not only businesses and economies around the globe more interlinked but institutional investors to play a more important, and sometimes an implicitly coordinated, role on many financial markets, leading to heightened market integration. In this regard, the availability of communication channels and the resulting quick spread of information make investor sentiments across countries and regions to respond much easily and faster to local or global events or concerns, leading to more intensified interlinkages across sentiments.

Numerous studies have investigated the effects of investor sentiment on stock returns. As such, they have studied the significance of both survey-based (direct) and market-based (indirect) sentiment measures on financial markets. For instance, Lemmon and Potniaguina (2006) find that the consumer confidence index is useful in forecasting small-cap stock returns as well as returns of stocks with low institutional ownership. Brown and Cliff (2005) argue that the role of uninformed demand shocks and limits to arbitrage can explain securities mispricing. Similar views are held by Baker and Wurgler (2006) who find that small, young, highly volatile, unprofitable, non-dividend paying, extreme growth and distressed stocks are usually a victim of investor sentiment, and have subjective valuations. Few studies have looked at the propagation of sentiment across international financial markets (Verma and Soydemir, 2006; Bathia et al. 2016). More recently, Audrino and Tetereva (2019) study the significance of the news sentiment spillover among the US and non-US industrial sectors and find evidence of the significant spillover effects. However, the extent to which investor sentiment is affected by the prevailing sentiment levels across countries or regions has not been investigated. Given that the sentiment of investors is the reflection of investor's behaviour and the fact that the financial system across different economies has become increasingly integrated, it becomes imperative to assess the extent of propagation of sentiment across major countries /regions. In this paper, we, therefore, address this research question by adopting the entropy causality approach.

As a proxy for investor sentiment, we use the 'survey-based' sentiment index of Sentix to determine the causality across five countries and regions, namely, United States, Latin America, Eurozone, Japan and Asia excluding Japan for the period January 2003 to November 2017. Since our study includes both developed (the United States, Eurozone and Japan) and developing markets (Latin America, Asia excluding Japan), it will be the first study to investigate the causality of sentiment across these markets. Prior studies have mainly looked at either time-series or cross-sectional relationships between investor sentiment and asset returns. Furthermore, these studies were mostly centred around developed markets (Baker and Wurgler, 2006; Schmeling, 2009; Bathia and Bredin, 2013). Our study on the causality of sentiment across developed and developing regions will provide a platform for comparing the significance of sentiment across these markets, therefore, providing evidence of the extent to which country/ region's investor sentiment matters the most.

Our choice of survey-based sentiment proxy of sentix is derived from the fact that the alternate measure of survey-based sentiment measure is hard to obtain at the regional level. Furthermore, the survey-based sentiment proxy is measured for different countries/ regions, and cover more heterogeneous and rich sets of questions than in other surveys-based proxies. For example, for the case of the US, the University of Michigan Consumer Confidence (UMCC) conducts monthly surveys of US households by posing just five questions of which only three are expectation-based. Furthermore, its survey sample size is very small, circa 500 households. The American Association of Institutional Investors (AAII) conducts weekly surveys of individual investors and constructs a sentiment index based on investors' responses about their expectation of the stock market in the next six months (i.e. bullish, bearish or neutral). The survey participants in the AAII have grown by over 170,000 since 1987.[1] In the case of Europe, the Directorate-General for Economic and Financial Affairs (DG ECFIN) conducts both business and consumer surveys across all EEA countries, which consist of around 15 questions, with a sample size of circa 1,500 across all countries.

[1] The information on the AAII survey can be accessed at the following link: http://www.aaii.com/journal/article/analyzing-the-aaii-sentiment-survey-without-hindsight.

Given the inconsistencies in conducting the above-mentioned investors' survey across different markets and countries, and in using different methodologies in deriving survey sentiment index, we use the sentiment index of sentix. The advantage of using sentix sentiment index is that it asks the same question to all investors across all the different countries/regions, and thus reflect more consistencies across these markets/regions. In fact, this sentiment index is constructed from the survey responses of around 1,600 financial analysts and institutional investors, who express their opinion about the current and expected economic conditions over the next six months. Accordingly, the sentix sentiment index reflects investors' expectations, covering both optimism and pessimism about future market returns. The constructed index that we use for each country/ region takes into consideration the sentiment of both individual and institutional investors and involves more than 36 different economic indicators. Furthermore, the data of the sentix sentiment index is available at monthly frequencies for each country/ region. Several studies have used the sentix index, but limited their analysis to specific asset classes (Schmeling, 2007; Heiden et al., 2010). For instance, Schmeling (2007) shows that the institutional and individual sentiment seems to act as a proxy for smart money and noise trader risk, respectively. Using private and institutional investors' sentiment data, Heiden et al. (2013) find that institutional sentiment significantly predicts returns over medium-term horizons in the EUR/USD market.

In determining the causality of sentiment across different economies, we, for the first time in the literature, use a novel approach of kernel-based multivariate causality, over and above the standard linear Granger causality and entropy-based tests, to study sentiment spillovers in major global regions. This methodology controls for the possible existence of the nonlinearity and regime changes (which we statistically show exists), and hence, is a robust method compared to the linear model-based tests. Our results, based on the robust nonlinear framework, show that causality runs from Eurozone to the US, Asia, and Japan. Furthermore, our findings show that Japan causes the Eurozone sentiment and Latin America causes Japanese sentiment. Interestingly, when we applied rolling estimations to detect time-varying causality for the cases of Eurozone and US, Eurozone and Asia, Eurozone and Japan, and Latin America and Japan, we found evidence of bi-directional spillovers during certain months of the recent global financial crisis, and thereafter. Overall, our findings indicate that the sentiment of Japan, Asia and the US are related quite strongly with that of the Eurozone as well as the sentiment of Japan and Latin America.

The rest of the paper is organized as follows: section 2 provides a brief review of the literature, section

3 presents the econometric approach, while section 4 discusses the data and empirical findings. Finally, section 5 concludes.

2. Literature Review

The qualms about the soundness of market efficiency emerged after the October 1987 stock market crash. The main reason for this market crash, according to Shiller (1987), was overpricing. The seminal study by Black (1986) showed that investors' trade on noise instead of fundamentals. De Long et al. (1990) formalized the role of sentiment in financial markets where they show that the change in sentiment leads to an increase in noise trading, mispricing and volatility when uninformed noise traders trade on sentiment and rational arbitrageurs experience limits to arbitrage. The authors further show that a number of financial market anomalies can be explained by the idea of noise trader risk. Other studies have also found evidence of investors' underreacting to earnings announcements and consistently overreacting to certain news, which results in securities mispricing (Jegadeesh and Titman, 1993; Kothari and Shanken, 1997). Daniel et al., (1998) propose a theory based on psychological biases, and show that investors overreact to private information signals and underreact to public information signals. Based on evidence from the above studies, investors depict irrational behaviour and may possibly make investment decisions based on noise instead of fundamentals.

The significance of investor sentiment in affecting asset prices has been studied extensively in the behavioural finance literature. For instance, Baker and Wurgler (2006) find that when beginning-of-period sentiment proxies are low, subsequent returns are relatively high for small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks. Furthermore, they show that sentiment has a larger effect on securities whose valuations are highly subjective and difficult to arbitrage. Baker et al., (2012) construct sentiment indices for six major stock markets and global markets as a whole and find that both global and local sentiment are contrarian predictors of the time-series of cross-sectional returns within markets. Furthermore, the authors find evidence that capital flows are a key mechanism through which global sentiment develops and propagates.[2] Sibley et al., (2016) study the relevance of the sentiment index and find that the ability of the sentiment index to predict cross-sectional stock returns is driven by the

[2] Also see Huang et al. (2014) who contruct aligned investor sentiment index and show that it has a greater predictive ability to forecast aggregate market returns.

risk/business cycle component. Li et al., (2020) find that during the period of high (low) sentiment, the stock price sensitivity to good (bad) earnings news increases (decreases) and observe that the effect of sentiment is more pronounced for young, high volatility, growth and distressed stocks. Gao et al., (2020) document an important role of global sentiment in stock markets. Using households' google search behaviour, the authors construct a sentiment index and find that sentiment is a contrarian predictor of country-level market returns. Overall, the above studies indicate the significance of sentiment in affecting asset returns.

Previous studies have also classified investor sentiment into two categories, viz. *direct* measure and *indirect* measure. The *direct* measure of sentiment includes 'survey-based' sentiment measures as they are directly obtained from surveying investors, whereas the *indirect* measure of sentiment includes 'market-based' sentiment proxies that are obtained from various financial market indicators (e.g. fund flow, derivative measures, closed-end fund discount, etc.) The monthly surveys are conducted across several developed and developing markets to determine investors' expectations about future economic conditions. The findings of survey sentiment in determining the predictive ability of stock returns are usually consistent across several markets. For instance, Fisher and Statman (2000, 2003) find that a rise in the US consumer confidence index is associated with an increase in bullishness of investor behaviour and subsequent lower returns. Using survey data as a measure of investor sentiment, Brown and Cliff (2005) indicate that an increase in investor sentiment plays a significant role in affecting asset valuation. Using the UMCC index and conference board index, Lemmon and Portniaguina (2006) find that the consumer confidence index is useful in forecasting returns of small-cap stocks and stocks with low institutional ownership. Furthermore, Schmeling (2009) finds a negative relationship between consumer confidence index and future stock returns for 18 industrialized nations. The author shows that the impact of sentiment on stock returns is higher for countries that have less market integrity and are culturally more prone to herd-like behaviour and overreaction. Bathia and Bredin (2013) examine the significance of the consumer confidence index on G7 stock market returns, and find that value stocks relative to growth stocks are significantly affected by the survey sentiment. Despite different numbers and types of survey questions, different sample sizes and different methods in calculating the consumer confidence index, the findings of survey-based sentiment proxies are generally consistent across several developed and developing markets.

The *indirect* measure of sentiment, known as the 'market-based' sentiment measure, reflects the collective behaviour of investors. Unlike survey-based sentiment measures, the findings for some of this market-based sentiment measure in affecting stock returns have been mixed. For instance, Lee et al. (1991) consider that the discount on closed-end funds (CEFD) is a proxy for the investor sentiment and find that when CEFD is high (low), investors are pessimistic (optimistic) about the future returns. However, these findings were subsequently challenged by several studies (e.g. Chen et al., 1993). Similarly, in the case of fund-flow, studies have linked the positive association between flow and stock returns to either the price pressure effect or the information effect (Warther, 1998; Brown et al. 2003; Bathia and Bredin, 2013). Several trading indicators, such as percentage change in short interest, change in margin debt, have been shown to reflect the levels of investor sentiment (Brown and Cliff, 2004). The information contained in a non-price derivative measure, e.g. put-call ratio and open-interest, has also been viewed as a measure of investor sentiment (Easley et al. 1998; Pan and Poteashman, 2006; Ji et al., 2020). Baker and Wurgler (2006) construct a sentiment index for the US market from six raw sentiment proxies after removing business cycle variations from each of these raw proxies. This measure of sentiment is considered to represent a reliable measure of market sentiment.

Previous studies, including Verma and Soydemir (2006) and Bathia et al. (2016), have documented the significance of the US sentiment spillover across other developed and emerging market economies. As a proxy for sentiment, Verma and Soydemir (2006) use a *direct* measure of sentiment, viz. individual and institutional investor sentiment index of the American Association of Individual Investors (AAII) and the Intelligence Investors (II) respectively, whereas, Bathia et al. (2016) use both a *direct* measure, the University of Michigan consumer confidence index (UMCC) and an *indirect* measure, Baker and Wurgler (2006) sentiment index. Both these studies have indeed found the relevance of survey-based sentiment index.

A number of studies have also considered other forms of sentiment measures which we call 'non-market' based sentiment measures. Specifically, this measure includes sentiment derived from textual data. For instance, Audrino and Tetereva (2019) use the Thomson Reuters Market Psych index (TRMI), a news-based sentiment index, and find evidence of sentiment spillover across industries.[3] As a proxy for investor sentiment, Bouri et al. (2021) use investor happiness, built on Twitter feed data, and examine its connectedness patterns across global stock markets within a quantile-on-quantile framework. They find that investor sentiment has a significant effect on both the return and volatility spillovers across major global stock markets.

[3] Also see Rehman et al. (2017) and Su and Li (2020) who study the significance of sentiment spillover across financial markets of developed and developing countries as well as commodity markets.

Given the relevance of survey-based sentiment, and the data availability issue for some of the above market and non-market based sentiment measures for the countries/ regions, we restrict our analysis to the survey-based sentiment index of 'sentix'. Specifically, we study the causality of sentiment across different countries/ regions, including the US, Latin America, Eurozone, Japan and Asia (excluding Japan), using monthly data of survey-based sentiment measure of Sentix.

3. Methodologies: Linear and Nonlinear Causality Tests

Besides, the standard linear Granger causality test, in this segment we discuss another linear causality test approach based on non-Gaussian assumptions, and also a nonlinear approach.

Hyärinen and Smith (2013) propose a new measure of the causal direction, or direction of effect between two non-Gaussian random variables. Their method is based on the likelihood ratio under the linear non-Gaussian acyclic model (LiNGAM). The authors extend the original method for estimating LiNGAM which was based on first applying independent component analysis (ICA) for the data, and then deducing the network connections from the results of ICA. In particular, they propose an approach that uses the ratio of the likelihoods of the models corresponding to the two directions of causal influence, which they extend to first-order approximations and higher-order cumulants. They argue that their approach is more resistant to noise than ICA based LiNGAM. Furthermore, they show that a likelihood ratio is likely to provide a statistically powerful method because of the general optimality properties of likelihood. The basics of the Granger-causality method based on non-Gaussian assumptions is elaborated as below.

We assume that ξ and η are non-Gaussian standardized variables with zero mean and unit variance. To measure the Granger causality from ξ to η, we define our first model as $\eta = \rho\xi + d,$ where ρ is the regression coefficient and d is the error term that is independent of ξ. Conversely, to measure the Granger causality from η to ξ, the second model can be written as $\xi = \rho\eta + e$, where e is the error term that is independent of η. Two important points emerge from the above two cases: (1) both models have ρ which is equal to the correlation coefficient, and; (2) we do not assume d or e to be normal, or to have zero cumulants, or even to be non-Gaussian. In fact, we do not make any assumptions on the distributions of error terms, and only assume that ξ and η are non-Gaussian.[4] The direction of Granger-causality between these two models (or variables) depends upon the value of

[4] This assumption is related to the identifiability theorem in the ICA, which states that one of the latent variables can be non-Gaussian (Comon, 1994).

their likelihoods and their ratios. The likelihood of the LiNGAM for the first case in which $\xi \rightarrow \eta$, following Hyärinen et al. (2010), is given by

$$logL(\xi \rightarrow \eta) = \left[\sum_t G_\xi(\xi_t) + G_d\left(\frac{\eta_t - \rho\xi_t}{\sqrt{1-\rho^2}}\right)\right] - Tlog(1-\rho^2). \quad (1)$$

where $G_\xi(u) = log\ p_\xi(u)$, and G_d is the standardised log-pdf of the residuals when regressing η on ξ. The last term here is a normalization term due to the use of standardized log-pdf, G_d. From this, we compute the likelihood ratio, which is normalized by 1/T for convenience:

$$R = \frac{1}{T}logL(\xi \rightarrow \eta) - \frac{1}{T}logL(\eta \rightarrow \xi) =$$

$$\frac{1}{T}\left[\sum_t G_\xi(\xi_t) + G_d\left(\frac{\eta_t - \rho\xi_t}{\sqrt{1-\rho^2}}\right)\right] - \left[\sum_t G_\eta(\eta_t) + G_e\left(\frac{\xi_t - \rho\eta_t}{\sqrt{1-\rho^2}}\right)\right]. \quad (2)$$

From equation 2, we compute *R*, and decide on the causal direction. If *R* is positive, we conclude $\xi \rightarrow \eta$, and if it is negative, we conclude $\eta \rightarrow \xi$. Hyärinen and Smith (2013) suggest that the statistically optimal way of estimating *R* would be to maximize the likelihood, which in turn may be estimated by the conventional least-squares solution to the linear regression problem. As argued by Hyärinen and Smith (2013), maximization of likelihood might be more robust against outliers, because log-likelihood functions often grow more slowly than the sum of squares of the residuals when moving away from the origin. They further argue that the likelihood ratio has a simple information-theoretic interpretation, which implies that one may use well-known entropy approximations for its practical computation (even where we do not want to postulate functional forms for the *G*'s). Taking the asymptotic limit of the likelihood ratio, we can obtain

$$R \longrightarrow -H(\xi) - H\left(\frac{\hat{d}}{\sigma_d}\right) + H(\eta) - H\left(\frac{\hat{e}}{\sigma_e}\right) \quad (3)$$

where we denote the differential entropy by H, the estimated residuals by $\hat{d} = \eta - \rho\xi$, $\hat{e} = \xi - \rho\eta$, and the variances of the estimated residuals by σ_d^2, σ_e^2. Thus, we can approximate the likelihood ratio using any general, possibly non-parametric, approximations of differential entropy, and in this regard, we use the maximum entropy approximations by Hyärinen (1998), which is computationally simple. In fact, we only need to approximate one-dimensional differential entropies, which is much simpler than approximating two-dimensional entropies. In this regard, the version of the approximation used is given by: $\widehat{H(u)}$=$H(v)$- $k_1[E\{logcoshu\}$- $\gamma]^2$ -)- $k_1[E\{uexp(-u^2)/2\}$- $\gamma]^2$, where $H(v)$=1/2($1+2log\pi$), and k_1, k_2 and γ are constants that are evaluated numerically.

Next, given the possibility of nonlinearity and structural breaks amongst the relationship between sentiment indices, we now turn to Marinazzo et al. (2008), wherein the authors introduced a novel approach to assess Granger causality that assumes nonlinearity and controls for overfitting to avoid the problem of spurious causalities.

Let $\{\xi_n\}_{n=1,\ldots,N+m}$ and $\{\eta_n\}_{n=1,\ldots,N+m}$ be two stationary time series, with autoregressive processes of order m for these two series as follows, with A and B being the regression coefficients:

$$\xi_n = \sum_{j=1}^{m} A_j \xi_{n-j} + e_n, \tag{4}$$

$$\xi_n = \sum_{j=1}^{m} A'_n \xi_{n-j} + \sum_{j=1}^{m} B_j \eta_{n-j} + e'_n. \tag{5}$$

Given that, Granger causality from η to ξ means that the variance of the residual e'_n is significantly lower than the variance of the residual e_n, the strength of Granger causality can be measured by an index as:

$$\delta(\eta \to \xi) = 1 - \frac{\langle {e'_n}^2 \rangle}{\langle e_n {e_n}^2 \rangle} \tag{6}$$

where $\langle\cdot\rangle$ represents averaging over n (note that, $\langle e' \rangle = \langle e \rangle = 0$). Exchanging the roles (dependent and independent variables) of the two time series in Eqs. (4) and (5), one can test causality in the opposite direction, i.e., whether ξ causes η.

Let $X_i = (\xi_i, \ldots, \xi_{i+m-1})^T$ and $Y_i = (\eta_i, \ldots, \eta_{i+m-1})^T$, where $x_i = \xi_{i+m-1}$ and $y_i = \eta_{i+m-1}$ for $i = 1, \ldots, N$. Note that, we treat these quantities as N realizations of the stochastic variables X, Y, and of x and y; respectively. Further, let us represent $\mathbf{X}$ as the $m \times N$ matrix having vectors X_i as the columns, and $\mathbf{Z}$ as the $2m \times N$ matrix having vectors $Z_i = (X_i^T, Y_i^T)^T$ as the columns. The values of x are organized in the vector $x = (x_1, \ldots, x_N)^T$. Broadly, in general terms, we assume that each component of X and Y has a zero mean, and that the vector $\boldsymbol{x}$ has a zero mean and is normalized, i.e., $\boldsymbol{X}^T\boldsymbol{X} = \mathbf{1}$. Given this, for each i =1,…,N, we define:

$$\hat{x}_i = \sum_{j=1}^{m} A_j \xi_{i+m-j}, \tag{7}$$

$$\hat{x}'_i = \sum_{j=1}^{m} A'_j \xi_{i+m-j} + \sum_{j=1}^{m} B_j \eta_{i+m-j} \tag{8}$$

where $\hat{x} = (\widehat{x_1}, \dots, \widehat{x_N})^T$ and $\widehat{x'} = (\widehat{x'_1}, \dots, \widehat{x'_N})^T$ are the values estimated by linear regressions in both cases, and have the following geometrical interpretation: Let $H \subseteq \Re^N$ be the range of the $N \times N$ matrix $\boldsymbol{K}=\mathbf{X}^{\boldsymbol{T}}\boldsymbol{X}$; $\hat{x}$ is the projection of $\boldsymbol{x}$ on *H*. So, denoting $v_1, \dots, v_m$ as (orthonormal) eigenvectors of $\boldsymbol{K}$ with non-vanishing eigenvalue, and denoting $P = \sum_{i=1}^{m} v_i v_1^T$ as the projector in the space *H*, we have $\hat{x} = PX$. Let $y = X - PX$, and $\widehat{x'} = P'X$, with P' being the projector in the 2*m*-dimensional space $H' \subseteq \Re^N$, which is equal to the range of the matrix $\boldsymbol{K'}= \mathbf{Z}^{\boldsymbol{T}}\boldsymbol{Z}$. Hence, it is easy to show that:

$$\delta(\eta \to \xi) = \frac{\widehat{\boldsymbol{X}}'^{\boldsymbol{T}}\widehat{\boldsymbol{X}} - \widehat{\boldsymbol{X}}^{\boldsymbol{T}}\widehat{\boldsymbol{X}}}{1 - \widehat{\boldsymbol{X}}^{\boldsymbol{T}}\widehat{\boldsymbol{X}}}. \tag{9}$$

Given that H' can be decomposed as $H' = H \oplus H^{\perp}$, where $H^{\perp}$ is the space of all vectors of H' which are orthogonal to all vectors of *H*, Eq. (9) can be re-written as:

$$\delta(\eta \to \xi) = \frac{\|H^{\perp}\boldsymbol{y}\|^2}{1 - \widehat{\boldsymbol{X}}^{\boldsymbol{T}}\widehat{\boldsymbol{X}}} \tag{10}$$

Note that $H^{\perp}$ is the range of the matrix $\widehat{K} = \boldsymbol{K'} - \boldsymbol{K'P} - \boldsymbol{P}(\boldsymbol{K'} - \boldsymbol{K'P}) = \boldsymbol{K'} - \boldsymbol{PK'} - \boldsymbol{K'P} + \boldsymbol{PK'P},$ so for any $\boldsymbol{u} \in \Re^N$, we have $\widehat{K}\boldsymbol{u} = \boldsymbol{v} - \boldsymbol{Py},$ where $\boldsymbol{v} = \boldsymbol{K'}(\boldsymbol{I} - \boldsymbol{P})\boldsymbol{u} \in H'$, and $\widehat{K}\boldsymbol{u} \in H^{\perp}$. It follows that $H^{\perp}$ is spanned by the set of the eigenvectors, $\boldsymbol{t}_1, \dots, \boldsymbol{t}_m$, with non-vanishing eigenvalues of $\widehat{K}$. Given this, we have that $\|H^{\perp}\boldsymbol{y}\|^2 = \sum_{i=1}^{m} r_i^2$, where $\boldsymbol{r}_i$ is the Pearson's correlation coefficient of $\boldsymbol{y}$ and $\boldsymbol{t}_i$. Let $\boldsymbol{\pi}_i$ be the probability that $\boldsymbol{r}_i$ is due to chance, obtained from a Student's *t*-test. Since we are dealing with multiple comparisons, we use the Bonferroni correction to select the eigenvectors, $\boldsymbol{t}_{i'}$, correlated with ***y***, with an expected fraction of false-positive *q* (equal to 0.05). Therefore, we can obtain a filtered linear Granger causality index by summing only over the $\{\boldsymbol{r}_{i'}\}$ such that $\boldsymbol{\pi}_{i'} < \frac{q}{m}$:

$$\delta_F(\eta \to \xi) = \frac{\sum_{i'} r_{i'}^2}{1 - \widehat{\boldsymbol{X}}^{\boldsymbol{T}}\widehat{\boldsymbol{X}}} \tag{11}$$

This index measures the causality from η to ξ.

Using methods from the theory of reproducing kernel Hilbert space, i.e., RKHS (see, Shawe-Taylor and Cristianini, 2004), the linear Granger causality can be generalized to the nonlinear case. Given a kernel function *K*, with the spectral representation $\boldsymbol{K}(\boldsymbol{X}, \boldsymbol{X'}) = \sum_{\boldsymbol{a}} \boldsymbol{\lambda}_{\boldsymbol{a}}\, \boldsymbol{\phi}_{\boldsymbol{a}}(\boldsymbol{X})\boldsymbol{\phi}_{\boldsymbol{a}}(\boldsymbol{X'})$ (see Mercer's theorem in Vapnik(1998)), we consider *H*, the range of the $N \times N$ Gram matrix $\mathbf{K}$ with the elements $\boldsymbol{K}(\boldsymbol{X}_{\boldsymbol{i}}, \boldsymbol{X}_{\boldsymbol{j}})$. In order to make the mean of all variables $\boldsymbol{\phi}_{\boldsymbol{a}}(\boldsymbol{X})$ equal to zero, we replace $\mathbf{K} \to \mathbf{K} - P_0\mathbf{K} - \mathbf{K}P_0 + P_0\mathbf{K}P_0$, where P_0 is the projector onto the one-dimensional subspace spanned by the vector such that each component is equal to unity (Shawe-Taylor and Cristianini, 2004). In what follows, we assume that this operation has been performed on each Gram matrix. As in the linear case, we calculate $\hat{x}$, the projection of $\mathbf{x}$ onto *H*. Due to the fact that spectral representation of $\boldsymbol{K}$, $\hat{x}$ coincides with the linear regression of $\mathbf{x}$ in the feature space spanned by $\sqrt{\boldsymbol{\lambda_a}}\boldsymbol{\phi_a}$, i.e., the eigenfunctions of *K*, the regression is nonlinear in the original variables.

While using both *X* and *Y* to predict *x*, we evaluate the Gram matrix $\boldsymbol{K'}$ with elements $K'_{ij} = K(Z_i, Z_j)$. The regression values now form the vector $\widehat{x'}$ as equal to the projection of $\mathbf{x}$ on H', i.e., the range of $\boldsymbol{K'}$. Before we evaluate the filtered causality index, as in the linear case, we note that not all kernels may be used to evaluate Granger causality. Indeed, if *Y* is statistically independent of *X* and *x*, then $\widehat{x'}$ and $\widehat{x'}$ should coincide in the limit $N\rightarrow\infty$. This property, i.e., the invariance of the risk minimizer when statistically independent variables are added to the set of input variables, is satisfied only by suitable kernels, as discussed in Ancona and Stramaglia (2006). In what follows, we consider two possible choices that fulfil the abovementioned invariance requirement.

We consider the inhomogeneous polynomial (IP) kernel of integer order *p*, which is: $\boldsymbol{K_p(X, X')} = \boldsymbol{(1 + X^T X')^p}$, for which the eigenfunctions are made of all the monomials in the input variables up to the *p*-th degree. The dimension of the space *H* is $m_1 = \frac{1}{B(p+1,\ m+1)} - 1$, where *B* is the beta function and where *p*=1 corresponds to the linear regression, while the dimension of space $\boldsymbol{H'}$ is $m_2 = \frac{1}{B(p+1,\ 2m+1)} - 1$. As in the linear case, we note that $H \subseteq H'$, and decompose $H' = H \oplus H^{\perp}$. Subsequently, we calculate $\widehat{K} = \boldsymbol{K' - PK' - K'P + PK'P}$, with the dimension of the range of $\widehat{K}$ being $m_3 = m_2 - m_1$. Along the same lines as those described in the linear case, we construct the kernel-Granger causality by taking into account only the eigenvectors of $\widehat{K}$ which pass the Bonferroni test, $\delta_F^K = \sum_{i'} r_{i'}^2$, with the sum running only over the eigenvectors of $\widehat{K}$ with probability $\boldsymbol{\pi}_{i'} < \frac{q}{m_3}$.

4. As indicated in the introduction section, the use of the kernel-based multivariate causality approach controls for the possible existence of the nonlinearity and regime changes, which makes it a more robust method than the linear model-based tests.**Data and Results**

4.1. Data

We use the economic sentiment index, a survey-based sentiment indicator, constructed and published by Sentix (www.sentix.de) on a monthly basis. The index is based on a monthly online survey among

1,600 financial analysts and institutional investors who are asked to express their opinion about the current and expected economic conditions over the next six months. It consists of 36 different economic indicators and ranges between -100 (very bad, strongly deteriorating) and +100 (very good, strongly improving), with zero level indicating neutrality. An index value above (below) zero indicates that the share of optimists is higher (lower) than the share of pessimists among participants. Our sample covers five countries/regions (United States (US), Latin America, Eurozone, Japan, Asia excluding Japan) for the period January 2003 to November 2017, as depicted by their availability from DataStream.[5] The sample period consists of 179 monthly observations for each country/region. As shown in Appendix Table A1, the index of Asia excluding Japan has the highest mean, whereas that of the United States has the highest standard deviation. All sentiment indices are negatively skewed, and their kurtosis values are larger than the coefficient associated with normal distributions in 2 out of 5 cases. The standard Augmented Dickey-Fuller (ADF; Dickey and Fuller (1981)), Phillips-Perron (PP; Phillips and Perron (1988)) Dickey-Fuller-Generalized Least Squres (DF-GLS; Elliot et al., (1996)), KPSS (Kiwotaki et al., (1992)), and Ng-Perron (NP; Ng and Perron (2001)) unit root tests reported in the table confirms that all series are stationary as required by our econometric approach. The data is plotted in Figure A1 in the Appendix. All indices seem to move in tandem, especially during the global financial crisis (GFC) where the US sentiment index, in particular, has reached the lowest levels. In early 2009, economic confidence in all the countries and regions under study rebounded sharply, and the level of most of the indices regained pre-GFC levels. However, the economic conditions in the Eurozone, in particular, have experienced a decline during 2012, which coincides with the Eurozone sovereign debt crisis. The sentiment index in Latin America has experienced a quite similar decline in late 2015 early 2016 as most of the economies in South America were hardly hit by commodity price collapse and an upsurge in the value of the US dollar.

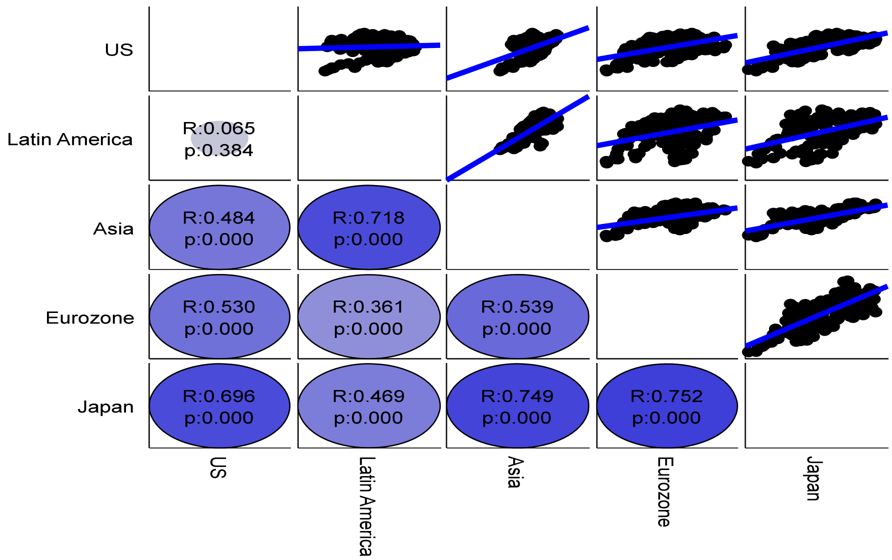
4.2. Empirical results

To get a preliminary indication as to how these variables are related, we present in Figure 1 the scatter plots and the associated correlation. We observe that the correlation between Asia and Latin America,

[5] The sentix data has been extracted from Datastream, Thomson Reuters. The data can be accessed from the following link - http://datastream.thomsonreuters.com/dsws/1.0/DSLogon.aspx?persisttoken=true&appgroup=DSExtranet&srcapp=Extranet&srcappver=1.0&prepopulate=&env=&redirect=https://infobase.thomsonreuters.com/infobase/

Japan and US, Asia and Japan, Eurozone and Japan is quite high i.e., close to 0.7 or above 0.7. But correlation does not necessarily translate into causality. The latter is the focus of our next analysis.

Figure 1: Pair-wise correlation and scatter plots of the series concerned



First, in Table 1, we present the results from standard Granger causality tests between the sentiment indices in both bivariate and multivariate (i.e., where all the five indices are included) settings. The lag length chosen was one as suggested by both the Akaike Information and Schwarz Information Criteria as shown in Table A1 in the Appendix of the paper; wherein Figure A2 also highlight that the vector autoregressive (VAR) model is stable as well. We observe a significant bivariate causality between the Eurozone and the US. Furthermore, Japan Granger causes the Eurozone. Japanese sentiment is also found to be caused by the US and the remaining Asian sentiment indices. In the multivariate setting, Latin America, Eurozone and Japan sentiment indices are found to be caused by all the remaining sentiment indices. Overall, the most affected sentiments are that of the Eurozone, Japan, and Latin America. However, one should note that in many of the instances in Table 1, the significant results are weak, and most of them are likely to disappear when controlling for multiple testing. But, it must be realized that this is a contemporaneous correlation and not depicting causality, which is based on lead-lag relationships.

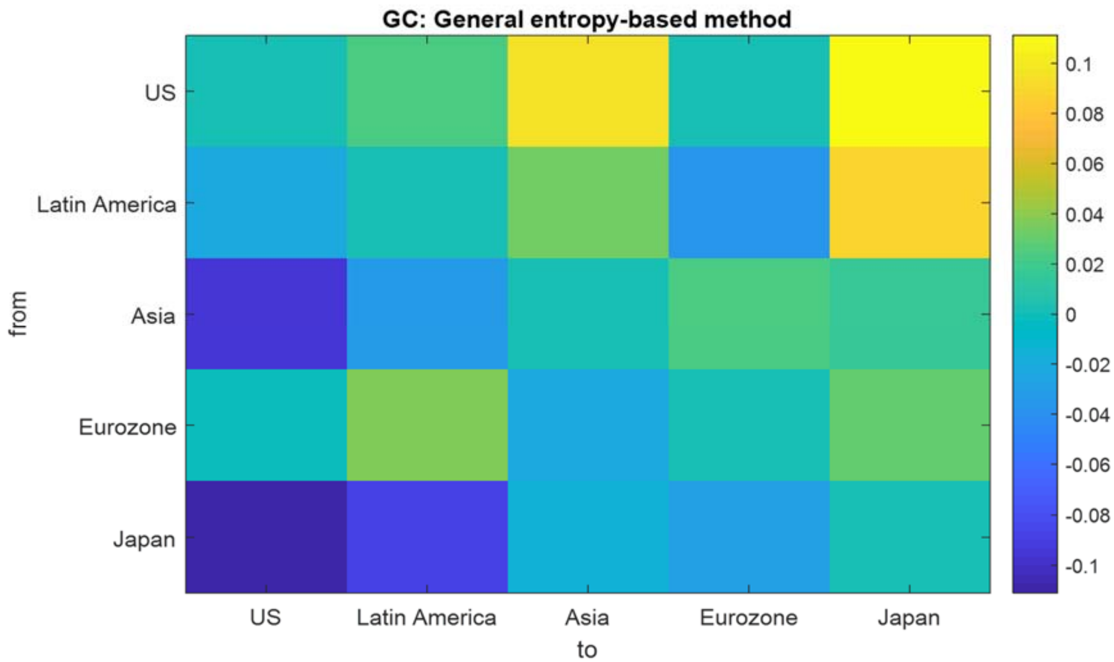
Table 1. Linear Granger Causality Test

Dependent variable	Independent variable	F-stat	P-value
US SENTIX	Latin America SENTIX	0.96409	0.3275
	Asia Excluding Japan	0.09998	0.7522
	Eurozone SENTIX	4.89368	0.0282**
	Japan SENTIX	0.49888	0.4809
Latin America SENTIX	US SENTIX	0.51481	0.4740
	Asia Excluding Japan	3.11539	0.0793*
	Eurozone SENTIX	0.35474	0.5522
	Japan SENTIX	0.36884	0.5444
Asia Excluding Japan	US SENTIX	9.1E-06	0.9976
	Latin America SENTIX	1.30186	0.2554
	Eurozone SENTIX	1.59651	0.2081
	Japan SENTIX	1.27460	0.2605
Eurozone SENTIX	US SENTIX	6.74050	0.0102**
	Latin America SENTIX	0.52556	0.4694
	Asia Excluding Japan	1.64913	0.2008
	Japan SENTIX	5.69946	0.0180**
Japan SENTIX	US SENTIX	4.87781	0.0285**
	Latin America SENTIX	0.03483	0.8522
	Asia Excluding Japan	9.35149	0.0026**
	Eurozone SENTIX	0.60787	0.4366
US SENTIX	All	6.478066	0.1662
Latin America SENTIX	All	10.65439	0.0307**
Asia Excluding Japan	All	3.461402	0.4838
Eurozone SENTIX	All	9.835493	0.0433**
Japan SENTIX	All	17.75216	0.0014**

Note: ** and * indicates rejection of the null hypothesis of no Granger causality at 5 percent and 10 percent levels of significance, respectively.

Given that our variables are non-normal, we now turn our attention to the Granger-causality results based on linear non-Gaussian acyclic models. For this case, we present the causality results based on the general Entropy method (while, for the sake of completeness, results from less-robust (Hyärinen and Smith (2013)) other methods have been presented in Figure A3 in the Appendix that tends to show varied strength of causality), using the heat-map plot in Figure 2. It is worth noting that in this figure, we plot the generated likelihood ratios (LR) matrix, and if entry (i,j) in that matrix is positive, it indicates that the estimate of causal direction is $i \rightarrow j$ and, if it is negative it will imply that the causal direction is $j \rightarrow i$. In this figure colour range is from dark blue (zero strength of Granger-causality) to dark yellow (high strength of Granger-causality). Our observations from Figure 2 show that there is strong evidence of causality from the US to Japan and Asia (excluding Japan), from Latin America to Japan. These results are, indeed, quite different from the linear Granger causality results presented in Table 1.

Figure 2: General Entropy-based Granger-causality



To motivate our nonlinear approach, we report in Tables 2 and 3, the Brock et al., (1996, BDS) test of nonlinearity (performed on the residuals of the equations involving the Granger causality tests), and Bai and Perron's (2003) multiple structural break results (performed on the equations used for the Granger causality tests) respectively, in both bivariate and multivariate settings. As can be seen, there is strong evidence of both nonlinearity and regime changes.

Table 2. Brock et al., (1996, BDS) Test of Nonlinearity

Dependent variable	Independent variable	Dimension				
		2	3	4	5	6
US SENTIX	Latin America SENTIX	4.257***	4.437***	-3.675***	-2.103**	-1.244
	Asia Excluding Japan	-2.777**	-3.674**	-4.377***	-2.502**	-1.496
	Eurozone SENTIX	0.893	-5.152***	-5.912***	-3.646***	-2.329**
	Japan SENTIX	3.646***	1.816*	-4.624***	-2.691**	-1.662*
Latin America SENTIX	US SENTIX	2.378**	2.155**	2.243**	2.226**	2.302**
	Asia Excluding Japan	4.253***	0.778	-4.755***	-2.784**	-1.729*
	Eurozone SENTIX	2.190**	1.976**	2.098**	2.127**	2.201**
	Japan SENTIX	2.141**	1.924**	2.095**	2.123**	2.189**
Asia Excluding Japan	US SENTIX	-3.936***	-2.633**	-4.973***	-2.914**	-1.838*
	Latin America SENTIX	-2.639**	-0.775	3.134**	-2.792**	-1.751*
	Eurozone SENTIX	-3.429***	-7.849***	-4.048***	-2.298**	-1.421
	Japan SENTIX	-4.112***	-7.559***	-3.895***	-2.187**	-1.315
Eurozone SENTIX	US SENTIX	2.184**	3.489***	-4.644***	-2.737**	-1.666*
	Latin America SENTIX	-0.982	4.241***	23.473***	-1.973**	-1.223
	Asia Excluding Japan	-2.327**	-2.163**	-2.832**	-1.553	-0.871
	Japan SENTIX	1.522	6.444***	29.773***	-1.716*	-1.005
Japan SENTIX	US SENTIX	2.033**	1.786*	1.890*	2.697**	3.307***
	Latin America SENTIX	2.420**	2.218**	2.127**	2.843**	3.484***
	Asia Excluding Japan	2.111**	10.635***	13.921***	-4.019***	-2.585**
	Eurozone SENTIX	2.524**	2.276**	2.210**	2.961**	3.643***
US SENTIX	All	3.146***	-4.311***	-5.196***	-3.128***	-1.972*
Latin America SENTIX	All	1.572	5.092***	4.437***	-4.360***	-2.880**
Asia Excluding Japan	All	-1.820*	3.970***	-5.171***	-3.076**	-1.995**
Eurozone SENTIX	All	5.864***	4.338***	-3.853***	-2.215**	-1.363
Japan SENTIX	All	-3.282***	-4.167***	-7.663***	-4.745***	-3.109***

Note: Entries correspond to the *z*-statistic of the BDS test with the null of *i.i.d.* residuals, with the test applied to the residuals recovered from the bivariate or multivariate (ALL) causality equations; ***, **, and * indicates rejection of the null hypothesis at 1 percent, 5 percent and 10 percent levels of significance, respectively.

Table 3. Bai-Perron (2003) Multiple Structural Break Test

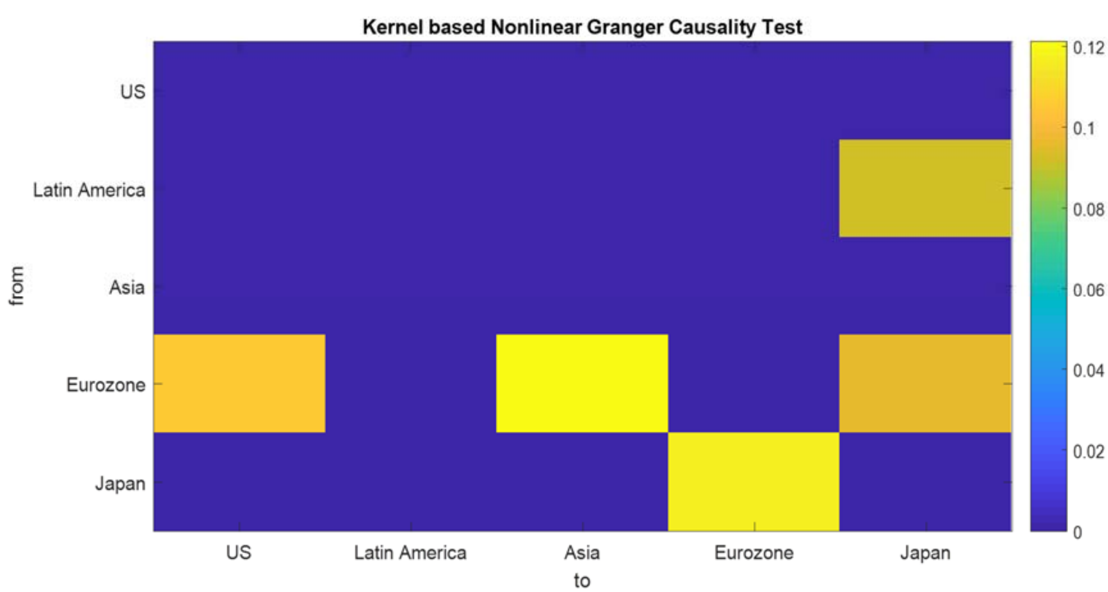
Dependent variable	Independent variable	Date
US SENTIX	Latin America SENTIX	2006M06, 2008M12, 2013M05
	Asia Excluding Japan	2006M06, 2008M12, 2012M01, 2014M03
	Eurozone SENTIX	2006M06, 2009M04, 2011M12, 2014M09
	Japan SENTIX	2005M10, 2009M04, 2012M01, 2014M03
Latin America SENTIX	US SENTIX	2005M04, 2008M10, 2011M03, 2013M07
	Asia Excluding Japan	2005M04, 2008M04, 2012M06, 2014M08
	Eurozone SENTIX	2009M08, 2013M07
	Japan SENTIX	2006M12, 2009M08, 2013M07
Asia Excluding Japan	US SENTIX	2008M07, 2011M02, 2013M07
	Latin America SENTIX	2005M04, 2007M11, 2013M10
	Eurozone SENTIX	2005M04, 2007M10, 2009M10, 2015M06
	Japan SENTIX	2005M04, 2009M08, 2013M05
Eurozone SENTIX	US SENTIX	2005M10, 2008M07, 2011M12, 2015M03
	Latin America SENTIX	2006M01, 2008M06, 2011M07, 2013M09
	Asia Excluding Japan	2005M08, 2007M11, 2011M07, 2013M09
	Japan SENTIX	2006M11, 2011M08, 2015M01
Japan SENTIX	US SENTIX	2005M06, 2008M10
	Latin America SENTIX	2007M08, 2010M04, 2013M05
	Asia Excluding Japan	2005M06, 2007M08, 2013M05
	Eurozone SENTIX	2006M11, 2009M08, 2013M01, 2015M04
US SENTIX	All	2007M09, 2009M11, 2013M07

Latin America SENTIX	All	2005M04, 2008M10, 2011M05, 2014M08
Asia Excluding Japan	All	2008M07, 2011M05, 2014M11
Eurozone SENTIX	All	2006M01, 2009M01, 2011M12, 2015M02
Japan SENTIX	All	2005M06, 2007M09, 2013M05

Note: Entries correspond to the monthly break dates detected by applying the Bai and Perron (2003) test of structural breaks on the bivariate or multivariate (ALL) causality equations.

Given this, we present the kernel-based non-linear Granger-causality in a multivariate setting using heat-map plots in Figure 3. Again as above, in this figure colour range is from dark blue (zero strength of Granger-causality) to dark yellow (high strength of Granger-causality). We observe from Figure 3, that strong evidence of Granger-causality is observed from Eurozone to the US, Asia, and Japan, with Japan also causing the Eurozone sentiment. Furthermore, Latin American sentiment causes Japanese sentiment. Though some of the conclusions of the linear models-based tests do carry over here, given the existence of nonlinearity and regime changes, we deem these results to be more robust than those reported in Table 1 and Figure 2 based on linear models.

Figure 3: Kernel-based non-linear Granger-causality in the multivariate setting



Given the existence of structural breaks, in Figures 4 to 7, we present the time-varying (i.e., based on a rolling window of 60 observations) results for the Granger causality of sentiment index of US, Latin America, Eurozone, Japan and Asia (excluding Japan), along with the rolling correlation coefficients between their pairs, based on our kernel-based nonlinear Granger causality test. Note the window size of 5 years, allows us to analyze from January 2008, i.e., we can analyze time-variation in the causal relationship of the sentiments during and post the recent global financial crisis. We consider four pairs, namely: Eurozone and US, Eurozone and Japan, Eurozone and Asia (excluding Japan), Latin America and Japan. For each pair, we present a figure to show the Granger-causality in both directions and correlations hence, results for each pair are presented in three-part of a single figure wherein the first two parts of the figure are related to presenting the results of Granger-causality; the third part of the figure presents correlation results. It is important to remember that the vertical axis in the first two plots in each figure represents the strength of causality and the last plot presents the correlation value between each pair. The non-Granger causality is indicated by the δ_F values being zero will indicate the zero strength of the Granger causality (or no Granger-causality). Contrarily, for values higher than the zero horizontal line, the evidence supports Granger-causality, and the higher the value, the higher the strength of a Granger-causality. The rolling causality allows us to detect the periods, which drives the causality for the full sample.

In Figure 4, the results of rolling causality between Eurozone and US indicate evidence of bi-directional predictability in December of 2006, and evidence of unidirectional causality from Eurozone to the US in August of 2009 and 2013, and March of 2015, and also unidirectional causality from the US to Eurozone in December of 2010. The overall rolling correlation results show that the relationship between the two sentiment indices is positive for the entire period except for December of 2006 and January of 2007, and October- November of 2017. Next, we turn to the results of rolling causality between Eurozone and Japan; as shown in Figure 5, Japan Granger causes Eurozone during April-May of 2015, and October of 2017, whereas Eurozone Granger causes Japan in June of 2009, November of 2013, and July to December of 2015. The overall correlation is positive during the entire study period. However, it became close to zero in January of 2008, August of 2013, and December of 2016-January of 2017.

Figure 4. Results for rolling Granger causality between Eurozone and the US

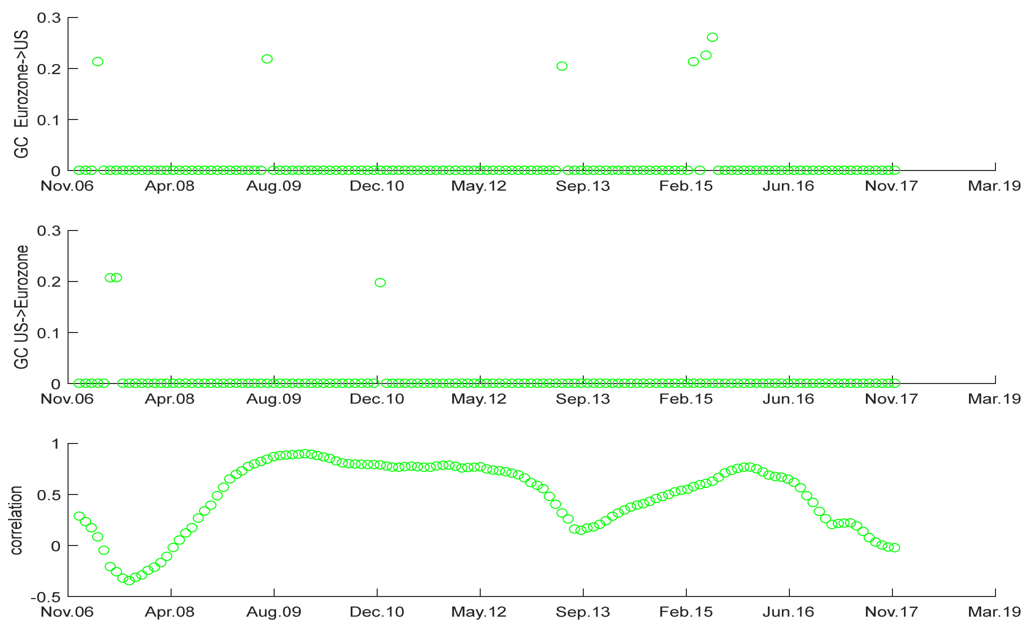


Figure 5. Results for rolling Granger causality between Eurozone and Japan

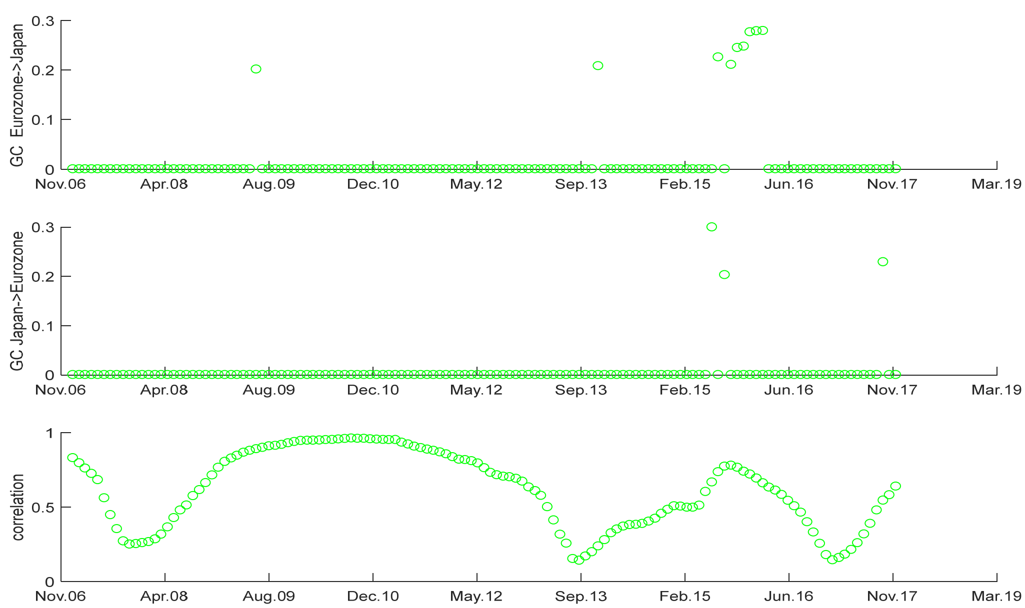


Figure 6. Results for rolling Granger causality between Eurozone and Asia (excluding Japan)

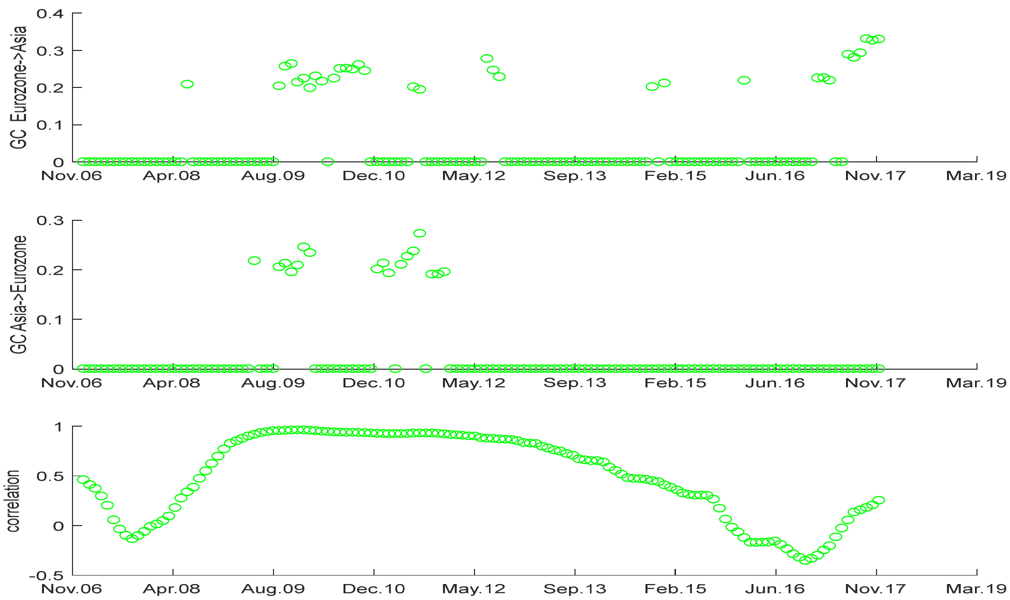
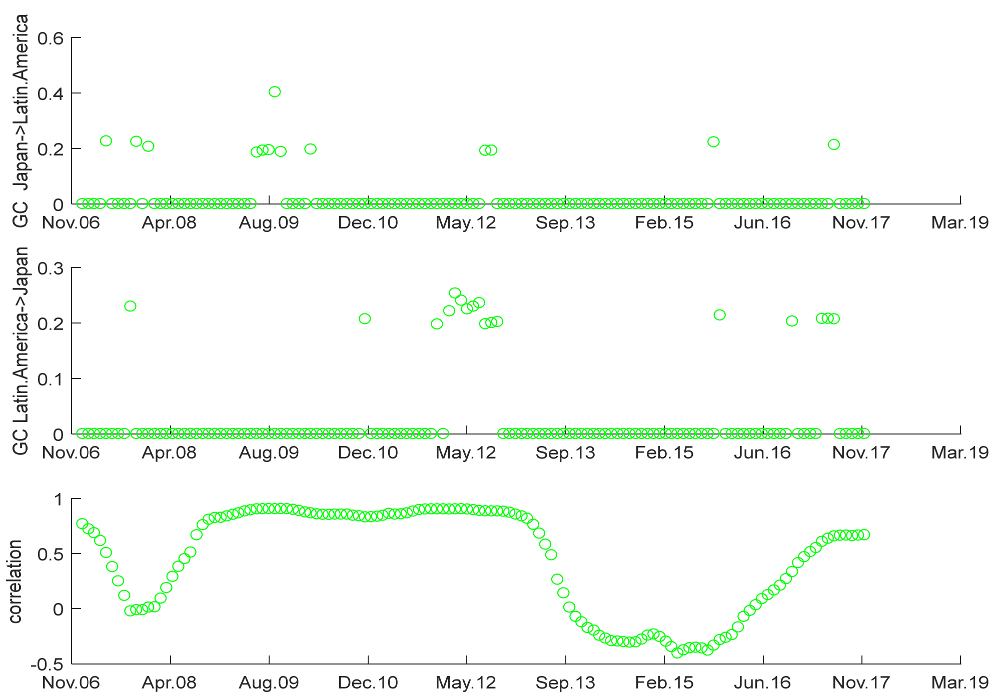


Figure 7. Results for rolling Granger causality between Japan and Latin America.



The results of causality between Eurozone and Asia (excluding Japan), as plotted in Figure 6, indicate that causality is stronger from Eurozone to Asia than vice versa. Specifically, Eurozone Granger causes Asia in May of 2008, August of 2009 to December of 2010, May of 2011, July of 2012, December of 2014, January of 2016 and 2017; whereas Asia (excluding Japan) Granger causes Eurozone in June of 2009, September to November of 2009, and the entire year of 2011. The overall correlation results are in general positive except from early 2016, with it tending to become positive towards the end of the sample. Some negative correlation is also observed in the mid-2007. Finally, in Figure 7, we present the results of causality between Japan and Latin America, which indicate Japan Granger causes Latin America in December of 2006, February of 2008, July to September of 2009, July of 2012, January of 2016 and September of 2017; whereas Latin America Granger-causes Japan in January of 2008, the entire year of 2012, January and December of 2016 and August of 2016. The overall correlations are positive till mid-2013 (with the exception of early 2008), and from September of 2013 to June of 2016, the correlation is negative, which again becomes positive in 2017. The negative relationship seem to potentially reflect a temporary deviation in the sentiment across countries and regions before a major crisis period such as the GFC (e.g., December 2006 - January 2007) or the result of a rising concern at the country or regional levels which fails to spill over to other countries or regions.

5. Conclusion

This paper analyzes sentiment spillovers across the US, Latin America, Eurozone, Japan and Asia (excluding Japan), based on monthly data covering the period from January 2003 to November 2017. Using a survey-based sentiment index of 'Sentix', we postulate this problem in the context of a rich causality testing framework. Though we start with standard linear and entropy-based causality tests, statistical evidence shows the existence of nonlinearity and structural breaks making the results from linear causality models unreliable. Hence, using a kernel-based multivariate nonlinear causality test, we find that causality runs from Eurozone to the US, Asia, and Japan, with Japan also causing the Eurozone sentiment, and Latin America causing Japanese sentiment. Interestingly, when we applied rolling estimations to detect time-varying causality for the cases of Eurozone and US, Eurozone and Asia, Eurozone and Japan, and Latin America and Japan, we found evidence of bi-directional spillovers during certain months of the recent global financial crisis, and thereafter.

Overall, our findings indicate that the sentiment of Japan, Asia, and the US are related quite strongly with that of the Eurozone, as well as the sentiment of Japan and Latin America. The importance of movements in sentiment on the macroeconomy and financial markets is quite well-recognized, hence, if along with a domestic shock to sentiment, there is also a foreign shock at the same time, especially one that originates from the Eurozone, the effect of the domestic sentiment shock in US, Japan and Asia are likely to be prolonged. Similar implications can also be drawn for Japan following a shock to Latin American sentiment and that of the Eurozone due to a change in Japanese sentiment. Given that the academic literature has shown that investor sentiment significantly affects asset prices, our findings of the presence of significant causation of sentiment across different countries/regions, should indeed be a concern for policymakers, as fluctuating sentiment levels may bring potential destabilizing effects in the financial markets especially during the time of crisis. The increased uncertainty about future economic conditions during the GFC, as evidenced by the lower value of the Sentix index (see figure A1), is associated with aggravating financial volatility. However, with the aftermath of the GFC, the introduction of financial regulatory reform in the US and other developed countries contributed to the rebounding of the economic confidence of investors across the world. This, therefore, indicates that the deteriorating sentiment, a sign of increased future uncertainty, should be taken seriously by policymakers wherein they can enact to bring in financial regulatory reform so as to better regulate and bring stability to the financial system.

Our analysis involves some limitations such as the use of low frequency (monthly) data on sentiment. Definitely, the availability of weekly survey sentiment data will represent a nice extension to our analysis as it might show more nuanced dynamics in the causal relationships across countries/regions. This can involve the turbulent period of the pandemic from early 2020. In addition, while we have performed the spillover analyses in time-domain in this paper, as an extension, we could conduct the same in frequency-domain, following the work of (Baruník and Křehlík, 2018).[6] Moreover, future analysis can also involve forecasting financial markets with sentiment spillovers based on machine learning methods while accounting for the COVID-19 outbreak.

[6] The frequency domain causality test of Breitung and Candelon (2006) can also be used, but it can at most include 3 variables in the model, while we have 5. Indeed, some sort of factor analysis can be performed to consider all the 5 variables in the system, but the causality is only derived for two variables at a time. Also, when we have one lag in the model, as is our case, the test-statistic of Breitung and Candelon (2006) is fixed across all frequencies, i.e., short-medium- and long-runs.

References

Ancona, N., Stramaglia, S., 2006. An Invariance Property of Predictors in Kernel-Induced Hypothesis Spaces. Neural Computation 18 (4): 749-759.

Audrino, F. and Tetereva, A., 2019. Sentiment spillover effects for US and European companies, Journal of Banking and Finance, 106, pp. 542–567.

Bai, J. and Perron, P., 2003. Computation and analysis of multiple structural change models. Journal of Applied Econometrics, 18(1): 1-22.

Ball, R., 2009. The global financial crisis and the efficient market hypothesis: what have we learned? Journal of Applied Corporate Finance 21: 8–16.

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

Baker, M., Wurgler, J, and Yuan, Y., 2012. Global, local and contagious investor sentiment. Journal of Financial Economics 104: 272–87.

Baruník, J., and Křehlík, T., 2018. Measuring the frequency dynamics of financial connectedness and systemic risk. Journal of Financial Econometrics 16(2): 271-296.

Bathia D, Bredin D. 2013. An examination of investor sentiment effect on 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.

Bouri, E., Demirer, R., Gabauer, D., and Gupta, R., 2021. Financial market connectedness: The role of investors' happiness. Finance Research Letters. https://doi.org/10.1016/j.frl.2021.102075 .

Breitung, J., and Candelon, B., 2006. Testing for Short and Long-Run Causality: A Frequency Domain Approach. Journal of Econometrics 132(2): 363-378.

Brock, W., Dechert, D., Scheinkman, J., LeBaron, B., 1996. A test for independence based on the correlation dimension. Econometric Reviews, 15, 197–235.

Brown, S., Goetzmann, W., Hiraki, T., Shiraishi, N., and Watanabe, N., 2003. Investor Sentiment in Japanese and US Daily Mutual Fund Flows. Working Paper. NBER 9470.

Brown, G., and Cliff, M., 2004. Investor sentiment and the near term stock market. Journal of Empirical Finance 11: 1–27.

Brown, G., and Cliff, M., 2005. Investor sentiment and asset valuation. Journal of Business 78: 405–440.

Chen, N., Kan, R., and Miller, M., 1993. Are the discounts on closed-end funds a sentiment index? Journal of Finance 58: 795-800.

Daniel, K., D. Hirshleifer, and Subrahmanyam, A., 1998. Investor psychology and security market under and overreactions. Journal of Finance 53(6): 1839–85.

De Long J., Shleifer, A., Summers, L., and Waldmann, R., 1990. Noise trader risk in financial markets. Journal of Political Economy 98. 703 – 738.

Dickey, D.A. and Fuller, W.A., 1981. Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica 49(4): 1057–1072.

Easley, D., O'Hara, M., and Srinivas, P., 1998. Option volume and stock prices: Evidence on where informed traders trade. Journal of Finance 53: 431-465.

Elliot, G., Rothenberg, T.J. and Stock, J.H., 1996. Efficient tests for an autoregressive unit root. Econometrica 64: 813-836.

Fisher, K., and Statman, M.,, 2000. Investor sentiment and stock returns. Financial Analysts Journal 56(2): 2: 16–23.

Fisher, K., and Statman, M., 2003. Consumer confidence and stock returns. Journal of Portfolio Management 30, no. 1: 115–27.

Gao, Z., Ren, H. and Zhang, B., 2020. Googling Investor Sentiment around the World, Journal of Financial and Quantitative Analysis, 55(2): 549–580.

Heiden, S., Klein, C., and Zwergel, B., 2013. Beyond Fundamentals: Investor Sentiment and Exchange Rate Forecasting. European Financial Management, 19(3): 558-578.

Huang, D., Jiang, F., Tu, J., and Zhou, G., 2014. Investor sentiment aligned: A powerful predictor of stock returns. The Review of Financial Studies, 20(3): 791-837.

Hyvärinen, A., 1998. New approximations of differential entropy for independent component analysis and projection pursuit. In Advances in Neural Information Processing Systems, MIT Press, 10: 273-279.

Hyvärinen, A., and Smith, A., 2013. Pairwise Likelihood Ratios for Estimating of Non-Gaussian Structural Equation Models, Journal of Machine Learning Research, 14: 111-152.

Hyvärinen, A., Zhang, K., Shimizu, S., and Hoyer, P., 2010. Estimation of a structural vector autoregression model using non-Gaussianity. Journal of Machine Learning Research, 11: 1709-1731.

Jegadeesh, N., and Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48(1): 65–91.

Ji, Q., Bahloul, W., Geng, J., and Gupta, R., 2020. Trading behaviour connectedness across commodity markets: Evidence from the hedgers' sentiment perspective. Research in International Business and Finance 52. 101114.

Kothari, S., and Shanken. J., 1997. Book-to-market, dividend yield and expected market returns: A time series analysis. Journal of Financial Economics 44(2): 169–203.

Kwiatkowski, D., Phillips, P.C.B., Schmidt, P. and Shin, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? Journal of Econometrics 54: 159-178.

Lee, C., Shleifer, A., and Thaler, R., 1991. Investor Sentiment and the Closed-End Puzzle. Journal of Finance 46: 75-109.

Lemmon M, and Portniaguina E., 2006. Consumer confidence and asset prices: some empirical evidence. Review of Financial Studies 19: 1499–1529.

Li, Z., Tian, M., Ouyang, G., and Wen, F., 2020. Relationship between investor sentiment and earnings news in high- and low-sentiment periods, International Journal of Finance and Economics, 1–18.

Marinazzo, D., Pellicoro, M., and Stramaglia, S., 2008. Kernel methods of nonlinear causality. Physical Review Letters 100: 144103-1-144103-4.

Ng, S., and Perron, P., 2001. Lag length selection and the construction of unit root tests with good size and power. Econometrica 69: 519-1554.

Pan, J., and Poteshman, A., 2006. The Information in Option Volume for Future Stock Prices. Review of Financial Studies 19: 871-908.

Phillips, P.C.B. and Perron, P. 1988. Testing for a unit root in time series regression. Biometrica 75(2): 335–346.

Rehman, M., Abidin, Z., Rizwan, F., Abbas, Z., and and Baig, S., 2017. How investor sentiments spillover from developed countries to developing countries?, Cogent Economics & Finance, 5(1), 1309096.

Schmeling, M., 2007. Institutional and individual sentiment: Smart money and noise trader risk? International Journal of Forecasting, 23(1): 127–145.

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

Sibley, S., Wang, Y., Xing, Y., and Zhang, X., 2016. The information content of the sentiment index, Journal of Banking and Finance 62, pp. 164–179.

Shawe-Taylor, J., and Cristianini, N., 2004. Kernel Methods for Pattern Analysis. Cambridge University Press, London, 2004.

Shiller, R.J., 1987. Investor Behaviour in the October 1987 Stock Market Crash: Survey Evidence. NBER Working Paper

Shiller, R.J., 1995. Conversation, Information, and Herd Behavior, American Economic Review 85(2): 181-185.

Su, X. and Li, Y., 2020. Dynamic sentiment spillovers among crude oil, gold, and Bitcoin markets: Evidence from time and frequency domain analyses. PLoS ONE 15(12).

Vapnik, V., 1998. Statistical Learning Theory. Wiley, New York, 1998.

Verma, R., and Soydemir, G., 2006. The impact of US individual and institutional investor sentiment on foreign stock market. Journal of Behavioural Finance 7: 128–144.

Warther, V., 1995. Aggregate mutual fund flows and security returns. Journal of Financial Economics 39: 209-235.

APPENDIX:

Table A1. Summary Statistics

	US	LATIN AMERICA	ASIA EXCLUDING JAPAN	EUROZONE	JAPAN
Mean	5.6582	7.5627	24.7950	3.2493	3.8260
Maximum	36.2885	33.1491	57.1256	42.0200	42.1177
Minimum	-53.9059	-30.2971	-23.6389	-42.6700	-47.2594
Std. Dev.	19.7222	15.5472	15.8451	18.3227	19.2811
Skewness	-0.9311	-0.6019	-0.5040	-0.3807	-0.1892
Kurtosis	3.3611	2.5039	3.5456	2.5211	2.6276
Jarque-Bera	26.8379	12.6441	9.7994	6.0334	2.1026
Probability	0.0000	0.0018	0.0074	0.0490	0.3495
Observations	179	179	179	179	179
ADF	-1.9672*	-2.0594**	-2.0230**	-2.2400**	-2.0426**
PP	-2.2477**	-2.3882**	-2.0047**	-2.2674**	-2.3893**
DF-GLS	-1.9856**	-0.9313	-2.1898**	-1.2141	-0.7764
KPSS	0.1738	0.2927	0.3204	0.1556	0.2581
MZ_a	-8.0762*	-20.9914**	-9.5226**	-10.0149**	-1.8794
MZ_t	-1.9449*	-3.2389**	-2.1820**	-2.0576**	-0.7579
MS_B	0.2408*	0.1543**	0.2291**	0.2055**	0.4033
MS_T	3.2820*	4.3460**	2.5729**	3.1441**	10.6742

Note: This table presents summary statistics of monthly levels of the Sentix economic sentiment index for the US, Latin America, Eurozone, Japan, and Asia excluding Japan. The sample period is from January 2003 to November 2017; ** and * indicates the rejection of the null hypothesis of the unit root tests at 5% and 10% levels respectively. MZ_a, MZ_t, MS_B, MS_T are the various Ng and Perron (2001) tests. Note that all the tests have a null of unit root, while the KPSS has a null of stationarity.

Table A2. Lag-Length Tests

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-3321.205	NA	5.41e+10	38.9030	38.9948	38.9403
1	-2379.148	1818.004	1188180.*	28.1772*	28.7283*	28.4008*
2	-2356.767	41.8836*	1226045.	28.2078	29.2183	28.6178
3	-2339.588	31.1433	1345980.	28.2993	29.7691	28.89565
4	-2333.147	11.2989	1678128.	28.5163	30.4454	29.2991
5	-2315.353	30.1776	1836033.	28.6006	30.9890	29.5697
6	-2303.812	18.8984	2167112.	28.7580	31.6057	29.9135
7	-2284.053	31.1983	2331217.	28.8193	32.1263	30.1612
8	-2259.962	36.6289	2393289.	28.8300	32.5963	30.3582

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Figure A1. Sentix Index Data Plots

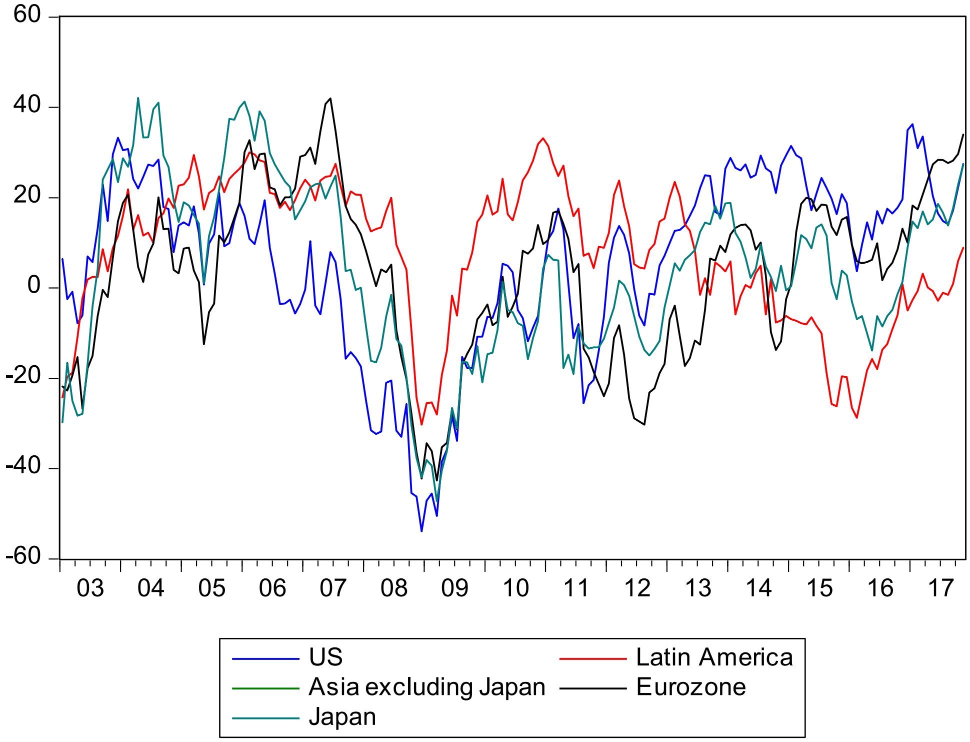


Figure A2. Stability of the VAR

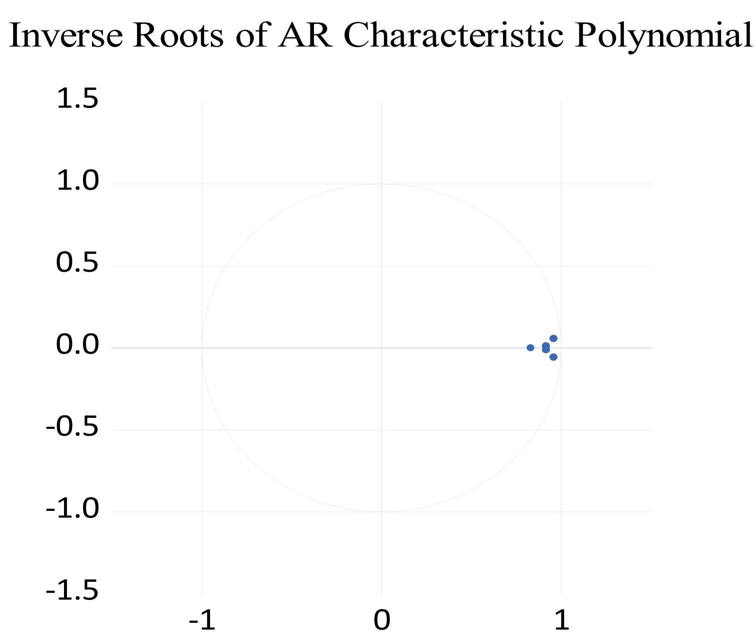
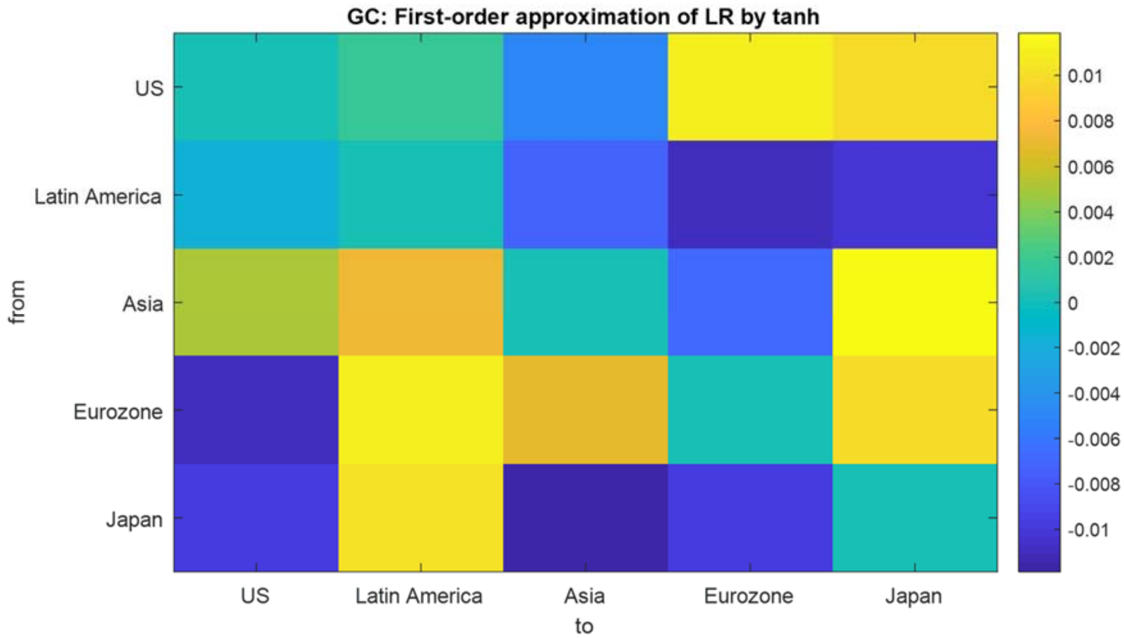
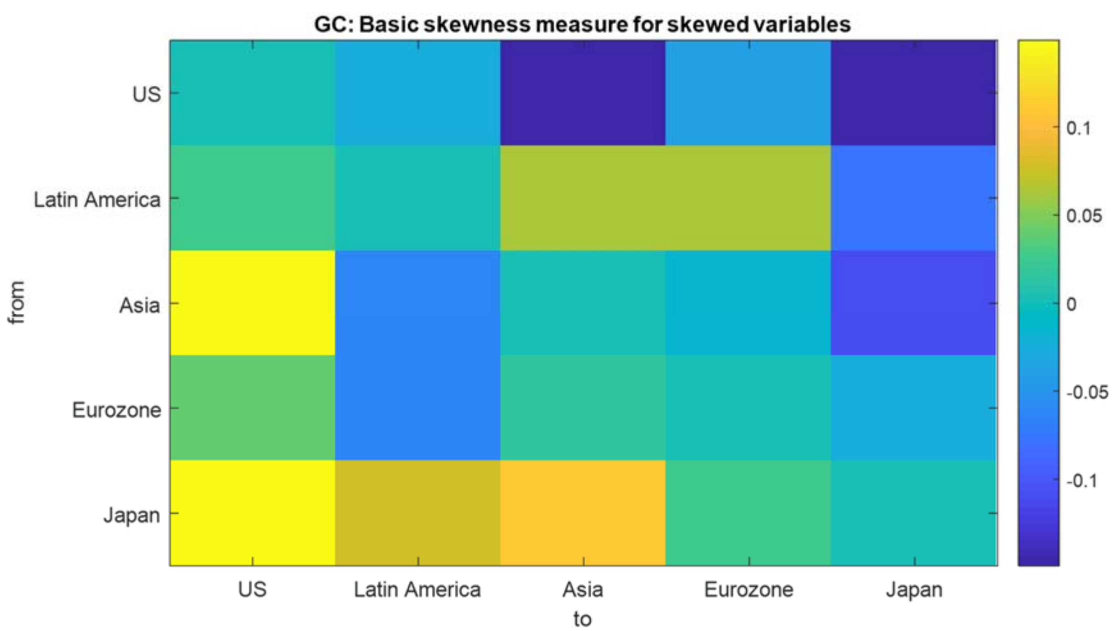
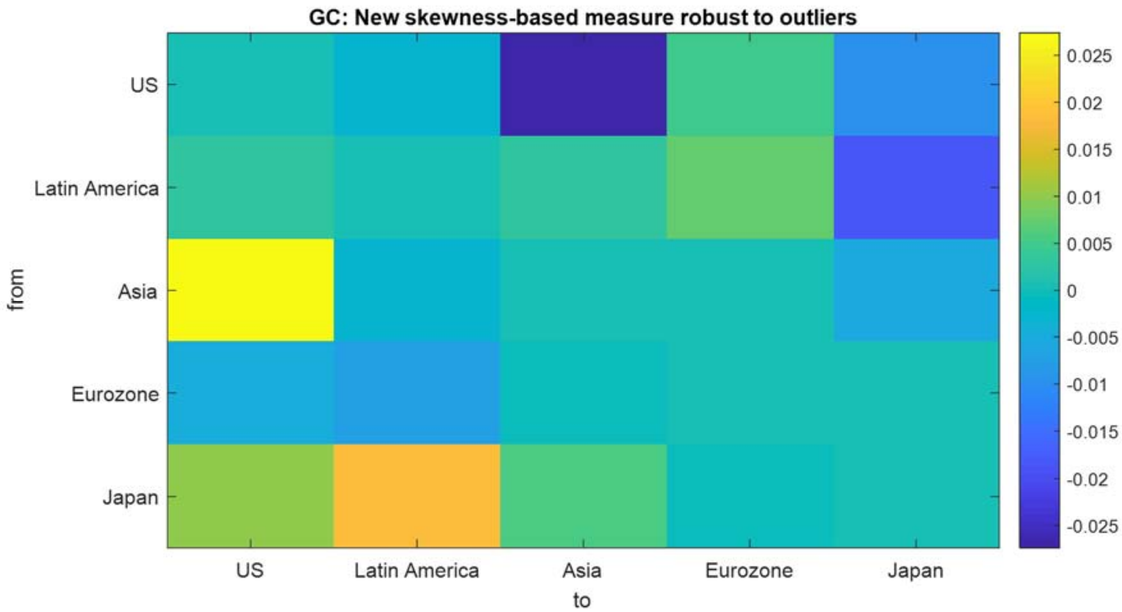
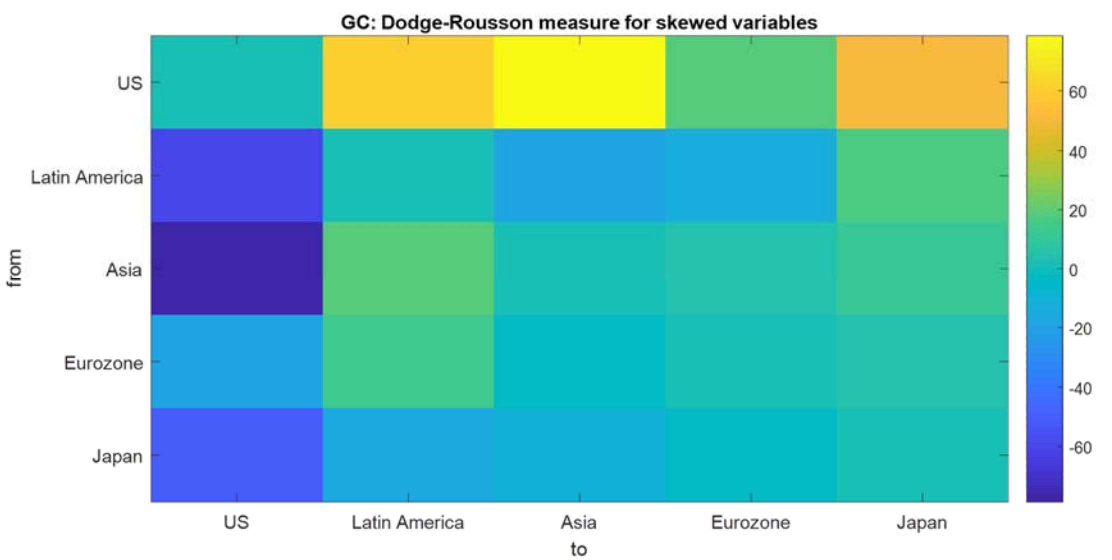


Figure A3. Additional Results from Linear Non-Gaussian Acyclic Models






GC: New skewness-based measure robust to outliers
US
Latin America
Asia
Eurozone
Japan
from
to
0.025
0.02
0.015
0.01
0.005
0
-0.005
-0.01
-0.015
-0.02
-0.025


GC: Dodge-Rousson measure for skewed variables
US
Latin America
Asia
Eurozone
Japan
from
to
60
40
20
0
-20
-40
-60