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A Note on the Asian Market Volatility During the COVID-19 Pandemic

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This paper provides a note on commonality in volatility for five developed Asian economies, namely Hong Kong, Japan, Russia, Singapore and South Korea. Additionally, we examine whether the COVID-19 pandemic changed the commonality in volatility within the Asian region. Overall, we find that commonality in volatility during the COVID-19 period is more prominent in the case of Singapore compared to other four economies.

I. Introduction

This note provides evidence on the role of COVID-19 in influencing commonality in volatility in five developed Asian economies, namely the special administrative region of the Peoples Republic of China, Hong Kong (HK), Japan, Russia, Singapore, and South Korea (S. Korea). In other words, we examine whether market volatility at the Asian regional level can explain stock market volatility at the country-level. Recent studies have shown that the COVID-19 pandemic has significantly affected global economies; see, for instance, Mishra et al. (2020), Salisu & Akanni (2020), Chen et al. (2020), Wang et al. (2020), Yue et al. (2020), Yu et al. (2020), Xiong et al. (2020), Shen et al. (2020), Gu et al. (2020), Haroon & Rizvi (2020), Iyke (2020), He et al. (2020), and Liu et al. (2020). According to Sha & Sharma (2020) and Phan & Narayan (2020), the COVID-19 pandemic represents the largest and most disturbing shock to the global economic system and it is therefore important to understand whether the country level volatility can be determined by the regional level stock market volatility.

Our hypothesis is motivated by evidence in the literature that aggregate stock market volatility explains sectoral level volatility (see Sharma et al., 2014). In other words, Sharma et al. (2014) hypothesize that volatility at an aggregate level can exert a "spillover effect" and/or a "contagion" effect at the disaggregate (firm) level. However, it has not been examined whether the volatility "spillover effect" and/or "contagion effect" exists during periods when stock markets are more vulnerable and volatile due to the obvious structural shifts, such as those observed as a result of the COVID-19 pandemic (see Devpura et al., 2019; and Zhang et al., 2020). Spillover is defined as a situation where a dominating market leads to a change in the less dominated market. An aggregate regional stock market, therefore, is a composite function of the number of stock markets in the region and, therefore, the country-level market and the aggregate regional market share some economic ties (see Sharma et al., 2014). Thus, volatility spillover occurs when volatility originates in the region and spills over to all the stock markets within that region. On the other hand, Forbes and Rigoben (2002, p. 2224) define contagion as "*it is only contagion if cross-market movements increase significantly after the shock*". In fact, a number of studies have argued that there is a significant increase in the degree of co-movement between stock returns in different countries following a shock (see for instance, Rigobon, 2003; Rodriguez, 2007).

Thus, our idea of examining commonality in volatility is important and also it is unique because we test whether commonality in volatility in the Asian stock markets observed during the pre-COVID-19 period remains also during the COVID-19 period. By doing so, our study contributes to two sets of literatures: (a) studies which examine the relationship between aggregate market volatility and firm level volatility; and (b) studies which examine the influence of COVID-19 on the stock market. First, we contribute by providing evidence that regardless of the volatility measure employed, the regional level market volatility has a statistically significant effect on country level volatility. Second, we contribute, by showing that the COVID-19 pandemic has a heterogenous effect on country level volatility. In the case of Singapore, for instance, we show that stock market volatility is strongly influenced by the aggregate Asian regional level market volatility during the COVID-19 pandemic period, whereas for the remaining four Asian economies, the overall effect is dependent on different proxies for volatility.

The balance of the paper is organised as follows. In the next section, we discuss data and provide a discussion on the empirical model. Section III discusses the main findings; and, in the final section, we provide some concluding remarks.

II. Data and Methodology

A. Data

In this section, we describe our dataset. In order to compute stock market volatility, we extract daily data on high price (HP), low price (LP), opening price (OP), and closing price (CP) of the Nikkei 225 stock index (Japan), the MOEX Russia index (Russia), the Heng Seng price index (HK), the Straits Times index (Singapore), and the Korea Se Composite price index (S. Korea). All price data are sourced from DataStream.

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Table 1: Data description and descriptive statistics

Panel A: Data description

Variable	Description
V_1	Parkinson (1980) approach: $V_1 = 0.361\left[\ln\left(\frac{HP}{LP}\right)\right]^2$
V_2	German & Klass (1980) approach: $V_2 = 0.5[\ln(HP) - \ln(LP)]^2 - [2\ln 2 - 1][\ln(CP) - \ln(CP)]^2$
V_3	Rogers & Satchell (1991) and Rogers et al. (1994) approach: $V_3 = [\ln(HP) - \ln(OP)][\ln(HP) - \ln(CP)] + [\ln(LP) - \ln(OP)][\ln(LP) - \ln(CP)]$
$MV1$, $MV2$, and $MV3$	Aggregate five Asian stock market volatility which is measured as follows: $MV1 = \sum_{i=1}^{n} V_{1i}$; $MV2 = \sum_{i=1}^{n} V_{2i}$; and $MV3 = \sum_{i=1}^{n} V_{3i}$. Note $n = 5$ which represents five Asian economies.

Panel B: Descriptive statistics

	Variable	Mean	Maximum	Minimum	Std. Dev.	Skewness	Prob of JB	Prob of ADF test	Sample size
	V_1	0.0001	0.0112	0.0000	0.0002	23.6262	0.0000	0.0000	
HK	V_2	0.0001	0.0104	0.0000	0.0002	23.4007	0.0000	0.0000	01/03/2000 – 09/25/2020 (5410 obs.)
	V_3	0.0001	0.0089	0.0000	0.0002	18.3253	0.0000	0.0000	
	V_1	0.0001	0.0068	0.0000	0.0002	12.6354	0.0000	0.0000	
Japan	V_2	0.0001	0.0061	-0.0004	0.0002	12.9398	0.0000	0.0000	01/03/2000 – 09/25/2020 (5410 obs.)
	V_3	0.0001	0.0092	-0.0000	0.0002	16.4319	0.0000	0.0000	
	V_1	0.0003	0.0274	0.0000	0.0009	14.3004	0.0000	0.0000	
Russia	V_2	0.0003	0.0164	-0.0006	0.0007	11.3217	0.0000	0.0000	01/08/2005 – 09/25/2020 (4623 obs.)
	V_3	0.0003	0.0205	-0.0005	0.0008	11.3925	0.0000	0.0000	
	V_1	0.0001	0.0055	0.0000	0.0002	13.7248	0.0000	0.0000	
Singapore	V_2	0.0001	0.0033	-0.0012	0.0002	9.9344	0.0000	0.0000	01/15/2008 – 09/25/2020 (3314 obs.)
	V_3	0.0001	0.0030	-0.0009	0.0002	8.9938	0.0000	0.0000	
	V_1	0.0001	0.0091	0.0000	0.0003	13.2155	0.0000	0.0000	
S. Korea	V_2	0.0001	0.0102	-0.0010	0.0003	14.6427	0.0000	0.0000	01/03/2000 – 09/25/2020 (5410 obs.)
	V_3	0.0001	0.0098	-0.0022	0.0003	12.0419	0.0000	0.0000	
$MV1$		0.0001	0.0064	0.0001	0.0002	14.7244	0.0000	0.0000	
$MV2$		-0.0044	0.0059	-0.1741	0.0209	-0.0001	0.0000	0.0001	
$MV3$		0.0001	0.0133	-0.0152	0.0009	1.7221	0.0000	0.0001	

In panel A of this table, we provide detailed description of data used in this study. Panel B reports descriptive statistics (mean, maximum, minimum, standard deviation (Std. Dev.), skewness, the probability of Jarque-Bera (JB) test which examines the null hypothesis of normality, and the ADF (1981) unit root test results (the probability of the null hypothesis that there is a unit root). The last column notes the sample period for each country.

To test the efficiency of volatility measures in our data and also the robustness of our results, we use three very common volatility measures which have been used in many insightful papers (see, for example, Sharma et al., 2014). Volatility measures at the country level and for the five aggregate Asian economies are defined in Panel A of Table 1.

B. Methodology

According to Sharma et al. (2014), the main focus of previous studies has been on measuring individual volatility regarding the firm or the market and the literature has established an analytical framework which links the volatility of the market as the collective volatility of firms that make up the market. Using their analytical framework, we propose that the country-level market volatility in the Asian region is essentially the collective volatility of markets that make up the region. The following time-series regression model is, therefore, employed:

$$V_{c,t} = \alpha + \beta_1 V_{r,t} + e_t \qquad (1)$$

$$h_t^2 = \gamma + \delta_1 e_{t-1}^2 + \delta_2 h_{t-1}^2 \qquad (2)$$

$$e_t = h_t \vartheta_t \$; \$\vartheta_t \sim N(0,1) \qquad (3)$$

In these equations, V_c represents volatility at the country level and V_r represents volatility at the region level, which is simply the sum of volatilities of the five Asian economies. We estimate Equation (1) using a standard GARCH (1,1) model by considering four sample periods to draw conclusions of the effects of the COVID-19 pandemic on Asian economies. Our first sample covers the full sample period (each country has a different start date, but the end date is the same, which is 09/25/2020). The second sample covers the period till 12/30/2019 and we refer to this as the pre-COVID-19 sample. The third sample contains data for the COVID-19 period (12/31/2019 – 09/25/2020) and for the final sample, we match the COVID-19 sample with a pre-COVID-19 sample in order to maintain the same number of observations (01/01/2019 – 12/30/2019). It is also important to note that given we use three different measures of volatility, we estimate Equation (1) three times for each country using different sample periods. A log likelihood function is maximised on the assumption of conditional normality of the country level volatility shock, e_t, and we derive the statistical significance based on the procedure recommended by Bollerslev & Wooldridge (1992). Equation (2) represents the variance equation of the GARCH estimation approach.

III. Results

A preliminary analysis of the data is presented in Panel B of Table 1. First, we note that regardless of the volatility measure, the null hypothesis of a unit root based on the ADF (1981) test is rejected at the 1% statistical significance level for all five Asian economies. This implies that all variables follow a stationary process. Second, we note that the mean value of all three volatility measures for all Asian economies is in the range 0.0001 – 0.0003; however, the skewness statistics are different for different measures of volatility. This implies that the Asian markets are different and aggregate volatility maybe connected to the country level volatility differently.

Next, we move to our main findings. The results pertaining to the commonality in volatility for each of the five Asian economies are reported in Table 2. Three sets of results are reported which are simply based on the use of three different measures of volatility. First, in Panel A results are based on the first measure of volatility, V_1. We note that in the case of Japan, Singapore, and S. Korea the impact of aggregate Asian regional market volatility on country-level volatility is greater during the COVID-19 period compared to the two pre-COVID-19 periods. However, the impact of Asian regional market volatility on country level volatility of HK and Russia is found to be more prominent when the COVID-19 period is excluded. In other words, our findings suggest that during the COVID-19 pandemic, there are potentially other factors which can better explain the country-level volatility of HK and Russia, while for Japan, Singapore and S. Korea, the commonality in volatility is much stronger during the COVID-19 period.

Next, when we consider the other two measures of volatility, we find that only in the case of Singapore, the estimated coefficient of regional market volatility is greater during the COVID-19 period. For the remaining four Asian economies, we find that the regional market volatility explains country-level volatility much better during pre-COVID-19 periods.

Overall, we note that regardless of the use of different measures of volatility, the aggregate Asian regional market volatility has a statistically significant effect on country-level market volatility for all five developed Asian economies. However, the strength of commonality in volatility is not only country-dependent but sensitive to different measures of volatility.

IV. Concluding remarks

There is limited work done with respect to “spillover” and/or “contagion effect” between market volatilities at aggregate and disaggregate levels. The shock to the global economy from COVID-19 has been faster and more severe. Markets have become volatile as a result of the pandemic. We, therefore, examine whether aggregate regional level market volatility has a significant effect on country-level market volatility in the case of five developed Asian economies. Using daily data, we show that there exists a significant relationship between Asian regional level stock market volatility and country-level stock market volatility. Additionally, we also report that in the case of Singapore, the regional level market volatility is more stronger during the COVID-19 period compared to pre-COVID-19 periods.

We would like to acknowledge that one limitation of our work is that we do not explain why the commonality in volatility increased only in the case of Singapore during the COVID-19 period compared to the other four Asian economies. Future studies can include other factors in the model and examine the robustness of our findings and may provide some insights on why the case of Singapore is different from the other Asian economies.

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Table 2: Results on commonality in volatility

		Hong Kong	Japan	Russia	Singapore	South Korea
Panel A: V_1	Full Sample	0.1086*** (0.0000)	0.1692*** (0.0000)	0.3483*** (0.0000)	0.0539*** (0.0000)	0.1094*** (0.0000)
	Pre-COVID19 Sample 1	0.1051*** (0.0000)	0.1687*** (0.0000)	0.3593*** (0.0000)	0.0414*** (0.0000)	0.1082*** (0.0000)
	Pre-COVID19 Sample 2	0.3478*** (0.0000)	0.1139*** (0.0000)	0.1355*** (0.0000)	0.1071*** (0.0000)	0.2432*** (0.0000)
	COVID19 sample	0.1256*** (0.0000)	0.2516*** (0.0000)	0.1639*** (0.0000)	0.1327*** (0.0000)	0.3084*** (0.0000)
Panel B: V_2	Full Sample	0.1209*** (0.0000)	0.1001*** (0.0000)	0.4384 (0.0000)	0.0626*** (0.0000)	0.0853*** (0.0000)
	Pre-COVID19 Sample 1	0.1204*** (0.0000)	0.0983*** (0.0000)	0.5883*** (0.0000)	0.0598*** (0.0000)	0.1052*** (0.0000)
	Pre-COVID19 Sample 2	0.2616*** (0.0000)	0.2650*** (0.0000)	0.1340*** (0.0000)	0.0733*** (0.0000)	0.2636*** (0.0000)
	COVID19 sample	0.1067*** (0.0000)	0.2523*** (0.0000)	0.1481*** (0.0000)	0.1328*** (0.0000)	0.0764*** (0.0000)
Panel C: V_3	Full Sample	0.1186*** (0.0000)	0.0551*** (0.0000)	0.6779*** (0.0000)	0.0369*** (0.0000)	0.0845*** (0.0000)
	Pre-COVID19 Sample 1	0.1189*** (0.0000)	0.0867*** (0.0000)	0.6844*** (0.0000)	0.0384*** (0.0000)	0.0831*** (0.0000)
	Pre-COVID19 Sample 2	0.2137*** (0.0000)	0.4325*** (0.0000)	0.1047*** (0.0000)	0.0643*** (0.0000)	0.2147*** (0.0000)
	COVID19 sample	0.0843*** (0.0000)	0.2977*** (0.0000)	0.2367*** (0.0000)	0.1124*** (0.0000)	0.1507*** (0.0000)

This table reports result based on the following regression model: $V_{c,t} = \alpha + \beta_1 V_{r,t} + e_t$. Here $V_{c,t}$ is country-level market volaility and $V_{r,t}$ represents market volatility at the regional level. We use three measures of volatility, which are defined in Table 1. We estimate the regression model using data for the full sample period, 2 pre-COVID-19 samples and a sample covering the COVID-19 period (12/31/2019 – 09/25/2020). The pre-COVID-19 sample 1 represents data prior to 12/31/2019 (each country has different start dates), whereas the pre-COVID-19 sample 2 contains data from 01/01/2019 – 12/30/2019. Finally, *** represents statistical significance at 1% level.

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