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Cross-stock market spillovers through variance risk premiums and equity flows

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ABSTRACT

We estimate variance risk premiums (VRPs) in stock markets of selected major advanced economies (AEs) and emerging market economies (EMEs) over 2007–2015, and decompose the VRP into variance-diffusive risk premium (DRP) and variance-jump risk premium (JRP). Daily VAR analysis reveals significant spillovers from US and developed Eurozone's VRPs to the other economies' VRPs, especially during the post-Global Financial Crisis (GFC) period. We also find that during the post-GFC period, shocks on the DRPs of the United States and the developed Eurozone have relatively strong and long-lived positive effects on other economies' VRPs, whereas shocks on their JRPs have relatively weak and short-lived positive effects. In addition, we show that increases in the size of US VRP, DRP and JRP tend to significantly reduce weekly equity fund flows to all other AEs and some EMEs during the post-GFC period, while the impacts are limited during the GFC period. Finally, US DRP plays a more important role than US JRP in the determination of equity fund flows to other AEs during the post-GFC period. Such results indicate the possibility of equity fund flows working as a channel of cross-stock market VRP spillovers.

1. Introduction

The Global Financial Crisis (GFC) of 2007–2009 has prompted renewed academic interest in financial market volatility. In particular, many papers have found that fluctuations in a measure of volatility such as the Chicago Board Options Exchange (CBOE) Market Volatility Index (in short, the VIX index) are strongly associated with variations in asset prices, leverage, credit provision, capital flows and, more generally, financial conditions. For example, Adrian and Shin (2010) show a close association between US dealer banks' leverage and the VIX index. Bruno et al. (2017) find negative correlations between global banks' cross-border lending to 12 Asia-Pacific economies and the VIX index. IMF (2014, 2015) shows that an increase in the VIX index reduces investor flows to global equity funds. Finally, Hofmann et al. (2016) find that the VIX index has a positive impact on bond yields of emerging market economies (EMEs) and thus their domestic financial conditions. At the same time, more attention has been given to the pricing and volatility of the VIX index traded at CBOE since 2004 as a financial product.

In recent years, both academics and practitioners have increasingly paid attention to risk premium accompanying the variance of asset returns. Since the variance of asset returns fluctuates over time (that is, volatility itself is volatile), market participants require risk premium for such fluctuations. This risk premium is called variance risk premium (VRP).

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Risk premium on volatility and volatility itself are very different, although both are concerned with asset prices in the future. Volatility indicates the dispersion of market participants' view on future price developments while risk premium on volatility implies the fear for increases in future price dispersion. For example, Bollerslev et al. (2009) show the predictive power of variance risk premium on the US stock market return, and a number of studies have followed suit.[1] Bollerslev et al. (2014) and Londono (2015) expand the scope to include other advanced economies (AEs) and find that country-level VRPs are highly correlated. They also report that shocks to the US VRP spill over to other countries' stock returns. This theme is different from stock market volatility spillovers (eg Baele (2005)).

This paper belongs to the literature on VRP spillovers. We further expand the sample countries to include some EMEs and consider the relationship between cross-country VRP spillovers and investor flows to US-based equity funds. In terms of the methodology to estimate VRP, we propose a parametric model approach to estimating VRP and its diffusive and jump components simultaneously by using publicly available data concerning stock index only.[2]

This paper consists of two parts. The first part explains our methodology to estimate VRP and its components. The second part uses the estimation results to quantitatively investigate cross-stock market spillovers through VRP and equity flows.

VRP is a natural extension of the general risk premium required for return risk, and is defined as the difference between variances under different probability measures; more formally, quadratic variation under the real probability measure and that under the risk-neutral probability measure. The estimator of the former is known as the realised variance (RV) computed from intra-day price data, while that of the latter as the model-free implied volatility (IV) or the VIX index which has been established and widely used in the financial industry.

In theory, VRP is defined as an instantaneous value, that is, by contemporaneous RV and IV. In practice, however, RV can only be estimated as an ex-post value, while IV as an ex-ante value. Because of this difference, we need a model for asset prices that bridges the two estimates to derive VRP.

Moreover, VRP can be decomposed into two risk premiums: variance-diffusive risk premium (DRP) and variance-jump risk premium (JRP). DRP originates from the continuous part of a return process, while JRP is derived from the discontinuous part of it. DRP evaluates the risk of ordinary and continuous changes in the scale of uncertainty that market participants seek to compensate for. Hence, it describes market investors' aversion to a predictable scale of uncertainty. By contrast, market participants claim JRP for the possibility of extraordinary and discontinuous price changes. It therefore represents markets' fear of an unpredictable scale of uncertainty. Market participants may require a substantial amount of JRP in addition to a large DRP during financial turmoil, as it is very difficult for them to anticipate a jump of returns. DRP and JRP are likely to be time-varying as investigated by Bollerslev and Todorov (2011).

In the first part of this paper, we develop a method for the estimation of DRP and JRP. In particular, we employ a jump-diffusion model of stock returns with stochastic volatility. In the parametric model, the volatility obeys a mean-reverting process, which is a standard setup, and the jump-arrival intensity (ie, the instantaneous arrival rate of jump) obeys a self-exciting process. We employ a self-exciting process for jump to express the clustering feature of jumps that is observed in stock markets, for example, during the GFC.

Based on the model under the real probability measure and the risk-neutral probability measure, we derive the parametric forms of quadratic variations for both diffusion and jump under the two probability measures. Then, we match the parametric forms with their estimators. While the estimator of quadratic variation for diffusion is known as the bipower variation (BV), that for jump is the difference between RV and BV of the same underlying return (Barndorff-Nielsen and Shephard, 2004). Using this approach, we derive DRP and JRP from IV, RV and BV. The parametric model enables us to do this estimation using easily accessible market data, which raises the applicability of our approach to stock markets in various countries. In particular, over the sample period from November 2007 to September 2015, we first estimate VRPs, DRPs and JRPs of the stock markets of the following seven economies: developed Eurozone, Hong Kong SAR, India, Japan, Korea, Mexico and the United States. The option-implied volatility index for headline equity index is available for each of these economies.

In the second part of this paper, using the estimation results of VRP, DRP and JRP for stock markets in different countries, we investigate their global spillovers that form a channel for global resonance of risk sentiment. Such investigation is in line with recent interest of academics and practitioners in VRP and its contagion. Central bank researchers started to investigate VRP as a proxy for market risk aversion. Raczko (2015) investigates cross-border contagion of crash and non-crash risks using VRPs. Barras and Malkhozov (2016) discuss the difference between VRP embedded in equity portfolios and that implied in option prices. Feunou et al. (2018) show that the term structure of variances reveals two important drivers of the bond premium, that is, the equity premium and the variance premium. Ornelas and Mauad (2019) investigate the predictability of commodity currency VRP and commodity VRP.

Among academics, besides the literature that we have referred to above, Maneesoonthorn et al. (2012) measure premiums for variance-jump and variance-diffusive risks, assuming stochastic volatility with contemporaneous jumps. Bollerslev and Todorov (2011) develop a method to measure JRP and highlight time-varying investors' fears. In addition to these papers,

[1] See Drechsler and Yaron (2011) and Gabaix (2012), among others. Zhou (2018) provides an extensive review of the literature concerning the predictability evidence on the variance risk premium.

[2] Bollerslev and Todorov (2011) and Bollerslev, Todorov and Xu (2015) propose model-free estimates of diffusive and jump-related VRP components. For the estimation in those papers, prices of out-of-the-money puts and calls of stock index at all strike prices need to be used while our parametric approach only use VIX-type implied volatility index and its intra-day trading data, both of which are publicly available.

many papers in the literature have addressed VRPs, including Broadie et al. (2007), Carr and Wu (2009), Bollerslev et al. (2009) and Bollerslev and Todorov (2011).[3]

While the aforementioned papers have deepened our understanding of the methods to estimate VRP and of certain features of the risk premium such as cross-stock market correlations among AEs, this paper extends the cross-stock market correlations of VRPs to include several EMEs, which is a novelty. To be fair, we acknowledge that one reason that EMEs have not been included in the literature is obviously the fact that data on option-implied volatility index such as the VIX index for headline equity indexes even for major EMEs in our sample have become only recently available.[4] This makes our sample starts relatively late but the sample covers a period including the GFC. Moreover, we recognise that the option-implied volatility index for EMEs could be subject to measurement errors because options traded in EMEs are not as liquid as those traded in AEs. We take this limitation into account when we show our estimation results, referring to potential biases from it.

First, looking at simple cross-stock market correlations of VRPs, we find that they are all positive and generally high, and that some market pairs have very high correlations. We also find that JRP correlations are higher than the corresponding DRP correlations during the post-GFC period, but that the opposite is true during the GFC period.

To formally examine the interactions of different economies' VRPs over time, we conduct vector autoregression (VAR) analysis. We find significant spillovers from US and developed Eurozone's VRPs to the other economies' VRPs especially during the post-GFC period. We also find that during the same period, shocks on US and developed Eurozone's DRPs have relatively strong and long-lived effects on other economies' VRPs, while shocks on the two economies' JRPs have relatively weak and short-lived effects on other economies' VRPs. We confirm that these results are generally robust even when we assume contemporaneous shocks to some markets whose trading hours overlap by conducting a structural VAR analysis applying the identification through heteroscedasticity (ITH) method initially proposed by Rigobon (2003) and further developed by Rigobon and Sack (2003), Lanne and Lütkepohl (2008), Sun, Bos and Li (2017) and Helmut and Schlaak (2019).[5,6]

Another novel contribution of this paper is that it considers a specific channel of contagion from VRP in the US stock market to VRPs in other stock markets via equity fund flows. In particular, we consider the impact of US VRP on equity fund flows to other economies. In addition, we consider contagion of US DRP and JRP, respectively, to equity fund flows.

As reported in IMF (2014, 2015), equity fund flows are known to be strongly correlated with measures of global investors' risk appetite such as the VIX index. Ideally, we would need high frequency data such as daily equity fund flows to match the daily movements of VRPs, but we do not use daily equity fund flow data because the coverage of such data in commercial databases is very limited and the daily data on portfolio equity investor flows from national sources are only available for a few economies with very short time series. Therefore, we use the weekly data on global equity fund flows from EPFR Global for our analysis.

We first conduct a simple ordinary least squares (OLS) estimation to gauge the impact of US VRP, DRP and JRP on global equity fund flows to the six individual sample economies other than the United States as well as to all AEs excluding the United States and all EMEs. We compare the relatively stable post-GFC period from January 2010 to September 2015 with the turbulent GFC period from November 2007 to December 2009. In Appendix C, we also use a simple regime-switching model to define relatively high and low volatility periods for each economy's stock market.

We find that over the post-GFC period, the coefficients of OLS estimation on US VRP, DRP and JRP are positive for all six individual economies and both regional groups and statistically significant for five individual economies and both regional groups. This means that when the US equity volatility market charges higher risk premium in absolute size (that is, more negative value of VRP, DRP and JRP), equity fund flows to these economies decrease.[7]

By contrast, during the GFC period, US VRP, DRP and JRP have significantly positive effects on equity fund flows to Japan, but no significant effect on equity fund flows to EMEs. Such contrasting results between the GFC period and post-GFC period indicate that the impact of the VRP in the US stock market on mutual fund flows to other economies' stock markets is more pronounced during relatively tranquil times, and that other factors may play a role in the spillover channels during the crisis period.

Next, we refine the OLS estimation by adding important control variables to the regression equations. They are intended to control effects of global factors, local factors and global investors, behaviour of following stock-return trend. The estimation results of this refinement assure that the simple OLS estimation results are robust.[8] Moreover, we find that during the GFC period, US JRP is a more important driver of equity fund flows to Japan than US DRP, but that during the tranquil post-GFC period, US DRP has a greater impact on equity fund flows to Japan and the developed Eurozone than US JRP.

[3] As VRP is premium asked for volatility changes, a close strand of literature investigates the characteristics of asset price volatility and its spillover. Aït-Sahalia et al. (2015) develop a jump contagion model using mutually exciting jump processes. Bekaert et al. (2014) analyse the transmission of a financial crisis across 415 country-related equity portfolios and find that country-specific factors have a larger impact than US-related factors during the GFC. Aït-Sahalia and Xiu (2016) decompose the quadratic variations of assets including S&P 500 futures into their diffusion and jump components and find that the percentage of jump variations in the quadratic variations remains fairly stable overall during the GFC: as for S&P 500 futures, the percentage is even smaller in the middle of the GFC than in a normal period.

[4] Qiao et al. (2019) estimate VRP for EMEs and consider return or flow predictability and information content.

[5] We are grateful for a referee's suggestion that we use the ITH method to cope with the issue of overlapping trading hours between two markets.

[6] Finta et al. (2017) use ITH for spillovers using intraday data on implied volatility. However, we do not have access to such intraday data for the markets we analyse.

[7] In the literature on variance risk premiums, it is customary to report the size of risk premium in negativity. The more negative a reported value is, the larger the risk premium is. We follow the convention in this paper.

The literature on the determinants of equity portfolio flows mainly focuses on global (or push) factors, regional factors and local (or pull) factors. For example, IMF (2014) provides a list of possible global factors relevant for equity portfolio flows such as the VIX index and the TED spread. IMF (2015) shows that an increase in the VIX index by one standard deviation tends to be associated with around 33% decline in monthly investor flows to equity funds, and that mutual fund investors shift away from equity funds to government bond funds when the VIX index rises. Lo Duca (2012) considers a model where regression coefficients endogenously change over time to see how the drivers of equity fund flows to EMEs change across periods. He finds that investors pay more attention to regional developments in EMEs when market tensions are elevated, such as the pre-Lehman bankruptcy period from August 2007 to mid-September 2008, the peak of sovereign debt problems in Europe in 2010, and the downgrade of the credit rating of the United States in August 2011. By contrast, he finds that in the aftermath of the Lehman bankruptcy, a general loss of confidence due to elevated market uncertainty measured by the average of the VIX index for the United States and the VDAX index for the euro area was an important factor driving equity fund flows. Our paper is different from these papers in the sense that we focus on VRP, which is derived from the VIX index, not the VIX index itself. That is, we aim to distil investors, risk premium itself associated with the volatility of stock returns and investigate its impact on cross-country equity fund flows.

The plan of the paper is as follows. Section 2 explains how we estimate VRP, DRP and JRP. Section 3 describes data used in the paper. Section 4 presents the estimation results on the VRP, DRP and JRP of each stock market. Then, in Section 5, we calculate cross-stock market correlations of VRPs, DRPs and JRPs and conduct VAR analysis showing the impact of US and developed Eurozone's VRPs on other economies' VRPs. Section 6 reports the empirical results from OLS regressions on the effects of US VRP, DRP and JRP on equity fund flows to other economies. Finally, Section 7 concludes.

2. Model for the estimation of volatility risk premium

In this section, we briefly describe asset price processes to define VRP, DRP and JRP, and introduce the estimation procedure. Appendices A and B provide the details.

2.1. The model

We assume fundamental asset price processes in a parametric form under both the real and the risk-neutral probability measures in order to determine DRP and JRP. In this section, we explain the main characteristics of the model and Appendix A provides details on the model.

An asset price evolves through a geometric jump-diffusion stochastic-volatility process with a mean-reverting variance and a self-exciting jump-arrival intensity processes. Such an expression of asset price process is conventional, especially after the GFC in which we observed volatility hikes with abrupt jump feature. In fact, the components are formulated much earlier than the GFC; the process for the volatility is called the Heston model (Heston, 1993), and the one for the jump-arrival intensity with self-exciting feature is introduced by Hawkes (1971).

The dynamics of an asset return y_t under the real probability measure is written as

$$dy_t = \mu(t)dt + \sqrt{v_t}dW_t + d\left(\sum_{n=1}^{N_t} z_n\right) \tag{1}$$

$$dv_t = \kappa(\theta - v_t)dt + \upsilon\sqrt{v_t}dW_t^v, \tag{2}$$

$$d\lambda_t = \alpha(\lambda_\infty - \lambda_t)dt + \beta dN_t, \tag{3}$$

where W_t and W_t^v are uncorrelated Brownian motions, N_t is the Poisson process with a stochastic jump-arrival intensity λ_t, v_t is a stochastic variance, and z_n is a jump size of the n-th jump after $t = 0$. In the variance process (2), $\kappa(> 0)$, $\theta(> 0)$ and υ (> 0) indicate a mean-reverting speed, a long-term mean and volatility of the stochastic diffusion variance, respectively. The stochastic term in Eq. (2) assures that the variance is always positive, given that its initial value is positive. In Eq. (3), $\alpha(> 0)$ and $\lambda_\infty(> 0)$ indicate a mean-reverting speed and a long-term mean of the jump-arrival intensity, respectively, and $\beta(> 0)$ indicates the impact of a jump in the return on the jump-arrival intensity. Since price jumps are known to be clustered temporally, the process is expected to show a good fit to jump estimates (Aït-Sahalia et al., 2015). We assume that the return process under the risk-neutral probability measure has the same form of equations with different parameters and stochastic variables. This assumption enables us to derive relationships of parameters under the two probability measures that are explicitly described in Section A.3 of Appendix A.

Based on the model, we can linearly decompose the quadratic variations under both the real and the risk-neutral measures into diffusion and jump parts. One-month quadratic variation of the diffusion part under the risk-neutral measure contains DRP, and the jump part contains JRP. If returns contain jumps with potentially infinite jump sizes, the market becomes incomplete and a potentially infinite number of risk-neutral measures exist. Therefore, we need to make an additional assumption to identify a unique risk-neutral measure and the accompanying JRP. We assume that the jump-arrival intensity can differ while the jump size remains the same under the two probability measures.

2.2. Estimation procedure

Three daily market measures, RV, BV and IV, of each underlying asset are used as the inputs in the model for the estimation of DRP, JRP and VRP. We employ the Markov chain Monte Carlo (MCMC) method with some techniques such as the block sampling to calibrate the model parameters and generate samples of the risk premiums (Shephard and Pitt, 1997, Watanabe and Omori, 2004). Appendix B provides details on the procedure and we give a brief sketch of the procedure in this section.

Let $\mathscr{D}_{t,t+\tau}$ and $\mathscr{J}_{t,t+\tau}$ denote diffusion and jump parts of one-day (τ) quadratic variations of returns, respectively, under the real measure. Barndorff-Nielsen and Shephard (2004) show that RV and BV are robust measures of $\mathscr{D}_{t,t+\tau} + \mathscr{J}_{t,t+\tau}$ and $\mathscr{D}_{t,t+\tau}$, respectively. On the other hand, $\mathscr{J}_{t,t+\tau}$ is described as the product of the quadratic jump size z_n^2 and the jump occurrence indicator (j_t, hereafter) which expresses the number of jumps in a unit of time. The prior of the former is assumed to obey the exponential distribution whereas that of the latter obeys the binominal distribution. Given these assumptions, we can sample jump-related parameters and variables, while successfully excluding measurement errors in the estimators of RV and BV.

The quadratic variations which correspond to RV and BV are described in terms of parameters and latent variables in the model for a return on an asset under the real probability measure, ie Eqs. (1), (2) and (3). With an additional assumption that the coefficients of risk premiums are piecewise constant over a one-month period after each time step, the quadratic variation that corresponds to IV is described as a linear equation of the stochastic variance, the jump-arrival intensity and the coefficients of DRP and JRP. Also, latent variables are transformed to the vector of autoregressive equations by discretising some equations in the model with additional assumptions. These steps, taken together, produce a form of vector state-space representation from which DRP and JRP are sampled through a forward-filtering backward-smoothing procedure.

3. Data

This paper considers daily data on the following seven major equity indexes for underlying assets: Nikkei 225 in Japan (Nikkei), KOSPI 200 in Korea (KOSPI), Hang Seng Index in Hong Kong SAR (HSI), NSE Nifty Index in India (Nifty), EuroSTOXX 50 in the developed Eurozone (EuroSTOXX),[9] Mexican Bolsa IPC Index in Mexico (MEXBOL) and S&P 500 Index in the United States (SPX). The sample period is from 6 November 2007 to 30 September 2015. Because the model incorporates IV, data on implied volatility indexes for the selected underlying assets should be available retroactively up to 2007. The sample period starts from the date the Indian VIX time series started, which was released latest among all the indexes.

Data for RV and BV are obtained from the Oxford-Man Institute Realised Library (Heber et al., 2009). While several methods have been proposed for the computation of RV and BV, we employ the standard one which uses five-minute returns for both RV and BV (see, for example, Liu et al., 2015). The corresponding IV is obtained from various sources chosen as follows: Nikkei VI for Nikkei released from the Japan Exchange Group, VKOSPI for KOSPI from the Korea Stock Exchange, VHSI for HSI from the Hong Kong Stock Exchange, India VIX for Nifty from the National Stock Exchange of India, VSTOXX for EuroSTOXX from Eurex, VIMEX for MEXBOL from Mexdar and VIX for SPX from CBOE. All daily data are converted into annual rates in variance dimension. Weekends, national holidays and market closing dates of individual economies are excluded from the sample. If the market of at least one economy is closed, the whole data on the date is excluded from the sample. As the number of missing data is large for Hong Kong SAR, DRP and JRP for Hong Kong SAR are separately estimated from other EMEs while data for AEs are used in the estimation to control global covariance among instantaneous volatilities, and also among DRPs and JRPs.

In the daily VAR regression analysis in Section 5, we consider global and local factors as control variables. For global factors, we consider a "world" nominal short-term interest rate.[10,11] As a local factor reflecting country fundamentals, we use the Citi Economic Surprise index from Bloomberg. An increase in this index means positive surprise.[12] Finally, in order to capture the return-chasing behaviour of retail investors in equity mutual funds and exchange-traded funds (ETFs), whose performance is measured by US dollar returns, we consider MSCI country-(or region-)level US dollar total return indexes. It should be noted that the US dollar return is the sum of FX return over a period and the local currency total return on equities.

[9] The EuroSTOXX 50 Index covers 50 blue-chip stocks from the following 11 developed Eurozone countries: Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain. This is different from the STOXX Europe 50 Index covering 50 blue-chip stocks from the following 17 European countries: Austria, Belgium, the Czech Republic, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom. Since we focus on the EuroSTOXX 50 Index in this paper, we use the term "developed Eurozone" to refer to the market and economy represented by the index.

[10] We calculate the world interest rate as a weighted average of short-term interest rates in AEs (Canada, France, Germany, Italy, Japan, Netherlands, Norway, Spain, Switzerland, Sweden, the United Kingdom and the United States) and EMEs (Argentina, Brazil, Chile, China, Chinese Taipei, Colombia, the Czech Republic, Hong Kong SAR, Hungary, India, Indonesia, Korea, Mexico, Malaysia, Peru, the Philippines, Poland, Russia, Singapore, Thailand, Turkey and Vietnam) using 2005 PPP-adjusted GDP as weights.

[11] We can alternatively use a "global" TED spread calculated as a weighted average of US TED spread (ie, 3-month US dollar Libor minus 3-month rate on Treasury bills) and euro area TED spread (ie, 3-month euro Libor minus 3-month rate on German bunds), using 2005 PPP-adjusted GDP as weights.

[12] We were not able to obtain Citi Economic Surprise index for India. Therefore, we do not use this variable in the regressions for India.

Table 1
Statistics of parameters.

		Japan	Korea	Hong Kong SAR	India	Developed Eurozone	Mexico	United States
	mean	5.099	4.948	5.251	5.068	5.267	5.034	4.937
κ	C.I.	(3.12, 7.04)	(3.00, 6.85)	(3.47, 7.46)	(3.08, 7.03)	(3.31, 7.20)	(3.01, 6.93)	(3.00, 6.84)
	C.D.	0.91	0.17	0.03	0.00	0.52	0.07	0.00
	mean	0.006	0.004	0.004	0.016	0.022	0.004	0.009
θ	C.I.	(0.00, 0.06)	(0.00, 0.05)	(0.00, 0.05)	(0.00, 0.10)	(0.00, 0.11)	(0.00, 0.05)	(0.00, 0.07)
	C.D.	0.63	0.00	0.00	0.30	0.05	0.57	0.02
	mean	9.602	8.713	8.747	8.506	8.383	8.610	8.777
α	C.I.	(5.33, 13.90)	(4.19, 13.12)	(4.29, 13.03)	(4.03, 12.93)	(3.83, 12.87)	(4.19, 13.00)	(4.41, 13.01)
	C.D.	0.65	0.00	0.24	0.02	0.29	0.33	0.83
	Mean	0.023	0.001	0.004	0.001	0.004	0.004	0.002
β	C.I.	(0.00, 0.11)	(0.00, 0.02)	(0.00, 0.03)	(0.00, 0.01)	(0.00, 0.03)	(0.00, 0.03)	(0.00, 0.02)
	C.D.	0.76	0.62	0.82	0.62	0.25	0.48	0.87
	Mean	0.103	0.052	0.050	0.057	0.059	0.070	0.072
λ_∞	C.I.	(0.00, 0.24)	(0.00, 0.17)	(0.00, 0.03)	(0.00, 0.18)	(0.00, 0.19)	(0.00, 0.21)	(0.00, 0.21)
	C.D.	0.36	0.03	0.81	0.00	0.31	0.01	0.78

C.I.: 95% credible interval; C.D.: convergence diagnostics (bandwidth 500 around 1000th and 5000th samples) by Geweke (1992).

In section 6, we investigate the impact of US VRP, DRP and JRP on mostly US-based investors' equity fund flows to the other economies' stock markets. For this exercise, we obtain weekly data on equity fund flows from EPFR Global.[13] In particular, we use the EPFR data on the estimated investor flows to individual economies calculated for all equity funds available in the country flow database. Considering that new funds are added over time to the EPFR database, we use flows/TNA as the measure for country flows in order to control for such entry bias. Here, TNA (total net assets) are at the beginning of each week during which the flows are measured. In Section 6, daily data on VRPs, DRPs and JRPs as well as the three control variables are converted to weekly averages to be consistent with the frequency of equity fund flow data used in this paper.

4. Estimation results for variance risk premiums

Table 1 shows the following statistics of parameters in the model: sample means, 95% confidence intervals (C.I.) and the convergence diagnostics (C.D.) proposed by Geweke (1992). We confirm from C.D. that the MCMC procedure converges enough. Concerning the parameters for variance, κ is distributed around 5 for all economies, while θ differs by economies, which disperses in the range from 0.004 to 0.022. Taking square root of these yields the long-term mean of diffusion volatilities in the range from 6% to 15%. As for the parameters for jump, α is sampled around 9, while β and λ_∞ are sampled in the range from 0.001 to 0.023, and from 0.05 to 0.1, respectively. Comparison between the estimated values of κ and α indicates the speed of convergence of jump-arrival intensity is generally faster than that of variance.

Fig. 1 shows one-month integrated VRP and its decomposition into DRP and JRP. The absolute value of VRP surges during crisis periods through both DRP and JRP, but the expansion is more through DRP rather than JRP especially in the middle of the crisis from the late 2008 to the early 2009. This result is in line with what Aït-Sahalia and Xiu (2016) find. They decompose the quadratic variations of assets including S&P 500 futures into their diffusion and jump components and find jumps are not the dominant effect during the crisis; both of diffusive and jump quadratic components increase, keeping split between the two in terms of contribution to the total quadratic variations stable in general. Specifically for S&P 500 futures, the percentage of jump's contribution is even smaller during the GFC than a normal period.

The intuition behind this finding is as follows. When a crisis mode begins, market participants face large uncertainty concerning market conditions and form widely dispersed views on price movements in the future. In other words, return uncertainty rises at the onset of a crisis. Such a change is appropriately expressed as a greater diffusion component in variance of returns in their expectation, which results in an increase in DRP. At the same time, they also incorporate larger tail risk in their expectation, which results in an increase in JRP. An increase in DRP expresses a larger risk premium for greater uncertainty, while an increase in JRP expresses a larger risk premium for tail risk. During a market turmoil, a rise in uncertainty exceeds an increase in tail risk, which results in a larger portion of DRP than JRP.

In technical interpretation, this means that an increase in the second moment of returns is relatively large vis-à-vis the higher moments in market participants' expectation during the crisis period. This echoes the finding in Aït-Sahalia and Xiu (2016) which the authors summarise in the following sentence in page 210: "Asset returns during the crisis evolved like a slow train wreck, rather than a succession of large disruptions." As for the non-crisis period, VRP expands occasionally, but not surprisingly, at by far smaller extents than during the GFC. As a notable result, a significant portion of VRP is contributed by JRP, indicating that even in the normal period, market participants are prepared for the tail risk to some extent. This result is reasonable and realistic. When the market is calm, the market participants tend not to ask for high risk premium for uncertainty concerning movements in returns while they still care about an abrupt and extreme change in returns as a possibility that is captured as tail risk. As the result, a certain level of JRP remains in the shrunken VRP.

[13] EPFR Global estimates fund flows incorporating portfolio reallocations at each equity fund instead of fixing estimated portfolio compositions. We do not have access to daily equity fund flow data from EPFR Global, so use weekly data instead.

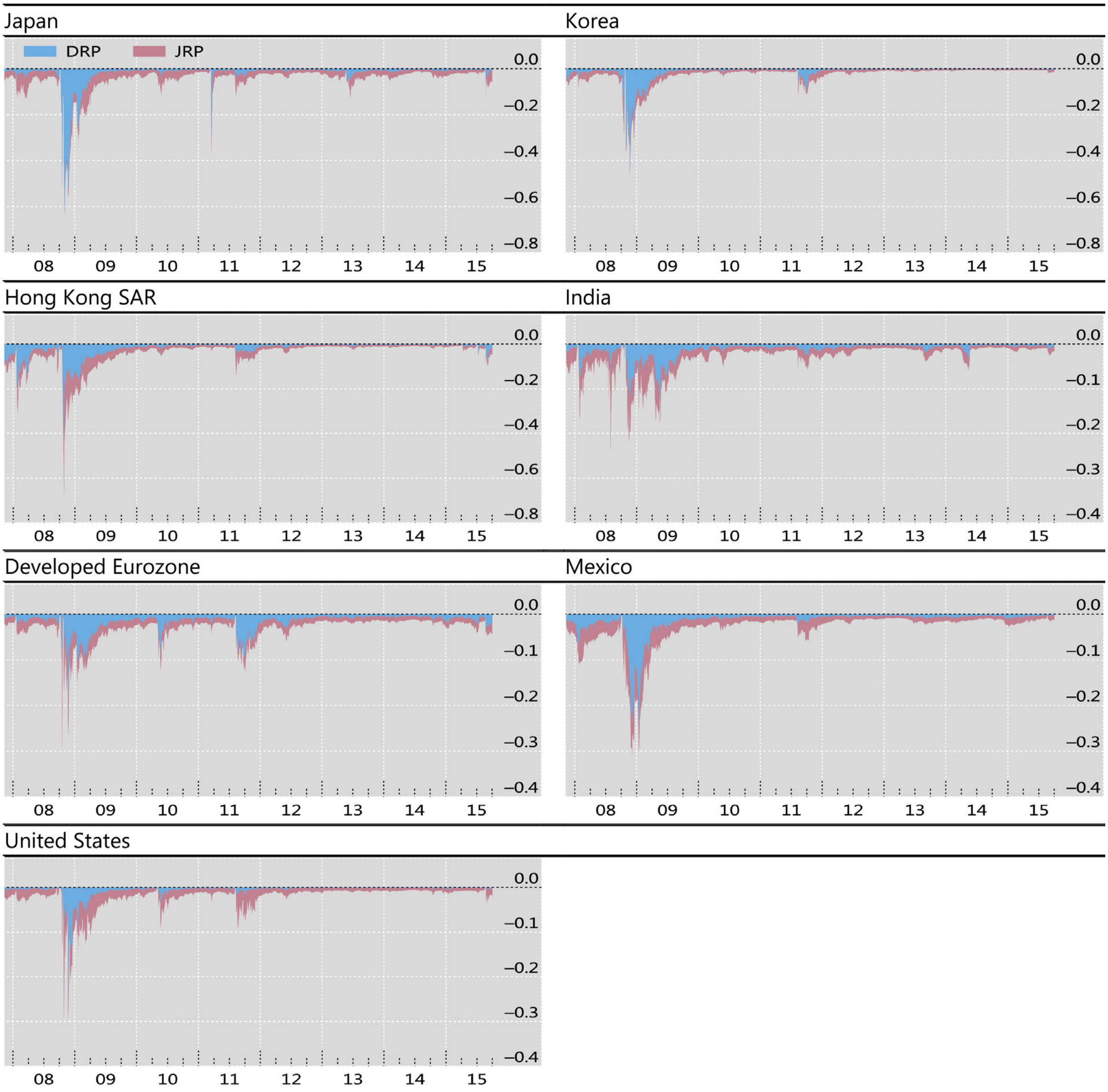

Fig. 1. VRP with its decomposition into DRP and JRP. Blue bar indicates DRP, while red bar indicates JRP. DRP and VRP are assumed to be proportional to instantaneous variance and jump-arrival intensity at each tie step, and their coefficient of proportionalities varies over time.Source: Authors' estimates.

Finally, Fig. 2 shows observed IV and the decomposition of theoretical IV into the diffusion part ($\mathscr{D}^*_{t,t+T}$) and the jump part ($\mathscr{I}^*_{t,t+T}$). In this figure, we immediately confirm that the model tracks IV well; the gap between IV and its theoretical counterpart, $\mathscr{D}^*_{t,t+T} + \mathscr{I}^*_{t,t+T}$, is small. Another finding is that the surge in IV in the midst of the GFC is attributable more to the diffusion part than to the jump part. This is similar to the feature in the risk premiums.

5. Cross-stock market spillovers of variance risk premiums

5.1. Cross-country correlation of VRPs, DRPs and JRPs

In the following two subsections, we investigate cross-market spillovers through the risk premiums by using the estimation results from the previous section. Tables 2–4 summarise cross-stock market correlations of daily VRPs, DRPs and JRPs. The correlations are calculated in two subsample periods: the GFC period from November 2007 to December 2009, and the post-GFC period from January 2010 to September 2015. Figures in the upper right triangular part, including the diagonal, of

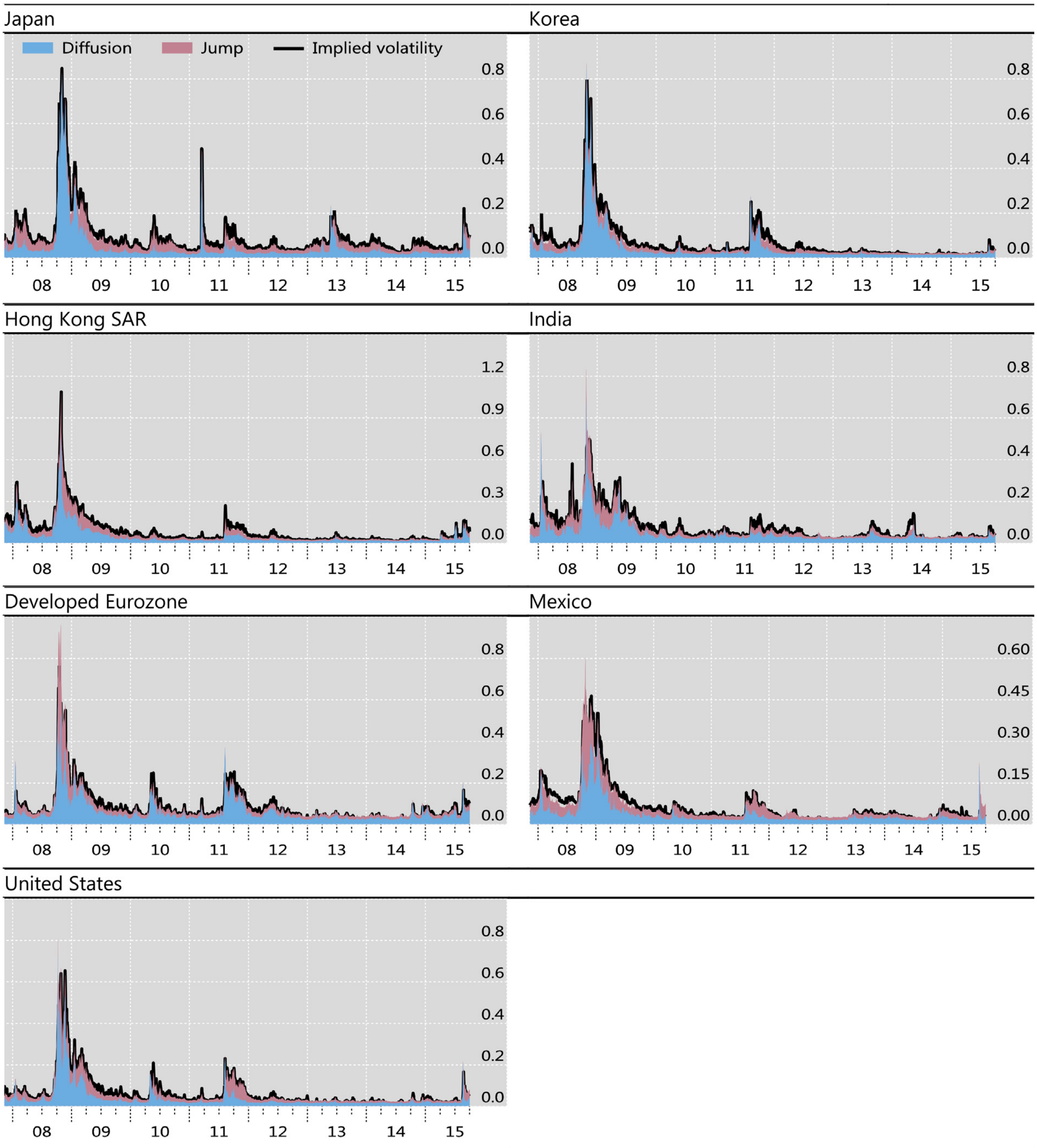

Fig. 2. Decomposition of IV. The light blue and red areas indicate diffusion and jump parts respectively, while the black line indicates IV. The diffusion part is composed of the quadratic variation of diffusion volatility and DRP, while the jump part is composed of the quadratic variation of jump and JRP. The difference between the sum of the two parts and IV indicates sampling and measurement errors.
Source: Authors' estimates.

each table indicate same-day correlations, whereas those in the lower left triangular part indicate timing correlations between the one-day lagged value for the economy in each row and the current value for the economy in each column.

Table 2 shows that the cross-stock market correlations of VRPs are all positive and generally high in terms of both the contemporaneous and one-day lagged correlations. Also, some market pairs, such as the US–developed Eurozone, developed Eurozone–Korea, and Hong Kong SAR–Korea, have relatively high VRP correlations greater than 0.8.

Table 2
Cross-market correlation of VRPs.

Post-Global Financial Crisis period (January 2010–September 2015)							
	Japan	Korea	Hong Kong SAR	India	Developed Eurozone	Mexico	United States
Japan	1.00	0.32	0.39	0.32	0.38	0.39	0.45
Korea	0.29	1.00	0.82	0.60	0.85	0.78	0.79
Hong Kong	0.39	0.81	1.00	0.52	0.80	0.62	0.74
India	0.31	0.60	0.49	1.00	0.60	0.66	0.58
Developed Eurozone	0.37	0.84	0.79	0.60	1.00	0.76	0.92
Mexico	0.37	0.79	0.61	0.66	0.76	1.00	0.77
United States	0.44	0.79	0.74	0.58	0.90	0.75	1.00
Global Financial Crisis period (November 2007–December 2009)							
	Japan	Korea	Hong Kong SAR	India	Developed Eurozone	Mexico	United States
Japan	1.00	0.92	0.73	0.49	0.86	0.81	0.82
Korea	0.86	1.00	0.59	0.52	0.86	0.82	0.80
Hong Kong	0.75	0.72	1.00	0.49	0.57	0.68	0.74
India	0.47	0.51	0.43	1.00	0.56	0.56	0.53
Developed Eurozone	0.80	0.81	0.56	0.56	1.00	0.75	0.85
Mexico	0.79	0.80	0.71	0.56	0.74	1.00	0.80
United States	0.83	0.82	0.66	0.54	0.81	0.80	1.00

Figures in the upper-right triangle including the diagonal indicate same-day correlations, whereas those in the lower-left triangle indicate correlations with one-day difference, which indicate the strength of spillover from economies in row to economies in column.

Table 3
Cross-market correlation of DRPs.

Post-Global Financial Crisis period (January 2010–September 2015)							
	Japan	Korea	Hong Kong SAR	India	Developed Eurozone	Mexico	United States
Japan	1.00	0.20	0.25	0.16	0.23	0.20	0.20
Korea	0.19	1.00	0.65	0.50	0.82	0.65	0.54
Hong Kong	0.24	0.62	1.00	0.38	0.72	0.33	0.39
India	0.15	0.49	0.36	1.00	0.52	0.50	0.39
Developed Eurozone	0.22	0.80	0.71	0.52	1.00	0.61	0.74
Mexico	0.20	0.68	0.33	0.51	0.62	1.00	0.63
United States	0.21	0.54	0.40	0.39	0.73	0.60	1.00
Global Financial Crisis period (November 2007–December 2009)							
	Japan	Korea	Hong Kong SAR	India	Developed Eurozone	Mexico	United States
Japan	1.00	0.90	0.54	0.40	0.71	0.68	0.78
Korea	0.85	1.00	0.49	0.49	0.80	0.75	0.84
Hong Kong	0.56	0.61	1.00	0.40	0.46	0.56	0.54
India	0.37	0.47	0.35	1.00	0.54	0.48	0.52
Developed Eurozone	0.67	0.77	0.39	0.53	1.00	0.71	0.79
Mexico	0.66	0.73	0.58	0.46	0.71	1.00	0.83
United States	0.77	0.83	0.52	0.51	0.76	0.84	1.00

Figures in the upper-right triangle including the diagonal indicate same-day correlations, whereas those in the lower-left triangle indicate correlations with one-day difference, which indicate the strength of spillover from economies in row to economies in column.

When we consider the correlations of the two components' of VRPs, that is, the cross-market correlations of DRPs and those of JRPs, we find that the DRP correlations are higher during the GFC period than during the post-GFC period (Table 3), but that the JRP correlations are lower during the GFC period than during the post-GFC period (Table 4).

A comparison of the correlations among all pairs of DRPs and those among the corresponding pairs of JRPs in each subsample period illuminates interesting observations (Tables 3 and 4). In particular, the DRP correlations tend to be higher for market pairs than the corresponding JRP correlations during the GFC period. By contrast, we find the opposite in the post-GFC period: the DRP correlations are lower than the corresponding JRP correlations. A possible interpretation of these patterns is that during the post-GFC period, the expected part of VRPs has been suppressed by major central banks' accommodative monetary policies, but that the unexpected part of VRPs driven by events of jump characteristic that have intermittently occurred is the main cause of global resonance of risk premium on volatility.

5.2. VAR analysis on the cross-country spillovers of VRPs

In the previous subsection, we calculated simple cross-market correlations between VRPs. In this subsection, we more precisely estimate the effects of a shock to an economy's VRP on another economy's VRP by VAR analysis.

Table 4
Cross-market correlation of JRPs.

Post-Global Financial Crisis period (January 2010–September 2015)	Japan	Korea	Hong Kong SAR	India	Developed Eurozone	Mexico	United States
Japan	1.00	0.34	0.47	0.43	0.39	0.47	0.51
Korea	0.31	1.00	0.75	0.58	0.70	0.71	0.76
Hong Kong	0.46	0.79	1.00	0.62	0.62	0.72	0.76
India	0.42	0.60	0.58	1.00	0.56	0.69	0.60
Developed Eurozone	0.36	0.69	0.60	0.54	1.00	0.63	0.76
Mexico	0.45	0.72	0.70	0.68	0.64	1.00	0.80
United States	0.50	0.77	0.77	0.60	0.76	0.78	1.00
Global Financial Crisis period (November 2007–December 2009)	**Japan**	**Korea**	**Hong Kong SAR**	**India**	**Developed Eurozone**	**Mexico**	**United States**
Japan	1.00	0.31	0.40	0.34	0.14	0.32	0.31
Korea	0.31	1.00	0.38	0.33	0.55	0.61	0.39
Hong Kong	0.40	0.43	1.00	0.42	0.44	0.66	0.74
India	0.35	0.34	0.37	1.00	0.28	0.53	0.38
Developed Eurozone	0.13	0.43	0.61	0.27	1.00	0.64	0.63
Mexico	0.32	0.58	0.74	0.54	0.59	1.00	0.69
United States	0.32	0.42	0.67	0.42	0.56	0.68	1.00

Figures in the upper-right triangle including the diagonal indicate same-day correlations, whereas those in the lower-left triangle indicate correlations with one-day difference, which indicate the strength of spillover from economies in row to economies in column.

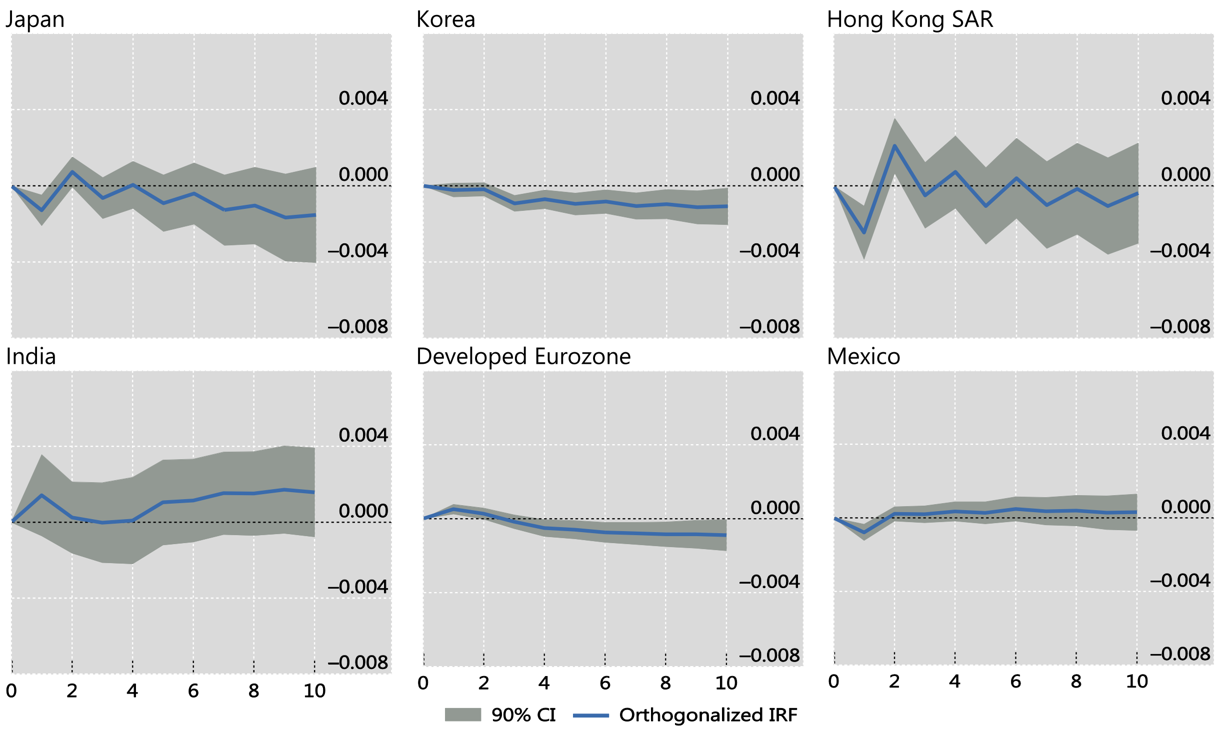

Fig. 3. Response of other economies' VRPs to US VRP shocks. Global Financial Crisis period (117 daily observations). See the text for the details on the VAR regression specifications.Source: Authors' estimates.

Before we conduct VAR analysis, we conduct Granger causality Wald tests among the VRPs of the seven economies over the full sample period, the GFC period and the post-GFC period to identify which economy's VRP significantly explains the variations of the other six sample economies' VRPs. In particular, we test the null hypothesis that an economy's VRPs at date t, $t-1$ and $t-2$ as endogenous variables jointly do not affect another economy's VRP. We find that VRPs of US and developed Eurozone stock markets significantly affect VRPs' of almost all the other economies' VRPs, respectively. Considering that these two economies are the largest globally, that the US stock market is arguably the most contagious market and that

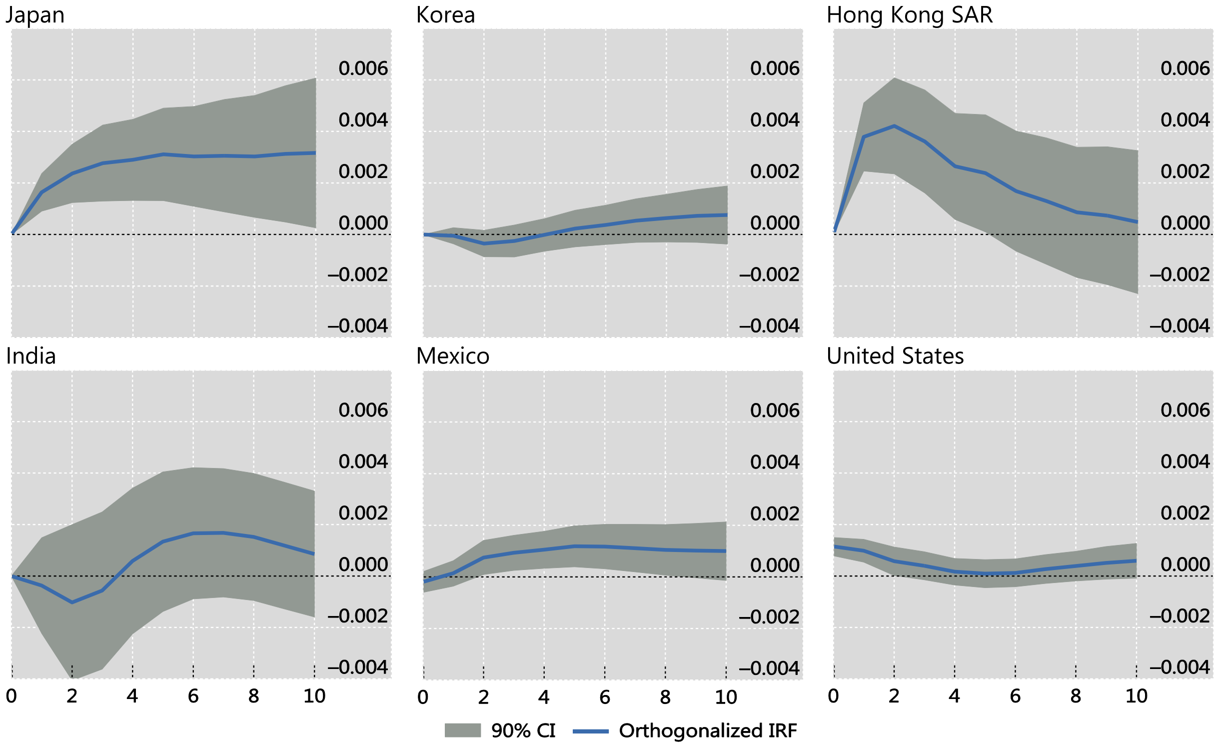

Fig. 4. Response of other economies' VRPs to developed Eurozone's VRP shocks. Global Financial Crisis period (117 daily observations). See the text for the details on the VAR regression specifications.Source: Authors' estimates.

the impact of the European debt crisis on global financial markets was considerably large, in this section we focus on both US and developed Eurozone's VRPs as the source of VRP shocks to the other economies.[14] We consider a few control variables in the VAR estimation. Besides the endogenous variables such as US and developed Eurozone's VRPs, the VAR system includes, as exogenous variables, the world nominal short-term interest rate as the global factor affecting all seven stock markets, and Citi Economic Surprise indexes for each economy as a local factor capturing news in macroeconomic fundamentals, and total return on a local stock index in US dollars in the previous business day.[15] The lagged total return on a local stock index is used to control for the effects of global investors' return-chasing behaviour.

For all VAR estimations below, the ordering in the error term matrix for Choleski decomposition from the top to bottom is Japan, Korea, Hong Kong SAR, India, developed Eurozone, Mexico and the United States. This order follows the market closing time in each economy on the same business day. Therefore, in impulse-response analysis for the VAR system, the effect of a shock to US endogenous variable on the other economy's variables does not show up in the contemporaneous business day, but from the next business day onward. We choose the number of lags for endogenous variables as 2 for the VAR system based on Schwarz Bayes information criteria in order to specify the VAR system to estimate in the most parsimonious way. In this subsection, we conduct VAR analysis over the two subsample periods, ie the GFC period and post-GFC period. The results from VAR analysis over the full sample period are provided in Appendix D.

Figs 3 and 4 show impulse response functions (IRFs) from VAR estimation over the GFC period. US VRP has a significant positive impact only on developed Eurozone's VRP on day 1 (Fig. 3), while developed Eurozone's VRP has a significant positive impact on Japan's VRP from day 1 to day 10, on Hong Kong's VRP from day 1 to day 5, on Mexico's VRP from day 3 to day 8, and on US VRP on the same day and day 1 (Fig. 4). Overall, we find that US VRP does not exhibit strong positive spillover effects on other economies' VRPs during the GFC period, but that developed Eurozone's VRP exerts strong influence on many other economies' VRP. One caveat is the relatively short time-series dimension of 117 observations.

Figs 5 and 6 present IRFs over the post-GFC period. US VRP has a significant positive impact on all the other six economies' VRPs in one day and on five out of the six economies' VRPs in two days (Fig. 5). On VRPs of Korea is the impact significant even in three days. Developed Eurozone's VRP has a significant positive impact on all the other six economies' VRPs up to day

[14] The Granger causality Wald tests also show that HK VRP significantly explains some other economies' VRPs, depending on subsample periods. To the extent that the equity market of Hong Kong SAR reflects the movements of China's stock markets, we can interpret the impact of HK VRP as the impact of the VRP of China, another large economy which could potentially affect other economies' VRPs. Interestingly, the test results suggest that HK VRP affects the VRPs of all three Asian economies – Japan, Korea and India – during the full sample period, the GFC period and the post-GFC period.

[15] We do not include the Citi Economic Surprise index for India since we are not able to obtain that series.

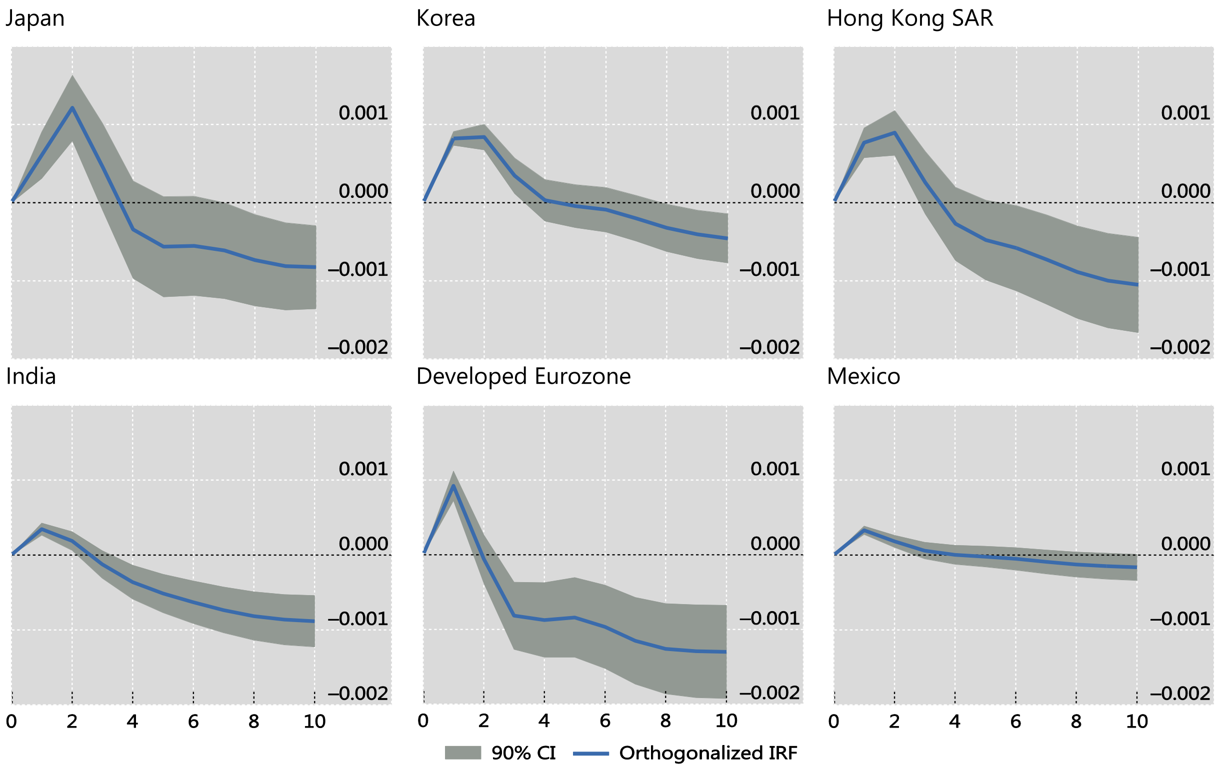

Fig. 5. Response of other economies' VRPs to US VRP shocks. Post-Global Financial Crisis period (688 daily observations). See the text for the details on the VAR regression specifications.
Source: Authors' estimates.

3 (Fig. 6). On five out of the other six economies, the significant positive impacts are even prolonged until 5-10 days. Compared to the GFC period, we obtain more significant spillover effects of US and developed Eurozone's VRPs on the other economies, respectively, during the post-GFC period.

We now consider the effects of US and developed Eurozone's DRPs and JRPs, two different risk premiums of distinct characteristics and VRP components, on other economies' VRPs to investigate which component drives the dynamics generating cross-country VRP spillovers. In particular, in the VAR system we replace US and developed Eurozone's VRPs with US and developed Eurozone's DRPs or JRPs. Here, we focus on the post-GFC period because cross-country VRP spillovers are clearly observed during this period.

Fig. 7 illustrates estimation results on the impact of US DRP on the other economies' VRPs, while Fig. 8 those on the impact of US JRP on the other economies' VRPs. We find that US DRP has a significant positive impact on all the other six economies' VRPs over the next 10 days (Fig. 7). By contrast, the IRFs for the VAR analysis involving US JRP shocks show that US JRP has significant positive effects on all the other six economies' VRPs in one day and significant positive effects on only three other economies' (Hong Kong SAR, Japan and Korea) VRPs in two days (Fig. 8). The effect changes from positive to negative on all the other six economies' VRPs over the three-day horizon. When we combine the stably increasing IRFs of US DRP with the volatile IRFs of US JRP that quickly change signs from positive to negative, then we obtain the IRFs of US VRP shown in Fig. 5. Therefore, the short-lived impact of US VRP on other economies' VRPs is driven by US JRP, not by US DRP.

Fig. 9 summarises estimation results on the impact of developed Eurozone's DRP on the other economies' VRPs, while Fig. 10 those on the impact of developed Eurozone's JRP on the other economies' VRPs. The IRFs for the VAR analysis using developed Eurozone's DRP as the shock show that developed Eurozone's DRP has a very strong positive impact on all the other six economies' VRPs over the first one to two days (that is, either the same day and the next day or day 1 and day 2, depending on the ordering) and the significant positive impact on five economies' VRPs lasts up to 6–10 days after the shock. By contrast, the IRFs for the VAR analysis using developed Eurozone's JRP as the shock show that developed Eurozone's JRP tends to have significant positive effects on all the other six economies' VRPs up to day 2, and then disappear from the third day on. Overall, developed Eurozone's DRP has a longer positive impact on other economies' VRPs than developed Eurozone's JRP has, and thus such effects of developed Eurozone's DRP and JRP are broadly similar to the long-lasting positive effects of US DRP and the short-lived positive effects of US JRP.

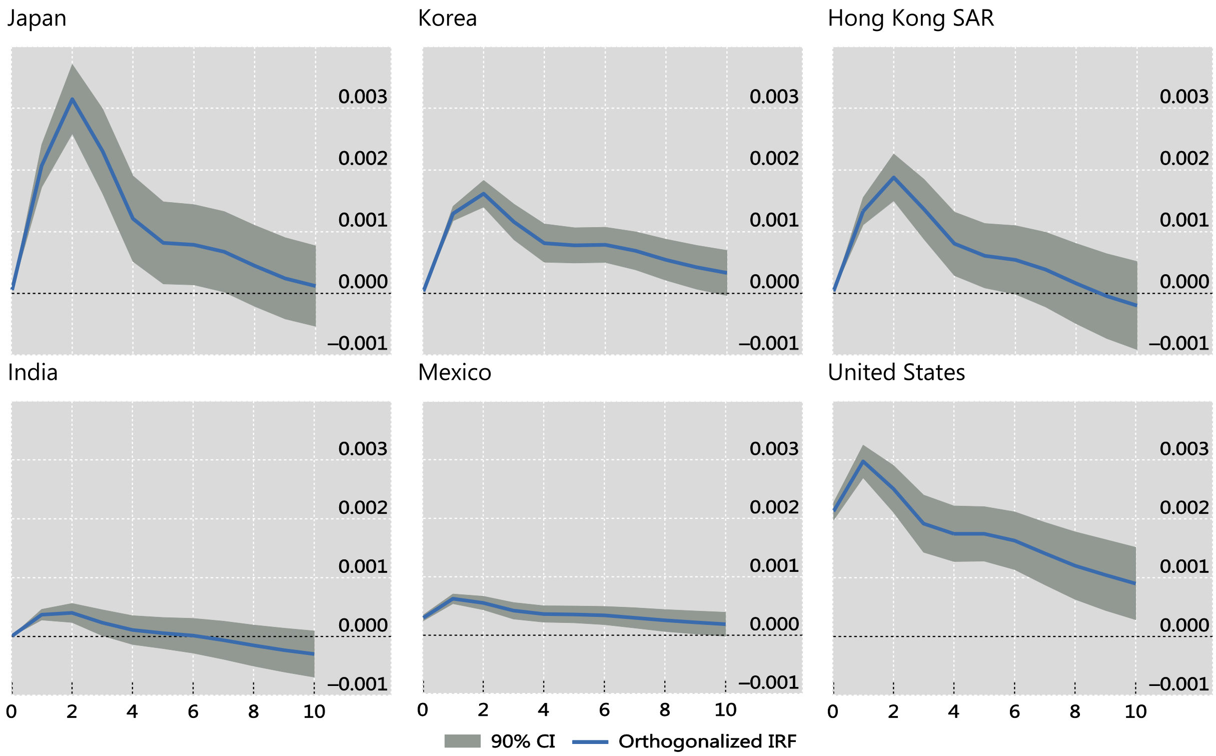

Fig. 6. Response of other economies' VRPs to developed Eurozone's VRP shocks. Post-Global Financial Crisis period (688 daily observations). See the text for the details on the VAR regression specifications.Source: Authors' estimates.

5.3. Structural VAR analysis on VRP spillovers via identification through heteroscedasticity

In Section 5.2, we showed orthogonalised IRFs assuming that a shock to an economy's VRP affects other economies' VRPs in the order of market closing time, while not considering contemporaneous (same day) shocks to the markets whose trading hours overlap. However, since the trading hours of some economies in our dataset significantly overlap, such as those of the United States and Mexico or those of the United States and developed Eurozone to a less extent, a contemporaneous shock in one market may affect the other. Therefore, the VAR analysis conducted in Section 5.2 using daily data may not be able to fully capture intraday interactions due to overlapping market opening hours between a pair of markets.

To check robustness and detect possible biases in the VAR analysis in Section 5.2, we construct a structural VAR model of VRPs to analyse structural IRFs, assuming contemporaneous shocks to VRPs of the economies with overlapping trading hours. For identification of the structural VAR model, we employ the identification through heteroscedasticity (ITH) method where the parameters of the structural VAR model are identified through exogenously determined regimes. In particular, structural parameters are identified by additional information in multiple covariance matrices, the number of which equals the number of regimes. The ITH method naturally fits our sample as it includes the GFC period during which VRPs and IVs showed a level shift.

Under ITH, we first estimate a reduced VAR model by generalised least squared (GLS), using covariance matrices for each regime obtained by OLS as input. Then we apply generalised method of moments (GMM) to decompose the GLS-estimated parameters into structural ones, using the full sample. When estimating IRFs, we apply bootstrapping of 10,000 times to obtain the mean and confidence interval. The required number of regimes for two or three dimensional VARs is two (Rigobon (2003)). We use the volatility regime for the United States identified in Appendix Fig. 1 with the threshold of 0.5.

Since the trading hours of the Mexican market mostly overlap with those of the US market, we first construct a two-dimensional structural VAR model of US and Mexican VRPs. The IRF of Mexican VRP to a structural shock to US VRP is plotted in the left-hand panel of Fig. 11. When we compare the structural IRF with the full-sample orthogonalised IRF in the lower-right panel of Appendix Fig. 2 for Mexico, we find that both IRFs are positive but statistically insignificant over ten days, except the structural IRF one day after the shocks. When we consider the IRF of US VRP to structural shocks to Mexican VRP (Fig. 11, right-hand panel), we find that Mexican VRP have positive but statistically insignificant effects on US VRP.

Given overlaps between the US and Mexican trading hours with those of developed Eurozone to a less extent, we also consider a three-dimensional model comprising developed Eurozone, US and Mexican VRPs. Fig. 12 depicts IRFs of US and Mexican VRPs to structural shocks to developed Eurozone VRP. When we compare the structural IRFs with the corresponding

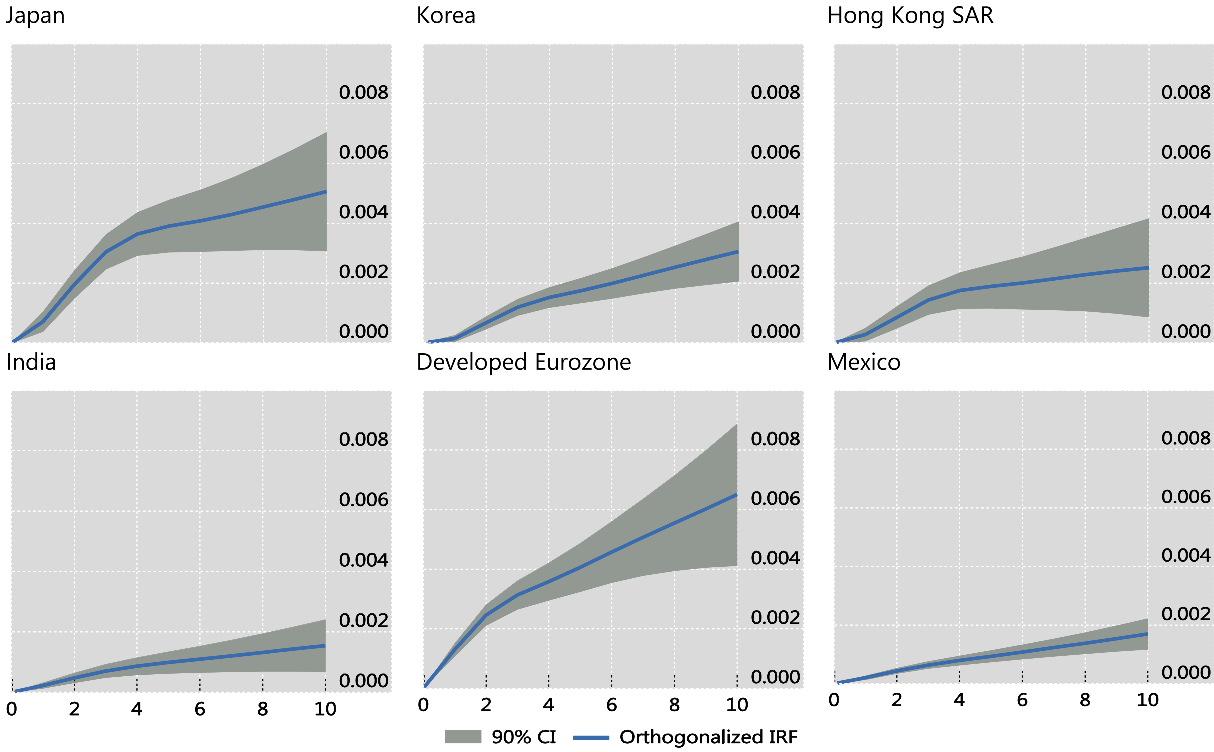

Fig. 7. Response of other economies' VRPs to US DRP shocks. Post-Global Financial Crisis period (688 daily observations). See the text for the details on the VAR regression specifications.
Source: Authors' estimates.

full-sample orthogonalised IRFs in the lower-centre and lower-right panels of Appendix Fig. 3, we find that US VRP shows positive and statistically significant response to developed Eurozone's VRP for both structural and orthogonalised IRFs, with weaker statistical significance for the structural IRF. We also find that Mexican VRP shows positive response for both structural and orthogonalised IRFs, with statistical insignificance for the structural IRF. These results indicate that the influence of developed Eurozone's VRP on US and Mexican VRPs in Appendix Fig. 3 is likely to be overstated.

To sum up, the results from orthogonalised impulse responses of VRPs reported in Section 5.2 based on the market closing time are generally robust when we consider via ITH contemporaneous shocks to the markets whose trading hours overlap significantly, although statistical significance becomes weaker when we consider structural VAR models of VRPs.

6. Impact of US VRPs on equity fund flows to other economies

This section discusses a possible linkage between cross-stock market VRP spillovers and equity fund flows. With the dominant presence of the US-based mutual funds in the global equity mutual fund flows, variations in equity fund flows could influence stock markets of their investment destination. Our conjecture is that variations in VRP in the US stock market would affect the equity fund flows from the US-based mutual funds to other economies' stock markets, and the variations in fund flows in turn would cause volatility of the stock prices of a market in which these funds invest, thereby affecting VRP in the market. It is possible that such a linkage works as a mechanism generating the cross-county correlations between VRPs.

In order to establish that equity fund flows are an important channel for cross-country VRP spillovers, we need to show both that US VRP significantly affects equity fund flows to other economies' equity markets in the first stage, and that such equity fund flows in turn affect the respective stock markets' VRPs in the second stage. However, since we have only weekly equity fund flow data available and do not have access to daily equity fund flow data, it is difficult to accurately measure the impact of lower-frequency fund flows (ie quantities which react to prices) on higher-frequency VRPs (ie prices) in the second stage. Therefore, in this section, we only consider the first stage regressions.

We first conduct simple OLS estimation to assess the degree of fund flow variation explained by US VRP. Then, narrowing down sample economies for fund flow destinations to the list of economies that we considered for the VAR analysis in Section 5, we include in the OLS estimation the same control variables that we used in the VAR analysis to yield stricter estimation results. When we run the OLS regressions, we focus on the two subsample periods, ie the GFC period and post-GFC period as in Section 5. Appendix E provides the results over the full sample period. In Appendix C, we also consider

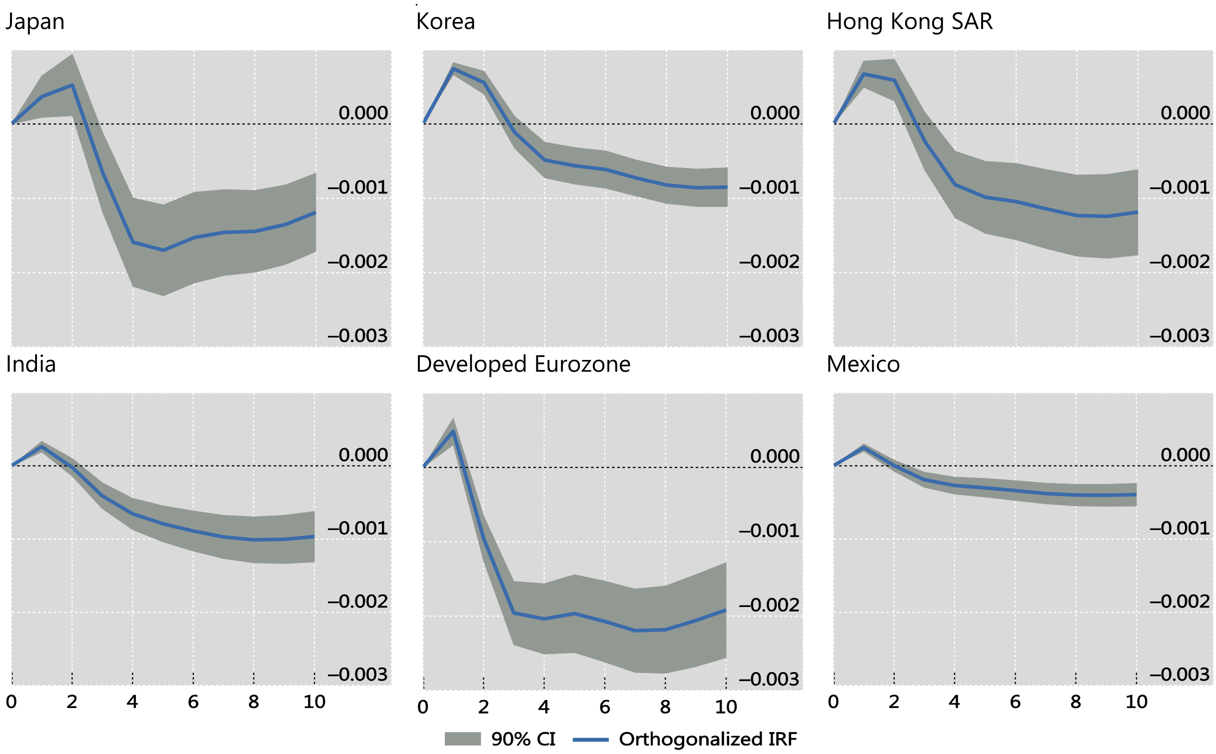

Fig. 8. Response of other economies' VRPs to US JRP shocks. Post-Global Financial Crisis period (688 daily observations). See the text for the details on the VAR regression specifications.
Source: Authors' estimates.

an alternative non-crisis period, defined as the low volatility regime period by a regime-switching model, for robustness check.

6.1. Simple OLS regression analysis on equity fund flows

We first conduct simple OLS estimation in weekly frequency to gauge the impact of US VRP, DRP and JRP on global equity fund flows to six economies including two AEs (developed Eurozone and Japan) and four EMEs (Hong Kong SAR, India, Korea and Mexico) as well as to all AEs excluding the United States and all EMEs. Table 5 shows the results over the GFC period, and Table 6 over the post-GFC period which is a relatively tranquil non-crisis period. Table 5 shows that during the GFC, a higher (ie less negative) value of US VRP, DRP and JRP was associated with greater equity fund flows to Japan. In particular, a 1 percentage point increase in (annual) US VRP increased the ratio of equity fund flows to Japan to TNA of equity funds investing in Japan by 1.9 percentage point. This result implies that, when investors in the US equity volatility market charged higher risk premium in absolute size (that is, more negative value of VRP, DRP and JRP) during the GFC, global equity fund investors decreased their investment in Japanese equities. Also, the coefficient on US JRP for Japan is more than twice that on US DRP, which implies that during the GFC period, US JRP was a more important driver of equity flows to Japan than US DRP. By contrast, a higher (ie less negative) value of US VRP and DRP had significant negative effects for equity fund flows to developed Eurozone during the GFC, which may be viewed as indicating that, when facing higher US risk premium in absolute size during the GFC, global equity fund investors increased their investment in developed Eurozone equities. However, it should be noted that this result becomes statistically insignificant when we include control variables as in Table 7. Finally, US VRP, DRP or JRP have no significant effect on equity fund flows to EMEs.

Table 6 reports the results over the post-GFC period. Now the coefficients on US VRP, DRP and JRP are positive for all six individual economies and statistically significant for five of them (developed Eurozone, Japan, Hong Kong SAR, India and Korea). Also, the size of the coefficients over the post-GFC period is much larger than over the GFC period. For example, a 1 percentage point increase in (annual) US VRP increased the ratio of equity fund flows to Japan to TNA of equity funds investing in Japan by 10.6 percentage points. These results indicate that in a tranquil period, a more negative value of US VRP, DRP and JRP (ie higher risk premium) exert strong negative influence on equity fund flows to non-US economies because global equity investors' heightened fears over market volatility measured by US VRP reduce their appetite to invest in equities globally and the relationship becomes tighter under tranquil market conditions. The results on individual econo-

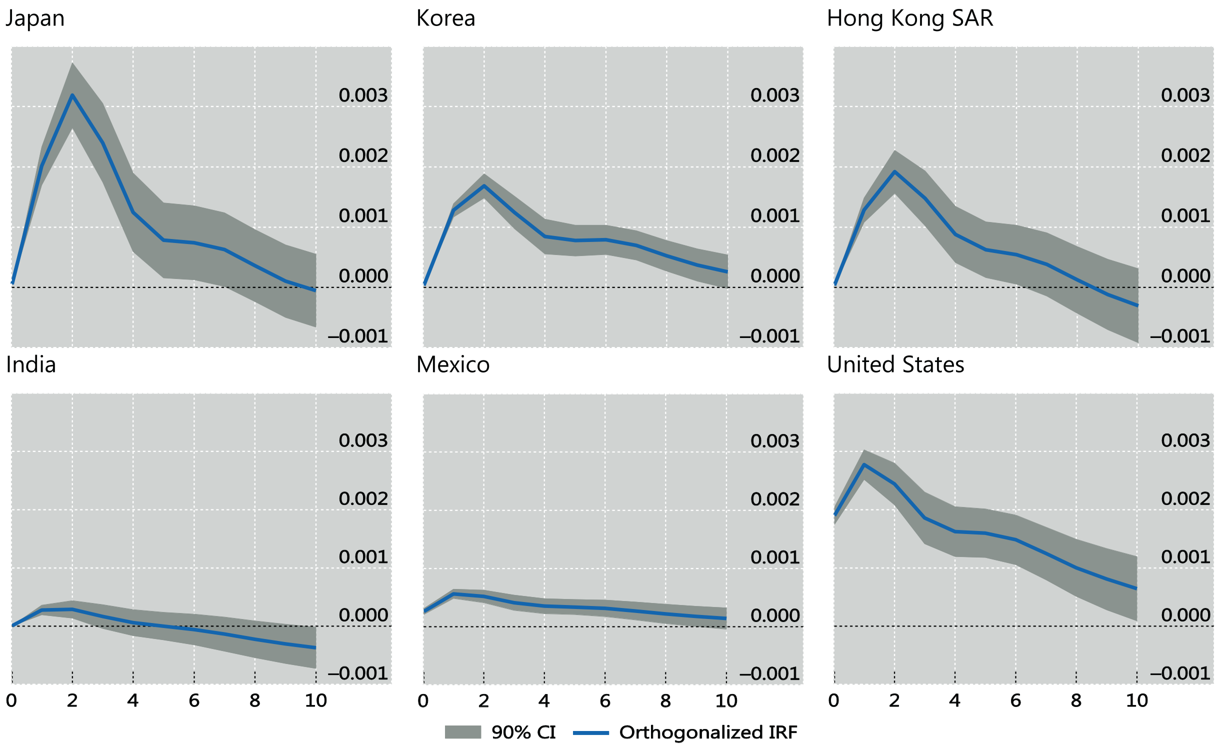

Fig. 9. Response of other economies' VRPs to developed Eurozone's DRP shocks. Post-Global Financial Crisis period (688 daily observations). See the text for the details on the VAR regression specifications.
Source: Authors' estimates.

mies parallel with our findings on the effect of US VRP on equity fund flows to two regions, AEs excluding the United States and all EMEs.

When we decompose US VRP into DRP and JRP during the post-GFC period, we do not find much differences in terms of statistical significance between the two risk premiums: US JRP has significant effects on equity fund flows to all regions and individual economies except Mexico, while US DRP has significant effects equity fund flows to all regions and individual economies except Korea and Mexico (Table 6). By contrast, in terms of economic significance, the coefficients on US DRP are much greater than those on US JRP for all regional groups and individual economies. These results suggest that US DRP is a more important driver of equity fund flows to other economies than US JRP during the tranquil non-crisis period.

6.2. The OLS regressions analysis on fund flows controlling for other factors

In this section, we include the control variables affecting equity fund flows to AEs and EMEs in the estimation, thereby doing regression analysis in a stricter manner. The sample economies are the same for the VAR analysis in Section 5. As for the control variables, we add one variable to the list of control variables used for the VAR analysis: the residual of OLS regressions of local economies' risk premiums on US risk premiums. The additional variable aims to control contemporaneous local market conditions in the regressions using weekly fund flow data.[16]

Tables 7 and 8 summarise the regression results. Table 7 shows overall weak results during the GFC period.[17] In particular, we find a significant impact of US VRP, DRP and JRP on equity fund flows to Japan. As for the impacts on equity fund flows to the developed Eurozone, the sign of the coefficients on US VRP and US JRP is positive, which is theoretically consistent. However, all of the coefficients are not significant. Among the EMEs, we only find a significant impact of US JRP on equity fund flows to Mexico. Overall, during the GFC period, we find more significant effects of US JRP on equity fund flows to Japan than those of US DRP. We obtain stronger results from the regression over the post-GFC period.[18]

[16] We appreciate the referee's comment on importance of controlling contemporaneous local market conditions.
[17] The weak results in Table 7 are consistent with findings in Bekaert et al. (2014). They suggest that equity portfolio flows to a sample of 55 countries including EMEs were affected most by domestic factors rather than US factors during the GFC. In their paper, the sample period is limited to the GFC period.
[18] We obtain overall similar but less economically significant results when we use alternative variables such as the contemporaneous local VRP or the difference between the contemporaneous local VRP and US VRP that are significantly correlated with the contemporaneous US VRP. The results from using the alternative variables are available from the authors upon request.

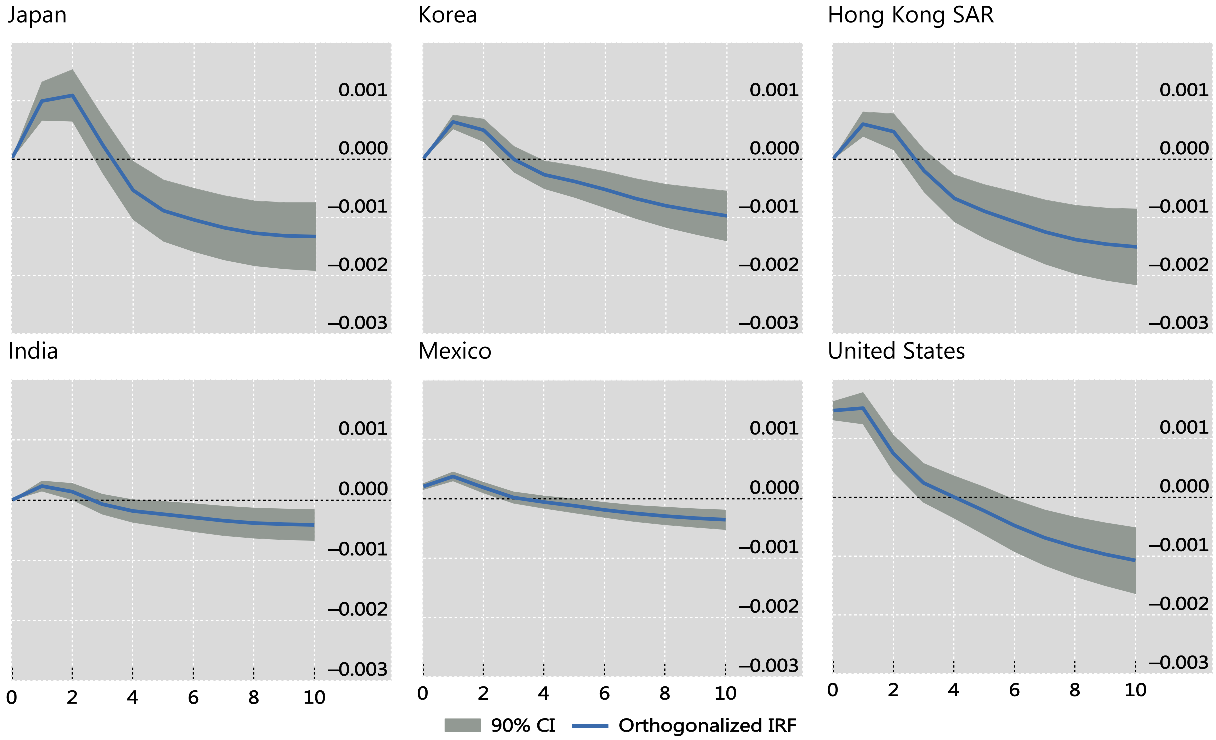

Fig. 10. Response of other economies' VRPs to developed Eurozone's JRP shocks. Post-Global Financial Crisis period (688 daily observations). See the text for the details on the VAR regression specifications.
Source: Authors' estimates.

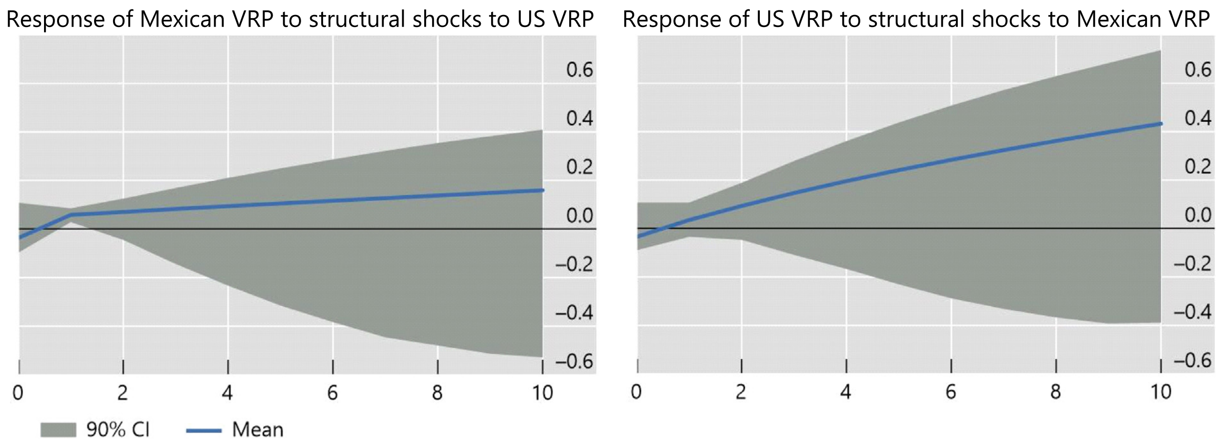

Fig. 11. Response of Mexican (US) VRP to structural shocks to US (Mexican) VRP under identification through heteroscedasticity. Full sample period (805 daily observations). See the text for the details on the structural VAR model of VRPs using the identification through heteroscedasticity method. The shadowed area shows the 90% confidence interval.
Source: Authors' estimates.

Table 8 shows a significant impact of US VRP, DRP and JRP on equity fund flows to both the developed Eurozone and Japan. Among the EMEs, we find a significant impact of US VRP on equity fund flows to Korea with US JRP having a large and strictly significant impact. We also find a significant impact of US DRP on equity fund flows to Hong Kong SAR and a weakly significant impact of US JRP on equity fund flows to India. When we compare the coefficients on the US DRP regressions with those on the US JRP regressions for the developed Eurozone and Japan, we find that the coefficients in the US DRP

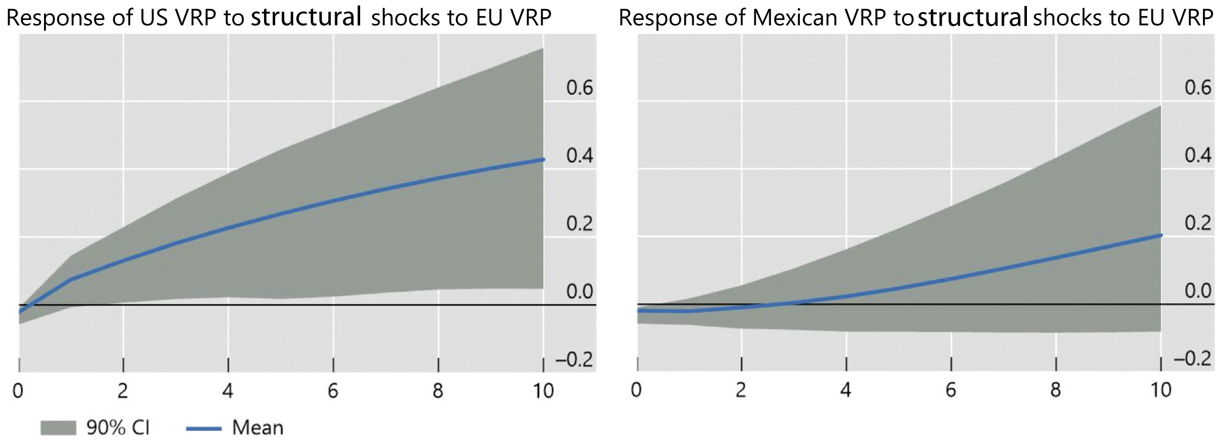

Fig. 12. Response of Mexican VRP to structural shocks to EU VRP to structural shocks to developed Eurozone (EU) VRP under identification through heteroscedasticity. Full sample period (805 daily observations). See the text for the details on the structural VAR model of VRPs using the identification through heteroscedasticity method. The shadowed area shows the 90% confidence interval.Source: Authors' estimates.

Table 5
Simple OLS regression results. Global Financial Crisis period.

Explanatory variable:	US VRP	US DRP	US JRP
Dependent variable: Equity fund flows to			
Advanced economies			
All advanced economies excluding the United States	−1.293* (−1.93)	−1.956** (−2.46)	−2.319 (−1.21)
Developed Eurozone	−2.042*** (−3.01)	−3.045*** (−3.58)	−3.765* (−1.94)
Japan	1.891*** (2.92)	2.284** (2.37)	4.754*** (3.05)
Emerging market economies			
All emerging market economies	0.356 (0.34)	0.947 (0.67)	−0.328 (−0.12)
Hong Kong SAR	0.421 (0.56)	1.121 (1.11)	−0.391 (−0.20)
India	1.004 (0.99)	1.870 (1.39)	0.966 (0.35)
Korea	−0.056 (−0.04)	0.516 (0.30)	−1.524 (−0.41)
Mexico	−0.206 (−0.12)	0.776 (0.29)	−2.945 (−0.79)
Number of observations	112	112	112

This table reports only the coefficients and *t*-statistics of the regression of a dependent variable on an explanatory variable, and does not report the constant term. Robust standard errors are used to calculate *t*-statistics. *, **, and *** indicate 10, 5 and 1 percent statistical significance of the estimated coefficient, respectively.

Table 6
Simple OLS regression results. Post-Global Financial Crisis period.

Explanatory variable:	US VRP	US DRP	US JRP
Dependent variable: Equity fund flows to			
Advanced economies			
All advanced economies excluding the United States	7.318*** (4.50)	31.978*** (4.51)	8.613*** (4.54)
Developed Eurozone	6.606*** (3.83)	27.941*** (3.17)	7.854*** (4.04)
Japan	10.623*** (6.31)	42.434*** (5.35)	12.845*** (6.05)
Emerging market economies			
All emerging market economies	4.316*** (2.72)	14.857* (1.81)	5.423*** (2.86)
Hong Kong SAR	6.126*** (3.50)	24.906*** (2.81)	7.370*** (3.45)
India	5.298*** (3.45)	17.200** (2.12)	6.746*** (3.68)
Korea	4.574*** (2.82)	12.753 (1.61)	6.003*** (3.10)
Mexico	1.848 (0.85)	11.664 (1.01)	1.867 (0.73)
Number of observations	299	299	299

This table reports only the coefficients and *t*-statistics of the regression of a dependent variable on an explanatory variable, and does not report the constant term. Robust standard errors are used to calculate *t*-statistics. *, **, and *** indicate 10, 5 and 1 percent statistical significance of the estimated coefficient, respectively.

Table 7
Results of OLS regression with control variables. Global Financial Crisis period.

Explanatory variable:	US VRP	US DRP	US JRP	Number of observations
Dependent variable: Equity fund flows to				
Advanced economies				
Developed Eurozone	0.030 (0.02)	−0.846 (−0.43)	3.908 (1.59)	108
Japan	5.388** (2.10)	6.889** (2.47)	8.473*** (3.25)	108
Emerging market economies				
Hong Kong SAR	1.406 (0.68)	1.454 (0.63)	1.974 (0.34)	99
India	3.348 (1.37)	4.083 (1.17)	4.700 (1.28)	108
Korea	3.291 (1.12)	5.691 (1.19)	−0.671 (−0.15)	108
Mexico	5.144 (1.07)	0.897 (0.15)	13.512** (2.35)	108

This table reports only the coefficients and *t*-statistics of the regression of a dependent variable on the key explanatory variable, and does not report the other control variables and the constant term in the regressions. The additional control variables for the regression that has US VRP, US DRP or US JRP as the key explanatory variable are the economy's lagged VRP, DRP or JRP, respectively, residuals of OLS regressions of local economies' risk premiums on US risk premiums, the Citi Economic Surprise Index of the economy, the world short-term interest rate, the Citi Economic Surprise Index of the United States, and the lagged stock market return of the economy. Note that we do not include the Citi Economic Surprise index for India since we are not able to obtain that series. Robust standard errors are used to calculate *t*-statistics. *, **, and *** indicate 10, 5 and 1 percent statistical significance of the estimated coefficient, respectively.

Table 8
Results of OLS regression with control variables. Post-Global Financial Crisis period.

Explanatory variable:	US VRP	US DRP	US JRP	
Dependent variable: Equity fund flows to				Number of observations
Advanced economies				
Developed Eurozone	12.928*** (2.87)	45.443*** (3.31)	12.084*** (3.30)	298
Japan	11.461*** (5.85)	47.600*** (5.50)	15.075*** (4.17)	298
Emerging market economies				
Hong Kong SAR	5.115 (1.30)	26.960** (2.56)	3.523 (0.45)	296
India	4.310 (1.50)	9.578 (1.10)	7.514* (1.77)	298
Korea	8.944** (2.06)	9.599 (0.62)	13.008*** (4.17)	298
Mexico	5.213 (1.04)	−0.794 (−0.05)	9.107 (1.55)	298

This table reports only the coefficients and *t*-statistics of the regression of a dependent variable on the key explanatory variable, and does not report the other control variables and the constant term in the regressions. The additional control variables for the regression that has US VRP, US DRP or US JRP as they key explanatory variable are the economy's lagged VRP, DRP or JRP, respectively, residuals of OLS regressions of local economies' risk premiums on US risk premiums, the Citi Economic Surprise Index of the economy, the world short-term interest rate, the Citi Economic Surprise Index of the United States, and the lagged stock market return of the economy. Note that we do not include the Citi Economic Surprise index for India since we are not able to obtain that series. Robust standard errors are used to calculate *t*-statistics. *, **, and *** indicate 10, 5 and 1 percent statistical significance of the estimated coefficient, respectively.

regressions are much larger than those for US JRP regressions. This means that during the post-GFC period, the spillover channel from US DRP to equity fund flows to other AEs was stronger than the spillover channel from US JRP.

7. Conclusion

In this paper, we first estimate variance risk premiums for seven stock markets in both AEs and EMEs over 2007–2015 using a jump-diffusion model with stochastic volatility of a mean-reverting variance and a self-exciting jump process, and decompose them into variance-diffusive risk premium and variance-jump risk premium. We then calculate cross-country correlations of VRPs, DRPs and JRPs, and analyse the impact of a rise in the VRPs of the US and developed Eurozone's stock markets to the ones in other economies, using a daily VAR model. Moreover, we test the significance of the premiums as a determinant of US based equity fund flows to stock markets of other economies, based on a conjecture that US based mutual fund flows are a path through which VRPs spill over globally.

This paper has three novel features. First, to our knowledge, this is the first paper estimating VRPs in selected EMEs' stock markets using a parametric model. Therefore, gauging the correlations of VRPs between AEs' and EMEs' stock markets is unprecedented too. Second, we decompose VRP into DRP and JRP and investigate the cross-market correlations between the different components. Finally, it investigates a specific channel for the VRPs' cross-stock market correlations. In particular, we investigate the impact of US VRP on US based equity fund flows to other economies' stock markets.

Concerning the correlations of VRPs, we find that cross-stock market correlations including the EMEs' stock markets are considerably high. Impulse-response analysis points to significant spillover from US and developed Eurozone's VRPs to the ones of other sample economies especially during the post-GFC period. We also find that during the post-GFC period, US and developed Eurozone's DRPs had relatively strong long-lived effects on other economies' VRPs, while their JRPs had relatively weak and short-lived effects. Finally, structural VAR analysis using the ITH methodology confirms that the results from the impulse response analysis are generally robust when we assume contemporaneous shocks to some markets whose trading hours overlap.

Simple OLS regression results show that increases in the size of US VRP tend to reduce equity fund flows to all other AEs and some EMEs during the post-GFC period, but less so during the GFC period. The regression analyses controlling the effects of global and local factors provide supporting evidence that such equity fund flows are a channel of spillover from US VRP to the VRPs of major AEs and a few EMEs during non-crisis tranquil periods, but less so during the GFC period. Finally, we find that DRPs tends to play a more important role than JRPs in the transmission of US VRP to equity fund flows to other economies during the post-GFC period.

Our findings suggest that when policymakers consider cross-border stock market spillovers, they need to look at not only the co-movement of stock market return and volatility between the two economies, but also the co-movement of the VRP and its two components in the two markets, which captures market investors' aversion to uncertainty. In particular, we show some evidence that during the tranquil periods, market investors' aversion to the predictable scale of uncertainty measured by DRP is a more important transmission channel than market investors' aversion to the unpredictable scale of uncertainty measured by JRP.

This paper also underlines the importance of policymakers considering specific channels or intermediaries of spillovers from one economy's stock market to another economy's stock market. Mutual funds investing in global equity markets we consider in this paper are one of important forms of intermediaries in cross-border equity market contagion. Other institutional investors such as insurance companies, pension funds and hedge funds also allocate sizable investments in various equity markets and adjust their investment strategies based on developments in stock market volatilities. Since cross-border portfolio equity flows generated by these mutual funds and institutional investors tend to have large effects on the exchange rate and domestic financial conditions of the recipient economies, it is crucial for policymakers to understand the possible spillover channels via portfolio equity flows and the behaviour of various types of investor, and contemplate on what are possible policy options that can be employed, if necessary, to mitigate the impact of excessive equity investment inflows or outflows on domestic financial markets and the real economy.

The analyses presented in this paper can potentially be refined in a few dimensions. For example, there is room for more precise categorisation of US based mutual funds in terms of each fund's investment destination. Also, in order to investigate the causality between VRPs of different economies' stock markets, it would be worth considering conducting event study in each stock market. Furthermore, the modelling and estimation for JRP could be refined, ideally to isolate a premium for tail risk from premiums for other risks such as liquidity risk. Finally, if we have access to daily equity fund flow data to the six economies considered in this paper, we can conduct the second-stage regression of an economy's VRP on equity fund flows to completely identify the transmission channel and investigate whether the cross-border spillovers of VRPs via equity fund flows are an important channel. Even so, we think that this paper sheds light on research topics that have not been delved into in the current literature.

CRediT authorship contribution statement

Masazumi Hattori: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Ilhyock Shim:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Yoshihiko Sugihara:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendices. Supplementary data

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