Cross-stock market spillovers through variance risk premiums and equity flows[1]

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Abstract

We estimate variance risk premiums (VRPs) in the stock markets of major advanced economies (AEs) and emerging market economies (EMEs) over 2007–15 and decompose the VRP into variance-diffusive risk premium (DRP) and variance-jump risk premium (JRP). Daily VAR analysis reveals significant spillovers from the VRPs of the United States and eurozone's AEs to the VRPs of other economic areas, especially during the post-Global Financial Crisis (GFC) period. We also find that during the post-GFC period, shocks to the DRPs of the United States and the eurozone's AEs have relatively strong and long-lived positive effects on the VRPs of other economic areas whereas shocks to 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. Finally, US DRP plays a more important role than US JRP in the determination of equity fund flows to all other AEs and some EMEs after the GFC, while the opposite holds true for equity fund flows to all other AEs during the GFC. Such results indicate the possibility of equity fund flows working as a channel of cross-market VRP spillovers.

Keywords: cross-stock market correlation, emerging market economy, equity fund flow, variance risk premium.

JEL classification: F32, G12, G15, G23.

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1. Introduction

The Global Financial Crisis (GFC) of 2007–09 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. At the same time, greater attention has been paid to the pricing and volatility of the VIX index, which has been traded as a financial contract on the CBOE since 2004.

Since the variance of asset returns fluctuates over time (that is, volatility itself is volatile), it is accompanied by a risk premium, namely variance risk premium (VRP). VRP is a natural extension of the general risk premium and is defined as the difference between variances or, more formally, as the difference between the quadratic variation under the real probability measure and the risk-neutral probability measure. The estimator of the former is known as the realised variance (RV) and is computed from intraday price data. The estimator of the latter is known as the model-free implied volatility (IV), as captured by the VIX index, which is widely used in the financial industry. In theory, both RV and IV are defined as instantaneous and contemporaneous values. In practice, however, RV can only be estimated as an ex-post value, while IV as an ex-ante value. Therefore, an asset price model that bridges the two estimates is required in order to derive VRP.

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 compensation for. Hence, it describes investors' aversion to the predictable scale of uncertainty, or "known unknowns". By contrast, market participants require JRP for the possibility of extraordinary and discontinuous price changes. It represents, therefore, markets' fear of the unpredictable scale of uncertainty, or "unknown unknowns". Market participants may require a substantial amount of JRP in addition to a large amount of DRP during financial turmoil because it is very difficult for them to anticipate jumps in returns. DRP and JRP are likely to be time-varying as investigated by Bollerslev and Todorov (2011).

This paper develops a methodology for the estimation of DRP and JRP. In particular, it employs a jump-diffusion model of stock returns with stochastic volatility, where the volatility and jump-arrival intensity obey a mean-reverting process and a self-exciting process, respectively. Based on the model under the real measure and the risk-neutral measure, the quadratic variations for both diffusion and jump under the two measures are theoretically derived. While the estimator of the former is known as the bipower variation (BV), that of the latter is the difference between the RV and the BV of the same underlying return (Barndorff-Nielsen and Shephard (2004)). Using these relationships, we derive DRP and JRP from IV, RV and BV.

In recent years, academics and practitioners have paid increasing attention to VRP and its contagion. Central bank researchers have also 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 (2015) discuss the difference between the VRP embedded in equity portfolios and that implied in option prices. Feunou et al (2015) 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 (2017) investigate the predictability of commodity currency VRP and commodity VRP.

Among academics, Aït-Sahalia et al (2014) develop a jump contagion model that uses 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. 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 the time-varying fear of investors. In addition to these papers, many others have addressed VRPs, including Brodie et al (2007), Bollerslev et al (2009), Carr and Wu (2009) and Bollerslev et al (2011).

The aforementioned papers have deepened our understanding of the methods used to estimate VRP and of certain features of the risk premium such as cross-stock market correlations among advanced economies (AEs). This paper extends the cross-stock market correlations of VRPs to include several emerging market economies (EMEs), which is a novelty.

In particular, over the sample period ranging from November 2007 to September 2015, we first estimate VRPs, DRPs and JRPs for the stock markets of the following seven economic areas: eurozone AEs, Hong Kong SAR, India, Japan, Korea, Mexico and the United States. We find that the simple cross-stock market correlations of VRPs 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 the opposite is true of 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 the US and eurozone AEs' VRPs to the other economies' VRPs, especially during the post-GFC period. We also find that during the same period, shocks to US and eurozone AEs' DRPs have relatively strong and long-lived effects on other economic areas' VRPs, while shocks to these two economic areas' JRPs have relatively weak and short-lived effects on other economic areas' VRPs.

Another novelty of this paper is that it considers a specific channel of stock market contagion from VRP in the US to VRPs in other economic areas via equity fund flows. In particular, we consider the impact of US VRP on global equity fund flows to other economic areas. The other novel feature is that we take a closer look at the contagion of US VRP to equity fund flows with its decomposition into DRP and JRP.

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 have access to such data. Therefore, we use weekly series on global equity fund flows from EPFR Global.

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 economic areas other than the United States as well as to two regional groupings (that is, all AEs (excluding the United States) and all EMEs). We compare the period ranging from January 2010 to September 2015, which is a relatively stable time, with the turbulent GFC period. In Appendix C, we also use a simple regime-switching model to define relatively high and low volatility periods for each economic area's stock market, focusing on the impact of US VRP, DRP and JRP over the low volatility regime period.

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 economic areas and both regional groupings and they are statistically significant for five individual economic areas (the eurozone AEs, Japan, Hong Kong SAR, India and Korea) and both regional groupings. This means that when investors in the US equity volatility market charge a higher risk premium in absolute terms (that is, more negative value of VRP, DRP and JRP), equity fund flows to these individual economic areas and regional groupings decrease.[5]

By contrast, during the GFC period, US VRP, DRP and JRP have significantly positive effects for Japan but significantly negative effects for the eurozone AEs. They have no significant effect on equity fund flows to EMEs. Such contrasting results between the GFC and post-GFC periods indicate that the impact of the US stock market's VRP on mutual fund flows to other economies' stock markets is more pronounced during relatively tranquil times and that other factors, such as local factors (eg country-specific fiscal and external imbalances) and certain global factors (eg world short-term interest rates), may be more influential for equity fund flows to EMEs during the GFC period. Finally, when we decompose US VRP into US DRP and JRP, we find that during the post-GFC period, US DRP is a more important driver of equity fund flows to other economic areas than US JRP.

Next, we refine the OLS estimation by adding important control variables to the regression equations. They are intended to control for the effects of global and local factors and the behaviour of global investors who follow stock-return trends. The results of this refinement confirm that simple OLS estimations are robust. Moreover, we find that during the GFC period, US JRP is a more important driver of equity fund flows to the eurozone AEs and Japan.

The literature on the determinants of equity portfolio flows focuses on global (ie push), regional and local (ie pull) factors. For example, IMF (2014) lists possible global factors for equity portfolio flows such as the VIX index and the US TED spread (defined as the spread between the 3-month eurodollar deposit rate and the 3-month US Treasury bill rate). IMF (2015) shows that over the period of 1998–2014, an increase in the VIX index of one standard deviation is associated approximately with a 33% decline in monthly investor flows to US-domiciled equity funds investing globally, including the US stock market, 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 in which 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 during the pre-Lehman bankruptcy period of August 2007 to mid-September 2008, the peak of sovereign debt problems in Europe in 2010 and the downgrade of the US sovereign rating in August 2011. By contrast, he finds that in the aftermath of the Lehman Brothers bankruptcy, a general loss of confidence

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

resulting from elevated market uncertainty – as 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 earlier efforts in the sense that we focus on VRP, which is derived as the difference between the realised variance and the VIX index, rather than as the VIX index itself. In other words, we aim to distil the investor risk premium that is itself associated with the volatility of equity 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 the data used in the paper. Section 4 presents the estimation results for the VRP, DRP and JRP of each stock market. Then, in Section 5, we calculate the cross-stock market correlations of VRPs, DRPs and JRPs, and conduct a VAR analysis showing the impact of the US and eurozone AEs' 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 economic areas. 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 sampling procedure. Appendices A and B provide the details.

2.1. The model

We assume fundamental asset price processes under both the real and the risk-neutral probability measures in order to determine DRP and JRP. 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. The dynamics of a return y_t on an asset under the real probability measure is written as

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

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

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

where W_t and W_t^v are Brownian motions, N_t is a 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 $t = 0$. κ and θ indicate a mean-reverting speed and a long-term mean of the stochastic diffusion volatility, respectively, while α and λ_∞ indicate a mean-reverting speed and a long-term mean of the jump-arrival intensity, respectively. β 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. We assume that the return process under the risk-neutral probability measure has the same form of equations with different parameters and stochastic variables.

Based on the model, the quadratic variations under both the real and the risk-neutral measures are linearly decomposed into diffusion and jump parts. One-month quadratic variation of the diffusion part under the risk-neutral measure, denoted by $\mathcal{D}_{t,t+T}^*$ where T indicates one month, contains DRP, and the jump part denoted by $\mathcal{J}_{t,t+T}^*$ 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. 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 changes while the jump size remains the same when the measure changes. The parametrisation of JRP is a natural extension of the jump-originated portion in the general (first-order) equity premium which is proportional to the difference between the Poisson compensator under the real measure and that under the risk-neutral measure. Appendix A provides details on the model.

2.2. Sampling 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.

Let $\mathcal{D}_{t,t+\tau}$ and $\mathcal{J}_{t,t+\tau}$ denote one-day (τ) quadratic variations of diffusion and jump, respectively, under the real measure. Barndorff-Nielsen and Shephard (2004) show that RV and BV are robust measures of $\mathcal{D}_{t,t+\tau} + \mathcal{J}_{t,t+\tau}$ and $\mathcal{D}_{t,t+\tau}$, respectively. On the other hand, $\mathcal{J}_{t,t+\tau}$ is described as the product of the quadratic jump size and the jump occurrence indicator j_t which is an approximation of $N_t - N_{t-\tau}$, where 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 model parameters and latent variables. With an additional assumption that the coefficient of risk premiums are piecewise constant over 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 the VRPs are sampled through a forward-filtering backward-smoothing procedure. Appendix B provides details on the 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 eurozone AEs (EuroSTOXX),[6] 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 or calculated retroactively up to 2007. The sample period starts from the date when 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. 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.[7,8] As a local factor reflecting country fundamentals, we use the Citi Economic Surprise index from Bloomberg. An increase in this index means positive surprise.[9] Finally, in order to capture the return-chasing behaviour of retail investors

6 The EuroSTOXX 50 Index covers 50 blue-chip stocks from the following 11 eurozone AEs: 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 "eurozone AEs" to refer to the markets and economies represented by the index.

7 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.

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

9 We were not able to obtain Citi Economic Surprise index for India. Therefore, we do not use this variable for India in the VAR analysis in Section 5.2 and the OLS regressions in Section 6.

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.

In Section 6, we investigate the impact of US VRP, DRP and JRP on mostly US-based investors' equity fund flows to the other economic areas' stock markets. For this exercise, we obtain weekly data on equity fund flows from EPFR Global.[10] In particular, we use the EPFR data on the estimated investor flows to individual economic areas 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 show 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. The mean-reverting speed of the instantaneous variance, κ, is distributed around 5 for all economies, while the mean of the long-term mean of the stochastic variance, θ, differs by economies, which disperses in the range from 0.004 to 0.022. This indicates that the long-term mean of diffusion volatility is diversified from 6% to 15%. The mean-reverting speed of jump-arrival intensity, α, is sampled around 9, while the means of β, the scale of intensity surge at price jump occurs, and of λ_∞, long-term mean of jump-arrival intensity, are sampled in the range from 0.001 to 0.023, and from 0.05 to 0.1, respectively. Those values imply that index prices jump from 12 to 25 times a year on average, and once a jump occurs, it increases its intensity by 2% to 5%. Also, the speed to convergence of jump-arrival intensity is generally faster than that of variance.

10 We do not have access to daily equity fund flow data from EPFR Global, so use weekly data instead.

Statistics of parameters

Table 1

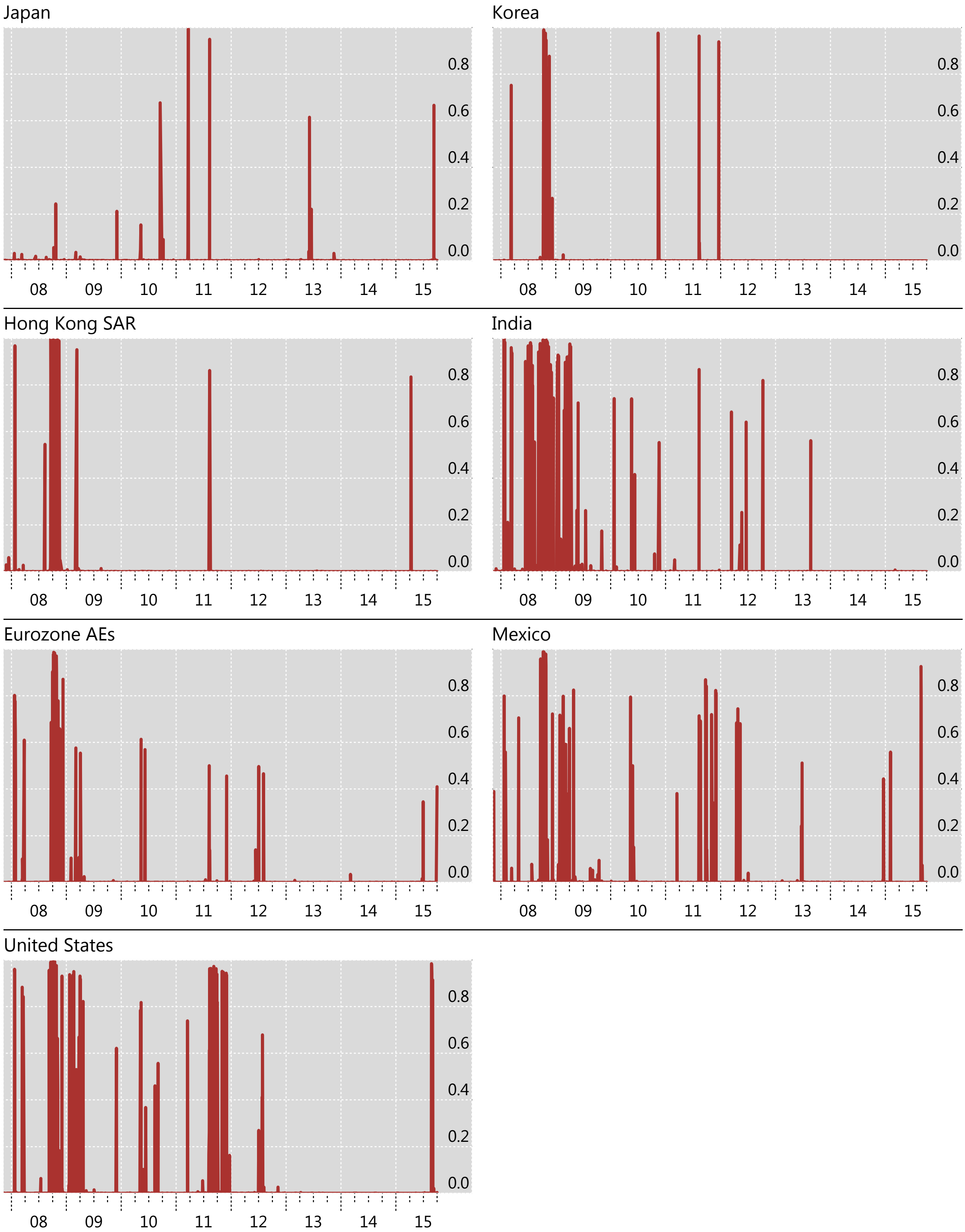
		Japan	Korea	Hong Kong SAR	India	Eurozone AEs	Mexico	United States
	mean	5.099	4.948	5.251	5.068	5.267	5.034	4.937
κ	C.I.	(3.12, 7.04)	(3.00, 6.85)	(3.47, 7.46)	(3.08, 7.03)	(3.31, 7.20)	(3.01, 6.93)	(3.00, 6.84)
	C.D.	0.91	0.17	0.03	0.00	0.52	0.07	0.00
	mean	0.006	0.004	0.004	0.016	0.022	0.004	0.009
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% confidence interval; C.D.: convergence diagnostics (bandwidth 500 around 1000th and 5000th samples) by Geweke (1992).

Graphs 1 and 2 present the jump indicator, j_t, and the jump-arrival intensity, λ_t, respectively. Apparently, jumps are clustered around 2008 in most of the economies and 2011 in some economies. This indicates that our model that incorporates self-excitation dynamics well matches the clustering feature of jumps. Jump intensities in Graph 2 reflects this feature as well, as they surge during the GFC and the European sovereign debt crisis in most of the economies. Interestingly, the latter crisis is not considered a clustered jump event in the eurozone AEs' equity markets, as the number of jumps observed in the eurozone AEs is relatively small compared to that of the other economies.

Jump indicators[1]

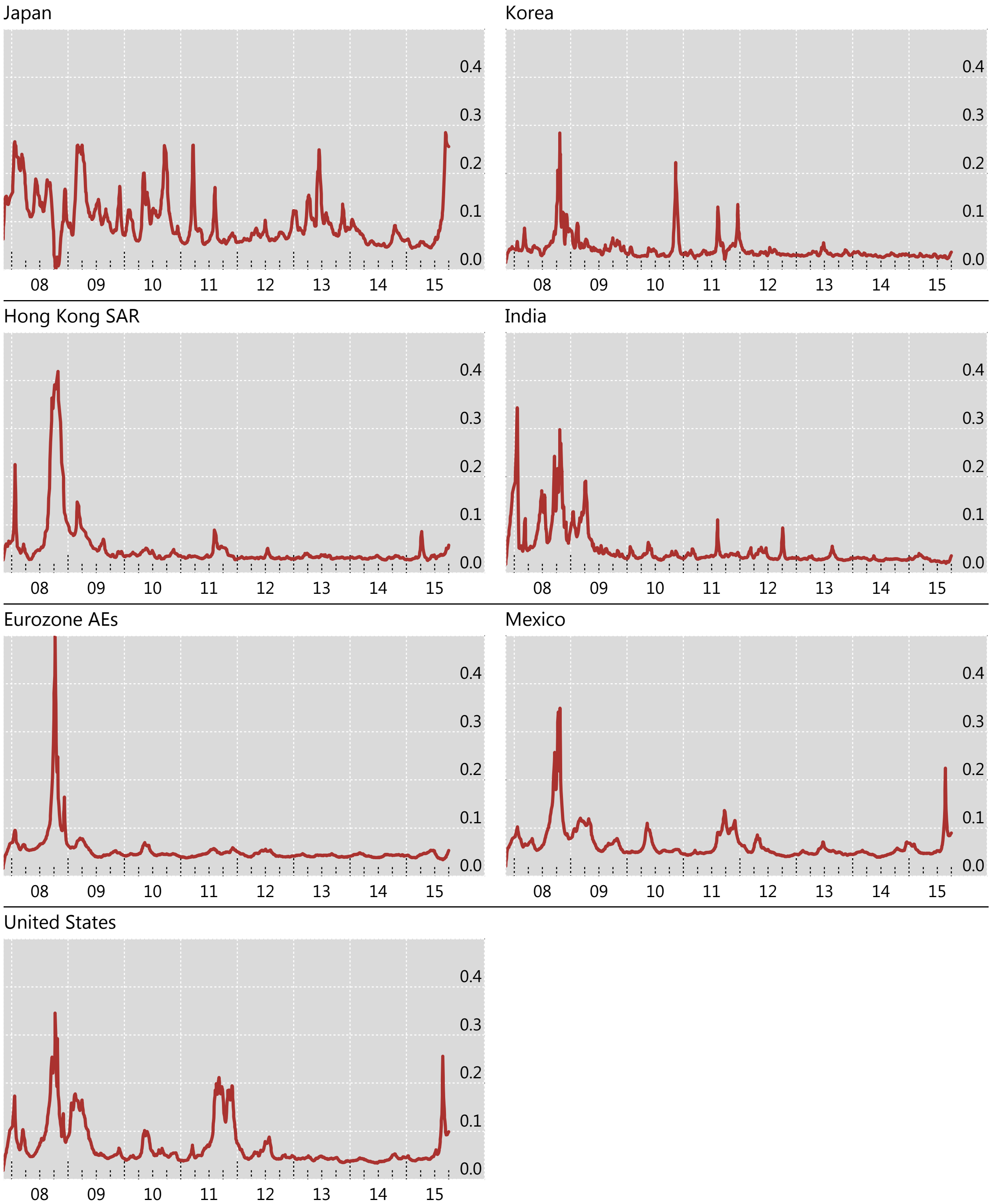
Graph 1



[1] Jump indicators indicate the probability jump occurrence. We calibrate the asset price model with the seven equity indexes assuming that at most one jump can occur in a trading day.

Source: Authors' estimates.

Jump-arrival intensities[1] Graph 2



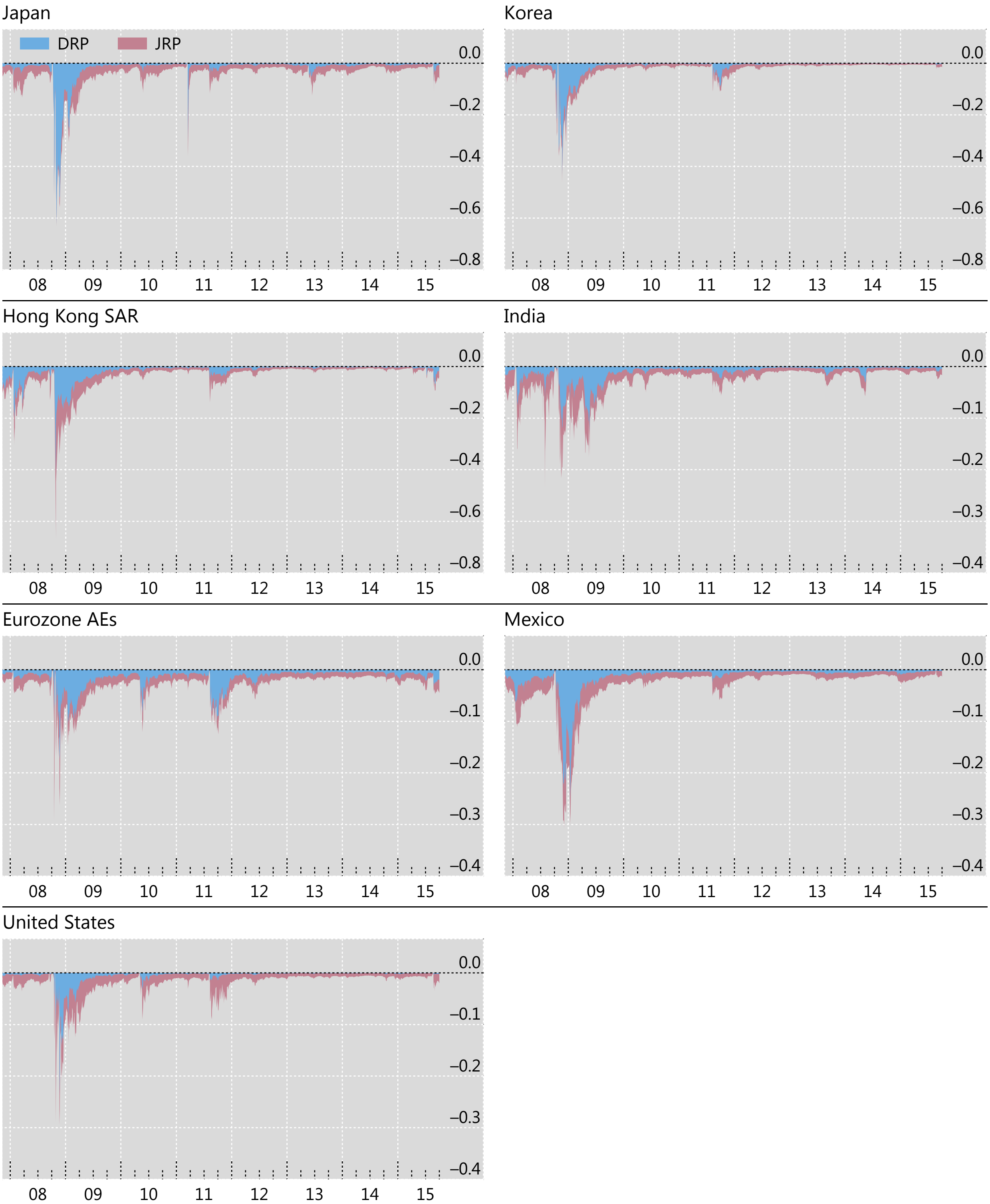
[1] Jump-arrival intensity indicates instantaneous arrival rate of jump. The jump-arrival intensity is estimated based on the assumption that the intensity surges to some degree if asset price jumps, and otherwise it reverts to a long-term mean.

Source: Authors' estimates.

Graph 3 shows one-month integrated VRP and its decomposition into DRP and JRP. The absolute value of VRP surges during crisis periods as shown in earlier studies, and the expansion is mostly through DRP in the early stage of crises, even though the jump-arrival intensity during the periods is high. The absolute value of JRP expands after a shock in some economies, lagging behind an increase in the absolute value of DRP, and decays. This partly stems from the model of jump-arrival intensity that assumes mean-reversion after a shock, and implies that market participants prepare for further unknown shocks after a large shock. A significant portion of VRP is contributed by JRP in the non-crisis period, indicating that even in the normal period, market participants are prepared for the tail risk to some extent.

Finally, Graph 4 shows observed IV and the decomposition of theoretical IV into the diffusion part ($\mathcal{D}^*_{t,t+T}$) and the jump part ($\mathcal{J}^*_{t,t+T}$). The surge in IV during crises is mostly explained by the diffusion part, and the expansion in the jump part is outstripped by the diffusion part, which is similar to the feature in the risk premiums. During normal (low volatility) periods, IV mostly consists of the diffusion part in most of the economies except Japan and Mexico where the jump part remains relatively large. From Graph 4, we also confirm that the model tracks IV well as the gap between IV and its theoretical counterpart, $\mathcal{D}^*_{t,t+T} + \mathcal{J}^*_{t,t+T}$, is small.

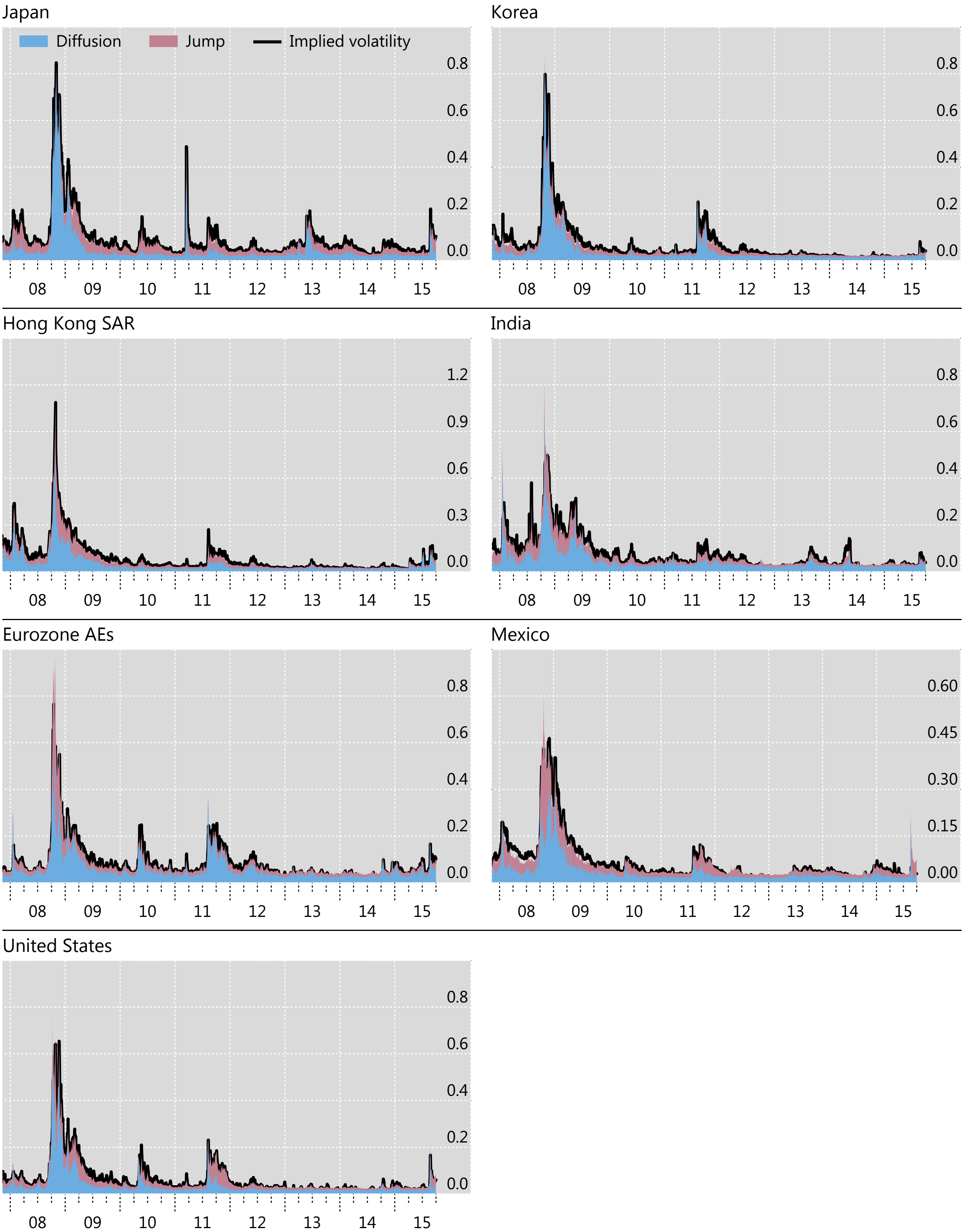
VRP with its decomposition into DRP and JRP[1] Graph 3



[1] 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.

Decomposition of IV[1] Graph 4



[1] The light blue and red areas indicate diffusion and jump parts respectively, while the dark blue 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.

5. Cross-stock market spillovers of variance risk premiums

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

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 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 economic area in each row and the current value for the economic area 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 United States−eurozone AEs, eurozone AEs−Korea, and Hong Kong SAR−Korea, have relatively high VRP correlations greater than 0.8.

Cross-market correlation of VRPs — Table 2

Post-Global Financial Crisis period (January 2010–September 2015)

	Japan	Korea	Hong Kong SAR	India	Eurozone AEs	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
Eurozone AEs	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	Eurozone AEs	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
Eurozone AEs	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 economic areas in row to economic areas 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.[11]

Cross-market correlation of DRPs

Table 3

Post-Global Financial Crisis period (January 2010–September 2015)

	Japan	Korea	Hong Kong SAR	India	Eurozone AEs	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
Eurozone AEs	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	Eurozone AEs	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
Eurozone AEs	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 economic areas in row to economic areas in column.

[11] One 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.

Cross-market correlation of JRPs

Table 4

Post-Global Financial Crisis period (January 2010–September 2015)

	Japan	Korea	Hong Kong SAR	India	Eurozone AEs	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
Eurozone AEs	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	Eurozone AEs	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
Eurozone AEs	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 economic areas in row to economic areas in column.

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 economic area's VRP on another economic area's VRP by VAR analysis.

Before we conduct VAR analysis, we conduct Granger causality Wald tests among the VRPs of the seven economic areas over the full sample period, the GFC period and the post-GFC period to identify which economic area's VRP significantly explains the variations of the other six sample economic areas' VRPs. In particular, we test the null hypothesis that an economic area's VRPs at date t, t–1 and t–2 as endogenous variables jointly do not affect another economic area's VRP. We find that the VRPs of the US and eurozone AEs' stock markets significantly affect the VRPs' of almost all the other economic areas' VRPs, respectively.[12] Considering that these two economic areas are the largest globally, that the US stock market is arguably the most contagious market and that the impact of the European debt crisis on global financial

[12] Specifically, for US VRP, the null hypothesis is strongly rejected in the tests involving five out of the other six economic areas VRPs. For the eurozone AEs' VRP, the null hypothesis is strongly rejected in the tests involving four of the other six economies.

markets was considerably large, in this section we focus on both the US and eurozone AEs' VRPs as the source of VRP shocks to the other economies.[13]

We consider a few control variables in the VAR estimation. Besides the endogenous variables such as the US and eurozone AEs' 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 economic area 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. 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, the eurozone AEs, Mexico and the United States. This order follows the market closing time in each economic area 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 economic areas' 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 two for the VAR system based on Schwarz Bayes information criteria in order to specify the VAR system to estimate in the most parsimonious way.

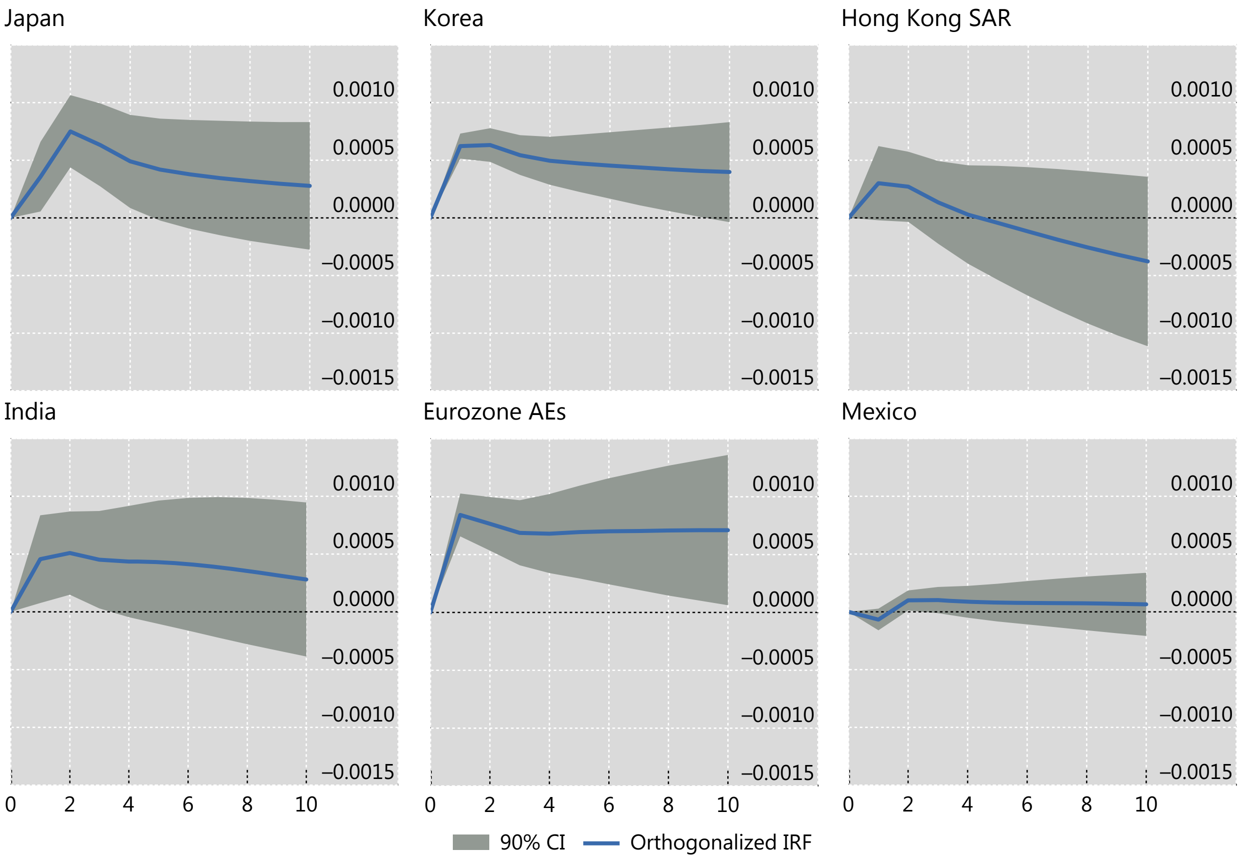
Graphs 5 and 6 show impulse response functions (IRFs) from VAR estimation over the full sample period. Graph 5 shows that US VRP has positive effects on all the other economic areas' VRPs over the 10-day horizon except for Mexico's VRP on day 1. The impact of US VRP on the VRPs of the eurozone AEs and Korea is very significant and more prolonged. Its impact on Japan's and India's VRPs is relatively short-lived. Finally, US VRP has a positive but insignificant impact on HK VRP. Compared to US VRP, the eurozone AEs' VRP exhibits much stronger spillover effects (Graph 6). In particular, the eurozone AEs' VRP has a significant positive impact on the VRPs of other two developed economies, Japan and the United States from day 1 to day 10, on the VRPs of Korea and Mexico, to a lesser extent, from the same day to day 10, and on the VRPs of Hong Kong SAR and India from day 1 to day 5. Overall, we find that US VRP and the eurozone AEs' VRP exhibit strong positive spillover effects on the other economic areas' VRPs when we conduct the VAR analysis over the full sample period.[14]

[13] The Granger causality Wald tests also show that HK VRP significantly explains some other economic areas' 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.

[14] As we explain below, these IRF results over the full sample period are generally between the IRF results from the post-GFC period sample showing strong spillover effects of the US and eurozone AEs' VRPs and the IRF results from the GFC period sample showing either weak or non-existing spillover effects of the US and eurozone AEs' VRPs.

Response of other economic areas' VRPs to US VRP shocks

Full sample period (805 daily observations) Graph 5

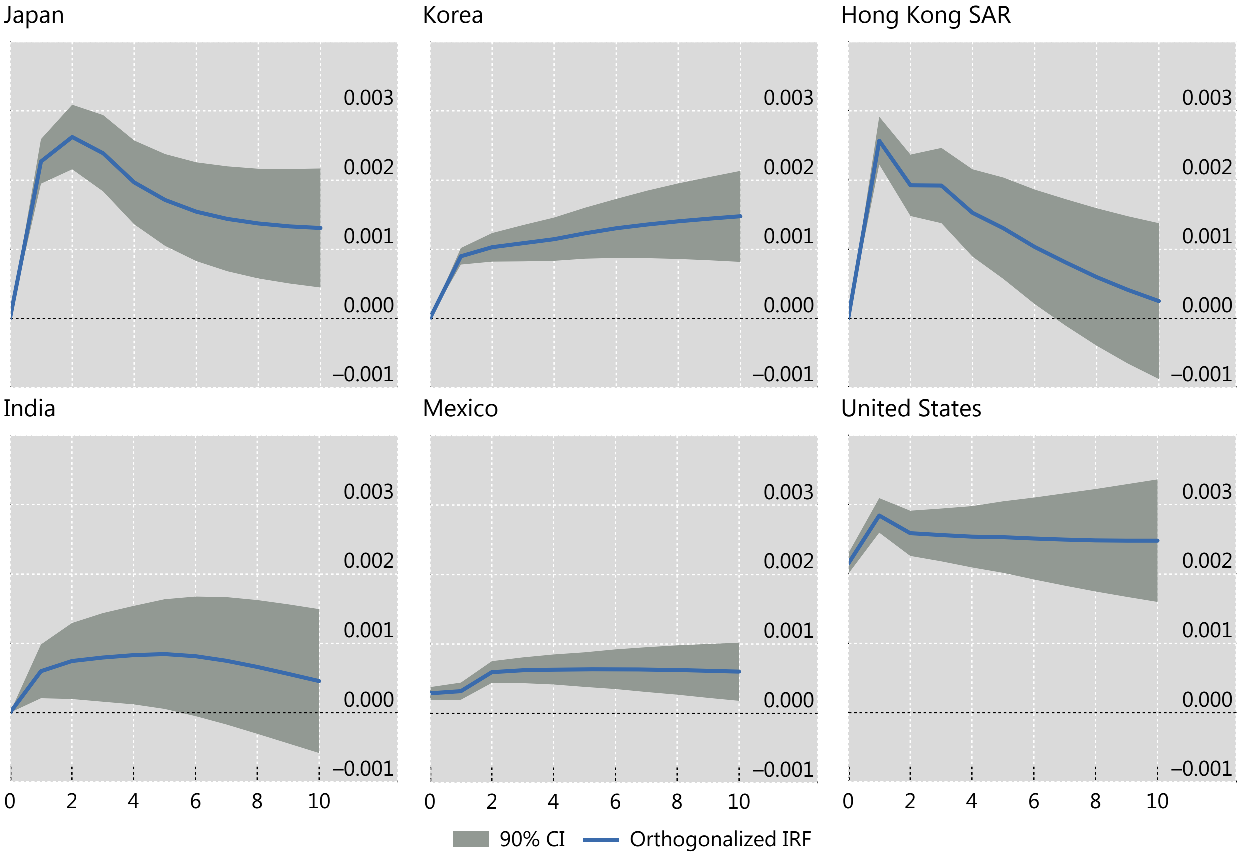


See the text for the details on the VAR regression specifications.

Source: Authors' estimates.

Response of other economies' VRPs to eurozone AEs' VRP shocks

Full sample period (805 daily observations) Graph 6



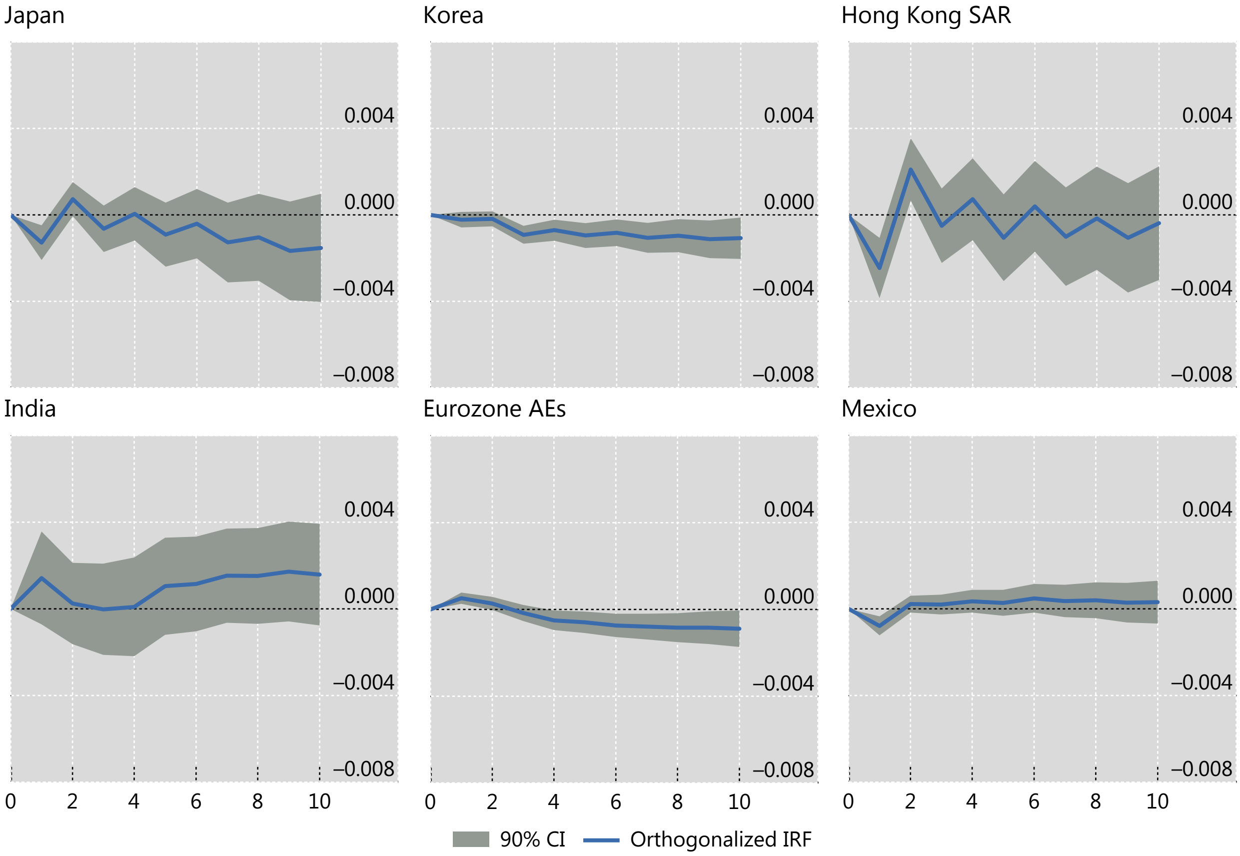
See the text for the details on the VAR regression specifications.

Source: Authors' estimates.

Now we turn to the same VAR analysis over the two subsample periods, ie the GFC period and post-GFC period. Graphs 7 and 8 show IRFs over the GFC period. US VRP has a significant positive impact only on the eurozone AEs' VRP on day 1 (Graph 7), while the eurozone AEs' VRP has a significant positive impact on Japan's VRP from day 1 to day 10, on Hong Kong SAR'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 (Graph 8). Overall, we find that US VRP does not exhibit strong positive spillover effects on other economic areas' VRPs during the GFC period, but that the eurozone AEs' VRP exerts strong influence on many other economies' VRP. One caveat here is the relatively short time-series dimension of 117 observations.

Response of other economic areas' VRPs to US VRP shocks

Global Financial Crisis period (117 daily observations) Graph 7

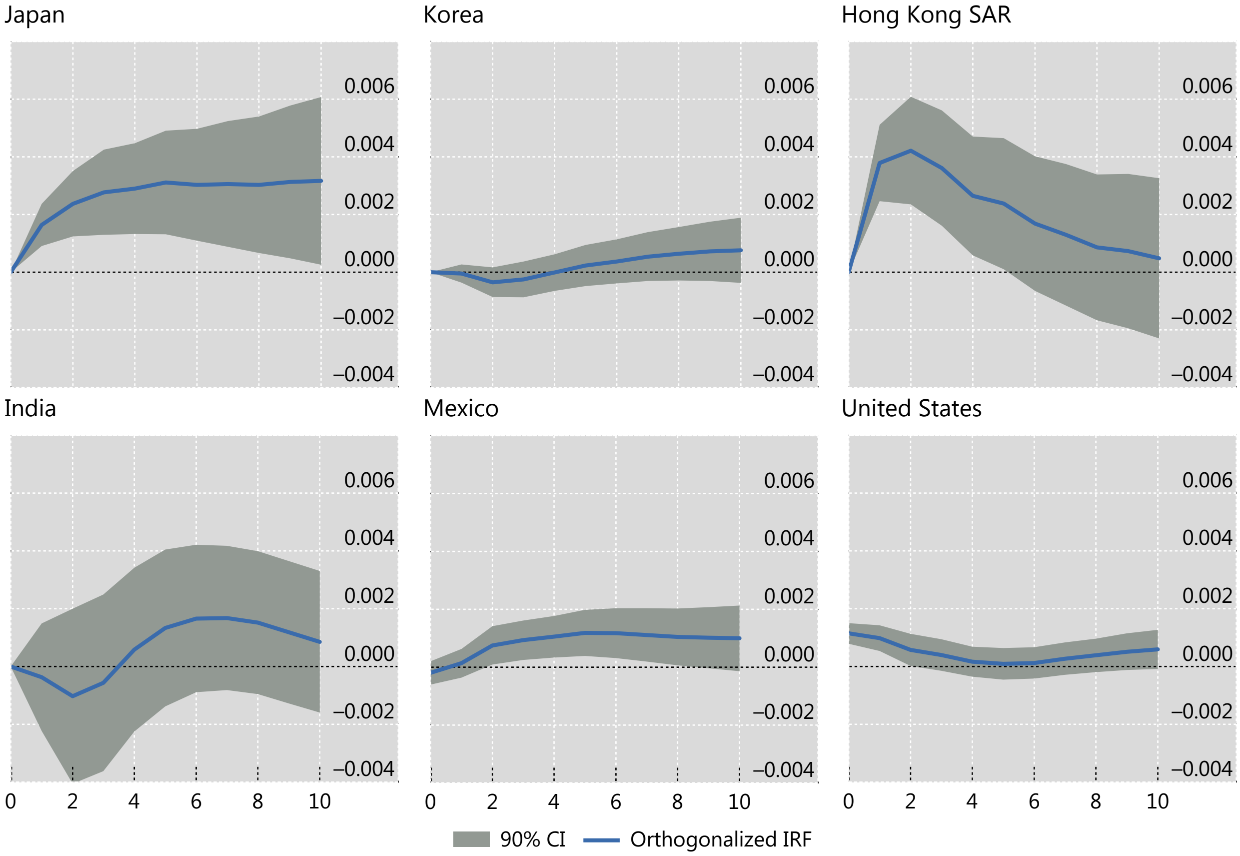


See the text for the details on the VAR regression specifications.

Source: Authors' estimates.

Response of other economies' VRPs to eurozone AEs' VRP shocks

Global Financial Crisis period (117 daily observations) Graph 8



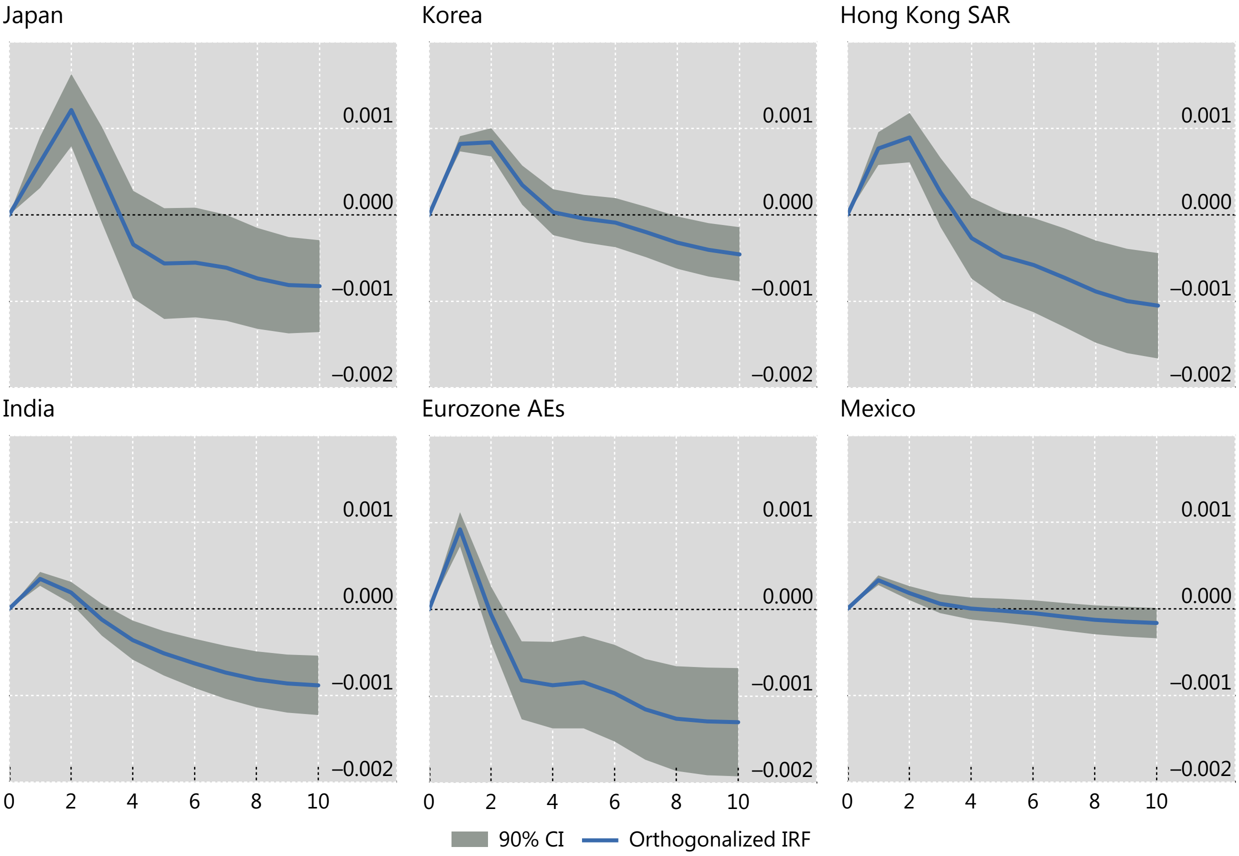
See the text for the details on the VAR regression specifications.

Source: Authors' estimates.

Graphs 9 and 10 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 economic areas' VRPs in two days (Graph 9). On Korea's VRP is the impact significant even in three days. The eurozone AEs' VRP has a significant positive impact on all the other six economies' VRPs up to day 3 (Graph 10). 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 the US and eurozone AEs' VRPs on the other economic areas' VRPs, respectively, during the post-GFC period.

Response of other economic areas' VRPs to US VRP shocks

Post-Global Financial Crisis period (688 daily observations) Graph 9

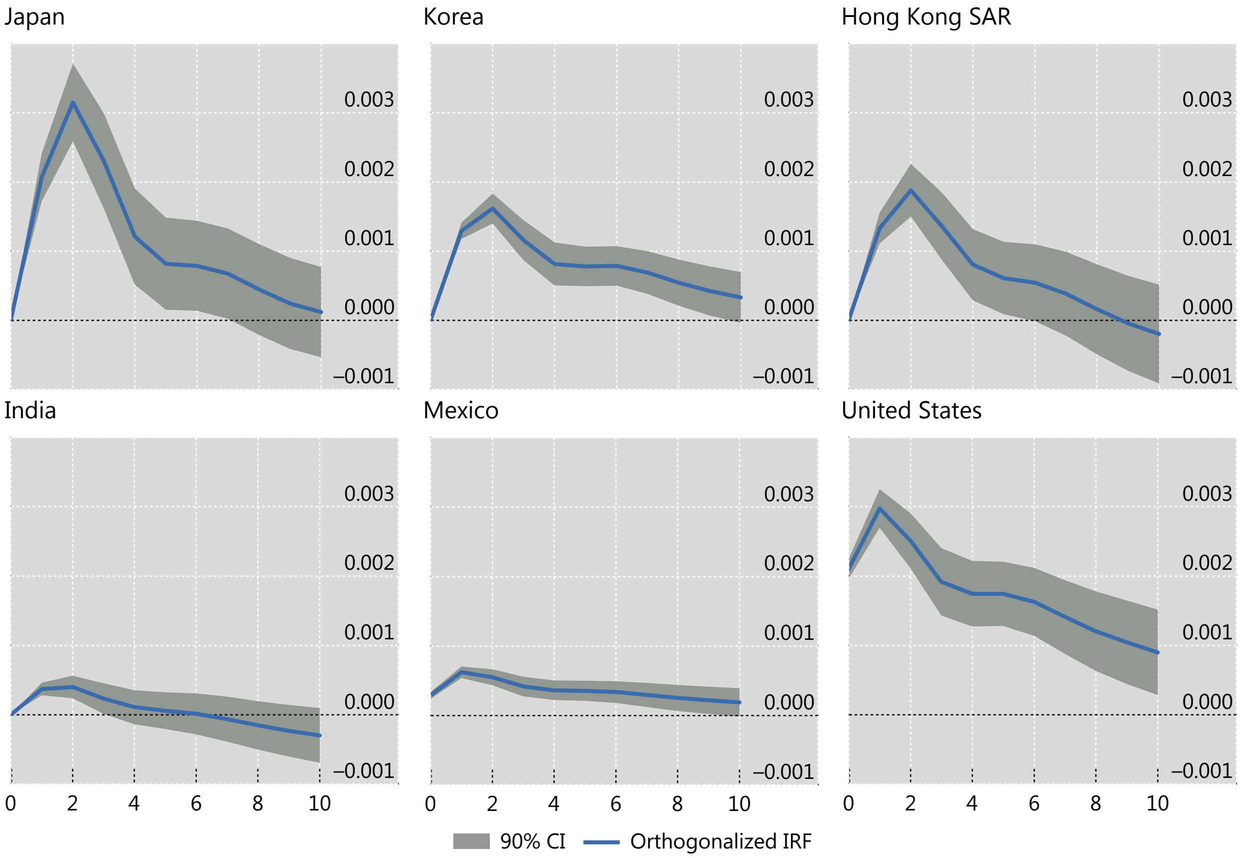


See the text for the details on the VAR regression specifications.

Source: Authors' estimates.

Response of other economies' VRPs to eurozone AEs' VRP shocks

Post-Global Financial Crisis period (688 daily observations) Graph 10



See the text for the details on the VAR regression specifications.

Source: Authors' estimates.

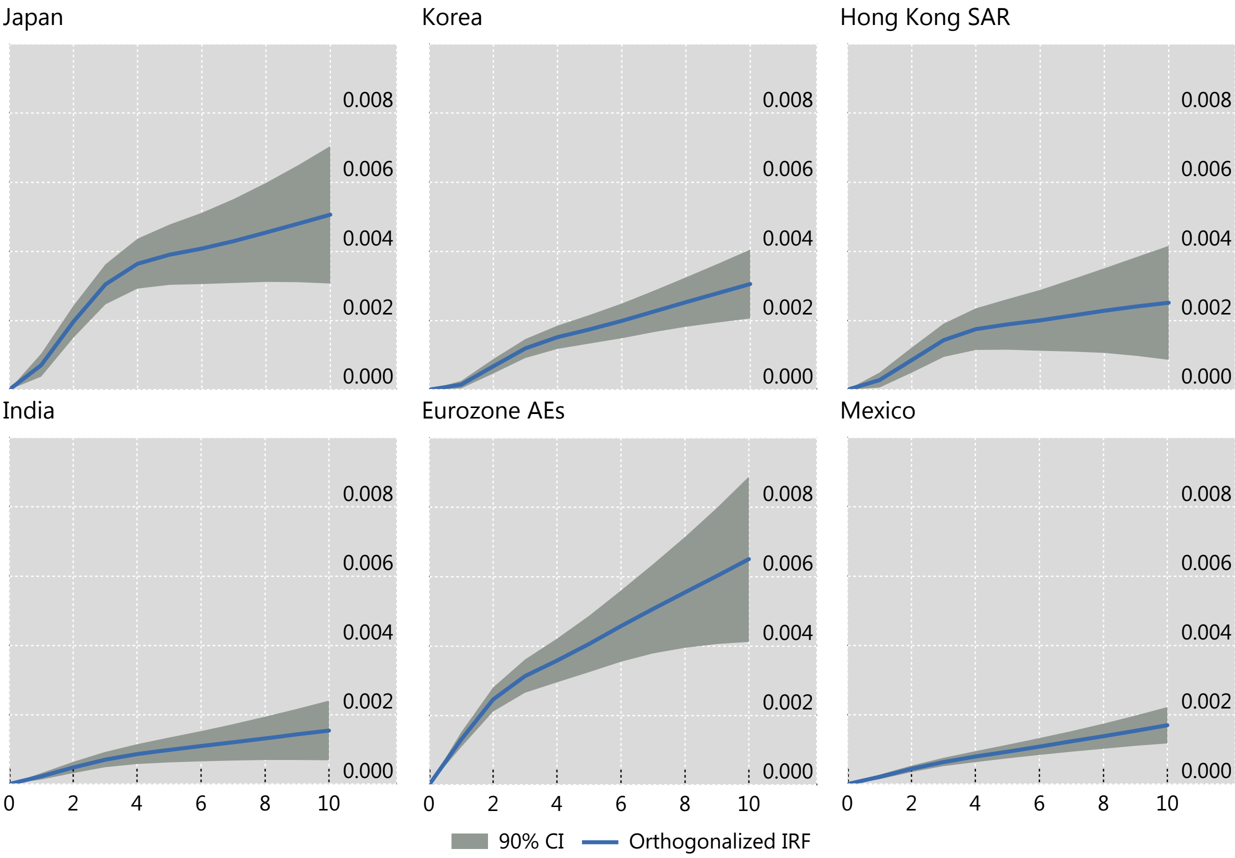
We now consider the effects of the US and eurozone AEs' DRPs and JRPs, two different risk premiums of distinct characteristics and the components of VRP, on other economic areas' VRPs to investigate which component drives the dynamics generating cross-country VRP spillovers. In particular, in the VAR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

Graph 11 illustrates estimation results on the impact of US DRP on the other economic areas' VRPs, while Graph 12 those on the impact of US JRP on the other economic areas' VRPs. We find that US DRP has a significant positive impact on all the other six economic areas' VRPs over the next 10 days (Graph 11). 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 economic areas' VRPs in one day and significant positive effects on only three other economies' (Hong Kong SAR, Japan and Korea) VRPs in two days (Graph 12). The effect changes from positive to negative on all the other six economic areas' 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 Graph 9.

Therefore, we can say that the short-lived impact of US VRP on other economic areas' VRPs are driven by US JRP, not by US DRP.

Response of other economic areas' VRPs to US DRP shocks

Post-Global Financial Crisis period (688 daily observations) Graph 11

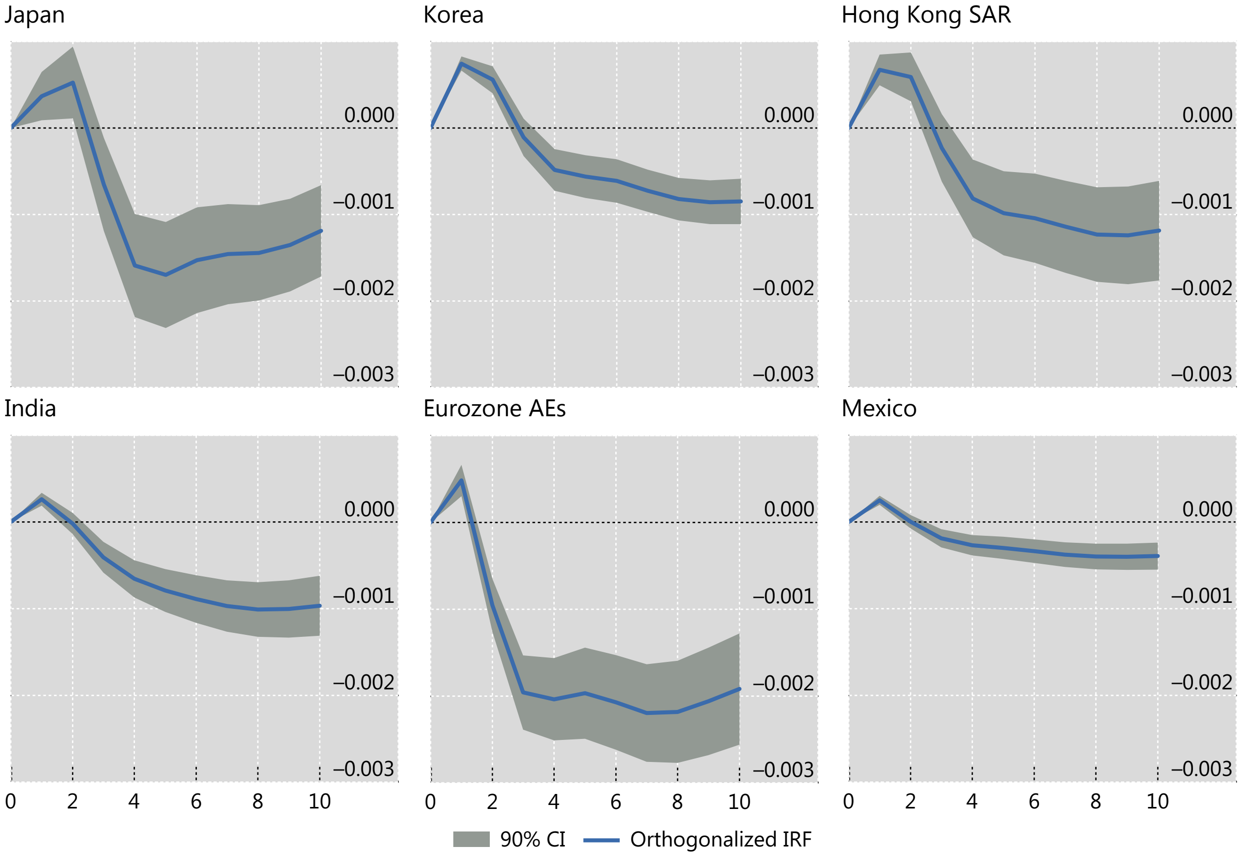


See the text for the details on the VAR regression specifications.

Source: Authors' estimates.

Response of other economic areas' VRPs to US JRP shocks

Post-Global Financial Crisis period (688 daily observations) Graph 12



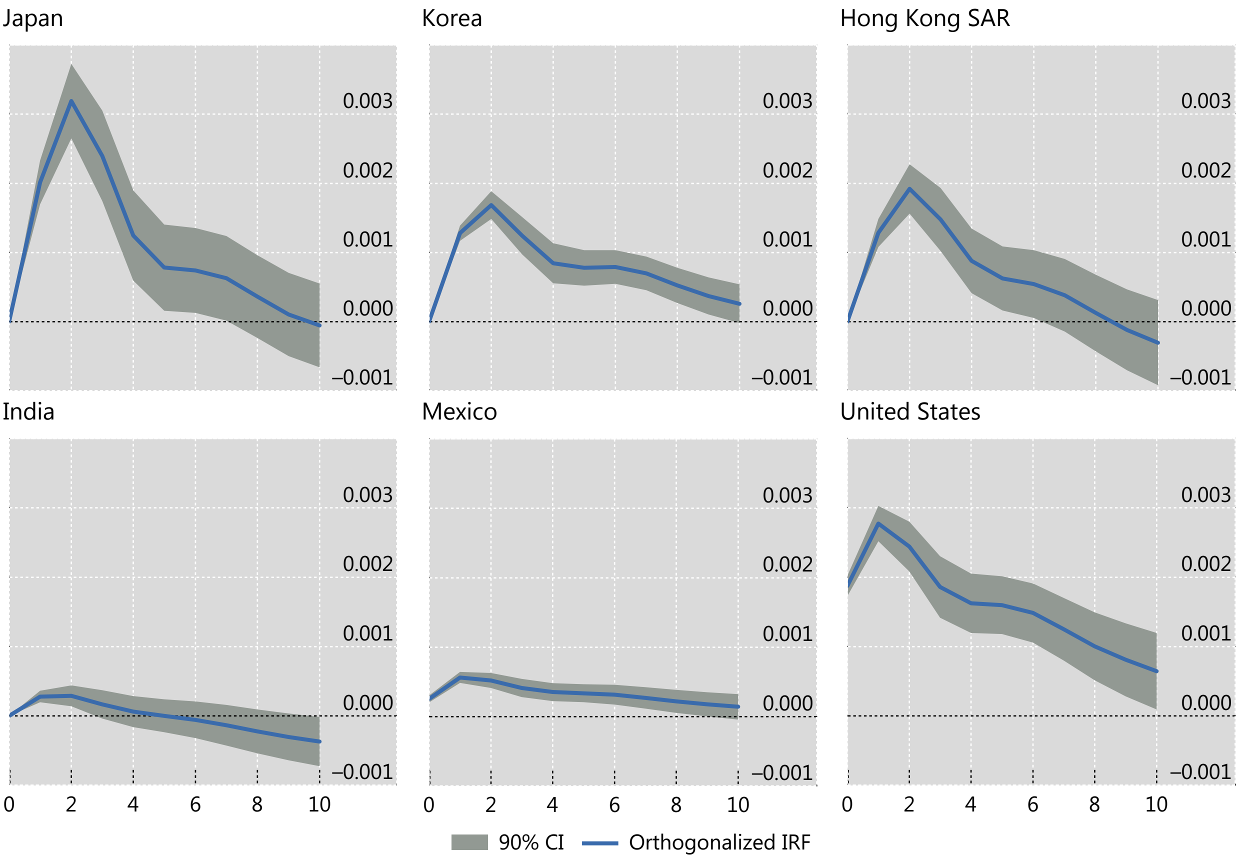
See the text for the details on the VAR regression specifications.

Source: Authors' estimates.

Graph 13 summarises estimation results on the impact of the eurozone AEs' DRP on the other economies' VRPs, while Graph 14 those on the impact of the eurozone AEs' JRP on the other economies' VRPs. The IRFs for the VAR analysis using the eurozone AEs' DRP as the shock show that the eurozone AEs' 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 the eurozone AEs' JRP as the shock show that the eurozone AEs' 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, the eurozone AEs' DRP has a longer positive impact on other economies' VRPs than the eurozone AEs' JRP has, and thus such effects of the eurozone AEs' DRP and JRP are broadly similar to the long-lasting positive effects of US DRP and the short-lived positive effects of US JRP.

Response of other economies' VRPs to eurozone AEs' DRP shocks

Post-Global Financial Crisis period (688 daily observations) Graph 13

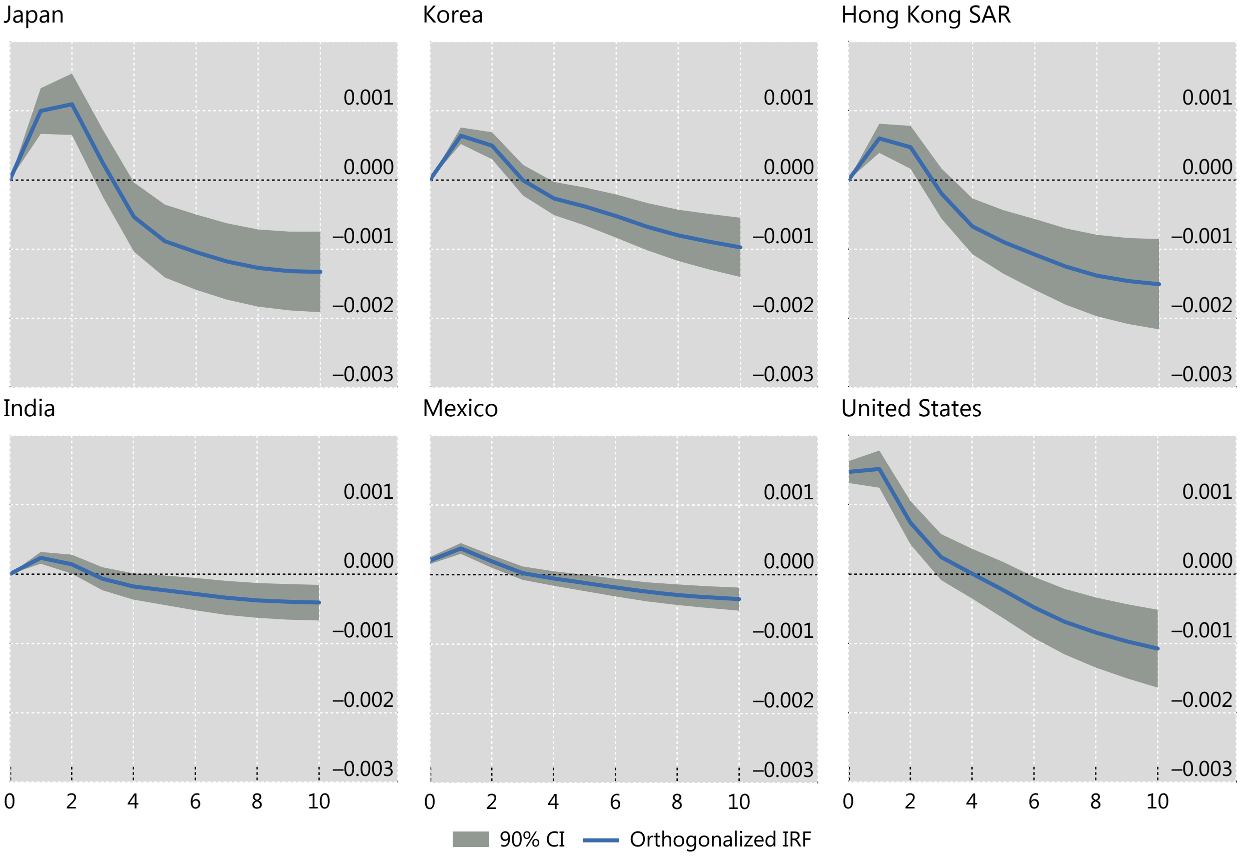


See the text for the details on the VAR regression specifications.

Source: Authors' estimates.

Response of other economies' VRPs to eurozone AEs' JRP shocks

Post-Global Financial Crisis period (688 daily observations) Graph 14



See the text for the details on the VAR regression specifications.

Source: Authors' estimates.

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

In Section 5, we reported daily cross-stock market correlations of VRPs, DRPs and JRPs. We find the correlations were very high during the GFC period. In the post-GFC period, the correlations were lower than the GFC period, but remained high enough to draw our attention as in other papers that consider these correlations. Our VAR analyses confirmed that the US and eurozone AEs' VRPs are a significant determinant of VRPs in many of other economic areas in the sample.

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 economic areas' stock markets, and the variations in the 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 economic areas' 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 or monthly 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 economic areas 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 consider the following three different sample periods: (i) full sample period; (ii) GFC period; and (iii) post-GFC period. In Appendix C, we also consider 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 seven economic areas including two AE economic areas (the eurozone AEs and Japan) and four EMEs (Hong Kong SAR, India, Korea and Mexico) as well as to two regional groupings (all AEs (excluding the United States) and all EMEs) over the sample period from November 2007 to September 2015. Table 5 provides regression results over the full sample period. Table 6 shows the results over the GFC period from November 2007 to December 2009, and Table 7 over the period from January 2010 to September 2015, which is a relatively tranquil non-crisis period.

Simple OLS regression results

Full sample period Table 5

Explanatory variable:	US VRP	US DRP	US JRP
Dependent variable: Equity fund flows to			
Advanced economies			
All advanced economies excluding the United States	1.542** (2.30)	1.104 (1.11)	4.447*** (3.67)
Eurozone AEs	0.680 (1.02)	−0.282 (−0.31)	2.985** (2.39)
Japan	5.490*** (6.65)	6.895*** (4.27)	11.890*** (8.89)
Emerging market economies			
All emerging market economies	0.604 (0.76)	0.815 (0.65)	1.232 (0.74)
Hong Kong SAR	1.896*** (3.55)	2.621*** (3.34)	3.785*** (3.01)
India	0.979 (1.31)	1.375 (1.19)	1.925 (1.22)
Korea	0.739 (0.68)	0.945 (0.57)	1.577 (0.71)
Mexico	−0.543 (−0.41)	−0.056 (−0.02)	−2.008 (−0.91)
Number of observations	411	411	411

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.

We begin by reporting the results from the regressions of the equity fund flows to investment destinations on US VRP, DRP and JRP over the full sample period. The second column of Table 5 shows that over the full sample period, US VRP is a significant explanatory variable for equity fund flows to Japan and Hong Kong SAR. The positive sign on the coefficient is what we expect: when investors in the US equity volatility market charge higher risk premium in absolute size (that is, more negative value of VRP, DRP and JRP), equity fund flows to non-US individual economic areas and regional groupings decrease.

When we decompose US VRP into US DRP and JRP, we find that US JRP has significant effects on equity fund flows to all AEs excluding the United States, the eurozone AEs, Japan and Hong Kong SAR, while US DRP has significant effects on equity fund flows to Japan and Hong Kong SAR only (Table 5, third and fourth columns). Also, the coefficients on US JRP are greater (ie more economically significant) than those on US DRP for all regional groupings and individual economies except Mexico. These results suggest that US JRP is a more important driver of equity fund flows to other economic areas than US DRP when we consider the impact of US VRP over the full sample period.

Simple OLS regression results

Global Financial Crisis period | Table 6

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)
Eurozone AEs	–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.

The full sample period includes both the GFC period and the post-GFC period. Since the dynamics of the VIX index and other volatility measures is very different between the two periods, we run the same regressions over the two separate subperiods. The OLS regression results over the GFC period reported in Table 6 show that US VRP, DRP and JRP have significantly positive effects for Japan, but significantly negative effects for the eurozone AEs. Most notably, they have no significant effect on equity fund flows to any of EMEs in the sample. We also find from the third and fourth columns of Table 6 that the coefficient on US JRP for Japan is still larger (ie more economically significant) than that on US DRP. This result implies that during the GFC period, US JRP was a more important driver of equity fund flows to Japan than US DRP.

Table 7 reports the results over the post-GFC period. Now the coefficients on US VRP, DRP and JRP are positive for all seven individual economic areas and statistically significant for five individual economic areas (the eurozone AEs, Japan, Hong Kong SAR, India and Korea). These results indicate that it is a tranquil period that US VRP, DRP and JRP exert very strong influence on equity fund flows to non-US economies. The results concerning individual economic areas parallel with our findings on the effect of US VRP on equity fund flows to the two regional groupings, that is, all AEs (excluding the United States) and all EMEs.

Simple OLS regression results

Post-Global Financial Crisis period Table 7

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)
Eurozone AEs	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.

When we decompose US VRP into US 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 regional groupings and individual economic areas except Mexico, while US DRP has significant effects equity fund flows to all regional groupings and individual economic areas except Korea and Mexico (Table 7, third and fourth columns). By contrast, in terms of economic significance, the coefficients on US DRP is much greater than those on US JRP for all regional groupings and individual economic areas. These results suggest that US DRP is a more important driver of equity fund flows to other economic areas than US JRP during the tranquil non-crisis period.

6.2. OLS regression 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 list of control variables is the same as for the VAR analysis in Section 5 and the sample economic areas for equity fund flows are also the same for the VAR analysis; the eurozone AEs, Hong Kong SAR, Japan, India, Korea and Mexico.

Tables 8–10 summarise the regression results. We again start by looking at the regression results over the full sample period. Table 8 shows that an increase in the absolute size of US VRP, DRP and JRP significantly decreases equity fund flows to Japan, and that an increase in the size of US JRP significantly deceases equity fund flows to the eurozone AEs. Among the EMEs, we only find a marginally significant impact of US DRP on equity fund flows to India.

Results of OLS regression with control variables

Full sample period Table 8

Explanatory variable: / Dependent variable: Equity fund flows to	US VRP	US DRP	US JRP	Number of observations
Advanced economies				
Eurozone AEs	−0.445 (−0.32)	−3.580*** (−3.37)	6.361*** (3.38)	406
Japan	6.809*** (5.31)	8.089*** (3.03)	8.302*** (5.10)	406
Emerging market economies				
Hong Kong SAR	1.626 (1.12)	0.926 (0.60)	3.784 (1.28)	395
India	1.986 (1.59)	2.920* (1.76)	2.010 (0.99)	406
Korea	0.990 (0.44)	0.973 (0.22)	0.262 (0.10)	406
Mexico	−0.231 (−0.11)	−0.678 (−0.16)	2.593 (0.84)	406

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 controls variables for the regression that has US VRP, US DRP or US JRP as the key explanatory variable are the economic area's lagged VRP, DRP or JRP, respectively, the Citi Economic Surprise Index of the economic area, the world short-term interest rate, the Citi Economic Surprise Index of the United States, and the lagged stock market return of the economic area. Robust standard errors are used to calculate *t*-statistics. *, **, and *** indicate 10, 5 and 1 percent statistical significance of the estimated coefficient, respectively.

As we showed from the simple OLS regression results in the previous section, these relatively weak results from the regressions over the full sample period may be driven by the insignificant results from the GFC period. Table 9 indeed shows overall weak results during the GFC period. In particular, we find a weakly significant impact of US VRP on equity fund flows to Japan and a weakly significant effect of US JRP on equity fund flows to the eurozone AEs and Japan. Among the EMEs, we again find a significant impact of US VRP and DRP on equity fund flows to India. Overall, during the GFC period, we find more significant effects of US JRP on the eurozone AEs and Japan than those of US DRP.

Results of OLS regression with control variables

Global Financial Crisis period Table 9

Explanatory variable:	US VRP	US DRP	US JRP	Number of observations
Dependent variable: Equity fund flows to				
Advanced economies				
Eurozone AEs	−0.617 (−0.39)	−3.329* (−1.81)	4.082* (1.69)	108
Japan	3.186* (1.74)	2.976 (1.36)	4.043* (1.74)	108
Emerging market economies				
Hong Kong SAR	1.409 (0.76)	1.418 (0.81)	1.744 (0.36)	99
India	3.416** (2.13)	4.916*** (2.78)	4.326 (1.42)	108
Korea	2.010 (0.76)	4.116 (0.85)	−0.513 (−0.15)	108
Mexico	2.650 (1.08)	3.066 (0.80)	7.378 (1.54)	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 controls variables for the regression that has US VRP, US DRP or US JRP as the key explanatory variable are the economic area's lagged VRP, DRP or JRP, respectively, the Citi Economic Surprise Index of the economic area, the world short-term interest rate, the Citi Economic Surprise Index of the United States, and the lagged stock market return of the economic area. Robust standard errors are used to calculate *t*-statistics. *, **, and *** indicate 10, 5 and 1 percent statistical significance of the estimated coefficient, respectively.

We obtain stronger results from the regression over the post-GFC period. Table 10 shows a significant impact of US VRP, DRP and JRP on equity fund flows to both the eurozone AEs and Japan. Among the EMEs, we only find a weakly significant impact of US DRP on equity fund flows to Hong Kong SAR and a significant impact of US JRP on equity fund flows to Korea. When we compare the coefficients on the US DRP regressions with those on the US JRP regressions for the eurozone AEs, Japan and Hong Kong SAR, we find that the coefficients in the US DRP 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 economic areas was stronger than the spillover channel from US JRP.

In summary, the results of the OLS regression analyses in this section show that US VRP affects equity fund flows to major stock markets in AEs and some EME. This effect is stronger during tranquil periods (that is, the post-GFC and the low volatility regime period) than during the GFC period. Also, the impact of US DRP on equity fund flows to other economic areas tends to be stronger for many economic areas than that of US JRP during the tranquil periods. Table 11 summarises the estimation results.

Results of OLS regression with control variables

Post-Global Financial Crisis period Table 10

Explanatory variable:	US VRP	US DRP	US JRP	Number of observations
Dependent variable: Equity fund flows to				
Advanced economies				
Eurozone AEs	11.308*** (2.71)	40.095*** (3.61)	7.905** (2.46)	298
Japan	11.199*** (6.13)	48.267*** (5.51)	12.400*** (4.83)	298
Emerging market economies				
Hong Kong SAR	0.975 (0.42)	19.140* (1.77)	−0.795 (−0.13)	296
India	2.089 (1.21)	7.257 (0.89)	3.235 (1.45)	298
Korea	3.966 (1.10)	6.884 (0.66)	8.160** (2.25)	298
Mexico	−8.131** (−2.07)	−17.180 (−1.26)	−8.369* (−1.67)	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 controls variables for the regression that has US VRP, US DRP or US JRP as they key explanatory variable are the economic area's lagged VRP, DRP or JRP, respectively, the Citi Economic Surprise Index of the economic area, the world short-term interest rate, the Citi Economic Surprise Index of the United States, and the lagged stock market return of the economic area. Robust standard errors are used to calculate *t*-statistics. *, **, and *** indicate 10, 5 and 1 percent statistical significance of the estimated coefficient, respectively.

Summary of results on US VRP's impact on equity fund flows Table 11

Explanatory variable	Dependent variable	Full sample period	Global Financial Crisis period	Tranquil periods: Post-Global Financial Crisis period	Tranquil periods: Low volatility regime period
US VRP	US equity fund flows to sample economies	**Japan**	*Japan* **India**	**Eurozone AEs** **Japan**	**Eurozone AEs** **Japan** *Hong Kong SAR* **India**
US DRP		**Japan** *India*	**India**	**Eurozone AEs** **Japan** *Hong Kong SAR*	**Eurozone AEs** **Japan**
US JRP		**Eurozone AEs** **Japan**	*Eurozone AEs* *Japan*	**Eurozone AEs** **Japan** **Korea**	**Eurozone AEs** **Japan** **India**

The name of an economic area in bold means that the coefficient on US VRP/DRP/JRP is positive and strongly significant at the 5% level, and the name in italic means that the coefficient on US VRP/DRP/JRP is positive and weakly significant at the 10% level. The results over the low volatility regime period are provided in Appendix C.

6.3. Assessment of control variables

In addition to the main variables of interest in the regressions whose coefficients are reported in Tables 8–10, the regressions provide interesting findings on other important control variables. Tables 12–14 show that the full regression results for the impact of US VRP on other economic areas, our baseline regression for the three different sample periods.

First, we find that the world short-term interest rate has a significant negative relationship with the normalised equity fund flows to all six economic areas consistently over the three different sample periods. Considering that a higher level of the world interest rate means a tighter global liquidity conditions, the negative impact of the world interest rate on equity fund flows is in line with our expectation.

Detailed OLS regression results

Full sample period — Table 12

Dependent variable: Equity fund flows at t to	Eurozone AEs	Japan	Hong Kong SAR	India	Korea	Mexico
Explanatory variable						
VRP of the economic area at t-1	0.388 (0.28)	−1.214** (−2.47)	−0.638 (−0.89)	−3.194*** (−2.62)	−2.309 (−1.25)	−1.859 (−1.12)
Citi Economic Surprise Index of the economic area at t	0.000 (0.24)	0.000 (0.98)	0.001*** (2.90)	- (-)	0.001* (1.86)	0.001** (2.17)
World short-term interest rate at t	−0.112*** (−5.24)	−0.155*** (−6.71)	−0.134*** (−4.10)	−0.124*** (−3.01)	−0.149*** (−4.95)	−0.097** (−2.42)
US VRP at t	−0.445 (−0.32)	6.809*** (5.31)	1.626 (1.12)	1.986 (1.59)	0.990 (0.44)	−0.231 (−0.11)
Citi Economic Surprise Index of the United States at t	−0.001*** (−2.77)	−0.001** (−2.31)	−0.000 (−1.20)	−0.000 (−1.06)	0.001 (1.32)	0.001 (1.25)
Stock market returns of the economic area at t-1	0.007 (1.34)	0.009 (0.94)	0.046*** (6.43)	0.038*** (5.91)	0.032*** (3.23)	0.035*** (3.40)
Constant	0.377*** (5.34)	0.657*** (8.39)	0.459*** (4.52)	0.397*** (3.37)	0.516*** (5.45)	0.270** (2.18)
Number of observations	406	406	395	406	406	406
Adjusted R-squared	0.1429	0.2316	0.2386	0.2039	0.1691	0.0891

This table reports the coefficients and *t*-statistics of the regressions. Robust standard errors are used to calculate *t*-statistics. Data on the Citi Economic Surprise Index of India are not available. *, **, and *** indicate 10, 5 and 1 percent statistical significance of the estimated coefficient, respectively.

Second, we find the expected signs on the impact of the local factor on equity fund flows, albeit less consistent than that of the lagged dependent variable and the world short-term interest rate. In particular, the coefficient on the Citi Economic

Surprise index of the five economic areas[15] in the regressions are positive over the two different sample periods (full sample period and post-GFC period) and statistically significant over the post-GFC period. This means that the positive surprise in economic news for the recipient economic areas increased equity fund flows into these economic areas. Similarly, we find the coefficient on Citi Economic Surprise index of the United States mostly negative over the three different sample periods and often statistically significant, especially for the eurozone AEs and Japan. This means that the positive surprise in economic news for the United States decreased equity fund flows into the six economic areas, supporting the substitution hypothesis under which good news in the United States induces US-based equity fund investors to move their investments away from other economic areas and back to the United States.

Detailed OLS regression results

Global Financial Crisis period — Table 13

Dependent variable: Equity fund flows at t to	Eurozone AEs	Japan	Hong Kong SAR	India	Korea	Mexico
Explanatory variable						
VRP of the economic area at t-1	−0.660 (−0.33)	−0.712 (−0.89)	−0.686 (−0.82)	−1.876 (−1.13)	−1.894 (−0.92)	−0.2639 (−0.14)
Citi Economic Surprise Index of the economic area at t	−0.000 (−0.00)	−0.001 (−1.11)	0.001 (0.78)	- (-)	−0.000 (−0.08)	−0.000 (−0.23)
World short-term interest rate at t	−0.112*** (−3.57)	−0.051* (−1.74)	−0.153*** (−3.77)	−0.228*** (−4.80)	−0.189*** (−4.58)	−0.257*** (−4.40)
US VRP at t	−0.617 (−0.39)	3.186* (1.74)	1.409 (0.76)	3.416** (2.13)	2.010 (0.76)	2.650 (1.08)
Citi Economic Surprise Index of the United States at t	−0.001 (−1.22)	0.001 (1.00)	−0.000 (−0.18)	−0.002* (−1.74)	0.001 (0.66)	−0.003** (−2.06)
Stock market returns of the economic area at t-1	0.006 (0.69)	0.030* (1.96)	0.041*** (3.63)	0.030*** (3.17)	0.025 (1.63)	0.021 (1.47)
Constant	0.314** (2.02)	0.086 (0.67)	0.557*** (4.17)	1.046*** (6.01)	0.814*** (3.96)	1.210*** (4.15)
Number of observations	108	108	99	108	108	108
Adjusted R-squared	0.1552	0.1261	0.3183	0.3146	0.2657	0.1659

This table reports the coefficients and *t*-statistics of the regressions. Robust standard errors are used to calculate *t*-statistics. Data on the Citi Economic Surprise Index of India are not available. *, **, and *** indicate 10, 5 and 1 percent statistical significance of the estimated coefficient, respectively.

[15] Note that we did not include the Citi Economic Surprise index as an instrument in the first-stage regression for India since we were not able to obtain that series.

Detailed OLS regression results

Post-Global Financial Crisis period — Table 14

Dependent variable: Equity fund flows at t to	Eurozone AEs	Japan	Hong Kong SAR	India	Korea	Mexico
Explanatory variable						
VRP of the economic area at t-1	−3.524 (−1.48)	−0.166 (−0.19)	4.379* (1.91)	1.646 (0.88)	−0.931 (−0.35)	17.671*** (3.23)
Citi Economic Surprise Index of the economic area at t	0.001*** (2.92)	0.001 (1.64)	0.001*** (2.95)	- (-)	0.002** (2.21	0.002** (2.15)
World short-term interest rate at t	0.016 (0.23)	−0.245** (−2.11)	−0.033 (−0.34)	−0.177* (−1.95)	−0.240* (−1.90)	−0.226 (−1.55)
US VRP at t	11.308*** (2.71)	11.199*** (6.13)	0.975 (0.42)	2.089 (1.21)	3.966 (1.10)	−8.131** (−2.07)
Citi Economic Surprise Index of the United States at t	−0.000* (−1.94)	−0.001** (−2.44)	−0.001 (−1.36)	−0.000 (−0.47)	0.000 (0.50)	0.001* (1.82)
Stock market returns of the economic area at t-1	0.002 (0.33)	−0.018 (−1.48)	0.044*** (4.81)	0.041*** (6.52)	0.033*** (4.38)	0.039*** (3.78)
Constant	0.048 (0.24)	1.034*** (2.96)	0.236 (0.80)	0.611** (2.28)	0.832** (2.25)	0.844* (1.94)
Number of observations	298	298	296	298	298	298
Adjusted R-squared	0.1787	0.1354	0.1762	0.1499	0.1317	0.1121

This table reports the coefficients and *t*-statistics of the regressions. Robust standard errors are used to calculate *t*-statistics. Data on the Citi Economic Surprise Index of India are not available. *, **, and *** indicate 10, 5 and 1 percent statistical significance of the estimated coefficient, respectively.

7. Conclusion

In this paper, we first estimate variance risk premiums for seven stock markets in both AEs and EMEs over 2007–15. We use a jump-diffusion model with stochastic volatility of a mean-reverting variance and a self-exciting jump process and decompose VRP into variance-diffusive risk premium and variance-jump risk premium. Using a daily VAR model, we then calculate the cross-country correlations of VRPs, DRPs and JRPs and analyse the impact of a rise in the VRPs of the US and eurozone AEs' stock markets on the ones of other economic areas. Moreover, we test the significance of the premiums as determinants of US-based equity fund flows to the stock markets of other economic areas, based on a conjecture that such fund flows are a path through which VRPs spill over globally.

This paper has three novel features. First, to our knowledge, it is the first to use a parametric model to estimate VRPs in selected EME stock markets. Therefore, gauging the correlations of VRPs between AE and EME stock markets is also unprecedented. Second, it decomposes VRPs into DRPs and JRPs and looks at the cross-stock market correlations between the different components. Finally, it investigates a specific channel for the VRPs' cross-stock market correlations. In particular, it investigates the impact of US VRP on US-based equity fund flows to other economic areas' stock markets.

Concerning the correlations between the VRPs, we find that cross-stock market correlations including EME stock markets are high. Impulse-response analysis points to significant spillovers from the US and eurozone AEs' VRPs to the ones of other sample economic areas, especially during the post-GFC period. We also find that post-GFC, the US and eurozone AEs' DRPs had relatively strong and long-lived effects on other economic areas' VRPs, while their JRPs had relatively weak and short-lived effects.

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

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

This paper also underlines the policy importance of considering specific channels or intermediaries in the generation of spillovers from one economy's stock market to another. We consider that mutual funds operating in global equity markets are an important source of cross-border equity market contagion. Other institutional investors such as insurance companies, pension funds and hedge funds also allocate sizable investments to various equity markets and adjust their investment strategies according to developments in stock market volatility. 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 recipient economies, it is crucial for policymakers to understand the possible spillover channels that operate via portfolio equity flows. It is also important for them to consider the behaviour of various types of investor and contemplate the possible policy actions that could be employed, if necessary, to mitigate the impact of excessive equity investment inflows or outflows on domestic financial markets and the real economy.

The analysis presented in this paper could potentially be refined along a few dimensions. For example, there would be room for a more precise categorisation of US-based mutual funds in terms of each fund's investment destination. Also, in order to investigate the causality between the VRPs of different economic areas' stock markets, it would be worth considering the conduct of event studies of 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 had access to daily equity fund flow data to the six economic areas considered in this paper, we could conduct second-stage regressions for an economy’s VRP on equity fund flows to more completely identify the transmission channels and investigate whether the cross-border spillovers of VRPs via equity fund flows are an important channel. Even so, we think that the empirical results reported in this paper shed light on research topics that have not been delved into in the current literature.

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Appendix A: The Model for variance risk premium

A.1 The model under the real probability measure

Suppose there are I economies and each economy has a represented asset-price index. Let $y_{i,t}$ denote the return of the index in the economy i ($i = 1, 2, \ldots, I$) at time t. We assume a jump diffusion process with a stochastic diffusion volatility and a self-exciting jump-arrival intensity for the dynamics of $y_{i,t}$. Let $\sigma_{i,t}$, $v_{i,t}$, $\lambda_{i,t}$ and $z_{i,n}$ denote a stochastic diffusion volatility, the square of the volatility, and the Poisson intensity for price-jump occurrence at time t, and the stochastic size of n-th jump in the economy i. The dynamics of a return of the economy i is written as

$$\begin{aligned} dy_{i,t} &= \mu_i(t)dt + \sigma_{i,t}dW_{i,t} + d\left(\sum_{n=1}^{N_{i,t}} z_{i,n}\right), && (1) \\ dv_{i,t} &= d\sigma_{i,t}^2 = \kappa_i(\theta_i - v_{i,t})dt + \nu_i\sigma_{i,t}dW_{i,t}^v, && (2) \\ d\lambda_{i,t} &= \alpha_i(\lambda_{\infty,i} - \lambda_{i,t})dt + \beta_i dN_{i,t}, && (3) \end{aligned}$$

where $W_{i,t}$ and $W_{i,t}^v$ are the Brownian motions, $N_{i,t}$ is the Poisson process, $\mu_i(t)$, κ_i, θ_i, ν_i, α_i, β_i and $\lambda_{\infty,i}$ are parameters (positive except for μ_i). We assume that the distortion in the return distribution is expressed through jumps, not through a correlation of the Brownian motions between the return and the variance processes, thus $dW_{i,t}dW_{j,t}^v = 0$ $(i, j = 1, \ldots, I)$. We also assume that the Brownian motion and the Poisson processes are independent of each other ($dW_{i,t}dN_{j,t} = 0$), while the Brownian motions can be correlated with those of other indexes.

The process for the variance in equation (2) is the Heston model for volatility (Heston (1993)), and the process for the jump-arrival intensity in equation (3) is the self-exciting point process introduced by Hawkes (1971). Since asset jumps are known to occur in clusters during financial turmoils, the self-exciting process is expected to replicate market prices better than the standard time-homogeneous jump-diffusion model. Aït-Sahalia et al (2015) reveal that this self-excitation feature is observed in the United States and other economies as well.

A.2 The model under the risk-neutral probability measure

The market described by equations (1) $-$ (3) is incomplete. To specify one possible risk-neutral probability measure for the market, the stochastic jump size is assumed to take the same value under both the real and the risk-neutral probability measures, while the jump-arrival intensity changes to a different value. In earlier studies, Broadie et al (2007) and Pan (2002) assume that the stochastic jump size changes while a scalar jump-arrival intensity remains the same at the measure change. But our assumption is natural for our model in which jump-arrival intensity is stochastic. This assumption along with a transformation of the variance process determines one risk-neutral measure. Hereafter, the variables with asterisk indicate those under the risk-neutral probability measure. The model under the risk-neutral measure is given by

$$dy_{i,t} = \mu_i^*(t)dt + \sigma_{i,t}dW_{i,t}^* + d\left(\sum_{n=1}^{N_{i,t}^*} z_{i,n}\right), \tag{4}$$

$$dv_{i,t} = \kappa_i^*(t)(\theta_i^*(t) - v_{i,t})dt + \nu_i\sigma_{i,t}dW_{i,t}^{v*}, \tag{5}$$

$$d\lambda_{i,t} = \alpha_i^*(t)(\lambda_{\infty,i}^*(t) - \lambda_{i,t})dt + \beta_i^*(t)dN_{i,t}^*. \tag{6}$$

Here, μ_i^*, κ_i^*, θ_i^*, α_i^*, β_i^* and $\lambda_{\infty,i}^*$ are time dependent parameters. $\mu_i^*(t)$ is determined such that expected returns grow at a riskless rate.

A.3 Risk premiums

Risk premiums are reflected in expected excess returns in general. Similarly, variance risk premium (VRP) for the economy i, denoted by VRP$_{i,t}$, is defined as the difference between the expected value of the change in variance under the real measure and that under the risk-neutral measure. VRP is decomposed into continuous and discontinuous parts. The continuous part (instantaneous variance-diffusive risk premium: DRP) is assumed to be proportional to squared diffusion volatility, while the jump part (instantaneous variance-jump risk premium: JRP) is to squared jump. The proportionality coefficients of DRP for the economy i, $\gamma_{i,t}$, and that of JRP, $\omega_{i,t}$, are defined such that $\mathbb{E}\left[dv_{i,t}\right] - \mathbb{E}^*[dv_{i,t}] = \gamma_{i,t}v_{i,t}dt$ and $\mathbb{E}\left[z_i^2 d\lambda_{i,t}\right] - \mathbb{E}^*[z_i^2 d\lambda_{i,t}] = \omega_{i,t}\lambda_{i,t}\mathbb{E}\left[z_i^2\right]dt$, respectively. The former reduces to $\kappa_i\theta_i = \kappa_i^*(t)\theta_i^*(t)$ and $\kappa_i^*(t) = \kappa_i + \gamma_{i,t}$ as in Heston (1993). The latter reduces to $\alpha_i\lambda_{\infty,i} = \alpha_i^*(t)\lambda_{\infty,i}^*(t)$ and $\beta_i - \alpha_i = \beta_i^*(t) - \alpha_i^*(t) + \omega_{i,t}$ in the same way. Using $\gamma_{i,t}$ and $\omega_{i,t}$, VRP, DRP and JRP are given by

$$\text{VRP}_{i,t} = \gamma_{i,t}v_{i,t} + \omega_{i,t}\lambda_{i,t}\mathbb{E}\left[z_i^2\right], \tag{7}$$

$$\text{DRP}_{i,t} = \gamma_{i,t}v_{i,t}, \tag{8}$$

$$\text{JRP}_{i,t} = \omega_{i,t}\lambda_{i,t}\mathbb{E}\left[z_i^2\right], \tag{9}$$

where $\mathbb{E}_t[X] = \mathbb{E}[X|\mathcal{F}_t]$ indicates the expected value of X given the information obtainable up to time t denoted by filtration $\mathcal{F}_t$. Note that $\mathbb{E}_t[z_{i,n}^2] = \mathbb{E}_t^*[z_{i,n}^2] = \mathbb{E}[z_i^2]$.

A.4 Quadratic variations

A.4.1 Quadratic variation under the real measure

While VRP defined by contemporaneous variances under the two measures cannot be observed in the market, the integrated variances, or the quadratic variation (QV), can be measured from market data. QV of the economy i at time t in a time interval τ is defined as

$$\text{QV}_{i,t,t+\tau} = \frac{1}{\tau}\int_t^{t+\tau} d[y_i, y_i]_s. \tag{10}$$

The QV is decomposed into the continuous (variance-oriented) part $\mathcal{D}_{i,t,t+\tau}$ and the discontinuous (jump-oriented) part $\mathcal{J}_{i,t,t+\tau}$ as

$$\mathsf{QV}_{i,t,t+\tau} = \underbrace{\frac{1}{\tau}\int_t^{t+\tau} v_{i,s} ds}_{\mathcal{D}_{i,t,t+\tau}} + \underbrace{\frac{1}{\tau}\sum_{n=N_{i,t}+1}^{N_{i,t+\tau}} z_{i,n}^2}_{\mathcal{J}_{i,t,t+\tau}}. \tag{11}$$

The continuous part reduces to

$$\mathcal{D}_{i,t,t+\tau} = a(\kappa_i,\tau)v_{i,t} + b(\kappa_i,\theta_i,\tau) + \underbrace{\frac{\nu_i}{\tau}\int_t^{t+\tau} ds \int_t^s e^{-\kappa_i(s-u)}\sigma_{i,u} dW_{i,u}}_{\varepsilon_{i,t}^{\mathsf{BV}}}, \tag{12}$$

where

$$a(\kappa,\tau) = \frac{1-e^{-\kappa\tau}}{\kappa\tau}, \quad b(\kappa,\theta,\tau) = \theta\left(1 - a(\kappa,\tau)\right). \tag{13}$$

Note that $\mathbb{E}\left[\varepsilon_{i,t}^{\mathsf{BV}}\right] = 0$. The discontinuous part in equation (11) can be further decomposed into deterministic and stochastic parts as

$$\mathcal{J}_{i,t,t+\tau} = c(\alpha_i,\beta_i,\tau)\lambda_{i,t-\tau} + d(\alpha_i,\beta_i,\lambda_{\infty,i},\tau) + \varepsilon_{i,t}^J, \tag{14}$$

where $\mathbb{E}\left[\varepsilon_{i,t}^J\right] = 0$ and

$$c(\alpha,\beta,\tau) = \frac{e^{(\beta-\alpha)\tau}-1}{\tau(\beta-\alpha)}\mathbb{E}\left[z_i^2\right], \quad d(\alpha,\beta,\lambda,\tau) = \frac{\alpha\lambda}{\beta-\alpha}\left(c(\alpha,\beta,\tau) - \mathbb{E}\left[z_i^2\right]\right). \tag{15}$$

A.4.2 Quadratic variation under the risk neutral measure

We consider the expected value of QV at time t in period T under the risk-neutral probability measure:

$$\mathbb{E}_t^*\left[\mathsf{QV}_{i,t,t+T}\right] = \underbrace{\mathbb{E}_t^*\left[\frac{1}{T}\int_t^{t+T} v_{i,s} ds\right]}_{\mathcal{D}_{i,t,t+T}^*} + \underbrace{\mathbb{E}_t^*\left[\frac{1}{T}\sum_{n=N_{i,t}+1}^{N_{i,t+T}} z_{i,n}^2\right]}_{\mathcal{J}_{i,t,t+T}^*}. \tag{16}$$

From the definition of DRP, the continuous part $\mathcal{D}_{i,t,t+T}^*$ is approximated to

$$\begin{aligned}\mathcal{D}_{i,t,t+T}^* &= \frac{1}{T}\mathbb{E}_t\int_0^T v_{i,t+s} ds - \frac{1}{T}\int_0^T ds \int_t^{t+s} du\gamma_{i,u}v_{i,u} \\ &\simeq \mathbb{E}_t\mathcal{D}_{i,t,t+T} - \frac{1}{T}\gamma_{i,t}\int_0^T ds\int_t^{t+s} duv_{i,u} \\ &= a(\kappa_i,T)v_{i,t} + b(\kappa_i,\theta_i,T) + e(\kappa_i,\theta_i,T,v_{i,t})\gamma_{i,t},\end{aligned} \tag{17}$$

where

$$e(\kappa,\theta,T,v) = -\frac{1}{\kappa^2 T}(\kappa T + e^{-\kappa T} - 1)(v-\theta) - \frac{T\theta}{2}. \tag{18}$$

Here, the coefficients of risk premium are approximated to be piecewise constant over the period from time t to $t+T$ under filtration $\mathcal{F}_t$, ie, $\gamma_{i,s}|\mathcal{F}_t = \gamma_{i,t}$ and $\omega_{i,s}|\mathcal{F}_t = \omega_{i,t}$

$(t \leq s \leq t+T)$. In analogy, the discontinuous part $\mathcal{J}^*_{i,t,t+T}$ is approximated to

$$\begin{aligned}\mathcal{J}^*_{i,t,t+T} &= \mathbb{E}_t \mathcal{J}_{i,t,t+T} - \frac{1}{T}\mathbb{E}\left[z_i^2\right]\int_0^T du \int_t^{t+u} ds \lambda_{i,s}\omega_{i,s} \\ &\simeq c(\alpha_i,\beta_i,T)\lambda_{i,t} + d(\alpha_i,\beta_i,\lambda_{\infty,i},T) + f(\alpha_i,\beta_i,\lambda_{\infty,i},T,\lambda_{i,t})\omega_{i,t}, \end{aligned} \tag{19}$$

where

$$f(\alpha,\beta,\lambda_\infty,T,\lambda) = \left[-\frac{e^{(\beta-\alpha)T}-1-T(\beta-\alpha)}{(\beta-\alpha)^2 T}\left(\lambda+\frac{\alpha\lambda_\infty}{\beta-\alpha}\right)+\frac{\alpha\lambda_\infty}{\beta-\alpha}\frac{T}{2}\right]\mathbb{E}\left[z_i^2\right]. \tag{20}$$

In summary,

$$\begin{aligned}\mathcal{D}^*_{i,t,t+T} + \mathcal{J}^*_{i,t,t+T} =& a\left(\kappa_i,T\right)v_{i,t} + b\left(\kappa_i,\theta_i,T\right) \\ &+ c\left(\alpha_i,\beta_i,T\right)\lambda_{i,t} + d\left(\alpha_i,\beta_i,\lambda_{i,\infty},T\right) \\ &+ e(\kappa_i,\theta_i,T,v_{i,t})\gamma_{i,t} + f(\alpha_i,\beta_i,\lambda_{\infty,i},T,\lambda_{i,t})\omega_{i,t} + \varepsilon^{\mathrm{IV}}_{i,t}, \end{aligned} \tag{21}$$

where $\varepsilon^{\mathrm{IV}}_{i,t}$ is an error that stems from the piecewise-constant assumption at each time step, the mean of which is zero.

Appendix B: Sampling methods

B.1 Estimators for QV

We employ three QVs — RV, BV and IV — for the input in the model to sample variance risk premiums. Barndorff-Nielsen and Shephard (2004) demonstrate that BV is a robust measure of QV of diffusion. Since RV is a robust measure of QV of returns, the difference between BV and RV (RV minus BV) is considered to be QV of jumps. RV, BV and IV are estimators for $\mathcal{D}_{i,t,t+\tau} + \mathcal{J}_{i,t,t+\tau}$, $\mathcal{D}_{i,t,t+\tau}$ and $\mathcal{D}^*_{i,t,t+T} + \mathcal{J}^*_{i,t,t+T}$, respectively.

Suppose that we record G equally-spaced time points during each time interval τ, and let $r_{i,t-k\tau/G}$ denote the $(H-k+1)$-th return in the interval, ie, the return from time $t-k\tau/G$ to $t-(k-1)\tau/G$. RV and BV employed in this paper are estimated as

$$\hat{\mathrm{RV}}_{i,t-\tau,t} = \frac{1}{\tau}\sum_{k=1}^{G} r^2_{i,t-k\tau/G}, \tag{22}$$

$$\hat{\mathrm{BV}}_{i,t-\tau,t} = \frac{\pi}{2\tau}\sum_{k=1}^{G-1} |r_{i,t-k\tau/G}||r_{i,t-(k+1)\tau/G}|. \tag{23}$$

Here, the hats on RV and BV indicate that those are observed variables. When G is large enough, $\mathrm{RV}_{i,t,\tau}$ and $\mathrm{BV}_{i,t,\tau}$ converge to $\mathcal{D}_{i,t,t+\tau} + \mathcal{J}_{i,t,t+\tau}$ and $\mathcal{D}_{i,t,t+\tau}$, respectively, in probability. In the estimation, τ/G is generally set at 5 minutes to exclude the effect of bid-ask bounces.

On the other hand, IV is estimated from the basket of option prices as the model-free representation of the expected variance under the risk-neutral measure. Let $B_i(t,T)$, $F_i(t,T)$ and $\Phi_i(t,T,S)$ denote the riskless zero-coupon bond price with maturity T, the forward price of the underlying asset of options at time T, and out-of-the-money European option prices with maturity T and strike price S for the economy i, respectively. IV is estimated as

$$\hat{\mathrm{IV}}_{i,t,t+T} = \frac{2}{TB_i(t,T)}\left[\int_0^{F_i(t,T)} \frac{\Phi_i(t,T,S)}{S^2}dS + \int_{F_i(t,T)}^{\infty} \frac{\Phi_i(t,T,S)}{S^2}dS\right]. \tag{24}$$

The integral in the above equation is discretised as explained in CBOE (2015).

B.2 MCMC procedures

We apply the Markov chain Monte Carlo (MCMC) to generate samples of risk premiums, instantaneous diffusion variance, jump intensity and model parameters. The MCMC is conducted 11,000 times while the first 1,000 samples are discarded as burn-in. The discussions below suppose that we have M samples observed at equally-spaced time steps, $t = t_1, t_2, \ldots, t_M$, where $t_m - t_{m-1} = \tau$ $(m = 2, \ldots, M)$.

B.2.1 Transformation of the model

First, we transform the model into the state-space form. Matching the model (equations (12), (14), (21)) with the estimators (equations (22), (23), (24)) yields the following three vector equations:

$$
\begin{aligned}
\mathsf{BV}_{t,t+\tau} =& \boldsymbol{A}(\boldsymbol{\kappa},\tau)\boldsymbol{v}_t + \boldsymbol{b}(\boldsymbol{\kappa},\boldsymbol{\theta},\tau) + \boldsymbol{\varepsilon}_t^{\mathsf{BV}}, && (25)\\
\mathsf{RV}_{t,t+\tau} =& \mathsf{BV}_{t-\tau,t} + \boldsymbol{C}(\boldsymbol{\alpha},\boldsymbol{\beta},T)\boldsymbol{\lambda}_t + \boldsymbol{d}(\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\lambda}_\infty,T) + \boldsymbol{\varepsilon}_t^{\mathsf{RV}}, && (26)\\
\mathsf{IV}_{t,t+T} =& \boldsymbol{A}(\boldsymbol{\kappa},\tau)\boldsymbol{v}_t + \boldsymbol{b}(\boldsymbol{\kappa},\boldsymbol{\theta},\tau) + \boldsymbol{C}(\boldsymbol{\alpha},\boldsymbol{\beta},T)\boldsymbol{\lambda}_t + \boldsymbol{d}(\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\lambda}_\infty,T)\\
&+ \boldsymbol{\Gamma}_t\boldsymbol{e}(\boldsymbol{\kappa},\boldsymbol{\theta},T,\boldsymbol{v}_t) + \boldsymbol{\Omega}_t\boldsymbol{f}(\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\lambda}_\infty,T,\boldsymbol{\lambda}_t) + \boldsymbol{\varepsilon}_t^{\mathsf{IV}}, && (27)
\end{aligned}
$$

where

$$
\begin{aligned}
\boldsymbol{\varepsilon}_t^{\mathsf{BV}} &\sim \mathcal{N}(\boldsymbol{0},\boldsymbol{\Sigma}_{\mathsf{BV}}),\\
\boldsymbol{\varepsilon}_t^{\mathsf{RV}} &\sim \mathcal{N}(\boldsymbol{0},\boldsymbol{\Sigma}_{\mathsf{RV}}),\\
\boldsymbol{\varepsilon}_t^{\mathsf{IV}} &\sim \mathcal{N}(\boldsymbol{0},\boldsymbol{\Sigma}_{\mathsf{IV}}).
\end{aligned}
$$

Bold lowercases denote I-dimensional column vectors of a parameter for all of the economies, eg, $\boldsymbol{\kappa} = (\kappa_1,\dots,\kappa_I)'$, and bold uppercases indicate diagonal matrices with the vector of correspondent lowercase on the diagonal, eg, $\boldsymbol{A}(\boldsymbol{\kappa},\tau) = \text{diag}\{a(\kappa_1,T),\dots,a(\kappa_I,T)\}$. The diagonal of $\boldsymbol{\Sigma}_{\mathsf{RV}}$ is the sum of ε_t^J and estimation errors.

On the other hand, latent state equations are summarised as follows.

$$
\begin{aligned}
\boldsymbol{v}_t &= \left(\boldsymbol{E}_I - \frac{1}{2}\boldsymbol{K}\tau\right)\boldsymbol{v}_{t-\tau} + \boldsymbol{K}\boldsymbol{\theta}\tau + \boldsymbol{\varepsilon}_t^v, && (28)\\
\boldsymbol{\lambda}_t &= \left(\boldsymbol{E}_I - \frac{1}{2}\boldsymbol{\Lambda}_\alpha\tau\right)\boldsymbol{\lambda}_{t-\tau} + \boldsymbol{\Lambda}_\alpha\boldsymbol{\lambda}_\infty\tau + \boldsymbol{\Lambda}_\beta\boldsymbol{j}_t, && (29)\\
\boldsymbol{\gamma}_t &= \boldsymbol{\gamma}_{t-\tau} + \boldsymbol{\varepsilon}_t^\gamma, && (30)\\
\boldsymbol{\omega}_t &= \boldsymbol{\omega}_{t-\tau} + \boldsymbol{\varepsilon}_t^\omega, && (31)
\end{aligned}
$$

where $\boldsymbol{\Lambda}_\alpha$ and $\boldsymbol{\Lambda}_\beta$ are matrices with $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ on the diagonal, $\boldsymbol{j}_t = \boldsymbol{N}_t - \boldsymbol{N}_{t-\tau}$, and $\boldsymbol{E}_k$ is the unit matrix with dimension k. Equations (28) and (29) are obtained by discretising equations (2) and (3), while equations (30) and (31) are introduced for the purpose of sampling $\boldsymbol{\gamma}_t$ and $\boldsymbol{\omega}_t$. These are assumed to evolve through the multivariate Brownian motion, hence $\boldsymbol{\varepsilon}_t^\gamma \sim \mathcal{N}(\boldsymbol{0},\boldsymbol{\Sigma}_\gamma)$ and $\boldsymbol{\varepsilon}_t^\omega \sim \mathcal{N}(\boldsymbol{0},\boldsymbol{\Sigma}_\omega)$. Note that $\boldsymbol{\varepsilon}_t^v$, $\boldsymbol{\varepsilon}_t^\gamma$ and $\boldsymbol{\varepsilon}_t^\omega$ are uncorrelated.

Although the model is reduced to the state-space form with three measurement equations (25) $-$ (27), and four state equations (28) $-$ (31), the estimation procedure is not straightforward because of nonlinearity in several equations and range restrictions in some parameters. Some approximations and assumptions are made in the sampling procedure as explained below.

B.2.2 Sampling procedure

The whole sampling procedure is summarised as follows.

1. Sample $\tilde{z}_{i,m}^2 \mid \mathsf{RV}_{i,t_m,t_m+\tau},\ \mathsf{BV}_{i,t_m,t_m+\tau},\ j_{i,t_m},\ \sigma_{i,\mathsf{RV}},\ \eta_{i,t_m}$ for $\{m,i\}$ such that $j_{i,t_m} = 1$, and set $z_{i,t_m} = \tilde{z}_{i,m}$ if $j_{i,t_m}\sum_{k=1}^m j_{i,t_k} = n$, otherwise zero.

2. Sample $\{\boldsymbol{j}_{t_m}\}_{m=1}^{M} \mid \left\{\mathsf{RV}_{t_m,t_m+\tau},\ \mathsf{BV}_{t_m,t_m+\tau},\ \boldsymbol{\lambda}_{t_m},\ \boldsymbol{z}_{t_m}^2\right\}_{m=1}^{M}, \boldsymbol{\Sigma}_{\mathsf{RV}}$.

3. Sample $\boldsymbol{\eta}_{t_m} \mid \{\tilde{\boldsymbol{z}}_{t_m}^2,\ \boldsymbol{j}_{t_m},\ \mathsf{RV}_{t_m}, \mathsf{BV}_{t_m}\}_{k=m-21}^{m}$.

4. Sample $\{\boldsymbol{\lambda}_{t_m}\}_{m=1}^{M} \mid \left\{\boldsymbol{\lambda}_{t_{m-1}},\ \boldsymbol{j}_{t_m},\ \boldsymbol{\eta}_{t_m}\right\}_{m=1}^{M}$, $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\lambda}_\infty$, $\boldsymbol{\Sigma}_{\mathsf{IV}}$ with the block sampling.

5. Sample $\boldsymbol{\Sigma}_{\mathsf{RV}} \mid \left\{\mathsf{RV}_{t_m,t_m+\tau},\ \mathsf{BV}_{t_m,t_m+\tau},\ \boldsymbol{j}_{t_m},\ \boldsymbol{z}_{t_m}^2,\ \boldsymbol{\lambda}_{t_m},\ \boldsymbol{\eta}_{t_m}\right\}_{m=1}^{M}$, $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\lambda}_\infty$.

6. Sample $\boldsymbol{\alpha},\ \boldsymbol{\beta},\ \boldsymbol{\lambda}_\infty \mid \left\{\boldsymbol{\lambda}_{t_m},\ \boldsymbol{j}_{t_m}\right\}_{m=1}^{M}$.

7. Sample $\boldsymbol{\kappa},\ \boldsymbol{\theta} \mid \{\mathsf{BV}_{t_m,\tau},\ \boldsymbol{v}_{t_m}\}_{m=1}^{M},\ \boldsymbol{\Sigma}_{\mathsf{BV}}$.

8. Sample $\{\boldsymbol{v}_{t_m}\}_{m=1}^{M} \mid \left\{\boldsymbol{v}_{t_{m-1}},\ \mathsf{BV}_{t_m,t_m+\tau}\right\}_{m=1}^{M}$, $\boldsymbol{\kappa}$, $\boldsymbol{\theta}$, $\boldsymbol{\Sigma}_{\mathsf{BV}}$.

9. Sample $\boldsymbol{\Sigma}_{\mathsf{BV}} \mid \{\mathsf{BV}_{t_m,t_m+\tau},\ \boldsymbol{v}_{t_m}\}_{m=1}^{M},\ \boldsymbol{\kappa},\ \boldsymbol{\theta}$.

10. Sample $\boldsymbol{\Sigma}_{\mathsf{IV}} \mid \left\{\mathsf{IV}_{t_m,t_m+T},\ \boldsymbol{\gamma}_{t_m},\ \boldsymbol{\omega}_{t_m},\ \boldsymbol{v}_{t_m},\ \boldsymbol{\lambda}_{t_m}\right\}_{m=1}^{M}$, $\boldsymbol{\kappa}$, $\boldsymbol{\theta}$, $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\lambda}_\infty$.

11. Sample $\{\boldsymbol{\gamma}_{t_m},\ \boldsymbol{\omega}_{t_m}\}_{m=1}^{M} \mid \{\mathsf{IV}_{t_m,t_m+T},\ \boldsymbol{v}_{t_m},\ \boldsymbol{\lambda}_{t_m}\}_{m=1}^{M}$, $\boldsymbol{\kappa}$, $\boldsymbol{\theta}$, $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\lambda}_\infty$, $\boldsymbol{\Sigma}_{\mathsf{IV}}$, $\boldsymbol{\Sigma}_\gamma$, $\boldsymbol{\Sigma}_\omega$ through the Kalman filter and the simulation smoother with the block sampling.

12. Sample $\boldsymbol{\Sigma}_\gamma,\ \boldsymbol{\Sigma}_\omega \mid \left\{\boldsymbol{\gamma}_{t_m},\ \boldsymbol{\omega}_{t_m}\right\}_{m=1}^{M}$.

The definitions of $\boldsymbol{\eta}_t$ and $\tilde{\boldsymbol{z}}_t^2$ are summarised in Appendix B.3.

B.3 Priors and posteriors

The subsection explains details of sampling for specific parameters and variables with their priors and posteriors.

B.3.1 Sampling the jump size

In order to sample the jump size, we consider another relationship among variables:

$$\hat{\mathsf{RV}}_{t,t+\tau} = \hat{\mathsf{BV}}_{t,t+\tau} + \bar{\boldsymbol{Z}}_t^2 \boldsymbol{j}_t + \boldsymbol{\varepsilon}_t^{\mathsf{RB}}, \quad \boldsymbol{\varepsilon}_t^{\mathsf{RB}} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_{\mathsf{RB}}), \tag{32}$$

where $\bar{\boldsymbol{Z}}_t^2 = \mathrm{diag}\{\bar{z}_{1,t}^2, \ldots, \bar{z}_{I,t}^2\}$ using $\bar{z}_{i,t}^2$ that equals $z_{i,n}^2$ when $j_{i,t_m} \sum_{k=1}^{m} j_{i,t_k} = n$, otherwise zero (for $i = 1, \ldots, I$). The prior for $z_{i,n}^2$ is assumed to evolve through the exponential distribution with a mean $1/\eta_i$, ie, $\boldsymbol{z}_n^2 \sim \mathcal{E}xp(\boldsymbol{\eta})$ where $\boldsymbol{\eta} = (\eta_1, \ldots, \eta_I)'$. At each time step m, $\tilde{z}_{i,m}^2 = \bar{z}_{i,t_m}^2$ is sampled as

$$\tilde{z}_{i,m}^2 \sim \mathcal{TN}_0(p_{z,i,m}, q_{z,i,m}^2). \tag{33}$$

Here, $p_{z,i,m} = -\eta_i \sigma_{\mathsf{RB},i}^2 j_{i,t_m} + \left(\hat{\mathsf{RV}}_{i,t_m,t_m+\tau} - \hat{\mathsf{BV}}_{i,t_m,t_m+\tau}\right)$ and $q_{z,i,m}^2 = \sigma_{\mathsf{RB},i}^2$ where $\sigma_{\mathsf{RB},i}^2$ is the i-th diagonal element of $\boldsymbol{\Sigma}_{\mathsf{RB}}$. $x \sim \mathcal{TN}_y$ indicates truncated Normal distribution with domain $x \geq y$. The sample of $z_{i,n}^2$ equals $\tilde{z}_{i,m}^2$ if $j_{i,t_m} \sum_{k=1}^{m} j_{i,t_k} = n$, otherwise zero.

B.3.2 Sampling jumps

As a price jump is very rare, the probability of the occurrence of more than two jumps in a day is by far smaller than that of one jump in a day, hence it is negligible. Then, $j_{i,t}$ is approximated to take 0 or 1, and consequently, $\boldsymbol{j}_t$ evolves through the Bernoulli process. Let $\tilde{\boldsymbol{j}}_k$ $(k = 1, \ldots, 2^I)$ denote I-dimensional vector of 0 and 1, where 1 in the i-th element indicates the price of the economy i jumps and 0 otherwise. The subscript k indicates the k-th combination of jumped/non-jumped asset prices in the total of 2^I combinations. Let $\tilde{\boldsymbol{J}} = (\tilde{\boldsymbol{j}}_1, \ldots, \tilde{\boldsymbol{j}}_{2^I})'$ denote a 2^I-by-I matrix which comprises all of the combinations. Further let

$$\begin{aligned}
\boldsymbol{\xi}_m &= \tilde{\boldsymbol{J}} \ln(\tau \boldsymbol{\lambda}_{t_m}) + (\mathbf{1}_{2^I,I} - \tilde{\boldsymbol{J}}) \ln(\mathbf{1}_{I,I} - \tau \boldsymbol{\lambda}_{t_m}),\\
\zeta_{k,m} &= -\frac{I}{2}\ln(2\pi) - \frac{1}{2}\ln|\boldsymbol{\Sigma}_{\mathsf{RB}}|\\
&\quad - \frac{1}{2}(\hat{\mathsf{RV}}_{t_m,t_m+\tau} - \hat{\mathsf{BV}}_{t_m,t_m+\tau} - \tilde{\boldsymbol{Z}}^2_m \tilde{\boldsymbol{j}}_k)' \boldsymbol{\Sigma}^{-1}_{\mathsf{RB}} (\hat{\mathsf{RV}}_{t_m,t_m+\tau} - \hat{\mathsf{BV}}_{t_m,t_m+\tau} - \tilde{\boldsymbol{Z}}^2_m \tilde{\boldsymbol{j}}_k),
\end{aligned}$$

where $\mathbf{1}_{x,y}$ is the x-by-y matrix of 1's, and $\tilde{\boldsymbol{Z}}^2_m = \mathrm{diag}\{\tilde{z}^2_{1,m}, \ldots, \tilde{z}^2_{I,m}\}$ using $\tilde{z}^2_{i,m}$ sampled by equation (33). The posterior probability of jump occurrence in the economy i is provided by

$$\Pr[j_{i,t_m} = 1] = \sum_{k=1}^{2^I} \boldsymbol{l}'_i \tilde{\boldsymbol{j}}_k e^{\xi_{k,m}+\zeta_{k,m}} \mathbf{1}'_{2^I,1} e^{-\boldsymbol{\xi}_m - \boldsymbol{\zeta}_m}, \qquad m = 1, \ldots, M,$$

where $\boldsymbol{\zeta}_m = (\zeta_{m,1}, \ldots, \zeta_{m,2^I})'$, $\boldsymbol{l}_i = (0, \cdots, 0, \overset{i}{1}, 0, \cdots, 0)'$ is the i-th unit vector with dimension I.

B.3.3 Sampling the reciprocal of the mean of squared jump size

The prior of the reciprocal of the mean of squared jump size, denoted by $\eta_i = \mathbb{E}\left[z_i^2\right]^{-1}$, is specified as the Gamma distribution. $\boldsymbol{\eta}$ can be a fixed or time-varying value as long as its reciprocal is the expected value of quadratic jump size. We assume that the prior for $\boldsymbol{\eta}$ is time varying since samples of $\boldsymbol{\eta}$ are very sensitive to their priors' location and dispersion. At each time step m, we set a stochastic window size $\pi_m = \tau + 2U_m(\varpi - \tau)$ where $U_m = \mathcal{U}(0,1)$ and ϖ is the mean of the window size. The prior Gamma distribution for η_i at time t_m, denoted by $\mathcal{G}(p_{\eta,i,m}, q_{\eta,i,m})$, is determined using the mean and variance of RV minus BV in the window from $t = t_m - \tau$ to t_m as

$$p_{\eta,i,m} = \frac{\mathbb{E}\left[\hat{\mathsf{RV}} - \hat{\mathsf{BV}}\right]}{\mathbb{V}\left[\hat{\mathsf{RV}} - \hat{\mathsf{BV}}\right]} + 2, \qquad q_{\eta,i,m} = \mathbb{E}\left[\hat{\mathsf{RV}} - \hat{\mathsf{BV}}\right]^2 (p_{\eta,i,m} - 1).$$

These formulations are derived from the mean and variance of the inverse-Gamma distribution. After trying four types of window size (from one to four weeks *ex post* at each time step), we find that four weeks is the best as its error variance $|\boldsymbol{\Sigma}_{\mathsf{IV}}|$ is the smallest. The posterior for $\boldsymbol{\eta}$ at time step t_m is derived as

$$\boldsymbol{\eta} \sim \mathcal{G}\left(\boldsymbol{p}_{\eta,m},\ \boldsymbol{q}_{\eta,m} + \sum_{k=m-21}^{m} \tilde{\boldsymbol{Z}}^2_k \boldsymbol{j}_{t_k}\right),$$

where $\boldsymbol{p}_{\eta,m} = (p_{\eta,1,m}, \ldots, p_{\eta,I,m})'$ and $\boldsymbol{q}_{\eta,m} = (q_{\eta,1,m}, \ldots, q_{\eta,I,m})'$.

B.3.4 Sampling the jump-arrival intensity

The jump-arrival intensity $\boldsymbol{\lambda}_t$ is sampled by the block sampling given the sample of $\boldsymbol{j}_t$. We divide the whole sample into $\psi + 1$ blocks. The knots $\{\phi_k\}_{k=1}^{\psi}$ are determined as

$$\phi_k = \left\lfloor \frac{M(k + U_k)}{\psi + 2} \right\rfloor,$$

where $U_k \sim \mathcal{U}(0,1)$. If $\phi_k = \phi_{k+1}$, the whole set $\{\phi_k\}_{k=1}^{\psi}$ is re-sampled until $\phi_k \neq \phi_{k+1}$. For sampling purpose, we add an error term with zero mean and covariance $\boldsymbol{\Sigma}_\lambda$ to equation (29). By this amendment, the model for $\boldsymbol{\lambda}_t$ is no longer the Hawkes process while self-excitation dynamics is maintained, and equations (27) and (29) formulate the state-space form with respect to $\boldsymbol{\lambda}_t$. Then, the sample in the k-th block $\{\boldsymbol{\lambda}_{t_k}\}_{m=\phi_k}^{\phi_{k+1}-1}$ is sampled by the forward-filtering backward-sampling (FFBS) procedure applying the Kalman filter and the simulation smoother (De Jong and Shephard (1995)). The same procedure is applied to all of the blocks.

B.3.5 Sampling the parameters in the jump-arrival intensity process

The jump related parameters, $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$ and $\boldsymbol{\lambda}_\infty$ are sampled given the sample of $\{\boldsymbol{\lambda}_t\}$. If the priors for $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$ and $\boldsymbol{\lambda}_\infty$ are specified as $\mathcal{N}(5\mathbf{1}_{I,1}, 5\boldsymbol{E}_I)$, $\mathcal{N}(\mathbf{1}_{I,1}, \boldsymbol{E}_I)$ and $\mathcal{N}(\mathbf{1}_{I,1}/100, \boldsymbol{E}_I)$, the posteriors are Normal and their sampling is standard.

The stability of λ_t requires $\alpha - \beta > 0 \because d\mathbb{E}[\lambda_t] = \{\alpha\lambda_\infty + (\beta - \alpha)\mathbb{E}[\lambda_t]\}dt$. The samples of those parameters fall within the preferable range without any controls.

B.3.6 Sampling the latent variance

The latent variance $\boldsymbol{v}_t$ is sampled from BV by FFBS. Because the likelihood function of the multivariate Heston model (Wishart autoregressive process) includes the hypergeometric function of matrix argument (Gourieroux et al (2009)), which stems to sampling difficulty, the squared-root-diffusion term is converted to $\varepsilon_t^v \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_v)$ while the posterior distribution is truncated at zero to maintain its positivity. The Kalman filter is applied to equations (27) and (28) from t_0 to t_M in the same way as the sampling of $\boldsymbol{\lambda}_t$.

B.3.7 Sampling the parameters in the latent variance process

The fixed parameters κ, θ and $\boldsymbol{\Sigma}_v$ are estimated from equations (25) and (28) given sampled $\boldsymbol{v}_t$. The sampling methods are straightforward if the priors are normal-inverse-Wishart conjugate, specified as $\kappa \sim \mathcal{N}(3\mathbf{1}_{I,1}, \boldsymbol{E}_I)$, $\theta \sim \mathcal{N}(\mathbf{1}_{I,1}/10, \boldsymbol{E}_I/100)$ and $\boldsymbol{\Sigma}_v \sim \mathcal{IW}(10, \boldsymbol{E}_I)$.

The positivity and stationarity of v_t requires $0 < \kappa < 1/\tau$ and $\theta > 0$. The confidence intervals for κ and θ fall within the ranges without any controls.

B.3.8 Sampling the coefficients of risk premiums

The sampling of the coefficients of variance-diffusive and variance-jump risk premiums, $\boldsymbol{\omega}_t$ and $\boldsymbol{\gamma}_t$, requires the block-sampling. We divide the sample dataset into 25 blocks with stochastic knots determined in the same way as Appendix B.3.4. Equation combinations (27) and (30), or (27) and (31), take the standard state space form with respect to $\boldsymbol{\gamma}_t$ or $\boldsymbol{\omega}_t$. In each block, FFBS is applied from t_0 to t_M in the same way as the sampling of $\boldsymbol{\lambda}_t$. Positive samples are discarded, because, strictly speaking, the premiums are generally paid for variance-risk takers.

B.3.9 Sampling covariances

The covariances $\boldsymbol{\Sigma}_{\mathsf{IV}},\ \boldsymbol{\Sigma}_{\mathsf{BV}},\ \boldsymbol{\Sigma}_{\mathsf{RV}},\ \boldsymbol{\Sigma}_{\mathsf{RB}},\ \boldsymbol{\Sigma}_{\lambda},\ \boldsymbol{\Sigma}_{\gamma}$ and $\boldsymbol{\Sigma}_{\omega}$ are sampled by the standard procedure if the priors are given by inverse-Wishart distributions.

Appendix C: Alternative definition of the non-crisis period

So far, we have divided the full sample period into the GFC period and the post-GFC period in the same way for all economic areas. However, the timing of financial market turbulence for these economic areas does not necessarily coincide. For example, many eurozone AEs experienced sizable financial market turbulences during the European sovereign debt crisis period, which did not overlap with the GFC period.

To accommodate the idiosyncratic nature of market turmoil across countries, we conduct a simple regime-switching analysis on IV to divide the full sample period into the weeks with high market volatility and those with low market volatility. In particular, we use the following regime-switching regressions to identify the high and low volatility regimes:

$$IV_t = \varphi + \delta S_t + \varepsilon_t,$$

where S_t takes 0 with probability p_t or 1 with $1 - p_t$, and ε_t is an error term with mean 0. IV is the squared percentile value. φ and δ are parameters. Using the standard EM algorithm (Dempster et al (1977)), we generate the regime-switching probability of the seven economic areas.

Appendix Graph 1 shows the regime-switching probability estimates for each of the seven economic areas. When we set the cut-off value at 0.5, which is a relatively low level, the number of weeks falling into the high volatility regime lies between 20 and 56 for the economic areas in the sample. Therefore, we only consider the low volatility regime period which has a sufficient number of observations for all economic areas.

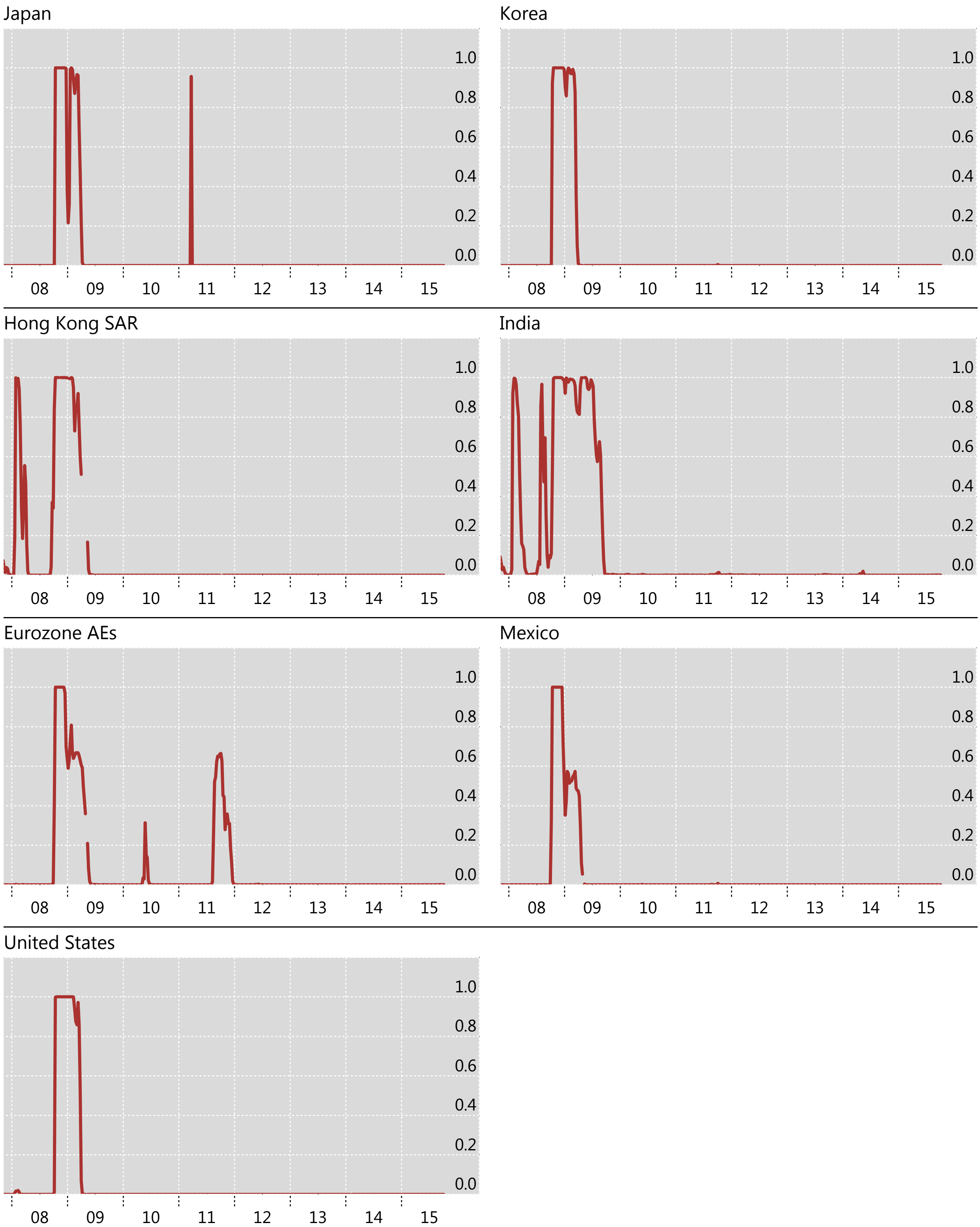
Appendix Table 1 provides the simple OLS estimation results over the low volatility regime. This is another way of defining a tranquil non-crisis period, which can be different across economic areas. We obtain similar results for all AEs to those over the post-GFC period reported in Table 7. However, among EMEs, the coefficients on US VRP, DRP and JRP are significantly positive for India, and significantly negative for Mexico. When we check the impact of US DRP and US JRP separately during the low volatility regime period, we again find not much difference in terms of statistical significance between the two risk premiums. In terms of economic significance, the coefficients on US DRP is again generally greater than those on US JRP. These results confirm that US DRP is a more important driver of equity fund flows to other economic areas than US JRP during the tranquil non-crisis period.

When we run OLS regressions including control variables over the low volatility regime period, we obtain stronger results than those over the post-GFC period. In particular, the results in Appendix Table 2 show that US VRP, DRP and JRP have positive and significant effects on equity fund flows to the eurozone AEs, Japan and India. We also find a weakly significant impact of US VRP on equity flows to Hong Kong SAR. When we compare the coefficients on the regressions for US DRP with those on the regressions for US JRP for the eurozone AEs, Japan, Hong Kong SAR and India, we again find that the coefficients of the US DRP regressions are generally larger than those of the US JRP regressions. These results confirm that during the tranquil non-crisis period, the spillover channel from US DRP to other economic areas via equity fund flows was stronger than the spillover channel from US JRP.

Finally, Appendix Table 3 shows that the coefficients on the control variables over the low volatility regime period are very similar to those over the post-GFC period.

Volatility regime[1]

Appendix Graph 1



[1] The charts plot the probability of the high volatility regime in the regime switching model. If the value exceeds 0.5, the period is recognised as in the high volatility regime, otherwise in the low volatility regime.

Source: Authors' estimates.

Simple OLS regression results

Low volatility regime period — Appendix Table 1

Explanatory variable:	US VRP	US DRP	US JRP	Number of observations
Dependent variable: Equity fund flows to				
Advanced economies				
Eurozone AEs	6.590*** (3.65)	21.962*** (3.13)	8.523*** (3.74)	377
Japan	8.698*** (7.63)	16.797*** (3.86)	12.545*** (7.32)	390
Emerging market economies				
Hong Kong SAR	2.351 (1.20)	5.669 (0.67)	3.250 (1.36)	373
India	4.647*** (3.00)	15.726** (1.99)	5.847*** (3.13)	355
Korea	−1.098 (−0.59)	−7.449 (−1.06)	−0.816 (−0.34)	389
Mexico	−3.941** (−2.24)	−10.363** (−1.98)	−4.976** (−2.11)	391

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.

Results of OLS regression with control variables

Low volatility regime period — Appendix Table 2

Explanatory variable: / Dependent variable: Equity fund flows to	US VRP	US DRP	US JRP	Number of observations
Advanced economies				
Eurozone AEs	10.124*** (3.02)	24.598*** (2.73)	11.916*** (3.63)	372
Japan	8.810*** (6.03)	20.115*** (4.11)	10.814*** (5.05)	385
Emerging market economies				
Hong Kong SAR	3.976* (1.77)	14.185 (1.51)	5.043 (1.42)	367
India	3.707** (2.00)	9.149 (1.08)	5.322** (2.35)	351
Korea	−0.614 (−0.21)	−10.512 (−1.45)	1.861 (0.60)	384
Mexico	−1.162 (−0.45)	−14.195 (−0.96)	1.303 (0.42)	386

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 controls variables for the regression that has US VRP, US DRP or US JRP as the key explanatory variable are the economic area's lagged VRP, DRP or JRP, respectively, the Citi Economic Surprise Index of the economic area, the world short-term interest rate, the Citi Economic Surprise Index of the United States, and the lagged stock market return of the economic area. Robust standard errors are used to calculate *t*-statistics. *, **, and *** indicate 10, 5 and 1 percent statistical significance of the estimated coefficient, respectively.

Detailed OLS regression results

Low volatility regime period Appendix Table 3

Dependent variable: Equity fund flows at t to	Eurozone AEs	Japan	Hong Kong SAR	India	Korea	Mexico
Explanatory variable						
VRP of the economic area at t-1	−3.756* (−1.84)	−0.770 (−1.01)	−0.501 (−0.44)	−2.721 (−1.47)	−0.992 (−0.43)	−3.003 (−1.26)
Citi Economic Surprise Index of the economic area at t	0.001** (2.25)	0.000 (0.85)	0.001*** (3.81)	- (-)	0.001* (1.89)	0.001** (2.24)
World short-term interest rate at t	−0.091*** (−4.02)	−0.148*** (−6.62)	−0.121*** (−4.05)	−0.084** (−2.05)	−0.129*** (−4.23)	−0.103** (−2.32)
US VRP at t	10.124*** (3.02)	8.810*** (6.03)	3.976* (1.77)	3.707** (2.00)	−0.614 (−0.21)	−1.162 (−0.45)
Citi Economic Surprise Index of the United States at t	−0.000 (−0.98)	−0.001** (−2.22)	−0.000 (−1.05)	−0.001 (−1.56)	0.001 (1.50)	0.001 (1.08)
Stock market returns of the economic area at t-1	0.013** (2.39)	0.003 (0.31)	0.050*** (6.40)	0.045*** (6.49)	0.040*** (5.83)	0.043*** (4.78)
Constant	0.350*** (5.15)	0.688*** (8.89)	0.457*** (4.97)	0.299** (2.52)	0.453*** (4.56)	0.249* (1.85)
Number of observations	372	385	367	351	384	386
Adjusted R-squared	0.2681	0.2041	0.2074	0.1634	0.1823	0.1030

This table reports the coefficients and *t*-statistics of the regressions. Robust standard errors are used to calculate *t*-statistics. Data on the Citi Economic Surprise Index of India are not available. *, **, and *** indicate 10, 5 and 1 percent statistical significance of the estimated coefficient, respectively.