How Vulnerable Are Financial Markets to COVID-19?

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Abstract: As the coronavirus pandemic (COVID-19) continues to spread over the world, a public health emergency has gradually deteriorated into an economic issue, which has raised the disputes over its severity and duration. Throughout history, financial crises, in most cases, were triggered by financial fragility. In this study, we carry out a comparative analysis between the US and South Korea, with a special attention to three key financial markets, including the stock market, the currency market and the bond market. By employing a composite model, VAR-GARCH-BEKK, we will attempt to capture both mean and volatility spillovers between the pandemic and financial markets, so as to explore the extent and in what ways does the COVID-19 influence the financial sector. The empirical results provide substantial evidence in the following areas: (i) South Korea seems more vulnerable since all financial markets are seen to be statistically associated with the growth in infections. (ii) For the US, only the stock market is negatively impacted by the confirmed cases in terms of conditional mean spillover model. (iii) According to the impulse response functions (IRFs), apart from the US dollar index, both the TED spread and stock returns respond significantly to innovations from the pandemic. (iv) There is little evidence to support the presence of volatility transmission from the pandemic to the financial markets in the two countries.

Keywords: COVID-19, VAR-GARCH-BEKK, return and volatility spillovers, financial markets, EMEs, advanced economies

1. Introduction

On January 30, 2020, the World Health Organization (WHO) declared a public health emergency of international concern in response to a coronavirus pandemic (COVID-19). Unlike Severe Acute Respiratory Syndrome (SARS) and Middle East Respiratory Syndrome (MERS), such an unprecedented event has not only raised concerns over health, but also over economic prospects as well as financial stability (Ali et al., 2020; Czech et al., 2020; Reinders et al., 2020). As of August 31, 2020, there were approximately 25 million confirmed cases of COVID-19 worldwide with a mortality rate of 3.54%, covering more than 210 countries and regions.

Coincidentally, the Centers for Disease Control and Prevention (CDC) in the US and South Korea reported the first confirmed case on January 20, both of which were associated with Wuhan, the center of pandemic outbreak in central China. Shortly thereafter the cumulative number of confirmed cases has been showing an upward trend, particularly in the US (See Figures 1a and 2a). Numerous emergency countermeasures to curb the proliferation of COVID-19 were subsequently taken by governments, such as physical and social distancing, self-isolation and quarantine as well as travel restriction. As public awareness of pandemic prevention continues to grow, the focus has shifted to the potential aftermath of COVID-19 that could trigger a financial depression or even financial meltdown in the future.

Figures 1b and 2b plot that the stock market performance in the two countries moved in lockstep from a holistic perspective. Stock indices plunged precipitously during the first month, followed by a rapid rebound from the bottom to pre-pandemic level. In the currency market, before the exchange rate continued to weaken, both the US dollar index and South Korean won were thrown into turmoil in the first half of sample period (see Figures 1c and 2c). The US TED spread presented a striking contrast to its counterpart, growing nearly tenfold in less than five weeks, then plummeted until returning to pre-pandemic level in early June. All the while the TED spread (South Korea) oscillated back and forth, reaching a peak of 0.351 on April 9 followed by a sustained decline (see Figures 1d and 2d).

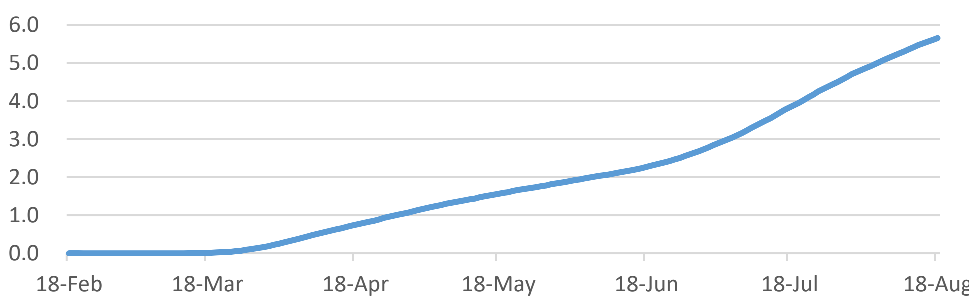
This comparative study of the US and South Korea is motivated by several incentives. To begin with, the US currently is the world's largest economy, whose financial hegemony is beyond controversy. A more sophisticated financial system and an effective transmission mechanism of monetary policy, to a great extent, enhance its abilities to fend off external risks. By contrast, in an attempt to impel capital market internationalization, the South Korean government deregulated its financial sector just starting in the 1980s. Unfortunately, almost without exception financial markets fell victim to the 1997-98 Asian Financial Crisis (AFC) and 2008-09 Global Financial Crisis (GFC) so that this small open economy has had to struggle with strengthening its ability to withstand external shocks. Therefore, it is worth studying whether the financial markets' performance in both of economies tend to differ amid COVID-19 particularly in the initial stage of the pandemic. Subsequently, given the heterogeneity of the financial sector, the monetary authorities unanimously responded with stimulus measures to address uncertainty, but not with a unified strategy. For instance, to facilitate financial system liquidity, the two countries slashed the base rate and purchased Treasury Bonds. However, unlike the US, the Bank of Korea (BOK) simultaneously took measures to facilitate funding in foreign exchange. These measures could lead to somewhat different consequences in an advanced economy and an emerging market economy (EME). Last but not least, despite the fact that expansionary policy, not surprisingly, is conducive to accelerating economic recovery in the short-run, there have been mounting concerns over the extent to which it may jeopardize the sustained financial stability in the mid- and long-term. More specifically, unconventional monetary policy, for instance, Quantitative Easing (QE), will drive up financial asset prices and further exacerbate both domestic and foreign financial markets' vulnerability to external and internal shocks, which could precipitate another recession (Bowman et al., 2015; Chen et al., 2014). Although the potential consequence of policy interventions will not be discussed in detail, hopefully, the aforementioned dilemma could arouse regulators' attention to policy assessment.

Remarkable contributions to the existing literature are at least twofold: (i) With a larger time series dataset, this study intends to quantify the impacts of COVID-19 on the financial sector, including stock markets, currency markets as well as bond markets. (ii) We elaborate on parallels and differences between a representative advanced economy and an EME in terms of financial markets' reaction to COVID-19 outbreak.

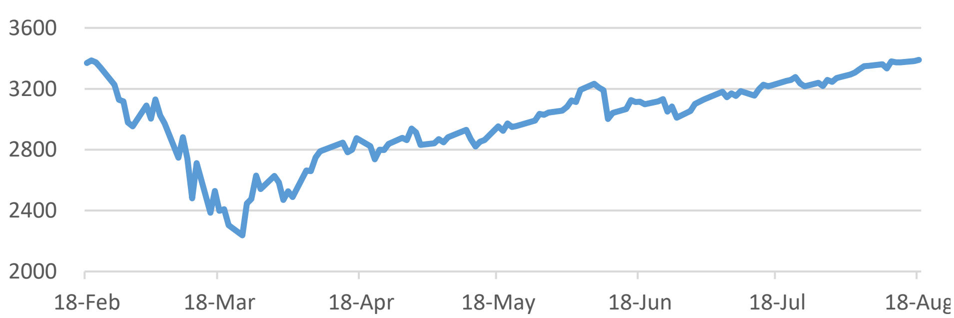
The remainder of this study is organized as follows: Section 2 discusses the existing literature that provide insight into the impact of COVID-19 on the financial sector in both EMEs and advanced economies, and the corresponding transmission mechanism. Section 3 provides a detailed description pertaining to data and model specification, followed by empirical results as well as interpretation in Section 4. The last section is concluding remarks.

Figure 1. Data Visualization for Confirmed Cases and Financial Markets (US)

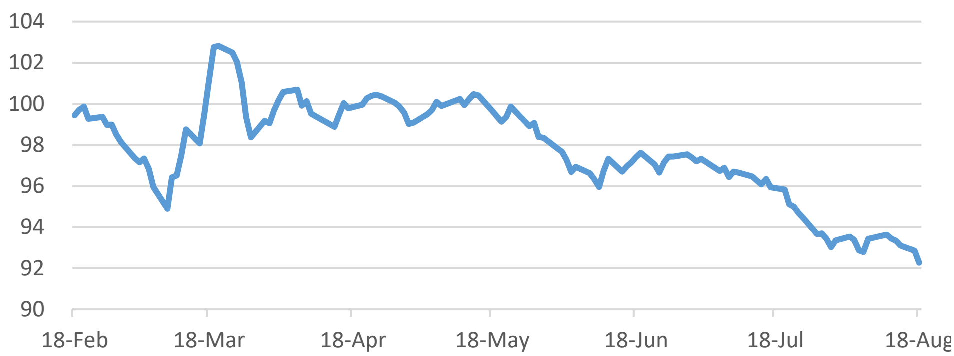
1a. Total Confirmed Cases (in million)



1b. Stock Index (S&P 500)



1c. Dollar Index Spot (1973.03 = 100)



1d. TED Spread (%)

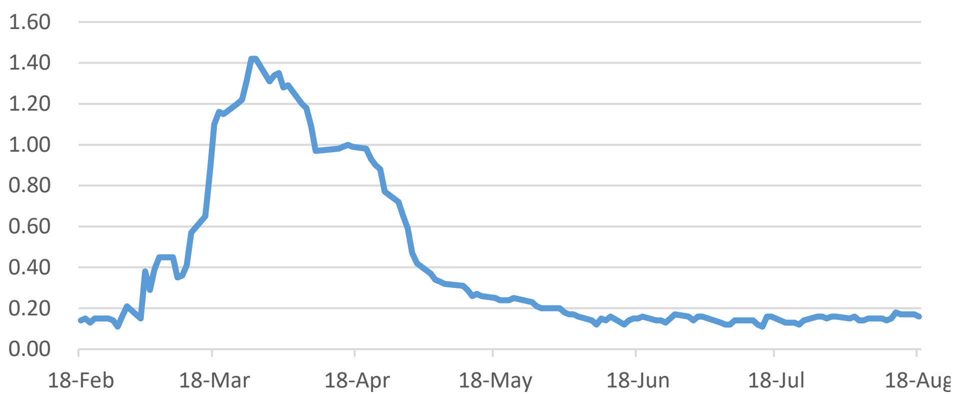
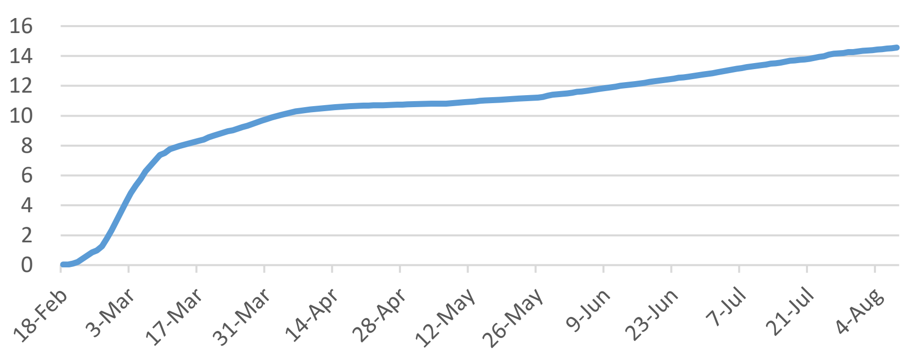
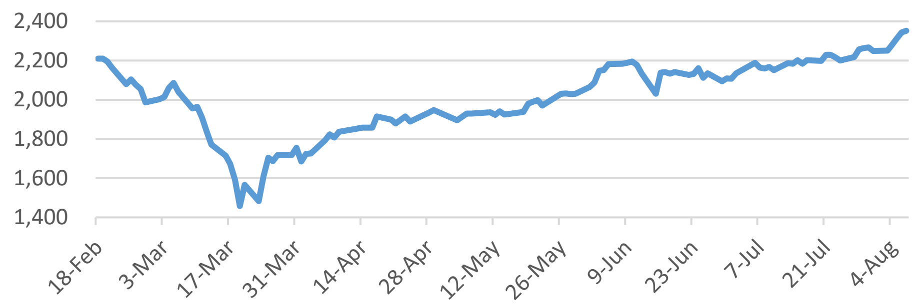


Figure 2. Data Visualization for Confirmed Cases and Financial Markets (South Korea)

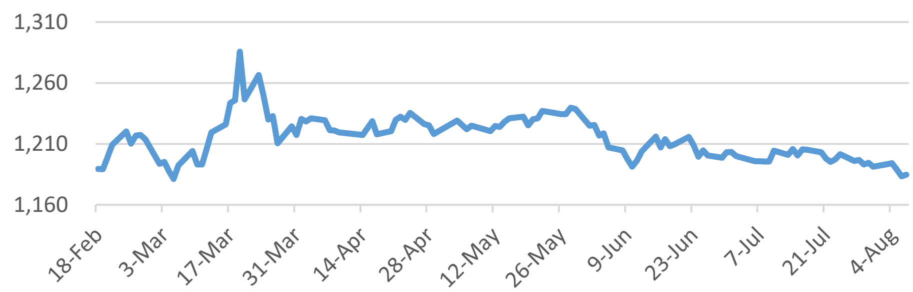
2a. Total Confirmed Cases (in thousand)



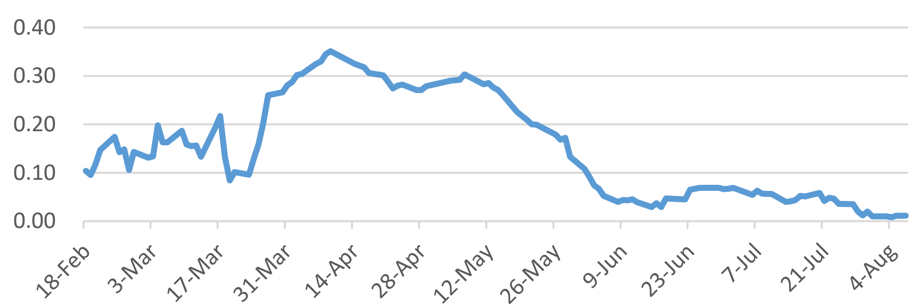
2b. Stock Index (KOSPI)



2c. Exchange Rate of South Korean Won Against US Dollar (Spot Price)



2d. TED Spread (%)



2. Literature Review

As the pandemic evolves, an extensive literature theoretically and empirically lays out to what extent and in what way it impacts the financial markets worldwide. This catastrophe inflicts losses on investors since the ever-increasing confirmed cases and death toll have a negative influence on the stock market (Al-Awadhi et al., 2020), whose reaction to growth in the number of confirmed cases is more proactive than that of deaths (Ashraf, 2020a). However, Topcu and Gulal (2020) unravel that the adverse impacts on emerging stock markets will gradually subside until it turns to be statistically insignificant over the sample period. He et al. (2020) highlight that the negative effects are not persistent, but have bidirectional spillover effects between countries in different continents.

Esteves and Sussman (2020) investigate global financial markets amid the pandemic with a large panel data set, finding that (i) OECD economies' daily depreciation of the exchange rate vis-à-vis the US dollar is positively influenced by growth in death toll, whose effects taper off due partly to the convergence trend. (ii) As far as long-term bond spreads are concerned, the shock due to death toll resulted in a drastic upward trend in the acceleration phase (February through April) in EMEs. While the spreads were immune to death rate in the deceleration stage (April through June), irrespective of EMEs or advanced economies. Iyke (2020) steps forward in providing a novel channel that helps predict exchange rate returns and volatility by using cumulative confirmed cases and deaths, both of which are fairly effective in the particular scenarios. Using the total confirmed cases, volatility prediction outperforms returns prediction for a one-day ahead forecast horizon, while returns prediction is superior over a five-day forward forecast, and a similar conclusion applies to death toll. All told, his empirical results make a convincing argument that COVID-19 has been producing profound impacts on the foreign exchange (FX) markets.

By employing the number of cases and deaths as proxy variables to capture the severity of pandemic, Ahmed et al. (2020) assert COVID-19 took a toll on EME financial markets that had experienced weakening currencies, rising spreads of credit default swaps (CDS) and declining equity valuations. Meanwhile, such effects resulted in a widening credit spread in advanced economies. Jinjarak et al. (2020) shed some light on traditional determinants that could bring about broadening divergence of spreads seem inadequate to account for unusual phenomenon in Eurozone sovereign spreads during the pandemic. Their empirical results point to COVID-19 related risks (e.g., mortality rate) and policies (e.g., Pandemic Emergency Purchase Program, PEPP) igniting the aberrant financial market behaviors.

Baker et al. (2020) suggest that dramatic influence on the stock market cannot roughly be attributable to the fatality rate of the virus, quick dissemination of information and global supply chains disruption, but a more plausible explanation seems to be that preventive measures against COVID-19 proposed by governments impose restrictions on personnel mobility and business activities (see also Ashraf, 2020b; Ozili and Arun, 2020). Liu et al. (2020) indicate that stock market stagnation has swept across many major economies, among which developed countries, including the UK and the US, have weathered the financial fallout slightly better than the Asian region, where financial markets are inundated with pessimistic and panic sentiments (see also Mishra and Mishra, 2020). Indeed, it is well documented that market sentiment interacts with the financial markets as investors are not entirely irrational (see also Shu and Chang, 2015). The media is presently flooded with news reports related to COVID-19, subtly evoking a gamut of emotions. Interestingly, negative sentiments are prevailing (Aslam et al., 2020), which possibly trigger a surging volatility and negative returns in the financial markets (Haroon and Rizvi, 2020). Beirne and his co-authors (2020) find that, against the backdrop of soaring risk aversion, financial markets in EMEs are more susceptible to COVID-19 because of massive capital outflows. With regard to the magnitude of vulnerability, the bond market and stock market rank first and second respectively, followed by currency market. Hofmann et al. (2020) discuss that EME bond markets are dependent overwhelmingly on external portfolio investors, implying a weaker ability to insulate themselves from external shocks. As a consequence, local bond markets inevitably suffer from capital outflows and domestic currency depreciations, which further give rise to a spike in bond spreads in the wake of COVID-19.

3. Data and Model Specification

3.1 Data and Preliminary Analyses

In this study, we employ total confirmed cases to capture the severity of ongoing COVID-19 pandemic, as does a considerable body of literature. Regarding financial markets, several indicators are taken into account, including stock index, exchange rate as well as spreads of short-term bond against risk-free bonds. Precisely, the S&P 500 and Korea Composite Stock Price Index (KOSPI) represent the US and South Korean stock market, respectively. The exchange rate of South Korean won against US dollar is in direct quotation, and the US dollar index acts a proxy for price of dollar. TED spread (US) is ready-to-use, while TED spread (South Korea) is calculated in a similar way as follows:

$$\text{TED spread (South Korea)} = \text{3-month KORIBOR rate} - \text{3-month MSBs rate} \quad (3.1)$$

Korea Interbank Offered Rates (KORIBOR), a South Korean version of LIBOR, are renewed on a daily basis after calculating the average interest rates of term deposits at 15 financial institutions, including commercial lenders, policy banks and branches of foreign banks. Monetary stabilization bonds (MSBs) are issued by the Bank of Korea (BOK), normally being considered risk-free. As to data source, pandemic-specific series are obtained from Worldometer, and data related to South Korean financial markets are from economic statistics system (ECOS BOK). The S&P 500 and US dollar index are from

Bloomberg, while TED spread (US) from Federal Reserve Bank of St. Louis. We firstly convert raw series[1] except TED spread to log percentage returns as below, then label new series with a suffix '*_gr*'.

$$R_t = 100.0 * [\ln(P_t/P_{t-1})] \tag{3.2}$$

There is a mismatch between confirmed cases and financial time series in terms of data accessibility on account of the presence of non-trading days in the financial markets. Therefore, cumulative cases reported on the non-trading days are excluded. Additionally, *ted_d* and *korted_d* are computed as the first difference based on TED spread (US) and TED spread (South Korea), respectively. Of particular note is that *usa_gr* and *kor_gr* are compared with the previous day rather than previous trading day, which applies to the rest of variables. It is a given that explosive growth in confirmed cases at the initial stage could cause outliers. Moreover, TED spread (South Korea) became negative starting from mid-August, coupled with obvious inflection points of the total confirmed cases in two countries, so the data at both ends have been truncated. Consequently, the sample period for the US is from February 18 through August 17, 2020, with a total of 124 daily observations. Spanning from February 18 to August 7, 2020, dataset is made up of 114 observations for South Korea.

Table 1. Descriptive Statistics (US)[1)]

Statistics	*usa_gr*	*sp_gr*	*usd_gr*	*ted_d*
Mean	0.0775	0.0028	-0.0553	0.0002
Std. Dev.	0.1264	2.9356	0.5494	0.0551
Min.	0.0000	-12.7652	-1.6946	-0.12
Max.	0.8473	8.9683	1.5880	0.24
Skewness	2.8232***[2)]	-0.6561***	0.5825***	1.6102***
Kurtosis	13.9189***	7.3560***	4.5121***	9.3799***
JB[3)]	786.9958***	106.9322***	18.8261***	263.8867***
ADF[4)]	-4.5872***	-16.3603***	-8.8360***	-7.9770***
PP[5)]	-4.4350***	-15.6932***	-8.9813***	-8.4154***
Q(24)[6)]	317.77***	55.90***	27.55	43.68***
$Q^2(24)$[7)]	81.10***	132.30***	145.42***	75.83***
ARCH(12)[8)]	123.08***	5.64***	6.39***	7.07***

[1] To ensure growth in confirmed cases have same order of magnitude, both *usa_gr* and *kor_gr* are not multiplied by 100.

Obs.	124	124	124	124

Notes: 1) Sample period is from February 18 through August 17, 2020.
2) *, **, *** denote the rejection of null hypotheses at 10%, 5% and 1% respectively.
3) Jarque-Bera statistic for normality test.
4) Augmented Dickey-Fuller test for unit root.
5) Phillips-Perron test for unit root.
6) Modified Ljung-Box test for autocorrelation, robust to heteroscedasticity.
7) McLeod-Li test for autocorrelation on the squares.
8) ARCH-LM test for conditional homoscedasticity.
Source: Compiled by the authors.

Table 2. Descriptive Statistics (South Korea)[1)]

Statistics	*kor_gr*	*kospi_gr*	*krw_gr*	*korted_d*
Mean	0.0372	0.0549	-0.0035	-0.0008
Std. Dev.	0.1148	2.3263	0.7508	0.0202
Min.	0.0002	-8.7670	-3.0964	-0.0850
Max.	0.8157	8.2513	3.1606	0.0640
Skewness	4.8271***[2)]	-0.1150	-0.0456	-0.0019
Kurtosis	29.4656***	6.1322***	7.2666***	6.6365***
JB[3)]	3802.8182***	46.8532***	86.5080***	62.8155***
ADF[4)]	-4.0306***	-11.2090***	-14.4822***	-9.5571***
PP[5)]	-3.5507***	-11.3453***	-14.0498***	-9.6932***
Q(24)[6)]	101.51***	14.16	26.97	22.22
$Q^2(24)$[7)]	50.99***	116.93***	64.15***	65.87***
ARCH(12)[8)]	6,596.06***	11.07***	4.28***	2.92***
Obs.	114	114	114	114

Notes: 1) Sample period is from February 18 through August 7, 2020.
2) *, **, *** denote the rejection of null hypotheses at 10%, 5% and 1% respectively.
3) Jarque-Bera statistic for normality test.
4) Augmented Dickey-Fuller test for unit root.
5) Phillips-Perron test for unit root.
6) Modified Ljung-Box test for autocorrelation, robust to heteroscedasticity.
7) McLeod-Li test for autocorrelation on the squares.
8) ARCH-LM test for conditional homoscedasticity.
Source: Compiled by the authors.

As seen in Table 1 and Table 2, all financial series appear to be volatile and leptokurtic, which can be found in *usa_gr* and *kor_gr* as well. More concretely, the average return of South Korean stock market is higher than that of the US over the sample period. Somewhat surprisingly, the mean values in both of the return series are positive, which may not be intuitive. With regard to FX markets, returns are negative but the South Korean won exhibits more volatile with a smaller mean and a greater standard deviation. The mean of *korted_d* is negative, as opposed to *ted_d*, but both are near-zero. The US, with an average daily growth of 7.75% in infections, is one of the worst-hit countries. The analogue value for South Korea is less than half that of the US, benefiting from more stringent and comprehensive prevention measures against COVID-19.

We conduct both ADF and PP tests to examine the presence of unit root. The results are consistent in that all series are stationary at a 1% significance level. Modified Ljung-Box Q test and McLeod-Li test display that most series are not serially independent in both level and quadratic terms. ARCH-LM tests reject the null hypothesis of conditional homoscedasticity, suggesting the presence of ARCH effects in all series.

3.2 Conditional Mean Equation

By specifying a conditional mean model in order to remove linear dependence, the variance will be adequately captured for further analysis (Tsay, 2005). To our knowledge, defining a mean model with intercepts only is the simplest approach to ensure that the 'filtered' residuals are serially uncorrelated individually and have no correlation with the lags of the other components. Besides, a broad set of models are feasible, such as AR, VAR, ARMA, ARIMA, VARMA, etc. The following advantages motivate us to employ Vector Autoregression (VAR) as the mean model in this study. Firstly, it's possible to estimate the dynamic relationship among endogenous variables without a *priori.* Secondly, we can perform postestimation tests based upon preliminary results. For instance, impulse response functions (IRFs) provide a much easier channel to demonstrate how the system reacts to specific isolated shocks. Thirdly, the composite model locally converges to a stable solution. The basic VAR(p) equation takes the form:

$$y_t = c + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_p y_{t-p} + Hx_t + \varepsilon_t , \qquad t = 1, 2, \ldots, T \qquad (3.3)$$

where y_{t-p} denotes pth-lag of endogenous variables (y_t), and c represents a k-vector of the constants serving as the intercept of the model. Φ_1 , $\cdots$, Φ_p and H are a time-invariant matrices ($k*k$), and a coefficient matrix ($k*d$) to be estimated, respectively. x_t indicates a d-vector of exogenous variables. $\boldsymbol{\varepsilon_t}$, a k-vector of error terms which must satisfy three conditions: i) Every error term has a mean of zero. ii) The contemporaneous covariance matrix of error terms is a positive-semidefinite matrix ($k*k$) denoted $\boldsymbol{\Sigma}$. iii) There is no serial correlation in individual error terms.

3.3 Conditional Variance Equation

Unlike common time series, heteroscedasticity and volatility clustering can generally be observed on financial data. We convert levels to log-returns, one of variance stabilizing transformations to eliminate the heteroscedasticity, albeit not thoroughly. Fluctuations in the financial markets are associated closely with uncertainty, which possibly results in leptokurtic distribution. Namely, both crests and troughs are likely to be continuous over a period of time. A large volatility is followed by a large volatility and vice versa for a small volatility.

To capture the aforementioned characteristics, autoregressive conditional heteroscedasticity (ARCH) process was originally introduced by Engle (1982). The GARCH model (Bollerslev, 1986), a generalized form of ARCH, is far more parsimonious than ARCH model since it has fewer parameters that allow for an infinite number of squared roots to influence the conditional variance. However, there are a few drawbacks to the standard GARCH model as follows (Zivot, 2008): i) Given the presence of leverage effects, response of financial markets to a negative innovation tend to be more volatile than to a positive shock with the same magnitude. ii) Empirical results will inevitably be biased if time series have non-Gaussian error distributions rather than the normal distribution. To tackle these problems, we take into consideration asymmetry and non-normality simultaneously in the following model specifications. Furthermore, as to multivariate GARCH, enforcing positive-definiteness of the conditional covariance matrices is always handicapped by numerical issues on one hand. And on the other hand, it fails to capture the relatively sophisticated relationship among variables, such as spillover effects (what we are most concerned about in this paper). To the best of our knowledge, the BEKK model proposed by Engle and Kroner (1995) allows a wide range of interactions, while imposing the restriction that the conditional variance always be positive. The BEKK model can be written as:

$$H_t = CC' + \Sigma_{j=1}^{q}\Sigma_{k=1}^{K}A'_{kj}\varepsilon_{t-j}\varepsilon'_{t-j}A_{kj} + \Sigma_{j=1}^{p}\Sigma_{k=1}^{K}B'_{kj}H_{t-j}B_{kj} \tag{3.4}$$

where C, A_{kj} and B_{kj} are $N * N$ parameter matrices, and C is a lower triangular matrix. More concretely, C is a constant matrix, while A and B are coefficient matrices of ARCH effects and GARCH effects, respectively. The coefficient matrix A is referred to as reaction parameter, measuring the past returns to the current conditional variances. While the coefficient matrix B can be interpreted as persistence parameter, capturing the past conditional variance to the current conditional variances. H denotes the time-varying variance and covariance matrix as to endogenous variables in the system. ε represents coefficient matrix of the residuals which is derived from mean equations. K^2 governs to which extent the generality of the process in equation 3.4 can be approximated by a BEKK representation.

Meanwhile, the asymmetric terms as shown below need to be added,

$$D' v_{t-j} v'_{t-j} D \tag{3.5}$$

where D is a $N * N$ matrix, and forcibly positive semi-definite. We then employ the most commonly used specification that the lag length is set to be one. For a 1,1 model ($q = p = 1$), the full BEKK recursion is specified as follows:

$$H_t = CC' + A' \varepsilon_{t-1} \varepsilon'_{t-1} A + B' H_{t-1} B + D' v_{t-1} v'_{t-1} D \tag{3.6}$$

In addition, the GARCH model is estimated by the maximum likelihood method, and the corresponding log-likelihood function is:

$$\ln \ell(\theta) = \frac{-TN}{2} \ln(2\pi) - \frac{1}{2} \sum_{t=1}^{T} (\ln|H_t| + \frac{1}{2} \varepsilon'_t H_t \varepsilon_t) \tag{3.7}$$

where T denotes the number of observations; θ is the parameter to be estimated. It's noteworthy that the calculation of H_t is based on a combination of preliminary simplex iterations, following BFGS numerical optimization algorithm as suggested in Doan (2013).

To sum up, we define a VAR-GARCH-BEKK model with t errors and asymmetric effects as the baseline specification. For a BEKK model, the number of parameters to be estimated is $(p+q+1)N^2 + N(N+1)/2$. In a quadruplex case (N=4), coupled with shape coefficient the model contains 59 parameters.

4. Empirical Results

To guarantee BEKK estimates give rise to a stable recursion, the eigenvalue stability condition is supposed to be satisfied. The sum of the VECH A and B matrices have eigenvalues far less than one, implying that the model specifications are appropriate.

Besides, the model will be stationary if the following conditions are satisfied (Schmitz and Ledebur, 2011). Firstly, both $[A(i,i)^2+B(i,i)^2]$ and $[A(j,j)^2+B(j,j)^2]$ must be less than one. Secondly, all diagonal elements must be statistically significant. Undoubtedly, the models are applicable in two scenarios. All the sums relatively stand off from one, suggesting that

[2] Unless otherwise noted, K in the following sections is assumed to be one.

the volatility in all series shows a faster mean reversion.

4.1 Estimation Results

Table 3. Estimation Results for the Conditional Mean Model (US)

	usa_gr[1)]	*sp_gr*	*usd_gr*	*ted_d*
usa_gr(-1)[2)]	0.9074**[3)] (6.5184)	-0.9492** (-6.1370)	0.4723 (0.7262)	0.0477 (1.5645)
sp_gr(-1)	0.0000 (0.0047)	0.0784** (-2.0656)	-0.0714** (-4.7035)	0.0028** (2.3542)
usd_gr(-1)	-0.0012 (-1.8914)	-0.4127** (-4.0450)	0.1747** (4.0411)	0.0008 (0.1693)
ted_d(-1)	-0.0262 (-1.8968)	3.5674 (1.1628)	-1.3637 (-1.4815)	0.0222 (0.1949)

Notes: 1) Variables in the first row are dependent variables.
2) Variables in the first column are independent variables.
3) ** Significant at 5% or better, and *t*-values are in the parentheses.
4) Constant terms are available on request.
Source: Compiled by the authors.

The lag length is chosen by the Schwarz information criterion (SIC) and Akaike information criterion (AIC), both of which slightly favors 1 over other numbers. Given that series are likely against the assumption of homoscedasticity, we make an attempt to set up a low-order VAR model with different lag length. Since various specifications fail to converge, the lag length (p=1) is selected.

Conditional mean models are employed to analyze return spillover effects across different markets or within the same market. As shown in Table 3, confirmed cases are influenced by its own lag, exogenous to financial markets. In addition to its own impacts, the current stock market return depends on the one-period lagged growth in number of infections and dollar index. There is no evidence of spillover effects from *usa_gr* or *ted_d* to FX market. *ted_d* is unaffected by itself as opposed to the other three variables, but depending solely on the past returns in stock market.

Taking a close look at off-diagonal elements, only unidirectional spillovers from infections to financial markets can be found, while there is a bidirectional linkage between stock and FX market. Beyond that, no significant spillover effects are detected. Coupled with signs, escalating cases are expected to lower one-period-ahead stock market returns. A bullish (bearish) stock market will exacerbate (mitigate) *ted_d,* to a certain extent. FX returns exhibit an inverse trajectory against the stock market. In other words, past positive returns in stock market are more likely to aggravate losses in the FX market in the current period, while negative returns in the stock market probably enhance yields in FX market.

Table 4. Estimation Results for the Conditional Variance Model (US)

Coefficient Matrix *A*[1)]				
	usa_gr[4)]	*sp_gr*	*usd_gr*	*ted_d*
usa_gr[5)]	0.5009**[6)]	-5.7882	0.6879	0.0457
	(6.0618)	(-1.7130)	(0.8033)	(1.1868)
sp_gr	0.0012	0.3220**	-0.0024	0.0059**
	(3.6379)	(3.0087)	(-0.1255)	(2.5516)
usd_gr	-0.0006	-0.1656	0.5262**	-0.0046
	(-0.6907)	(-0.3383)	(3.7785)	(-0.5915)
ted_d	-0.0439	1.5285**	-1.9139	0.2874**
	(-2.8177)	(2.6673)	(-1.4912)	(3.2574)
Coefficient Matrix *B*[2)]				
	usa_gr	*sp_gr*	*usd_gr*	*ted_d*
usa_gr	0.7346**	3.4173	-0.1298	-0.0719
	(14.1037)	(1.2508)	(-0.2047)	(-1.0213)
sp_gr	-0.0002	0.3770**	0.0672**	-0.0032**
	(-1.0371)	(4.0286)	(3.1975)	(-2.2644)
usd_gr	-0.0001	0.8245	0.5671**	-0.0146
	(-0.1338)	(1.4028)	(4.1280)	(-1.5931)
ted_d	-0.0127	-2.6293**	2.9325**	0.2655**
	(-1.0297)	(-4.8774)	(2.8019)	(3.4167)
Coefficient Matrix *D*[3)]				
	usa_gr	*sp_gr*	*usd_gr*	*ted_d*
usa_gr	0.0676	8.8990	1.6199	-0.095
	(0.4243)	(1.1790)	(0.8815)	(-0.7678)
sp_gr	-0.0007	0.3932**	0.0124	-0.0174**
	(-1.6138)	(2.8394)	(0.4433)	(-4.7869)
usd_gr	0.0015	0.9410**	0.1317**	0.0222
	(0.7963)	(4.0896)	(2.6602)	(1.6004)
ted_d	0.0015	-1.8203	2.3162	1.2659**
	(0.0434)	(-1.5888)	(0.8732)	(4.7638)
Shape		4.4900**		
		(5.0978)		
Usable obs.		123		

Log likelihood	417.11
Multivariate Q(10)[7)]	135.68 (0.9188)
Multivariate ARCH(2)[7)]	237.38** (0.0362)

Notes: 1) Estimated ARCH parameters, see text for details.
2) Estimated GARCH parameters, see text for details.
3) Estimated asymmetric parameters, see text for details.
4) Variables in horizontal lines are response variables.
5) Variables in vertical lines are shock variables.
6) ** Significant at 5% or better, and *t*-values are in the parentheses.
7) Model diagnostics, see text for details.
8) Constant terms are available on request.
Source: Compiled by the authors.

Conditional variance models are defined as the transmission of volatility from market to market, and the results related to the US are demonstrated in Table 4. As expected, the diagonal parameters in Matrix *A* are statistically significant, which provides sufficient evidence that the volatility in all series responds significantly to their own past innovations. As far as the magnitude is concerned, the past returns to the current conditional variances in FX market top the list, followed by confirmed cases, stock market and TED spread[3]. Furthermore, the present variance of confirmed cases depend merely on its own lagged innovations, as does the FX market. Past shocks in the stock market and TED spread have an effect on their own variances, and bi-directional ARCH effect between two markets can be inferred. Apart from the aforementioned, neither unidirectional nor bi-directional ARCH effect remains across the financial markets.

According to GARCH parameters, we found that the responses of volatility in each series are significantly influenced by their own past volatility. To be more specific, the response of volatility in confirmed cases to its own past volatility is 0.5396. The analogue values in the financial markets are 0.1421 (stock market), 0.3216 (FX market) and 0.0705 (TED spread), respectively. Additionally, there are no GARCH effects from confirmed cases to financial markets, and vice versa. Unlike ARCH parameters, the FX market's volatility is influenced by previous volatility in stock market, TED spread and its own market simultaneously. The growth rate in the dollar index tends to fluctuate more intensely under the volatility shock from TED spread.

As to asymmetric parameters, financial series without exception are affected by their own asymmetric shocks. The volatility under a negative shock (bad news) is greater than that under a positive shock (good news) in that all coefficients are significantly positive.

[3] It can be derived by the quadratic terms of ARCH parameters.

Interestingly, there is no evidence to substantiate asymmetric shock effects of confirmed cases on the financial markets — that is — whether the status quo of COVID-19 pandemic improves or worsens, it will not mitigate or intensify the volatility of financial market in the near future. In addition, the stock market is characterized by the FX market's asymmetric shocks. External shocks in the FX market have unidirectional asymmetric effects on TED spread. Note that, the shape parameter is statistically significant at 1%, implying the presence of fat-tailed conditional residuals.

The residuals from the model, in principle, should be neither serially correlated nor exhibiting remaining ARCH effects. Both multivariate Q test and multivariate ARCH test are diagnostics for the multivariate GARCH model and its variations. The former doesn't reject the null hypothesis, showing it to be serially uncorrelated. Despite the fact that the latter test fails to hold the adequacy of the model at conventional significance level, lack of evidence support misspecification under 1%.

Table 5. Estimation Results for the Conditional Mean Model (South Korea)

	kor_gr[1)]	*kospi_gr*	*krw_gr*	*korted_d*
kor_gr(-1)[2)]	0.7699**[3)] (17.2541)	-3.8705** (-4.7280)	1.1826** (5.3525)	0.0501** (12.0992)
kospi_gr(-1)	0.0002 (1.4467)	0.2271** (3.5843)	-0.0277 (-1.2228)	0.0015** (2.0252)
krw_gr(-1)	0.0005 (1.0127)	0.5904** (2.5666)	-0.1396 (-1.6676)	0.0009 (0.3927)
korted_d(-1)	0.0136 (1.3831)	2.4461** (4.2186)	-4.7595 (-1.7929)	-0.3723** (-5.5050)

Notes: 1) Variables in the first row are dependent variables.
2) Variables in the first column are independent variables.
3) ** Significant at 5% or better, and *t*-values are in the parentheses.
4) Constant terms are available on request.
Source: Compiled by the authors.

In the same vein, estimation results in Table 5 can be interpreted as follows: (i) Except for FX market returns, the rest of series are affected by their own lags at 1% significance level. (ii) The growth rate in confirmed cases exerts mean spillover effects on financial markets and not vice versa, which implies the presence of unidirectional causality. (iii) Although the presently weaker South Korean won will fuel stock market in the future, the inverse does not hold because the coefficient (φ_{23}) is insignificant at the conventional level. (iv) There is a positive bi-directional spillover effect between the change rate in TED spread and stock market returns. (v) The FX market and TED spread are mutually exogenous in the system.

Table 6. Estimation Results for the Conditional Variance Model (South Korea)

Coefficient Matrix *A*[1]				
	kor_gr[4]	*kospi_gr*	*krw_gr*	*korted_d*
kor_gr[5]	0.3763**[6] (2.9510)	4.3043 (1.5990)	-0.2670 (-0.2075)	-0.0082 (-0.2978)
kospi_gr	-0.0004 (-1.2727)	-0.2179** (-2.3734)	-0.0483 (-0.9407)	0.0014 (1.0051)
krw_gr	-0.0005 (-0.6542)	1.7848** (4.6521)	-0.4871** (-4.1335)	-0.0108** (-2.1226)
korted_d	-0.0163 (-1.0089)	-6.0827** (-6.0608)	1.5547** (3.6011)	0.7658** (5.5665)
Coefficient Matrix *B*[2]				
	kor_gr	*kospi_gr*	*krw_gr*	*korted_d*
kor_gr	0.7040** (10.5250)	7.7063** (2.3887)	-2.5912 (-1.5529)	-0.0059 (-0.1826)
kospi_gr	-0.0002 (-1.2524)	-0.0123** (-2.0825)	0.2455** (3.9468)	-0.0021** (-2.8101)
krw_gr	-0.0005 (-1.2559)	-0.2809 (-0.4379)	0.7306** (3.2117)	0.0005 (0.1509)
korted_d	0.0176 (1.7510)	3.3857** (5.7817)	-5.3707 (-1.8492)	0.3163** (5.6875)
Coefficient Matrix *D*[3]				
	kor_gr	*kospi_gr*	*krw_gr*	*korted_d*
kor_gr	-0.0425 (-0.2682)	-5.7733** (-3.0604)	1.9180** (2.9866)	0.5517** (2.6858)
kospi_gr	-0.0001 (-0.3795)	0.7828** (5.1744)	-0.1418** (-2.7060)	0.0062** (3.1779)
krw_gr	0.0009 (1.1814)	0.0804 (0.1332)	0.1847 (0.9146)	0.0007 (0.1471)
korted_d	-0.0177 (-1.0271)	2.5837 (1.8871)	-1.7910** (-3.4814)	-0.6161** (-3.6388)
Shape		7.9750** (3.7512)		
Usable obs.		113		

Log likelihood	612.46
Multivariate Q(10)[7)]	165.79 (0.3605)
Multivariate ARCH(2)[7)]	250.30** (0.0101)

Notes: 1) Estimated ARCH parameters, see text for details.
2) Estimated GARCH parameters, see text for details.
3) Estimated asymmetric parameters, see text for details.
4) Variables in horizontal lines are response variables.
5) Variables in vertical lines are shock variables.
6) ** Significant at 5% or better, and *t*-values are in the parentheses.
7) Model diagnostics, see text for details.
8) Constant terms are available on request.
Source: Compiled by the authors.

Consistent with the findings in the US, all diagonal elements in upper panel (Table 6) are significant at 1%, and confirmed cases exhibit exogeneity within the system. However, the linkage across financial markets in South Korea seems to be more interactive in terms of significance of off-diagonal coefficients. With regard to GARCH effects, the only difference is the significance level of the persistence parameter $B(4,3)$.

Particular attention will be paid to asymmetry. The lower panel demonstrates financial markets are closely related to spreading trend of COVID-19. More precisely, in comparison with a positive event (e.g., a major breakthrough made in vaccine R&D), an unanticipated negative shock to confirmed cases (e.g., cluster infection) could spark greater fluctuations in the financial markets.

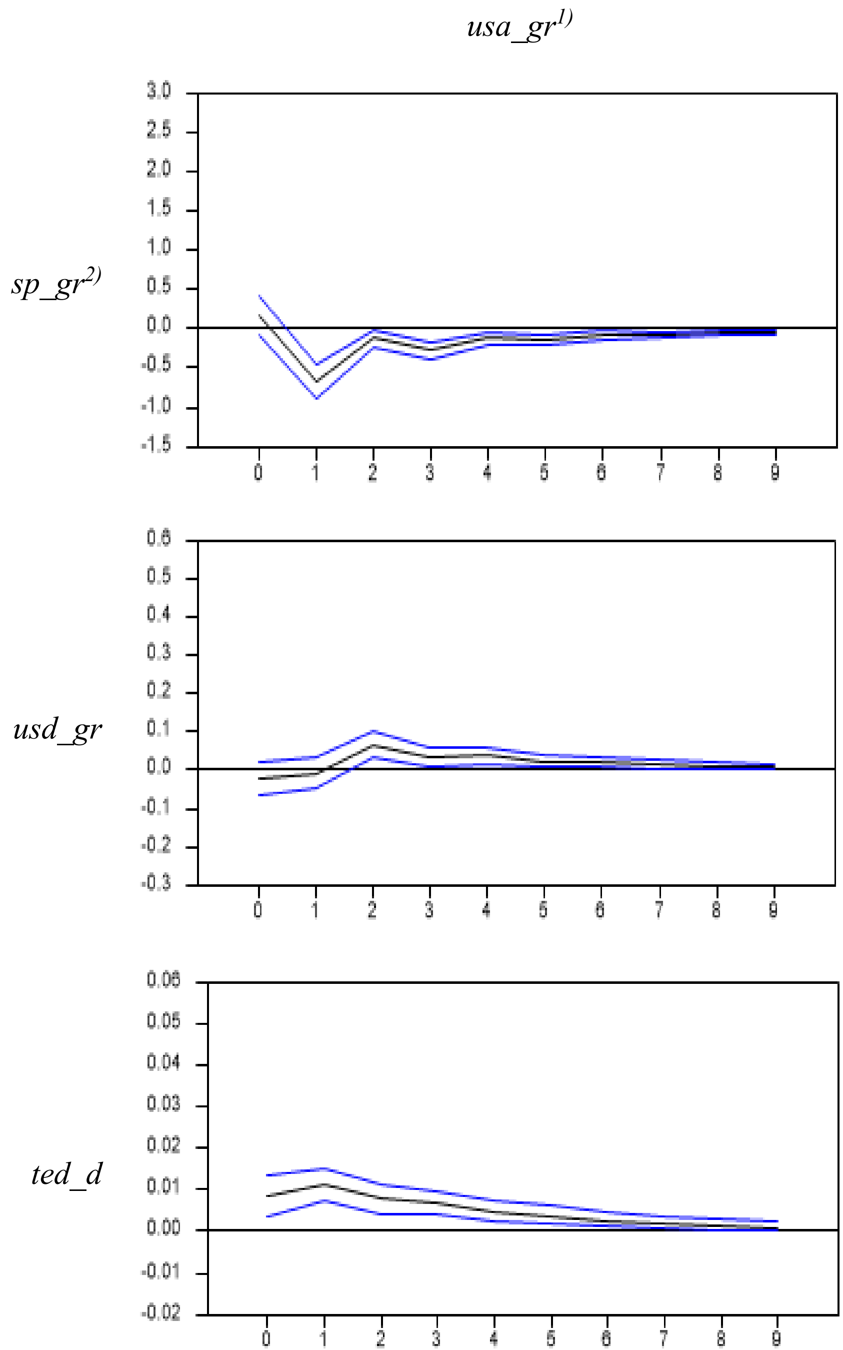
4.2 Impulse Response Functions (IRFs)

Despite generalized impulse response functions (GIRFs)[4] being invariant to the ordering of the variables, the results are subject to strict assumptions. To prevent misleading statistical inference (Kim, 2013), we employ the IRFs to map out how the system reacts to specific isolated shocks. Prior to orthogonalization of the covariance matrix, we need to be satisfied that the residuals are correlated. On the one hand, the confirmed cases empirically and theoretically have an impact upon financial markets, and not vice versa. The transmission mechanism across financial markets is ambiguous on the other. Consequently, with the Choleski factorization in the following order: growth rate in confirmed cases, stock market returns, FX market returns followed by change rates in TED spread, Figures 3 and 4 demonstrate responses to a common shock with Monte Carlo error

[4] Koop et al. (1996).

bands[5]. Our results are robust since the IRFs with different orderings are quite similar[6].

Figure 3. Impulse Response Functions with Monte Carlo Error Bands (US)



Notes: 1) Variable in the first row is impulse variable.
2) Variables in the first column are response variables.

5 Number of Monte Carlo draws is 10,000.

6 Available upon request.

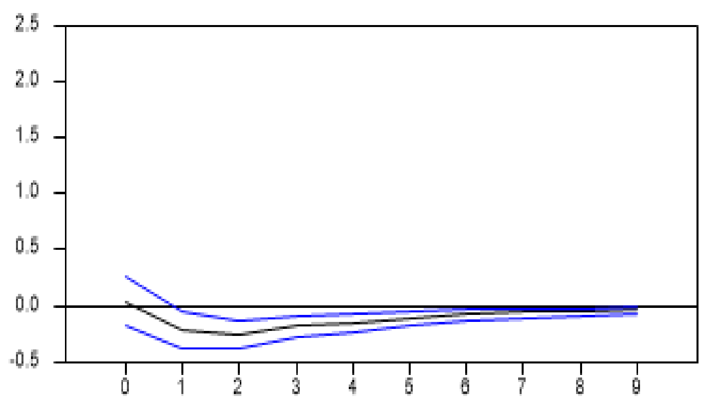
In the US, the response of the stock market to shocks in confirmed cases is positive but insignificant in the initial stage, then it reaches a trough on the next day followed by slight oscillation along the horizontal line. Given that all series are in percentages, a 1% shock to confirmed cases is likely to produce no more than a 0.75% response in the stock market over the sample period. Response of the dollar index to confirmed cases is barely significant throughout the whole period. With a 1% positive shock from confirmed cases, the TED spread begin to rise, and subsequently peak on the second trading day. The bond market is least affected by infections, hovering below 0.01% over the horizon (see Figure 3).

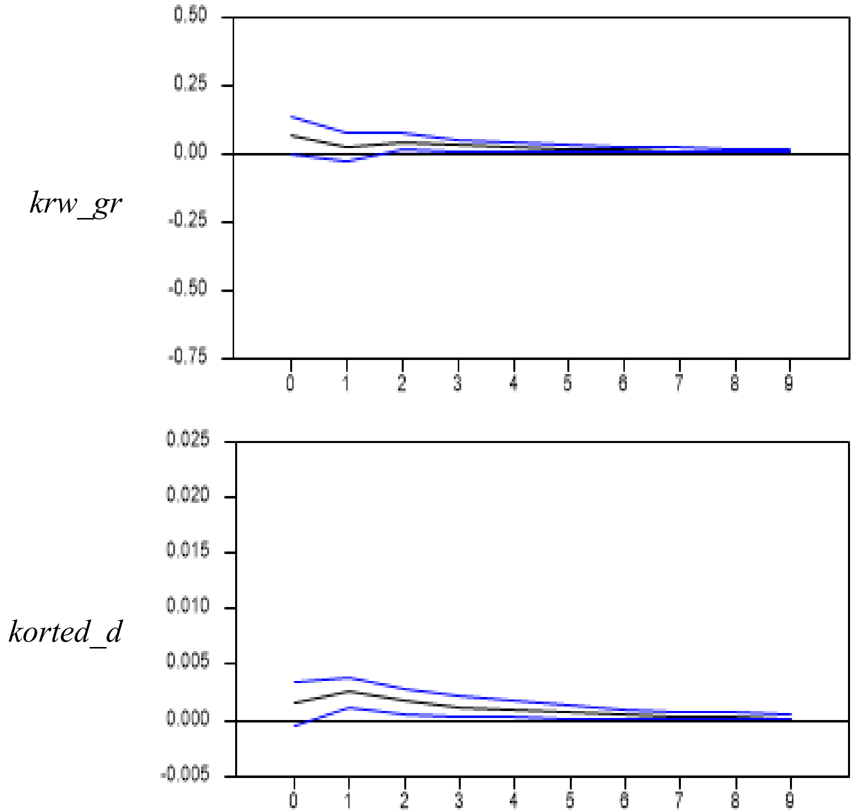
As shown in Figure 4, the response of the South Korean stock market returns is significantly negative before dying out. On the other hand, the South Korean won undergoes an ascending trend, reflecting depreciation against US dollar. Confirmed cases have significant positive effects on TED spread, even though the response mildly and steadily declines from the second period. The response of the stock market (-0.25%) is greater than the exchange rate (0.10%), followed by TED spread (0.003%) in terms of magnitude at the peak point.

Figure 4. Impulse Response Functions with Monte Carlo Error Bands (South Korea)

kor_gr[1)]

kospi_gr[2)]





Notes: 1) Variable in the first row is impulse variable.
2) Variables in the first column are response variables.

Investment behavior is closely associated with investors' risk preferences and expectations of economic outlook, through which the pandemic plays a vital role in the financial markets. As risk aversion has spiked amid escalating concerns over uncertainty, a flight-to-safety episode is underway. Given this, countries considerably resilient to external shocks are more attractive to global capital flows, which is one of the main determinants driving the exchange rate. Conversely, financial markets being filled with pessimistic or panic sentiments stand a chance of a broad fear-driven sell-off, followed by currency depreciation. Similarly, domestic and foreign investors snapping up safe-haven financial assets could wreak havoc upon an economy, accompanied with a slump in stock returns and increasing credit spreads. This theoretical framework helps to explain what we observed under the onslaught of COVID-19. However, there is a major difference in FX market between two economies. The depreciation of South Korean won results in part from a capital outflow tsunami, which seems incapable of illustrating dollar index movements under innovations. One conceivable interpretation is that the liquidity unleashed by QE neutralizes a surging demand for US dollar.

5. Concluding Remarks

This study facilitates a full-scale comparison between the US and South Korea in the financial sector amid the COVID-19 pandemic. By applying the VAR-GARCH-BEKK model, our results confirm the presence of negative mean spillovers to the US and South Korean stock markets from the spread of the pandemic. In line with IRFs, the ongoing pandemic crisis will erode stock returns in the foreseeable future, though its long-run impacts dissipate within a certain period. The unidirectional mean spillover effects can be viewed from pandemic outbreaks to currency market and bond market in South Korea, an EME with relatively weak financial system soundness. However, from the perspective of coefficients in conditional mean model, the US dollar and TED spread seem intact, thanks partly to synergy between liquidity drain and replenishment. Specifically, the trajectory of *usd_gr* and *ted_d* corroborate dollar depreciation, widening TED spread under external shocks, respectively. Meanwhile, Out of risk aversion, both the public and private sector are enthusiastic about purchasing dollar-denominated financial assets. Besides, there is little evidence to support the presence of volatility transmission from pandemic to financial markets in two countries.

So far, the snowballing confirmed cases and deaths related to COVID-19 have been amplifying panic among the public. Owing to great uncertainty over severity and duration, the extent of the impact which the ongoing pandemic will have on the global financial markets remain unclear. As previously discussed, chaos and turbulence in the time of COVID-19 are mainly in the form of descending stock indices, soaring credit premiums, and deteriorating liquidity in the FX markets, exposing the fragility of an economy (IMF, 2020). Against this background, governments and central banks resort to fiscal stimulus package and monetary policy to insulate short-term disruptions from being trapped in long-lasting turmoil. However, maintaining a delicate balance between steady economic growth and financial markets stability is likely to be a puzzle to policymakers and regulators.

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