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Financial Spillover in Emerging Asia: A Tale of Three Crises

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Abstract
By measuring time-varying financial spillovers of five asset classes, we analyze the propagation of shocks originating in the United States and Japan into countries of emerging Asia (EA). We compare the scale and nature of spillovers during the 2008–09 Global Financial Crisis (GFC), the 2013 "taper tantrum" (TT), and the ongoing COVID-19 pandemic (C-19). Based on the direct and indirect spillovers, the intensity of the spillover effect was largest during C-19 due to its global and multidimensional nature, and the United States was a net transmitter of spillovers particularly in bonds and equity markets. TT was an important episode for EA as it marked the beginning of the region's financial volatility and increased spillovers especially in bonds market. The impulse responses reveal that most spillovers were transmitted rapidly, in a matter of days. In times of recession whereby financial stability is in danger of being affected by spillovers, a concrete financial cooperation remains absent in EA although formal institutions designed to deal with the contagion have been put in place.

1. Introduction

Financial markets have always seen dramatic movements during a crisis. Influenced by financial frictions, contagions and spillovers often ensue. The 2008–09 Global Financial Crisis (GFC) was obviously severe, generating a strong spillover across countries and asset classes; a jolt of "taper tantrum" (TT) in 2013 from the phasing out of quantitative easing by the U.S. Federal Reserve hit emerging markets disproportionately; and the ongoing COVID-19 (C-19) is predicted to be more severe than the GFC and TT. Insofar as financial conditions of other countries are affecting domestic financial stability, the case of emerging

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Asia (EA) is relevant as the region received a large amount of capital inflows. A financial jolt in a major economy like the United States can significantly affect markets in EA, and the affected markets can indirectly create spillovers to others within EA. The scale and nature of spillovers, however, remain to be investigated. This is what we attempt to do in this paper.

Measuring financial spillover always poses a methodological challenge. It is often problematic to distinguish contagion and spillover from interdependence (Vodenska and Becker 2019). The results are likely biased due to model misspecification (Rigobon 2016). To the extent that financial markets in each country have changed over the years, the size and nature of the relationship between those markets have also changed. Alterations may thus occur not because of crisis-driven spillover but because the economy grows and financial integration and trade relations change.

Efforts have been made to improve ways to measure spillover across asset classes and countries. The most common approach has been to use cointegration and causality, autoregressive conditional heteroskedasticity (ARCH), general autoregressive conditional heteroskedasticity (GARCH), and the vector autoregression (VAR). Karolyi and Stulz (1996) used GARCH to analyze the U.S.–Japan stock return co-movements, and Chancharoenchai and Dibooglu (2006) looked at the interactions between six Southeast Asian stock markets with the United States and Japanese market during the 1997–98 Asian Financial Crisis (AFC). Azis et al. (2013) analyzed the spillover from the United States and Europe to the Asian markets during the GFC and the Eurozone crisis, respectively, and Hwang et al. (2013) looked at the stock market co-movements among the United States and emerging economies during the GFC.

In this paper, we compare the time-varying financial spillover of five asset classes (bm10 = 10-year bond, bm5 = 5-year bond, eq = equity, mm = money market, and fx = foreign exchange) during GFC, TT, and C-19. We use GARCH with Baba–Engle–Kraft–Kroner (BEKK) process and the multivariate vector autoregression (M-VAR) to delineate the propagation of shocks originating in the United States to nine countries in EA, and shocks in Japan to EA.[1] Of the three episodes, C-19 dispatched the most intense spillover, and in terms of indirect link C-19 displayed a similar degree of severity in shock spillover as in TT, but more severe in volatility. Specifically, in the bonds market, the spillover index in TT exceeded that in GFC.

The remainder of the paper is structured as follows. After discussing the methodology and data in the next section, we analyze the direct, indirect and dynamic spillovers in Section 3, followed by a concluding summary.

1 Country abbreviations as follows: us = United States; jp = Japan, cn = China, in = India, id = Indonesia, my = Malaysia, ph = the Philippines, sg = Singapore, kr = Korea, and th = Thailand.

2. Methodology and data

To the extent that measuring spillovers by using correlations ignores the fact that conditional probabilities are likely to increase when there is a propagation of shocks (such as fears of infection during C-19), the VAR model has been used by focusing on the variance decomposition. However, to account for cross-market influences with many assets involved (as in our current study), it is more suitable to use the conditional volatility of returns in multivariate GARCH with BEKK process, from which one can model the time-varying conditional variances and covariances without estimating too many parameters. Given the conditional covariance matrix

$$H_t = E\left(\varepsilon_t \varepsilon_t' I_{t-1}\right) = \Omega'\Omega + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + B'H_{t-1}B,$$

if we have three regions (e.g., EA, the United States, and Japan), where A and B are 3×3 matrices of parameters, and $\{e_t^{us}, e_t^{jp}, e_t^{ea}\}$ denotes the combined error term from the conditional mean specifications, under a condition of no spillover from EA to the United States and Japan the parameterization of A and B matrices would be

$$A = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \text{ and } B = \begin{bmatrix} b_{11} & 0 & 0 \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}.$$

Applying this to model the residual vectors $\varepsilon_t | I_{t-1} \sim N(0, H_t)$ of the VAR mean equations, we can write

$$H = \Omega'\Omega + \sum_{j=1}^{q}\sum_{k=1}^{K} A_{kj}'(\varepsilon_{t-j}\varepsilon_{t-j}')A_{kj} + \sum_{j=1}^{p}\sum_{k=1}^{K} B_{kj}'H_{t-j}B_{kj},$$

where A_{kj} and B_{kj} are $N \times N$ parameter matrices. A_{kj} is a parameter matrix of a_{lm} elements that indicate the extent of market shock spillover, and B_{kj} is a parameter matrix of b_{lm} elements that reflect market volatility spillover between markets l and m.

To capture the indirect spillover, we use pairwise bivariate first order (K = 1) BEKK model

$$H = \Omega'\Omega + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + B'H_{t-1}B$$

$$\begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{21} & \Omega_{22} \end{bmatrix}\begin{bmatrix} \Omega_{11} & \Omega_{21} \\ \Omega_{12} & \Omega_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{bmatrix}\begin{bmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \end{bmatrix}\begin{bmatrix} \varepsilon_{1,t-1} & \varepsilon_{2,t-1} \end{bmatrix}\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$
$$+ \begin{bmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{bmatrix}\begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix}\begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix},$$

where $h_{12,t} = h_{21,t} = h_{cov,t}$. $h_{11,t}$ and $h_{22,t}$ are the conditional variance equations of markets $l = 1$ and $m = 2$. The parameters of interest are the off-diagonal elements of A and B. The shock spillover is captured by a_{lm}, and the volatility spillover by b_{lm} (where $l \neq m$).[2]

We apply this on week-on-week returns of the five asset types, $r_{i,t} = ln(y_{i,t}/y_{i,t-5}) * 100$, to estimate the direct spillover during 1 September 2008–30 April 2009 for GFC; 1 May–31 December 2013 for TT; and 1 January–31 August 2020 for C-19. We use data from Eikon Thomson Reuters, Bloomberg Terminal, and individual countries' central banks. To estimate the indirect spillover, we use the optimal lag-length based on Schwarz Bayesian Information Criterion and apply the sequential process from ten countries and five asset types, from which we generate 2,352 permutations. To synthesize the overall scale of spillovers, we also generate the spillover index as in Diebold and Yilmaz (2009) by aggregating spillover effects across markets. For the dynamic analysis, we use the orthogonalized impulse response function by using the GDP for inter-country ordering, and eq → bm10 → bm5 for inter-asset ordering.

3. Analysis

As expected, there are a large number of significant coefficients associated with shock spillovers during the GFC.[3] The spillover effects of shocks in the United States and Japan on their own markets were substantial. In particular, a shock in bm5.us had an effect on eq.us, while a shock in eq.jp and mm.jp caused a jolt in fx.jp, among others. Across countries, a shock in bm10.us hit bm10 in almost all EA countries except India and China. For bm5.us, considerably more assets and countries in EA were affected by, respectively, shock spillover and volatility spillover. All assets in the two mature markets influenced at least one asset class in Singapore.

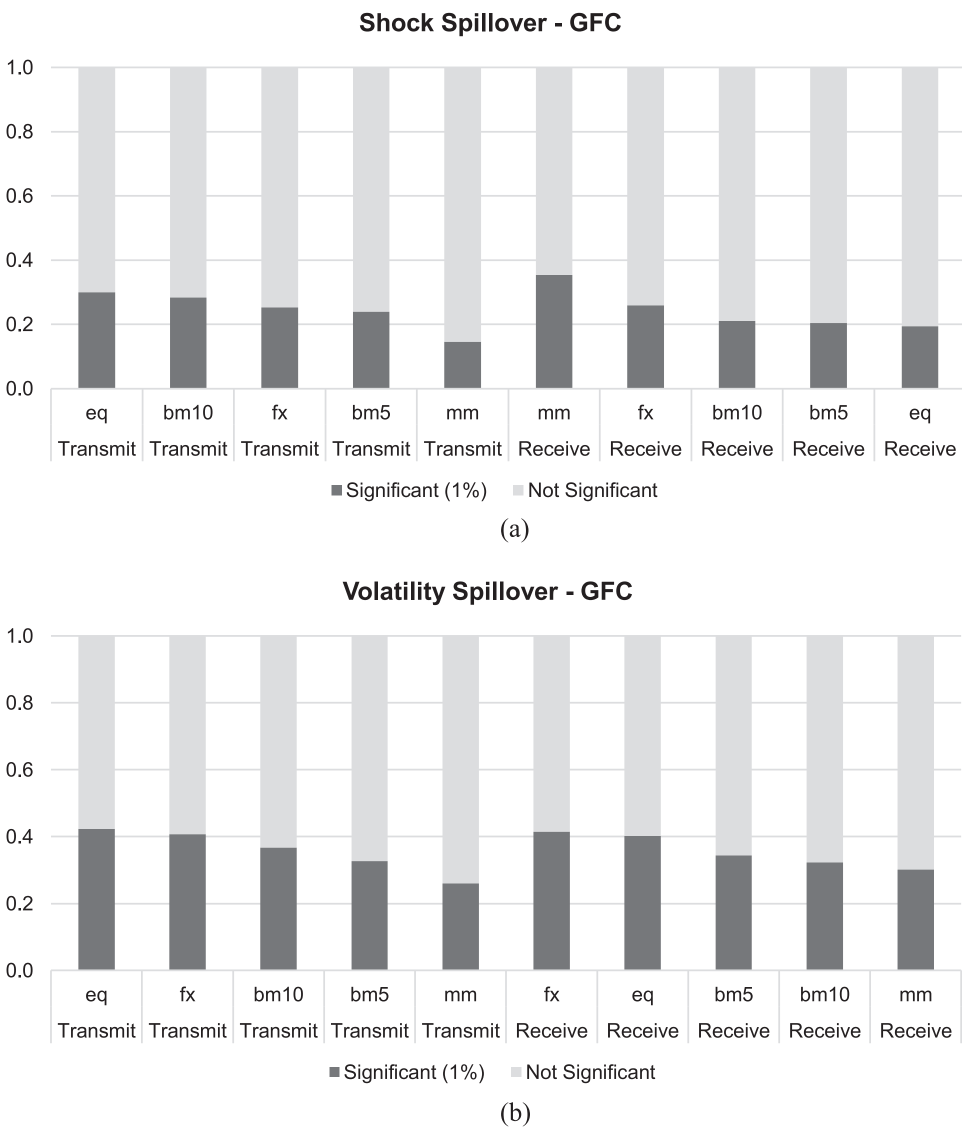
Comparing the "transmitters" (right-hand side of the equation) and "receivers" (left-hand side), the largest transmitter of spillover was eq followed by bm10, while the largest receivers were mm and fx. A clear dominance of eq and fx was confirmed when we look at the volatility spillover (Figures 1a, 1b). The global nature and severity of GFC, combined with increased financial integration driven by the interest rate differential and trade integration in EA, played an important role in eq spillover.

The overall picture was different during TT, where the spillover effects of a shock in the United States were felt by all Chinese assets, and those of Japan affected eq.cn, mm.cn, and fx.cn. Financial markets in Southeast Asia and India felt the tremors during TT, while

2 To overcome volatility clustering that often characterizes financial data, we use GARCH(1,1) process (i.e., $p = q = 1$); and $K = 1$.

3 A complete list of the significant coefficients is available from the authors.

Figure 1. Transmitters and receivers by asset classes: (a) Shock spillover during GFC; (b) Volatility spillover during GFC



the equity markets in almost all EA countries except India and Korea were affected by bm10.us, and the foreign exchange market felt the impact of bm5.us shock except in Indonesia, India, and China. In terms of volatility, the spillover effect struck even more countries and asset classes. Fluctuations in the U.S. market raised the volatility for most assets in EA countries. Increased volatility in mm.us struck China (largest effect), the Philippines, Thailand, Indonesia, and Korea. For the rest of EA, at least one asset type turned volatile. In results not reported here, the spillover effects of eq.jp were felt in all countries except the Philippines, and the largest number of affected assets occurred in Singapore and Korea.

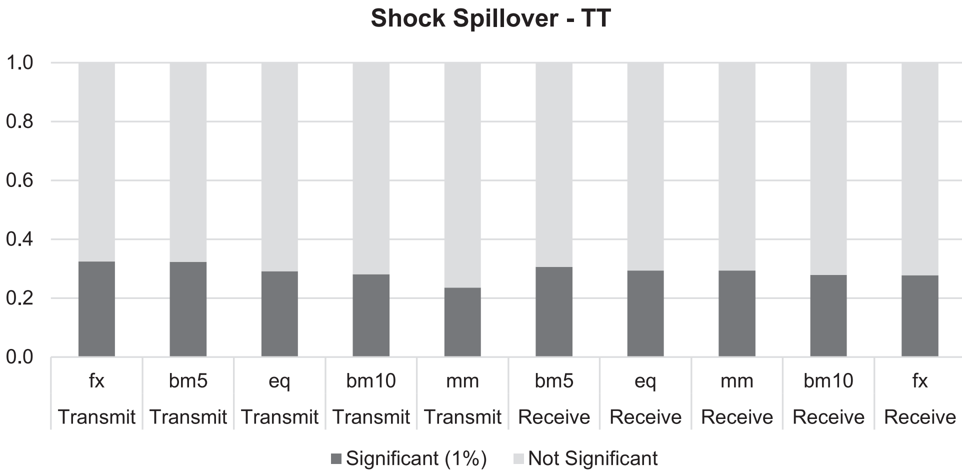
Looking at the results more closely, it was the bonds market that dominated the finan-cial spillover during TT. There were 31 and 69 significant bonds market coefficients in shock and volatility spillover, respectively. More importantly, as shown in Figure 2a, bm5 along with fx were not only the major transmitters but also the largest receivers of shock spillovers during TT. In terms of volatility spillover, Figure 2b shows that bonds return (particularly of bm5) played an even more dominant role, with close to 50 percent of associated spillovers being statistically significant as transmitter and receiver. Putting this all together in a spillover index, Figure 5 shows that indeed the spillovers in the bonds market during TT was larger than during GFC (for other assets, GFC spillover was larger).

The development prior and during TT explains such a trend. Having learned the hard lesson of currency mismatch during the AFC, countries in EA escalated efforts to develop their local currency bonds market. Meanwhile, triggered by fears that the market would crumble following the Fed's policy of quantitative easing (QE) in 2009, funds from ad-vanced economies flocked into EA. Both events caused the bonds market in EA to surge, resulting in increased liquidity and a growing sense of strength and stability. The local currency bonds market became the darling of foreign investors seeking a safe haven. But things abruptly changed in mid 2013 when investors learned that the Fed was planning to put the brakes on the QE. The resulting collective reactionary panic caused capital flows to reverse (Figure 4). The episode led to a spike in the U.S. bond yields, followed by a strong spillover to EA described above. It is also important to note that the correlation between non-resident bond outflows and bond yields in EA increased during the period (IIF 2020).

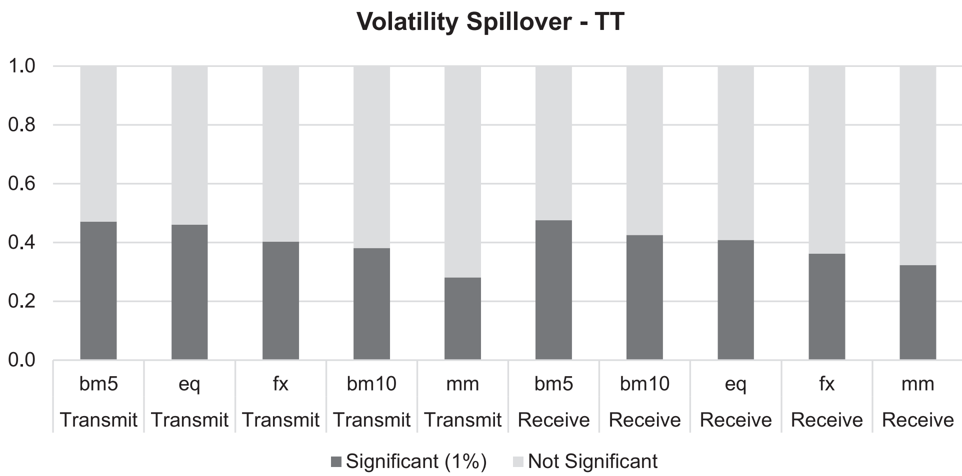
It took more than two years before inflows returned to EA, followed by fluctuating flows, before falling into a sudden stop in C-19. As C-19 began to spread from China's Hubei province to become a global pandemic, data on non-resident portfolio flows show that the first eight months of 2020 witnessed the largest EA outflow ever (see again Figure 4). The financial markets around the world including EA plummeted and volatility surged, triggering another round of financial spillover. Using data up to 31 August 2020, our calculations show that all countries in EA experienced their own shock and volatility persistence. More countries were affected by shocks in the United States than in Japan, and compared to TT the number of countries affected by U.S. shocks were larger.[4] A jolt in the U.S. bond market

4 Details are available from authors.

Figure 2. Transmitters and receivers by asset classes: (a) Shock spillover during TT; (b) Volatility spillover during TT



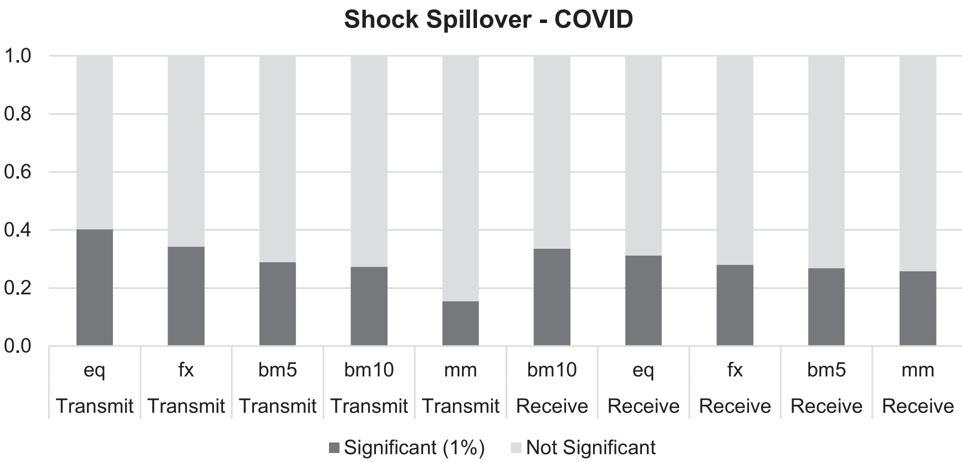
(a)



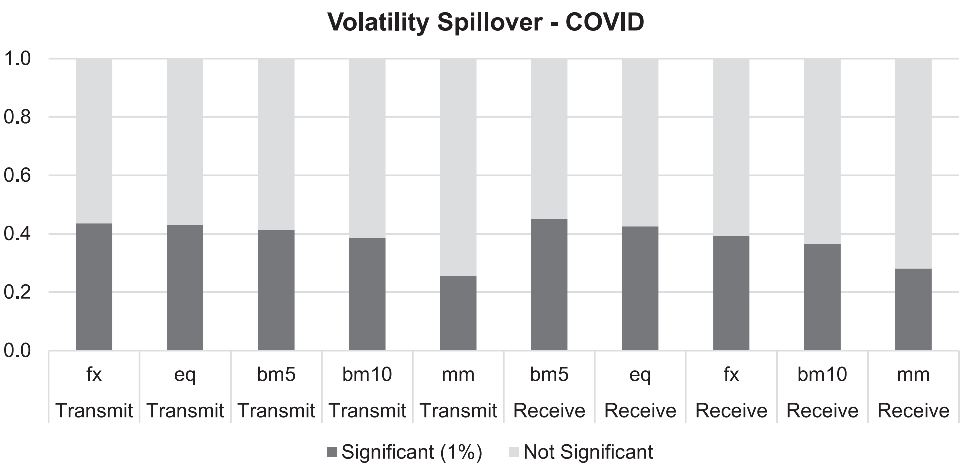
(b)

was felt by all countries in EA, and shocks in eq.us and mm.us affected not more than three asset types in each country. Meanwhile, the effects of all shocks originated in Japan were felt strongest in Thailand. Wider effects also occurred in the volatility spillover. While all countries felt the jolt in the United States and Japan, the effects of the earlier shocks were more widespread; the only exceptions were shocks in mm.jp, bm10.jp, and bm5.us. In Q1

Figure 3. Transmitters and receivers by asset classes: (a) Shock spillover during COVID-19; (b) Volatility spillover during COVID-19



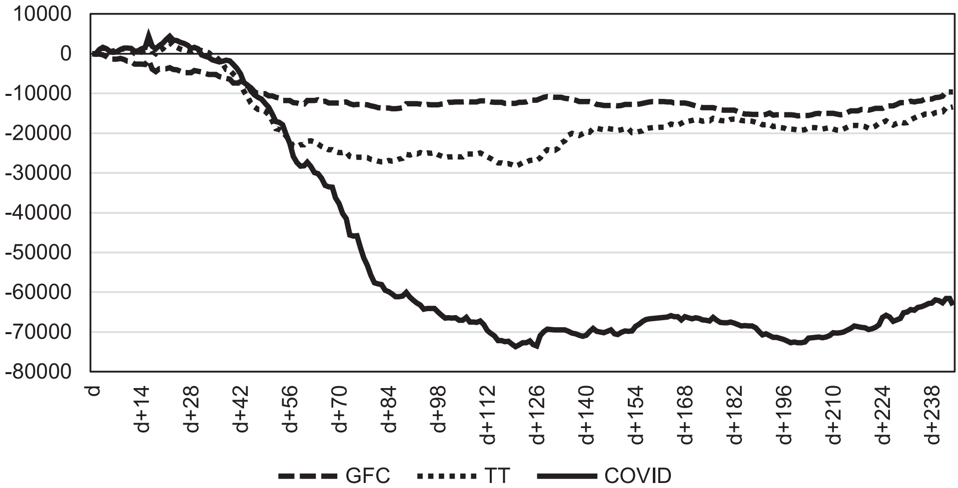
(a)



(b)

particular, bm.us affected all countries, and eq.us increased the volatility of bonds in Japan, Korea, Thailand, the Philippines, Malaysia, and China, while mm.us affected markets in Japan, Thailand, Indonesia, Korea, India, Malaysia, and Singapore. For the volatility shocks that originated in Japan, eq.jp affected all assets in India and at least one asset in each EA country. Volatilities in bm5.jp struck four assets in India, and three in the Philippines and

Figure 4. Cumulative balance of payments portfolio flows to select emerging Asia countries



Source: *IIF (2020).*

Note: *Variable is daily net non-resident purchases of the country's stocks and bonds in US$ millions, as proxy for portfolio flows measured in the balance of payments. Sample countries for equity flows are Indonesia, India, South Korea, Thailand and the Philippines, and for debt flows is India. Data displayed exclude China's equity flows, Indonesia's debt flows, Thailand's debt flows, and Malaysia's equity and debt flows to ensure comparability across three episodes. Inclusion of these flows in GFC and TT, for which data are available, maintains the same conclusion of capital flow reversals in all three episodes with the largest during COVID-19 episode.*

Figure 5. Spillover index

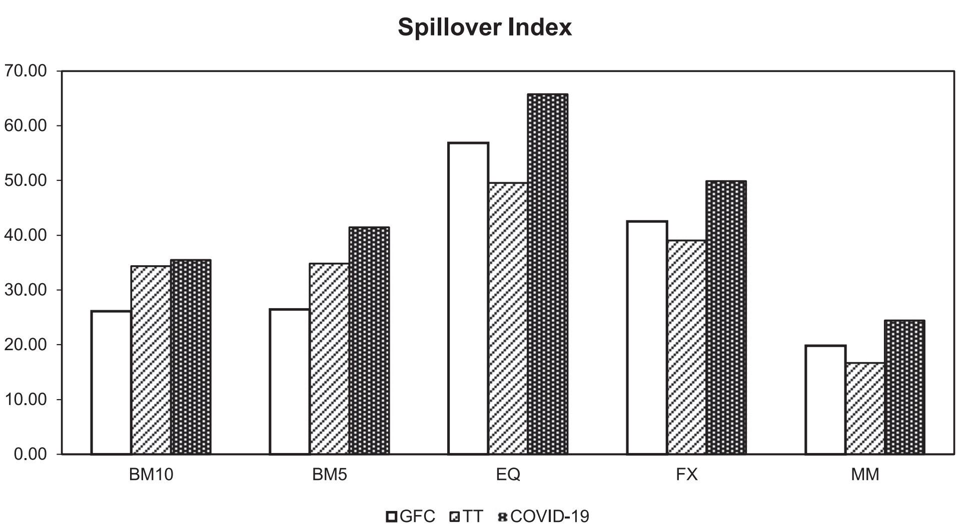


Table 1. Net transmitter and receiver from spillover index

BM10	China	Indonesia	India	Japan	Korea	Malaysia	Philippines	Singapore	Thailand	US
2008	0.95	8.14	−1.56	−39.54	−3.88	−17.43	−2.13	−31.33	−12.77	99.55
2013	−0.78	−17.10	28.11	−19.82	−21.03	−40.40	−21.35	−36.19	−19.38	147.93
2020	−6.93	6.19	−5.22	−5.41	−12.67	−19.74	−21.70	−45.92	−2.12	113.52
BM5	**China**	**Indonesia**	**India**	**Japan**	**Korea**	**Malaysia**	**Philippines**	**Singapore**	**Thailand**	**US**
2008	−11.15	−14.18	14.08	−6.34	−4.86	−14.41	−11.91	−12.62	0.62	60.76
2013	−10.14	16.51	−8.77	−20.77	−45.46	−24.36	−7.47	−18.88	−8.25	127.60
2020	13.52	−14.94	−14.75	11.46	−17.04	−48.56	−32.46	13.44	8.75	80.59
Equity	**China**	**Indonesia**	**India**	**Japan**	**Korea**	**Malaysia**	**Philippines**	**Singapore**	**Thailand**	**US**
2008	6.73	−30.96	1.94	−34.99	−2.77	−46.31	−58.32	−32.94	−46.86	244.50
2013	−4.58	2.73	6.48	−29.26	−29.21	−52.51	−28.55	−67.38	−46.43	248.72
2020	20.90	−67.77	−20.12	−9.39	−52.36	−50.74	−60.34	−84.43	9.87	314.39
MM	**China**	**Indonesia**	**India**	**Japan**	**Korea**	**Malaysia**	**Philippines**	**Singapore**	**Thailand**	**US**
2008	25.97	−2.40	−26.71	5.86	6.73	−11.93	−1.91	9.37	−13.78	8.80
2013	10.75	10.11	−13.55	4.18	−6.79	0.48	−3.62	−0.62	−3.02	2.08
2020	−2.01	4.08	35.64	5.32	−33.42	−13.33	−15.33	−1.59	3.24	17.40

Note: *Positive sign means net transmitter, and negative means net receiver. Notable pattern shows that the United States as the highest net transmitter for BM10, BM5, and EQ while EA is the highest net transmitter for MM. Net receiver is dominated by EA countries.*

Malaysia. Clearly, the financial spillover during C-19 was more extensive than during GFC and TT.

A wider spread of the spillover effects during C-19 was somewhat more similar to the GFC than TT, but the intensity was clearly higher. Looking at the distribution of transmitting and receiving assets, the largest transmitters of shock spillover were eq and fx, and the largest receivers were bm10 and eq (Figure 3a). Thus, spillover across asset classes was unmistakably strong during C-19. Figure 3b shows that unlike the case of GFC, the largest transmitters (fx and eq) were different from the largest receivers (bm5 and eq). A resounding assertion about the spread of asset classes is further established by the spillover index shown in Figure 5, in which the spillover during C-19 across all asset classes was clearly the largest. Across countries, we evaluate the transmitter role by comparing the VAR results "to others" and "from others" to determine whether or not a country was a net transmitter of spillovers (a positive/negative number indicates net transmitter/receiver). Insofar as eq, bm, and fx were detected earlier for being the most important transmitters, Table 1 shows that the United States was clearly a net transmitters of spillover for bm5, bm10, and eq.

Indeed, data on bm5.us and bm10.us show sharp fluctuations, especially after March 2020. Unlike a normal period where investors rush to buy U.S. Treasuries when the market stock plunges, most investors during C-19 sold Treasuries along with stocks, causing a positive returns correlation. Only the demand for Treasury bonds of shorter maturities continued to hold up.[5] A different pattern also occurred in U.S. corporate bonds. Investment-grade

5 Concerns over inflation uncertainty did not seem to explain the ominous sign (no increase in demand for the Treasury Inflation-Protected Securities or TIPS). Instead, forced by either losses on

bonds that functioned well during GFC suffered a sharp fall in price during C-19. The fall was even sharper than in the less liquid but riskier high-yield bonds. This affected not only the depth and liquidity of the bonds market—hence increased spread and volatility—but also other credit markets, as investors shifted toward cash-futures basis trade. As many businesses suffered from cash flow problems, the spillover effects intensified, causing spread to rise. This explains the significance of spillover effects across assets within the United States, particularly of bm5.us and bm10.us on eq.us and mm.us. Extensive and long-standing connectedness with financial markets in EA subsequently caused spillover effects in EA countries and made the United States a net spillover transmitter of bm5, bm10 and eq. The fluctuation in the U.S. equity market itself could not be explained entirely by events related to C-19. During 2020:Q1, the price fall was partly driven by the Russia–Saudi Arabia oil price war that led to a collapse of crude oil prices, and eventually a crash in the stock market. Beginning in late March, however, the stock prices recovered swiftly, powered by high-flying stocks like Apple, Microsoft, and Google's parent Alphabet, as investors bet these companies could prevail in a stay-at-home economy, despite the fact that the overall economy remained in the doldrums. As many episodes in the past have shown, it is hard to deny that the link between stock prices and fundamentals have been anything other than loose. Among countries in EA, data also show that the reaction of stock markets during C-19 was not influenced by fundamentals and the situation before the crisis, rather by the health policies implemented.

Our next task is to analyze the indirect spillover and market interconnectedness within EA. As spillovers endured, inflicting each other within EA, market conditions and domestic policy determine the nature and scale of indirect spillover. During C-19, where virtually all countries loosened their monetary policy, the effects on returns of financial assets varied, so did the effects of the latter on other countries' markets. The "flight to quality" that caused equity and bond markets to diverge did not have uniform effects in and across countries. As falling prices induced more uncertainty in the financial market, volatility rose and was amplified by deteriorating confidence among investors. The response of the money market was equally diverse. In the foreign exchange market, the fluctuations driven by volatile capital flows had different effects on trade flows and currency across countries.

By applying GARCH-BEKK in a pairwise (inter-country inter-asset) fashion, and evaluating both the number and type of link (uni- or bi-directional), it is revealed that indirect spillover during C-19 was most intense. Without looking at the detailed print, for shock spillover, the number of links in C-19 was the same as in TT, and larger than in GFC. But for volatility spillover, it was larger than in GFC and TT. Across asset classes, there was

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other positions or the need to settle short-term debts large institutions scrambled for immediate liquidity and cash.

clearly more bidirectional (spillback) than unidirectional links; this applies for both shock and volatility spillover. The only obvious unidirectional links in shock spillover were those toward mm. Across countries, the bidirectional link was also dominant. In the shock spillover during GFC, only India, Malaysia, and Thailand received a predominantly unidirectional spillover (from four out of nine countries) while the corresponding list during TT consists of Japan, Indonesia, and Thailand. Spillovers associated with other countries were predominantly bidirectional.

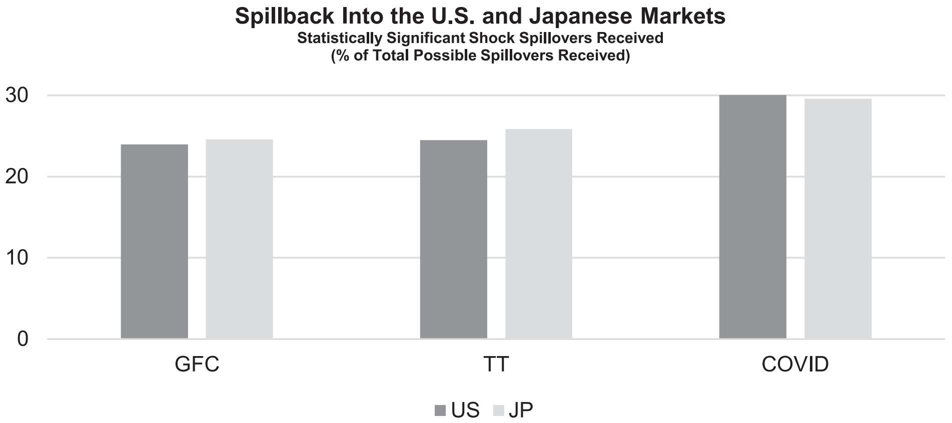
During C-19, links for volatility spillover continued to be dominated by spillback, and the number of bidirectional link was higher than in GFC and TT. More importantly, looking at the U.S. market as a shock origin, a lack of unidirectional link emanating from this mature market is noteworthy as it indicates a considerable spillback or a growing importance of financial spillovers from EA to the United States (IMF 2016). Figures 6a and 6b show the increased spillback of shock and volatility into the United States and Japan from GFC to TT. The increased trend continued from TT to C-19 for shock, but receded for volatility. The latter can be explained partly by the aggressive policy response of the U.S. Fed and Bank of Japan to mitigate the price decline in financial market, combined with the limited effect of news and other non-fundamental factors in EA. Overwhelming cases of bidirectional link also occurred in Japan and China, reflecting the effect of the region's increased integration on these two countries (Azis 2014).

To the extent that the incidence of bidirectional links was more widespread than unidirectional links, it is of interest to determine which shocks generated the largest response, which EA countries and asset classes reacted the most, and in which episode the largest response occurred.[6] The impulse response functions (IRF) results show that innovations in the source markets rapidly transmitted across countries and asset classes where the most intense transmission occurred during the first three to five days, before tapering off after two weeks. In all cases, the responses to internal shocks were larger than external shocks, although responses to the latter were fairly substantial, and in some cases having negative coefficients (implying that the response varied depending on factors such as domestic policy and capital flows). The largest number of pairs (8) showing greater responses to external shocks than to own shocks occurred in Singapore, followed by Malaysia and Indonesia (6 pairs each). In all cases, the most significant shocks were originated in eq.us and bm10.us, many of which show negative coefficients.

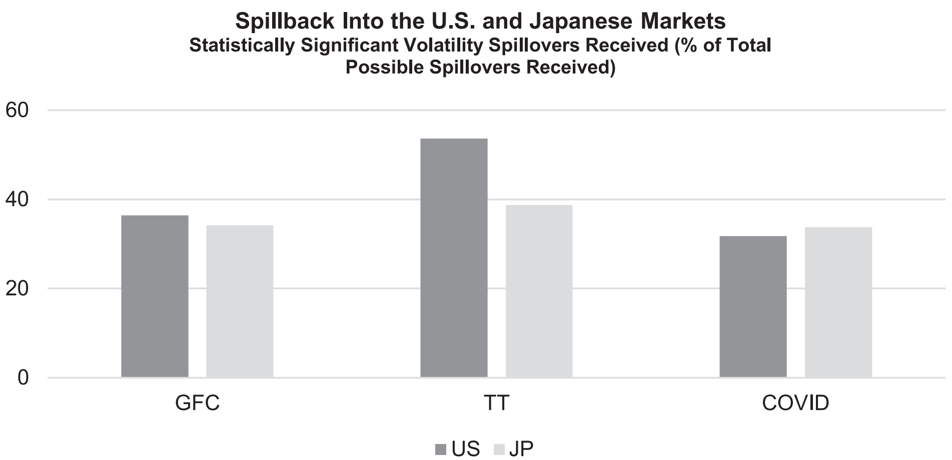
Summing up the responses, shocks in eq.us had the most important role in propagating financial turbulence in EA, particularly in the region's equity market. Most responses of

6 For this purpose we use the impulse response functions (IRF) based on the Cholesky decomposed IRF applied to bm10.us, bm5.jp, and eq.us, and use the same counterpart assets for the affected markets (there are 27 pairs of IRF for each country of EA ex Japan).

Figure 6. (a) United States and Japan as receiver of shock spillovers; (b) United States and Japan as receiver of volatility spillovers



(a)



(b)

Note: *(a) This chart is based on the pairwise GARCH-BEKK estimated coefficients where the United States or Japan is the receiver of shock spillover (left-hand side of the equation), from any country and asset type. The bars represent the percentage of those coefficients that are statistically significant for each episode. (b) This chart is based on the pairwise GARCH-BEKK estimated coefficients where the United States or Japan is the receiver of volatility spillover (left-hand side of the equation), from any country and asset type. The bars represent the percentage of those coefficients that are statistically significant for each episode.*

the region's bm10 to eq.us were largest during C-19, except in China, Indonesia, and India where responses were larger during GFC. In terms of the responses to eq.us, those of EA's equity markets were all positive.

Results of IRF also show that the largest responses of EA to external shocks occurred during C-19, except for China, Indonesia, and India. The same applies to own shocks, except in China, Indonesia, India, the Philippines, and Singapore where larger responses occurred during the GFC. For bm10.us shock, most responses were largest during C-19 except in Indonesia and India (larger during GFC). In Japan, bm10.jp was the only market that reacted in the opposite direction after the first four days of C-19. Japan's enormous bond market may have defied the pressure during the early stage of the crisis. The region's bm5 reaction to bm5.jp shock that moved in the opposite direction during the pandemic's early days occurred in India, Malaysia, and the Philippines. A similar pattern (from negative to positive) was also detected in the region's equity market as a response to bm5.jp shock.

Thus, the IRF analysis shows that the speed of contagion was a lot faster than in goods trade, and similar to the earlier results from GARCH-BEKK, when measured by responses to external shocks, the spillover associated with financial market interconnectedness was significant especially during C-19. Decades of financial liberalization that led to increased integration must have played a role; when crisis struck, contagion more easily ensued. In good times, everyone gained from integration, in bad times collective losses are difficult to avoid.

4. Summary

We find that financial contagion from the shocks in the U.S. market into EA were significant and continued to be larger than the effect of shocks in Japan. The United States was a net transmitter of spillovers, particularly in bonds and equity returns. The IRF shows that in general, the average period of transmission of spillover was around three to five days. To the extent that data during C-19 show return volatility of some assets in Japan was actually higher than in the United States, high cross-border flows between EA and the United States must have been part of the reason why shocks in the United States were more consequential. Indeed, unlike in trade, in finance EA has been more integrated with mature markets including the United States. Any policy changes and new development in the latter had a greater effect on EA's financial markets, but not the other way round. Increased integration also explains why a spillback of shocks into the U.S. market (detected by the IMF [2016]) continued to rise over the three crisis periods.

In the bonds market, TT was an important episode for EA. As the region's efforts to develop local currency bonds coincided with massive capital inflows after QE, the bonds market surged. However, it abruptly reversed during summer 2013 when funds began to flow out following the Fed announcement about QE tapering. This marked the beginning of financial market volatility in EA ("Third Phase" of global liquidity; see Azis and Shin [2015]). As a result, the spillover index of bonds market was higher than in GFC. But compared with the spillover during GFC and TT, the one during C-19 was more severe. Aside from involving a public health component and costs of human life, the global and multidimensional nature of C-19 affected the real economy and financial sector through a negative series of events that built on and reinforced each other in a vicious circle. The severity was also reflected in a sharp reversal of capital flows (EA's record portfolio outflows; Figure 4).

This finding has implications on liquidity and financial cooperation. As financial spillover can lead to increased costs of borrowing and tightened liquidity, if unattended, it could have a devastating effect in times when countries need to raise a large amount of spending for C-19-related needs. Even in countries with a good record of keeping prudent fiscal policy, the available savings are likely inadequate. Given the scale of spillover, the effectiveness of macroprudential policy will also be limited.

The need to closely cooperate and reconnect with each other and support each other is now greater than ever. For countries in EA, the basic infrastructure for financial cooperation has been in place, most notably the Chiang Mai Initiative Multilateralization supported by various ASEAN initiatives (e.g., the Asian Bond Market Initiative), and sub-regional initiatives. However, these initiatives have hardly had a good record of generating concrete cooperation. At the time of writing, no meaningful action has been proposed.[7] The present is far from being a reassuring situation.

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