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What Wavelet-Based Quantiles Can Suggest about the Stocks-Bond Interaction in the Emerging East Asian Economies?

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Abstract

This paper investigates bidirectional interdependence between 10Y bond yields and stock returns in the eight emerging East Asian economies. The method of choice is wavelet-based quantile approach, which can provide an answer about spillover effect in different market conditions and in different time horizons. We find that shock spillover effect is much more intense from the bond markets to the stock markets in all the selected economies, than vice-versa. Also, the nexus is dominantly positive in the more developed financial markets in both tranquil and crisis periods, particularly in the short and midterm horizons, which is an indication that capital reallocation takes place between these markets in a search for safer and more profitable investments. As for the less developed East Asian economies, we find negative quantile parameters in all quantiles and in all wavelet scales, which suggests that dividend discount model is a decisive factor that drives the stock-bond interdependence in all time horizons.

1. Introduction

Government bonds of emerging markets, denominated in local currency, have grown considerably since the mid-1990s. Adler and Song (2009), Cavallo and Valenzuela (2009) and Hassan et al. (2015) contended that improved domestic institutions and market infrastructure in emerging markets as well as their strong economic growth provide alluring investment opportunities for global and domestic investors. Also, the transfer of currency risk from sovereign bond issuer to foreign investors also contributes to the rise of bond markets in emerging countries, because it mitigates the currency mismatch of bonds issuers and improves its overall creditworthiness. Bhattacharyay (2013) found that Asian economies have witnessed remarkable growth in bond financing from 1998 to 2008. He claimed that domestic currency bond markets in East Asia reached around US$ 13.2 trillion in 2008, which is three times the US$ 4.5 trillion level in 1998. More recent study of Miyajima et al. (2015), revealed that interest of foreign investors for emerging market bonds is particularly strong due to their favourable characteristics such as attractive yield differential *vis-à-vis* developed markets, expected currency appreciation, declining

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currency volatility and credit quality strengthening. Therefore, ever growing bond markets in Asian emerging economies, galvanize market practitioners and academics to better understand the co-movements between stock and bond markets in these countries. This is the case because stock and bonds are frequently the two main elements in portfolios, and the portfolio strategies are very sensitive to the correlation structure between financial assets (see Christiansen, 2008; Kai and Dietz, 2014; Mirović et al., 2017). Besides, due to information spillovers across financial markets, investment decisions are likely to have cross-market influences (see Frank and Hesse, 2009).

Ferrando et al. (2017) claimed that vast majority of the existing studies focused primarily on highly developed financial markets, while analysis of emerging markets was left pretty much disregarded. The reason lies in a fact that many emerging countries stepped forward with the issuance of long-term government bond relatively recently, that is, in last 15 years. In addition, it should be said that existing literature in a field of the stock-bond relations is mainly based upon low frequency data (see e.g. Yang et al. 2009; Christiansen, 2010; Adam et al., 2015). However, observation of only short-range horizons is insufficient for a comprehensive analysis, because stock and bond markets comprise thousands of heterogeneous agents, who operate over different time horizons, ranging from days to years. Ferrer et al. (2016) contended that investors with very short term-horizons (e.g. day traders and chartist) pursue speculative activities, whereby their decisions are largely driven by sporadic events, market sentiment or psychological factors. On the contrary, long-time agents (e.g. fundamentalists, mutual funds and big institutional investors) are keen to understand macroeconomic fundamentals, such as interest rates, because their investment activities are related to the long-term developments. Thus, a reasonable assumption is that the degree of the interdependence between bond yields and stock returns may vary across different investment horizons.

Having in mind all that have been said, this paper tries to thoroughly investigate the interdependence between national 10Y government bond yields and domestic stock market returns in some of the largest emerging East Asian economies. The emphasis is put on the magnitude of spillover effect between national stock and bond markets, their lead (lag) relationship as well as the level of their correlation. Following economies are considered – China, Honk Kong, South Korea, Thailand, Singapore, Indonesia, Taiwan and Philippines. Table 1 contains some basic facts on the selected stock and bond markets.

Table1 Some Basic Characteristics about Selected Emerging Asian Markets

Stock indices	*Market capitalization**	*Trading volume*	*Bonds*	*Bond ratings♦*	*Debt/GDP♣ in %*
SSEC	7,320,740	18,300	China	A+	47.6
HSI	3,193,240	1,730	Hong Kong	AA+	38.4
KOSPI	1,254,540	377	South Korea	AA	38
SET	432,956	5,310	Thailand	BBB+	41.8
JCI	425,768	5,300	Indonesia	BBB	28.7
STI	640,428	251	Singapore	AAA	110.5
TWSE	272,479	1,780	Taiwan	A+	31.2
FTWIPHLL	239,738	NA	Philippines	BBB+	42.1

Notes: Stock market capitalization and trading volume are portrayed in millions of USD in 2016.
Source: *www.indexmundi.com/facts/indicators/CM.MKT.LCAP.CD/rankings
♣ Reference year for the Debt/GDP ratio is 2017. Source: https://tradingeconomics.com/

♦ Credit ratings for sovereign bonds according to Standard & Poor's credit agency.

The investigation is conducted by merging two different methodologies – quantile regression (QR) and wavelet decomposition analysis. The former method provides the knowledge about asymmetric spillover effect between observed variables under different market conditions, including states of downturn (lower quantiles), normality (intermediate quantiles) and upturn (upper quantiles) markets. Some of the studies, among others, that use QR technique for their research are Živkov et al. (2014), Uyar and Uyar (2018) and Vilerts (2018). On the other hand, the latter method decomposes the time–scale relationships between stocks and bonds, allowing researchers to test the dynamic dependence at different scales or horizons, whereas it circumvents the problem of sample size reduction at the same time. Many recent papers applied wavelet decomposition methodology to analyse various economic phenomena at different time-horizons (see e.g. Madaleno and Pinho, 2012; Dajčman, 2012; Barunik and Vacha, 2013; Lee and Lee, 2016; Altar et al., 2017; Živkov et al., 2018; Živkov et al., 2019). Utilizing wavelet-based quantile approach, we are in a position to deepen the investigation of the co-movement between stock and bonds in terms of specific investment horizons, but also to examine the changes in different degrees of market dependence. Mensi et al. (2016) asserted that the usage of these two approaches simultaneously, provides a unique opportunity to gauge the asymmetric tail dependence under both the extreme market conditions and the different time-scale domains. In order to determine the lead-lag nexus between stock returns and bond yields, we utilize phase difference approach of Aguiar-Conraria and Soares (2011). This methodology gives an insight about the direction of correlation as well as about the lead-lag relationship at specific frequency band and throughout the observed sample (see Tsai and Chang, 2018; Si et al., 2018). To the best of our knowledge, this is the first paper that conducts an extensive stock-bond analysis, combining both wavelet and QR methodologies and covering relatively wide range of emerging Asian economies, which provides a holistic picture on the entire relationship.

Beside introduction, the rest of the paper is structured as follows. Second section provides theoretical underpinning between stock returns and bond yields. Third section gives an overview of the applied methodologies – quantile regression, wavelet decomposition and phase difference. Fourth section introduces dataset. Fifth section presents and explains the wavelet-based quantile results. Sixth section contains phase difference findings. Seventh section explicates implications for market participants, while the last section concludes.

2.Theoretical Underpinning

Financial theory does not provide clear-cut conclusion about stock-bond relations, but it rather proposes that the interlink can be both positive and negative. The studies of Ilmanen (2003) and Yang et al. (2009) stand in that line. The former article investigated the US stock–bond correlation, reporting that the correlation between these two assets was positive through most of the 1900s, but negative in the early 1930s, the late 1950s, and recently. The latter paper showed that stock-bond nexus has shifted from sizably positive to predominantly negative in last 150 years.

Several factors explain negative correlation. Firstly, interest rate is a constituent part in the dividend discount models (DDM), whereby the rise of interest rate negatively affects the cost of capital. Consequently, due to the reduction in the present value of future cash flows, equity prices fall. Secondly, Ferrer et al. (2016) asserted that the rise of interest rates aggravates debt service payments of firms, which sends negative signals to stock investors, decreases demand for stocks, and eventually impacts share prices negatively.

On the other hand, positive stock-bond relation is mainly related to flight-to-quality behaviour, whereby investors shift from riskier stocks towards safer investments such as government bonds in turbulent market periods. Due to the increased demand for bonds, a decrease in government bond yield follows, which generates a positive correlation between changes in sovereign bond yields and stock returns (see Gulko, 2002; Connolly et al., 2005). Conversely, a positive correlation can occur in the bullish periods. In other words, if stock markets exhibit a tendency to rise, then investors increase investments in stock markets and decrease investments in bond markets. This behaviour instigates the rise of stock prices and fall of bond prices. Fixed bond interest rates accompanied with the falling bond price, result in the increased bond yields. In addition, inflation also can galvanize positive correlation in some occasions. According to the Fisher's decomposition[1] equation, the higher (lower) inflation expectations lead to the higher (lower) bond yields. However, the impact of growth and inflation expectations on stock prices is not straightforward. Ilmanen (2003) stated that rising inflation may have no effect on stock prices, and that happen if the discount rates and expected growth rate of dividends are equally impacted by the rising inflation expectations. Nevertheless, Andersson et al. (2008) demonstrated that in the case of high inflation expectations, the discount rate effect may outweigh the changes in the expected future dividends, which tends to have a negative impact on stock prices.

3.Methodology

3.1 Quantile Regression

In order to measure the complex dependence between stocks and bonds, assuming different market conditions, we use quantile regression approach by Koenker and Bassett (1978). Koenker (2005) asserted that when normality conjecture is severely violated and when data contain numerous outliers, QR would be appropriate because the quantile functions provide more accurate results, regarding the impact of conditional variables on dependent variable. In other words, QR provides information about the average dependence as well as the extreme tail dependence, that is, upper and lower tails. Maestri (2013) argued that QR relaxes the restrictive assumption that the error terms are identically distributed at all points of the conditional distribution. In other words, due to a semiparametric nature of QR, no parametric distributional form (e.g. Normal, Student, Poisson) needs to be assumed.

Under the assumption that y is linearly dependent on x, then τ^{th} conditional quantile function of y is given as follows:

$$Q_y(\tau|x) = inf\{b|F_y(b|x) \geq \tau\} = \sum_k \beta_k(\tau)x_k = x'\beta(\tau), \tag{1}$$

[1] Nominal bond yield (n) = real interest rate (r) + expected inflation rate (π) + term premium (θ).

where b denotes an element of the conditional distribution function of y given x. $F_y(b|x)$ stands for the conditional distribution function of y given x, while parameter $\beta(\tau)$ for $\tau \in (0,1)$ defines the dependence relationship between vector x and the τ^{th} conditional quantile of y. x' represents $n \times 1$ vector, which contains constant and independent variable. This research tries to examine bidirectional spillover effect between 10Y bond yields and stock returns, regarding τ^{th} quantile of the dependent variable distribution, thus when y is stock returns, then x stands for bond yield, and *vice-versa*.

The coefficients $\beta(\tau)$ for a given τ are estimated by minimizing the following objective function, that is, the average of asymmetrically weighted absolute errors with weight ϕ on positive errors and weigh (1 - ϕ) on negative errors:

$$Min\frac{1}{T}\left[\phi\sum_{y_t \geq x'\beta}|y_t - x'\beta(\tau)| + (1-\phi)\sum_{y_t < x'\beta}|y_t - x'\beta(\tau)|\right]. \qquad (2)$$

Expression (2) implies the minimization of the sum of asymmetrically weighted absolute error terms, where positive and negative residuals are weighted differently depending on the quantile chosen. According to Lin and Lin (2013), $\phi\sum_{y_t \geq x'\beta}|y_t - x'\beta(\tau)|$ represents the sum of absolute value of the positive error, while $(1-\phi)\sum_{y_t \geq x'\beta}|y_t - x'\beta(\tau)|$ stands for the sum of absolute value of the negative error. Each is given different weights, whereby a greater weight is placed on observations closer to the given quantile τ. They are, therefore, known as 'asymmetric weighted average absolute error'. For instance, if one wants to analyze the 0.90 quantile, the positive (negative) residuals are given a weight of 90 (10) percent. This means that the effect of positive error is amplified while reducing but not completely removing the effect of negative error. The special case of β = 0.5 corresponds to the median regression, where all residuals are equally weighted. The estimator for β does not have an explicit form, thus the resulting minimization problem can be solved by the linear programming algorithm.

3.2 Wavelets and Multiscale Analysis of the Correlation

Motivated by the fact that various market participants act at different time horizons, we apply the wavelet methodology to diversity between short, medium and long run factors that drive cyclical variations. Wavelets are regarded as a powerful mathematical tool for signal processing that can decompose time series into their time-frequency components. Gencay et al. (2002) contended that wavelets can ensure an appropriate trade-off between resolution in the time and frequency domains, while traditional Fourier analysis lacks this ability, in terms that it only stresses the frequency domain at the expense of the time domain. Therefore, wavelets are efficient and convenient method to analyse complex signals.

Generally, there are two basic wavelet functions: the father wavelet (ϕ) and the mother wavelet (ψ). Wavelets are nonlinear functions that can be rescaled and moved to form a basis in a Hilbert space of square integrable functions ($f \in L^2$). The father wavelets augment the representation of the smooth or low frequency parts of a signal with an integral equal to 1, and the mother wavelets are helpful in describing the details of high frequency components with an integral equal to 0. The long-term trend over the scale of the time series is portrayed by the father wavelet, whilst the mother wavelet delineates fluctuations in the trend. The most commonly used wavelets are the orthogonal ones, and the approximation to a continuous signal series *y(t)* in $L^2(R)$ is given as following:

$$\mathrm{y(t)} = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t) \tag{3}$$

where symbol J denotes the number of multi-resolution components or scales, and k ranges from 1 to the number of coefficients in the corresponding component. The coefficients $s_{J,k}$, $d_{J,k}$, …, $d_{1,k}$ stand for the wavelet-transform coefficients that can be approximated by the following integrals:

$$s_{J,k} \approx \int f(\mathrm{t})\phi_{J,k}(t)dt \tag{4}$$

$$d_{j,k} \approx \int f(\mathrm{t})\psi_{j,k}(t)dt, \qquad j = 1,2,\dots,J. \tag{5}$$

These coefficients calibrate the contribution of the corresponding wavelet function to the total signal. The functions $\phi_{J,k}$ and $\psi_{j,k}$ are the approximating wavelet functions, that is, the scaled and translated versions of ϕ and ψ. Generally, these functions are generated from ϕ and ψ in the following way:

$$\phi_{J,k}(t) = 2^{-J/2}\phi\left(\frac{t-2^J k}{2^J}\right), \qquad \psi_{j,k}(t) = 2^{-j/2}\psi\left(\frac{t-2^j k}{2^j}\right). \tag{6}$$

According to the expression (6), the scale or dilation factor is 2^j, whereas the translation or location parameter is $2^j k$. As much as j grows, so does the scale factor 2^j, which is a measure of the width of the functions $\phi_{J,k}(t)$ and $\psi_{j,k}(t)$, and it affects the underlying functions to get shorter and more dilated. Besides, when j increases, the translation steps automatically get larger in order to accommodate the level of scale parameter 2^j.

Most commonly used types of wavelet transformations are the discrete wavelet transformation (DWT) and the maximum overlap discrete wavelet transformation (MODWT). The former utilizes orthonormal transformation of the original series, while the latter is based on a highly redundant non-orthogonal transformation. For our empirical investigation, we employ the MODWT, which is a linear filtering operation that transforms series into coefficients related to variations over a set of scales. For multi-resolution analysis in MODWT, the decomposed signals are given in the following way:

$$S_J(t) = \sum_k S_{J,k}\phi_{J,k}(t), \tag{7}$$

$$D_j(t) = \sum_k d_{j,k}\psi_{j,k}(t) \tag{8}$$

where symbols $S_J(t)$ and $D_j(t)$ represent the fluctuation and scaling coefficients, respectively, at the j-th level wavelet that reconstructs the signal in terms of a specific frequency (trending and fluctuation components). Therefore, an empirical time series y(t) can be expressed in terms of those signals as:

$$y(t) = S_J(t) + D_J(t) + D_{J-1}(t) + \cdots + D_1(t). \tag{9}$$

We perform multiresolution analysis with 6 levels of time scales using MODWT with Daubechies least asymmetric (LA) wavelet filter of length L= 8, which is also known as LA(8) wavelet filter. According to Nikkinen et al. (2011), LA(8) wavelet filter has been widely used and applied in the financial literature because it has been shown that LA(8) provides the best performance for the wavelet time series decomposition.

Using afore explained multi-resolution analysis, we can present the dependence structure of a stochastic process between stocks and bonds on a scale-by-scale basis, that is, we can compute wavelet correlation. Let assume a bivariate stochastic process $\mathbb{Z}_t = (x_t, y_t)$ of two time-series, x(t) and y(t), whereby $\widehat{D}_{j,t} = \left(\widehat{D}_{x,j,t}, \widehat{D}_{y,j,t}\right)$ is a scale J wavelet coefficient computed from $\mathbb{Z}_t$. Each wavelet coefficient is obtained by applying the MODWT process in $\mathbb{Z}_t$. The time-dependent wavelet variance for scale J of each time series is then presented as $\sigma^2_{x,j,t} = Var\left(\widehat{D}_{x,j,t}\right)$ and $\sigma^2_{y,j,t} = Var\left(\widehat{D}_{y,j,t}\right)$, while time-dependent wavelet covariance for scale J is $\gamma_{x,y,j,t} = COV\left(\widehat{D}_{x,j,t}, \widehat{D}_{y,j,t}\right)$. Then, wavelet correlation coefficient can be calculated as follows:

$$\rho_{x,y,j,t} = \frac{COV(\widehat{D}_{x,j,t}, \widehat{D}_{y,j,t})}{\left(Var(\widehat{D}_{x,j,t}) Var(\widehat{D}_{y,j,t})\right)^{1/2}} \tag{10}$$

According to Gencay et al. (2002), a nonlinear transformation, defined as $h\rho = tanh^{-1}(\rho)$, is required to produce reasonable confidence intervals for the Fischer's z-transformation correlation coefficient. Assuming estimated correlation coefficient $\hat{\rho}$, based on N independent Gaussian observations $\sqrt{N-3}[h(\hat{\rho}) - h(\rho)] \sim N(0,1)$, the confidence interval $1 - \alpha$ can be estimated for the wavelet correlation according to the following expression:

$$anh \left\{ h\left[\hat{\rho}_{x,y}(J)\right] \pm \xi_{\alpha/2} \left(\frac{1}{\widehat{N}_J} - 3\right)^{1/2} \right\} \tag{11}$$

where $\widehat{N}_j$ is the number of MODWT coefficients associated with scale J, whereas $\xi_{\alpha/2}$ satisfies $P\left[-\xi_{\alpha/2} \leq Z \leq \xi_{\alpha/2}\right] = 1 - \alpha$, and Z has a standard normal distribution.

3.3 Phase Difference

In addition to discrete wavelet analysis (MODWT), which is used to obtain static quantile parameters and wavelet correlations, we also consider continuous wavelet approach, that is, one segment of it – phase difference. Unlike discrete wavelet approach, phase difference can show how direction of the correlation evolve over time as well as the lead-lag relationship between two time-series. More specifically, phase difference describes details about the delays in the oscillation (cycles) between the two time-series under study in different time-horizons. Following Torrence and Webster (1999), phase difference is defined as follows:

$$\phi_{xy}(u,s) = tan^{-1}\left(\frac{\Im\{S(s^{-1}W_{xy}(u,s))\}}{\Re\{S(s^{-1}W_{xy}(u,s))\}}\right) \tag{12}$$

where $W_{xy}(u,s) = W_x(u,s)W_y(u,s)$ is the cross wavelet transform of two time-series, x(t) and y(t) in the continuous wavelet approach, whereas W_x and W_y are the wavelet transforms of x and y, respectively. Symbol u denotes a position index, while s determines the wavelet scale. $\Im$ and $\Re$ are the imaginary and real parts of the smooth power spectrum, respectively.

For our research, we refer to paper of Aguiar-Conraria et al. (2011) and utilize their phase difference method[2], which is capable of determining the average phase-position at specific frequency band. According to these authors, if ϕ_{xy} ∈ (π/2, 0) ∪ (0, -π/2) then the series move in phase. If phase difference is in realm (π/2, 0) then the time-series y leads x. The time-series x leads y if ϕ_{xy} ∈ (-π/2, 0). An anti-phase situation, that is, negative correlation, happens if we have a phase difference in an area ϕ_{xy} ∈ (-π/2, π) ∪ (-π, π/2). If ϕ_{xy} ∈ (π/2, π) then x is leading. Otherwise, time series y is leading if ϕ_{xy} ∈ (-π, -π/2). Phase difference of zero indicates that the time series move together, analogous to positive correlation, at the specified frequency.

4. Dataset

We consider daily closing stock indices of eight East Asian emerging markets, which are – SSEC (China), HSI (Hong Kong), KOSPI (South Korea), SET (Thailand), STI (Singapore), JCI (Indonesia), TWSE (Taiwan) and FTWIPHLL (Philippines). Also, we opt for respective regional 10Y government bond, and several factors support this decision. Firstly, long-term interest rates provide stronger signals to the market participants, than short-term rates, which has a significant effect on investment decisions and profitability of companies. Secondly, long-term interest rates reflect very well market expectations about future outlook for economy and determine to a large extent the cost of borrowing funds. Last but not least, long-term government bonds can be viewed as closer maturity substitutes for stocks.

We decide to observe relatively long time-period in order to cover several global and regional events, which have been characterized by high levels of volatility of the assets. These events, among others, are the Iraqi invasion in 2003, the recent global financial crisis – GFC (2007-2009), the euro-zone sovereign debt crisis (2009-2011), the 2014 oil price plunge. The length of our samples is determined by the availability of the 10Y bond data. Therefore, the inception date for Hong Kong, South Korea, Thailand, Singapore, Taiwan and Philippines is January 2, 2002. For China it is June 7, 2002, and for Indonesia it is August 27, 2004. The end period for all time-series is December 31, 2017. Due to the unavailability of some 10Y bond data, the daily dates are synchronized between two markets according to the existing observations. All time-series are collected from Investing.com. Stock returns (r) are calculated as the first log difference of closing stock price indices (P), according to

[2] The results were obtained by applying ASToolbox of Aguiar-Conraria and Soares (2011).

$r_{i,t} = 100 \times \log(P_{i,t}/P_{i,t-1})$, while changes in 10Y bond yields are computed as the first difference in the level of bond yields between two consecutive observations. We perform the quantile regression computation with the wavelet decomposed series, whereby we observe six wavelet scales, which can provide an insight about stock-bond nexus at different time horizons. These horizons correspond to: scale 1 (2-4 days), scale 2 (4-8 days), scale 3 (8-16 days), scale 4 (16-32 days), scale 5 (32-64 days) and scale 6 (64-128 days). We treat first four scales as the short-term dynamics, midterm is represented by fifth scale, while sixth scale correspond to the long-term dynamics. Descriptive statistics for row empirical series is presented in Table 1, while Figure 1 presents their empirical movements.

Table 2 Descriptive Statistics of Stock Returns and 10Y Bond Yields

	Mean	*St. dev.*	*Skewness*	*Kurtosis*	*JB*	*DF-GLS*	*KPSS*
Panel A. Stock indices							
SSEC	0.022	1.611	-0.456	7.662	3,541	-20.686	0.087
HSI	0.025	1.467	0.055	12.867	15,940	-23.482	0.045
KOSPI	0.040	1.283	-0.453	9.911	7,403	-2.859	0.133
SET	0.048	1.224	-0.511	8.925	5,843	-22.372	0.115
JCI	0.061	1.340	-0.666	10.713	8,046	-8.502	0.128
STI	0.018	1.079	-0.162	9.227	6,495	-6.399	0.084
TWSE	0.011	1.239	-0.309	6.468	1,981	-13.246	0.049
FTWIPHLL	0.049	1.341	-0.384	9.052	6,088	-55.085	0.057
Panel B. 10Y bonds							
China	0.001	0.062	-0.205	9.751	7,178	-54.149	0.152
Hong Kong	-0.001	0.060	0.268	5.805	1,335	-6.259	0.145
South Korea	-0.001	0.053	-0.131	12.373	13,397	-4.705	0.087
Thailand	-0.001	0.063	0.481	9.263	6,491	-3.074	0.043
Indonesia	-0.002	0.178	-0.508	57.608	391,777	-33.479	0.033
Singapore	-0.000	0.055	1.546	87.318	1,189,177	-13.820	0.029
Taiwan	-0.000	0.053	-0.293	140.849	3,034,113	-8.543	0.205
Philippines	-0.002	0.140	0.577	25.683	84,386	-8.799	0.151

Notes: JB stands for values of Jarque-Bera coefficients of normality. Assuming only constant, critical values at 1% and 5% for DF-GLS test with 5 lags are -2.566 and -1.941, respectively. Critical values at 1% and 5% for KPSS test are 0.739 and 0.463, respectively.

The average daily stock return, over the full sample period, is positive, whereby JCI has the highest mean and FTWIPHLL follows. This indicates the general increasing trend in stock prices during the period of study. On the other hand, the average daily change for 10-year government bond yields is predominantly negative and very close to zero, reflecting the clear downward trend. Table 1 indicates that yields on long-term government bonds have lower volatility than stock returns for all the countries. The sign of skewness is negative for all the equity returns, while mixed signs characterize 10-year bond yields. Kurtosis heavily exceeds the reference value of the normal distribution (equal to 3) for all the considered time-series, which particularly applies for the bond yield differentials. This finding suggests the existence of heavy tails compared to the Gaussian distribution. The JB test statistics corroborate this evidence at one percent significance level. Since we detect heavy tails and extreme values, our wavelet-based quantile approach is appropriate due to the following reasons. Firstly, wavelet method is suitable for finding extreme movements and for empirical signals that contains numerous outliers (see e.g. Jammazi, 2012 and Dewandaru et al., 2014). Secondly, quantile regression estimators are fairly robust to deviations from normality and performs very well in extreme value environment, since quantile functions provide information about the average dependence as well as the extreme tail dependence. In order to determine the level of integration of the variables, we perform Dickey–Fuller GLS unit root test and the Kwiatkowski–Phillips–Schmidt–Shin stationarity test. All tests indicate that selected series of the stock returns and the government bond yield differentials are stationary. These findings concur with the earlier works on the stock-bond interlink (see Thuraisamy, 2014; Shamsuddin, 2014).

Figure 1 Empirical Dynamics of Selected Stock Indices and 10Y Government Bond Yields

Notes: Black and grey lines denote the empirical movements of stock index and 10Y bond yield, respectively.

5. Empirical Wavelet-Based Quantile Regression Results

This section presents the bidirectional dependence structure between the stock returns and bond yield, calculated via wavelet-based quantile approach, and Tables 2 and 3[3] show the estimated coefficients at seven quantiles and six wavelet scales. Considering seven quantiles that range from 0.05 to 0.95, we can see how the stock and bond markets interact in periods of severe financial stress, but also in moderate market conditions and in periods of high bull market states. The sign of quantile coefficients can hint whether positive or negative correlation explains the interlink between stock and bond markets. In other words, if positive (negative) sign is predominant throughout the quantiles and across wavelet scales, it means that stock returns and bond yields move in the same (opposite) direction at different time-horizons. As we have mentioned earlier, the most likely reason why negative sign occurs is the fact that rising interest rates increase the cost of capital, which consequently reduces the present value of future cash flows, thereby lowering companies' equity prices.

On the other hand, positive sign is mainly related to the transfer of capital funds between stock and bond markets in a search of safer and more profitable investments. In periods of increased market stress, flight-to-quality behaviour arises, which means that investors shift from riskier stocks toward safer government bonds, causing an increased demand for bonds that consequently decreases bond yields. Reverse happens in the bullish periods, that is, if positive expectations about future stock markets' prospects dominates among investors, then capital funds have tendency to move from bond markets towards stock markets, which lowers the bond prices and increases bond yields. Also, it should be said that after GFC, central banks of the US and other developed countries conducted extremely low interest rate policy, which resulted in capital flows to stock markets of emerging countries. These developments spur stock prices to rise, and when it is coupled with increasing bond yields, it could create positive quantile parameters between stock returns and bond yields.

Tables 2 and 3 suggest that most of the estimated quantile coefficients are highly statistically significant, whereby they vary across quantiles and wavelet scales, and bear predominantly positive or negative sign depending on the country under observation. Also, it is evident that quantile parameters are much higher when spillover goes from bond yields to stock returns, than *vice-versa*. Taking into account both spillover directions, we can see that highly significant negative quantile coefficients are dominant across all wavelet frequencies in Indonesia and Philippines. In the case of Thailand, negative and highly statistically significant quantile parameters are visible at longer time horizons, that is, at fifth and particularly sixth wavelet scales. In short time-horizon, quantile parameters are mostly insignificant in the case of Thailand. In the Hong Kong and Singaporean cases, all parameters are highly statistically significant, where positive quantile parameters prevail at short and midterm, whereas negative parameters can be found at long-term.

[3] In order to provide visual depiction of estimated quantile parameters, which might enhance the readability of the results, we present quantile regression plots for D1, D5 and D6 wavelet scales in the Appendix, which correspond to short-term, midterm and long-term horizons.

Table 2 Spillover Effect from 10Y Bond Yield Differential Toward Stocks Returns

	Quantile estimates						
	0.05-th	*0.2-th*	*0.35-th*	*0.5-th*	*0.65-th*	*0.8-th*	*0.95-th*
China							
D1	0.7420	-0.1890	-0.5423	-0.2322	-0.5601	-0.2222	0.2932
D2	-0.2196	-0.3870	0.1438	0.1249	0.4498	0.1425	0.3894
D3	0.9728	0.9175	0.4872	0.3449	0.1592	1.4730	-0.2222
D4	1.1726	2.2539***	0.1781	-1.1443*	-0.1334	0.4529	-3.5382*
D5	5.6428**	2.3315***	3.4766***	3.7805***	2.5157***	5.3591***	1.7020
D6	8.3588***	3.5637***	2.2276**	4.1229***	4.4080***	6.4282***	1.3444
Hong Kong							
D1	5.8582***	4.2896***	4.2787***	4.2165***	3.6097***	3.6669***	3.7227***
D2	4.1091***	3.3346***	2.9840***	2.4733***	2.5392***	2.6647***	4.2182***
D3	3.7927***	4.8535***	4.4139***	4.1175v	4.7628***	5.2945***	7.5583***
D4	5.9180***	4.6886***	4.9419***	4.8585***	5.2683	5.6163***	5.8652***
D5	4.9632***	2.8665***	2.7294***	1.7774***	1.3280***	1.4658***	3.0706***
D6	-4.9252***	-3.7852***	-3.4099***	-4.3030***	-3.7803***	-4.7210***	-9.7000***
South Korea							
D1	3.7001***	3.6576***	3.1379***	3.1921***	2.7669***	2.7643***	2.9873***
D2	3.4161***	2.9802***	2.3817***	2.2855***	2.5865***	2.3976***	2.2592***
D3	4.0323***	4.5494***	2.9604***	3.5469***	3.7479***	3.8434***	4.8246***
D4	2.1715***	3.2772***	2.9766***	2.5426***	2.3744***	2.0169***	2.3087***
D5	1.6873***	1.7224***	1.6469***	1.4690***	0.5074	-0.6307	-1.6193
D6	4.8965***	3.9337***	2.5640***	3.9576***	3.7811***	4.3212***	2.7577***
Thailand							
D1	1.6455***	0.3519	0.4230	0.4019	0.2818	0.4220	1.5994***
D2	-0.2096	0.3971	0.5092	0.3242	0.5632	0.5597	0.5764
D3	-0.6808	-0.9768*	-1.1690**	-1.3723***	-1.3675***	-0.8643*	1.0084
D4	-0.1488	-0.6841*	-0.3123	-0.2581	-0.7187*	-0.9538**	-0.1307
D5	-1.9828***	-0.8413***	-1.0076***	-0.7537*	-0.7207*	-0.5354	0.1314
D6	-2.5348***	-2.6928***	-2.8089***	-2.8589***	-3.5449***	-5.1793***	-3.7576***
Indonesia							
D1	-0.4673***	-0.3244***	-0.4540**	-0.3882**	-0.2441**	-0.2392	-0.6103***
D2	-1.5467***	-1.8538***	-1.5984***	-1.5199***	-1.6574***	-1.7482***	-1.4969***
D3	-4.0461***	-4.1520***	-3.9033***	-3.7960***	-3.9693***	-4.1044***	-4.6170***
D4	-3.8007***	-4.1173***	-4.1753***	-4.2019***	-4.0329***	-4.1393***	-3.9013***
D5	-5.0382***	-4.4166***	-4.2829***	-4.2145***	-4.4800***	-4.9925***	-4.4753***
D6	-4.8851***	-4.8659***	-4.8065***	-4.7561***	-4.8587***	-5.0518***	-5.5113***
Singapore							
D1	3.9981***	2.8946***	2.3532***	2.2233***	2.4247***	3.1781***	4.3883***
D2	3.8583***	2.5012***	1.9609***	1.6451***	1.5127***	1.3755***	2.6029***
D3	2.4155***	2.6179***	2.4227***	3.0373***	2.8270***	3.4114***	3.6065***
D4	4.9359***	4.3743***	3.6870***	4.2836***	4.5488***	4.9987***	6.0447***
D5	4.0693***	2.2638***	2.2296***	2.3280***	3.1158***	4.2289***	2.9159***
D6	-1.7440*	-3.4890***	-2.9751***	-3.2365***	-3.9576***	-5.0882***	-7.4331***
Taiwan							
D1	3.2848***	2.4818***	2.3761***	2.4714***	2.7600***	2.7372***	2.5568***
D2	5.0359***	4.6088***	3.9050***	4.0032***	4.5515***	4.2611***	3.8949***
D3	12.0835***	9.1751***	7.6184***	7.7149***	8.3522***	10.3795***	11.3157***
D4	9.0939***	8.1470***	7.7616***	8.0129***	8.7577***	10.6383***	12.9041***
D5	6.2938***	6.2672***	4.6068***	4.9324***	5.9378***	7.3898***	6.1589***
D6	5.2276***	2.7306***	2.6253***	2.0401**	2.5632***	5.1096***	12.0083***
Philippines							
D1	-0.7261***	-0.6847***	-0.5797***	-0.6100***	-0.7176***	-0.7596***	-1.2259***
D2	-1.4071***	-0.8675***	-0.7560***	-0.8573***	-1.0483***	-1.2851***	-1.4089***
D3	-1.8866***	-0.9875***	-0.8755***	-0.9877***	-0.9544***	-1.3107***	-2.1917***
D4	-2.9300***	-1.9324***	-1.7705***	-1.6419***	-1.9960***	-2.3446***	-3.0237***
D5	-2.9689***	-2.7761***	-2.7031***	-2.9401***	-3.1989***	-2.6864***	-2.5553***
D6	-5.5591***	-4.9637***	-5.3810***	-5.0754***	-5.1645***	-5.0633***	-3.5328***

Notes: ***, **, * represent statistical significance at the 1%, 5% and 10% level, respectively.

The Chinese quantile parameters are mostly insignificant in the short-horizon, but they take positive value in the midterm and long-term horizons. In the cases of

Taiwan and South Korea, we find only highly statistical positive parameters across quantiles and wavelet scales, which indicates that stock returns and bond yields co-move in the same sense during the bear, normal and bull periods.

The rationale behind such diversified parameter signs among selected countries could be found in a level of markets' development. In other words, capital mobility between stock and bond markets is relatively modest in less developed financial markets such as Indonesia, Philippines and Thailand. In these countries, investors do not transfer their funds frequently between these markets in a search of more profitable investments, thus the stock-bond interlink is rather explained by DDM, which supports negative correlation. In other words, in turbulent periods, investors do not shift from equity to bond markets, but rather abandon both markets, which causes stock prices fall and bond yield rise. This type of dynamics is clearly visible in Indonesian and Filipino plots in Figure 1 around the time of GFC. Also, it is interesting to note that magnitude of negative quantile coefficients is greater at higher wavelet scales in all less developed markets, that is, Indonesia, Philippines and Thailand (see Table 2). This is in line with the assertion that DDM stands behind the stock-bond nexus in these countries. In other words, at longer time-horizons, the impact of interest rates on stock prices is greater than in shorter time-horizons, because more future cash flows are divided by higher discount factor.

Conversely, in more developed markets, such as Hong Kong, Singapore, South Korea and Taiwan, the positive parameters support the claim that cross-market capital transfers most likely stand behind the stock-bond relations. It means that in tranquil periods as well as in periods of market turmoil, investors choose more safer and more profitable market to invest. It applies particularly for crisis periods, when investors abandon riskier stock markets and invest in a safer bond market, which induces fall in both stock prices and bond yields (see Figure 1 around GFC period). Interestingly, Table 2 suggests that positive quantile parameters are greater at shorter time-horizons (third and fourth wavelet scales) than at longer time-horizons (fifth and sixth wavelet scales) in all developed East Asian markets. This finding supports the notion that capital funds change position between these markets in shorter time-frames in a search for more lucrative and safer investments, which is not the case with the less developed financial markets. For instance, Table 2 suggests that spillover effect in the cases of Hong Kong and Singapore is the strongest at D4 scale, but it is also very strong at very short time horizon (D1 scale). South Korea has very strong short-term spillover effect, but the spillover impact from bonds toward stocks is also high at the longest time horizon (between 64 and 128 days). Of all the selected East Asian markets, Taiwan has the highest spillover effect from bond to stocks and it happens at D3 and D4 wavelet scales, that is, at short-term. Some Taiwanese upper and lower tail parameters even exceed the magnitude of 12. This finding is in line with descriptive statistics' presentation in Table 1, which suggest that Taiwanese bonds are the asset with the highest kurtosis that goes beyond 140. In other words, Taiwanese bond series contain highest number of extreme outliers, which consequently induce high spillover effect on Taiwanese stocks. As for the Chinese quantile parameters, these are positive and statistically significant only at mid and long-term, taking into account both spillover directions, which indicates that, in Chinese markets, transfer of capital between stock and bond occurs only in relatively longer time-horizons.

Table 3 Spillover Effect from Stock Returns Toward 10Y Bond Yield Differential

	Quantile estimates						
	0.05-th	*0.2-th*	*0.35-th*	*0.5-th*	*0.65-th*	*0.8-th*	*0.95-th*
China							
D1	-0.0013	-0.0008	-0.0007	-0.0004	-0.0005	-0.0004	0.0008
D2	-0.0013	-0.0006	0.0001	0.0000	0.0003	0.0002	-0.0003
D3	0.0019	0.0003	0.0004	0.0005	0.0002	-0.0002	0.0009
D4	-0.0001	0.0001	-0.0003	0.0003	0.0005	0.0005	-0.0007
D5	0.0018*	0.0014***	0.0019***	0.0028***	0.0024***	0.0027***	0.0024***
D6	0.0023***	0.0021***	0.0019***	0.0009**	0.0019***	0.0033***	0.0028***
Hong Kong							
D1	0.0064***	0.0078***	0.0080***	0.0082***	0.0084***	0.0088***	0.0094***
D2	0.0052***	0.0057***	0.0061***	0.0062***	0.0065***	0.0051***	0.0066***
D3	0.0081***	0.0084***	0.0082***	0.0082***	0.0082***	0.0094***	0.0099***
D4	0.0094***	0.0090***	0.0095***	0.0100***	0.0108***	0.0108***	0.0097***
D5	0.0046**	0.0015***	0.0026***	0.0043***	0.0055***	0.0054***	0.0069***
D6	-0.0115***	-0.0083***	-0.0051***	-0.0061***	-0.0077***	-0.0095***	-0.0152***
South Korea* **							
D1	0.0037***	0.0061***	0.0064***	0.0055***	0.0051***	0.0049***	0.0069***
D2	0.0056***	0.0057***	0.0063***	0.0061***	0.0059***	0.0053***	0.0013
D3	0.0060***	0.0065***	0.0076***	0.0072***	0.0071***	0.0058***	0.0048***
D4	0.0061***	0.0040***	0.0034***	0.0019***	0.0024***	0.0035***	0.0019
D5	0.0023*	0.0040***	0.0040***	0.0035***	0.0044***	0.0036***	0.0009
D6	0.0073***	0.0098***	0.0090***	0.0103***	0.0076***	0.0041***	0.0125***
Thailand							
D1	0.0024	0.0011	0.0028***	0.0021***	0.0018**	0.0029***	0.0041**
D2	0.0015	-0.0002	-0.0009	-0.0001	-0.0004	0.0004	0.0017
D3	-0.0011	-0.0025***	-0.0028***	-0.0026***	-0.0019***	-0.0025***	-0.0022*
D4	0.0005	0.0000	-0.0004	-0.0017	-0.0016	-0.0020*	-0.0020***
D5	-0.0008	0.0007	-0.0027**	-0.0045***	-0.0043***	-0.0035***	-0.0031**
D6	-0.0149***	-0.0087***	-0.0091***	-0.0112***	-0.0100***	-0.0090***	-0.0175***
Indonesia							
D1	-0.0146**	-0.0067**	-0.0063***	-0.0077***	-0.0078***	-0.0076***	-0.0080
D2	-0.0302***	-0.0188***	-0.0159***	-0.0150***	-0.0172***	-0.0209***	-0.0288***
D3	-0.0575***	-0.0362***	-0.0324***	-0.0307***	-0.0305***	-0.0353***	-0.0537***
D4	-0.0543***	-0.0438***	-0.0404***	-0.0387***	-0.0394***	-0.0402***	-0.0464***
D5	-0.0718***	-0.0578***	-0.0588***	-0.0582***	-0.0598***	-0.0608***	-0.0842***
D6	-0.1248***	-0.0823***	-0.0758***	-0.0751***	-0.0796***	-0.0837***	-0.1249***
Singapore							
D1	0.0090***	0.0080***	0.0085***	0.0081***	0.0081***	0.0092***	0.0104***
D2	0.0093***	0.0064***	0.0063***	0.0059***	0.0063***	0.0069***	0.0083***
D3	0.0100***	0.0070***	0.0077***	0.0077***	0.0069***	0.0064***	0.0082***
D4	0.0080***	0.0096***	0.0097***	0.0097***	0.0095***	0.0095***	0.0119***
D5	0.0076***	0.0062***	0.0055***	0.0051***	0.0051***	0.0074***	0.0069***
D6	-0.0123***	-0.0053***	-0.0044***	-0.0047***	-0.0052***	-0.0070***	-0.0192***
Taiwan							
D1	0.0080***	0.0061***	0.0051***	0.0050***	0.0051***	0.0061***	0.0077***
D2	0.0078***	0.0047***	0.0042***	0.0042***	0.0044***	0.0053***	0.0073***
D3	0.0076***	0.0066***	0.0059***	0.0055***	0.0054***	0.0060***	0.0079***
D4	0.0076***	0.0065***	0.0052***	0.0050***	0.0051***	0.0060***	0.0079***
D5	0.0091***	0.0045***	0.0036***	0.0029***	0.0037***	0.0029***	0.0042***
D6	0.0069***	0.0040***	0.0033***	0.0031***	0.0021***	0.0020***	0.0017
Philippines							
D1	-0.0176***	-0.0090***	-0.0056***	-0.0047***	-0.0061***	-0.0097***	-0.0229**
D2	-0.0205***	-0.0104***	-0.0067***	-0.0049***	-0.0054***	-0.0078***	-0.0089**
D3	-0.0097***	-0.0069***	-0.0065***	-0.0066***	-0.0075***	-0.0082***	-0.0054***
D4	-0.0163***	-0.0101***	-0.0075***	-0.0074***	-0.0086***	-0.0092***	-0.0249***
D5	-0.0233***	-0.0151***	-0.0174***	-0.0169***	-0.0162***	-0.0155***	-0.0132***
D6	-0.0629***	-0.0469***	-0.0390***	-0.0353***	-0.0379***	-0.0403***	-0.0512***

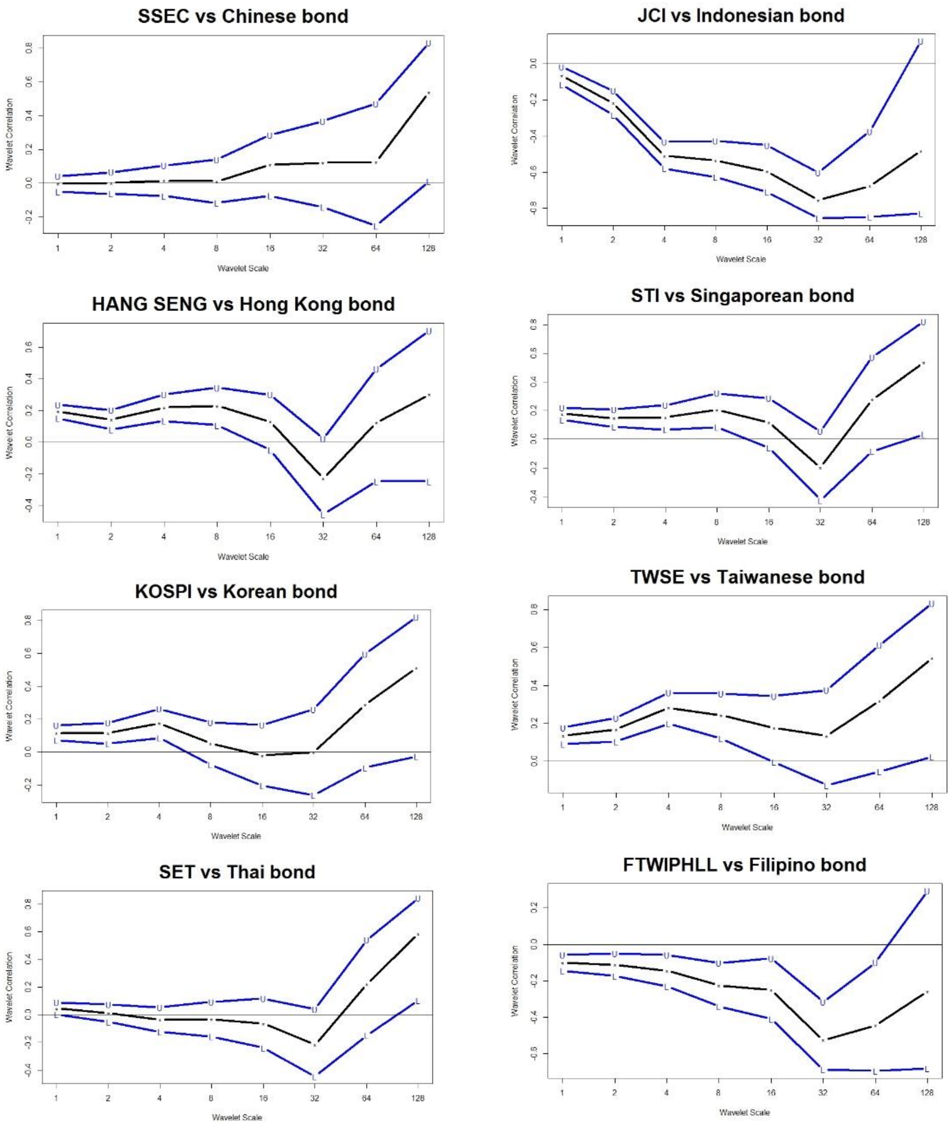
Notes: ***, **, * represent statistical significance at the 1%, 5% and 10% level, respectively.

Observing the tail quantiles as well as more moderate quantiles and median quantile, we can assess the bidirectional dependence structure between these markets in periods of extreme market stress, moderate market conditions and market booms. Tail quantile parameters in the less developed East Asian markets are not much larger than their median counterparts, whereas in some cases (Indonesia at D4 scale) quantile tail parameters are even lower than median ones. This is an indication that capital reallocation does not occur in crisis periods in these economies. On the other hand, it is interesting to note that in all more developed East Asian financial markets, tail parameters, are higher than median parameters at very short time horizons, that is, at D1 and D2 wavelet scales, which particularly applies for the left tail quantile parameters. It means that in periods of increased market turmoil, shocks transfers from bond markets to stock markets, and we find the strongest effect in Hong Kong stock market, while Singaporean stock market follows at D1 and D2 scales. This coincide with the results of Ferrando et al. (2017), who researched stock-bond relations in Spanish economy, also using the quantile regression methodology. They found that the effect of 10-year sovereign bond rate fluctuations on industry equity returns varies across quantiles and has a tendency to be more pronounced during extreme market conditions in the stock market than during normal regimes. They argued that in times of enhanced market stress in either up or down, market participants ignore their own information and exhibit herding behavior, which can be excessively optimistic or pessimistic and may lead to a disproportionate response to changes in equity fundamentals such as interest rates.

Since left quantile tail parameters are very high relative to medium ones in all more developed East Asian markets, we can suspect that beside national stock-bond relations, there are also present cross-country market linkages, which can be described as contagion effect (see e.g. Dungey and Gajurel, 2014; Klinger and Teply, 2016; Abad and Chulia, 2016). This assertion can be underpinned by the finding that Thai left and right tail parameters are high and positive in very short time-horizon, that is, at D1 scale. Thailand financial markets characterize relatively low liquidity and thin trading, thus positive quantile parameters, which are associated with the cross-market capital transfers, are not something that is expected to be found. However, Thai positive tail parameters indicate that contagion effect probably occurred in Thai markets during recent global financial crisis. Baur and Lucey (2009) claimed that the flight-to-quality phenomenon is a common feature in a crisis period across different countries, whereby stock markets fall and bond markets increase simultaneously.

In order to further enrich our quantile regression findings, we calculate wavelet correlations, which observes the strength of correlation across six wavelet scales, and the results are presented at Figure 2. It is evident that signs of wavelet correlations mostly coincide with the sign of the wavelet-based quantile regression coefficients. Also, Figure 2 indicates that the level of negative correlation in Indonesian case is particularly high and goes up to 80% in midterm and long-term horizons. Comparing to the strength of the Filipino and Thai negative correlations, Indonesian correlation is much higher. The rationale for this finding could be found in the level of average annual inflation, and Table 4 contains these results. It can be seen that Indonesia has by far the highest inflation of all the East Asian economies, which implies that inflation expectations are also high. According to Fisher's equation, inflation expectations can be easily embedded in the nominal bond interest rates, and consequently the higher nominal interest rates lower the equity prices when they are calculated via DDM. It is worth to mention that high inflation expectations also affect short-range wavelet correlation between stock returns and bond yields.

Figure 2 Wavelet Correlations Between Stock Returns and 10Y Bond Yields



Notes: The "U" line represents the upper bound, while the "L" line stands for the lower bound at 95% confidence level. Doted lines represent wavelet correlations.

As can be seen in Figure 2, very short wavelet correlation (up to 4 days) reach almost 50% in case of Indonesia, while all other short-term correlations do not exceed 20%. In addition, it is obvious that at longer time horizons, negative correlations are stronger than in shorter time horizons, which is in line with the DDM concept.

Table 4 Average Inflation Between 2002-2017 for Selected East Asian Economies

	China	*Hong Kong*	*S. Korea*	*Thailand*	*Indonesia*	*Singapore*	*Taiwan*	*Philippines*
Avg. inf.	2.41	0.15	2.51	2.20	6.91	1.74	1.03	3.89

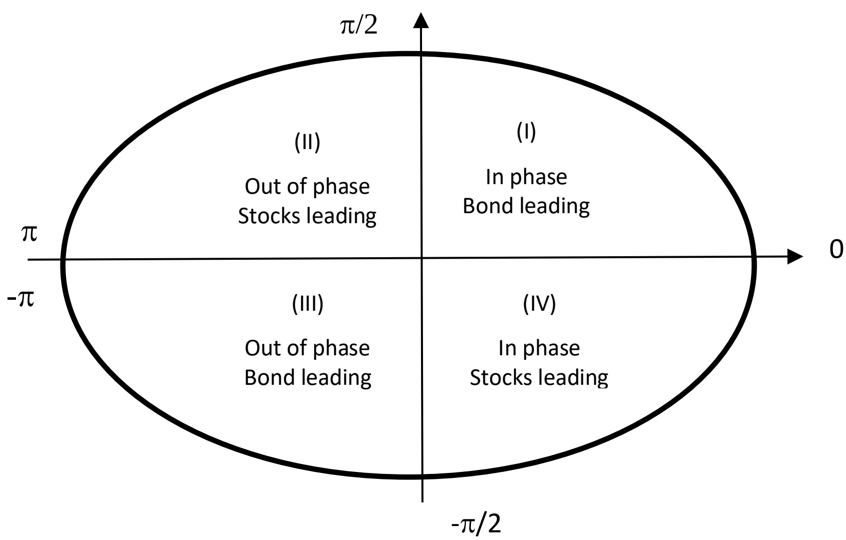
Source: International financial statistics.

On the other hand, positive correlation is mostly an aftermath of the portfolio rebalancing activities, and it can be seen that positive correlations are not as strong as negative correlations can be. In other words, the highest peak that is reached by positive correlation is around 40-50% at long-term horizons, while negative correlation goes beyond 70% in case of Indonesia.

6. Complementary Analysis via Phase Difference

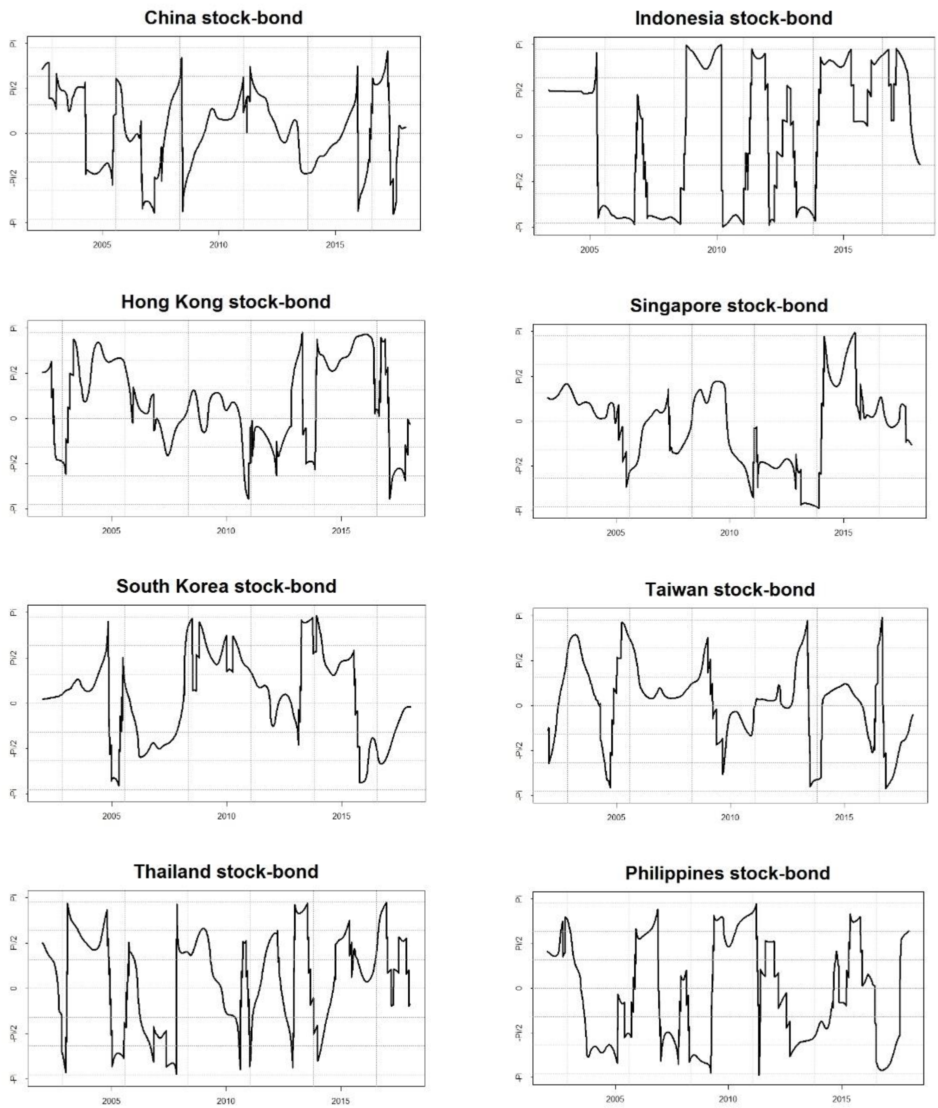
In order to determine the lead-lag relationship between stock returns and 10Y bond yields, we apply the phase difference methodology of Aguiar-Conraria and Soares (2011), which is capable of determining a direction of correlation and lead-lag relations between the two variables throughout the sample and at specific frequency band. Dajčman (2013) explained that knowing the lead-lag relationship could be useful for investors, because empirical movements of leading variable can be utilized to forecast the realizations of the lagging time series, which eventually can help in setting up investment positions.

Figure 3 Phase Difference Circle



Due to the fact that strong minimal phase difference does not exist under minimum dependency, we only calculate phase difference in the midterm and long-term, while results for the short-term is omitted. As Figure 2 suggests, relatively high correlation between stock returns and bond yields is only visible in midterm and long-term horizons. In order to facilitate an interpretation of phase difference plots, we present graphically a lead-lag relationship between stocks and bond via phase difference circle in Figure 3.

Figure 4 Phase Difference at 32-64 Frequency Band

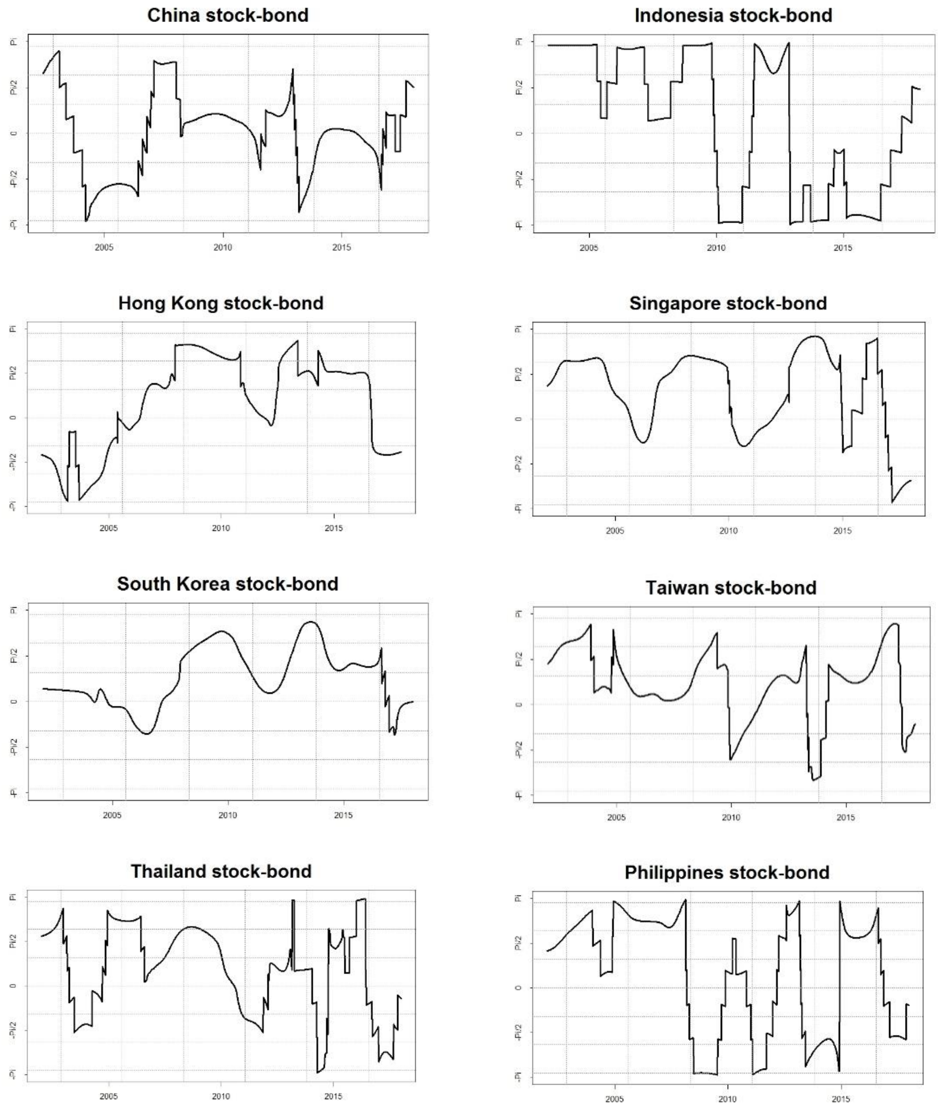


Observing Figures 4 and 5, it can be noticed that phase difference dynamics mostly coincide with the wavelet-based quantile estimates and the wavelet correlation results, which contributes to the robustness of our overall findings. Looking at Figure 4, it can be seen that phase difference is dominantly in a realm between $\pi/2$ and $-\pi/2$ in developed East Asian markets, which indicates to positive correlation and which is in accordance with the D5 quantile parameters. Unlike quantile parameters, phase difference can determine which variable leading and which one is legging, and particularly useful is to gain an insight which variable has leading role in a crisis period, e.g. global financial crisis, and which one has an upper hand in tranquil periods. According to Figure 4, leading role had stocks in Hong Kong, South Korea and Singapore around GFC period, while in Taiwan, that was government bond.

On the other hand, phase difference suggests that negative correlation was present during GFC in Indonesia, Thailand and Philippines, whereby bonds had the leading role. For Indonesia, Thailand and Philippines, phase difference coincides very well with the D5 quantile parameters in terms of correlation direction, since all D5 quantile parameters bear negative sign. As for China, it is not quite clear what is the direction of correlation, because phase difference finds itself frequently in both in-phase and anti-phase positions.

Looking at plots in the long-term frequency band, it is apparent that phase difference dynamics in the long-term is more stable and smoother in comparison with the midterm phase differences. Unlike midterm plots, Hong Kong and Singaporean long-term phase differences spend more time in anti-phase domain, that is, beyond $\pi/2$ and $-\pi/2$ boundaries, which is in line with estimated quantile parameters, since all D6 quantile parameters have negative sign for these two economies. Explanation for these findings could be that DDM determines the stock-bond relations in the long term in these economies, rather than capital reallocations. Also, it should be said that due to the fact that phase difference is predominantly beyond $\pi/2$ border, it means that stock market has a leading role in these countries. In South Korean case, we find some anti-phase sequences, but they are not as conspicuous as in the cases of Hong Kong and Singapore. This result also concurs with the quantile parameter estimates, since all D6 parameters have positive sign. South Korean phase difference mostly take position between zero and $\pi/2$, which suggests that bond leads for most of the time in long-run. In the cases of Taiwan and China, phase difference moves mostly between $\pi/2$ and $-\pi/2$ boundaries, which indicates that positive correlation stands behind stock-bond nexus even in the long-term. In Taiwan, bond has an advantage till 2010, while afterwards it is stock that is leading. In the Chinese case it not clear which asset has a dominant role because phase difference moves interchangeably above and below zero. For Indonesia, Thailand and Philippines, phase difference is mostly in an anti-phase situation, which is in accordance with the quantile regression parameters. In Indonesia, stock has leading role till 2010 and in 2012, while from 2012 to 2016 it is bond that is leading. In case of Philippines, stocks have leading role till 2009 and in 2013 and 2015, whereas bond leads in 2009, 2011 and 2014. It interesting to mention that, during GFC, stocks have leading role in most of the selected economies, taking into account both more developed and less developed East Asian markets.

Figure 5 Phase Difference at 64-128 Frequency Band



7. Implications for Market Participants

The results of this paper could help investors and portfolio managers who invest in East Asian region at various investment horizons to make a decision about their portfolio allocations. This paper also promotes a better understanding of how diversification benefits vary between different states of economy, that is, in tranquil and crisis periods. In the more developed East Asian financial markets, the interdependence is overwhelmingly positive, particularly in the short and midterm horizons. Taking into account that positive correlation between stock returns and bond yield produces negative correlation between stock and bond prices, it strongly ensures opportunities for diversification and hedging in the more developed East Asian economies, which is particularly highlighted in the short-term in turbulent periods. In other words, the results indicate that bond of these emerging markets could serve as safe haven and hedging tool for investors in periods of market distress.

On the other hand, negative quantile parameters are dominant in all quantiles and at all wavelet scales in the less developed East Asian economies. Due to the fact that negative correlation between stock returns and bond yield imply positive correlation between stock and bond prices, it means that the diversification potential in the less developed East Asian economies is very limited. It also signifies that capital mobility does not occur frequently between these markets, which also applies for crisis periods. In other words, these results suggest that investors in less developed East Asian financial markets most likely rebalance their portfolios in crisis periods by selling both stocks and government bonds, and move their funds, probably, in gold market.

In addition, by providing an information whether capital funds abandon both markets or they just move from one market to the other in crisis, could serve as guidelines for governments' macroprudential regulation efforts. In fact, having an indication that sovereign ratings will not fall down in turbulent times could increase the perception about the emerging market's credit risk profile. On the other hand, in countries in which capital leaves both markets in turbulent times, it is a sign that government should put more work to increase domestic bond confidentiality and overall creditworthiness.

8. Conclusion

This paper tries to thoroughly determine how stock returns and 10Y bond yield interact in eight emerging East Asian economies. Our method of choice is the wavelet-based quantile approach, which can provide an answer about bidirectional dependence structure between these markets under different market conditions and in different time horizons.

The results indicate that shock spillover effect is much more intense from bond markets towards stock markets in all the selected economies, than *vice-versa*. Spillover impact from bond toward stocks is the strongest in Taiwan, whereas Hong Kong follows. In addition, in more developed financial markets, such as Hong Kong, South Korea, Singapore and Taiwan, the nexus is dominantly positive, particularly in the short and midterm horizons. It suggests that capital reallocation takes place between stock and bond markets in these economies in a search for safer and more profitable investments in both tranquil and crisis periods. In the long term horizon, we find negative quantile parameters in Hong Kong and Singapore, which explains that the discount dividend model stands behind stock-bond interlink in long-run in these two economies. As for the less developed East Asian economies, the negative quantile parameters are overwhelmingly present in all quantiles and in all wavelet scales. It signifies that transfer of capital does not occur frequently between these markets, and it also means that DDM is the decisive factor that drives the stock-bond interdependence in all time horizons.

In addition, the tail quantile parameters are significantly higher than the median ones in the more developed financial markets, while in the less developed economies this is not the case. This is an indication that in turbulent periods investors shift from riskier stock market towards safer bond markets in the more developed East Asian economies, whereas both markets get abandoned by investors in turbulent times in the less developed East Asian economies. Phase difference findings contribute to the robustness of the quantile estimates, also suggesting that stocks had the leading role in most of the selected economies during GFC in the long-term horizon. In addition, wavelet correlation results indicate that higher annual inflation increases wavelet correlations between stock returns and bond yield in short-term.

Taking into account the shock spillover effect as well as the level of correlation between stock and bond markets, this paper could provide a useful information for investors who combine stock and bonds in a portfolio, and who act in different time-horizons in the East Asian region.

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