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Keywords

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JEL Classification

C32, E31, E32

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Higher-order comoment contagion among G20 equity markets during the COVID-19 pandemic*

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Abstract

We study the distribution of equity returns in the G20 equity markets to test for contagion following the first official report of a COVID-19 case in China in December 2019 and the subsequent announcement of a global pandemic in March 2020. We find evidence of contagion of Chinese equity market tail risk in early 2020 followed by widespread evidence of contagion across multiple channels from the U.S. to G20 equity markets after the pandemic announcement. Our results suggest that global equity markets may be exposed to unpriced pandemic risk factors with implications for portfolio diversification, risk management and financial stability.

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1 Introduction

The behavior of global equity markets offers a barometer of systemic financial stability, with coordinated retrenchments across markets often signaling financial dislocations. The spread of COVID-19 precipitated such retrenchments. Confronted with a shock that precipitates a coordinated global sell-off, the question of how shocks propagate among markets assumes particular importance. Policymakers charged with maintaining financial stability are concerned with whether shocks are transmitted among equity markets differently in adverse relative to normal states. If so, then there is said to be financial market contagion (Dungey et al., 2005).

We test for contagion among the equity markets of the G20 economies during the COVID-19 crisis by exploiting information on the joint distributions of equity returns among market-pairs. The comoment contagion tests of Forbes and Rigobon (2002), Fry et al. (2010), Fry-McKibbin and Hsiao (2018) and Fry-McKibbin et al. (2019) compare selected comoments of the joint distribution in a crisis period against their values in a pre-crisis benchmark period. Comoment changes are evidence of contagion. The correlation contagion test focuses on contagion among returns, while the covolatility contagion test focuses on contagion of volatility. The other tests are of coskewness contagion (focusing on return volatility in one market and returns in another market) and cokurtosis contagion (focusing on return skewness in one market and returns in another market).

A key attribute of these tests is that they are model-free and computationally cheap. They can be used in close-to-real-time to provide timely diagnostic information on the channels of contagion during fast-moving crises. In past crises, contagion has more often been detected among higher-order comoment relationships than through correlation. Financial market volatility is often linked to high-risk and high-return investments (e.g. Sharpe, 1964), while variations in the skewness of returns can arise due to regime dependent risk preferences, as described in Black (1972).

We define the pre-crisis period as the year ending December 30, 2019, before the announcement of the first COVID-19 case in China. We consider two crisis periods. COVID phase 1 begins with the first documented case of COVID-19 in China on December 31, 2019, and ends on March 10, 2020. Phase 2 begins with the WHO's declaration of a pandemic on March 11, 2020 and ends on August 20, 2020.[1]

Because phase 1 relates to an event localized to China, we test for contagion from the Chinese equity market to other markets at this time. We

[1]See `https://www.who.int/news-room/detail/29-06-2020-covidtimeline`.

find little evidence of contagion from the level or volatility of Chinese equity returns but considerable evidence of contagion arising from their skewness, which suggests that investors were primarily concerned with Chinese tail risk. In phase 2, the COVID crisis is no longer localized but represents a global crisis. Because the U.S. equity market is the world's largest and the U.S. is the country with the most laboratory-confirmed COVID-19 cases and fatalities at the time of writing, we test for contagion from the U.S. to all other markets during Phase 2. The evidence of contagion is strong, with higher-order comoment contagion affecting every market and correlation contagion affecting all but four markets. Our results are consistent with the influence of previously unpriced pandemic risk factors on global equity markets.

2 Comoment Contagion Tests

The comoment contagion tests test for significant changes in the comoments between the daily log-returns in asset markets i and j, $i, j = 1, 2, \ldots, N$, $i \neq j$, in sample periods x (pre-COVID phase) and y (COVID phase 1 or 2). The phases contain observations for T_x and T_y trading days, respectively. The daily log-returns for each market, $r_{i,t}$ and $r_{j,t}$, are centered and standardized using their respective sample means ($\hat{\mu}_{i,x}$, $\hat{\mu}_{j,x}$, $\hat{\mu}_{i,y}$, $\hat{\mu}_{j,y}$) and standard deviations ($\hat{\sigma}_{i,x}$, $\hat{\sigma}_{j,x}$, $\hat{\sigma}_{i,y}$, $\hat{\sigma}_{j,y}$).

2.1 Correlation Contagion Test

Denote the unconditional correlation of asset returns in periods x and y as $\hat{\rho}_x$ and $\hat{\rho}_y$, respectively. The conditional correlation in period y, $\hat{\vartheta}_{y|x_i}$, is:

$$\hat{\vartheta}_{y|x_i} = \frac{\hat{\rho}_y}{\sqrt{1 + \left(\frac{\hat{s}^2_{y,i} - \hat{s}^2_{x,i}}{\hat{s}^2_{x,i}}\right)(1 - \hat{\rho}^2_y)}}, \tag{1}$$

where $\hat{s}^2_{x,i}$ and $\hat{s}^2_{y,i}$ denote the sample variances of asset returns in periods x and y, respectively, and $\left(\hat{s}^2_{y,i} - \hat{s}^2_{x,i}\right)/\hat{s}^2_{x,i}$ captures the change in the ratio of the variance in market j relative to i between periods x and y.

The correlation contagion test of Fry et al. (2010) tests for a change in the correlation between daily log-returns in markets i and j in periods x and y. The test statistic is:

$$CR = \left[\frac{\hat{\vartheta}_{y|x_i} - \hat{\rho}_x}{\sqrt{(\mathrm{var}(\hat{\vartheta}_{y|x_i} - \hat{\rho}_x)}}\right]^2. \tag{2}$$

The expression for the variance of the test statistic, $\text{var}(\hat{\vartheta}_{y|x_i} - \hat{\rho}_x)$, is provided in Fry et al. (2010).

2.2 Coskewness Contagion Tests

The coskewness contagion statistics of Fry et al. (2010) test for significant changes in interdependence, measured by the third-order comoments of the joint distribution of returns in markets i and j between periods x and y. The CS_{12} statistic tests for a change in dependence between returns in market i and the variance of returns in market j. The CS_{21} statistic tests for a change in dependence between the variance of returns in market i and returns in market j. The CS_{12} test statistic is:

$$CS_{12} = \left[\frac{\hat{\varphi}_y(r_i, r_j^2) - \hat{\varphi}_x(r_i, r_j^2)}{\sqrt{\frac{4\hat{\vartheta}_{y|x_i}+2}{T_y} + \frac{4\hat{\rho}_x^2+2}{T_x}}} \right]^2, \tag{3}$$

where $\hat{\varphi}_x(r_i, r_j^2)$ and $\hat{\varphi}_y(r_i, r_j^2)$ are sample coskewness coefficients in periods x and y, defined as:

$$\hat{\varphi}_x(r_i, r_j^2) = \frac{1}{T_x} \sum_{t=1}^{T_x} \left(\frac{r_{i,t} - \hat{\mu}_{i,x}}{\hat{\sigma}_{i,x}} \right) \left(\frac{r_{j,t} - \hat{\mu}_{j,x}}{\hat{\sigma}_{j,x}} \right)^2 \quad \text{and} \tag{4}$$

$$\hat{\varphi}_y(r_i, r_j^2) = \frac{1}{T_y} \sum_{t=1}^{T_y} \left(\frac{r_{i,t} - \hat{\mu}_{i,y}}{\hat{\sigma}_{i,y}} \right) \left(\frac{r_{j,t} - \hat{\mu}_{j,y}}{\hat{\sigma}_{j,y}} \right)^2. \tag{5}$$

The CS_{21} test statistic reverses the exponents in (3), so that $\hat{\varphi}_x(r_i^2, r_j)$ and $\hat{\varphi}_y(r_i^2, r_j)$ are the relevant sample coskewness statistics, the definitions of which follow easily from (4) and (5).

2.3 Cokurtosis Contagion Tests

Fry-McKibbin and Hsiao (2018) and Fry-McKibbin et al. (2019) develop three cokurtosis contagion tests to look for significant changes in the fourth-order comoments of the joint distribution of returns. The CK_{13} test statistic tests for changes in dependence between returns in market i and the skewness of returns in market j. The statistic is:

$$CK_{13} = \left[\frac{\hat{\xi}_y(r_i, r_j^3) - \hat{\xi}_x(r_i, r_j^3)}{\sqrt{\frac{18\hat{\vartheta}_{y|x_i}^2+6}{T_y} + \frac{18\hat{\rho}_x^2+6}{T_x}}} \right]^2, \tag{6}$$

where $\hat{\xi}_x(r_i, r_j^3)$ and $\hat{\xi}_y(r_i, r_j^3)$ are the following sample cokurtosis coefficients for periods x and y:

$$\hat{\xi}_x(r_i, r_j^3) = \frac{1}{T_x}\sum_{t=1}^{T_x}\left(\frac{r_{i,t}-\hat{\mu}_{i,x}}{\hat{\sigma}_{i,x}}\right)\left(\frac{r_{j,t}-\hat{\mu}_{j,x}}{\hat{\sigma}_{j,x}}\right)^3 - 3\hat{\rho}_x \quad \text{and} \tag{7}$$

$$\hat{\xi}_y(r_i, r_j^3) = \frac{1}{T_y}\sum_{t=1}^{T_y}\left(\frac{r_{i,t}-\hat{\mu}_{i,y}}{\hat{\sigma}_{i,y}}\right)\left(\frac{r_{j,t}-\hat{\mu}_{j,y}}{\hat{\sigma}_{j,y}}\right)^3 - 3\hat{\vartheta}_{y|x_i}. \tag{8}$$

The CK_{31} test statistic is a test for changes in the dependence between the skewness of returns in market i and the returns in market j and simply reverses the exponents in (6). Finally, the covolatility contagion test statistic, CV, tests for changes in the interdependence of the return volatilities in markets i and j. The statistic is:

$$CV = \left[\frac{\hat{\Phi}_y(r_i^2, r_j^2) - \hat{\Phi}_x(r_i^2, r_j^2)}{\sqrt{\frac{4\hat{\vartheta}^4_{y|x_i}+16\hat{\vartheta}^2_{y|x_i}+4}{T_y} + \frac{4\hat{\rho}_x^4+16\hat{\rho}_x^2+4}{T_x}}}\right]^2, \tag{9}$$

where the sample covolatilities in periods x and y are:

$$\hat{\Phi}_x(r_i^2, r_j^2) = \frac{1}{T_x}\sum_{t=1}^{T_x}\left(\frac{r_{i,t}-\hat{\mu}_{i,x}}{\hat{\sigma}_{i,x}}\right)^2\left(\frac{r_{j,t}-\hat{\mu}_{j,x}}{\hat{\sigma}_{j,x}}\right)^2 - (1+2\hat{\rho}_x^2), \tag{10}$$

and:

$$\hat{\Phi}_y(r_i^2, r_j^2) = \frac{1}{T_y}\sum_{t=1}^{T_y}\left(\frac{r_{i,t}-\hat{\mu}_{i,y}}{\hat{\sigma}_{i,y}}\right)^2\left(\frac{r_{j,t}-\hat{\mu}_{j,y}}{\hat{\sigma}_{j,y}}\right)^2 - (1+2\hat{\vartheta}^2_{y|x_i}). \tag{11}$$

2.4 Finite Sample Properties

The null limit distributions of all of the comoment contagion test statistics are χ^2_1. In this section, we test the quality of these asymptotic approximations in the finite sample sizes relevant to our application by simulation.

2.4.1 Size

We generate data under the null hypothesis of no contagion between markets from the independent bivariate generalized normal distribution using the inverse-transform method, as follows:

$$f(r_i, r_j) = \exp\left[-\frac{(r_i^2 + r_j^2)}{2} - \eta\right], \tag{12}$$

where η is the normalizing constant. We set $T_x = 260$ and $T_y = \{51, 117\}$, which reflects to the number of trading days in the pre-COVID phase and in COVID phases 1 and 2.

The empirical size estimates for each test using the asymptotic 5% critical value are shown in Table 1 Panel (A). For $T_y = 51$ and $T_y = 117$, the correlation contagion test is over-sized and the higher-order tests under-sized, although the asymptotic approximation is better for the larger sample.

Table 1: Empirical size and simulated critical values of the contagion tests.

Statistic	Experiment Type	
	Phase 1	Phase 2
	$T_x = 260$, $T_y = 51$	$T_x = 260$, $T_y = 117$
Panel (A) Size using asymptotic critical value		
CR	0.068	0.056
CS_{12}	0.043	0.047
CK_{13}	0.036	0.044
CV	0.032	0.044
Panel (B) Simulated finite-sample critical values		
CR	4.467	4.041
CS_{12}	3.579	3.782
CS_{21}	3.557	3.785
CK_{13}	3.235	3.615
CK_{31}	3.219	3.660
CV	3.133	3.547

T_x and T_y denote the number of trading days in the pre-COVID and COVID phases. Our analysis is conducted at the 5% significance level using 500,000 replications.

To correct this mis-sizing, we simulate finite-sample critical values for the sample sizes used in our analysis, as shown in Table 1 Panel (B).

2.4.2 Power

We conduct three experiments to investigate the finite sample power of the tests. Experiment I examines the power of the contagion tests when contagion operates through the correlation channel only in the simulated COVID phases. For this experiment, the Data Generating Process (DGP) is:

$$f(r_i, r_j) = \exp\left[-\left(\frac{r_i^2 + r_j^2 - 2\rho r_i r_j}{2(1-\rho^2)}\right) - \eta\right]. \tag{13}$$

We set the correlation parameter $\rho = 0$ in the simulated pre-COVID phase and allow it to vary in $\rho = \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}$ during the simulated COVID phases.

Experiment II examines the power of the tests when the DGP exhibits coskewness contagion of the type corresponding to the CS_{12} test statistic in the simulated COVID phases. The DGP is:[2]

$$f(r_i, r_j) = \exp\left[-\frac{r_i^2 + r_j^2}{2} + \theta_1 r_i^1 r_j^2 - 0.5 r_i^2 r_j^2 - \eta\right]. \tag{14}$$

In the pre-COVID phase, the coskewness parameter is $\theta_1 = 0$, while it varies in $\theta_1 = \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}$ during the COVID phases.

Experiment III examines the power of the tests when covolatility contagion characterizes the COVID phases. The DGP is:

$$f(r_i, r_j) = \exp\left[-\frac{r_i^2 + r_j^2}{2} - \theta_2 r_i^2 r_j^2 - \eta\right], \tag{15}$$

with the covolatility parameter $\theta_2 = 0$ in the pre-COVID phase and varying over $\theta_2 = \{0.3, 0.6, 0.9, 1.2, 1.5, 1.8, 2.1, 2.7, 3.0\}$ during the COVID phases.

The simulation results in Table 2 reveal that, when a given channel of contagion operates under the DGP, the corresponding comoment contagion test has power that increases with sample size in the COVID phase and the distance between the null and alternative hypotheses. We find little evidence of false positives, meaning that each comoment contagion test does not detect contagion channels other than the channel it is designed to detect.

3 Contagion during the COVID Crises

3.1 Higher-order Comoment Relationships

Table 3 summarizes the comoments of the joint distributions of returns for selected G20 stock markets with respect to both the Chinese and U.S. markets in the pre-COVID period, the Chinese market in COVID phase 1, and the U.S. market in COVID phase 2.[3] Market i is either China or the U.S.,

[2]The term $0.5 r_i^2 r_j^2$ ensures that the distribution is bounded.

[3]The dataset contains broad stock indices for each country obtained from Bloomberg, as follows (series identifiers in parentheses): Argentine S&P MERVAL (MERVAL:IND); Australian S&P/ASX 300 (AS52:IND); Brazilian Bovespa Index (IBOV:IND); Canadian S&P/TSX Composite (SPTSX:IND); Chinese Shanghai Composite (SHCOMP:IND); French CAC 40 (CAC:IND); German DAX 30 (DAX:IND); Indian Nifty 50 (NIFTY:IND); Indonesian Jakarta Composite (JCI:IND); Italian FTSE MIB (FTSEMIB:IND); Japanese Nikkei 225 (NKY:IND); Korean KOSPI (KOSPI:IND); Mexican Bolsa IPC (MEXBOL:IND); Russian MOEX Russia (IMOEX:IND); Saudi Ara-

Table 2: Power properties of the contagion tests.

Statistic	Power									
Experiment I: Correlation contagion										
$\rho =$	0.00	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
Phase 1: T_x=260, T_y=51										
CR	0.05	0.10	0.26	0.52	0.79	0.95	1.00	1.00	1.00	1.00
CS_{12}	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
CK_{13}	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.03	0.03
CV	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.04
Phase 2: T_x=260, T_y=117										
CR	0.05	0.15	0.44	0.80	0.97	1.00	1.00	1.00	1.00	1.00
CS_{12}	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
CK_{13}	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04
CV	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04
Experiment II: Coskewness contagion										
$\theta_1 =$	0.00	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
Phase 1: T_x=260, T_y=51										
CR	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
CS_{12}	0.05	0.05	0.07	0.10	0.14	0.20	0.28	0.40	0.54	0.70
CK_{13}	0.05	0.05	0.05	0.05	0.06	0.06	0.07	0.08	0.09	0.09
CV	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.06	0.06	0.08
Phase 2: T_x=260, T_y=117										
CR	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04
CS_{12}	0.05	0.06	0.09	0.14	0.22	0.33	0.47	0.63	0.80	0.92
CK_{13}	0.05	0.05	0.05	0.05	0.06	0.06	0.07	0.08	0.09	0.08
CV	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.06	0.06	0.08
Experiment III: Covolatility contagion										
$\theta_2 =$	0.00	0.60	0.90	1.20	1.50	1.80	2.10	2.40	2.70	3.00
Phase 1: T_x=260, T_y=51										
CR	0.05	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00
CS_{12}	0.05	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
CK_{13}	0.05	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
CV	0.05	0.30	0.42	0.50	0.58	0.63	0.68	0.72	0.75	0.78
Phase 2: T_x=260, T_y=117										
CR	0.05	0.02	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00
CS_{12}	0.05	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
CK_{13}	0.05	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
CV	0.05	0.58	0.73	0.82	0.88	0.92	0.94	0.96	0.97	0.98

The parameters controlling contagion are ρ (correlation), θ_1 (coskewness) and θ_2 (covolatility). The number of replications is 500,000.

while market j = {Brazil, China, Japan, U.K., U.S.}, $j \neq i$. The table reveals that return correlations increase in the COVID phases for all market pairs, indicating increased return comovements during the crisis. The same is true of covolatility in most cases, indicating an intensification of volatility spillovers during the crisis. Likewise, we observe a general strengthening of the relationship between returns and tail risk during the crisis. By contrast, return coskewness generally falls, perhaps reflecting the aggregate behavior of risk-averse investors, who prefer negative coskewness (Ingersoll, 1987).

Table 3: Comoment statistics for selected G20 equity returns (in percent) during the pre-COVID phase, COVID phase 1 and COVID phase 2.

	Correl. $(r_i^1 r_j^1)$	Coskew. $(r_i^1 r_j^2)$	Coskew. $(r_i^2 r_j^1)$	Cokurt. $(r_i^1 r_j^3)$	Cokurt. $(r_i^3 r_j^1)$	Covol. $(r_i^2 r_j^2)$
Pre-COVID phase ($i = China$)						
Brazil	0.07	-0.08	-0.13	0.36	0.64	1.17
Japan	0.35	-0.11	-0.05	1.55	1.21	1.33
U.K.	0.30	-0.01	-0.13	1.51	1.44	1.37
U.S.	0.21	-0.09	-0.02	1.25	1.25	1.26
COVID phase 1 ($i = China$)						
Brazil	0.18	-0.56	0.27	3.84	-1.43	1.88
Japan	0.46	0.07	-0.52	1.19	3.12	1.24
U.K.	0.41	-0.69	-0.41	3.30	1.64	1.69
U.S.	0.29	0.00	0.18	2.67	-0.15	1.57
Pre-COVID phase ($i = U.S.$)						
Brazil	0.41	-0.45	-0.45	1.94	2.79	2.64
China	0.21	-0.02	-0.09	1.25	1.25	1.26
Japan	-0.08	0.09	0.04	-0.50	-0.70	1.28
U.K.	0.61	-0.18	-0.28	3.15	3.64	3.03
COVID phase 2 ($i = U.S.$)						
Brazil	0.78	-0.97	-0.84	7.30	7.82	7.44
China	0.31	-0.25	-0.65	1.61	3.63	2.22
Japan	0.24	0.62	-0.43	0.27	2.20	3.87
U.K.	0.75	-0.68	-0.61	7.45	6.35	6.34

The source of contagion is denoted by i = {China, U.S.}, while the destination market is denoted by j = {Brazil, China, Japan, U.K., U.S}, $j \neq i$.

bian Tadawul All Share (ASEIDX:IND); South African JSE Africa Top 40 Tradeable (OP40:IND); Turkish Borsa Istanbul 100 (XU100:IND); UK FTSE 100 (UKX:IND); US Dow Jones Industrial Average (INDU:IND).

3.2 Contagion Tests

Table 4 reports the comoment contagion test statistics, with the source of contagion being the Chinese equity market in COVID phase 1 and the U.S. equity market in phase 2.[4]

3.2.1 COVID Phase 1

Table 4 Panel (A) reveals little evidence of contagion from Chinese returns to either the mean, volatility or skewness of foreign equity returns during COVID phase 1. At the 5% level of significance, the null hypothesis of no contagion is rejected once in the case of correlation (for Korea), twice for the CS_{12} coskewness test (for Argentina and Australia) and twice for the CK_{13} cokurtosis test (for Argentina and Russia).

There is somewhat stronger evidence of contagion of Chinese equity market volatility. Six markets experienced contagion of Chinese volatility onto domestic returns, while five experienced contagion of Chinese volatility onto domestic volatility. However, the strongest evidence of contagion from China arises through the CK_{31} cokurtosis test, where the null hypothesis of no contagion is rejected at the 5% level of significance in 11 of 18 cases. This indicates that tail risks in the Chinese equity market were incorporated into foreign equity returns more strongly during COVID phase 1 than they had been previously. This suggests that equity investors were more concerned with tail risk than uncertainty in the early stages of the COVID crisis. At this time, many investors may have expected the COVID crisis to remain localized and to pose significant downside risks for Chinese equity.

Despite the relatively widespread evidence of contagion of Chinese tail risk during COVID phase 1, we are only able to reject the null hypothesis for 1/4 of the contagion tests conducted at the 5% level of significance. Furthermore, at this level of significance, we find no evidence of contagion from the Chinese equity market to the Canadian, Japanese, Mexican, South African or U.S. equity markets. This list includes the largest equity markets in the world and in Asia, so the contagion arising from China in COVID phase 1 cannot be considered a global phenomenon.

3.2.2 COVID Phase 2

The proportion of active contagion channels jumps to 82% in COVID phase 2 when the U.S. is the source. The Chinese market experiences contagion

[4] Matlab implementations of the comoment contagion tests that we use are available from `www.greenwoodeconomics.com/comoment_contagion.html`.

through the fewest channels (three), while eleven markets experience contagion through at least five channels. To underscore the weight of evidence of contagion during phase 2, note that every market experiences cokurtosis contagion and all but one market experiences covolatility contagion. Furthermore, even though correlation contagion has been shown to be less prevalent than higher-order comoment contagion in a range of historical financial crises (e.g. Forbes and Rigobon, 2002; Fry-McKibbin et al., 2019), we find that correlation contagion affects 14 of 18 markets.

3.3 Rolling-sample Analysis

As a final exercise, in Figure 1, we perform rolling-sample analysis to shed light on contagion dynamics in the period since the first confirmed COVID-19 case. First, consider the case where China is the source of contagion. The figure reveals strong evidence of contagion of Chinese tail risk until mid-March. In addition, there is some evidence of contagion of Chinese returns in late-March and April but no evidence of other forms of contagion from China. Overall, this is consistent with our preceding analysis.

Now consider the case where the U.S. is the source of contagion. The jump in the median test statistics for all contagion channels in mid-March is striking, and reflects the impact of the pandemic announcement. This is wholly in keeping with our earlier analysis. It is interesting to see additional evidence of contagion of U.S. higher moment risk starting in mid-June before ending abruptly in late-July, which coincides with the announcement of a $1tn stimulus package in the U.S. and Jerome Powell's committment to using the 'full range of tools to support the economy'.[5]

4 Discussion and Conclusions

Our results provide several insights into the impact of the pandemic on global equity markets. We conjecture that equity returns may be exposed to pandemic risk factors that were unpriced before the COVID crisis due to the absence of a recent global pandemic. During COVID phase 1, investors would have been uncertain about the risk of COVID-19 becoming a pandemic and appear to have focused mainly on downside risks emanating from China. It is noteworthy that the only market to experience correlation contagion

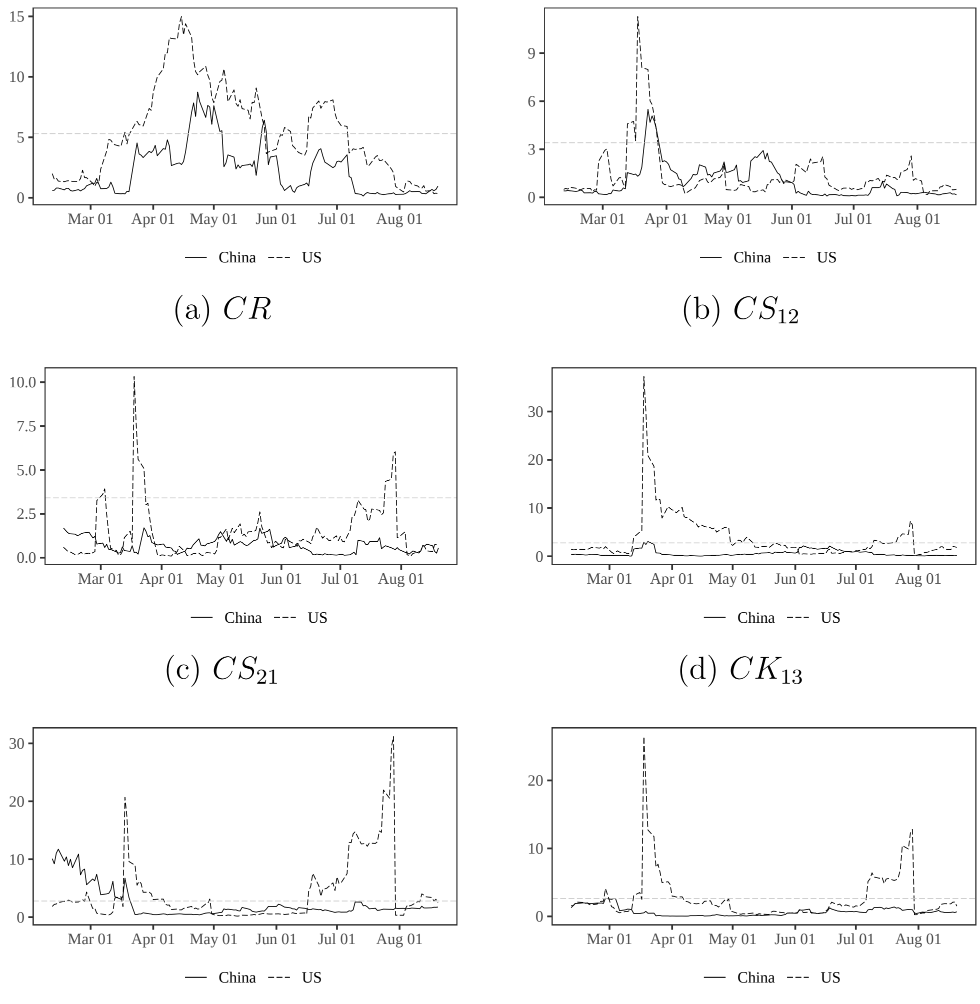
[5]For further information, see https://edition.cnn.com/2020/07/27/politics/senate-republican-stimulus-proposal/index.html and https://www.federalreserve.gov/mediacenter/files/FOMCpresconf20200729.pdf.

Table 4: Comoment tests of contagion during COVID phase 1 and COVID phase 2.

	Panel (A) COVID phase 1						Panel (B) COVID phase 2					
	CR	CS_{12}	CS_{21}	CK_{13}	CK_{31}	CV	CR	CS_{12}	CS_{21}	CK_{13}	CK_{31}	CV
Argentina	0.0	31.6*	30.2*	990.8*	229.5*	28.5*	4.9*	51.8*	4.8*	5092.0*	30.4*	109.7*
Australia	0.2	3.8*	22.0*	0.1	64.0*	2.6	6.8*	15.8*	11.1*	66.4*	61.5*	65.4*
Brazil	0.2	0.0	4.0*	0.6	12.2*	0.4	10.3*	9.9*	5.1*	69.3*	57.2*	72.3*
Canada	0.1	0.2	1.2	0.0	1.5	1.1	37.4*	17.0*	5.9*	75.5*	37.3*	59.5*
China	.	.	.	.	.	.	2.6	3.3	4.3*	14.3*	11.9*	0.0
France	1.2	0.0	0.1	0.0	8.9*	0.3	52.3*	6.9*	2.4	83.5*	46.1*	70.3*
Germany	1.9	1.1	0.1	0.1	22.6*	0.1	47.7*	6.4*	2.3	94.6*	48.3*	74.8*
India	0.2	1.4	21.1*	2.1	119.0*	12.8*	5.3*	4.9*	5.8*	65.3*	27.5*	12.4*
Indonesia	0.6	0.6	0.3	0.6	11.6*	3.4*	0.0	0.1	6.1*	59.1*	49.6*	31.9*
Italy	4.1	0.4	0.6	0.7	40.8*	0.6	34.9*	58.3*	16.2*	544.8*	104.4*	292.5*
Japan	2.6	1.7	0.0	0.0	0.0	0.8	5.9*	0.7	11.9*	30.9*	85.6*	58.9*
Korea	7.0*	3.4	5.4*	0.0	18.6*	0.1	15.5*	0.0	0.0	42.5*	20.8*	22.6*
Mexico	0.0	0.2	0.0	0.6	0.3	0.2	5.0*	2.6	0.6	12.1*	12.2*	6.9*
Russia	1.3	3.1	0.1	6.5*	3.4*	0.3	14.9*	3.4	0.0	24.3*	32.5*	22.6*
Saudi Arabia	0.1	0.0	0.1	0.2	2.5	7.6*	0.5	13.4*	1.6	83.5*	12.3*	4.8*
South Africa	3.1	0.8	0.5	0.4	0.9	0.9	19.7*	10.4*	4.4*	40.7*	50.7*	43.6*
Turkey	0.1	0.1	0.2	0.4	0.1	4.1*	0.3	3.6	5.4*	32.5*	81.3*	62.4*
U.K.	0.3	0.9	6.2*	0.5	23.7*	0.4	24.3*	6.4*	2.8	51.4*	40.7*	53.5*
U.S.	0.2	3.4	0.1	1.4	1.5	0.3	.	.	.	.	.	.

This table reports contagion test statistics based on changes in covolatility (CV), cokurtosis (CK_{13}, CK_{31}), coskewness (CS_{12}, CS_{21}) and correlation (CR) during COVID phase 1 and COVID phase 2 compared to the pre-COVID phase (December 30, 2018, to December 30, 2019). China is the source of contagion in COVID phase 1, and the U.S. is the source of contagion in COVID phase 2. Asterisks indicate the significance of the test statistics at the 5% level based on simulated finite sample critical values.

Figure 1: Rolling Sample Analysis



(a) CR (b) CS_{12} (c) CS_{21} (d) CK_{13} (e) CK_{31} (f) CV

The figure reports the rolling-sample median of each test statistic across all 18 counterparty countries when China (solid line) and the U.S. (dashed) is the source of contagion. The pre-COVID phase is 01/01/2019–12/30/2019, while the crisis phase is a rolling 30-day period starting on 12/31/2019. The end date of the rolling crisis period is recorded on the horizontal axis and simulated finite sample critical values are plotted as horizontal dashed lines.

from China at this time was Korea, which experienced an early COVID-19 outbreak.[6]

The WHO's pandemic announcement signaled that the virus would spread globally and that the public health responses necessary to address its spread would significantly impact global economic activity. This eliminated the uncertainty surrounding the potential for a pandemic and fueled coordinated sell-offs across global equity markets, as many investors withdrew from equity in favor of safer asset classes. Such coordination across markets is consistent with the overwhelming evidence of contagion in phase 2.

Interestingly, we find fewer significant channels of equity market contagion from the U.S. to China than to any other country during phase 2. This may reflect the fact that China experienced a wave of COVID-19 cases and made significant progress in tackling the spread of the virus prior to the pandemic announcement, moving its business cycle out of phase with economies in earlier stages of their respective COVID-19 crises. This suggests that a fruitful avenue for future research may be to examine whether the transmission of shocks through financial markets changes as the pandemic progresses. It also suggests that equity markets may respond to government interventions differently, depending on the degree of disease transmission and the timing of policy interventions.

The overwhelming evidence of contagion in phase 2 indicates that policymakers were right to be concerned about the risks posed by equity market turmoil in the wake of the pandemic announcement. The massive interventions undertaken by many central banks attest to the extent of this concern. The primary short-term impact of these interventions was to prevent illiquidity and thereby to maintain financial stability. However, unconventional monetary policies may also have unintended consequences on capital flows, asset price inflation and the distribution of wealth, among other phenomena. These unintended effects merit further study. Likewise, the likely existence of previously unpriced pandemic risk factors raises urgent questions for the conduct of portfolio management and hedging strategies, questions that raise additional welfare considerations in the context of individual and household savings and pension investments. These areas should be a priority for economic policy and financial regulation moving forward.

[6]The other country that is notable for evidence of contagion in COVID phase 1 is Argentina, although this may be rooted in its protracted recession.

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