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Abstract

This paper adopts a nonparametric quantile causality approach to examine the causal effects of the U.S. and Japan stock markets on the stock markets of the Pacific-Rim region. This approach allows us to detect not only nonlinear causalities in conditional return (mean) and conditional volatility (variance), but also the asymmetries of causalities under extreme market conditions (bullish vs. bearish states). Our results provide significant evidence of causality in return and volatility at different points of the conditional distributions of returns, with the greater effects from the U.S. than from Japan. Asymmetric quantile causality patterns are particularly pronounced in the case of Japan.

JEL Classifications: C32; C58; G10; Q02

Keywords: Return spillover; equity markets; Pacific-Rim

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1. Introduction

Over recent decades, financial markets around the world have become more liberalized in terms of effective removal of investment barriers, capital mobility, and financial reforms (Henry, 2000; Bekaert and Harvey, 2000; Ang, 2014). This movement can be seen in markets of both developed and developing countries and is further facilitated by the advances in computer technology and information processing. These factors have not only increased their financial integration (Bekaert and Harvey, 1995; Gerard et al., 2003; Carrieri et al., 2007; Arouri et al., 2012), but also their exposure and sensitivity to shocks, volatility spillovers and contagion effects originating from the rest of the world (Kim and Rogers, 1995; Forbes and Rigobon, 2002; Jayech, 2015). As a result, the linkages and interdependence between national stock markets may have grown stronger and have major implications for corporate investment and financing strategies as well as for international diversification. Strong interdependence would reduce the insulation of the domestic market from any global shock and limit potential gains from international diversifications. Thus, a better understanding of the nature and extent of return and volatility linkages across different financial markets adds to insights on diversification and hedging strategies for investors and appropriate policy actions for regulation bodies and governments.

In this study, we develop a novel nonparametric quantile causality approach to measure stock market linkages, based on the implementation of causality-in-quantiles tests. This approach combines the frameworks of k^{th} order causality of Nishiyama et al. (2011) and quantile causality of Jeong et al. (2012), and hence, can be considered to be a more general version of the former. Methodologically, the causality-in-quantile approach employed in our study has several novelties. First, it is robust to misspecification errors as it detects the underlying dependence structure between the examined time series. This could prove to be particularly important because it is well known that stock returns display nonlinear dynamics. Second, this methodology offers the possibility to test for causality that may exist in the tails of the joint distribution of the variables, thus not only for causality-in-mean (1st moment). Finally, we are also able to investigate causality-in-variance thereby volatility spillovers, as some times when causality in the conditional mean may not exist, yet higher order interdependencies may emerge.

At the empirical stage, we particularly focus on the causal effects of the United States and Japan stock markets on 15 other stock markets of the Pacific-Rim region, to the extent that these two leading countries play an important role in international financial landscape and that changes in their economic and financial policies exert important influences on the rest of world. Past studies such as Ng (2000), Kim (2005), Singh et al. (2010), Zhou et al. (2012), and Liu (2014) have documented increased transmission of return and volatility shocks among these markets over recent periods, but the econometric methods they employ do not permit one to separate the extreme movements from normal interactions. In addition, the evidence on the relative dominance of the United States over Japan in terms of their influences on other markets of the Pacific-Rim region is mixed.

Our results from the causality-in-quantile tests point out the dominance of the US markets, as compared to Japan, in terms of return and volatility causal interactions with the other stock markets in the Pacific-Rim economies. This finding holds true for all market states (bear, normal or bull regimes) in these economies. We also uncover important return and volatility causality at different quantiles of the whole conditional distributions of returns, which are not captured by commonly-used conditional mean-based tests. For instance, the Japanese stock market is found to exert return causality in tails on other markets, and variance causality around the median of the conditional distribution of the Pacific-Rim stock markets. The straightforward implication of this result is that investors and portfolio managers should care about the extremely negative shocks affecting Japan through reducing their holdings of Japanese-related assets under bearish market conditions.

The remainder of this paper is organized as follows. Section 2 briefly reviews the related literature. Section 3 introduces the causality-in-quantile approach we employ to test the causality in return and in variance. Section 4 describes the data used and reports the empirical results. Section 5 concludes the paper.

2. Related literature

Our work is broadly related to three important strands of the previous literature. The first one has focused on the correlations and interactions between markets of developed countries (e.g., Eun and Shim, 1989; Hamao et al., 1990; King et al., 1994). These studies commonly show that developed financial markets are interconnected and that the volatility of the U.S. stock market is transmitted to other developed markets. Subsequent studies have shifted their attention to the relationship between emerging and developed markets, given the increased financial liberalization and global integration (Bekaert and Harvey, 1995; Bekaert and Harvey, 1997; Janakiramanan and Lamba, 1998; Ng, 2000; Pukthuanthong and Roll, 2009). For example, Bekaert and Harvey (1997) document that capital market liberalization often leads to a higher correlation between local and international markets. Based on R-square integration measure, Pukthuanthong and Roll (2009) show a general trend of an increase in market integration for 82 developed and emerging markets over the last three decades, but the patterns of change are country-specific. Janakiramanan and Lamba (1998), and Ng (2000) report that before 1996, volatility in the US and Japanese equity markets spilled over significantly to the stock markets of the Pacific Basin region (Hong Kong, Korea, Malaysia, Singapore, Taiwan, and Thailand).

The second strand of literature examines the stock market linkages through discriminating between interdependence (in terms of both return and volatility) and contagion. In terms of interdependence, previous studies refer it to a state of normal linkages between markets whereby market linkages are driven by fundamentals (e.g., Kallberg and Pasquariello, 2008; Baele and Inghelbrecht, 2010). It means that stock market linkages can be completely explained by common observed factors that are the result of the cross-market real and financial linkages. Events such as sudden expectation shifts or herding are excluded from this set of common fundamentals, and the high levels of market comovement are often associated with the concept of interdependence. Previous research such as Forbes and Rigobon (2002), Corsetti et al. (2005), and Billio and Caporin (2010) typically document evidence of dynamic changes in the fundamentals through time, which explains the time-varying interdependence across international stock markets. Past studies also examine the interdependence of financial markets using linear and nonlinear causality tests in both time and frequency domains (see, e.g., Bekiros and Marcellino, 2013 for foreign exchange markets; Ding et al., 2014 for real estate and stock markets; Choudhry et al., 2015 for gold and stock markets). It is worth noting that most of these studies have focused on developed markets, and especially interdependence among U.S., Japanese, Asian and major European markets.

Some studies have also looked at the interrelations among emerging and developed equity markets (see, e.g., Samarakoon, 2011; Liu, 2013).

On the other hand, contagion is characterized by strong and sudden changes in the measured market linkages (correlation) following a shock affecting a particular market or a group of markets. This definition, which dates back to Forbes and Rigobon (2002), has also been largely employed in subsequent studies to study the contagion issue in the context of cross-market comovement in returns (e.g., Caporale et al., 2005; Pesaran and Pick, 2007; Baele and Inghelbrecht, 2010). Some studies have generalized this contagion definition to consider the volatility contagion with respect to significant shifts in the second moment of returns (e.g., Chakrabarti and Roll, 2002; Chiang and Wang, 2011; Beirne et al., 2013). An important rationale behind the consideration of volatility contagion is that contagion tests based on return correlation are potentially influenced by the presence of conditional heteroscedasticity in the return series as noted by Loretan and English (2000) and Forbes and Rigobon (2002), which could lead to wrong conclusions about the structural stability of market relations. While most studies show evidence of some interdependence and some contagion, several studies have shown that the standard correlation measures employed in the existing literature on contagion are not able to offer insights about when contagion takes over from interdependence (Pesaran and Pick, 2007; Dungey et al., 2010). In particular, Dungey et al. (2006) presents some guidance on some of the factors that can either limit or enhance the prospects for contagion type effects. These factors include, among others, the strong economic fundamentals as a device to guard against contagion, the relatively greater sensitivity of emerging markets to contagion effects, and the channel played by developed markets in transmitting shocks around the world.

When investigating the interdependence and contagious effects among financial markets, the issue of volatility transmission has also received important attention from researchers and practitioners. This gives rise to the third strand of literature which attempts to measure the volatility spillovers across markets, essentially under two perspectives (Weber and Strohsal, 2012): i) volatility spillover as the consequence of potentially correlated information flow; and ii) volatility spillover as reflecting the transmission of uncertainty or valuation insecurity among market participants. Studies that investigate these effects are, among others, Hamao et al. (1990), Lin et al. (1994), Baur and Jung (2006), and Jung and Maderitsch (2014). These studies commonly use the multivariate GARCH, regime switching and stochastic volatility models, and find significant and substantial cross-market volatility spillovers, with the dominant role of the US market as a source for volatility transmission. Departing from the methods above, Diebold and Yilmaz (2009) provide new measures of return and volatility spillovers of international equity markets based on forecast-error variance decompositions in a VAR framework. Diebold and Yilmaz (2011a) discuss the return and volatility spillover among five American countries using this method, while Yilmaz (2010) used the same to evaluate the return and volatility spillover among major Asian countries. More importantly, Diebold and Yilmaz (2011b) further improve their method in 2009 and use the upgraded model to explore the spillover among major American financial assets including stocks, bonds, foreign exchanges, and commodities from 1999 to 2009, with special attention to the volatility interaction during the subprime mortgage crisis.

Our study contributes to the above-mentioned strands of literature by focusing on market linkages and volatility transmission, but we rather tackle the issue of causality in both return and volatility and make it deeper by implementing a causality-in-quantile framework. The empirical evidence about causality over the entire conditional distributions of returns would be important for a number of aspects in finance including the application of value-at-risk and hedging strategies.

3. Methodology

The primary method for inferring causality in financial applications was developed by Granger that takes two time series and determines whether one predicts, or causes, the other. However, it is now common that the conditional mean is a questionable element of analysis if the distributions of variables are non-elliptic or fat tailed as the case of financial returns. In addition, a tail area causality relationship may be quite different from causality relationships based on the center of distribution (see Lee and Yang (2007)). It is well known that the correlations across financial variables depend on the market regime (Lin et al., 1994; Ang and Bekaert, 2002; Longin and Solnik, 2001; Ang and Chen, 2002). In periods with extreme market conditions, financial co-movement across financial variables is stronger as well as contagion and volatility spillovers. Also, the importance of Granger causality in quantile is motivated by their importance for risk management and portfolio diversification (Hong et al., 2009) and the robustness properties of conditional quintile.

Granger causality tests based on conditional mean might be misleading when causality exists only in certain regions of the conditional joint distribution of the variables. This difficulty might be overcome by extending the linear Granger causality test to linear quintile regression. Lee and Yang (2007) developed linear Granger test in quintile, and the tests was shown to detect causal relations that exists in the tails of the conditional distribution. However, the linear causality tests may still fail to detect non-linear causal relationships. Financial and economic variables do behave highly nonlinearly in the tails of the distribution, while their behavior might be linear in the conditional mean which is an overall summary of the conditional distribution. Nishiyama et al. (2011) developed nonparametric Granger causality tests based on kernel density estimation that overcomes the issues relating to the nonlinearity of the relationship between the variables. To fill the gap in the literature both in terms of the causality in the conditional and nonlinearity of the relationship, Jeong et al. (2012) introduces a nonparametric test of Granger causality in quantile based on the kernel density method. The Granger causality in quantile is defined as follows:

1. x_t does not cause y_t in the θ-quantile with respect to $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$ if
$$Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}) = Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}) \quad (1)$$
2. x_t is a prima facie cause y_t in the θ-quantile with respect to $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$ if
$$Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}) \neq Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}) \quad (2)$$

where $Q_\theta(y_t | \cdot)$ is the θth conditional quantile of y_t given $\cdot$, which depends on t and $0 < \theta < 1$.

Let us consider $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, $Z_t = (X_t, Y_t)$, and $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ which are the conditional distribution function y_t given Z_{t-1} and Y_{t-1}, respectively.

The conditional distribution $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ is assumed to be absolutely continuous in y_t for almost all Z_{t-1}. If we denote $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we have,

$$F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta \qquad \text{w.p.1}$$

Consequently, the hypotheses to be tested based on definitions (1) and (2) are

$$H_0 = P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} = 1 \quad \text{a.s.} \tag{3}$$

$$H_1 = P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} < 1 \quad \text{a.s.} \tag{4}$$

Jeong et al. (2012) follow Zheng (1998) and reduce the problem of testing quantile restriction to a problem that can be specified as a test of a particular type of mean restriction by using a distance measure $J = \{\varepsilon_t E(\varepsilon_t|Z_{t-1}) f_Z(Z_{t-1})\}$, where ε_t is the regression error term and $f_Z(Z_{t-1})$ is the marginal density function of Z_{t-1}. The regression error ε_t arises from the fact that the null hypothesis in (3) can only be true if only if $E[\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})|Z_{t-1}\}] = \theta$ or equivalently $\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is the indicator function. Jeong et al. (2012) specify the distance function as

$$J = E\left[\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} - \theta\}^2 f_Z(Z_{t-1})\right] \tag{5}$$

Here, we point out that $J \geq 0$ and the equality holds only under null hypothesis H_0 in equation (3), while $J > 0$ holds only under the alternative H_1 in equation (4). The result in Fan and Li (1999) establishes that a feasible test statistic based on the distance measure J in equation (5) has the leading term that follows a second order degenerate U-statistic and Jeong et al. (2012) show that under the β-mixing process, the asymptotic distribution of the statistic is asymptotically normal.

Jeong et al. (2012) shows that the feasible kernel-based test statistic, based on , has the following form:

$$\hat{J}_T = \frac{1}{T(1-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \tag{6}$$

where $K(\cdot)$ is the kernel function with bandwidth h and $\hat{\varepsilon}_t$ is the estimate of the unknown regression error, which is estimated from

$$\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq \hat{Q}_\theta(Y_{t-1}) - \theta\} \tag{7}$$

where $\hat{Q}_\theta(Y_{t-1})$ is estimate of the θth conditional quantile of y_t given Y_{t-1}. $\hat{Q}_\theta(Y_{t-1})$ can be estimated by the nonparametric kernel method as

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}^{-1}_{y_t|Y_{t-1}}(\theta|Y_{t-1}) \tag{8}$$

Here, $\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ is the Nadarya-Watson kernel estimator and given by

$$\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1}) = \frac{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)\mathbf{1}(y_s \leq y_t)}{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)} \tag{9}$$

with the kernel function $L(\cdot)$ and bandwidth h.

Empirical studies show that volatility transmission (King and Wadhwani, 1990; King et al., 1994; Ng, 2000, Caporale et al. 2005, 2006) across financial markets is observed particularly during market crash periods (Bae and Karolyi, 1994; Claessens, 2001; Bekaert and Ng, 2005; Bartram and Wang, 2005), which is also known as a contagion effect. The recent empirical literature focuses on dependence of financial time series not only on the first moment, but also on the second, third and fourth moments (Friend and Westerfild, 1980; Hwang and Satchell, 1999; Forbes and Rigobon, 2002; Jondeau and Rockinger, 2009). In view of this recent evidence, it is of interest for us also to test for Granger causality in the variance from the US and Japanese stock markets to other Pacific-Rim stock markets. Testing for Granger causality in the second or higher moments has some complications and the procedure for such tests should be carefully defined. It is almost certain that one would find causality in the mth moment, if there is causality in the kth moment for $k < m$. This property must be taken into account for specifying the causality in higher-order moment restrictions.

Following Nishiyama et al. (2011), we generalize the nonparametric Granger quantile causality test to testing for nonparametric Granger quantile causality in variance. Nishiyama et al. (2011) construct nonparametric Granger causality tests using the same density weighted approach in Jeong et al. (2011) and show that density weighted nonparametric tests in higher moments have the same asymptotic normal distribution as the test for causality in first moment, although some stronger moment conditions might be necessary. In order to illustrate the causality in higher order moments let

$$y_t = g(Y_{t-1}) + \sigma(X_{t-1})\varepsilon_t \tag{10}$$

where ε_t is a white noise process, and $g(\cdot)$ and $\sigma(\cdot)$ are unknown functions that satisfy certain conditions for stationarity. The specification in equation (10), does not allow predictive power (Granger causality) from X_{t-1} to y_t, but certainly allows predictive power (in the Granger causality sense) from X_{t-1} to y_t^2. Note that, $\sigma(\cdot)$ is a general nonlinear function and we do not need to explicitly specify squares of X_{t-1} for the specification of the Granger causality in variance. Analogous to quantile causality in mean, we can specify the null and alternative hypotheses for quantile causality in variance as follows:

$$H_0 = P\left\{F_{y_t^2|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \quad \text{a.s.} \tag{11}$$

$$H_1 = P\left\{F_{y_t^2|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \quad \text{a.s.} \tag{12}$$

The feasible test statistic for testing the null hypothesis H_0 in equation (11) can be obtained by replacing y_t in equations (6)-(9) with y_t^2. A problem may arise with the definition of given in equation (11). We are almost sure to conclude for causality in the second moment (variance) when there is causality in the conditional first moment (mean). We can illustrate this with the following model:

$$y_t = g(X_{t-1}, Y_{t-1}) + \epsilon_t \tag{13}$$

Higher order quantile causality for a model like in equation (13) can be tested using the following null and alternative hypotheses:

$$H_0 = P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \quad \text{a.s.} \quad \text{for } k = 1,2,\dots,K \tag{14}$$

$$H_1 = P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \quad \text{a.s.} \quad \text{for } k = 1,2,\dots,K \tag{15}$$

Under this definition, x_t Granger causes y_t in quantile θ up to Kth moment. For the null specified in equation (14), we can easily construct the test statistic in equation (6) for each k. As pointed out by Nishiyama et al. (2011), there is no easy way of combining these statistics into one statistic for the joint null in equation (14), because the statistics constructed for $k = 1,2,\dots,K$ are mutually correlated. One may resort to bootstrap testing approach to compute the correlation and drive the empirical distribution of the statistic for the joint null. The bootstrap approach is computationally too demanding in our case due to more than 6000 observations and already computationally expensive kernel density estimation.

In order to avoid the high computation cost, we follow the sequential testing approach in Nishiyama et al. (2011). In this approach, we first test for nonparametric Granger causality in the first moment ($k = 1$), if the null of non-causality is rejected then we stop and interpret this result as a strong indication of possible Granger quantile causality in variance as well. However, if the null for $k = 1$ is not rejected, then there might still be causality in the second moment and, thus, we construct the tests for $k = 2$. This approach allows us to test the existence of causality only in variance as well as the causality in the mean and variance successively.

In the empirical implementation of the feasible causality in quantile tests there are there important choices: the bandwidth h, the lag order p, and the kernel type for the kernels $K(\cdot)$ and $L(\cdot)$ in equations (6) and (9), respectively. In the empirical implementation, we determine the lag order p using the Bayesian Information Criterion (BIC) in a linear bivariate vector autoregressive (VAR) model.[1] The bandwidth h is selected using the least squares cross-validation method of Rudemo (1982) and Bowman (1984). We use Gaussian kernels for both $K(\cdot)$ and $L(\cdot)$.

4. Data and Results

4.1 Data

Our data involves the daily MSCI (Morgan Stanley Capital International) stock price indices in US dollars of the various countries under consideration. The sample periods vary across countries over the period from 26 June 1989 to 25 June 2014. Percentage stock market returns are obtained by taking first-differences of the natural logarithms of their price and multiplying by 100.[2] This transformation ensures the stationarity of the data, which is suitable for further analysis.

Table 1 reports the descriptive statistics of the various stock returns as well as sample periods and number of observations for each country. Over the sampled period, except for Taiwan and Japan, all markets recorded positive mean returns. Some Asian-

[1] For the bivariate models involving Japan the optimal lag-length was found to be one, except for the case of Malaysia, where it was two. For the models involving the US, the optimal lag-length was generally one as well, except for the cases of Australia, Canada, South Korea, Singapore, Taiwan and Thailand. This result implies that effect of shocks originating from the US lasts longer when compared to the same originating from Japan, especially for Australia, Canada, South Korea, Singapore, Taiwan and Thailand.

[2] Complete details of the various unit root tests are available upon request from the authors.

Pacific markets (Indonesia, China, South Korea and Thailand) are more volatile than the developed markets. This gives credence to the stylized assertion that developed markets are less risky compared to emerging markets. In all markets, stock returns show asymmetric distribution with a positive kurtosis, and negative skewness, barring the cases of South Korea, Philippines, China and Japan. Hence, not surprisingly the Jarque-Bera test rejects the null hypothesis of return normality at the 1% level of significance.

We used the Ljung-Box test with lags one and four to assess the sample autocorrelation. The null hypothesis of no autocorrelation is rejected for all countries except for New Zealand. For Australia and Japan the null was not rejected for lag one. In addition, the ARCH test was used to determine the presence of conditional heteroscedasticity in the series. For all markets the null hypothesis of no conditional heteroscedasticity is rejected at 1% level of significance.

Figure 1 plots the stock returns of the countries involved. Supporting the statistics reported in Table 1, Figure 1 shows volatility switching behavior in all series. All series also have frequent large outlier returns as well as strong volatility clustering behavior. In particular, it can be seen that all stock markets in the Pacific-Rim region experienced extremely large fluctuations during the 2008-2009 global financial crisis. The same pattern of change is observed during the 1997-1998 Asian financial crisis for most of them, except for Australia, Canada, Chile, Colombia and China. These stylized features thus motivate the use of the nonparametric and quantile causality approach in the study as it can capture the causality not only in the center but also in the tails of the return distributions.

4.2 Empirical Results

Though the objective of our paper is to analyze causal relationships between stock markets in the United States or Japan with those in other Pacific-Rim economies using a nonparametric quantile causality test in the mean and variance of stock returns, we first present the results from standard and existing Granger causality tests in the conditional mean and variance (Hafner and Herwartz (HH), 2006; and two-versions (robust and non-robust) of Nakatani and Teräsvirta (NT), 2010) for the sake of comparability. The results are reported in Table 2. The Granger non-causality test in mean shows that Japan leads the stock markets of Australia, Hong Kong, Mexico, Singapore, Taiwan and New Zealand at the 5% level of significance and better. Causality is detected at the 10% level for Canada, Chile and Philippines. Not surprisingly, the United States is found to cause strongly all the markets at the 1% level of significance.

Recognizing the possibility of volatility spillovers, we test for causality in the conditional variance using the two above-mentioned tests. Japan is found to cause the conditional variance in the stock returns of Chile, Columbia, South Korea and Taiwan. Regarding the United States, there is clear evidence of volatility spillovers from the United States to the other markets, based on at least one of the two tests of causality in conditional variance, with the exception of Chile, and surprisingly China.

Although the above standard tests of causality in conditional mean and variance are important, they are less informative than the quantile-based causality test. Indeed, the latter allows us to study causality over the entire conditional distribution of stock returns for a specific country. Hence, this test is able to provide insightful information about the returns and volatility spillovers during different phases (broadly, bearish, normal and bullish) of the stock markets. In this case, the obtained results are likely to be of more value to both portfolio managers and investors. Moreover, the nonparametric nature of the quantile causality test is based on a data-driven specification, and does not impose linearity, which is likely to be violated in the presence of structural breaks in the relationships between stock returns, thus leading to spurious conclusions. The results from the quantile causality test in for the returns and volatility is depicted in Figure 2.

As far as causality in stock returns is concerned, Japan is found to cause stock returns for Australia, Columbia, South Korea, Thailand and China over the entire conditional distribution, and primarily at the tails for all other countries except for Taiwan, where the highest causality is found around the median, with some evidence of the same in the tails as well. Note that these Pacific-Rim countries are among the main trading (export and import) partners of Japan, except for Columbia. As far as causality in variance is concerned, there is clear evidence of causality (except for Australia, Hong Kong and Taiwan for which causality is at best weak), primarily around the median (except for Columbia) of the conditional distribution of the variance of stock returns. Clearly, when we compare our results with those reported in Table 2 based on the standard causality tests, we see evidence of the rejection of the null of non-causality to be much stronger for at least some parts of conditional distribution based on our proposed quantile causality tests.

Next we turn to the causality impacts from the United States. Except for the case of Columbia, where evidence of causality in returns is weak, though existent, the US stock markets are found to strongly cause returns for all the other countries over the entire conditional distribution (over and above the mean of the distribution, as shown in Table 2) of the stock returns for the other countries. In addition, when compared to Japan, the influence of United States on the stock returns of the other countries is relatively stronger than Japan. Barring the cases of Mexico and Taiwan to some extent, where the causality in variance is restricted to the upper tail of the distribution, the US stock markets are found to cause volatility spillovers in all the markets at all points of the conditional distribution of stock returns volatility of the various economies.

To sum up, the importance of the US economy is confirmed in terms of returns and volatility spillovers to other Pacific-Rim economies, when compared to Japan, irrespective of the whether the stock market is in bear, normal or bull regimes in these economies. Also, our results highlight the importance of considering causality over the entire conditional distribution for the mean and variances of the Pacific-Rim countries, instead of just conditional mean-based tests, especially for the case of Japan; where we seem to observe causality in tails (bear and bull regimes) for the returns, and volatility spillover around the median (normal regime) of the conditional distribution of the Pacific-Rim countries.

It is finally important to point out here that we analyze the causal impact of the stock market return and volatility in Japan and the United States on stock return and its volatility of the Pacific Rim countries over their respective conditional distributions, unlike previous studies discussed in the literature, especially that of Janakiramanan and Lamba (1998), and Ng (2000), which deal with the Pacific-Rim countries but do not distinguish extreme movements from normal ones. While the former is a vector autoregression based study and thus relies on a conditional mean-based analysis, the latter uses a volatility spillover model. By using our nonparametric causality-in-quantile approach, which guards against misspecification due to nonlinearity and also covers the entire conditional distribution, we highlight the importance of US stock returns relative to that of Japan in affecting the stock returns and volatility of the Pacific-Rim countries.

We also identify under what prevailing regimes in these stock markets, the results on returns and volatility spillovers hold.

5. Conclusion

Over the past 15 years, there has been a growing interest among the portfolio managers in the emerging capital markets as they are expected to provide higher asset returns compared to the developed markets. However, with opening of the economies, the increasing integration between the emerging and the developed markets has led to information and sentiment spillover from one market to another. Clear-cut evidence on the directional causality from each of these markets would thus help investors to make necessary adjustments for their diversified portfolios and policymakers to prevent potentially harmful and contagious effects of crisis shocks affecting stock markets in the United States and Japan.

In this paper we shed new light on the aspect of causal interactions among stock markets of the Pacific-Rim region. A special attention is devoted to the causality from the United States and Japan to other markets of this region. Our daily dataset covers the period from 25 June 1985 to 25 June 2014 enables the investigation of the causality with a long-term perspective. In particular, we look at the patterns of market linkages from a novel nonparametric quantile causality approach that captures the causalities in both return and variance at different points of the conditional return distributions. In this way, we are able to discriminate between causality in extreme market states (bearish versus bullish) and causality in normal times.

The obtained results confirm the relative importance of the return and volatility shocks originating from the US and Japanese markets, given the evidence of significant return and volatility causality. The impacts from the United States are however greater than those from Japan, a result that corroborates the findings of some previous studies (Wei et al., 1995; Miyakoshi, 2003; Zhou et al., 2012). For instance, Miyakoshi (2003) documents, from a bivariate EGARCH model, the dominant influence of the US stock market to seven Asian equity markets, while Japan's impact is not significant. Similarly, Zhou et al. (2012) use the Diebold and Yilmaz's (2011b) forecast-error variance decompositions in a generalized vector autoregressive framework, and finds evidence of dominant volatility impacts of the US market on other markets (China, Hong Kong, India, South Korea, Singapore, and Taiwan), during the subprime mortgage crisis. Finally, the presence of causality in tails suggests the usefulness and relevance of our approach, and thus casts doubt on the suitability of the traditional conditional mean-based causality test, which in turn, provides an incomplete picture. Our results, based on the causality-in-quantiles approach, have important implications from the point of view of portfolio diversification. While, there are likely to be hardly any diversification gains for US-based investors by investing into the Pacific-Rim stock markets, Japanese investors could still have diversification gains, especially when the Pacific-Rim countries are functioning in their normal mode.

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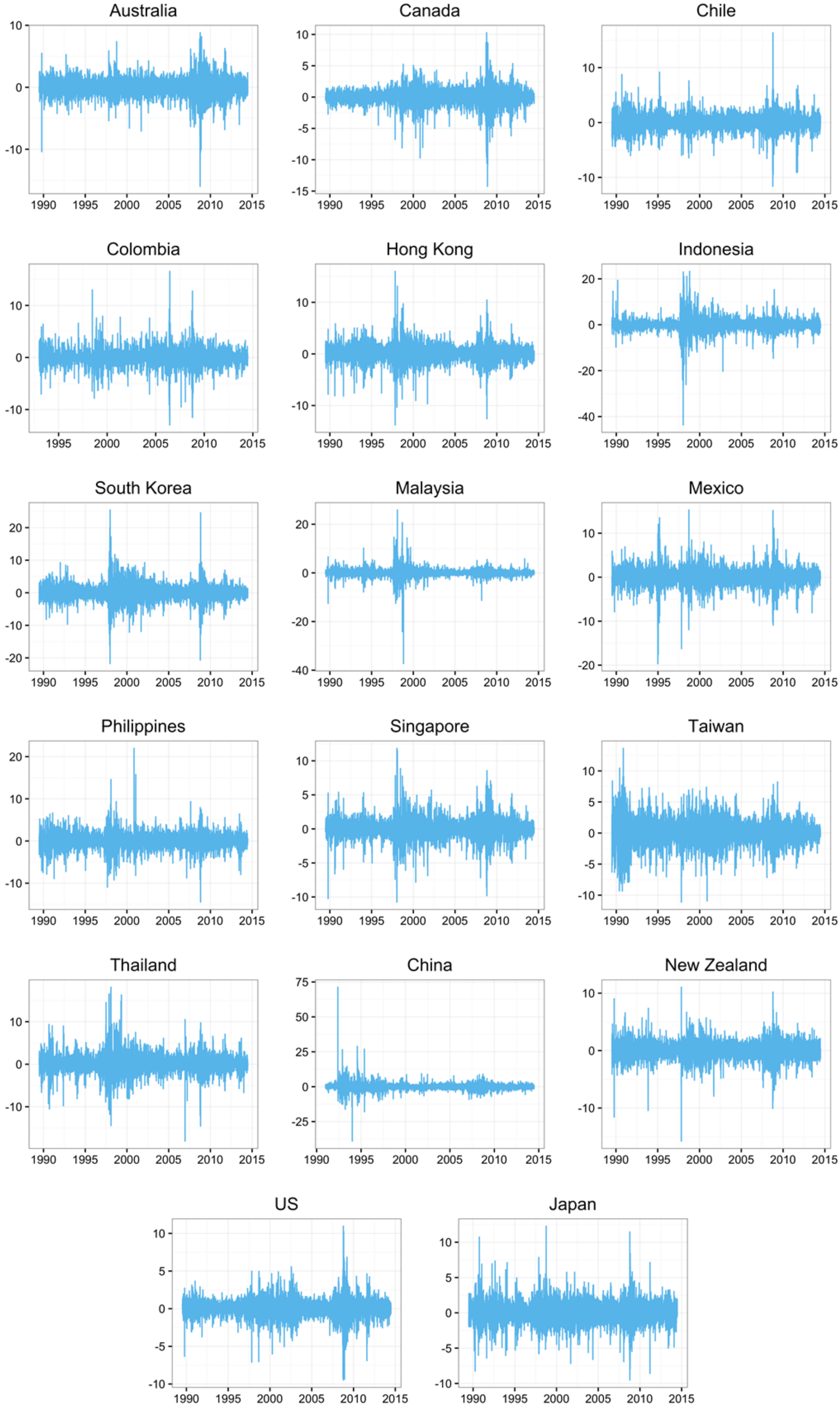
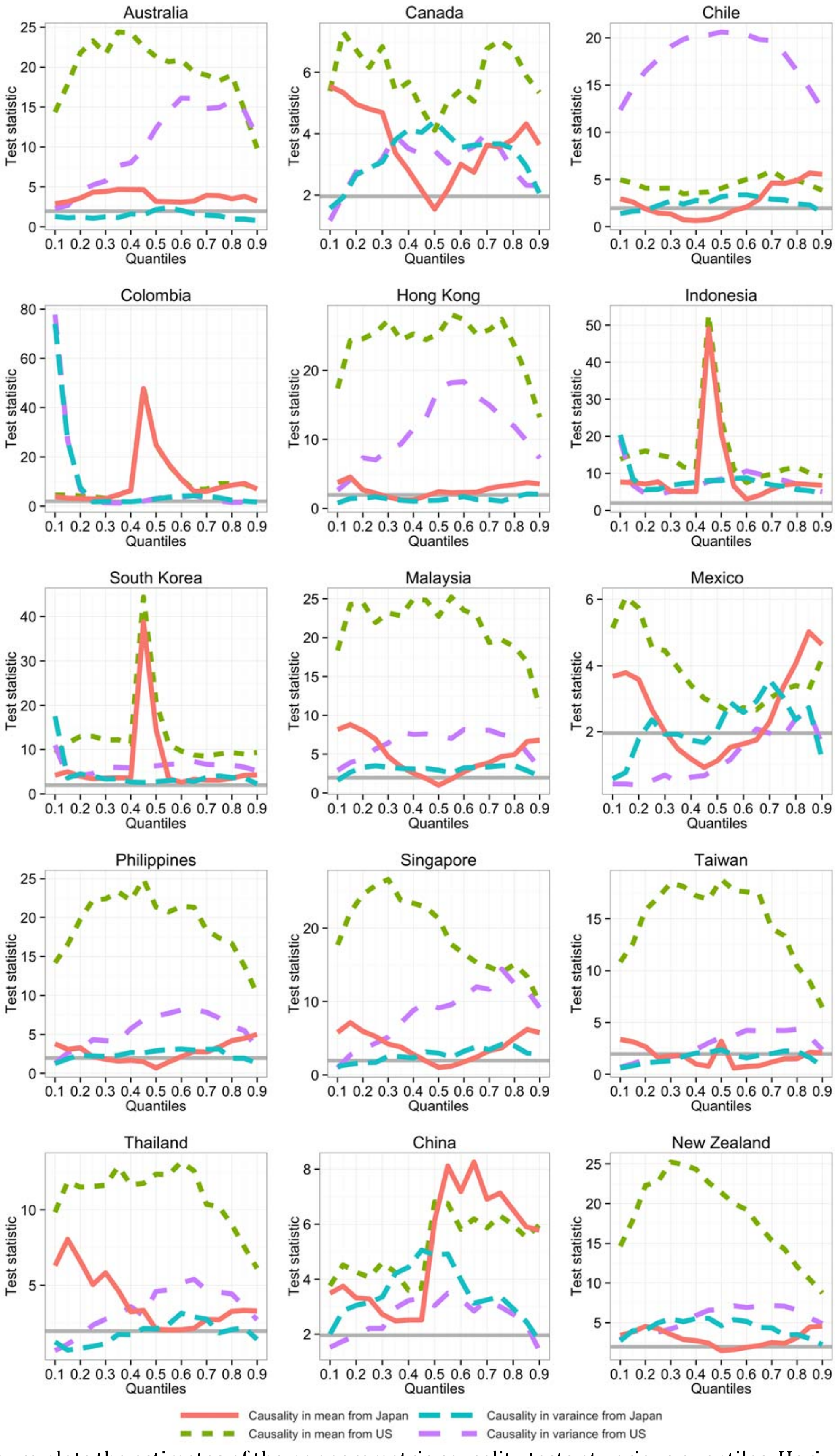
Figure 1: Dynamics of Percentage Return Series



Note: Figure plots the return series (in %) described in Table 1. See notes to Table 1.

Figure 2: Causality in mean and variance from the US and Japanese stock markets at various quantiles



Note: Figure plots the estimates of the nonparametric causality tests at various quantiles. Horizontal solid line in gray color represents the 5% critical value.

Table 1: Descriptive Statistics for the Return Series

	n	Mean	S.D.	Min	Max	Skewness	Kurtosis	JB	$Q(1)$	$Q(5)$	ARCH(1)	ARCH(5)	Sample Period
Australia	6523	0.023	1.3893	-15.9754	8.8086	-0.7114	9.5751	25488.9690***	0.4432	13.4906**	362.6219***	1747.2551***	06/26/1989-06/25/2014
Canada	6523	0.025	1.2562	-14.2449	10.2781	-0.8091	11.7634	38350.6270***	27.3967***	80.9109***	531.2871***	1235.0737***	06/26/1989-06/25/2014
Chile	6523	0.0377	1.3609	-11.6176	16.3603	-0.0626	8.5526	19901.2340***	128.0066***	143.0752***	451.5666***	1148.0475***	06/26/1989-06/25/2014
Colombia	5604	0.0456	1.5672	-12.9678	16.5514	-0.1193	9.6287	21681.8610***	151.0398***	168.6997***	400.6645***	1034.7584***	12/31/1992-06/25/2014
Hong Kong	6523	0.032	1.5333	-13.7697	16.0024	-0.0827	8.6829	20515.4230***	3.6498*	20.2293***	742.4159***	1068.9440***	06/26/1989-06/25/2014
Indonesia	6523	0.0124	2.5371	-43.6718	23.2622	-0.8993	30.1629	248323.4490***	80.0302***	111.5507***	386.0851***	944.7942***	06/26/1989-06/25/2014
South Korea	6523	0.0134	2.2827	-21.7723	25.4234	0.1506	12.2876	41092.5010***	10.9272***	70.4624***	178.1405***	1104.1040***	06/26/1989-06/25/2014
Malaysia	6523	0.0187	1.6396	-37.3034	25.8573	-1.1165	71.9517	1409334.4180***	60.2154***	97.6557***	149.9152***	229.2240***	06/26/1989-06/25/2014
Mexico	6523	0.0505	1.8265	-19.6568	15.274	-0.3987	10.1604	28253.1870***	76.4700***	83.9001***	159.6305***	910.5895***	06/26/1989-06/25/2014
Philippines	6523	0.016	1.7166	-14.4916	21.9715	0.2685	9.877	26614.5540***	117.5551***	127.5428***	160.5975***	268.7666***	06/26/1989-06/25/2014
Singapore	6523	0.0197	1.3675	-10.7608	11.8413	-0.1031	7.1833	14048.2360***	30.0409***	33.9799***	449.5255***	978.8311***	06/26/1989-06/25/2014
Taiwan	6523	-0.0047	1.8757	-11.1252	13.6379	-0.0416	3.4778	3293.0190***	8.4653***	19.8362***	199.2356***	863.9789***	06/26/1989-06/25/2014
Thailand	6523	0.0108	2.0256	-18.0758	18.102	0.3265	9.5923	25144.0740***	110.8117***	123.4350***	332.7832***	671.9702***	06/26/1989-06/25/2014
China	6125	0.042	2.4213	-38.9573	71.2299	4.2878	146.1648	5474724.0120***	5.4343**	28.1944***	2.5122	26.5106***	01/02/1991-06/25/2014
New Zealand	6513	0.009	1.4174	-15.7574	11.0277	-0.416	7.1135	13932.1090***	1.5171	4.6679	364.4343***	622.5412***	07/07/1989-06/25/2014
US	6513	0.0276	1.1253	-9.4695	10.9572	-0.2656	9.2041	23084.8270***	23.8010***	35.7542***	289.5629***	1283.6646***	07/07/1989-06/25/2014
Japan	6523	-0.0051	1.4592	-9.5175	12.2722	0.1132	4.4299	5353.0470***	0.2398	20.7413***	138.9077***	602.5054***	06/26/1989-06/25/2014

Note: The table gives the descriptive statistics for log returns. All values are in percent. The sample periods vary across series over 06/26/1989-06/25/2014 with n observations. In addition to the mean, the standard deviation (S.D.), minimum (min), maximum (max), skewness, and kurtosis statistics, the table reports the Jarque-Bera normality test (JB), the Ljung-Box first [$Q(1)$] and the fourth [$Q(5)$ autocorrelation tests, and the first [ARCH(1)] and the fourth [ARCH(5)] order Lagrange multiplier (LM) tests for the autoregressive conditional heteroscedasticity (ARCH). The asterisks ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 2: Causality Tests in Conditional Mean and Conditional Variance

Variables	Japan				US			
Y / X	Granger *F*	HH	NT-NR	NT-R	Granger *F*	HH	NT-NR	NT-R
Australia	6.5674**	8.9101*	5.548	4.1065	1053.0267***	274.8102***	234.6117***	14.5448***
Canada	3.0452*	0.0171	0.4317	0.4397	68.0612***	0.3924	8.0656*	12.8896**
Chile	3.4252*	8.3589*	31.1390***	5.7051	86.1384***	1.0497	6.0732	3.2633
Colombia	6.5805**	6.2463	21.0931***	8.2236*	119.2407***	9.0821*	11.9305**	10.0873**
Hong Kong	12.9414***	3.9913	7.5218	10.2428**	988.0646***	184.5033***	188.2755***	11.1999**
Indonesia	0.3626	2.9198	4.1174	3.1268	279.1438***	18.1630***	19.3263***	13.2812***
South Korea	0.0175	12.6393**	11.5710**	10.7479**	305.9852***	84.7462***	65.5041***	32.6639***
Malaysia	0.3205	3.5074	4.2034	10.8926**	393.0107***	115.0421***	83.1635***	2.4695
Mexico	9.3705***	2.7604	2.828	3.4421	64.0700***	8.4880*	79.4862***	8.1680*
Philippines	3.2713*	0.5508	0.6006	2.4001	752.5325***	16.9860***	9.0397*	14.1321***
Singapore	17.4069***	4.6438	3.0423	3.2982	377.5396***	153.0568***	408.7667***	15.5522***
Taiwan	8.3280***	11.9887**	7.1234	3.2778	267.8553***	30.5497***	43.4444***	22.1059***
Thailand	2.5505	2.1793	0.6394	1.3052	173.3315***	11.6992**	11.4893**	9.5581**
China	0.1103	0.8741	0.0356	0.2735	21.0700***	0.8646	0.6533	5.9447
New Zealand	20.6800***	5.8046	5.653	6.4222	1196.1127***	197.0514***	80.2897***	14.6090***

Note: The table reports causality tests for testing null hypothesis of non-causality from variable X (Japan or US) to variable Y (column variable). Granger F is the Granger test of non-causality in conditional mean calculated as an F statistic. The Granger non-causality test is performed on a bivariate VAR model with the order of the VAR selected by the Bayesian Information Criterion. HH test is the Hafner and Herwartz (2006) LM test of causality on conditional variance. NT-R is the Nakatani and Teräsvirta (2010) robust LM test of the causality in conditional variance, while the NT-NR is the non-robust version of the Nakatani and Teräsvirta (2010) test. For the HH, NT-R, and NT-NR tests, the univariate specification for conditional variances is a GARCH(1,1) model. We compute HH, NT-R, and NT-NR tests to tests only causality in conditional variance from Xvariable (Japan or US) to Y variable. * indicates the rejection of the null hypothesis of non-causality.