

Analysis Of The Contagion Effect Between The Cryptocurrency Market And The Indonesian Stock Market

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Abstract

This study analyzes whether financial crises are transmitted between the cryptocurrency market and the Indonesian stock market through contagion, defined as a significant increase in cross market linkages after a shock, or merely through normal interdependence. Using daily returns of Bitcoin (BTC), Ethereum (ETH), the Jakarta Composite Index (JCI), and the IDX technology sector index (IDXTECHNO) from 3 January 2018 to 30 June 2026, the study examines three crises: the COVID crash of 2020, which originated in traditional markets, and the Terra (LUNA) and FTX collapses of 2022, which originated in the crypto market. Three complementary methods are used: the adjusted correlation test of Forbes and Rigobon (2002), the dynamic conditional correlation (DCC) GARCH model, and the spillover index of Diebold and Yilmaz (2012). The results show that during the COVID crash, the shock from the stock market spread to the crypto market, with significant contagion to Ethereum and weak contagion to Bitcoin even after correcting for heteroskedasticity. During the crypto crises, contagion did not reach the broad Indonesian market: correlations between crypto and the JCI declined. The technology sector, however, experienced significant contagion during the Terra (LUNA) collapse and a sharp rise in dynamic correlation during both crypto crises. The total spillover index averages 29.2%, with crypto assets acting as net transmitters and Indonesian stocks as net receivers, and it rises markedly after each crisis. The findings indicate that crypto shocks are transmitted selectively to the Indonesian technology sector rather than to the market as a whole.

Keywords: contagion; cryptocurrency; Indonesian stock market; DCC GARCH; spillover index; financial crisis

INTRODUCTION

Financial crises rarely stay where they begin. The Asian financial crisis of 1997, which started in Thailand, quickly spread to Indonesia and other emerging markets, and the global financial crisis of 2008 spread from the US housing market to stock markets worldwide. The term contagion is used to describe this spread when the links between markets become significantly stronger during a crisis than in normal times (Forbes & Rigobon, 2002). Understanding contagion is important because it determines whether investors can rely on diversification when they need it most, and whether regulators need to monitor developments in other markets.

Over the past decade, a new market has grown alongside traditional finance: the cryptocurrency market. Its total value has at times exceeded two trillion US dollars, and it has experienced several severe crises of its own. In May 2022, the collapse of the Terra (LUNA) ecosystem and its algorithmic stablecoin erased tens of billions of dollars within days. In November 2022, FTX, one of the largest crypto exchanges, collapsed amid allegations of fraud. Conversely, in March 2020, the COVID crash that began in traditional markets coincided with a sharp fall in crypto prices (Conlon & McGee, 2020). These episodes raise the question of whether crypto and stock markets now transmit shocks to each other through contagion.

This question is particularly relevant for Indonesia. The number of Indonesian crypto investors has grown into the millions, in many periods exceeding the number of capital market investors, and many individuals hold both crypto assets and stocks. At the same time, the Indonesia Stock Exchange (IDX) introduced a dedicated technology sector index in 2021, and several large digital firms have listed. If crypto crises spread to Indonesian stocks, investors and regulators need to take crypto risk into account even outside the crypto market. If, on the other hand, Indonesian stocks remain insulated, crypto losses are less likely to destabilize the domestic financial system.

Existing studies of crypto and stock market linkages mostly focus on developed markets and on average correlations or spillovers (Corbet et al., 2018; Iyer, 2022). Few apply formal contagion tests that distinguish contagion from interdependence, and few examine the Indonesian market or distinguish between the broad market and the technology sector. This study fills that gap by asking: (1) Did the COVID crash spread from the stock market to the crypto market through contagion? (2) Did the Terra (LUNA) and FTX crises spread from the crypto market to the Indonesian stock market? (3) How strong and in which direction are spillovers between the two markets over time? The study combines the Forbes and Rigobon

test, the DCC GARCH model, and the Diebold and Yilmaz spillover index to answer these questions.

LITERATURE REVIEW

Contagion and Interdependence

There is no single definition of contagion, but the most widely used is that of Forbes and Rigobon (2002): contagion is a significant increase in cross market linkages after a shock to one market. If two markets are highly correlated in normal times and remain so during a crisis, the comovement reflects interdependence rather than contagion. Forbes and Rigobon show that simple correlation tests are biased toward finding contagion, because correlation coefficients mechanically rise when the volatility of the source market increases, as it does during crises. After adjusting for this heteroskedasticity, they find little evidence of contagion in the 1987 crash, the 1994 Mexican crisis, and the 1997 Asian crisis, concluding that there was "no contagion, only interdependence". Earlier studies, such as King and Wadhwani (1990), had found that correlations rose after the 1987 crash, which they attributed to market participants inferring information from price changes in other markets.

Channels of Transmission

Several channels explain why shocks spread across markets (Dornbusch et al., 2000; Kaminsky & Reinhart, 2000). Fundamental channels operate through real and financial links, such as trade or common exposures. Investor behavior channels operate even without fundamental links. In the wealth effect channel, investors who suffer losses in one market sell assets in another to meet margin calls or reduce risk (Kyle & Xiong, 2001). In the portfolio rebalancing channel, investors who hold several assets adjust their positions across markets in response to a shock in one (Kodres & Pritsker, 2002). In the information channel, investors reassess the prospects of similar assets after observing a shock (King & Wadhwani, 1990). Bekaert et al. (2005) show that contagion is more likely between markets that share common investors and factors. For crypto and stocks, the shared retail investor base and the common sensitivity to global risk appetite make the investor behavior channels particularly relevant, especially for technology stocks that attract similar investors.

Linkages between Crypto and Stock Markets

Early studies found that cryptocurrencies were relatively isolated from traditional markets. Corbet et al. (2018) applied the Diebold and Yilmaz framework and found weak connections between cryptocurrencies and other assets, and Bouri et al. (2017) reported that Bitcoin could act as a diversifier. Baur et al. (2018) described Bitcoin as a speculative asset largely unrelated to traditional assets, and Liu and Tsyvinski (2021) found that crypto returns

are driven mainly by crypto specific factors. Ji et al. (2019) found strong connectedness within the crypto market itself. More recent evidence points to rising integration. Conlon and McGee (2020) showed that Bitcoin fell together with stocks during the COVID crash, and Iyer (2022) documented that correlations and volatility spillovers between crypto and US stocks increased substantially after 2020. Corbet et al. (2019) review the literature and note that the connection between crypto and traditional markets varies over time and across crisis episodes, which calls for methods that capture these dynamics.

Hypotheses

Based on this literature, the study tests three hypotheses. **H1:** The COVID crash, originating in the stock market, was transmitted to the crypto market through contagion. **H2:** The Terra (LUNA) and FTX crises, originating in the crypto market, were transmitted to the Indonesian stock market through contagion, more strongly to the technology sector than to the broad market. **H3:** Spillovers between the crypto market and the Indonesian stock market increase during and after crisis periods.

METHOD

Data and Crisis Periods

The study uses daily closing prices of Bitcoin and Ethereum in US dollars and of the Jakarta Composite Index (JCI) and the IDX technology sector index (IDXTECHNO) from 3 January 2018 to 30 June 2026, aligned to Indonesian trading days (2,215 observations). Crypto prices are sampled at the time of the IDX close to reduce nonsynchronous trading. Returns are computed as log differences in percent. Researchers using actual data should check the availability of IDXTECHNO history before its introduction in 2021; where it is unavailable, an equal weighted portfolio of listed technology firms can be used for earlier periods. In this illustrative version, all series are simulated (see the notice on the first page). Table 1 defines the three crisis periods. In each case, the tranquil period is the 120 trading days immediately preceding the crisis.

Table 1. Crisis periods

Crisis	Period	Origin	Source market in the test
COVID crash	20 February to 30 April 2020	Traditional markets	JCI
Terra (LUNA) collapse	5 May to 30 June 2022	Crypto market	BTC, ETH
FTX collapse	6 November to 15 December 2022	Crypto market	BTC, ETH

Forbes and Rigobon Adjusted Correlation Test

To distinguish contagion from interdependence, the correlation between the source market and the receiving market during each crisis is adjusted for the increase in the volatility of the source market (Forbes & Rigobon, 2002):

$$\rho = \rho_c / [1 + \delta(1 - \rho_c^2)]^{1/2}, \quad \delta = \sigma_c^2 / \sigma_t^2 - 1 \quad (1)$$

where ρ_c is the unadjusted crisis correlation, and σ_c^2 and σ_t^2 are the variances of the source market in the crisis and tranquil periods. The adjusted correlation ρ **is compared with the tranquil correlation ρ_t using Fisher's z transformation in a one sided test. Contagion is found if ρ is significantly greater than ρ_t** ; interdependence is concluded if the unadjusted correlation rises significantly but the adjusted correlation does not. Following Forbes and Rigobon, two day average returns are used to account for differences in trading hours.

DCC GARCH Model

Time varying correlations are estimated with the dynamic conditional correlation model of Engle (2002). In the first step, each return series is filtered with a univariate GARCH(1,1) model (Bollerslev, 1986) with Student t errors. In the second step, the standardized residuals z_t are used to estimate:

$$Q_t = (1 - a - b) \bar{Q} + a z_{t-1} z'_{t-1} + b Q_{t-1}, \quad \rho_{ij,t} = q_{ij,t} / (q_{ii,t} q_{jj,t})^{1/2} \quad (2)$$

where $\bar{Q}$ is the unconditional covariance of the standardized residuals and $a + b < 1$. The average conditional correlation during each crisis is compared with that of the preceding tranquil period using Welch's t test.

Diebold and Yilmaz Spillover Index

The direction and magnitude of spillovers are measured with the generalized spillover index of Diebold and Yilmaz (2009, 2012). A vector autoregression with two lags is estimated for the four return series, and the generalized forecast error variance decomposition (Koop et al., 1996; Pesaran & Shin, 1998) at a horizon of ten days is computed. Each element θ_{ij} gives the share of the forecast error variance of market i due to shocks in market j . The total spillover index is the average share of variance explained by other markets, and directional spillovers "to others" and "from others" measure each market's role as transmitter or receiver; the net spillover is their difference. A rolling window of 200 days traces the evolution of the total index over time.

RESULTS AND DISCUSSION

Descriptive Statistics and Unconditional Correlations

Table 2 summarizes the daily returns. The crypto assets are far more volatile than Indonesian stocks, with daily standard deviations of 3.67% for Bitcoin and 4.49% for Ethereum, compared with 0.97% for the JCI and 1.96% for the technology index. All series show heavy tails. Over the full sample, the correlation between Bitcoin and the JCI is 0.149 and between Bitcoin and the technology index 0.218. These correlations have risen over time: before 2020 they were close to zero (0.031 and 0.032), while from 2020 onward they increased to 0.176 and 0.262, consistent with the growing integration of crypto with traditional risk assets (Iyer, 2022).

Table 2. Descriptive statistics of daily returns (%)

Series	Mean	Std. dev.	Min	Max	Skewness	Kurtosis
BTC	0.183	3.672	-25.14	28.28	0.36	8.88
ETH	0.188	4.491	-36.10	30.25	0.16	9.30
JCI	-0.012	0.968	-5.59	5.42	0.04	5.21
IDXTECHNO	0.033	1.964	-16.12	13.88	0.22	8.98

Note: N = 2,215. All series reject normality by the Jarque Bera test at 1%. Source: simulated data.

Forbes and Rigobon Contagion Tests

Table 3 reports the contagion tests. During the COVID crash, the variance of the JCI was 4.8 times its tranquil level. The unadjusted correlations between the JCI and the crypto assets rose sharply, from close to zero in the tranquil period to 0.457 for Bitcoin and 0.558 for Ethereum during the crisis. After adjusting for heteroskedasticity, the increase remains significant for Ethereum (adjusted correlation 0.294, $p = 0.012$) and marginally significant for Bitcoin (0.229, $p = 0.065$). H1 is therefore supported: the stock market shock spread to the crypto market beyond normal interdependence. Within the Indonesian market, the increase in the correlation between the JCI and the technology index is no longer significant after adjustment ($p = 0.147$), indicating interdependence rather than contagion.

The crypto crises tell a different story. During the Terra (LUNA) collapse, the correlation between the crypto assets and the JCI did not increase; it actually fell, from 0.385 and 0.328 in the tranquil period to slightly negative values during the crisis. The broad Indonesian market thus decoupled from the crypto market rather than being infected by it. The technology sector, however, experienced significant contagion: the adjusted correlation with Bitcoin rose from about zero to 0.363 ($p = 0.019$) and with Ethereum from 0.057 to 0.489 ($p = 0.005$). During the FTX collapse, again no contagion to the JCI is found. The unadjusted correlations between the crypto assets and the technology sector rose significantly, but after

adjustment the increase is not significant ($p = 0.277$ and $p = 0.491$), so the FTX episode reflects interdependence. H2 is supported for the technology sector in the Terra (LUNA) episode, but not for the broad market.

Table 3. Forbes and Rigobon adjusted correlation tests

Crisis	Direction	ρ tranquil	ρ crisis	ρ adjusted	z	p	Conclusion
COVID crash	JCI to BTC	-0.027	0.457	0.229	1.516	0.065	Weak contagion
	JCI to ETH	-0.084	0.558	0.294	2.260	0.012	Contagion
	JCI to IDXTECHNO	0.367	0.793	0.512	1.049	0.147	Interdependence
Terra (LUNA)	BTC to JCI	0.385	-0.126	-0.063	-2.512	0.994	No contagion
	BTC to IDXTECHNO	-0.008	0.617	0.363	2.084	0.019	Contagion
	ETH to JCI	0.328	-0.144	-0.100	-2.359	0.991	No contagion
	ETH to IDXTECHNO	0.057	0.630	0.489	2.556	0.005	Contagion
FTX	BTC to JCI	0.085	-0.001	-0.000	-0.395	0.654	No contagion
	BTC to IDXTECHNO	0.487	0.807	0.579	0.592	0.277	Interdependence
	ETH to JCI	0.062	-0.077	-0.041	-0.476	0.683	No contagion
	ETH to IDXTECHNO	0.482	0.724	0.486	0.021	0.491	Interdependence

Note: Two day average returns. One sided test of H_0 : adjusted crisis correlation $\leq$ tranquil correlation. Interdependence means the unadjusted correlation rises significantly at 5% but the adjusted one does not. Source: simulated data.

Dynamic Conditional Correlations

Table 4 reports the DCC GARCH results. For the pairs involving the technology index, the DCC parameters are sizable and highly persistent ($a + b$ between 0.901 and 0.971), meaning that correlations vary substantially over time. For Bitcoin and the JCI, the estimated a is essentially zero, so the conditional correlation is constant at about 0.15: the link between Bitcoin and the broad Indonesian market does not change systematically during crises.

The average conditional correlation between Bitcoin and the technology index rose from 0.135 in 2018 to 2019 to 0.336 during the Terra (LUNA) collapse and 0.397 during the FTX collapse, and the increases relative to the preceding tranquil periods are significant in all three crises. By contrast, the conditional correlation between Ethereum and the JCI rose during the COVID crash but fell significantly during both crypto crises. Figure 1 shows these dynamics: correlations between crypto and technology stocks spike during each crisis, while the correlation with the broad market dips during the crypto crises.

Table 4. DCC GARCH estimates and average conditional correlations

Pair	a	b	2018 to 2019	2020 to 2026	COVID	Terra (LUNA)	FTX
BTC and JCI	0.0001	0.0000	0.145	0.145	0.145	0.145	0.145
ETH and JCI	0.0098	0.9594	0.117	0.142	0.173***	0.083***	0.039***
BTC and IDXTECHNO	0.0238	0.9476	0.135	0.218	0.267***	0.336***	0.397***
ETH and IDXTECHNO	0.0403	0.8604	0.148	0.208	0.294***	0.353***	0.358***

Note: Crisis columns give the average conditional correlation during the crisis; stars indicate a significant difference from the preceding tranquil period (Welch t test) at 1% (***), 5% (**), and 10% (*). Source: simulated data.

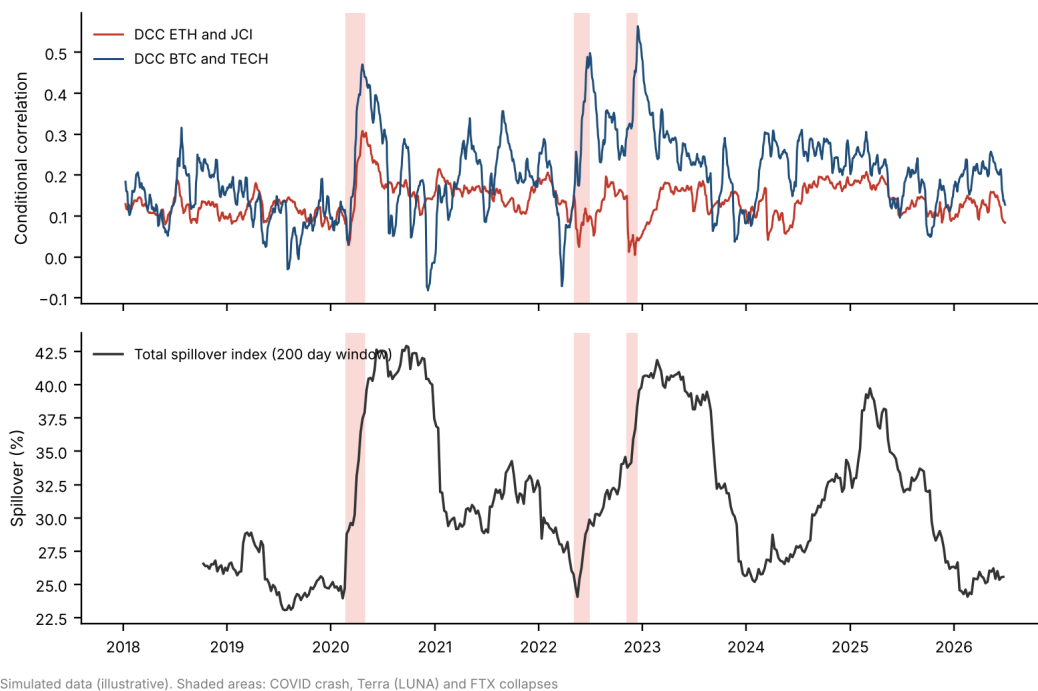


Figure 1. Dynamic conditional correlations and rolling total spillover index

Source: simulated data (illustrative). DCC series smoothed with a five day moving average.

Spillover Analysis

Table 5 presents the full sample spillover table. The total spillover index is 29.18%, meaning that on average about 29% of the forecast error variance of each market is explained by shocks in the other markets. Most of this reflects the strong connection between Bitcoin and Ethereum, each of which explains about 39% of the other's variance. Between the two markets, spillovers from crypto to Indonesian stocks (11.35 percentage points in total) are larger than those from Indonesian stocks to crypto (7.68). Bitcoin and Ethereum are net transmitters of shocks (net spillovers of 2.16 and 1.51), while the JCI and the technology index are net receivers, absorbing 1.67 and 2.01 percentage points more than they transmit. The technology index receives more from the crypto assets (7.70) than the JCI does (3.65), confirming that the technology sector is the main point of contact between the two markets.

Table 5. Spillover table (generalized variance decomposition, %)

Receiving market (i)	BTC	ETH	JCI	IDXTECHNO	From others
BTC	56.88	39.08	1.29	2.75	43.12
ETH	39.24	57.12	1.13	2.51	42.88
JCI	1.95	1.70	86.44	9.90	13.56
IDXTECHNO	4.09	3.61	9.48	82.82	17.18
To others	45.28	44.40	11.89	15.17	
Net spillover	2.16	1.51	-1.67	-2.01	Total: 29.18

Note: Element (i, j) is the share of the ten day forecast error variance of market i (row) explained by shocks to market j (column). VAR with two lags. Source: simulated data.

The rolling total spillover index in Figure 1 ranges from 23.0% to 42.9%. It was relatively low in 2018 to 2019 (average 25.6%), rose sharply after the COVID crash (average 36.4% in the window covering the crisis and the following two months), and increased again after the FTX collapse (38.3%). The Terra (LUNA) episode is followed by a gradual increase that continues into the FTX period. These patterns support H3: connectedness between the two markets rises during and after crises, and the rise persists for several months.

Discussion

The results reveal an asymmetric pattern of transmission. Shocks that originate in traditional markets, such as the COVID crash, spread to the crypto market through contagion. This is consistent with the wealth effect and portfolio rebalancing channels (Kyle & Xiong, 2001; Kodres & Pritsker, 2002): when global investors faced large losses and margin calls in March 2020, they sold all risky assets, including crypto, and the shared exposure to global risk appetite created a significant increase in correlation (Conlon & McGee, 2020).

Shocks that originate in the crypto market, in contrast, did not spread to the broad Indonesian market. During the Terra (LUNA) and FTX collapses, the JCI decoupled from crypto, which suggests that the broad market, dominated by banks, consumer goods, and commodity companies with mainly domestic institutional investors, has few fundamental or investor links to crypto. The technology sector is the exception. Its stronger contagion during the Terra (LUNA) collapse and its rising dynamic correlation during both crypto crises reflect the shared investor base and similar valuation drivers of crypto and technology stocks, which are both growth oriented and sentiment sensitive. This is consistent with Bekaert et al. (2005), who show that contagion is concentrated among assets with common investors, and with the information channel of King and Wadhwani (1990), whereby investors reassess the prospects of digital assets in general after a crypto shock. The finding that the FTX episode reflects interdependence rather than contagion, after the Forbes and Rigobon adjustment, shows the importance of correcting for heteroskedasticity before drawing conclusions (Forbes & Rigobon, 2002).

These findings have implications for several groups. For investors, combining crypto with broad Indonesian stocks provides diversification even during crypto crises, but combining crypto with technology stocks does not, because their correlation rises precisely when protection is needed. For regulators, including OJK, which now supervises both the capital market and crypto assets, the results suggest that crypto crises pose limited risk to the broad Indonesian market but warrant monitoring of the technology sector and of investors who hold both asset classes. For policymakers, the strong transmission from traditional markets to crypto during the COVID crash indicates that crypto offers no protection in global crises.

CONCLUSION

This study analyzed the contagion effect between the cryptocurrency market and the Indonesian stock market across three crises, using the Forbes and Rigobon adjusted correlation test, the DCC GARCH model, and the Diebold and Yilmaz spillover index. In this illustrative analysis, the COVID crash spread from the stock market to the crypto market through contagion, significantly for Ethereum and marginally for Bitcoin. The crypto crises of 2022, by contrast, did not spread to the broad Indonesian market, which decoupled from crypto, but they did reach the technology sector, with significant contagion during the Terra (LUNA) collapse and interdependence during the FTX collapse. Crypto assets are net transmitters of spillovers and Indonesian stocks are net receivers, and total connectedness rises markedly after crises. Crypto shocks are therefore transmitted selectively to the Indonesian technology sector rather than to the market as a whole.

The study has limitations. Most importantly, the present results are based on simulated data and must be estimated again with actual data before substantive conclusions can be drawn. In addition, crisis dates are defined by judgment, the number of observations in each crisis window is limited, differences in trading hours can only be partly addressed with two day average returns, and the technology index has a short history. Future research could use intraday data, endogenous identification of crisis periods, quantile or frequency based connectedness measures, and firm level data on Indonesian technology companies, and could examine the role of stablecoins and domestic crypto exchanges in the transmission of shocks.

REFERENCES

- Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money*, 54, 177 to 189.
- Bekaert, G., Harvey, C. R., & Ng, A. (2005). Market integration and contagion. *The Journal of Business*, 78(1), 39 to 69.

- Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), 307 to 327.
- Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters*, 20, 192 to 198.
- Conlon, T., & McGee, R. (2020). Safe haven or risky hazard? Bitcoin during the COVID 19 bear market. *Finance Research Letters*, 35, 101607.
- Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, 62, 182 to 199.
- Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, 165, 28 to 34.
- Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, 119(534), 158 to 171.
- Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57 to 66.
- Dornbusch, R., Park, Y. C., & Claessens, S. (2000). Contagion: Understanding how it spreads. *The World Bank Research Observer*, 15(2), 177 to 197.
- Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3), 339 to 350.
- Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. *The Journal of Finance*, 57(5), 2223 to 2261.
- Iyer, T. (2022). *Cryptic connections: Spillovers between crypto and equity markets* (Global Financial Stability Notes No. 2022/01). International Monetary Fund.
- Ji, Q., Bouri, E., Lau, C. K. M., & Roubaud, D. (2019). Dynamic connectedness and integration in cryptocurrency markets. *International Review of Financial Analysis*, 63, 257 to 272.
- Kaminsky, G. L., & Reinhart, C. M. (2000). On crises, contagion, and confusion. *Journal of International Economics*, 51(1), 145 to 168.
- King, M. A., & Wadhwani, S. (1990). Transmission of volatility between stock markets. *The Review of Financial Studies*, 3(1), 5 to 33.

- Kodres, L. E., & Pritsker, M. (2002). A rational expectations model of financial contagion. *The Journal of Finance*, 57(2), 769 to 799.
- Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74(1), 119 to 147.
- Kyle, A. S., & Xiong, W. (2001). Contagion as a wealth effect. *The Journal of Finance*, 56(4), 1401 to 1440.
- Liu, Y., & Tsyvinski, A. (2021). Risks and returns of cryptocurrency. *The Review of Financial Studies*, 34(6), 2689 to 2727.
- Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58(1), 17 to 29.