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DISCUSSION PAPER SERIES

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ABSTRACT

Transmission of US and EU Economic Policy Uncertainty Shock to Asian Economies in Bad and Good Times

This study empirically examines the fragility of five major Asian economies (China, Hong Kong, India, Japan, and South Korea) to economic policy uncertainty (EPU) of US and EU, and oil prices in different state of the economies. To investigate these dynamics, we use the relative tail dependence by means of the spillover index of Diebold and Yilmaz (2009, 2012) obtained from Quantile Vector Autoregressive (QVAR) model, a robust and semiparametric model, which does not require specification of the full distribution of error terms. The distinguishing feature of our approach from the previous studies is the determination of sign and intensity of asymmetric spillover dynamics from external shocks to Asian economies and variables covering a wide range of macroeconomic aspects. Our results indicate that the spillover indices from EPU and oil price shocks to Asian economies significantly vary across quantiles. The results from sub-sample analysis show that the US EPU has an asymmetric effect on macro variables of China, Hong Kong, and South Korea during the quantitative easing period (QE) and the reverse QE (RQE) periods while the EU EPU makes Asian markets vulnerable during the Eurozone debt crisis. The large-scale asset purchases (LSAPs) of ECB and BoJ seem to reduce Asian market fragilities after 2015. Last but not least, we get partial evidence to support an asymmetric effect of the crude oil shocks on some Asian markets.

JEL Classification: C32, E44, F42, G01

Keywords: economic policy uncertainty, oil price change, quantile VAR, relative-tail-dependence

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1. Introduction

Economic policy uncertainty (EPU) appears to increase rapidly after major economic, financial and political shocks, such as the 1997–98 Asian financial crisis, September 11 terrorists attack, Gulf War II, Lehman failure and 2008 Global Financial Crisis (GFC), FOMC announcements, European sovereign debt crisis, and trade wars. Policy decision-makers, business circles, portfolio investors and even households across the globe worry such kinds of uncertainty arising from the United States (US) and European Union (EU)–the world's largest economies (IMF, 2013). Spillover from US EPU and EU EPU would have crucial global consequences due to their relatively large size and strong trade and financial linkages with other economies. For instance, the rising economic policy uncertainty may decrease international trade through declining economic activity and import demand. Furthermore, the global risk aversion caused by economic uncertainty may result in sudden movements in international financial markets and rapid capital outflows from developing countries. Moreover, the rise of uncertainties after such events may reduce investment by fostering a progressively widespread wait-and-see attitude and lead firms to postpone spending projects until anticipations for economic activity became more obvious (see Bloom, 2009 and Caggiano *et al.*, 2017). In addition to the investment, economic uncertainty also deteriorates the consumption behavior of households with the concept of the savings driven by precautionary motives (Caballero, 1990).

Besides economic policy uncertainty, oil price and oil price volatility also play a significant role in economic activity through supply and demand channels. The oil price rise may decrease the supply of other goods due to incremental cost. Blanchard and Gali (2007) and Herrera and Pesavento (2009) examine the relationship between oil prices and various macroeconomic variables. They find a strong relationship between them. Due to this close relationship, the oil price expectedly affects national income. Moreover, the financialization of commodity markets starts to play a significant role in price changes in addition to other macroeconomic forces, including the demand from commodity-intensive industrializing economies (Silvennoinen and Thorp, 2013). With the financialization of the oil market after the early 2000s, there has been an increase in speculative attacks in the oil market and this situation leads oil prices to impact not only on production of goods but also on the financial assets. Before 2008, the oil price with other commodities increased sharply and the underlying reasons are tried to be explained by several important views. Some prominent views included strong global growth, abundant liquidity created by the ultra-low-interest rate environment, speculative bubbles and risks from geopolitical uncertainty (Frankel and Rose, 2010). However, it was different after 2008 since central banks such as Federal Reserve (Fed), Bank of England and Bank of Japan (BoJ) resorted to enlarging its balance sheet to inject liquidity directly into the economy via purchasing predetermined amounts of government bonds or other financial assets. This excessive liquidity through quantitative easing programs results in an increase in demand riskier assets includes commodity (Glick and Leduc, 2012).

In the wake of the financial crisis and serious recession, the central banks of advanced countries launched large asset purchasing programs (LASPs), known as quantitative easing (QE), at different times. Tillmann (2016) states that QE has considerable effects on EME's financial conditions and plays a substantial role in explaining capital inflows, equity prices, and exchange rates. The timing of disclosure of these QEs, the amount of financial asset purchased, the announcement of future tapering and whether central banks will eventually reduce the balance sheets or not trigger economic uncertainty in the financial markets. This shows us that countries that provide significant relief from globally abundant money during QE periods may face a devastating impact during the reverse-quantitative easing (RQE) period. In this context, the asymmetric effect of unconventional monetary policy is widely discussed in the literature on whether monetary contraction shocks have a greater impact on economies than monetary expansion shocks[1]. The asymmetric effect of monetary policy is particularly important for emerging markets (EMEs) because EMEs' real and financial markets can be hit hard if they do not take precautionary macroeconomic policy measures during and after QE (Basri, 2017).

Fisher (1933) and Keynes (1936), in their seminal works, emphasize that business cycles have asymmetric behaviour. Moreover, their studies indicate that the business cycles shock may have different effects rely upon the state of various macroeconomic variables. Some of the previous studies done by Neftci (1984), Granger (2003), Engle and Manganelli (2004), Balcilar *et al.* (2020) point out that macroeconomic shocks have asymmetric spillover dynamics. The findings obtained from various studies such as Engle and Manganelli (2004), Schüler (2014), Nodari (2014), White *et al.* (2015), Caggiano *et al.* (2016), Linnemann and Winkler (2016) Balcilar *et al.* (2016a, 2020) among others indicate that parameters of the model need to adopt the varying dynamic response strength in the tails of the distribution where shock are larger. Therefore, we use QVAR model in this study since it allows the flexibility us to specify continuum of models

[1] See Cover (1992), Weise (1999), and Florio (2004).

with different parameters corresponding to selected quantiles. The evidence from studies of Balcilar *et al.* (2016b; 2016c) indicates that the EPU series are strongly countercyclical with varying shock sizes. Therefore, the dynamic effects of the uncertainty cannot be fully estimated by the linear vector autoregressive (VAR) model based spillover measures.

Our study contributes to the existing literature in three ways. First, we propose a QVAR model based[2] spillover estimation to investigate the fragility effect of economic policy uncertainty (EPU) and oil price shocks on five major Asian economies using the QVAR model, which allows us to examine heterogenous responses that vary with the state of the economy. The QVAR is a semiparametric model that is robust to outliers and offers a rich framework that allows parameters of the model change with quantiles, which captures different state of the economy, such as the bad and good times. Second, we use relative tail dependence (proposed by Ando *et al.*, 2018) by means of the spillover index (hereafter DY index) of Diebold and Yilmaz (2009, 2012). Thus, another distinguishing feature of our approach from the previous studies such as Diebold and Yilmaz (2009, 2012) among others, which used the linear VAR model, is the determination of sign and intensity of asymmetric spillover dynamics from external shocks to these economies using QVAR model based spillover estimation approach. Third, we use a large set of variables covering all aspects of the economy. The variables used in the study include, asset market variables (stock, bond, and foreign exchange), supply and demand side (industrial production, consumer prices), countries' own economic policy uncertainty, and external variables (US EPU, EU EPU, and oil prices). Large set of variables in the model reduces possibility of specification errors and offers a rich framework for analysis. For instance, previous studies do not include country's own EPU in the their models. By including local EPU in the model, we both analyze external EPU spillover to local EPU and also control for the effect of local EPU when we study external EPU spillovers.

The key motivation for choosing these Asian countries is that they have a serious economic size and have close commercial and financial relations with the US and EU. Furthermore, the fact that the real shocks identified by Matheson and Stavrev (2014) emanating from the US and EU generate larger portfolio inflows to Asia than to other regions as shown in Osorio and Vesperoni (2016) is another motivating factor to use these countries in this study. We use news-based EPU

[2] The alternatives are nonlinear VAR models such as the Markov switching and (smooth transition) threshold models. We do not consider these models in this study since the QVAR approach has the flexibility specifying a continuum of models with different parameters corresponding to selected quantiles. The nonlinear VAR models on the other hand allow only a small number of regimes or different parametrization.

indices developed by Baker *et al.* (2016) and crude oil prices as affecting factors, while we utilize industrial production, consumer price index, stock market return, bond market return, exchange rate as affected factors. Moreover, we use monthly data for China and Hong Kong for the period 1998M1–2019M4; for India for the period 2003M1–2019M4; for Japan for the period 1987M1–2019M4; for South Korea for the period 1990M1–2019M4.

In this study, we obtain three main results: the first one is that the spillover indices become different at various quantiles for recipient economies. In general, our empirical findings show that the spillover effects from the oil market and global economic uncertainties increase at the edge of distribution. The second result with regards to the full sample RTD shows that Chinese and Hong Kong markets are highly immune against external shocks, while the South Korean economy is the most fragile among other Asian countries. The last results obtained from this study show that the US EPU shock has a notable influence on Asian economies except Japanese and Indian markets during RQE for different periods considered in this study. Of the five, Hong Kong and South Korea are the most affected countries in contrast to US EPU shocks. The continuation of capital inflows into India and its macroeconomic measures and the expansionary unconventional monetary policy of BoJ can be seen as the main reason for the strength of these countries. Furthermore, the EU EPU makes fragile mostly China and South Korea during the Eurozone debt crisis, while it has a devastating effect on other economies during the pre-crisis period. Moreover, our results reveal that the oil market mostly makes fragile some Asian markets during the commodity boom periods before the 2008 GFC. Additionally, the CPI, IP, bond, and stock markets of India and Japan are the most vulnerable to domestic economic uncertainty shocks during all analysis period. And finally, we find that the QE of BoJ after 2015 reduce the Japanese CPI, IP, bond and stock market fragilities but not enough.

The remainder of this study is organized as follows. Section 2 overviews the corresponding literature. Section 3 describes the methodology. Next, we describe data and present the empirical results with discussions in Section 4. And lastly, Section 5 concludes the paper.

2. Literature Review

There is a growing interest in the literature pertaining to the link between economic policy uncertainty and international financial markets. For instance, Colombo (2013) shows that the US EPU leads to a larger fall in European industrial production and prices than the EU EPU itself.

Moreover, Sum (2013) examines the effect of US EPU on five ASEAN countries (Indonesia, Malaysia, Philippines, Singapore, and Thailand) using Granger causality tests and he finds that US EPU harms stock market returns of related countries. Klößner and Sekkel (2014) investigate uncertainty spillover among six developed countries (Canada, France, Germany, Italy, UK, and the US) for the period of January 1997 to September 2013. They find that uncertainty spillover that increases notably around turbulent times, accounts for more than 25 % of the dynamics of policy uncertainty index. Moreover, Chuliá *et al.* (2017) analyze the impact of US policy and US equity market uncertainties on domestic and other stock market returns. They find evidence that an uncertainty shock lessens stock market returns both in developed and developing countries in uncertain times. A recent study carried out by Balcilar *et al.* (2019a) finds strong evidence regarding the prediction power of domestic and global (China, the European Area, Japan, and the US) EPU in Hong Kong, Malaysia, and South Korea stock markets. Furthermore, Bhattarai *et al.* (2019) investigate the spillover indices of US uncertainty shocks on fifteen emerging market economies (EMEs) by utilizing the panel VAR method. They find evidence that the US uncertainty has harmful effects on EME stock prices, exchange rates, country spreads, and capital inflows into them. US uncertainty also causes to decline of EME output and consumer prices while boosting net exports. Following the DY index, Zhang *et al.* (2019) try to understand the rationale of recent US-China trade conflicts by analyzing the influence of both the US and China on stock, credit, energy and commodity markets. On the other hand, some important studies such as Han and Yin (2016), Luk *et al.* (2017), Cheng (2017), Lee (2018), Kido (2018) and Huang *et al.* (2019) can be exemplified to examine the spillover effect from external and/or domestic economic policy uncertainty on Asian economies which are discussed in this study.

In parallel with the literature dealing with uncertainty, lots of studies examine the nexus between the oil market and financial/macroeconomic variables for Asian economies. For instance, Cunado and Perez de Gracia (2005) find strong evidence that oil prices have crucial impact on both economic activity and consumer price indexes in six Asian countries (Japan, Malaysia, Philippines, Singapore, South Korea, and Thailand) despite the fact that its effect is limited to the short run and the definition of oil price in local currency. In contrast to their findings, Ran and Voon (2012) illustrate that the impact of oil prices on real economic activity in Hong Kong, Singapore, South Korea, and Taiwan is negligible. Sarwar *et al.* (2019) examine the volatility spillover between the stock market and crude oil returns for China, India, and Japan by using BEKK-GARCH, DCC-GARCH, cDCC-GARCH, and GO-GARCH. The results support the unidirectional spillover from the stock market to the oil market for India, bidirectional spillover for Japan and, no evidence of volatility spillover for China. Furthermore, the spillover index between crude oil and miscellaneous financial/economic fundamentals are investigated by recent studies such as Ding *et al.* (2017), Peng *et al.* (2018), Xu et al (2019), Wang and Wang (2019), Kumar et al (2019), Yoon *et al.* (2019), Yun and Yoon (2019) for different region including Asian countries.

Karras (2013) investigates two types of asymmetric effects of monetary base shocks on the US economy by using quarterly data over the 1950-2011 period. He finds that the monetary base contractions have larger effects on the economy than monetary base expansions. Chari et al (2017) indicate that the monetary policy shocks on capital flow from the US to a range of EMEs during Taper Tantrum are much higher and statistically significant than during the QE period. The possible effect of ending quantitative easing on Brazil, India, Indonesia, South Africa, and Turkey are examined by Basri (2017) within the framework of the macroeconomic measures taken by the related countries. He tries to find underlying causes of how India and China managed monetary policy and achieved escaping fragile five during the taper tantrum. Using a VAR-X, Tillmann et al (2019) investigate the asymmetric spillover effects of U.S. monetary policy on emerging economies and find that a U.S. tightening has stronger impacts on emerging financial markets than an easing policy does. Besides, the asymmetric impact of the burst in unconventional monetary policies by the Fed and ECB on the financial and macroeconomic variables in EMEs is found by Apostolou and Beirne (2019). There are also various studies such as Mork *et al.* (1994), Ferderer (1996) and Balke *et al.* (2002), etc. investigate the asymmetric relationship between oil price changes and output growth in the literature.

3. Methodology

There is a vast literature in macroeconomics and finance examining dynamic spillovers among time series variables using the DY methodology. The DY methodology is based on the $n \times (n-1)$ bilateral linkages among n variables using the h-step ahead forecast error variance decomposition (FEVD) of a linear VAR model. The DY methodology has been found useful to study dynamic interactions among variables in many contexts, e.g. equity markets (Diebold and Yilmaz, 2009), foreign exchange markets (Baruník et. al. 2016, 2017; Greenwood-Nimmo *et al.*, 2016), sovereign and corporate credit spreads (e.g. Bostanci and Yilmaz, 2015; Greenwood-Nimmo *et al.*, 2019), asset markets and international spillovers (Balcilar *et al.* 2019b, 2020).

Although it provides rich tools of description, forecasting, and structural inference for the dynamic interaction among multivariate time series, the conventional linear VAR model is a constant coefficient model. As noted by several studies macroeconomic shocks have asymmetric spillover dynamics (see e.g. Neftci, 1984; Granger 2003; Engle and Manganelli. 2004; Balcilar *et al.* 2020). In their seminal works Fisher (1933) and Keynes (1936), respectively, point out that business cycles have asymmetric behavior and business cycle shocks may have stronger or milder effect depending on the state of various macroeconomic variables.

Constant coefficient linear VAR models cannot represent the asymmetric interactions of multivariate macroeconomic variables and spillover measures based on them might not reflect the true spillovers. Constant coefficient models are also specification about the conditional mean and they are estimated using conditional mean estimators such as the ordinary least squares. Succession of small and varied shock may have significant effects on the structure of the economic model. Nevertheless, constant coefficient models ignore these effects, particularly for the highly aggregate series. Perhaps, large shock propagates more strongly than small shocks, which is the leading definition of contagion, but the linear VAR does not address the shock size and, therefore, spillover measure based on it will be the same for all shock sizes. Moreover, the constant coefficient VAR model relies on conditional mean estimators such as the least squares (Diebold and Yilmaz, 2009, 2012) and the least absolute shrinkage and selection operator (LASSO) as well as its elastic net extension (Demirer *et al.*, 2018).

The reliance on the conditional mean estimator is an important drawback of these models as the conditional mean estimator captures the dynamic response of the variables to shocks around the mean. Therefore, spillover estimates from these models corresponds to central tendencies. A tension arises here because the dynamic response in a conditional mean model reflects the response to average shocks and response of the variables is the same in all parts (quantiles) of the conditional distribution. However, uncertainty increases during downturns implying that the uncertainty shocks are larger during recessions (see e.g. Jurado *et al.* 2015; Bloom *et al.* 2018). The linear VAR model does not have the flexibility of adopting to varying shock sizes and estimates the same spillover for all support of the conditional distribution, generalizing the relationship that prevails in the conditional mean to entire conditional distribution. Moreover, in the linear VAR model, a change in one variable implies a complete shift of the distribution, thus the response in all quantiles of the variables changes but scale and shape of the distribution stay fixed. The empirical evidence in numerous studies cited above show that large shocks may leave dynamic interactions among variables fixed in the center of the distribution but dynamics in tails may change abruptly. Thus, asymmetric dynamics over recessions (bad) and expansions (good) times–state dependence–and the dependence of propagation of shocks on the shock size calls into question the representativeness of spillover measures obtained from the linear VAR models for the true inter-linkages of underlying time series variables.

Koenker and Xiao (2006) examine implications of the quantile approach in univariate autoregressive (QAR) models and Galvao *et al.* (2013) expose the quantile time series framework as a modelling approach of asymmetric business cycles where high realizations (large positive shocks) correspond to high quantiles while low realizations (large negative shock) correspond to low quantiles. Unlike the linear VAR models, which implicitly assumes that the relationships that hold in the conditional mean also holds at all conditional quantiles, different effects of tail events or the tail-dependence among variables can be distinctly analyzed. Thus, the QVAR modelling framework is particularly suitable for the analysis spillover effects of EPU in the presence of extreme events, importance of which has been brought to forefront by the recent global recession following the 2007-2008 subprime crises.

Generalization of the QAR model of Koenker and Xiao (2006) to multivariate QVAR case was first introduced by Cecchetti and Li (2008). Schüler (2014), Linnemann and Winkler (2016), and Zhu *et al.* (2016) also presents empirical applications of the QVAR to examine asymmetric interactions in the financial and economic time series. In this study, we further generalize the QVAR approach to spillover indices based on multivariate quantile estimation method of Montes-Rojas (2017, 2019) and FEVDs arising from it. In order to present the QVAR model used in our study, we consider an n-dimensional multivariate time series process $Y_t = \left(Y_{1,t}, Y_{2,t}, \dots, Y_{n,t}\right)'$ with time index $t = 1,2, \dots, T$. Furthermore, for a QVAR model of order p, denoted QVAR(p), the $k \times 1$, where $k = np$, covariate vector is defined by $X_t = \left(Y'_{t-1}, Y'_{t-2}, \dots., Y'_{t-p}\right)'$. Let the vector of quantiles $\theta = \left(\theta_1, \theta_2, \dots, \theta_p\right)'$ represent quantiles of Y_t, i.e. θ_i is the quantile of variable $Y_{i,t}$, $i = 1,2, \dots, n$. Generally, the quantiles θ_i are not required to be equal. For instance, we can consider 0.10th quantile of one variable while the quantile of the other variable may be set at 0.90the in a two-variable case. The reduced form QVAR model at the quantiles θ can be written as

$$Q_\theta(Y_t|X_t) = C_\theta + A_\theta X_t, \qquad t = 1,2, \dots, T \tag{1}$$

where Q is an $n \times 1$ vector which corresponds to the multivariate quantiles of variables Y_t, $A_\theta = (A'_{\theta,1}, A'_{\theta,2}, \dots, A'_{\theta,n})'$ is an $n \times k$ matrix of coefficients with each of $A_{\theta,i}$, $i = 1,2, \dots, n$, representing $1 \times k$ vector of coefficients for the jth element of Y_t, and C_θ is an $n \times 1$ vector of coefficients. The QVAR model given in equation (1) resembles the linear VAR model which specifies the conditional mean of Y_t as $E(Y_t|X_t)= C + AX_t$, where C and A are $n \times 1$ and $n \times k$ coefficient matrices. The QVAR is specified for the $n \times 1$ multivariate quantiles Q of Y_t, while the linear VAR is specified for $n \times 1$ vector of conditional means $E(Y_t|X_t)$. The conditional mean is only one element of the conditional distribution of Y_t, which sparingly illustrates the richness of quantile approach as it can be estimated for the entire conditional quantiles not only for one element.

The QVAR model in equation (1) is about the estimation of n-dimensional response of Y_t conditional on the covariates X_t. Therefore, it requires estimation of multivariate quantiles which is an estimation problem with several alternative solution methods. Serfling (2003) reviews available methods for estimating multivariate quantiles. Indeed, none of these have all the desirable properties of the univariate quantile regression (QR). For the univariate case with $n = 1$, the QVAR model is reduced to QAR model and its estimation has been studied by Koenker and Xiao (2006), which follows the same procedure introduced in Koenker and Bassett (1978). For the univariate case, given the conditional distribution function $F(y) = P(Y \leq y|X = x)$ of Y_t, univariate conditional quantiles for the scalar quantiles $\theta \in (0,1)$ are defined as $q_\theta(x) = \inf\{y : F(y) \geq \theta\}$. Then, the traditional regression quantiles are obtained as $q_\theta(x) = F^{-1}(\theta)$. For this case, Koenker and Bassett (1978) uses an L_1 characterization and obtains the regression quantiles by minimizing $\sum_{t=1}^{T} \rho_\theta(Y_t - A - BX_t)$ where $\rho_\theta(z)$ is the check function defined as $\rho_\theta(z) = z(\theta - \mathbf{1}(z < 0))$, where $\mathbf{1}(\cdot)$ is the indicator function. The solution leads to a linear programming problem, hence the univariate QR estimator is semiparametric since it does not require full specification of the error distribution.

Quantiles are order statistics and conditional quantiles in a univariate case are uniquely identified since the order on the real line $\mathbb{R}$ naturally prompts unique ordering or ranking both observations Y_t and the quantiles $q_\theta(x)$ of the underlying conditional distribution F. The possibility of straightforward generalization to multivariate case is thwarted, because a unique natural order does not exist for $\mathbb{R}^n$ for $n \geq 2$. Therefore, the definitions, statistics, and concepts–quantiles, check functions, distribution functions, signs, and ranks–all playing a fundamental role for statistical inference in QR analysis do not easily generalize to QVAR model.

In order to circumvent this issue Cecchetti and Li (2008), Schüler (2014), Linnemann and Winkler (2016), and Zhu *et al.* (2016) estimate each equation of the model separately, reducing the model essentially to a univariate one. White *et al.* (2015), Chavleishviliand and Manganelli (2016), Ando *et al.* (2018), Han *et al.* (2019) also obtain forecasts, impulse response functions (IRF), or FEVDs using the same univariate QR approach. The equation by equation estimation approach to QVAR does not determine quantiles of all n variables simultaneously, therefore it is not truly multivariate. Statistical inference based on univariate estimation approach to QVAR is, therefore, problematic since conditional quantiles are not jointly determined.

There have been several approaches to generalize the univariate quantile definition to multivariate case (see, for a review, Serfling, 2002). In this study, we use the directional quantile approach proposed by Hallin *et al.* (2010) to analyze the distributional and quantile properties of multivariate data based on the directional quantile notion, initially introduced by Chaudhuri (1996), Koltchinskii (1997), and Wei (2008), end further extended by Paindaveine and Šiman (2011, 2012 and Fraiman and Pateiro-López (2012). Montes-Rojas (2017) extends the Hallin *et al.* (2010) with directional quantiles where directions are orthogonal to each other and span the domain of response variables. The directional approach involves reducing the multivariate problem to set of univariate ones with the help of univariate distributions relating to the n-dimensional case. We prefer the version of the directional approach introduced by Montes-Rojas (2017), because it can be implemented using usual QR and asymptotics can be studied. In the directional approach with orthogonal direction, the $\theta = \left(\theta_1, \theta_2, \dots, \theta_p\right)'$ is factored as $\theta = \breve{\theta}u$, where the scalar $\breve{\theta} = \|\theta\| \in (0,1)$ is the magnitude and $u \in \mathbb{R}^n$ with $\|u\| = 1$ is the direction, and $\|\cdot\|$ denotes the Euclidian norm.

Unlike the equation-by-equation estimation approach (see e.g. Cecchetti and Li, 2008; Schüler 2014; White *et al.* 2015; Chavleishvili and Manganelli, 2016; Linnemann and Winkler, 2016, Zhu *et al.* 2016; Ando *et al.* 2018, Han *et al.* 2019), which ignores the all other variables when determining the conditional quantile of one of the variables, say variable i, we use thr multivariate directional quantile approach which estimates the conditional quantile of variable i based on the covariates and quantiles of all other variables. The multivariate system of equations is based on the individual QR equations:

$$q_{i,\theta_i}\left(Y_{it} \middle| X_t, Y_{-i,t}\right) = Q_{\theta_i}\left(Y_{i,t} \middle| X_t, Y_{-i,t}\right) = c_{\theta_i} + b'_{\theta_i} Y_{-i,t} + a'_{\theta_i} X_t \tag{2}$$

where a_{θ_i} and b_{θ_i}, $i = 1,2,\dots,n$, are vectors of dimension $k \times 1$ and $(n-1) \times 1$, respectively, c_{θ_i} are $n \times 1$ scalars, and we use the notation $-i$ to signify the exclusion of the element i from the corresponding vector, i.e. $(n-1) \times 1$ vector defined as $Y_{-i,t} = \left(Y_{1,t}, Y_{2,t}, \dots, Y_{i-1,t,} Y_{i+1,t}, \dots, Y_{n,t}\right)'$. Note that equation (2) corresponds to a particular direction of the space $Y_t \in \mathcal{Y} \subseteq \mathbb{R}^n$. The individual QRs in equation (2) specifies θ_i-quantile of Y_{it} conditional on $Y_{-i,t}$, $n-1$ contemperenous variables of all other elements in Y_t, and the lagged variables X_t. The reduced form QVAR model is formed by the system of conditional quantiles $Q_\theta(Y_t|X_t) = (q_{1,\theta}(Y_{1,t}|X_t), q_{2,\theta}(Y_{2,t}|X_t), \dots, q_{n,\theta}(Y_{n,t}|X_t)'$ from the following system of equations:

$$
\begin{aligned}
q_{1,\theta}\left(Y_{1,t}\middle|X_t\right) &= c_{\theta_1} + b'_{\theta_1} Q_{-1,\theta}(Y_t|X_t) + a'_{\theta_1} X_t \\
q_{2,\theta}\left(Y_{2,t}\middle|X_t\right) &= c_{\theta_2} + b'_{\theta_2} Q_{-2,\theta}(Y_t|X_t) + a'_{\theta_2} X_t \\
&\vdots \\
q_{n,\theta}\left(Y_{n,t}\middle|X_t\right) &= c_{\theta_n} + b'_{\theta_n} Q_{-n,\theta}(Y_t|X_t) + a'_{\theta_n} X_t
\end{aligned} \tag{3}
$$

where $Q_{-i,\theta}(Y_{,}|X_t)$ denotes the vector of quantiles in $Q_\theta(Y_t|X_t)$ excluding $q_{i,\theta}(Y_{i,t}|X_t)$, i.e. $Q_{-i,\theta}(Y_t|X_t) = (q_{1,\theta}(\cdot), \dots, q_{i-1,\theta}(\cdot), q_{i+1,\theta}(\cdot), \dots, q_{n,\theta}(\cdot)'$. Here, $q_{i,\theta}\left(Y_{i,t}\middle|X_t\right)$ corresponds to individual time-series QRs for the each of ith variable. Based on Hallin *et al.* (2010), Montes-Rojas (2017) shot that all the n directions together form an orthonormal basis and the solution is a fixed point, which obtains the simultaneous solution of all equations in equation (3).

In order to show the solution to equation (3) define an $n \times n$ matrix B_θ as $B_\theta = (B_{\theta_1}, B_{\theta_2}, \dots, B_{\theta_n})'$ where B_{θ_i} is an $1 \times n$ vector formed by augmenting ith position of b_{θ_i} with 0, that is $B_{\theta_i} = \left(b_{\theta_i,1}, b_{\theta_i,2}, \dots, b_{\theta_i,i-1,} 0, b_{\theta_i,i+1}, \dots, b_{\theta_i,n}\right)$ where $b_{\theta_i,i}$ is the ith element of b_{θ_i}. Define also $n \times k$ matrix $a_\theta = (a_{\theta_1}, a_{\theta_2} \dots, a_{\theta_n})'$ and $n \times 1$ vector $c_\theta = (c_{\theta_1}, c_{\theta_1}, \dots, c_{\theta_1})'$. Then, we can obtain the QVAR model in equation (1) as:

$$
Q_\theta(Y_t|X_t) = (I_n - B_\theta)^{-1}(c_\theta + a_\theta X_t) = C_\theta + A_\theta X_t \tag{4}
$$

where I_n is an n-dimensional identity matrix, $C_\theta = (I_n - B_\theta)^{-1} c_\theta$, and $A_\theta = (I_n - B_\theta)^{-1} a_\theta$. This solution procedure differs from the univariate QR procedure used in the previous studies. For a given θ, the solution in equation (4) is obtained by (1) estimating n distinct univariate QR models for each of the variable $Y_{i,t}$ against other $n-1$ variables $Y_{-i,t}$ and the lagged variables X_t, and (2) solving for a system of equations in n unknowns, given by $Q_\theta(Y_t|X_t)$, and n equations, each coming from a different directional quantile model. Moreover, the quantiles θ_i for variables in $Y_{i,t}$, $i = 1,2,\dots,n$, can be different from each other, which is an important flexibility.

The spillover analysis requires FEVDs which are in turn need the estimates of IRFs. FEVDs needed for DY spillover indices are usually based on the generalized impulse response functions (GIRF) proposed by Koop *et al.* (1996) and Pesaran and Shin (1998) with further improvement by Lanne and Nyberg (2016) to make proportions of FEVDs accounted for by shocks in all variables sum to unity for the each of variables. The QVAR is a semiparametric model, which does not require specification of the full distribution of error terms, therefor no joint distribution–and, thus no correlation structure among error terms–exist. Indeed, the QVAR model is reduced form and, therefore, it is not a structural model. Additionally, a system of residuals in a reduced form additive model does not exist for the QVAR. Instead, co-movement of the endogenous variables is replicated by indexing them with the quantiles θ. These features of the QVAR model cause a challenge for analyzing the dynamic properties, such as the IRF. Indeed, we do not have properly defined residual covariance matrices to use in the IRF calculations. White *et al.* (2015), Chavleishvili and Manganelli (2016), Ando *et al.* (2018), and Han *et al.* (2019) each take different approaches to generate the IRFs of QVAR, either based univariate QR estimation or pseudo IRFs, each having one or more issues as they ignore the simultaneity or use a pseudo structure.

Given the issues in estimation correlation structure of the residuals, we adopt the counterfactual change approach of Montes-Rojas (2018) to obtain the FEVDs. We use the Lanne and Nyberg (2016)'s approach to calculate FEVDs, which require IRFs, which in turn are based on counterfactual change forecasts. To illustrate the method, define the lag polynomial $A(\theta, L) = \sum_{j=1}^{p} A_{\theta,\cdot j} L^j$ in the lag operator L, where $A_{\theta,\cdot h} = (A_{\theta,1,h}, A_{\theta,2,h}, \dots, A_{\theta,n,h})$ is an $1 \times n$ h-lag coefficient vector for all endogenous variables in Y_t, for $j = 1,2,\dots,p$. Using the lag polynomial $A_\theta X_t$ is given by

$$A_\theta X_t = A(\theta, L) Y_t = \sum_{j=1}^{p} A_{\theta,\cdot j} Y_{t-j}$$

QVAR model in equation (4) can be written as

$$Q_\theta(Y_t | X_t) = C_\theta + A(\theta, L) X_t \tag{5}$$

Now, consider h-step forecast of Y_t with each step associated by an $n \times 1$ quantile vector θ_j, generating a quantile path $\theta_{1\cdots h} = \{\theta_1, \theta_2, \dots, \theta_h\}$. In this way, we generate a quantile dependent path forecast. The h-step quantile forecast is given by

$$Q_{\theta_{1\cdots h}}(Y_{t+h}|X_t) = C_{\theta_h} + A(\theta_h, L)Q_{\theta_{1\cdots k}}(Y_{t+k}|X_t)$$

where $Q_{\theta_{1\cdots k}}(Y_{t+k}|X_t) = Y_{t-k}$ if $L^k(t+h) \leq t$ and $Q_{\theta_{1\cdots k}} = \{\theta_1, \theta_2, \dots, \theta_k\}$ is the k-step quantile path for $k = 1,2, \dots, h-1$. Using the definition in equation (5), the h-step forecast can be written as

$$Q_{\theta_{1\cdots h}}(Y_{t+h}|X_t) = C_{\theta_h} + \left[\prod_{j=1}^{h} A_{\theta_j}\right] X_t + \sum_{j=1}^{h-1}\left[\prod_{k=j+1}^{h} A_{\theta_k}\right] C_{\theta_j} \tag{6}$$

We can similarly calculate the counterfactual change forecast $Q_{\theta_{1\cdots h}}(Y_{t+h} + \delta|X_t)$ for a counterfactual change $\delta = (\delta_1, \delta_2, \dots, \delta_n)'$, $\delta \in \mathcal{Y} \subseteq \mathbb{R}^m$, using equation (6).

Using the h-step ahead base forecast $Q_{\theta_{1\cdots h}}(Y_{t+h}|X_t)$ and the h-step ahead change forecast $Q_{\theta_{1\cdots h}}(Y_{t+h} + \delta|X_t)$, quantile response function (QIRF) for a quantile path $\{\theta_1, \theta_2, \dots, \theta_h\}$ and shock δ can be written as[3]

$$\text{QIRF}(h, \delta) = Q_{\theta_{1\cdots h}}(Y_{t+h} + \delta|X_t) - Q_{\theta_{1\cdots h}}(Y_{t+h}|X_t) \tag{7}$$

Therefore, following Lanne and Nyberg (2016), the h-step-ahead generalized FEVD denoted by $\lambda_{\theta,ij}(h)$ is used to compute quantile specific DY spillover index as shown in equation (8). The quantile-specific FEVD can be defined as

$$\lambda_{\theta,ij}(h) = \frac{\sum_{l=0}^{h} \text{QIRF}\left(l, \delta_j\right)_i^2}{\sum_{j=1}^{n}\sum_{l=0}^{h} \text{QIRF}\left(l, \delta_j\right)_i^2}, \qquad i,j = 1,2, \dots, n \tag{8}$$

where i and j denote variable and shock, respectively. Sum of the $\lambda_{\theta,ij}(h)$ over all shocks is equal to 1 by construction, i.e. $\sum_{j=1}^{n} \lambda_{\theta,ij}(h) = 1$. Therefore, $\sum_{i,j=1}^{n} \lambda_{\theta,ij}(h) = n$. Given this clarification, the total spillover index for quantile θ can be constructed as follows:

$$S_\theta^T(h) = \frac{\sum_{i,j=1,i\neq j}^{n} \lambda_{\theta,ij}\,(h)}{\sum_{i,j=1}^{N} \lambda_{\theta,ij}\,(h)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{n} \lambda_{\theta,ij}\,(h)}{n} \times 100 \tag{9}$$

[3] Although, the QIRF is defined using two paths one without a shock (base forecast) and one with a shock (change forecast) in the line of the GIRF of Koop *et al.* (1996), Pesaran and Shin (1998), Lanne and Nyberg (2016), it is not equivalent to GIRF. The QIRF requires the identification of the contemporaneous correlations among the shocks, which we do using orthogonalization based on the Cholesky factorization of a mean based VAR.

where $S_{\theta}^{T}(h)$ represents the total spillover index. Furthermore, we compute the directional spillover index by focusing clearly on two main spillover dimensions: the directional spillovers received by variable i from other variables j, and the directional spillovers transmitted by variable i to other variables j. The directional spillovers received by variable i from other variables j is computed as

$$DS_{\theta,i\leftarrow j}(h) = \frac{\sum_{j=1,j\neq i}^{n} \lambda_{\theta,ij}\,(h)}{\sum_{i,j=1}^{n} \lambda_{\theta,ij}\,(h)} \times 100 = \frac{\sum_{j=1,j\neq i}^{n} \lambda_{\theta,ij}\,(h)}{n} \times 100 \tag{10}$$

Analogously, the directional spillovers transmitted by variable i to other variables j are given by

$$DS_{\theta,i\rightarrow j}(h) = \frac{\sum_{j=1,j\neq i}^{n} \lambda_{\theta,ij}\,(h)}{\sum_{i,j=1}^{N} \lambda_{\theta,ij}\,(h)} \times 100 = \frac{\sum_{j=1,j\neq i}^{N} \lambda_{\theta,ij}\,(H)}{n} \times 100 \tag{11}$$

Finally, using the directional spillovers in equations (10) and (11), the net spillover for variable i for each quantile θ is computed as:

$$NS_{\theta,i}(h) = DS_{\theta,i\rightarrow j}(h) - DS_{\theta,i\leftarrow j}(h) \tag{12}$$

which is expressed as the difference between the gross shocks transmitted to and those received from all other variables.

4. Data and Empirical Results

We use monthly data of industrial production index (IP), consumer price index (CPI), real Brent crude oil price (BRENT), nominal effective exchange rate (NEER), stock market indices (STOCK), 10-year Treasury bond yield (BOND) and economic uncertainty index (EPU) for the economies examined in this study. We take the year-on-year growth rate of IP, CPI, BRENT, NEER, and STOCK. We calculate the real Brent crude oil price in local currency. We choose Shanghai composite index, Hang Seng index, Bombay stock exchange index, Tokyo stock exchange index and Kospi stock price index as the proxy of stock markets for China, Hong Kong, India, Japan, and South Korea, respectively. While the EPU indices for 5 Asian countries as well as the US and EU are obtained from the EPU web site located at https://www.policyuncertainty.com, other data collected from Thomson Reuters DataStream. Due to data availability, we use different observation periods for related Asian countries. The data spans from 1998M1 to 2019M4 for China and Hong Kong; from 2003M1 to 2019M4 for India; from 1987M1 to 2019M4 for Japan; from 1990M1 to 2019M4 for South Korea. Although this situation may produce slightly different empirical results among countries, keeping the number of observations as long as possible provides valuable information in time-varying analysis for Japan and South Korea.

Figure 1 presents the dynamics of the corresponding IP, CPI, BOND, STOCK, NEER, EPU and BRENT series of Asian countries, US EPU, and EU EPU over time. The CPI is on an upward trend in Hong Kong, whereas it has a continuous decline in South Korea during the period. Furthermore, the CPI, which increases until 2010, falls back at 4% level in recent times. While the IP growth fluctuates around a positive trend in Hong Kong, it fluctuates around a certain constant level in other countries. The common property of IP series is that all of them experience a sudden decrease after the 2008 GFC. Furthermore, the 10-year Treasury bond yield of Hong Kong, Japan, and South Korea decline consistently after the beginning over time. As for STOCK, NEER, and BRENT return, we can see that these series display an irregular pattern over the analysis period. Finally, the EPU series of Asian countries, except India, show an upward trend, while this situation exists for the US EPU and EU EPU after the 2008 GFC.

Table 1 provides descriptive statistics for the variables used in this study. Among others, the Chinese average inflation takes a negative value. Furthermore, the average industrial production growth is negative in China and Hong Kong while positive in other countries. Interestingly, the Indian 10-year Treasury bond market with the highest return is one of the least risky bond markets. As for the stock market, we can see that the Bombay stock market has a high return with high risk among other recipient economies. On the contrary, the Hang Seng stock market is found to have the highest volatility among five Asian countries, though its return is much less than the Bombay stock exchange index. Besides, the bond market and stock market return of some countries have negative skewness, meaning a long-left tail, implying a greater chance of negative return outcomes. From this point of view, investors and portfolio managers who have positions to Hang Seng, Bombay and Tokyo stock markets and the Indian bond market have come across extreme risks according to other market investors. Moreover, the HKD and KRW are the only two depreciated currencies in mean, whereas others are appreciated over the analysis period. As seen in the table, the kurtosis of the related variables, except for Japanese industrial production and KRW, is lower than the normal distribution, implying the investments in these markets are less risky. And finally, the EPU series of all countries show the same character; in other words, they have a positive mean with reasonable volatility level. On the one hand, the results of the Jarque-Bera (JB) test are consistent with the abovementioned deviations from the normal distribution.

In addition to these test statistics, we investigate the normality of related series. As can be seen in the right-hand side of Table 1, the results of the Ljung-Box test statistics of first [Q(1)] and the fourth [Q(4)] autocorrelation tests fail to support the null hypothesis of the white noise process (i.e., i.i.d. process) for all series. Furthermore, the fourth [ARCH (4)] order Lagrange multiplier (LM) test is used to test series on autoregressive conditional heteroskedasticity and the null of no ARCH effects is strongly rejected for all series. Table 2 displays the unit root tests for the level and first difference of related series using four tests: the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979), Elliott–Rothenberg–Stock (ERS) test (Elliott *et al.*, 1996), the Phillips–Perron (PP) test (Phillips and Perron, 1988), and the KPSS stationarity test proposed by Kwiatkowski *et al.* (1992). The ERS unit root test can be used to complement the widely employed ADF and PP tests in the literature. When the series include a linear trend, the use of ERS can considerably improve the power of the unit root test over the other standard unit tests (Elliott *et al.*, 1996). These four test statistics provide mixed results regarding the stationarity of series, but we prefer using all series at level to avoid loss of information.

QVAR results

Linear VAR models are used in most of the studies that measure the DY spillover index between financial and economic assets, assuming that the distribution structure of the assets is non-elliptical. A typical feature of these studies is that they depend on linear conditional mean estimators such as ordinary least squares. Therefore, the spillover among markets is calculated on average shocks. These findings naturally may give erroneous results in the case of a non-normal distribution which has a fat-tailed and leptokurtic characteristic. The QVAR approach also provides particular insights into the impacts of foreign and domestic economic factors on related financial and economic fundamentals of recipient countries in different market circumstances, namely, bearish, normal and bullish markets. Consequently, we investigate the impact of shocks obtained from lower to upper tails of distributions step by step by using QVAR models for both full-sample and time-varying analysis. The larger negative and positive shocks can be calculated from the left and right tail of the conditional distribution respectively. We confine the spillover index results coming from just oil price and economic policy uncertainties to other financial and macroeconomic fundamentals of recipient countries in line with the main purpose of the study.

We determine the lag order p of the QVAR models using Akaike information criterion (AIC) in a mean based VAR model. The order lag order for India is determined as 2 and 1 for other countries. Since the QVAR model is reduced form, the shocks used in QRIF might be contemporaneously correlated. In order to resolve this problem, we use orthogonalization based on Cholesky factorization of the contemporaneous residual covariance matrix obtained from a mean based VAR, where variables are ordered as BRENT, USEPU (or EUEPU), EPU, NEER, STOCK, BOND, CPI and IP. The QRIF step is 12 for all countries, i.e. $h = 12$.[4] Table 3-7 of the Appendix shows full-sample results of spillover indices across related assets over quantiles 0.05, 0.25, 0.50, 0.75 and, 0.95 for each of the variables for China, Hong Kong, India, Japan, and South Korea, respectively. To distinctly uncover the dynamics at various quantiles, we keep the quantiles fixed for all steps. As seen in the tables, the spillover index is much higher at 0.05th and 0.95th quantiles than in the center of the conditional distribution. Therefore, we can say that the linear VAR model underestimates the spillover indices for all countries in both tails. For example, the total spillover indices across related variables are much higher (more than twice) when there is large negative (at 0.05th quantiles) and large positive (at 0.95th quantiles) shocks compared to shocks around the average value. On the other hand, our results tend to suggest that the spillovers from external shocks to corresponding Asian markets get minimums at 0.50 quantiles when comparing other quantiles. This implies that the spillover among markets crawls at ordinary times. However, in periods of increased market volatility and uncertainty, the spillover effect from external factors to Asian markets increases significantly. However, some situations that contradict this observation were also included in our analysis. For example, the spillover effect from the US EPU to the Chinese stock market and Chinese EPU is at the highest 0.50 quantile, but lowest at 0.95 quantiles. We can exemplify the same situation from BRENT to NEER for Hong Kong, India, South Korea, and Japan and from US EPU to domestic EPU for India. This is generally the case for findings where the spillover effect is high in all quantiles.

[4] Results in our study are not sensitive to forecast horizon for alternative choices 8 and 16. Results are also robust to lag order choice when lag order is increased by 1. We do not report these alternative results to save space, but they are available from the authors upon request.

It is hard to evaluate all full sample spillover indices at various quantiles as shown in Table 3-7 because there is lots of information there. To make the results more understandable and better analyze the good and bad market conditions of the inter-market spillover, we follow Ando *et al.* (2018) and calculate relative tail-dependence (RTD) as shown in Table 8. RTD can be defined as the difference between the spillover index at higher and lower quantiles. We subtract spillover indices at 0.05 quantiles from spillover indices at 0.95 quantiles. The more positive RTD means the more destabilizing market situation, while the more negative RTD means the more stabilizing market situation. In other words, increases (decreases) in RTD as evidence of rising (falling) financial fragility for analyzed countries. From this perspective, our full sample RTD result implies that global economic policy uncertainties make fragile all Asian countries' domestic EPU except China and Hong Kong. Among other Hong Kong markets, the oil price change and global EPU make vulnerable mostly Hong Kong dollars when we compare it to other markets. As for Indian markets, we find strong evidence that mostly the domestic and global economic policy uncertainty shocks make vulnerable Indian markets rather than the crude oil market. Similarly, we can see that the Japanese currency market becomes vulnerable to unrest in the oil market, whereas global and local EPU shocks have a significant fragility impact on Japanese bond and stock markets. Furthermore, it can be said that nearly all South Korean markets are fragile against external shocks. As we mentioned above, the negative value of RTD can be seen as toughness of markets. Hence, nearly whole markets in China are highly resistant to domestic EPU and EU EPU shocks. The same situation exists for Indian markets against oil price shocks.

Time-varying QVAR results

Considering that macroeconomic policies have changed in structurally different periods, full sample analysis results are insufficient to make political inferences. To address this issue, we calculate time-varying 5% RTD obtained by averaging the rolling quantile spillover indices during structurally different periods[5] to investigate the asymmetric response of Asian markets to EPU and oil price shocks. Thus, we can see the impact of unconventional monetary policy on Asian economies and have a chance to see which country and markets are more resistant against during QE and RQE. Figure 2 indicates rolling 5% RTD from EPUs and the oil market to other

[5] We investigate RTDs in three different time intervals. The first time-interval, i.e. 2004M1-2008M8, represents pre-crisis and financialization of commodity; 2008M9-2014M11 represents after crisis period and indicates the dominant effect of QEs of central banks; the last time interval (2014M2-2019M4) includes the RQE of Fed, the QE of ECB and BoJ with the relatively moderate oil price.

market assets. The bars shown in Figure 2 in different colors show the market fragility of Asian countries during the corresponding sub-periods. We also indicate foreign direct investment (FDI) and portfolio investment (PI) data for the US, EU, and 5 Asian countries during related sub-periods in different colors as seen in Figure 3. As QE drove capital from advanced countries to other markets, it led to temporary relief and increased financial market activity in recipient countries. However, it ultimately results in a large amount of capital outflow from recipient countries and can trigger serious damages to market functioning in the destination countries during reverse QE.

FDI is seen as a long-term investment since it is building or purchasing businesses in foreign countries. Conversely, PI can be viewed as a short-term investment because it is purchasing securities of foreign countries, such as stocks, government bonds, corporate bonds, Treasury bills, real estate investment trusts (REITs), exchange-traded funds (ETFs), mutual funds and certificates of deposit. As seen in Figure 3, huge amounts of foreign investment come as FDI into China and this can be shown as an important factor to reduce the Chinese market fragility against external shocks. However, there is a significant decrease in capital inflows or capital outflows from China in the third period. This can be attributed to the shift in US foreign trade policy with the Trump administration in action after 2016. As shown in Figure 2, the US EPU makes Chinese markets more fragile during this sub-period. Besides, the spillover from EU EPU makes also it vulnerable to all Chinese markets during the EU debt crisis. Given the high trade volume of the EU and China, this situation is parallel to our expectations. On the other hand, we could not find any evidence that oil prices and domestic EPU have a significant impact on the Chinese market.

Furthermore, we obtain important evidence regarding the Hong Kong domestic unrest which began after 2014 with the Umbrella Revolution, a series of sit-in street protests due to the Standing Committee of the National People's Congress (NPCSC) decision about the electoral system. These unrests look cause fragility on Hong Kong markets as we see in Figure 2. While the RTDs from domestic EPU to Hong Kong markets are negative (i.e. do not cause fragility) during the first and second analysis time interval, domestic EPU-induced shocks have become quite depressing for the domestic markets of Hong Kong. Besides, we evidence that the US EPU shock makes fragile nearly the whole Hong Kong markets when the Fed starts to reduce asset purchasing and then decrease its balance sheet. It can be deduced that the Hong Kong markets are vulnerable in contrast to RQE programs implemented by the Fed. The EU EPU does not create significant pressure on the Hong Kong market like US EPU. For example, we do not get evidence positive RTD from EU EPU to other markets during the Eurozone debt crisis period.

The fragility impact of external economic policy uncertainties on Indian markets varies substantially during different global economic conditions. For instance, we do not see the major role of US EPU on Indian markets after FED starts reverse QE. The remarkable portfolio and foreign direct investment into the Indian market can explain this situation. Although the US capital flow slows down after RQE, the capital flows from the EU and Japan to the Indian market continue to feed Indian markets. Interestingly, the EU EPU brings significant vulnerabilities to Indian financial markets during ECB QE which naturally unwinds international markets with close ties with the EU. We think that the main reason for this situation is Brexit exit referring to the United Kingdom's decision in a mids-2016 referendum to leave the EU. Our empirical results partially show that the Indian EPU plays a stronger and more consistent role in Indian markets except for Indian Rupi than external policy uncertainty and oil price changes.

Our results tend to suggest that Japan's domestic economic uncertainties create serious fragility on its markets compared to other external factors. These fragilities are seriously high during all observation periods after 2004 except for the currency market. The adverse effect from domestic EPU to Japanese markets decrease slightly after BoJ launch severe asset purchasing. The RTDs from Japanese EPU to other markets reduce but remain at high levels during this Japanese QE3 period. Furthermore, we do not find any evidence to support the US RQE program has a significant impact on Japanese markets. However, we obtain clear evidence that the EU EPU makes vulnerable Japanese IP, CPI, bond and stock markets, especially before 2008 GFC. As for the South Korean market, we see that the Korean financial and real markets are highly fragile from US and EU economic policy shocks when we compare other Asian countries. Especially, during the Fed RQE period, the RDT from US EPU to South Korean markets except the currency market reach very high value. During Fed carry out unconventional monetary policy, South Korean industrial production, inflation, and the currency market become more fragile against US EPU shocks. We see the same scenario for the effect of EU EPU shocks on Korean markets during the eurozone crisis. However, this fragility intensity of EU EPU shock decreases significantly after the ECB launches its expanded asset purchase program. These findings are clear evidence to support the reverse impact of asynchronous quantitative easing programs of advanced countries. While the Fed RQE makes more vulnerable to South Korea markets, the ECB QE program relives related markets after 2015. Moreover, the impact of the oil price market on South Korean markets is not as significant as global EPUs.

As we mentioned above, we naturally expect there is an asymmetric effect between the expansionary and contractionary unconventional monetary policy of the Fed on Asian markets. With easing liquidity, the Asian markets might face less fragile effects from US economic policy uncertainty; however, the possible massive capital outflows from related Asian markets during the Fed RQE period quite likely make Asian economies more vulnerable. We find evidence to support this argument for China, Hong Kong, and South Korea as seen in Figure 2. The US EPU makes more vulnerable corresponding markets in these countries during the RQE period of Fed. Figure 3 may explain these findings. As we see that, the net FDI and PI outflows from China, Hong Kong, and South Korea accelerate when the Fed implies reducing LSAPs. Moreover, the capital flows throughout India continues to increase even during the RQE period. Hence, the RQE of the Fed has no devastating impact on Indian markets due to the continued flow of capital. We think that the QE of ECB and BoJ neutralize the fragile effect of Fed RQE on Indian markets during this period. However, the escalating political uncertainty in the EU with Brexit exit has a significant fragile impact on India's financial markets during this period. Namely, we can deduce that the adverse shocks originated from Brexit exit dominate the beneficial shocks of ECB QE for India. Moreover, our findings reveal that the EU EPU makes fragile many Asian markets during the first sub-period as seen in Figure 2.

As for the oil market impact on Asian economies, we find that the oil price changes make worse Indian and Japan inflation outlook, industrial production, and Hong Kong stock market during the commodity boom before 2008 GFC. However, this fragility disappears in these markets after the 2008 GFC although the oil price remains at a high level. The differences in the underlying causes of the oil price increase in these two periods can be considered as the main reason for this discrepancy. While the main reason for the increase in oil price before 2008 is the huge oil demand of EMEs, the Fed QE policy is seen as the main reason for the oil market boom after 2008 GFC (Saghaian and Reed, 2015). In this context, we can say that the main factor causing fragility in Asian markets is not directly from the QE-rising oil price, but directly from the Fed's unconventional monetary policy after the 2008 GFC. Moreover, we find that the oil market does not create severe fragility to Asian markets when oil price fluctuates moderate level (i.e. third analysis period). When we compare the commodity boom period before the 2008 GFC and period of relatively low and stable oil prices, we can say that there is partial asymmetric behavior of oil prices on some Asian markets. In fact, this is an indication of how complex the fragility effect between markets has become due to the intertwined structures.

5. Conclusion

The rise of EPU during major economic, financial and political unrest in advanced countries and sudden oil price increase causes international spillover throughout international markets via some transmission mechanisms. This spillover mechanism among international markets has a fragile effect on the economies of the country. This study investigates the fragility effect of economic policy uncertainty (EPU) and oil price shocks on five major Asian economies (i.e. China, Hong Kong, India, Japan, and South Korea). To do this, we propose a QVAR model-based spillover estimation approach. Thus, the main contribution of this study to the available literature is the determination of sign and intensity of asymmetric spillover dynamics from external shocks to these economies using QVAR model-based spillover estimation approach. In investigate the asymmetric spillover dynamics from external shocks to these economies, we also use relative tail dependence from QVAR model-based spillover estimation results for both full-sample and three sub-sample periods (i.e. 2004M1-2008M8, 2008M9-2014M11, and 2014M2-2019M4).

Our empirical findings show that the spillover indices, which take very high values at the edge of the distribution, become different at various quantiles for these Asian economies. This provides evidence that the spillover effect from external shocks on Asian economies increases more during bullish and bearish market conditions than ordinary times. Moreover, the full sample RTD results indicate that, in general, while China and Hong Kong are highly immune to external shocks, South Korea is the least resistant countries among other Asian economies. This implies, among other Asian countries, South Korea should be more careful against external shocks rather than internal shocks. Furthermore, the empirical findings regarding RTDs in different periods show that the US EPU makes Chinese, Hong Kong and South Korean markets more fragile during Fed’s contractionary unconventional monetary policy period than the expansionary unconventional monetary policy period. These findings can be seen as evidence of the asymmetric effect of the Fed's unconventional monetary policy on the related Asian markets. Moreover, the empirical findings show that Chinese and South Korean economies become more fragile against the EU EPU shocks during the Eurozone debt crisis, while it has a destructive impact on other economies during the pre-crisis period. Additionally, we find evidence to support the asymmetric effect of the oil market on some Asian markets. The CPI of India and Japan and the IP and stock markets of Hong Kong are more vulnerable to oil price shocks during the commodity boom before the 2008 GFC. This situation does not exist for the commodity boom period after the 2008 GFC. This finding suggests that the underlying causes of both commodity booms are different. Namely, this study supports some academic studies (such as Fratzscher *et al.*, 2012) which claim that the impact of QE is the main driver of asset price increase after the 2008 GFC.

India and Japan are the most vulnerable markets against their domestic economic uncertainty during all analysis period. However, these two countries are more immune to US EPU shocks among other Asian countries during the Fed's RQE period. While foreign direct investment and portfolio investment flow to India continued to increase in this period, the fragility effect decreased for India; Japan's recent and biggest asset purchase can be said to reduce this fragility effect for Japan. The main reasons why Fed RQE is not fragile for India, which has a devastating effect on almost all EMEs, is that the flow of international funds into India continues to increase during this period and India's various macroeconomic policy measures to ease financial markets (Basri, 2017). Our findings also show that Brexit leads the fragility effect of EU EPU on Indian financial markets. On the other hand, the main reason for this situation in Japan is that the BoJ, unlike the Fed, starts to LSAPs after 2015. Last but not least, we also find that the BoJ's QE policy decreases the Japanese market fragility but not enough.

Our findings are important to policy-decision makers, business environments, portfolio investors and even households because both economic policy uncertainty and oil price change gradually affect the consumption and investment decisions of these economic agents. In particular, asynchronous unconventional monetary policies in recent years in developed countries cause serious confusion in other countries and reduce the possible effects of conventional monetary and fiscal policies against these situations in these countries. So, they should follow and pay more attention to economic events and news stemming from the rest of the world and react to this global economic uncertainty with accurate policy actions. No country, including developed countries, can avoid the spillover indices from global uncertainties completely, but they may prevent extreme spillover movements among markets by informing the market accurately and thus avoiding asymmetric information. Furthermore, recipient economies should establish economic policy coordination with the US and EU to reduce global EPU spillover on their markets and thereby minimize financial stability risks. Policymakers should also inform markets in a timely and transparent manner about the possible consequences of internal and external shocks and make credible plans to overcome such shocks.

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Table 1 Descriptive statistics for related series

Series	N	Mean	S.D.	Min	Max	Skewness	Kurtosis	JB	Q.1.	Q.4.	ARCH.1.	ARCH.4.
							China (January 1998 – April 2019)					
CPI	256	-0.03	2.75	-9.96	5.68	-0.68	1.38	41.39***	221.67***	684.72***	207.39***	210.39***
IP	256	-0.22	4.07	-14.73	15.40	0.48	3.12	117.39***	31.24***	119.17***	39.30***	44.16***
BOND	256	3.58	0.52	2.51	5.14	0.33	-0.23	5.12*	219.15***	671.99***	144.34***	147.41***
STOCK	256	4.07	34.80	-123.68	117.55	0.44	2.13	58.25***	231.62***	711.70***	205.16***	212.64***
NEER	256	1.48	5.64	-9.208	18.12	0.40	-0.17	7.23**	228.43***	666.76***	186.09***	195.24***
BRENT	256	5.20	34.98	-100.47	94.98	-0.39	0.12	6.62**	211.13***	604.32***	161.53***	160.97***
EPU	256	4.80	0.77	2.21	6.84	0.09	0.23	1.06	140.87***	475.93***	57.49***	79.30***
							Hong Kong (April 1998 – April 2019)					
CPI	253	1.22	2.90	-6.25	7.42	-0.53	-0.52	14.78***	235.82***	874.86***	198.52***	197.78***
IP	253	-2.23	4.79	-15.16	7.22	-0.71	-0.38	22.67***	246.16***	841.94***	225.05***	232.23***
BOND	253	3.54	2.15	0.56	10.45	0.87	-0.02	32.56***	244.69***	892.24***	229.56***	234.07***
STOCK	253	3.82	25.21	-80.85	61.70	-0.68	0.87	28.53***	214.39***	582.31***	167.92***	170.82***
NEER	253	-0.48	5.52	-12.8	12.41	0.20	-0.56	4.81*	210.61***	578.60***	152.42***	153.15***
BRENT	253	5.45	37.43	-100.81	101.86	-0.40	0.08	7.04**	213.48***	626.54***	167.91***	166.87***
EPU	253	4.68	0.57	3.14	6.05	-0.14	-0.26	1.45	103.55***	256.59***	32.78***	31.91***
							India (January 2003 – April 2019)					
CPI	195	6.41	2.86	1.45	14.94	0.60	-0.39	13.03***	182.00***	642.80***	157.02***	156.53***
IP	195	5.75	4.39	-8.62	22.24	0.70	1.80	43.95***	97.56***	340.13***	70.02***	77.37***
BOND	195	7.55	0.84	5.30	9.51	-0.50	-0.06	8.03**	176.92***	576.80***	146.70***	145.50***
STOCK	195	12.20	29.97	-81.42	72.15	-0.91	1.19	39.79***	169.31***	493.94***	140.77***	141.57***
NEER	195	1.46	7.95	-16.74	30.37	0.61	0.58	15.49***	125.48***	354.87***	54.95***	62.12***
BRENT	195	2.07	32.47	-89.30	61.09	-0.75	0.06	18.62***	159.64***	443.93***	121.99***	124.52***
EPU	195	4.40	0.53	3.22	5.65	0.15	-0.67	3.54	100.83***	322.35***	33.47***	42.64***
							Japan (January 1987 – April 2019)					
CPI	388	0.52	1.23	-2.51	3.83	0.73	0.14	35.38***	358.71***	1232.21***	325.17***	325.19***
IP	388	0.90	7.60	-41.97	26.25	-1.65	7.39	1071.84***	332.75***	962.29***	328.05***	337.61***
BOND	388	2.24	1.92	-0.23	8.27	0.99	-0.06	63.57***	381.39***	1478.59***	359.78***	358.68***
STOCK	388	0.66	22.83	-62.51	51.92	-0.11	-0.36	2.66	341.10***	1040.81***	276.63***	275.31***
NEER	388	2.23	10.45	-25.00	32.84	-0.03	-0.19	0.54	351.97***	1115.19***	297.65***	300.46***
BRENT	388	3.13	32.84	-119.35	90.77	-0.48	0.36	17.22***	305.69***	808.54***	212.29***	215.45***
EPU	388	4.57	0.30	3.83	5.47	0.51	0.41	19.62***	254.04***	703.34***	136.22***	139.44***
							South Korea (January 1990 – April 2019)					
CPI	352	3.51	2.21	0.16	9.62	0.85	0.12	43.28***	334.58***	1177.08***	319.63***	319.41***
IP	352	5.77	7.21	-23.51	30.35	0.03	2.50	93.83***	296.11***	883.79***	246.83***	250.44***
BOND	352	7.15	4.65	1.24	17.00	0.67	-0.93	38.48***	348.06***	1346.92***	337.39***	336.89***
STOCK	352	3.00	28.41	-91.72	110.65	0.10	1.90	54.92***	301.78***	851.55***	261.36***	265.65***
NEER	352	-0.83	11.22	-57.31	34.68	-1.80	5.81	694.39***	307.37***	808.58***	272.31***	297.99***
BRENT	352	2.78	29.31	-93.82	87.66	-0.16	0.64	7.90**	260.11***	661.45***	162.17***	161.57***
EPU	352	4.55	0.55	3.11	5.97	-0.08	-0.41	2.67	198.66***	523.71***	79.47***	79.89***
							Other Variables (January 1987 – April 2019)					
US EPU	388	4.66	0.35	3.80	5.65	0.33	-0.15	7.57**	201.55***	486.05***	55.37***	55.32***
EU EPU	388	4.73	0.46	3.52	6.07	0.15	-0.40	3.80	261.64***	860.41***	133.63***	145.29***

Notes: This table reports the descriptive statistics for the time series used in this study. In addition to the mean, the standard deviation (SD), minimum (min), maximum (max), skewness, and kurtosis statistics, the table gives also the Jarque-Bera normality test (JB), the Ljung-Box first [Q(1)] and the fourth [Q(4)] autocorrelation tests, and the first [ARCH(1)] and the fourth [ARCH(4)] order Lagrange multiplier (LM) tests for the autoregressive conditional heteroscedasticity (ARCH). The asterisks ***, * and, * denote significance at the 1%, 5%, and 10% levels, respectively. Also, the US EPU and EU EPU series are taken similar to Japanese data with the longest observations to get more robust descriptive statistics.

Table 2 Unit root tests for level and differenced series for each country's model

		ADF (Const)	ADF (Trend)	ERS (Const)	ERS (Trend)	KPSS (Const)	KPSS (Trend)	PP (Const)	PP (Trend)		ADF (Const)	ADF (Trend)	ERS (Const)	ERS (Trend)	KPSS (Const)	KPSS (Trend)	PP (Const)	PP (Trend)
China	CPI	-2.54	-2.53	2.325**	7.5	0.48**	0.20**	-2.29	-2.49	D(CPI)	-3.44**	-3.46**	0.04***	0.09***	0.04	0.02	-3.91***	-3.92**
	IP	-2.05	-2.79	3.725*	10.38	0.66**	0.35***	-5.01***	-5.75***	D(IP)	-5.01***	-6.49***	0.06***	0.20***	0.3	0.05	-12.40***	-12.58***
	BOND	-3.80***	-3.80**	0.770***	2.79***	0.05	0.05	-3.42**	-3.42*	D(BOND)	-3.95***	-3.94**	0.04***	0.11***	0.03	0.03	-3.78***	-3.77**
	STOCK	-1.96	-2.85	13.777	7.71	1.01***	0.07	-1.93	-2.38	D(STOCK)	-3.28**	-3.28*	0.15***	0.57***	0.07	0.06	-3.43**	-3.44**
	NEER	-0.77	-2.45	35.833	13.23	1.32***	0.28***	-0.92	-1.82	D(NEER)	-4.67***	-4.66***	0.54***	1.55***	0.14	0.08	-3.46***	-3.50**
	BRENT	-2.59*	-2.46	15.366	11.23	0.96***	0.33***	-1.92	-2.08	D(BRENT)	-3.90***	-4.09***	0.59***	1.41***	0.27	0.05	-4.35***	-4.55***
	EPU	-2.17	-4.25***	4.236*	5.93*	1.18***	0.13*	-5.38***	-8.69***	D(EPU)	-5.07***	-5.12***	0.22***	0.81***	0.1	0.05	-10.03***	-10.07***
Honk Kong	CPI	1.08	-4.08***	181.386	387.34	1.33***	0.38***	2.43	-3.73**	D(CPI)	-2.32	-2.27	21.87	12.73	1.16***	0.32***	-2.15	-2.53
	IP	-2.25	-1.78	142.027	41.83	1.36***	0.28***	-4.01***	-1.75	D(IP)	-3.17**	-3.45**	3.12**	3.42***	0.34	0.04	-2.68*	-2.76
	BOND	-1.55	-2.54	138.11	30.73	1.48***	0.31***	-2.12	-2.57	D(BOND)	-4.62***	-4.77***	0.35***	1.15***	0.2	0.03	-4.32***	-4.39***
	STOCK	-1.81	-3.06	17.56	4.62**	1.39***	0.08	-1.61	-3	D(STOCK)	-4.33***	-4.31***	0.22***	0.50***	0.08	0.04	-3.75***	-3.77**
	NEER	-1.46	-1.62	17.375	14.24	1.04***	0.30***	-1.64	-1.66	D(NEER)	-3.46***	-3.51**	0.43***	1.49***	0.18	0.09	-3.82***	-3.87**
	BRENT	-3.13**	-2.68	31.16	23.21	0.80***	0.36***	-2.34	-2.01	D(BRENT)	-4.80***	-4.74***	0.60***	1.86***	0.46*	0.06	-3.98***	-4.34***
	EPU	-4.45***	-8.00***	2.349**	5.00**	0.88***	0.11	-7.09***	-8.37***	D(EPU)	-6.27***	-6.27***	0.36***	0.84***	0.06	0.06	-11.56***	-11.55***
India	CPI	-1.28	0.21	2562.08	60.81	1.40***	0.20**	-0.84	-0.11	D(CPI)	-1.73	-2.06	4.99	15.71	0.35*	0.32***	-1.73	-1.91
	IP	-1.57	-2.22	506.63	24.31	1.37***	0.33***	-1.17	-2.54	D(IP)	-3.25**	-3.50**	0.55***	1.67***	0.52**	0.04	-5.66***	-6.34***
	BOND	-2.98**	-2.81	3.591*	7.07	0.39*	0.23***	-2.59*	-2.6	D(BOND)	-4.08***	-4.28***	0.61***	1.25***	0.19	0.06	-3.89***	-4.04***
	STOCK	-2.53	-2.76	71.915	28.94	0.88***	0.21**	-2.76*	-2.72	D(STOCK)	-3.16**	-3.27*	1.93**	1.94***	0.39*	0.11	-3.51***	-3.59**
	NEER	-1.71	-2.05	21.629	9.64	1.11***	0.27***	-1.87	-2.54	D(NEER)	-3.27**	-3.55**	0.23***	0.80***	0.29	0.1	-4.81***	-5.03***
	BRENT	-2.53	-2.93	2.984**	8.83	0.29	0.22***	-2.31	-2.45	D(BRENT)	-4.13***	-4.14***	0.66***	2.18***	0.24	0.1	-3.63***	-3.78**
	EPU	-2.77*	-2.71	2.836**	7.13	0.3	0.26***	-5.13***	-5.13***	D(EPU)	-3.98***	-4.07***	0.82***	2.69***	0.2	0.07	-7.84***	-7.90***
Japan	CPI	-3.53***	-2.84	283.01	135.28	1.05***	0.34***	-3.91***	-2.95	D(CPI)	-3.09**	-3.27*	1.38***	4.26**	0.53**	0.27***	-2.93**	-3.07
	IP	-3.92***	-4.00***	12.604	9.81	0.39*	0.07	-3.63***	-3.67**	D(IP)	-5.16***	-5.16***	0.02***	0.05***	0.06	0.06	-5.05***	-5.04***
	BOND	-1.12	-1.62	69.407	17.36	1.91***	0.31***	-1.16	-2.3	D(BOND)	-6.17***	-6.34***	1.90***	5.37**	0.37*	0.11	-12.72***	-12.97***
	STOCK	-2.24	-2.04	4.804	9.98	0.82***	0.26***	-1.95	-1.87	D(STOCK)	-4.10***	-4.13***	0.20***	0.67***	0.13	0.04	-4.34***	-4.38***
	NEER	-2.54	-2.31	49.045	24.82	1.33***	0.35***	-2.65*	-2.11	D(NEER)	-3.92***	-3.99***	0.83***	1.30***	0.25	0.04	-3.77***	-3.83**
	BRENT	-1.65	-3.05	5.121	8.76	1.76***	0.24***	-1.6	-3	D(BRENT)	-5.31***	-5.29***	0.55***	1.22***	0.12	0.1	-5.32***	-5.31***
	EPU	-4.19***	-4.35***	1.077***	1.63***	0.42*	0.1	-6.23***	-6.56***	D(EPU)	-7.12***	-7.11***	0.41***	1.24***	0.03	0.03	-8.20***	-8.19***
South Korea	CPI	-5.38***	-2.25	4074.65	295.99	2.12***	0.47***	-7.34***	-2.59	D(CPI)	-3.80***	-4.98***	13.52	5.09**	1.43***	0.13*	-3.00**	-3.89**
	IP	-1.88	-0.93	536.14	31.25	2.13***	0.45***	-2.11	-1.16	D(IP)	-4.18***	-4.44***	0.32***	0.55***	0.45*	0.06	-4.37***	-4.62***
	BOND	-1.74	-3.07	37.77	5.01**	1.96***	0.33***	-1.3	-2.5	D(BOND)	-4.52***	-4.52***	0.02***	0.04***	0.05	0.05	-4.71***	-4.70***
	STOCK	-1.44	-2.92	8.21	10.68	1.79***	0.24***	-1.15	-3.12	D(STOCK)	-5.00***	-5.00***	0.02***	0.05***	0.06	0.06	-4.67***	-4.66***
	NEER	-2.66*	-2.89	9.33	7.22	0.95***	0.15*	-2.79*	-2.98	D(NEER)	-4.38***	-4.40***	0.11***	0.31***	0.08	0.03	-4.32***	-4.32***
	BRENT	-1.62	-3.19*	6.14	6.68*	1.56***	0.25***	-1.86	-2.87	D(BRENT)	-5.00***	-4.99***	0.23***	0.82***	0.13	0.13*	-5.38***	-5.37***
	EPU	-5.55***	-7.40***	0.64***	2.14***	1.47***	0.07	-6.62***	-9.07***	D(EPU)	-8.48***	-8.46***	0.46***	0.98***	0.05	0.05	-10.72***	-10.71***
Others	USEPU	-6.73***	-7.18***	0.318***	1.17***	0.66**	0.12	-7.75***	-8.41***	D(USEPU)	-9.29***	-9.32***	0.80***	2.45***	0.08	0.04	-10.68***	-10.69***
	EUEPU	-3.45***	-4.98***	8.399	4.32**	1.65***	0.18**	-5.59***	-9.26***	D(EUEPU)	-8.15***	-8.13***	0.36***	1.04***	0.04	0.04	-11.21***	-11.20***

Table 3 Static connectedness spillover tables for selected variables for China at various quantiles

(a) 0.05

	From (j)				
To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
CPI	10.77	8.57	9.26	9.85	79.02
IP	10.18	14.08	11.31	14.58	88.93
BOND	13.07	9.95	8.40	10.27	83.94
STOCK	8.01	11.75	11.27	12.74	90.86
NEER	10.33	14.13	10.90	12.97	84.45
EPU	9.69	14.28	11.55	14.55	85.73
To others	80.61	98.17	85.64	102.34	777.97
Direct. incl. own	88.58	112.45	97.94	117.02	TCI
Net spillovers	-11.42	12.45	-2.06	17.02	86.44

(b) 0.25

	From (j)				
To (i)	BRENT	EPU	USEPU	EUEPU	From others
CPI	6.98	4.59	7.39	7.47	70.64
IP	6.05	2.58	6.46	5.92	40.05
BOND	8.84	1.95	2.80	2.07	41.25
STOCK	5.00	6.08	12.97	11.17	63.41
NEER	7.92	8.16	9.55	11.61	63.21
EPU	3.09	30.73	18.06	25.79	69.27
To others	43.76	58.68	85.44	93.70	520.85
Direct. incl. own	94.88	89.40	120.20	134.80	TCI
Net spillovers	-5.12	-10.60	20.20	34.80	57.87

(c) 0.50

	From (j)				
To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
CPI	1.87	3.18	1.04	0.74	64.39
IP	1.40	1.70	1.16	0.51	19.56
BOND	0.37	1.43	2.00	0.98	13.34
STOCK	0.69	2.49	13.91	5.01	33.63
NEER	0.66	0.14	0.25	0.13	8.01
EPU	0.68	52.57	7.48	31.76	47.43
To others	6.39	28.35	43.52	74.99	305.77
Direct. incl. own	72.02	80.92	93.31	140.17	TCI
Net spillovers	-27.98	-19.08	-6.69	40.17	33.98

(d) 0.75

	From (j)				
To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
CPI	6.48	5.34	8.51	8.91	68.5
IP	4.21	3.77	8.13	6.49	42.73
BOND	2.81	4.41	1.18	2.61	20.83
STOCK	4.09	7.41	15.99	15.61	64.57
NEER	1.65	2.92	12.27	5.54	42.85
EPU	7.47	39.57	13.44	23.53	60.43
To others	38.00	58.68	87.69	95.75	510.38
Direct. incl. own	63.06	98.25	118.33	129.58	TCI
Net spillovers	-36.94	-1.75	18.33	29.58	56.71

(e) 0.95

	From (j)				
To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
CPI	10.96	8.81	11.73	10.24	84.55
IP	10.04	8.51	11.17	10.59	83.56
BOND	8.47	7.69	9.09	7.72	79.25
STOCK	9.29	8.61	8.40	9.07	75.91
NEER	10.62	6.99	10.6	8.22	79.20
EPU	8.25	19.69	12.68	14.42	80.31
To others	75.17	73.48	89.23	82.74	734.31
Direct. incl. own	87.92	93.17	105.91	101.77	TCI
Net spillovers	-12.08	-6.83	5.91	1.77	81.59

Note: To save space and avoid unnecessary detail, we shorten original spillover tables and just put purposeful results. Tables containing all results are available from the authors upon request. This situation also exists for the following tables.

Table 4 Static connectedness spillover tables for selected variables for Hong Kong at various quantiles

(a) 0.05

	From (j)				
To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
CPI	10.11	14.63	10.97	12.41	85.39
IP	10.67	11.57	9.52	11.15	84.78
BOND	10.72	13.40	10.00	10.36	81.23
STOCK	10.90	12.55	11.14	12.10	91.97
NEER	9.19	9.37	8.08	9.04	78.65
EPU	10.50	15.46	11.03	12.16	84.55
To others	82.27	96.28	86.61	92.88	756.60
Direct. incl. own	95.26	111.73	104.30	112.15	TCI
Net spillovers	-4.75	11.73	4.30	12.15	84.07

(b) 0.25

	From (j)				
To (i)	BRENT	EPU	USEPU	EUEPU	From others
CPI	1.40	8.18	4.45	5.69	43.99
IP	2.85	1.98	1.22	1.19	44.95
BOND	3.04	6.40	15.42	15.93	63.15
STOCK	5.58	7.91	8.45	8.91	62.98
NEER	1.58	9.05	6.71	7.27	42.29
EPU	5.42	35.53	15.63	16.24	64.47
To others	29.33	64.64	83.57	88.68	503.00
Direct. incl. own	64.77	100.17	122.25	133.38	TCI
Net spillovers	-35.23	0.17	22.25	33.38	55.89

(c) 0.50

	From (j)				
To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
CPI	0.44	0.32	0.38	2.75	21.94
IP	0.34	0.47	0.05	0.26	53.46
BOND	2.44	0.10	8.13	7.06	36.31
STOCK	2.26	0.24	5.72	2.89	31.93
NEER	38.61	1.21	0.28	0.71	61.39
EPU	0.77	6.03	19.70	64.16	35.84
To others	9.27	12.73	37.43	59.27	348.08
Direct. incl. own	47.88	78.34	90.03	123.43	TCI
Net spillovers	-52.12	-21.66	-9.97	23.43	38.68

(d) 0.75

	From (j)				
To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
CPI	2.93	3.62	2.10	2.80	30.78
IP	2.38	1.51	1.35	0.91	53.02
BOND	6.39	1.54	1.10	1.57	29.60
STOCK	8.87	2.56	0.26	2.78	24.61
NEER	47.15	1.73	3.64	3.88	52.85
EPU	9.03	9.41	26.04	41.60	58.40
To others	39.06	34.96	49.13	53.98	407.03
Direct. incl. own	86.21	79.51	95.27	95.58	TCI
Net spillovers	-13.79	-20.5	-4.73	-4.42	45.23

(e) 0.95

	From (j)				
To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
CPI	10.16	13.65	11.44	10.68	84.25
IP	8.93	13.80	10.71	11.20	83.97
BOND	7.96	12.64	9.53	10.07	82.01
STOCK	10.52	11.27	10.31	10.56	85.45
NEER	15.02	11.96	11.38	9.54	84.98
EPU	10.14	11.77	12.03	12.76	87.24
To others	75.57	99.44	88.12	87.54	759.87
Direct. incl. own	90.59	116.67	104.52	100.3	TCI
Net spillovers	-9.41	16.67	4.52	0.30	84.43

Table 5 Static connectedness spillover tables for selected variables for India at various quantiles

(a) 0.05

	From (j)				
To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
CPI	13.59	9.07	10.33	8.38	81.48
IP	11.13	13.01	10.28	13.20	86.90
BOND	16.81	9.36	6.47	8.56	78.61
STOCK	13.60	12.28	9.98	11.33	89.74
NEER	13.66	7.18	7.71	8.10	82.89
EPU	13.71	15.06	10.75	10.54	84.94
To others	101.59	84.71	78.59	85.97	742
Direct. incl. own	126.25	99.76	97.48	104.96	TCI
Net spillovers	26.25	-0.24	-2.52	4.96	82.44

(b) 0.25

	From (j)				
To (i)	BRENT	EPU	USEPU	EUEPU	From others
CPI	6.41	15.28	4.82	1.82	49.30
IP	3.71	2.45	6.89	9.52	52.94
BOND	8.11	7.96	2.71	3.92	46.15
STOCK	9.58	1.81	0.75	0.96	43.49
NEER	0.98	1.83	3.14	7.29	29.20
EPU	7.79	32.34	10.82	10.26	67.66
To others	44.74	55.72	61.29	69.46	463.83
Direct. incl. own	90.07	88.06	97.25	113.09	TCI
Net spillovers	-9.93	-11.95	-2.75	13.09	51.54

(c) 0.50

	From (j)				
To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
CPI	0.79	5.90	0.07	0.90	23.85
IP	1.35	4.58	4.68	6.55	42.20
BOND	4.49	0.34	3.62	10.07	38.15
STOCK	3.10	2.86	1.10	2.21	35.67
NEER	69.15	2.95	1.23	0.55	30.85
EPU	5.92	0.86	21.03	66.20	33.80
To others	22.36	21.15	36.09	64.62	318.46
Direct. incl. own	91.52	71.67	84.83	130.81	TCI
Net spillovers	-8.48	-28.33	-15.17	30.81	35.39

(d) 0.75

	From (j)				
To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
CPI	5.84	15.63	6.43	3.90	54.14
IP	5.98	1.89	1.60	3.76	55.78
BOND	12.81	12.36	3.99	1.05	50.32
STOCK	11.94	2.40	4.82	8.11	54.32
NEER	45.04	3.63	5.43	6.08	54.96
EPU	14.34	7.30	20.39	37.64	62.36
To others	76.69	59.21	59.22	69.82	512.73
Direct. incl. own	121.73	87.59	92.41	107.46	TCI
Net spillovers	21.73	-12.41	-7.59	7.46	56.97

(e) 0.95

	From (j)				
To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
CPI	10.78	15.01	10.40	8.46	85.20
IP	11.05	14.01	10.26	8.20	88.36
BOND	11.90	14.04	10.36	8.49	89.39
STOCK	11.36	13.31	9.61	7.48	83.84
NEER	12.37	12.47	10.78	9.61	87.63
EPU	9.55	14.22	12.51	15.44	84.56
To others	84.31	111.54	84.10	73.65	772.73
Direct. incl. own	96.69	126.56	100.64	89.09	TCI
Net spillovers	-3.31	26.56	0.64	-10.91	85.86

Table 6 Static connectedness spillover tables for selected variables for Japan at various quantiles

(a) 0.05

To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
	From (j)				
CPI	12.90	9.52	10.38	9.43	82.87
IP	12.98	9.89	10.67	10.59	82.76
BOND	10.64	6.79	6.93	7.45	63.41
STOCK	15.00	9.74	8.27	8.76	78.40
NEER	11.99	10.08	10.10	11.23	85.55
EPU	10.98	18.64	10.61	11.30	81.36
To others	93.63	81.51	84.57	85.48	721.93
Direct. incl. own	108.31	100.14	103.18	104.6	TCI
Net spillovers	8.31	0.14	3.18	4.60	80.21

(b) 0.25

To (i)	BRENT	EPU	USEPU	EUEPU	From others
	From (j)				
CPI	14.75	2.85	5.73	6.78	63.95
IP	8.38	1.58	1.25	4.51	44.41
BOND	7.22	0.59	4.05	1.80	32.79
STOCK	4.87	0.33	3.90	3.98	27.95
NEER	0.55	8.00	8.87	7.98	44.05
EPU	60.86	1.76	1.43	2.97	39.15
To others	44.62	39.05	60.34	65.34	408.88
Direct. incl. own	105.47	92.75	102.64	112.75	TCI
Net spillovers	5.47	-7.25	2.64	12.75	45.43

(c) 0.50

To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
	From (j)				
CPI	14.02	2.01	0.25	0.65	31.06
IP	10.11	1.08	0.47	1.45	37.37
BOND	0.54	4.43	0.55	3.85	13.22
STOCK	0.51	6.49	1.32	1.11	13.26
NEER	66.35	1.87	1.73	3.29	33.65
EPU	1.48	9.47	17.91	59.92	40.08
To others	36.77	40.41	30.97	46.22	270.81
Direct. incl. own	103.12	108.72	86.87	106.14	TCI
Net spillovers	3.12	8.72	-13.13	6.14	30.09

(d) 0.75

To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
	From (j)				
CPI	19.09	6.03	4.52	4.23	59.90
IP	10.42	1.96	5.67	6.83	55.27
BOND	4.48	0.89	1.28	0.39	21.98
STOCK	4.07	0.61	1.27	3.62	21.94
NEER	60.96	3.36	2.70	2.71	39.05
EPU	7.23	16.35	19.75	35.36	64.64
To others	52.30	61.52	52.51	58.40	413.85
Direct. incl. own	113.26	114.33	94.58	93.77	TCI
Net spillovers	13.26	14.33	-5.42	-6.23	45.98

(e) 0.95

To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
	From (j)				
CPI	12.30	9.93	10.48	10.8	85.96
IP	11.04	8.93	8.78	12.13	84.90
BOND	10.09	10.97	9.87	9.50	84.25
STOCK	9.64	11.85	9.08	10.51	81.48
NEER	15.47	10.81	11.99	11.44	84.54
EPU	11.21	13.48	14.95	16.02	83.98
To others	85.73	93.18	95.03	90.50	751.99
Direct. incl. own	101.19	113.63	112.66	106.52	TCI
Net spillovers	1.19	13.63	12.66	6.52	83.55

Table 7 Static connectedness spillover tables for selected variables for South Korea at various quantiles

(a) 0.05

To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
	From (j)				
CPI	17.39	8.34	8.50	10.98	80.27
IP	8.58	6.98	8.64	9.64	86.89
BOND	8.80	7.55	8.20	10.33	86.82
STOCK	4.38	7.81	9.32	9.92	74.81
NEER	4.02	5.94	6.27	7.67	77.90
EPU	6.86	15.88	11.21	11.48	84.12
To others	68.59	68.68	78.41	86.64	725.15
Direct. incl. own	91.50	84.55	98.09	109.70	TCI
Net spillovers	-8.50	-15.45	-1.91	9.70	80.57

(b) 0.25

To (i)	BRENT	EPU	USEPU	EUEPU	From others
	From (j)				
CPI	15.32	3.30	1.29	0.88	48.89
IP	5.01	3.55	6.84	3.47	73.45
BOND	4.68	4.50	5.17	6.45	63.66
STOCK	3.51	0.65	3.30	0.74	35.95
NEER	0.27	0.70	0.79	2.40	25.38
EPU	4.70	41.24	19.44	15.23	58.76
To others	42.94	43.83	61.63	52.62	458.83
Direct. incl. own	95.18	85.08	105.19	104.07	TCI
Net spillovers	-4.82	-14.92	5.19	4.07	50.98

(c) 0.50

To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
	From (j)				
CPI	11.38	0.97	0.05	0.71	43.27
IP	1.92	0.41	0.36	7.26	58.42
BOND	1.32	0.66	0.09	0.01	24.98
STOCK	10.59	0.59	0.42	3.52	19.71
NEER	71.46	1.31	0.41	6.22	28.54
EPU	0.93	5.38	17.79	69.61	30.39
To others	40.75	22.95	36.11	54.39	328.47
Direct. incl. own	112.21	81.49	90.50	124.00	TCI
Net spillovers	12.21	-18.51	-9.51	24.00	36.50

(d) 0.75

To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
	From (j)				
CPI	14.91	8.63	7.11	4.59	66.57
IP	4.34	5.70	4.08	0.82	57.47
BOND	3.28	3.18	1.13	1.67	41.11
STOCK	1.92	8.04	3.46	0.76	38.69
NEER	48.50	2.66	5.85	2.57	51.50
EPU	12.91	11.16	20.26	43.51	56.49
To others	52.88	57.79	65.46	47.26	464.22
Direct. incl. own	101.38	102.8	103.49	90.77	TCI
Net spillovers	1.38	2.80	3.49	-9.23	51.58

(e) 0.95

To (i)	BRENT	EPU	USEPU	EUEPU	**From others**
	From (j)				
CPI	13.60	11.55	10.54	9.46	83.75
IP	11.60	10.22	10.55	9.24	81.52
BOND	10.61	8.39	9.19	7.24	70.74
STOCK	13.11	10.84	10.61	10.09	84.57
NEER	20.65	8.96	12.38	9.06	79.35
EPU	10.38	12.68	14.36	19.94	80.06
To others	88.83	83.74	90.29	79.17	716.20
Direct. incl. own	109.49	102.31	108.58	99.11	TCI
Net spillovers	9.49	2.31	8.58	-0.89	79.58

Table 8 Empirical findings of full sample relative tail-dependence ($RTD_{5\%} = S_{0.95} - S_{0.05}$)

(a) China

	From (j)			
To (i)	BRENT	EPU	USEPU	EUEPU
CPI	0.19	0.23	2.47	0.39
IP	-0.14	-5.57	-0.14	-3.99
BOND	-4.60	-2.26	0.69	-2.55
STOCK	1.28	-3.14	-2.87	-3.67
NEER	0.29	-7.14	-0.30	-4.75
EPU	-1.44	5.41	1.13	-0.13

(b) Hong Kong

	From (j)			
To (i)	BRENT	EPU	USEPU	EUEPU
CPI	0.05	-0.98	0.47	-1.73
IP	-1.74	2.23	1.19	0.05
BOND	-2.76	-0.76	-0.47	-0.29
STOCK	-0.38	-1.28	-0.83	-1.54
NEER	5.83	2.59	3.30	0.50
EPU	-0.36	-3.69	1.00	0.60

(c) India

	From (j)			
To (i)	BRENT	EPU	USEPU	EUEPU
CPI	-2.81	5.94	0.07	0.08
IP	-0.08	1.00	-0.02	-5.00
BOND	-4.91	4.68	3.89	-0.07
STOCK	-2.24	1.03	-0.37	-3.85
NEER	-1.29	5.29	3.07	1.51
EPU	-4.16	-0.84	1.76	4.90

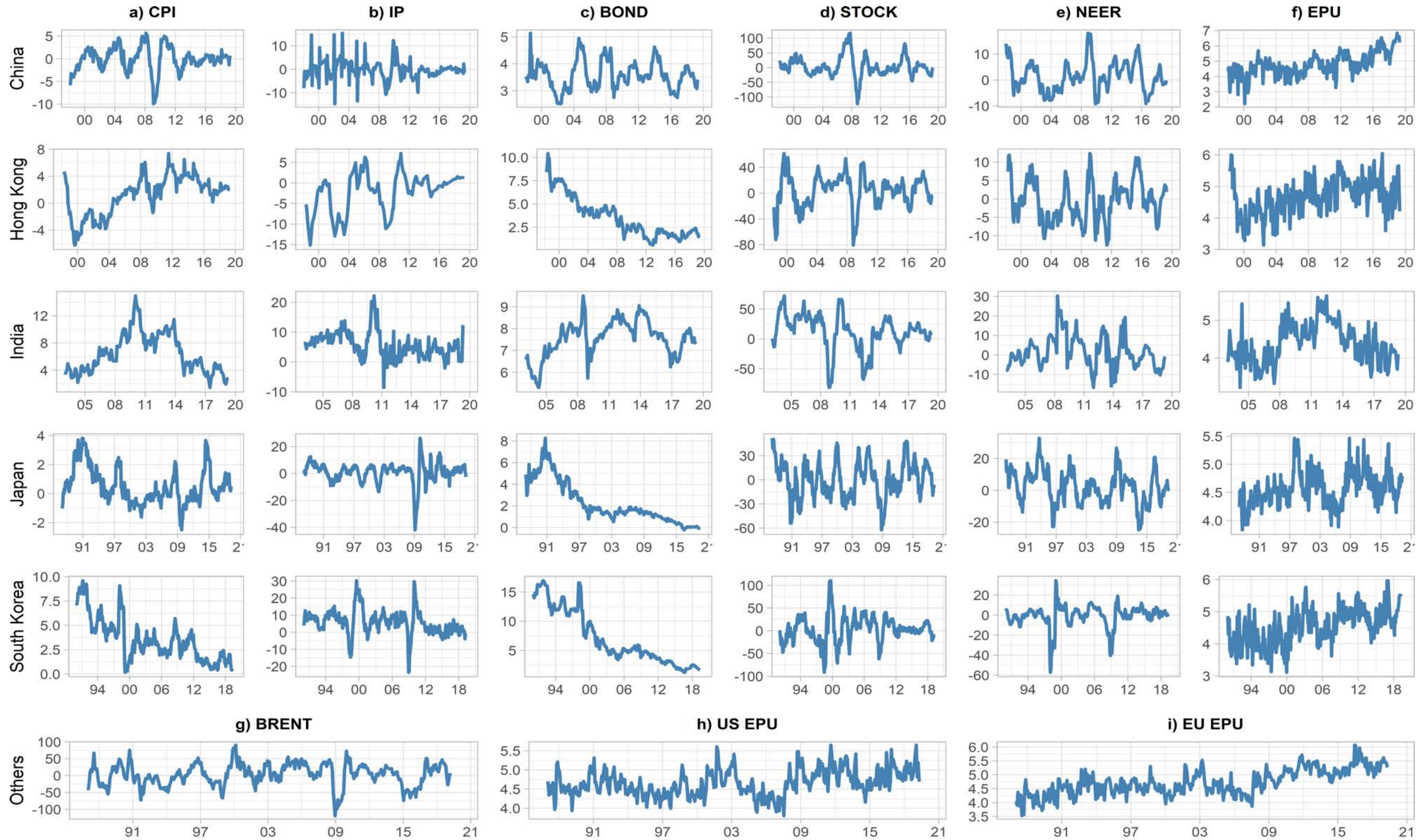
(d) Japan

	From (j)			
To (i)	BRENT	EPU	USEPU	EUEPU
CPI	-0.60	0.41	0.10	1.37
IP	-1.94	-0.96	-1.89	1.54
BOND	-0.55	4.18	2.94	2.05
STOCK	-5.36	2.11	0.81	1.75
NEER	3.48	0.73	1.89	0.21
EPU	0.23	-5.16	4.34	4.72

(e) South Korea

	From (j)			
To (i)	BRENT	EPU	USEPU	EUEPU
CPI	-3.79	3.21	2.04	-1.52
IP	3.02	3.24	1.91	-0.4
BOND	1.81	0.84	0.99	-3.09
STOCK	8.73	3.03	1.29	0.17
NEER	16.63	3.02	6.11	1.39
EPU	3.52	-3.2	3.15	8.46

Figure 1 Time series of all variables



Note: The Brent, US EPU and EU EPU data are plotted according to Japan’s time span which is the longest observations in all countries.

Figure 2 The plot of spillover from Brent, domestic EPU, US EPU, and EU EPU to other markets in different time intervals

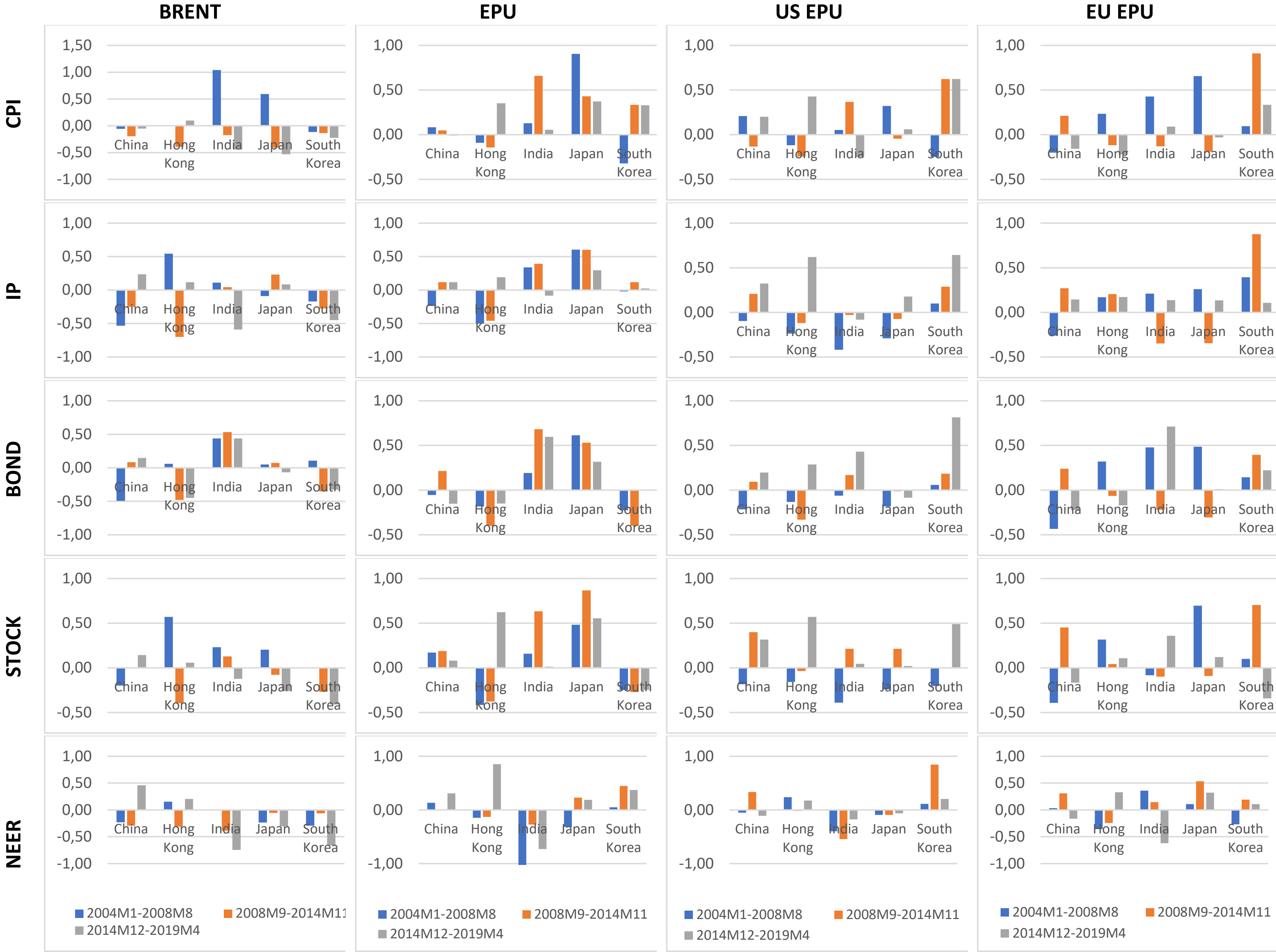
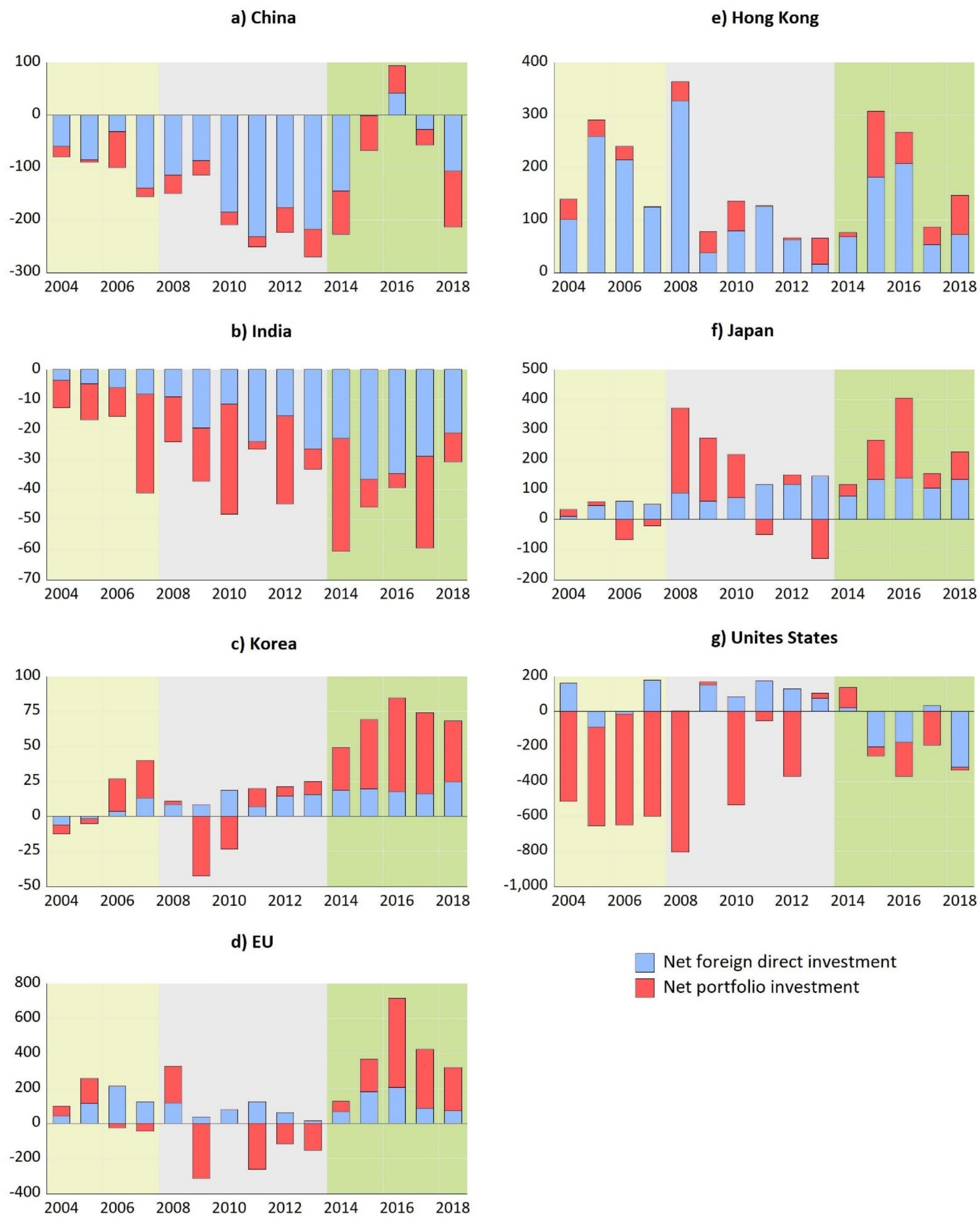


Figure 3 Foreign direct investment and portfolio investment outlook for related countries



Source: World Bank Indicators