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# Revealing investors' sentiment amid Covid-19: the Big Data evidence based on internet searches[1]

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[1] This presentation was prepared for the WSC. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the event.

# Revealing investors' sentiment amid COVID-19: the Big Data evidence based on internet searches

*Jean Christine A. Armas and Pamela Kaye A. Tuazon*

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- Government Response Stringency Index (GRSI)
- Construction of the Covid-19 Risk Attitude (CRA) Index
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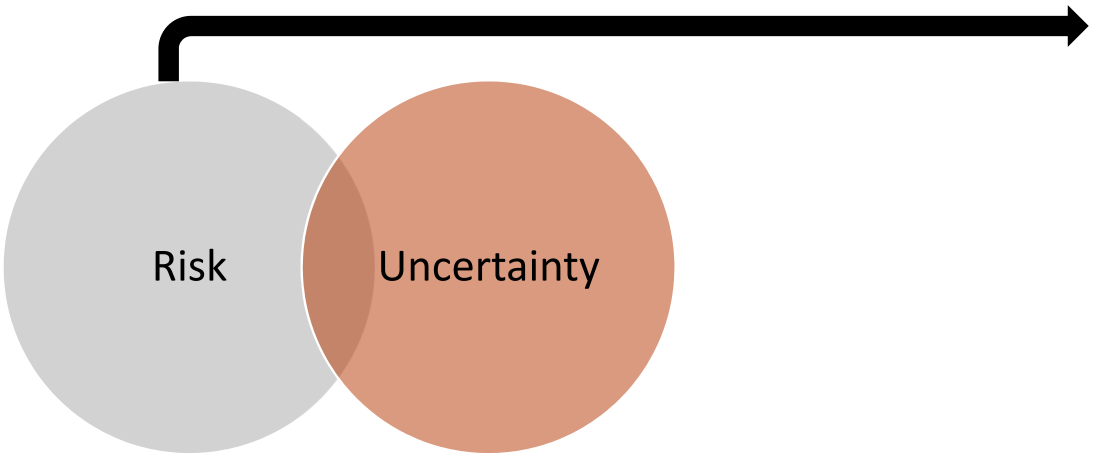
# *Research Objectives*

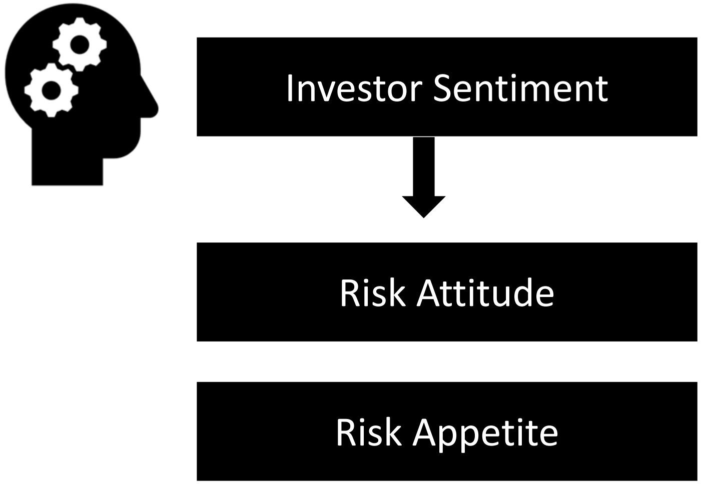
- To test whether or not the claim of Amstad, et al. (2020) that movements in some Asian stock markets not significantly correlated to the CRA index holds true.
- To construct the Covid-19 Risk Attitude (CRA) index for the Philippines and select Asian countries using daily internet-based search queries from 31 December 2019 to 03 July 2020.
- To understand the differential responses of select Asian stock markets, categorized according to the country's income classification, to the pandemic.

## *Related Literature*

***How are stock markets behaving amidst COVID-19?***

***Are investors indifferent, over or under reacting towards this seemingly no-end-in-sight-epidemic?***

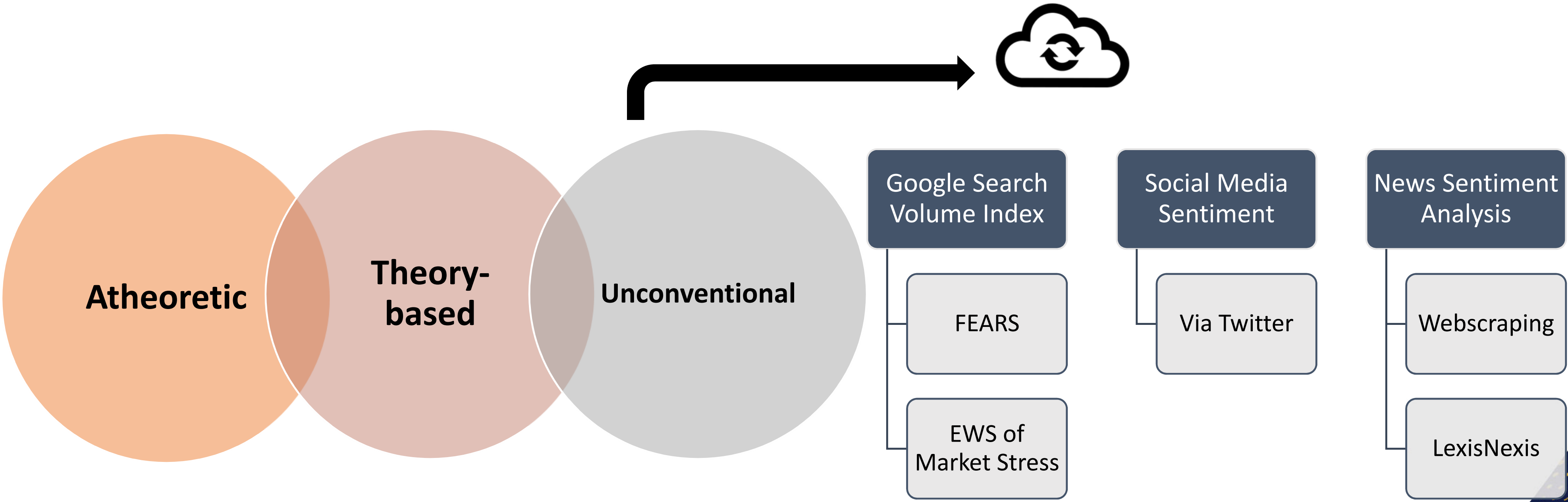


# Related Literature

## *Measuring Investor Risk Appetite*

***What if times are extraordinarily pessimistic?***



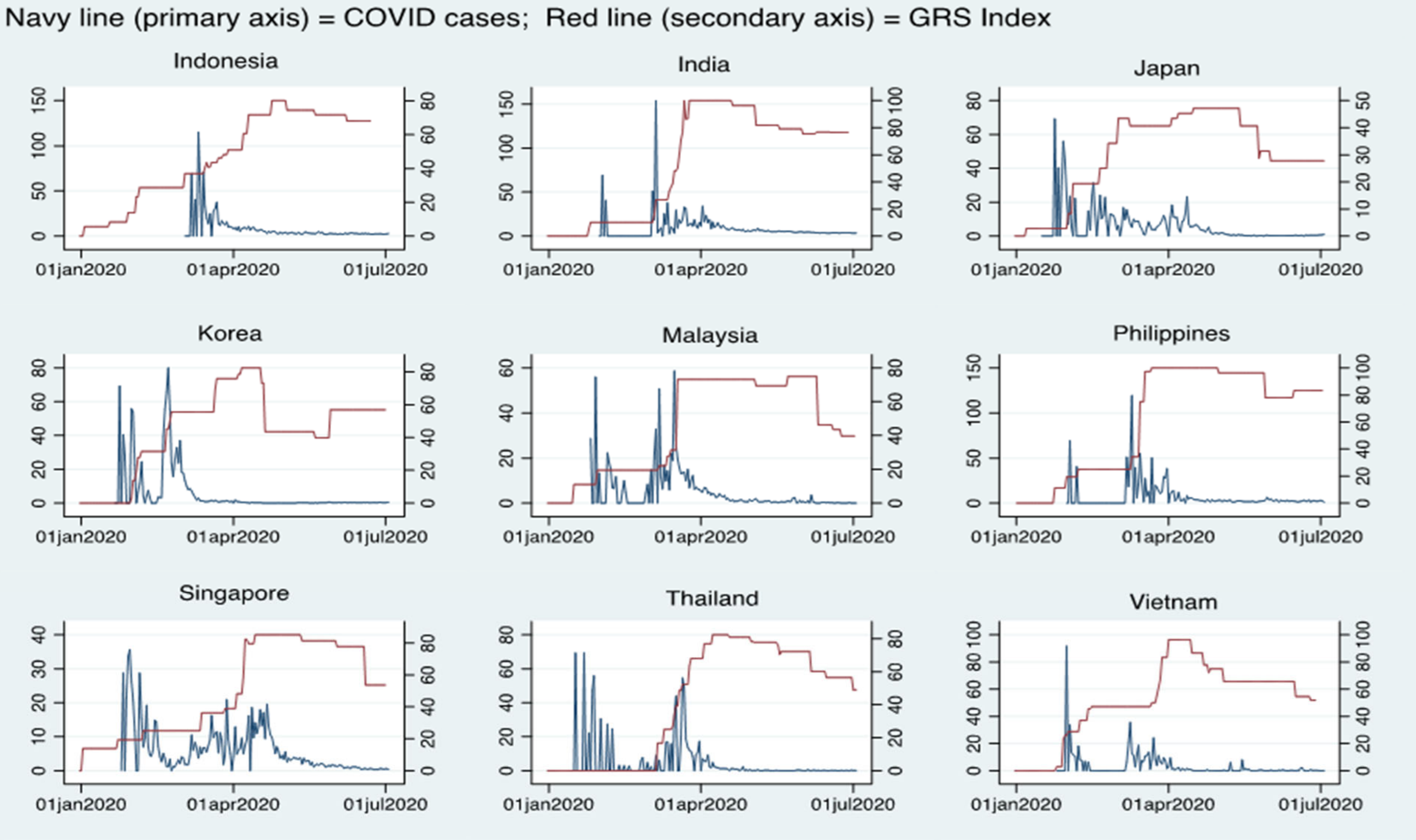
# *Variables and Data Characteristics*

| Variables | Description | Source |
|---|---|---|
| **Stock price index** | Derived as percentage change in the closing prices of major stock index in country $i$ at time $t$. | Thomson Reuters Eikon |
| **Oil price** | Calculated as percentage change in Brent crude oil prices at time $t$. | Federal Reserve Economic Data (FRED) |
| **Number of COVID-19 positive cases** | Measured as percentage change in the number of COVID-19 cumulative cases in country $i$ at time $t$. | European Centre for Disease Prevention and Control (ECDC) |
| **Volatility of stock price index (VIX)** | Computed as change in the market's expectation of 30-day implied volatility in the US stock market at time $t$, which is constructed from S&P 500 option prices. | FRED |

# *Variables and Data Characteristics*

| Variables | Description | Source |
|---|---|---|
| **COVID-19 Risk Attitude (CRA) index** | Measured as change in the CRA index in country $i$ at time $t$. | Google Trends; authors' calculations |
| **Government response stringency index** | Computed as the simple average of the number of measures that each government in country $i$ adopted at time $t$. | Hale, T., Webster, S., Petherick, A., Phillips, T., and Kira, B. (2020), **Oxford COVID-19 Government Response Tracker,** Blavatnik School of Government |
| **Trade-weighted US dollar index (broad)** | Calculated as percentage change in trade-weighted US dollar index at time $t$. | FRED |

# *Government Response Stringency Index (GRSI)*




Source: Oxford Covid-19 Gov't. Response Tracker; Authors' calculations

# Construction of the COVID-19 Risk Attitude (CRA) Index

$$CRA_{i,t} = \frac{1}{K}\sum_{k=1}^{4} SVI_{k,i,t} \qquad eq.(1)$$

Where:

$K$ is the total number of search terms

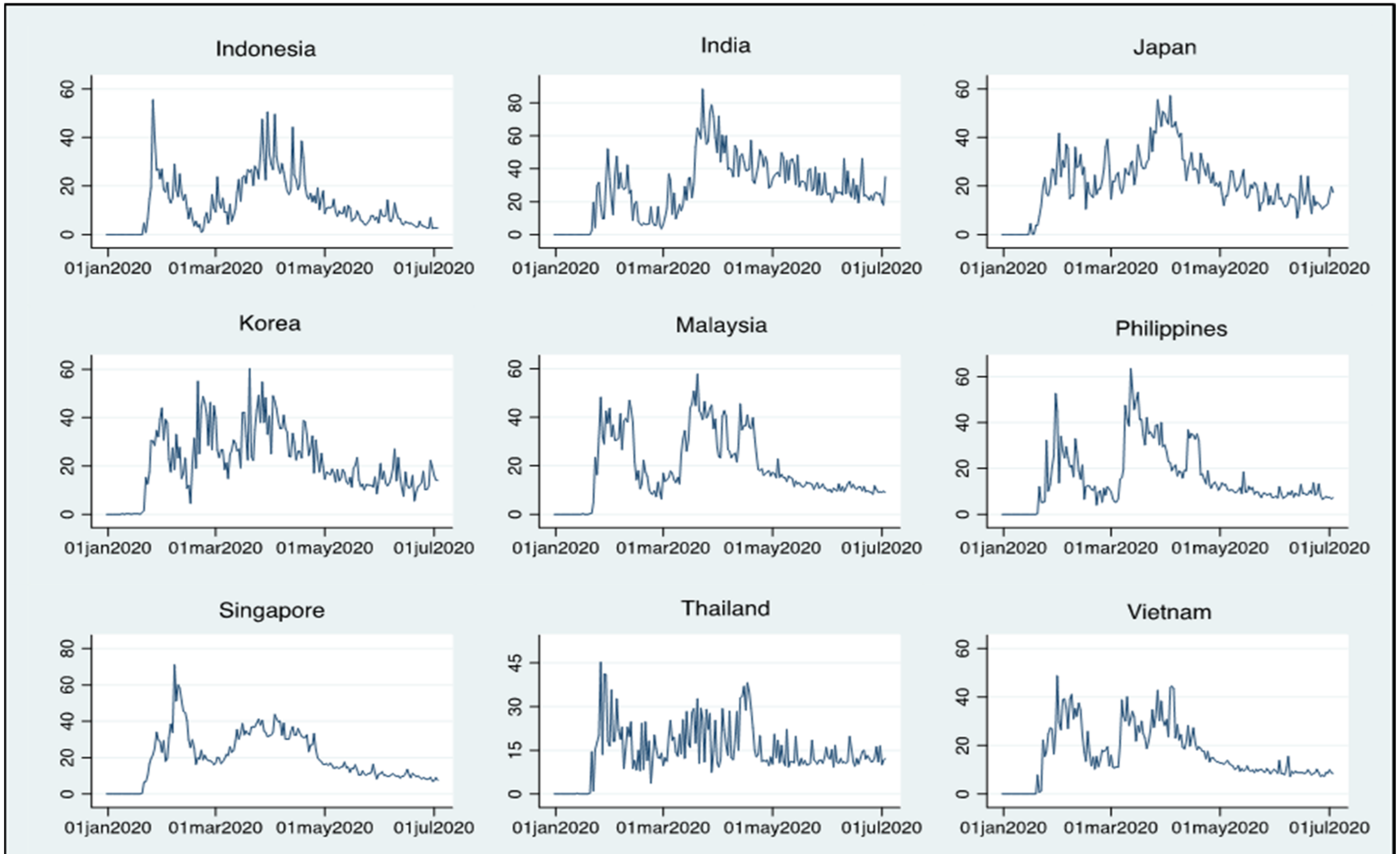
(i.e., coronavirus, COVID-19, 2019-nCoV, nCov)

$i = 1,2, \ldots N$, $N$ is the total number of countries under study

$T$ is the total number of time series observations

$SVI$ is the search volume index, where each query inputted into Google Trends is normalized to 100 for the highest search volume in country $i$ at time $t$.

# Country-Level COVID-19 Risk Attitude (CRA) Index




Source: Authors' calculations; Google Trends

# Model Specifications

## A. Baseline Model

$$\Delta ln(sp_{it}) = \alpha_0 + \beta_1 \Delta ln(op_t) + \gamma_2 \Delta ln(twusd_t) + \varphi_3 \Delta vix_t + \omega_4 \Delta ln(cases_{it}) + \tau_5 \Delta CRA_{it} + \vartheta_i + \mu_{it} \qquad eq.(2)$$

Where:

$\Delta \ln(sp_{it})$ = log difference of stock price index in country $i$ at time $t$ – an approximation to the growth rate of daily stock price index

$\Delta ln(op_t)$ = log difference of Brent crude oil price at time $t$

$\Delta ln(twusd_t)$ = log difference of trade-weighted US dollar index at time $t$

$\Delta vix_t$ = change in the volatility of stock price index

$\Delta ln(cases_{it})$ = log difference of COVID-19 cumulative cases in country $i$ at time $t$

$\Delta CRA_{it}$ = change in CRA index in country $i$ at time $t$

$\vartheta_i$ = captures the unobserved country-specific fixed effects

$\mu_{it}$ = observation specific errors (time varying unobservables

# *Model Specifications*

## *B. Cross-country Classifications by Income Group*

$$\Delta ln(sp_{it}) = \alpha_0 + \beta_1 \Delta ln(op_t) + \gamma_2 \Delta ln(twusd_t) + \varphi_3 \Delta vix_t + \omega_4 \Delta ln(cases_{it}) + \delta_5 \Delta CRA_{it} * income\ class + \vartheta_i + \mu_{it} \qquad eq.(3)$$

Where:

$\Delta CRA_{it} * income\ class$ = interaction term between the level of CRA index and country groupings by income

$income\ class$ = dummy variable that is categorized into three (3) clusters:

(i) higher income economies – Japan, Korea and Singapore

(ii) upper-middle income – Indonesia, Malaysia and Thailand

(iii) lower-middle income – India, Philippines, and Vietnam

## *Robustness of the Model*

$$\Delta\ln(sp_{it}) = \alpha_0 + \beta_1\Delta\ln(op_t) + \gamma_2\Delta ln(twusd_t) + \varphi_3\Delta vix_t + \omega_4\Delta ln(cases_{it}) + \tau_5\Delta CRA_{it} + \psi_6 GRSI_{it} + \vartheta_i + \mu_{it} \qquad eq.(4)$$

**Inclusion of the variable GRSI**

To check the consistency of the impact of investors' sentiment towards the pandemic-related risks

**Limiting the period to Outbreak & Fever Phases**

*Outbreak* period spans from 20 January to 21 February

*Fever* phase ranges from 22 February to 31 March

## *Estimation Methodology*

**Random Effects Panel Regression (using Driscoll-Kraay standard errors)**

- Selected model by Hausman specification test
- Takes into account the possibility that cross-country specific differences might have some influence on the dependent variable
- Driscoll-Kraay standard errors corrects for the cross-sectional autocorrelation in the residuals

# Research Findings

## Impact of the COVID-19 Risk Attitude Index to Asian Stock Markets

| Predictor Variables | Baseline Model (eq. 2) | Model for country groupings, by income (eq. 3) |
|---|---|---|
| *Impact of investors' sentiment to Asian stock markets* | | |
| $\Delta ln\ (cases_{it})$ | -0.003<br>(0.004) | -0.003<br>(0.005) |
| $\Delta CRA_{it}$ | 0.023*<br>(0.012) | |
| *Impact of fundamentals to Asian stock markets* | | |
| $\Delta ln\ (op_t)$ | 0.008**<br>(0.003) | 0.008**<br>(0.004) |
| $\Delta ln(twusd_t)$ | -1.507***<br>(0.185) | -1.493***<br>(0.179) |
| $\Delta vix_t$ | 0.003<br>(0.020) | 0.001<br>(0.020) |
| No. of observations | 784 | 784 |
| No. of countries | 9 | 9 |

*Note: Driscoll-Kraay standard errors are in parentheses; ***, **,* denotes p-value less than the 1%, 5% and 10% levels of significance, respectively.*

# Research Findings

## *Differential Effects of the Pandemic to Stock Markets, by Income Group*

| Predictor Variables | Baseline Model (eq. 2) | Model for country groupings, by income (eq. 3) |
|---|---|---|
| *Impact of investors' sentiment to Asian stock markets* | | |
| $\Delta ln\ (cases_{it})$ | -0.003<br>(0.004) | -0.003<br>(0.005) |
| $\Delta CRA_{it}$ | 0.023*<br>(0.012) | |
| *Impact of COVID-19 to Asian stock markets, by income category* | | |
| $\Delta CRA_{it} * high$ | | 0.050*<br>(0.027) |
| $\Delta CRA_{it} * uppermid$ | | 0.024*<br>(0.013) |
| $\Delta CRA_{it} * lowermid$ *(benchmark/reference)* | | |
| No. of observations | 784 | 784 |
| No. of countries | 9 | 9 |

*Note: Driscoll-Kraay standard errors are in parentheses; ***, **,* denotes p-value less than the 1%, 5% and 10% levels of significance, respectively.*

## *Research Findings*

### *Robustness of the Model*

| Predictor Variables | Controlling for GRSI (eq. 4) | Outbreak & Fever Phases (20 Jan – 31 Mar 2020) |
|---|---|---|
| *Impact of investors' sentiment to Asian stock markets* | | |
| $\Delta ln\ (cases_{it})$ | -0.002<br>(0.004) | -0.002<br>(0.004) |
| $\Delta CRA_{it}$ | 0.023*<br>(0.012) | 0.029*<br>(0.016) |
| *Robustness checks* | | |
| $GRSI_{it}$ | 0.004*<br>(0.002) | 0.011<br>(0.009) |
| No. of observations | 780 | 319 |
| No. of countries | 9 | 9 |

*Note: Driscoll-Kraay standard errors are in parentheses; ***, **,* denotes p-value less than the 1%, 5% and 10% levels of significance, respectively.*

# *Conclusions*

## Key Takeaways

| | | |
|---|---|---|
| The CRA index is a significant predictor variable for stock price movements. Across all model specifications Asian stock markets, in general, do not exhibit absolute pessimism towards the pandemic. | As governments pull out all the stops to soften, if not to totally eradicate, the impact of the pandemic, Asian stock investors appear to relatively gain market confidence. | The effect of the variable CRA index in high-income and upper-middle income countries to stock prices is positive and statistically significant while the opposite is observed in lower-middle income countries. |

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# Revealing investors' sentiment amid COVID-19: the Big Data evidence based on internet searches

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**Abstract:**

*As the global economy grounded to a screeching halt during the wake of the coronavirus outbreak, the seemingly odd response of stock markets has raised both concerns and questions. Whether the dynamics in the behaviour of stock market is driven by the oscillation between the market fundamentals and investors' attitude in the face of pandemic is an open question that needs to be answered and tested.*

*Using random effects panel regression model and pandemic-related daily internet search keywords to construct the Covid-19 Risk Attitude (CRA) index, this study finds that select Asian stock markets are not sensitive to the (negative) impact of the epidemic as most of these countries were prompt in containing the spread of the virus. This claim is supported by the positive effect of government response stringency index to Asian stock prices. Taking into account the heterogeneity in the responses of the markets under study, this paper argues that stock markets in high and upper-middle income Asian countries are not negatively affected by investors' sentiment towards pandemic-related risks.*

**Keywords:**
government policy regulation and public health; stock market; panel data models; investor attitude; big data

## 1. Introduction:

A number of research studies related to measuring investors' risk attitude and quantifying its effects amid COVID-19 have been proposed and published. The first set of this growing research study was discussed in the context of the US – (Baker et al., 2020; Giglio et al., 2020). And, while there have been some papers that included Asian economies, the discussion was not as extensive as that of Western and European countries (Amstad et al., 2020). In the Philippine setting, measuring investors' sentiment using big data or based on internet search keywords has not been addressed thus far. This is the research gap that this paper aims to contribute into the literature.

The specific research objectives below spin-off from the paper's main objective, which is to measure investors' risk attitude towards the pandemic and quantify its impact to select Asian stock markets:

(i) To construct the Covid-19 Risk Attitude (CRA) index for the Philippines and select Asian countries using daily internet-based search queries from 31 December 2019 to 03 July 2020;

(ii) To test whether or not the claim of Amstad, et al. (2020) on some Asian stock markets not significantly correlated to the CRA index holds true;[1] and

(iii) To understand the heterogeneous investors' sentiment in select Asian stock markets, categorized according to the country's income classification, to the pandemic.

## 2. Methodology:

Capitalizing on the optimal use of Google, which is the world's largest search engine, this study follows the general approach adopted by Amstad et al (2020) to construct the CRA index. More formally, the CRA index is estimated by aggregating the daily search volume terms (i.e., coronavirus, COVID-19, nCoV, 2019-nCoV) via Google Trends from 31 December 2019 to 03 July 2020 for the nine (9) select Asian countries (equation 1):

$$CRA_{i,t} = \frac{1}{K}\sum_{k=1}^{4} SVI_{k,i,t} \quad (1)$$

where $K$ is the total number of search terms used in this study, $i = 1,2, \dots N$, $t = 1,2, \dots T$, $N$ is the total number of countries under study while $T$ is the total number of time series observations. The $SVI$ is the search volume index where each query inputted into Google Trends is normalized to 100 for the highest search volume in country $i$ at time $t$. Following the underlying assumptions of Amstad et al (2020), the frequency of searches related to the Covid-19 pandemic is a proxy for the public's or an individual's level of concern on the pandemic and its economic consequences.

### Baseline Model:

This study, which is applied and focused in the context of Asian economies, follows the general approach of the recent works of Amstad et al (2020) and Capelle-Blanchard & Desroziers (2020). To test the paper's research objectives empirically, the baseline model will be estimated as:

$$\begin{gathered} \Delta ln(sp_{it}) = \alpha_0 + \beta_1 \Delta ln(op_t) + \gamma_2 \Delta ln(twusd_t) + \varphi_3 \Delta vix_t + \\ \omega_4 \Delta ln\ (cases_{it}) + \tau_5 \Delta CRA_{it} + \vartheta_i + \mu_{it} \end{gathered} \quad (2)$$

where the dependent variable $\Delta \ln\ (sp_{it})$ is the log difference of stock price index in country $i$ at time $t$ – an approximation to the growth rate of daily stock price index. The independent variables that represent the market fundamentals are $op_t$ and $twusd_t$, which represents the Brent crude oil price and trade-weighted US dollar index at time $t$, respectively.

To measure and quantify investors' sentiment towards the risk associated with the pandemic, the variables COVID-19 cumulative cases and CRA index were added to the model estimation. As these two variables are likely to introduce collinearity, these indicators were concurrently estimated instead of regressing the variables separately in the model.

The total error term, $e_{it}$, is categorised into: (i) $\vartheta_i$ captures the unobserved country-specific fixed effects; and (ii) $\mu_{it}$, which is the observation specific errors (time varying unobservables). Both $\vartheta_i$ and $\mu_{it}$ follows an independent, identical distribution (IID) with zero mean and constant variance $\sim IID\ (0, \sigma^2)$.

[1] The Asian stock markets included in the study made by Amstad, et al (2020) are China, Japan, South Korea, Singapore and Indonesia.

**Cross-country classifications by income group model:**

Rather than evaluating investors' behaviour towards the COVID-19 across economies in absolute terms, this study compares the stock price movements in select Asian countries and attribute the heterogeneous reactions of stock markets to country differences (e.g., pre-existing macroeconomic and financial conditions, level of financial development, institutional characteristics, among others). The third research objective of this paper will be examined by extending the benchmark model, equation (2), as follows:

$$\Delta ln(sp_{it}) = \alpha_0 + \beta_1 \Delta ln(op_t) + \gamma_2 \Delta ln(twusd_t) + \varphi_3 \Delta vix_t + \omega_4 \Delta ln\,(cases_{it}) + \delta_5 \Delta CRA_{it} * income\ class + \vartheta_i + \mu_{it} \quad (3)$$

where $\Delta CRA_{it} * income\ class$ is the interaction term between the level of CRA index and country groupings by income. The dummy variable, $income\ class$, is categorized into three (3) clusters: (i) higher income economies – Japan, Korea and Singapore; (ii) upper-middle income – Indonesia, Malaysia and Thailand; and (iii) lower-middle income (reference group) – India, Philippines, and Vietnam.[2]

**Robustness of the Model:**

To ensure the robustness of the model and ascertain that the empirical results are not provisional on the authors' data selection, sample coverage and time period, some modifications were considered in the regression. First, the authors incorporated the GRSI as control variable to check the consistency of the impact of investors' sentiment towards the pandemic-related risks. This is represented in the extended equation below:

$$\Delta \ln\,(sp_{it}) = \alpha_0 + \beta_1 \Delta \ln\,(op_t) + \gamma_2 \Delta ln(twusd_t) + \varphi_3 \Delta vix_t + \omega_4 \Delta ln\,(cases_{it}) + \tau_5 \Delta CRA_{it} + \psi_6 GRSI_{it} + \vartheta_i + \mu_{it} \quad eq.(4)$$

Second, we checked the robustness of the model by limiting the time period to *Outbreak* and *Fever* phases and excluding the *Incubation* stage as in Capelle-Blanchard & Desroziers (2020). The *Incubation* phase ranges from 02 January to 17 January while the *Outbreak* period spans from 20 January to 21 February. This paper, however, extends the *Fever* phase from 20 March to 31 March to fully consider the impact of the virus to stock price index for the entire period of March 2020.

**Estimation Methodology:**

The econometric approach that this paper will employ is panel regression, particularly the random effects (RE) model to test empirically the objectives of this research. The conventional way to choose which between the fixed effects (FE) and RE models to use best is through the Hausman test.[3] Under the RE model, the estimates are based on the identifying assumption that the error terms follow an IID with zero mean and constant variance $\sim IID\,(0, \sigma^2)$. The advantage of using the RE estimator is that the variation across countries is assumed to be random and uncorrelated with the explanatory variables in the model (Torres-Reyna, 2007).

[2] The income groupings are: (i) low income class ≤ \$1,035; (ii) lower-middle income = \$1,036-\$4,045; (iii) upper middle income = \$4,046-\$12,535; and (iv) high income > \$12,536.
Source: The World Bank

[3] Hausman test suggests the use of RE model.

## 3. Result:

**Impact of the COVID-19 Risk Attitude Index to Asian Stock Markets:**

In addition to market fundamentals, this paper finds that CRA index is important in predicting stock price movements in Asian countries. Contrary to the findings of Amstad et al (2020) that Asian stock markets are not significantly correlated with CRA index, this study shows that CRA index enters positively and statistically significant in equation 2.

**Table 1: Models for Predictors of Stock Price Index**

| **Predictor Variables** | **Baseline Model (eq. 2)** | **Model for country groupings, by income (eq. 3)** |
|---|---|---|
| *Impact of investors' sentiment to Asian stock markets* | | |
| $\Delta ln\ (cases_{it})$ | -0.003<br>(0.004) | -0.003<br>(0.005) |
| $\Delta CRA_{it}$ | 0.023*<br>(0.012) | |
| *Impact of fundamentals to Asian stock markets* | | |
| $\Delta ln\ (op_t)$ | 0.008**<br>(0.003) | 0.008**<br>(0.004) |
| $\Delta ln(twusd_t)$ | -1.507***<br>(0.185) | -1.493***<br>(0.179) |
| $\Delta vix_t$ | 0.003<br>(0.020) | 0.001<br>(0.020) |
| *Impact of COVID-19 to Asian stock markets, by income category* | | |
| $\Delta CRA_{it} * high$ | | 0.050*<br>(0.027) |
| $\Delta CRA_{it} * uppermid$ | | 0.024*<br>(0.013) |
| $\Delta CRA_{it} * lowermid$ *(benchmark/reference)* | | |
| No. of observations | 784 | 784 |
| No. of countries | 9 | 9 |

*Note: Driscoll-Kraay standard errors are in parentheses; ***, **,* denotes p-value less than the 1%, 5% and 10% levels of significance, respectively.*

The findings suggest that the perceived negative effect of the pandemic to stock markets is non-evident in the context of Asian markets under study. Looking at Table 1, column 2, the coefficient associated with the investors' risk attitude index is estimated to be at 0.023. This implies that despite the increase in the investors' sentiment-revealing daily internet search volume index, Asian stock price indices is expected to increase by 2.3 percent on the average.

The empirical findings of this study reveal a myriad of plausible reasons. One is the claim of Amstad et al (2020) that Asian stock markets, unlike Western and European countries, are less sensitive to the negative impact of COVID-19 since most of the Asian countries entered the pandemic relatively earlier and therefore, were able to introduce prompt policy adjustments to combat the further spread of the virus. Second is the prudent use of technological applications to curb the virus outbreak like contact tracing and location tracking that started first in Asia, especially in countries with better digital infrastructures (Cantu et al, 2020). Third is the assumption that the experiences of most of the Asian countries included in this study during the 2002-2004 SARS outbreak have better equipped them in terms of dealing with the current pandemic.

## Different Asian Investors' Sentiment to the Pandemic, by Income Group:

Seen on the whole, the stock investors' risk perception and general fear towards the negative impact of the pandemic is not as intense and pronounced as that in the European or American markets (Amstad et al, 2020). As compared to the lower-middle income countries – India, Philippines and Vietnam – the impact of CRA index to stock price index is positive and statistically significant for both high (Japan, Korea, Singapore) and upper-middle income countries (Indonesia, Thailand, Malaysia). Singapore, Japan, Korea were the first to press digital infrastructures into use in Asia to stem the virus outbreak (Chandran, 2020). Such prompt responses by these countries might have given stock investors a boost and confidence in the market.

## Impact of Pandemic-related Government Responses to Stock Markets:

The inclusion of GRSI as a control variable in the model specification (eq.4) confirms the consistency of the direction of sign (i.e., positive) of the estimated coefficients for CRA index in all equations. The variable GRSI is positive and statistically significant, which means that as governments intensified their wide range of strict measures to stem the spread of the virus, Asian stock markets seem to gain market confidence.

**Table 2: Models for Robustness Checks**

| Predictor Variables | Controlling for GRSI (eq. 4) | Outbreak & Fever Phases (20 Jan – 31 Mar 2020) |
|---|---|---|
| *Impact of investors' sentiment to Asian stock markets* | | |
| $\Delta ln\ (cases_{it})$ | -0.002<br>(0.004) | -0.002<br>(0.004) |
| $\Delta CRA_{it}$ | 0.023*<br>(0.012) | 0.029*<br>(0.016) |
| *Impact of fundamentals to Asian stock markets* | | |
| $\Delta ln\ (op_t)$ | 0.008**<br>(0.004) | 0.034<br>(0.032) |
| $\Delta ln(twusd_t)$ | -1.488***<br>(0.185) | -1.608***<br>(0.277) |
| $\Delta vix_t$ | 0.004<br>(0.020) | 0.004<br>(0.020) |
| *Robustness checks* | | |
| $GRSI_{it}$ | 0.004*<br>(0.002) | 0.011<br>(0.009) |
| No. of observations | 780 | 319 |
| No. of countries | 9 | 9 |

*Note: Driscoll-Kraay standard errors are in parentheses; ***, **,* denotes p-value less than the 1%, 5% and 10% levels of significance, respectively.*

## Asian Stock Markets' Response over the *'Outbreak'* and '*Fever'* Phases:

Overall, the impact of CRA index to Asian stock prices remains consistent regardless of the model specifications even if the model was estimated by limiting the time period to *Outbreak* and *Fever* phases only. To some degree, this result is supported by the claim of Amstad et al (2020) that the negative effect of the CRA index is less pronounced in a number of Asian equity markets than in America and Europe since the former went through the epidemic earlier and policy re-adjustments were effected accordingly.

## 4. Discussion and Conclusion:

The dynamics of the stock markets' behavior towards the global pandemic brought the public, not only the economists, to ask the question – *Is the glass half-empty or half-full?* In this paper, we tried to provide answers to some questions and/or issues with regard to stock price movements. In particular, the main objective of this research is to measure investor risk attitude towards COVID-19 and quantify its impact to select Asian stock prices by leveraging on the use of big data – internet search volume index.

In addition to market fundamentals, the CRA index is a significant predictor variable for variations in Asian stock prices. Across all model specifications, this study finds out that Asian stock markets, in general, do not exhibit absolute pessimism towards the pandemic. This paper argues that as governments pull out all the stops to soften, if not to totally eradicate, the impact of the dreaded coronavirus, Asian stock investors appear to relatively gain market confidence. This claim is corroborated by the positive effect of GRSI to equity prices where a suite of government responses – ranging from containment measures to economic relief operations and health facilities investments – have been enacted relatively prompt. Further, the main story holds true even when the time series observations were limited to *'Outbreak'* and *'Fever'* phases only.

Finally, since different countries have different pre-existing institutional characteristics or macroeconomic conditions, this research tested for the heterogenous response of select Asian countries by grouping these countries according to their income classification. The effect of the variable CRA index in high-income and upper-middle income countries to stock prices is positive and statistically significant while the opposite is observed in lower-middle income countries.

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### Abstract

*As the global economy grounded to a screeching halt during the wake of the coronavirus outbreak, the seemingly odd response of stock markets has raised both concerns and questions. Whether the dynamics in the behaviour of stock market is driven by the oscillation between the market fundamentals and investors' attitude in the face of pandemic is an open question that needs to be answered and tested.*

*Using random effects panel regression model and pandemic-related daily internet search keywords to construct the Covid-19 Risk Attitude (CRA) index, this study finds that select Asian stock markets are not sensitive to the (negative) impact of the epidemic as most of these countries were prompt in containing the spread of the virus. This claim is supported by the positive effect of government response stringency index to Asian stock prices. Taking into account the heterogeneity in the responses of the markets under study, this paper argues that stock markets in high and upper-middle income Asian countries are not negatively affected by investors' sentiment towards pandemic-related risks.*

**JEL Classification:** I18, G10, C33

**Keywords:** government policy, regulation and public health, stock market, panel data models, investor attitude, big data

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# Revealing investors' sentiment amid COVID-19: the Big Data evidence based on internet searches

## 1. Background

Through the decades, the world's economic system has flourished and eroded in a seemingly natural cycle of markets' booms and busts. However, notable historic events continue to challenge established economic theories and assumptions, as more granular information attempt to provide novel perspectives in trying to explain various conventional and unconventional economic phenomena.

In the past months, the world has witnessed the unravelling of an unprecedented event — a global pandemic that grounded the economy to a near standstill and paved the way towards the birth of the *"new normal"*. A virus strain, which allegedly started from Wuhan and fastidiously spread around the world in a matter of months (WHO, 2020), is set to change the economic, social, and political landscapes in the coming years.

### 1.1. The COVID-19 Timeline.[2]

The Wuhan Municipal Health Commission reported a cluster of pneumonia cases with "unknown aetiology" last 31 December 2019, citing the city's seafood market as the possible source (ECDC, 2020). Hubei's capital is one of the prominent commercial and industrial centres in China (Torsello & Winkler, 2020), thus could have contributed to its rapid and unforeseen spread. A study conducted by the Harvard Medical School later revealed that the virus must have started spreading as early as Fall *(August)* 2019 (Nsoesie et.al, 2020).

At the beginning of the year, the WHO tagged the emerging novel virus as the *"2019-nCov"* and later on declared a global health emergency due to its rate of spread. In February 2020, the WHO formally announced the change of the virus' official name from *"2019-nCov"* to *"COVID-19"*. Subsequently, in March 2020, the WHO announced the COVID-19 outbreak as a "global pandemic", which led to stringent lockdowns across countries. By middle to late March 2020, the epicenters of the virus have shifted from China to Europe[3] and the United States (US). At the end of March, the United Nations' (U.N.) Secretary-General heralded COVID-19 pandemic as the *"world's worst crisis"* since the World War II, asserting that this economic and health crisis will lead to a recession *"that probably has no parallel in the recent past"* (Lederer, 2020).

In April 2020, Wuhan announced its steady recovery and publicized that it has treated all of its COVID-19 patients. However, by May 2020, the WHO made a grim projection that the virus could infect millions[4], if swift measures will not be instituted. In the Asian region, India has already surpassed China's reported numbers of infections. By the end of May, Brazil, Russia

[2] Source: World Health Organization (WHO). Timeline of WHO's response to COVID-19. (Updated as of 30 July 2020).
[3] Italy and Spain were the hardest hit countries in Europe.
[4] With Africa as the most probable largest hit.

and the US recorded the highest number of infections in the world, while UK began emerging as one of the virus epicentres.

In early June 2020, Russia, UK and some EU countries gradually eased their stringent lockdown measures. On the contrary, the US recur to "near-peak" numbers of infections and fatalities, which coincided with the WHO's announcement that the pandemic was "getting worse globally". Most recently, in July 2020, the WHO reported a marked rise of cases in India, Brazil, UAE, Hong Kong, Australia, Saudi Arabia, including the Philippines. In response, the WHO holds virtual summits for COVID-19 research and innovation to fast track the development of its cure. By end July 2020, cases have breached 17 million and continues to rise as of writing.

### 1.2. The Economic Fallout of COVID-19

Governments worldwide are likewise racing against time to mitigate the atrocities of the global pandemic. The stern policies of lockdowns, temporary business closures, border controls and limited global trade led some experts to believe that we are *"nearing the point of de-globalization"* (Barua, 2020).

In April 2020, the International Monetary Fund (IMF) announced that global growth will contract by three (3) percent in 2020, the highest decrease since the Great Depression in the 1930s. This figure is a downgrade of 6.3 percentage points from the January 2020 projection, a major revision within a short span of time (WEO, 2020). In May 2020, the United Nations (UN) made a similar pronouncement wherein it predicted that the world economy would shrink by 3.2 percent, which offsets the global economic gains for the last four years (Economic Times, 2020). By June 2020, the Organization for Economic Co-operation and Development (OECD) made a bold declaration that "the pandemic had triggered the worst global recession in nearly a century even without a second wave of infections" with global economic outlook highly uncertain (OECD, 2020).

The *"Great Lockdown"* could be far more detrimental than the most recent Global Financial Crisis (GFC), hence, its adverse economic effects will surely spill over until 2021. More critically, no economic territory is spared. All countries are in recession, with growth projection of -6.1 percent for advanced economies, and -1.0 percent (in 2020) and -2.2 percent (in 2021) for the developing economies (Gopinath, 2020).

The dismal yet absolute pronouncements about the pandemic plus the high level of economic interconnectedness among countries meant heightened exposure to economic risks. While the extent and severity of the epidemic's impact to the global economy are still indeterminate, the financial markets have already reacted peculiarly. In particular, stock markets around the world cratered following WHO's declaration of global pandemic (Zhang et al, 2020). As economic risks associated with the pandemic build-up, countries introduced various fiscal relief packages to prop up the economy. Similarly, central banks worldwide responded with monetary easing and reserve reductions (including the Philippine central bank),[5] with Emerging Markets (EM) and Asian markets (AM) having more room to cut rates further, relative to its counterparts in the advanced economies.

Undoubtedly, the global pandemic has put financial markets and economists in an unchartered territory that whatever novel insights or developments this pandemic may bring forth will be of invaluable worth. Economic agents continue to grapple and adjust to the "new" market conditions of limited physical operations, restricted mobility, and bankruptcies. With these "new" market conditions, we ask the questions: *How are stock markets behaving amidst COVID-19? Are investors indifferent, over or under reacting towards this seemingly no end in sight epidemic?*

A number of research studies related to measuring investors' risk attitude and quantifying its effects amid COVID-19 have been proposed and published. The first set of this growing research study was discussed in the context of the US – (Baker et al., 2020; Giglio et al., 2020). And, while there have been some papers that included Asian economies, the discussion was not as extensive as that of Western and European countries (Amstad et al., 2020). In the Philippine setting, measuring investors' sentiment using big data or based on internet search keywords has not been addressed thus far. This is the research gap that this paper aims to contribute into the literature.

### 1.3. Research Objectives

The specific research objectives below spin-off from the paper's main objective, which is to measure investors' risk attitude towards the pandemic and quantify its impact to select Asian stock markets:

(i) To construct the Covid-19 Risk Attitude (CRA) index for the Philippines and select Asian countries using daily internet-based search queries from 31 December 2019 to 03 July 2020;

(ii) To test whether or not the claim of Amstad, et al. (2020) on some Asian stock markets not significantly correlated to the CRA index holds true;[6] and

(iii) To understand the heterogeneous investors' sentiment in select Asian stock markets, categorized according to the country's income classification, to the pandemic.[7]

The paper is outlined as follows: Section 2 reviews the theoretical and empirical literature. Section 3 elaborates on the data, model specification and methodology used in this study. Section 4 presents and analyzes the results. Section 5 concludes with policy implications.

[5] As of August 2020, policy rate reductions aggregated to 175 basis points.
Source: www.bsp.gov.ph/monetary/monetary.asp

[6] The Asian stock markets included in the study made by Amstad, et al (2020) are China, Japan, South Korea, Singapore and Indonesia.

[7] The select Asian countries are classified according to their income clusters using the World Bank's *Country Classification by Income Group* as of June 2020.

## 2. Review of Related Literature

In the midst of pandemics, economic risks and uncertainties elevate. Market players adjust their behaviour in congruence with the stringent policies and measures undertaken by the governments to ensure the health and safety of the public. Economic outlooks blur as border controls are tightened, trading activities are limited, and business closures become imminent.

Risk and uncertainty are closely related concepts, but the stark difference lie in the postulation that risk is measurable since it is "expected with varying degrees of probabilities", while uncertainty is often subjective and difficult to quantify (Alpers, 2019). Hence, measuring and managing risks and uncertainties are postulated to be distinct yet worthwhile activities.

In this paper, we will zero in on quantifying risk, specifically the investors' risk attitude, with the end-goal of aiding strategic policy decisions to be more agile during periods of uncertainty.

### 2.1. Theoretical Framework

#### *On Terminologies: Investor Sentiment, Risk Attitude, and Risk Appetite*

*Investor Sentiment.* As per convention, asset pricing has been heavily based on the traditional factors of payoffs and expected returns. However, as sentiments became quantifiable and measurable, this psychological factor has gained traction in explaining price movements. Zhang (2008) presented the diverging methods of asset pricing in which the *traditional approach* rested upon the assumption that asset prices are determined through *"rational assessments of expected future payoffs"* which are only affected by information on interest rates and future cash flows. On the contrary, the *alternative approach* injects the concept of behavioural finance where investor sentiments significantly affect the pricing mechanism. Bandopadhyaya and Jones (2016) further postulated that on one hand, individual investor sentiments cancel out when they are differing; on the other hand, when there is a consensus in investor sentiments, such attitude could significantly affect price movements. Baek et.al (2005) specified that such effect and influence are magnified in the short-run, thereby, making investor sentiment a more critical explanatory factor for price movements rather than the traditional fundamentals.

*Risk Attitude.* In linking investor sentiment with risk attitude, we propose to define the latter simply as the *investors' sentiment towards risk*. More formally, Rohrmann (2005) defines risk attitude as the "generic orientation or mindset towards taking or avoiding risk when deciding how to proceed in situations with uncertain outcomes". Rohrmann further sub-divided risk attitude into *risk propensity* as the attitude towards taking risks and *risk aversion* as the attitude towards avoiding risks.

*Risk Appetite.* Gai and Vause (2004) forwarded the idea that "risk aversion" and "risk appetite" may be considered as synonymous terminologies. However, the slight distinction between "risk aversion" and "risk appetite" rests upon the observation that the former is subjective yet stable over time, while the latter is objective and varies with the perceived level of the current uncertainties in the market. More specifically, "risk aversion" is an investor's inherent attitude towards uncertainty, while "risk appetite" includes the reaction to the overall uncertainty on the current fundamental market factors affecting prices in the equation (ECB, 2007). Hence, it would be more worthwhile to track "risk appetite" in deciphering asset price movements.

For the purpose of this paper, the terminologies "risk appetite" and "risk attitude" will be utilized in the discussions of the index to be constructed. Moreover, we will define risk attitude as the inclination of a person to evaluate the adverse economic effects of the pandemic (Amstad et al., 2020).

***On Measuring Risk Appetite and Risk Attitude.*** In order to capitalize on the observable shifts in risk attitude in crafting proactive policies, one must quantify this sentiment factor to accurately gauge its effects. Illing and Aaron (2012) categorizes the measurement approaches into (1) atheoretic and (2) theory-based.

Atheoretic measures build risk appetite indices by using statistical methods to aggregate information from market prices *(e.g. volatility, asset class spread, liquidity risk, credit risk, etc.)*. Meanwhile, theory-based measures employ economic or financial models to build the indices as applied to a single financial market.

The theory-based measures were likewise denoted as "market-based measures" (ECB, 2007) and generally follows three approaches: (a) structured market-based method, which investigates the correlation of volatility and returns; (b) method-based, which examines the implied probability density function of prices with investors' expectations and degree of uncertainty; and (c) traditional structure, which looks at the infamous Capital Asset Pricing Model (CAPM) and complements it with investors' perception. The different measures of investor sentiment towards risk are presented in Appendix 1.

*How, then, do we determine the most suitable methodology in building a risk attitude index? What if times are extraordinarily pessimistic?*

***Measuring Risk Attitude During Extraordinary Times.*** Through the years, investors have weathered market crises and bounced back to more stable positions. In the past decade alone, the market reacted to the 2001 U.S. terror attack, the 2008 Global Financial Crisis and now (2020), the COVID-19 crisis. Due to these unforeseen events, the economic path is neither predictable nor may be tracked with absolute precision.

Interestingly, according to Illing and Aaron (2012), a number of marked economic events in the past emerged to be driven by investors' risk attitude. Among them are the Asian Financial Crisis (1997), Russian debt default (1998) and the bust of high-technology share prices or the dot-com burst (2000). This led to a movement in which researchers and institutions alike developed a *risk appetite index* to examine and predict market movements for policies; while the private sector utilized said index to optimize returns. Hence, extraordinary episodes (such as pandemics), warrant an investigation on whether or not investors' risk attitude indeed impact asset prices.

On the macro scale, we witnessed the public sector's response to manage the economic effects of the pandemic. The US federal funds rate has been cut last March by 0.5 percent to a target range of 1-1.25 percent in a first inter-meeting rate cut in more than 10 years,[8] due to the "evolving risks of economic activity" attributed to the pandemic. In an explanatory pronouncement, US Federal Reserve Chairman Jerome Powell emphasized that the rate cut was prompted by the view that COVID-19 was having a *"material impact on the economic outlook",* hence on business confidence (Cox, 2020). Meanwhile, China (one of the world's largest producers) has yet to resume full production capacity; thereby, adding on to Asia's downside risk. With border controls and trade restraints, supply chain disruptions are imminent, which could in turn cause an economic contagion.

On the micro scale, investors are poised to review their portfolios as risk aversion builds up. Such evaluation is heavily dependent on their levels of risk tolerance and their immediate versus long-term needs. *How then do we measure these micro movements to track macro movements?*

Given the mobility restrictions of a pandemic lockdown, conducting surveys to measure investors' risk attitude are non-viable and impractical at some level. Providentially, the world is replete with technological resource that could easily gather copious amounts of information in a single click. Such is the utility of big data – the widely available, high volume, high frequency, novel information source that triggers timely and proactive policies and decisions.

## 2.2. Empirical Studies

As formalized by De Long et al (1990), investor sentiment influences the behavior of financial markets. While there is an impression that markets react irrationally and randomly in times of unexpected crises, it is still far from being conclusive. It is against this premise that several empirical studies related to investigating the impact of investors' risk attitude to equity price movements were executed.[9]

In the recent years, innovative approaches that make the most of digital infrastructures such as the use of internet search-based data to measure investor sentiment and predict stock market behavior has gained traction because of its potential to reveal *attitudes* (Beer et al, 2013; Da et al, 2015; and Ho et al, 2017). Beer et al (2013) found that the French investor sentiment index are significant predictors of the behavior of mutual fund investors. In the same year, Preis et al (2013) utilized Google search volume index for finance-related keywords to identify early warning signs of possible stress in the stock market. They argued that the search volume index for terms relevant to financial markets shoots up prior to the collapse of the market.

In a similar yet unique approach, Mao et al (2015) leveraged on the availability of social media via Twitter updates to investigate the power of online investor "bullishness sentiment indicator" in predicting international stock market movements. They claimed that bullish sentiments expressed by investors in Twitter are strong explanatory variable for increases in

[8] Since 2008.

[9] Stocks and equity are interchangeably used in this paper.

stock returns. Meanwhile, Da et al (2015) constructed the Financial and Economic Attitudes Revealed by Search (FEARS) index by aggregating internet search volume queries related to concerns of American households such as "bankruptcy", "unemployment", "recession", among others. They also discovered that the sentiment-revealing index is able to predict: (i) short-term stock returns reversal; (ii) temporary increases in stock volatility; and (iii) mutual fund flows.

The investment horizon remains bleak as we are yet to see the light at the end of the tunnel for the COVID-19 pandemic. The peculiar role of investors' risk attitude in understanding stock price movements became more pronounced following the global epidemic. A risk-averse investor may react via examining the intrinsic value of assets and act conservatively, while a risk-taker may bet on the companies who might weather the tides of the pandemic (and either they will relish gains or suffer losses).

Distinguished economists John Kay and Mervyn King's *"Radical Uncertainty: Decision-Making Beyond the Numbers"* was published during the height of the pandemic in March this year (Sandbu, 2020). It postulates that during times of enormous or unprecedented uncertainty, market players can neither determine all possible outcomes nor assign probabilities to them. Hence, one must be aware of these limitations in order to decide aptly. They posited that in times of "radical uncertainty", a market player copes by using narrative and intuition. Likewise, Malkiel & Shiller (2020) argued that the COVID-19 crisis presented an exceptional illustration of how investors' unpredictable risk attitude towards the pandemic can subject the market to greater volatility.

Using the CRA index to analyze the behavior of 61 stock markets, Amstad et al (2020) found that stock markets react strongly and negatively to COVID-19 in more financially developed Western and American economies. Similarly, Ramelli and Wagner (2020) proved the significant influence of the pandemic risk attitude to stock market returns, arguing that real shocks from the global health pandemic amplified the feverish reaction of stock markets. In this paper, we will examine how an investor's risk attitude towards COVID-19 influence Asian stock markets, depending on their surrounding market context (e.g., developed vs. developing country, country's economic policies on the pandemic, and localized lockdown measures, among others).

## 3. Data and Methodology

This section provides details on the variables used, the construction of the CRA index[10], model specifications and estimation methodology employed in this paper.

### 3.1. Variables and Data Characteristics

The paper uses data on select Asian stock markets to test how these markets react to the pandemic. The period covered in this study starts from 31 December 2019 to capture the time when the novel coronavirus was first identified in Wuhan, China.[11] Since a number of

[10] The construction of this index will be discussed in the subsequent sections.
[11] Source: World Health Organization (WHO)

research studies in this field were conducted during the height of the outbreak and enhanced quarantine or lockdown, there is a greater likelihood that these studies fail to consider the possible rebound of the stock market. Hence, this study extends the period coverage up to 03 July 2020, when most of the countries have already lifted or relaxed their containment measures. The variables used in this study are shown in Table 1. The panel data summary statistics is presented in Appendix 2.

**Table 1: Description of variables**

| Variables | Description | Source |
|---|---|---|
| Stock price index | Derived as percentage change in the closing prices of major stock index in country $i$ at time $t$. | Thomson Reuters Eikon |
| Oil price | Calculated as percentage change in Brent crude oil prices at time $t$. [12] | Federal Reserve Economic Data (FRED) |
| Number of COVID-19 positive cases | Measured as percentage change in the number of COVID-19 cumulative cases in country $i$ at time $t$. | European Centre for Disease Prevention and Control (ECDC) |
| Volatility of stock price index (VIX) | Computed as change in the market's expectation of 30-day implied volatility in the US stock market at time $t$, which is constructed from S&P 500 option prices.[13] | FRED |
| Trade-weighted US dollar index (broad) | Calculated as percentage change in trade-weighted US dollar index at time $t$. | FRED |
| COVID-19 Risk Attitude (CRA) index | Measured as change in the CRA index in country $i$ at time $t$. | Google Trends; authors' calculations |
| Government response stringency index | Computed as the simple average of the number of measures that each government in country $i$ adopted at time $t$. [14] | Hale, T., Webster, S., Petherick, A., Phillips, T., and Kira, B. (2020), Oxford COVID-19 Government Response Tracker, Blavatnik School of Government |

### 3.2. Construction of the COVID-19 Risk Attitude (CRA) Index

The unanticipated outbreak of COVID-19 that immensely shocked the global markets brings into fore the question on *"how to measure investors' risk attitude and quantify its impact to stock market in a more direct and timely manner?"*. The unconventional approach that has gained traction in the recent years is the use of big data or internet search-based indices to quantify investors' sentiment.

Capitalizing on the optimal use of Google, which is the world's largest search engine, this study follows the general approach adopted by Amstad et al (2020) to construct the CRA index. It is important to note that the proper and objective identification of all pertinent

[12] The Brent crude oil is a blended crude stream produced in the North Sea region which serves as a reference for pricing a number of other crude streams. Source: https://www.eia.gov/dnav/pet/TblDefs/pet_pri_spt_tbldef2.asp

[13] Source: http://www.cboe.com/vix.

[14] The details will be explained in the following sections.

sentiment-telling internet search terms is crucial to the construction of the CRA index. While the calculated CRA index in their research involves only two sentiment-revealing search keywords (i.e., COVID-19 and coronavirus), we extended the relevant search queries to include "2019-nCoV" and "nCoV" since it was only on 11 February 2020 that the WHO officially referred the virus as "COVID-19".

More formally, the CRA index is estimated by aggregating the daily search volume terms (i.e., coronavirus, COVID-19, nCoV, 2019-nCoV) via Google Trends from 31 December 2019 to 03 July 2020 for the nine (9) select Asian countries (equation 1):

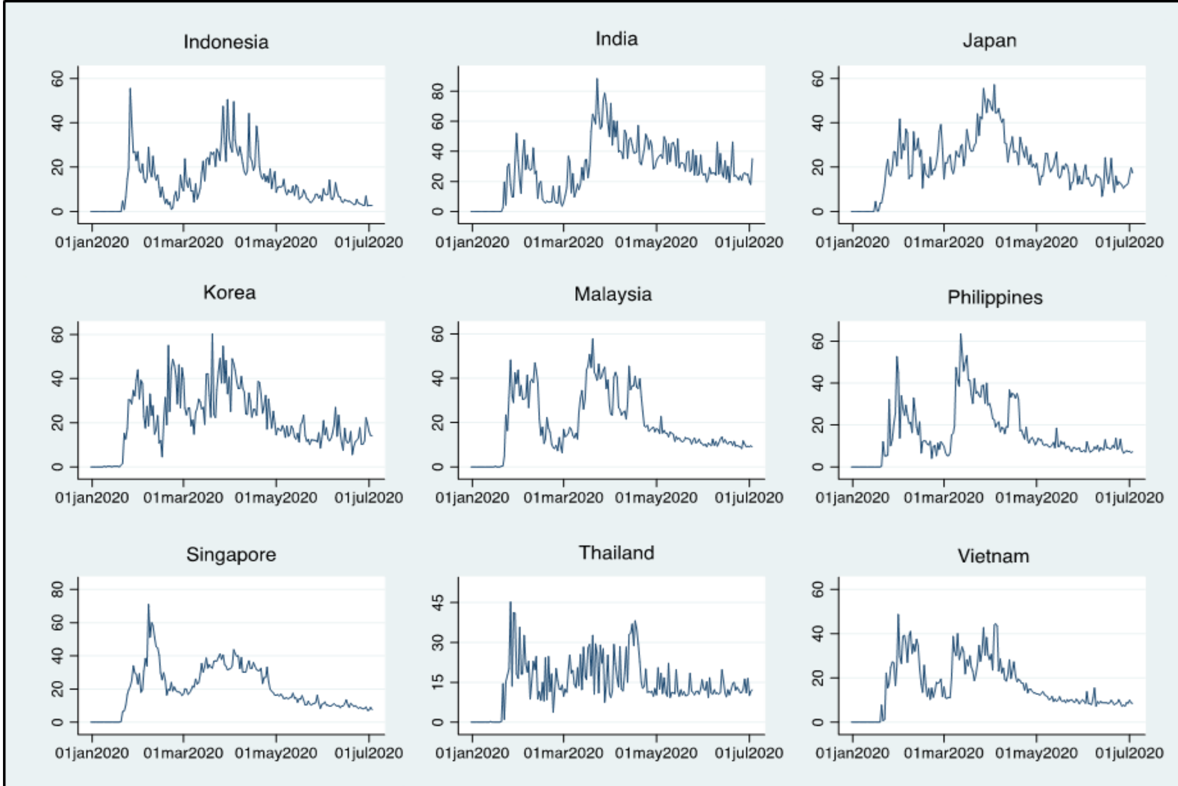
$$CRA_{i,t} = \frac{1}{K}\sum_{k=1}^{4} SVI_{k,i,t} \tag{1}$$

where $K$ is the total number of search terms used in this study, $i = 1,2,\ldots N$, $t = 1,2,\ldots T$, $N$ is the total number of countries under study while $T$ is the total number of time series observations. The $SVI$ is the search volume index where each query inputted into Google Trends is normalized to 100 for the highest search volume in country $i$ at time $t$. Following the underlying assumptions of Amstad et al (2020), the frequency of searches related to the Covid-19 pandemic is a proxy for the public's or an individual's level of concern on the pandemic and its economic consequences.

To gauge the level of public attention towards the epidemic at the country-level, Figure 1 presents the CRA index for select Asian countries from 31 December 2019 to 03 July 2020. Similar patterns on CRA index can be observed across these countries where the peak is seen to be evident during the early stages of the pandemic. The number of sentiment-telling search queries started to pick up following the declaration of WHO on 30 January 2020 that the coronavirus outbreak is a global public health emergency.[15] The increasing trend in the index continues until April 2020 before it slowly wanes (Figure 1).

[15] Source: https://www.who.int/news-room/detail/29-06-2020-covidtimeline

Figure 1: Country-level CRA Index



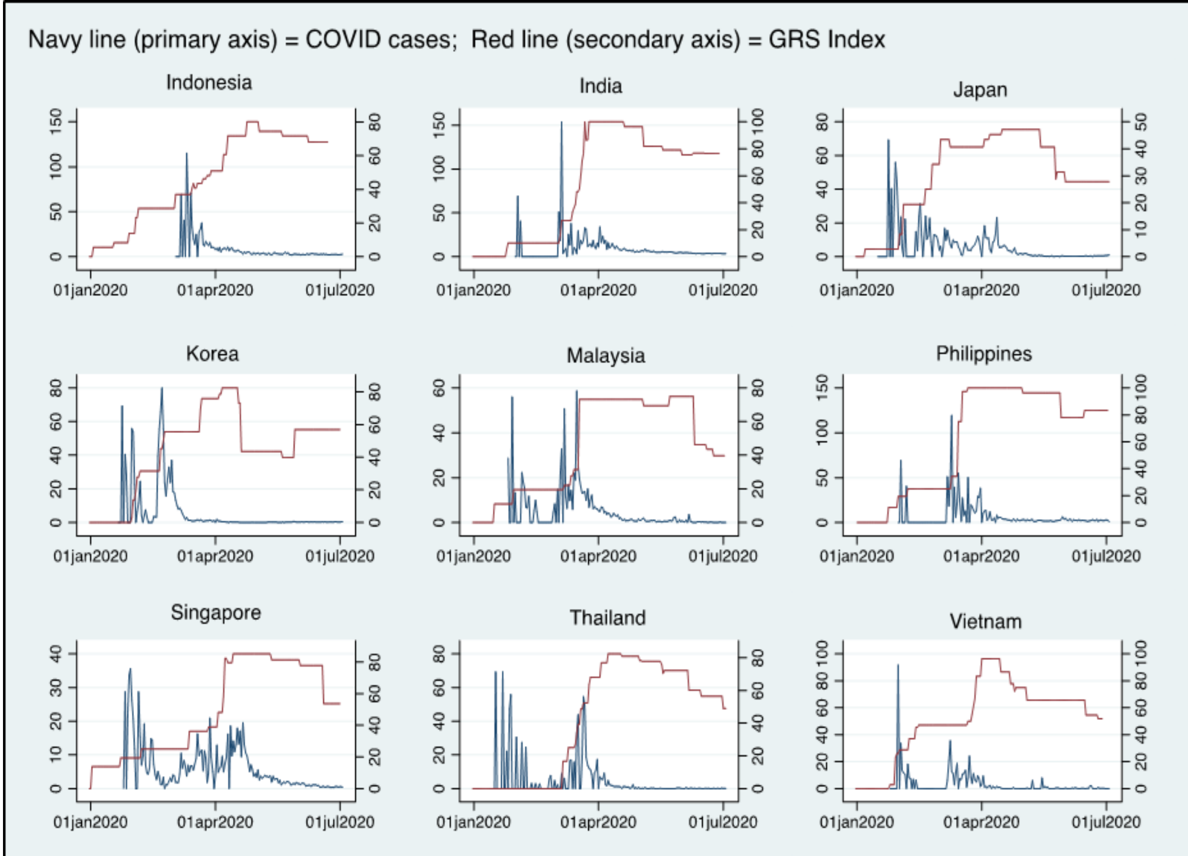

Source: Authors' calculations; Google Trends

### 3.3. Government Response Stringency Index (GRSI)

While the world faces the same public health conundrum, each nation has its distinct strategies and measures to contain the spread of the virus and thus, *'flatten the curve'*. To account for the different responses of government towards battling the pandemic, this study includes the variable Government Response Stringency Index (GRSI).

Hale et al (2020) calculated the index by simply taking the mean score of component indicators. The index has four (4) sub-indices, namely: (i) government response; (ii) containment and health; (iii) stringency; and (iv) economic support. The GRSI takes on a value between 0 to 100, with 100 being the strictest response. It should be noted, however, that the index does not necessarily entail the effectiveness or relevance of government's response to the epidemic. Figure 2 compares the daily percentage change in the number of COVID-19 cumulative cases with the government interventions adopted across Asian countries under research.

Figure 2: Cross-country reported COVID-19 cumulative cases and GRSI




Source: Oxford Covid-19 Gov't. Response Tracker; Authors' calculations

The government responses strengthen throughout the virus outbreak and, for most of the Asian countries, the index started to ratchet up as the daily percentage change in the number of COVID-19 cumulative cases shoot up. However, there are still variations across these countries as to the degree at which the stringency of these responses was taken on board (Figure 2).

### 3.4. Model Specification

The specifications used in this study to estimate the model and test the robustness of this model will be discussed in this section.

#### 3.4.1. Baseline Model

This study, which is applied and focused in the context of Asian economies, follows the general approach of the recent works of Amstad et al (2020) and Capelle-Blanchard & Desroziers (2020). To test the paper's research objectives empirically, the baseline model will be estimated as:

$$\Delta ln(sp_{it}) = \alpha_0 + \beta_1 \Delta ln(op_t) + \gamma_2 \Delta ln(twusd_t) + \varphi_3 \Delta vix_t + \omega_4 \Delta ln\,(cases_{it}) + \tau_5 \Delta CRA_{it} + \vartheta_i + \mu_{it} \tag{2}$$

where the dependent variable $\Delta\ln\,(sp_{it})$ is the log difference of stock price index in country $i$ at time $t$ – an approximation to the growth rate of daily stock price index. The independent variables that represent the market fundamentals are $op_t$ and $twusd_t$, which represents the Brent crude oil price and trade-weighted US dollar index at time $t$, respectively. The variable oil price is incorporated to take into account impact of the discord between two of the world's major oil producers – Russia and Saudi Arabia during the 1st quarter of 2020.[16] Similarly, the inclusion of trade-weighted USD index captures the relative strength of US dollar against other foreign currencies. Meanwhile, the volatility of stock price index, $vix_t$, is a widely used and recognized international benchmark indicator of stock market volatility.

To measure and quantify investors' sentiment towards the risk associated with the pandemic, the variables COVID-19 cumulative cases and CRA index were added to the model estimation. As these two variables are likely to introduce collinearity, these indicators were concurrently estimated instead of regressing the variables separately in the model.

The total error term, $e_{it}$, is categorised into: (i) $\vartheta_i$ captures the unobserved country-specific fixed effects; and (ii) $\mu_{it}$, which is the observation specific errors (time varying unobservables). Both $\vartheta_i$ and $\mu_{it}$ follows an independent, identical distribution (IID) with zero mean and constant variance $\sim IID\ (0, \sigma^2)$.

### 3.4.2. Cross-country Classifications by Income Group

Rather than evaluating investors' behaviour towards the COVID-19 across economies in absolute terms, this study compares the stock price movements in select Asian countries and attribute the heterogeneous reactions of stock markets to country differences (e.g., pre-existing macroeconomic and financial conditions, level of financial development, institutional characteristics, among others). One difference that this study considers looking at is the country's income classification.[17] The third research objective of this paper will be examined by extending the benchmark model, equation (2), as follows:

$$\begin{gathered}\Delta ln(sp_{it}) = \alpha_0 + \beta_1 \Delta ln(op_t) + \gamma_2 \Delta ln(twusd_t) + \varphi_3 \Delta vix_t + \\ \omega_4 \Delta ln\,(cases_{it}) + \delta_5 \Delta CRA_{it} * income\ class + \vartheta_i + \mu_{it}\end{gathered} \tag{3}$$

where $\Delta CRA_{it} * income\ class$ is the interaction term between the level of CRA index and country groupings by income. The dummy variable, $income\ class$, is categorized into three (3) clusters: (i) higher income economies – Japan, Korea and Singapore; (ii) upper-middle income – Indonesia, Malaysia and Thailand; and (iii) lower-middle income (reference group) – India, Philippines, and Vietnam. The country groupings were based on the World Bank's income classification according to 2019 Gross National Income (GNI) per capita of each economy.[18]

[16] Source: https://www.spglobal.com/platts/en/market-insights/latest-news/oil/040420-opec-emergency-meeting-faces-_delay-as-russia-rift-with-saudi-grows.

[17] Higher income Asian economies are assumed to be more financially developed.

[18] The income groupings are: (i) low income class ≤ \$1,035; (ii) lower-middle income = \$1,036-\$4,045; (iii) upper middle income = \$4,046-\$12,535; and (iv) high income > \$12,536.
Source: The World Bank

### 3.4.3. Robustness of the Model

To ensure the robustness of the model and ascertain that the empirical results are not provisional on the authors' data selection, sample coverage and time period, some modifications were considered in the regression. First, the authors incorporated the GRSI as control variable to check the consistency of the impact of investors' sentiment towards the pandemic-related risks, as measured by CRA index, to stock price movements in country $i$ at time $t$. This is represented in the extended equation below:

$$\Delta \ln (sp_{it}) = \alpha_0 + \beta_1 \Delta \ln (op_t) + \gamma_2 \Delta ln(twusd_t) + \varphi_3 \Delta vix_t + \omega_4 \Delta ln\,(cases_{it}) + \tau_5 \Delta CRA_{it} + \psi_6 GRSI_{it} + \vartheta_i + \mu_{it} \qquad eq.(4)$$

Second, we checked the robustness of the model by limiting the time period to *Outbreak* and *Fever* phases and excluding the *Incubation* stage as in Capelle-Blanchard & Desroziers (2020). The *Incubation* phase ranges from 02 January to 17 January while the *Outbreak* period spans from 20 January to 21 February. This paper, however, deviates from their method to extend the *Fever* phase from 20 March to 31 March to fully consider the impact of the virus to S&P 500 index the entire period of March 2020.[19]

### 3.5. Estimation Methodology

The econometric approach that this paper will employ is panel regression, particularly the random effects (RE) model to test empirically the objectives of this research. The conventional way to choose which between the fixed effects (FE) and RE models to use best is through the Hausman test.[20] Under the RE model, the estimates are based on the identifying assumption that the error terms follow an IID with zero mean and constant variance $\sim IID\ (0, \sigma^2)$. The advantage of using the RE estimator is that the variation across countries is assumed to be random and uncorrelated with the explanatory variables in the model (Torres-Reyna, 2007). Since country-specific differences (e.g. level of financial development, macroeconomic and institutional characteristics of select Asian countries) might have some influence on the dependent variable (i.e., stock price index), the RE model would be the best option.

When using panel regression, typical econometric and specification problems arise such as within-group autocorrelation and cross-sectional dependence (Wooldridge, 2010). To make sure that the validity of statistical inference is not attenuated by these econometric issues, diagnostic tests were performed. The cross-sectional dependence (CSD) Pesaran test for serial correlation reveals that there is autocorrelation in the residuals. To correct for cross-sectional dependence, an auxiliary regression was employed in the main regression through the use of Driscoll-Kraay (1998) standard errors as proposed by Wooldridge.

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[19] The S&P 500 index hit another lowest record-making in history at 12.5 percent for the month of March. Source: https://www.valuationresearch.com/pure-perspectives/covid-19-event-timeline/.

[20] Hausman test suggests the use of RE model.

## 4. Empirical Results

The research objectives of this paper as identified in Section 1 will be addressed in this section. An in-depth analysis will be provided on the following topics: (4.1.) impact of the COVID-19 Risk Attitude Index to Asian stock markets; (4.2.) different Asian investors' sentiment to the pandemic, by income group; (4.3) impact of pandemic-related government responses to stock markets; and (4.4) Asian stock markets' response over the *'outbreak'* and *'fever'* phases.

### 4.1. Impact of the COVID-19 Risk Attitude Index to Asian Stock Markets

In addition to market fundamentals, this paper finds that CRA index is important in predicting stock price movements in Asian countries. The parameter estimates for equations 2 and 3, which are specified in Sections 3.4.1 and 3.4.2, respectively, are presented in Table 2. Contrary to the findings of Amstad et al (2020) that Asian stock markets are not significantly correlated with CRA index, this study shows that CRA index enters positively and statistically significant in equation 2.

Table 2: Models for Predictors of Stock Price Index

| Predictor Variables | Baseline Model (eq. 2) | Model for country groupings, by income (eq. 3) |
|---|---|---|
| *Impact of investors' sentiment to Asian stock markets* | | |
| $\Delta ln\ (cases_{it})$ | -0.003 | -0.003 |
| | (0.004) | (0.005) |
| $\Delta CRA_{it}$ | 0.023* | |
| | (0.012) | |
| *Impact of fundamentals to Asian stock markets* | | |
| $\Delta ln\ (op_t)$ | 0.008** | 0.008** |
| | (0.003) | (0.004) |
| $\Delta ln(twusd_t)$ | -1.507*** | -1.493*** |
| | (0.185) | (0.179) |
| $\Delta vix_t$ | 0.003 | 0.001 |
| | (0.020) | (0.020) |
| *Impact of COVID-19 to Asian stock markets, by income category* | | |
| $\Delta CRA_{it} * high$ | | 0.050* |
| | | (0.027) |
| $\Delta CRA_{it} * uppermid$ | | 0.024* |
| | | (0.013) |
| $\Delta CRA_{it} * lowermid$ *(benchmark/reference)* | | |
| No. of observations | 784 | 784 |
| No. of countries | 9 | 9 |

*Note: Driscoll-Kraay standard errors are in parentheses; ***, **,* denotes p-value less than the 1%, 5% and 10% levels of significance, respectively.*

The findings suggest that the perceived negative effect of the pandemic to stock markets is non-evident in the context of Asian markets under study. Looking at Table 2, column 2, the coefficient associated with the investors' risk attitude index is estimated to be at 0.023.

This implies that despite the increase in the investors' sentiment-revealing daily internet search volume index, Asian stock price indices is expected to increase by 2.3 percent on the average.

The empirical findings of this study reveal a myriad of plausible reasons. One is the claim of Amstad et al (2020) that Asian stock markets, unlike Western and European countries, are less sensitive to the negative impact of COVID-19 since most of the Asian countries entered the pandemic relatively earlier and therefore, was able to introduce prompt policy adjustments to combat the further spread of the virus. Second is the prudent use of technological applications to curb the virus outbreak like contact tracing and location tracking that started first in Asia, especially in countries with better digital infrastructures (Cantu et al, 2020). Third is the assumption that the experiences of most of the Asian countries included in this study during the 2002-2004 SARS outbreak have better equipped them in terms of dealing with the current pandemic.

Moreover, Table 2 shows that the daily rate of spread of virus $\Delta\ln(cases_{it})$ is not a significant predictor of stock price movements. What was not predicted by the growth in the number of daily COVID-19 cumulative cases have been explained by the CRA index, making the index a good measure of capturing investors' general sentiment amid the pandemic.

With reference to the traditional drivers of stock price, oil price and trade-weighted US dollar index are significant predictor variables of stock market. The signs of the estimated coefficients are consistent and significant in all model specifications (equations 2 and 3). On the average, a one percent increase in Brent crude oil prices is expected to positively affect Asian stock price indices by 0.01 percent. As apprehensions over the coronavirus impact to the world economy intensified, the US dollar index strengthened against a basket of other foreign currencies. Consequently, investors were impelled to offload riskier assets such as stocks in exchange for holding safer ones, especially the US dollar despite the fact that the US economy is also at risk (Miller, 2020; The Straits Times, 2020). Hence, bringing stock prices to fall and are estimated to drop to negative territory by approximately 1.5 percent (Table 2, columns 2 and 3). Miller (2020) further argued that whenever the world economy enters into unprecedented and unpredicted crisis, the demand for US dollar by investors around the globe tend to ratchet up.

### 4.2. Different Asian Investors' Sentiment to the Pandemic, by Income Group

Seen on the whole, the stock investors' risk perception and general fear towards the negative impact of the pandemic is not as intense and pronounced as that in the European or American markets (Amstad et al, 2020). However, since the Asian countries considered in this study are diverse and distinct in terms of the stage of economic and financial development, this section will provide further validation on the consistency of the estimated coefficient for CRA index in equation 2. The empirical results are reported in Table 2, column 3.

As compared to the lower-middle income countries – India, Philippines and Vietnam – the impact of CRA index to stock price index is positive and statistically significant for both high (Japan, Korea, Singapore) and upper-middle income countries (Indonesia, Thailand, Malaysia). Singapore, Japan, Korea were the first to press digital infrastructures into use in Asia to stem the virus outbreak (Chandran, 2020). Such prompt responses by these countries might have given stock investors a boost and confidence in the market. Meanwhile, the estimated coefficient of CRA index in lower-middle income countries is negative. While inference is invalid since it is statistically insignificant, the results could possibly hint of the countries' relatively underdeveloped financial system. Furthermore, following the extrapolations of Amstad et al (2020) on advanced versus developing economies, lower-middle income Asian economies have less integrated and less efficient markets, with a slimmer investor base relative to the high and upper-middle income countries in comparison.

### 4.3. Impact of Pandemic-related Government Responses to Stock Markets

The inclusion of GRSI as a control variable in the model specification (eq.4) confirms the consistency of the direction of sign (i.e., positive) of the estimated coefficients for CRA index in all equations. The variable GRSI is positive and statistically significant, which means that as governments intensified their wide range of strict measures to stem the spread of the virus, Asian stock markets seem to gain market confidence.

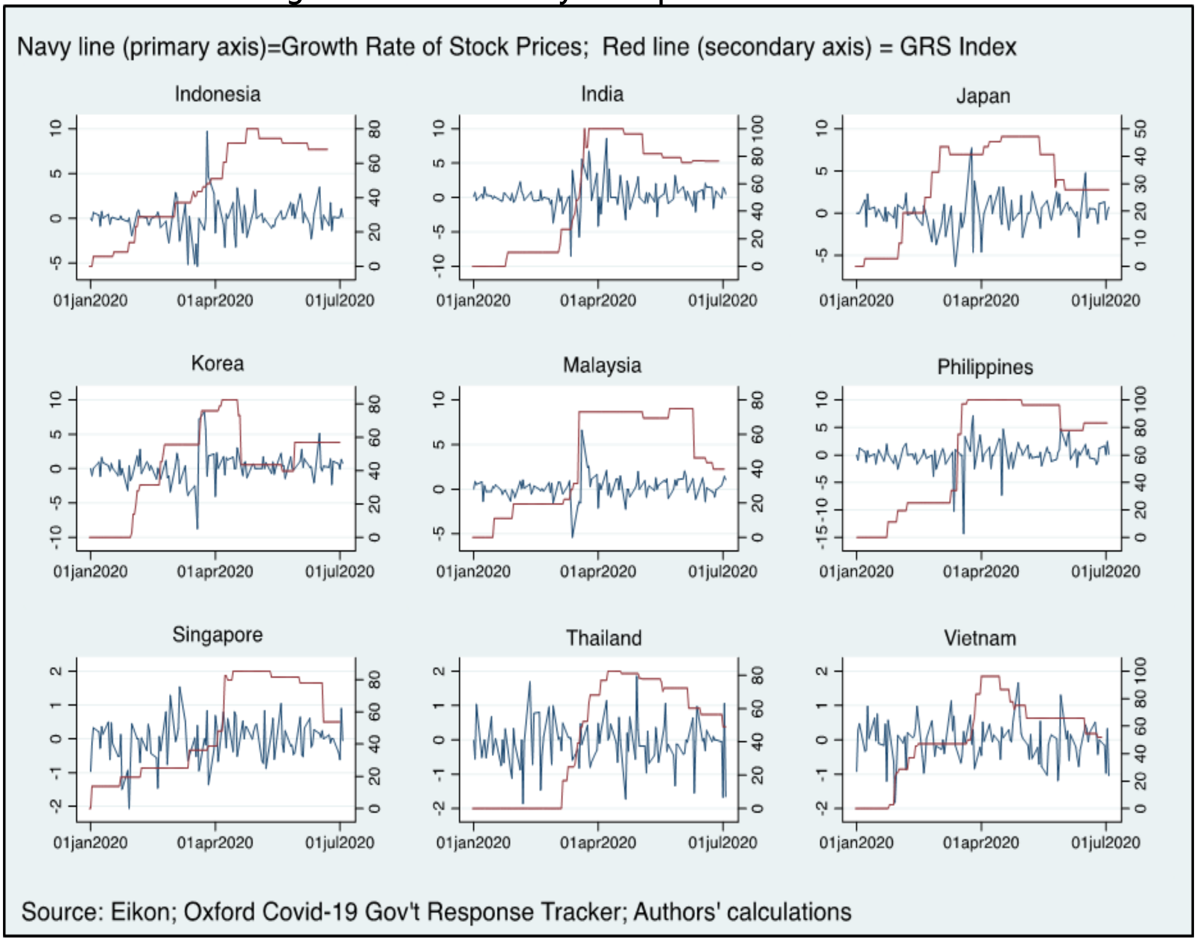
**Table 3: Models for Robustness Checks**

| Predictor Variables | Controlling for GRSI (eq. 4) | Outbreak & Fever Phases (20 Jan – 31 Mar 2020) |
|---|---|---|
| *Impact of investors' sentiment to Asian stock markets* | | |
| $\Delta ln\ (cases_{it})$ | -0.002 | -0.002 |
| | (0.004) | (0.004) |
| $\Delta CRA_{it}$ | 0.023* | 0.029* |
| | (0.012) | (0.016) |
| *Impact of fundamentals to Asian stock markets* | | |
| $\Delta ln\ (op_t)$ | 0.008** | 0.034 |
| | (0.004) | (0.032) |
| $\Delta ln(twusd_t)$ | -1.488*** | -1.608*** |
| | (0.185) | (0.277) |
| $\Delta vix_t$ | 0.004 | 0.004 |
| | (0.020) | (0.020) |
| *Robustness checks* | | |
| $GRSI_{it}$ | 0.004* | 0.011 |
| | (0.002) | (0.009) |
| No. of observations | 780 | 319 |
| No. of countries | 9 | 9 |

*Note: Driscoll-Kraay standard errors are in parentheses; ***, **,* denotes p-value less than the 1%, 5% and 10% levels of significance, respectively.*

The figure below distinctly shows that as the level of government's response measures gets stricter, stock prices tend to bounce back (Figure 3), signalling market's confidence amid the pandemic. Intuitively, this suggests that investors respond to the government's cue – that is, more stringent measures signalling a more active fight against the pandemic that shortens the waiting time for recovery, both in public health and in the economy. Broadly, the graph shows that the highest peak in the stock prices in most of the select Asian countries is seen around the month of April where majority of these countries have already implemented containment measures, economic relief operations, healthcare investments and other pandemic-related responses.

Figure 3: Cross-country stock price indices and GRSI




### 4.4. Asian Stock Markets' Response over the *'Outbreak'* and '*Fever'* Phases

Overall, the impact of CRA index to Asian stock prices remains consistent regardless of the model specifications even if the model was estimated by limiting the time period to *Outbreak* and *Fever* phases only. In fact, the estimated coefficient for the impact of CRA index to stock prices is a little bit higher (Table 3, column 3) vis-à-vis the specification in equation 4 (Table 3, column 2). To some degree, this result is supported by the claim of Amstad et al (2020) that the negative effect of the CRA index is less pronounced in a number of Asian equity markets than in America and Europe since the former went through the epidemic earlier and policy re-adjustments were effected accordingly.

## 5. Conclusion

The dynamics of the stock markets' behavior towards the global pandemic brought the public, not only the economists, to ask the question – *Is the glass half-empty or half-full?* In this paper, we tried to provide answers to some questions and/or issues with regard to stock price movements. In particular, the main objective of this research is to measure investor risk attitude towards COVID-19 and quantify its impact to select Asian stock prices by leveraging on the use of big data – internet search volume index.

In addition to market fundamentals, the CRA index is a significant predictor variable for variations in Asian stock prices. Across all model specifications, this study finds out that Asian stock markets, in general, do not exhibit absolute pessimism towards the pandemic. This paper argues that as governments pull out all the stops to soften, if not to totally eradicate, the impact of the dreaded coronavirus, Asian stock investors appear to relatively gain market confidence. This claim is corroborated by the positive effect of GRSI to equity prices where a suite of government responses – ranging from containment measures to economic relief operations and health facilities investments – have been enacted relatively prompt. Further, the main story holds true even when the time series observations were limited to *'Outbreak'* and *'Fever'* phases only.

Finally, since different countries have different pre-existing institutional characteristics or macroeconomic conditions, this research tested for the heterogenous response of select Asian countries by grouping these countries according to their income classification. The effect of the variable CRA index in high-income and upper-middle income countries to stock prices is positive and statistically significant while the opposite is observed in lower-middle income countries.

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## Appendix 1: Different Measures of Investor Sentiment Towards Risk

| Index | Brief Description |
|---|---|
| Chicago Board Options Exchange Volatility Index (VIX) | The CBOE's VIX is measured via the investors' buying and selling of the S&P 500 options to mitigate their risk exposure based on the market's expectation of the 30-day implied volatility in the US stock market at a specified time ($t$).<br>*VIX, which measures the implied volatility of the S&P 500 options, will be used as one of the variables in the proposed model of this paper. |
| JP Morgan's Risk Tolerance Indices<br>a. Global (JPM G-10 RTI)<br>b. Emerging Markets the (JPM EM RTI) | The JPM G-10 RTI uses the US swap spread for liquidity risk, the aforementioned VIX for equity market risk, EMBI+ for credit risk in Emerging Markets and the Trade-weighted Swiss France for the "risk appetite" in the currency markets. Meanwhile, the JPM EM RTI uses only the VIX and EMBI+ with a 30-70 weight. |
| Dresdner Kleinwort's Aggregate Risk Perception Index (ARPI) | The ARPI uses high-frequency data on the spreads and volatilities from the fixed income basket to measure global and political risk, the equity basket for equity investment risk, the liquidity basket for liquidity risk, the commodity basket for energy risk and the credit basket for credit risk.[21] |
| Goldman Sachs Risk Aversion Index (GS) | The GS uses the real US per-capita consumption growth, returns on real rate on three-month US T-bills and returns on inflation-adjusted S&P 500 Index. |
| State Street Investor Confidence Index (ICI) | The ICI measures the changes in the international holdings of large institutional investors,[22] by comparing the dollar flow of the day versus the dollar holdings in the previous day (given the country and the day).[23] |
| Tarashev, Tsatsaronis and Karampatos Risk-Appetite Index (from the Bank of International Settlement or BIS) | The BIS index compares the probability of future asset returns (based on spot prices' historical patter) vis-à-vis the probability of the returns through the effective risk preferences of the investors largely driven by options prices.[24] |
| Gai and Vause from the Bank of England (FSI) | The FSI follows that of the BIS, with difference emanating from calculating the ration of the whole probability distributions rather than just the tails. |
| Credit Suisse Global Risk Appetite Index (CS) | The CS uses a pool of safe and risky assets (via 7-10 year government bonds and equities & EM bonds, respectively).[25] |
| Kumar and Persuad's (2002): Global Risk Appetite Index (GRAI) | The GRAI is measured by ranking assets in terms of their level of "riskiness"[26] and their level of "excess returns".[27] |

[21] The method used a 2-step Principal Component Analysis (PCA) (e.g., within baskets and among the principal components of the baskets).

[22] Those with 22 million security transactions annually across 45 countries.

[23] Thus, simply the market capitalization in each country over time.

[24] The index is calculated as the ratio of the left tails of the probability distributions.

[25] The index is calculated through a cross-sectional linear regression of excess returns and volatilities of the assets, with the slope of the regression line as the risk appetite index.

[26] Based on past returns.

[27] Based on the difference between future and spot prices at time (t). The principle being that the correlation between the ranking of risk and return should be close to 0 for changes in "riskiness". The correlation should be positive for increasing risk appetite (RA) and negative for decreasing RA.

| | |
|---|---|
| Ding et al (2010): Surveys-based risk attitude measure | Using a survey among Peking University students which inquires on an individual's reservation price for a "hypothetical lottery" and a self-scale assessment of risk attitude (0-10 scale, with 0 as the most risk averse). |

## Appendix 2: Panel Data Summary Statistics

| Variables | | Mean | Standard Deviation | Min | Max | Observations |
|---|---|---|---|---|---|---|
| $\Delta ln\ (sp_{it})$ | overall | 0.07 | 1.71 | -14.32 | 9.70 | N = 963 |
| | between | | 0.14 | -0.10 | 0.34 | n = 9 |
| | within | | 1.70 | -14.32 | 9.77 | T = 107 |
| $\Delta ln\ (op_t)$ | overall | 0.18 | 10.25 | -64.37 | 41.20 | N = 927 |
| | between | | 0.00 | 0.18 | 0.18 | n = 9 |
| | within | | 10.25 | -64.37 | 41.20 | T = 103 |
| $\Delta ln(twusd_t)$ | overall | 0.03 | 0.48 | -1.94 | 1.92 | N = 927 |
| | between | | 0.00 | 0.03 | 0.03 | n = 9 |
| | within | | 0.48 | -1.94 | 1.92 | T = 103 |
| $\Delta vix_t$ | overall | -0.04 | 4.11 | -17.64 | 21.57 | N = 954 |
| | between | | 0.00 | -0.04 | -0.04 | n = 9 |
| | within | | 4.11 | -17.64 | 21.57 | T = 106 |
| $\Delta ln\ (cases_{it})$ | overall | 5.93 | 12.21 | 0.00 | 154.04 | N = 1422 |
| | between | | 1.72 | 3.22 | 8.61 | n = 9 |
| | within | | 12.10 | -2.68 | 151.37 | T-bar = 158 |
| $\Delta CRA_{it}$ | overall | 0.07 | 7.36 | -36.50 | 37.75 | N = 1665 |
| | between | | 0.05 | 0.01 | 0.19 | n = 9 |
| | within | | 7.36 | -36.51 | 37.74 | T = 185 |
| $GRSI_{it}$ | overall | 46.95 | 31.00 | 0.00 | 100.00 | N = 1646 |
| | between | | 8.77 | 29.82 | 61.51 | n = 9 |
| | within | | 29.86 | -14.56 | 93.38 | T = 182.89 |