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Learning from SARS: Return and volatility connectedness in COVID-19

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ABSTRACT

Using a sample of the G20 countries, we examine the impact of COVID-19 on stock return and volatility connectedness, and whether the connectedness measures behave differently for countries with SARS 2003 experience. We find that both stock return and volatility connectedness increase across the phases of the COVID-19 pandemic which is more pronounced as the severity of the pandemic builds up. However, the degree of connectedness is significantly lower in countries with SARS 2003 death experience. Our results are robust to different measures of COVID-19 severity and controlling for a number of cross-country differences in economic development.

1. Introduction

The spread of the Coronavirus Disease (COVID-19), which started in January 2020 has severely impacted the global financial markets over a short period of time. It is argued that no previous infectious disease, including the Spanish Flu (1900) has had such an influence on the financial markets (Baker et al., 2020). The objective of this paper is to assess the impact of COVID-19 on the dynamic connectedness of stock return and volatility in global financial markets. More importantly, we assess whether return and volatility connectedness differ in countries with previous experience with the Severe Acute Respiratory Syndrome (SARS) in 2003. Our study is driven by both the rapid spread of COVID-19 and its severe effect on global financial markets.

We conjecture that there is greater heterogeneity in the timing and intensity of investors' responses to COVID-19 between a country (market)-pair with alike pandemic experience compared to a country pair without such prior experience. Accordingly, stock market connectedness in the former pair tends to be significantly lower than the latter pair. Our rationale is based on the behaviourist theory of investing, which incorporates elements of psychology to explain market imperfections. Ru et al. (2020) find supporting evidence for the imprint theory (see Marquis and Tilcsik, 2017) in behavioural bias of investors, such that investors with early experience on similar crises tend to react more quickly to COVID-19 than those without such imprints. Previous studies have documented that prior experience with similar events can affect individual's risk aversion (Guisoet al., 2015;Bernie et al., 2017) and investments (e.g., Huang, 2019). While investors should add stocks that minimise the risk of their portfolios, in practice investors choose stock which they are familiar with. A prominent example in the literature is the home bias in stock holdings (Huberman, 2001 and Wang et al., 2011). Investors have richer knowledge of stocks in their home countries and hence prefer to exploit this to their advantage. This implies that perception about the situation is an important factor that drives the decision-making process (Nguyen et al., 2019).

Our study contributes to the literature in several ways. First, we join the rapidly growing discussion of the economic impact of

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COVID-19 on global financial markets (Baker et al., 2020; S. Corbet et al., 2020; Zaremba et al., 2020; Zhang et al., 2020). Secondly, we contribute to the literature of connectedness and contagion by assessing the impact of COVID-19 on stock return and volatility connectedness (S. Corbet et al., 2020). Thirdly, by analysing phases of the pandemic, we address how quickly return and volatility connectedness vary alongside the severity of the pandemic. Last but not least, we contribute to the behavioural theory of markets by investigating how return and volatility connectedness change conditional on prior experience in SARS 2003 (Ru et al., 2020; S. Corbet et al., 2020).

Our results can be summarised as follows: (1) similar to other crises, stock return and volatility connectedness increase as the severity of the pandemic builds up; (2) both return and volatility connectedness decrease among countries with experience in SARS 2003.

The remainder of the paper is as follows. Section 2 presents the data and modelling framework. Section 3 discusses the results of our empirical analysis and finally Section 4 concludes the paper.

2. Data and methodology

2.1. Data

Our sample period is from the 22nd January 2020 to 20th May 2020. The start of our sample period is the day when Johns Hopkins University started to publish the daily confirmed and death case statistics in COVID-19.[1] Our initial sample includes countries in the Group of Twenty (G20), which consists of governments of 19 countries and the European Union. The choice of G20 is driven by their systemic importance to the world economy.[2] We obtain and merge our data from four sources. Firstly, we measure return and volatility connectedness using the 5-minute interval stock prices from Thomson Reuters Tick History (TRTH). Secondly, we extract daily interest rates, foreign exchange volatility and GDP growth from Datastream. Thirdly, the number of confirmed cases and death tolls of COVID-19 are obtained from the Coronavirus Resource Centre of Johns Hopkins University. Lastly, the number of deaths of each country during SARS in 2003 is collected from the website of the World Health Organisation (WHO). Our sample includes 11,696 observations over an 86-day period.

2.2. Connectedness

To measure return and volatility connectedness, we employ the approach of F.X. Diebold and Yilmaz (2012; F.X. 2014). More specifically, we construct the generalized total return and volatility connectedness index of each pairwise countries in G20 within a bivariate fractionally integrated Vector Autoregressive (FIVAR) model. The FIVAR model allows flexibility to capture the stationarity (or short-memory) of the stock returns as well as the long-memory behavior of the volatility. The bivariate FIVAR model can be specified as follows:

$$\left(I_2 - \sum_{l=1}^{p} \mathrm{A}_l L^l\right) B(L) R_t = \epsilon_t \tag{1}$$

where R_t is a vector of the stock return in country i and j in case of return connectedness analysis, i.e. $R_t = (RR_{i,t},\ RR_{j,t})'$, or a vector of the two stock volatilities in case of volatility connectedness analysis, i.e. $R_t = (RV_{i,t},\ RV_{j,t})'$. $RR_t$and RV_t are respectively realized return and realized volatility, which are calculated using the 5-minute stock prices of the G20 country.[3] The error term, $\epsilon_t \sim \ i.i.d.\ (0, \Sigma)$, with $\Sigma = \{\sigma_{rc}; r, c = 1, 2\}$ as its variance-covariance matrix. $\mathrm{A}_l$is the (2×2) coefficient matrix associated with R_{t-l}, and I_2 denotes the (2×2) identity matrix. L is the lag operator while p is the lag order of the model. $B(L) = \mathrm{diag}\ \{(1-L)^{d_1},\ (1-L)^{d_2}\}$with d denotes the memory degrees of the stock volatilities.[4]

We firstly calculate the generalized forecast error variance decomposition (GFEV) matrix from Model (1) with a rolling window of 200 days and a forecast horizon of 10 days.[5] The $(r,\ c)$ element of the GFEV matrix at day t can be calculated as,

$$GFEV_{r,c}(t) = \frac{\sigma_{cc}^{-1} \sum_{h=0}^{t-1} \left(e_r'\ \Lambda_h \Sigma e_c\right)^2}{\sum_{h=0}^{t-1} \left(e_r'\ \Lambda_h \Sigma \Lambda_h' e_c\right)} \tag{2}$$

[1] Confirmed and death cases data is retrieved from https://coronavirus.jhu.edu/map.html.

[2] G20 includes Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Republic of Korea, Mexico, Russia, Saudi Arabia, South Africa, South Korea, Turkey, the United Kingdom and the Unite States of America. Our study, however, excludes Mexico due to its 5-minute stock prices are unavailable.

[3] See for example, Andersen *et al.* (2003), Do *et al.*, (2014). $RR_t = \sum_{n=1}^{M} r_{n,t}$, and $RV_t = \sum_{n=1}^{M} r_{n,t}^2$, where $r_{n,t}$is the nth 5-minute logarithmic stock return in day t.

[4] In case of return connectedness analysis, d is restricted to be zero due to the stationarity of the stock returns, which makes our bivariate FIVAR model equivalent with a bivariate VAR model. We estimate our bivariate FIVAR model using Yip *et al.* (2017) approach.

[5] We ensure consistency of our main results by performing a number of robustness checks with alternative choices of the window sizes of 150 days and forecasting horizons of 7 days. Our results remain unchanged.

Table 1
Summary statistics.

	Mean	Median	Std.dev	Min	Max	N
Return connectedness	19.372	18.420	12.045	0.029	48.729	11,696
Volatility connectedness	20.217	20.616	12.555	0.041	48.942	11,696
COVID_stage= 2	0.337	0.000	0.473	0.000	1.000	11,696
COVID_stage= 3	0.593	1.000	0.491	0.000	1.000	11,696
SARS_deathi,j = *1*	0.382	0.000	0.486	0.000	1.000	11,696
SARS_deathi,j = *2*	0.044	0.000	0.205	0.000	1.000	11,696
COVID_global_confirm	12.599	12.679	2.269	6.321	15.424	11,696
COVID_global_death	9.456	9.535	2.662	2.890	12.701	11,696
Interest rate Diff	−1.141	−0.511	4.053	−22.526	22.150	11,696
Exchange Vol Diff	−0.414	−0.268	7.463	−26.875	24.488	11,696
GDP growth Diff	0.135	0.200	2.645	−5.800	6.000	11,696

This table presents the mean, median, standard deviation (Std.dev), maximum (Max) and minimum (Min) values of various variable for 11,696 country-pair-date observations from 22nd January 2020 to 20th May 2020. Return and Volatility connectedness are constructed using F.X. Diebold and Yilmaz (2012, F.X. 2014)'s approach within a FIVAR framework. COVID*_stage*=*2* is a dummy variable if the date is between 30th January to 10th March 2020, and zero otherwise. COVID*_stage*=3 is a dummy variable if the date is after 10th March 2020, and zero otherwise. *SARS_deathi,j* = *1* is a dummy variable if one of a pair of countries experienced death cases in SARS, and zero otherwise. *SARS_deathi,j* = *2* is a dummy variable if both of a pair of countries experienced death cases in SARS, and zero otherwise. *COVID_global_confirm* is the natural logarithm of one plus the number of accumulative global confirmed cases in COVID-19 on each day. *COVID_global_death* is the natural logarithm of one plus the number of accumulative global death cases in COVID-19 on each day. *Interest rate Diff* is the difference of daily rate of 1-month T-bills between a pair of countries. and. *Exchange Vol Diff* is the difference of exchange rate fluctuation over the previous 21 trading days. *GDP growth Diff* is the difference in the GDP growth rate between two countries in each pair.

As shown in Do et al. (2013, 2014), to incorporate the Diebold and Yilmaz approach in a FIVAR model, the moving coefficient matrix Λ_h need to be adjusted with the long memory degree (d) as, $\Lambda_h = \sum_{l=0}^{h} \Xi_l^{(d)} \Phi_{h-l}$, where $\Xi_l^{(d)} = diag\{\frac{\Gamma(l+d_1)}{\Gamma(d_1)\Gamma(l+1)}; \frac{\Gamma(l+d_2)}{\Gamma(d_2)\Gamma(l+1)}\}$ is a (2×2) diagonal matrix, and $\Phi_h$is calculated recursively as, $\Phi_h = \sum_{l=1}^{p} \Phi_{h-l} \mathrm{A}_l$. We note that, $\Phi_0 = \Lambda_0 = I_2$, and $e_r$is the identity vector with unity as its rth element.

Next, we construct the total generalized connectedness between country i and j at day t using the normalized GFEV ($\widetilde{GFEV}$) as,

$$Total\ Connectedness_{i,j,t} = \frac{\sum_{r,c=1,\ \ r\neq c}^{2} \widetilde{GFEV}_{rc}(t)}{2} \times 100 \tag{3}$$

where, $\widetilde{GFEV}_{rc}(t) = \frac{GFEV_{rc}(t)}{\sum_{c=1}^{2} GFEV_{rc}(t)}$.

2.3. Empirical modelling

To capture the experience in SARS 2003 of each pair of G20 countries, we create a category variable $SARS\_death_{i,j}$, in which $SARS\_death_{i,j} = 0$ when neither country in the pair experienced SARS death; if only one country reported deaths in SARS in 2003 in a pair, $SARS\_death_{i,j} = 1$; whereas $SARS\_death_{i,j} = 2$ when both countries in the pair experienced death in SARS. We use $SARS\_death_{i,j} = 0$ as the base case in our model. To illustrate, China reported 349 deaths from SARS, which is the highest number in the world. Canada reported 43 deaths, whereas Germany and Indonesia reported 0 death. As such, China-Canada is a pair in which both reported deaths from SARS. China-Germany constitutes a pair in which only one country reported death from SARS. Germany-Indonesia represents a pair with no prior death experience in SARS. Our model can be specified as follows:

$$Total\ Connectedess_{i,j,t} = \alpha_{i,j} + \beta_{SARS} SARS\_death_{i,j} + \varepsilon_{i,j,t} \tag{4}$$

where $TotalConnectedess_{i,j,\ t}$ is the total return or volatility connectedness between country i and j on day t calculated as in Eq. (3).

As COVID-19 spread across the world and its severity has evolved, we create a category variable *COVID_stages* to capture three stages of COVID-19 development in our sample. The first stage is from 22nd January to 29th January 2020, when COVID-19 was mostly transmitted within China. The second stage is from 30th January to 10th March 2020, the period over which COVID-19 gradually spreads across the world, so that the WHO declared global public health emergency on 30th January 2020. In the third stage, the severe impact of COVID-19 was recognized and declared as a global pandemic by the WHO. We incorporate the development of COVID-19 within the following model:

$$Total\ Connectedess_{i,j,t} = \alpha_{i,j} + \beta_{COVID} COVID\_stages_t + \beta_{SARS} SARS\_death_{i,j} + \beta_I COVID\_stages_t * SARS\_death_{i,j} + \varepsilon_{i,j,t} \tag{5}$$

Table 2
Connectedness, SARS experience and development of COVID-19.

	Return connectedness		Volatility connectedness	
	(1)	(2)	(3)	(4)
COVID_stage= 2		2.643***		3.457***
		(0.527)		(0.562)
COVID_stage= 3		15.624***		14.339***
		(0.507)		(0.541)
SARS_deathi,j = 1	−0.987***	1.672**	0.031	2.710***
	(0.234)	(0.759)	(0.241)	(0.810)
SARS_deathi,j = 2	−4.512***	0.659	−2.414***	0.403
	(0.560)	(1.798)	(0.577)	(1.919)
COVID_stage= 2× *SARS_deathi,j = 1*		−0.817		−2.145**
		(0.833)		(0.889)
COVID_stage= 2× *SARS_deathi,j = 2*		−1.869		−2.657
		(1.971)		(2.104)
COVID_stage= 3× *SARS_deathi,j = 1*		−4.069***		−3.343***
		(0.802)		(0.855)
COVID_stage= 3× *SARS_deathi,j = 2*		−7.838***		−3.403*
		(1.897)		(2.024)
Interest rate Diff	0.227***	0.370***	0.606***	0.732***
	(0.037)	(0.032)	(0.038)	(0.034)
Exchange Vol Diff	−0.189***	−0.277***	−0.191***	−0.270***
	(0.019)	(0.017)	(0.020)	(0.018)
GDP growth Diff	0.000	−0.126***	0.191***	0.079*
	(0.051)	(0.045)	(0.053)	(0.048)
Constant	20.130***	10.133***	20.897***	11.369***
	(0.154)	(0.481)	(0.159)	(0.513)
Observations	11,696	11,696	11,696	11,696
Adjusted R-squared	0.018	0.258	0.041	0.223

This table presents the panel regression results of return and volatility connectedness, along with other control variables by estimating baseline Eq. (1). The dependent variable is *Return connectedness* for columns 1–2. The dependent variable for columns 3- 4 is *Volatility connectedness*. COVID*_stage=2* is a dummy variable if the date is between 30th January to 10th March 2020, and zero otherwise. COVID*_stage*=3 is a dummy variable if the date is after 10th March 2020, and zero otherwise. *SARS_deathi,j = 1* is a dummy variable if one of a pair of countries experienced death cases in SARS, and zero otherwise. *SARS_deathi,j = 2* is a dummy variable if both of a pair of countries experienced death cases in SARS, and zero otherwise. *Interest rate Diff* is the difference of daily rate of 1-month T-bills between a pair of countries. and. *Exchange Vol Diff* is the difference of exchange rate fluctuation over the previous 21 trading days. *GDP growth Diff* is the difference in the GDP growth rate between two countries in each pair. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors cluster by countries are reported in the parentheses.

Next, instead of the discrete COVID-19 development stages, we investigate how stock market connectedness varies with COVID-19 confirmed or death cases conditional on countries' experiences in SARS in the following equations:

$$Total\ Connectedess_{i,j,t} = \alpha_{i,j} + \beta_{SARS} SARS\_death_{i,j} + \beta_{COVID_g} COVID\_global_t + \beta_{Ig} COVID\_global_t * SARS\_death_{i,j} + \varepsilon_{i,j,t} \tag{6}$$

where $COVID\_global_t$ is natural logarithm of the number of one plus the accumulative global COVID-19 confirmed or death cases on day *t*.

$$Total\ Connectedess_{i,j,t} = \alpha_{i,j} + \beta_{SARS_i} SARS_i + \beta_{SARS_j} SARS_j + \beta_{COVID_i} COVID_{i,t} + \beta_{COVID_j} COVID_{j,t} + \beta_{I_i} SARS_i * COVID_{i,t} + \beta_{Ij} SARS_j * COVID_{j,t} + \varepsilon_{i,j,t} \tag{7}$$

where $SARS_i$ ($SARS_j$) is dummy variable that equals one if country *i* (*j*) experienced SARS death cases and zero otherwise. $COVID_{i,t}$ ($COVID_{j,t}$) is the natural logarithm of the number of one plus accumulative COVID-19 confirmed or death cases from country *i* (*j*) on day *t*.

Furthermore, we also add three control variables in all models to consider the cross-country differences in economic development, including interest rates (proxied by 3-month government bonds), foreign exchange volatility over the previous 21 trading days and quarterly GDP growth. Given that our dependent variable is between a pair of country, we estimate the within-pair differences for the aforementioned control variables.

3. Results

Table 1 presents the summary statistics of the key variables in the regression. Over our sample, 7%, 33.7%, and 59.3% of the observations fall in the first, second and third stage of COVID-19, respectively. 38.2% of the pairs of countries in our sample contain one party with deaths in SARS, while only 4.4% of the pairs contain both countries with death in SARS.

Regression outputs of Eq. (4) and (5) are reported in Table 2. The estimates of Eq. (4) (columns 1 and 3) show that the relation between connectedness and $SARS_death_{i,j} = 2$is negatively significant. This result implies when both countries in a pair experienced SARS death(s) in 2003, their connectedness is lower in the COVID-19 period compared to the case in which none of them reported death due to SARS. Considering the stages of the COVID-19 development, the estimated results of Eq. (5) (columns 2 and 4) show that both return and volatility connectedness increase as COVID-19 becomes more severe. This is illustrated by the positively significant coefficients associated with the second and third stages of COVID-19. This equally suggests a stronger return and volatility spillover effect between stock markets when market fear is higher with the surge in the severity of the pandemic.

Overall, we find that the positive impact of COVID-19 development on connectedness reduces significantly if there was SARS death experience in 2003. This is shown by the significant and negative coefficients associated with the interaction between the $COVID_stages$and $SARS\_death_{i,j}$. In addition, for the same 2003 SARS death experience category, the role of the SARS death experience in shifting down the market connectedness is more significant as the severity of COVID-19 increases. Our results can be explained by a behavioral bias of investors in stock markets: investors in markets with prior experience on similar pandemic can be more concerned about the risks of COVID-19 and, therefore, react timely compared to those without such experience. Our results are consistent with studies which document that countries with prior pandemic experience underreact in stock markets as compared to countries without prior pandemic (e.g., Ru et al., 2020; Ramelli and Wagner, 2020). Hassan et al. (2020)assess the costs, benefits and risk of listed firms in the U.S. and over 80 countries in COVID-19 and other pandemics including SARS 2003 and H1N1 2009. Firms with prior pandemic experience are found to make better decisions in the coronavirus outbreak. In turn, this may lead to a greater heterogeneity in timing and extremity of investors responses in the market pair with SARS death experience compared to the market pair without such experience, causing a lower connectedness in the former pair.[6]

In addition to the use of discrete stages to measure the severity of COVID-19, we perform analyses using global and country-specific confirmed or death cases. Columns (1–2) and (5–6) of Table 3 present results of return and volatility connectedness using global severity of COVID-19, respectively. Columns (3–4) and (7–8) show results using severity of COVID-19 at country level. Consistent with Tables 2, both return and volatility connectedness are positively related with the severity of COVID-19, as reflected by the significantly positive coefficients of $COVID\_global\_death$, $COVID\_global\_confirm$, $COVID\_death_i$, $COVID\_confirm_i$, $COVID\_death_j$, and $COVID\_confirm_j$. That is, global stock markets become more connected as the severity of the pandemic builds up. The interaction term between the number of global/country-specific confirmed/death cases and countries' experience in SARS is also negatively significant, suggesting that the connectedness between countries with experience in SARS is further reduced in spite of the development of COVID-19. In other words, our findings remain robust when either considering discrete or continuous measures of the COVID-19 severity, and either using global or country-specific measures of this pandemic. As a robustness check, we replace the global cases number with confirmed or death cases in the U.S. in the regressions and document similar results.

4. Conclusion

Our study provides evidence of the impact of COVID-19 pandemic on stock market connectedness. In general, connectedness in global financial markets is intensified with the rapid development of the pandemic. We also find that connectedness is considerably lower if a country experienced SARS death(s) in 2003. Our findings are associated with behavioral biases of investors in stock markets, in which investors with early experience of the similar pandemic tend to react faster and stronger to COVID-19 compared to those without such prior experience. This is because the former group of investors are more alarmed about similar risks faced in the past, while the latter group of investors tend to neglect those risks.

Credit author statement

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Dr Hung Do: Methodology Software Writing
Dr Xiaolu Hu: Conceptualization; Modelling Writing
Dr Angel Zhong: Conceptualization Modelling Writing

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2020.101796.

[6] We repeat our analysis with different definitions of the development of the COVID-19 pandemic. We classify our sample period into 2 stages with 11th March 2020 (when the WHO declared COVID-19 as a global pandemic) as a tipping point. Regression outputs are reported in Table A1 in the appendix. Our findings remain qualitatively similar.

Table 3
Connectedness, SARS experience and number of COVID-19 cases.

	Return connectedness				Volatility connectedness			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SARS_deathi,j = 1	6.749***	4.051***			4.284***	2.716***		
	(1.170)	(0.762)			(1.240)	(0.809)		
SARS_deathi,j = 2	10.949***	5.509***			0.724	−0.521		
	(2.770)	(1.805)			(2.936)	(1.915)		
COVID_global_confirm	2.574***				2.197***			
	(0.058)				(0.061)			
COVID_global_death		2.239***				1.910***		
		(0.049)				(0.052)		
SARS_deathi,j = 1× COVID_global_confirm	−0.616***				−0.340***			
	(0.091)				(0.097)			
SARS_deathi,j = 2× COVID_global_confirm	−1.236***				−0.257			
	(0.216)				(0.229)			
SARS_deathi,j = 1× COVID_global_death		−0.536***				−0.287***		
		(0.077)				(0.082)		
SARS_deathi,j = 2× COVID_global_death		−1.072***				−0.211		
		(0.183)				(0.195)		
$SARS_i$			3.630***	1.632***			3.378***	2.251***
			(0.448)	(0.361)			(0.485)	(0.393)
$SARS_j$			6.725***	5.005***			5.786***	4.741***
			(0.426)	(0.345)			(0.461)	(0.376)
$COVID\_Confirm_i$			1.272***				1.508***	
			(0.037)				(0.040)	
$COVID\_Confirm_j$			0.607***				0.046	
			(0.040)				(0.043)	
$COVID\_Death_i$				1.223***				1.300***
				(0.040)				(0.044)
$COVID\_Death_j$				0.971***				0.448***
				(0.046)				(0.050)
$SARS_i \times COVID\_Confirm_i$			−0.740***				−0.455***	
			(0.054)				(0.059)	
$SARS_j \times COVID\_Confirm_j$			−1.242***				−1.007***	
			(0.052)				(0.056)	
$SARS_i \times COVID\_Death_i$				−0.730***				−0.458***
				(0.062)				(0.068)
$SARS_j \times COVID\_Death_j$				−1.702***				−1.483***
				(0.063)				(0.068)
Interest rate Diff	0.371***	0.377***	0.417***	0.322***	0.731***	0.736***	0.854***	0.685***
	(0.033)	(0.033)	(0.031)	(0.031)	(0.035)	(0.035)	(0.034)	(0.034)
Exchange Vol Diff	−0.279***	−0.283***	−0.208***	−0.161***	−0.270***	−0.274***	−0.149***	−0.088***
	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)
GDP growth Diff	−0.128***	−0.133***	−0.220***	−0.124***	0.079	0.074	−0.086*	0.048
	(0.046)	(0.046)	(0.044)	(0.045)	(0.049)	(0.049)	(0.048)	(0.049)
Constant	−12.141***	−0.870*	8.215***	12.169***	−6.641***	2.981***	11.263***	14.661***
	(0.741)	(0.483)	(0.219)	(0.183)	(0.786)	(0.512)	(0.237)	(0.199)
Observations	11,696	11,696	11,696	11,696	11,696	11,696	11,696	11,696
Adjusted R-squared	0.206	0.213	0.322	0.290	0.179	0.185	0.271	0.226

Columns 1–2 and columns 5–6 present the panel regression results of return and volatility connectedness, along with other control variables by estimating Eq. (2). Column2 3–4 and columns 7–8 illustrate he OLS regression results by estimating Eq. (3). The dependent variable is *Return connectedness* for columns 1–4. The dependent variable for columns 5- 8 is *Volatility connectedness. SARS_deathi,j = 1* is a dummy variable if one of a pair of countries experienced death cases in SARS, and zero otherwise. *SARS_deathi,j = 2* is a dummy variable if both of a pair of countries experienced death cases in SARS, and zero otherwise. *COVID_global_confirm* is the natural logarithm of one plus the number of accumulative global confirmed cases in COVID-19 on each day. *COVID_global_death* is the natural logarithm of one plus the number of accumulative global death cases in COVID-19 on each day. where $SARS_i$ and $SARS_j$ are dummy variables equal one if country *i* or country *j* experience SARS death cases and zero otherwise. $COVID\_Confirm_i(COVID\_Death_i)$ and $COVID\_Confirm_j(COVID\_Death_j)$ are natural logarithm of the number of one plus accumulative confirmed (death) COVID-19 cases from country *i*and country *j* on each day respectively. *Interest rate Diff* is the difference of daily rate of 1-month T-bills between a pair of countries. and. *Exchange Vol Diff* is the difference of exchange rate fluctuation over the previous 21 trading days. *GDP growth Diff* is the difference in the GDP growth rate between two countries in each pair. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors cluster by countries are reported in the parentheses.

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