(COVID-19)-INDUCED FLIGHT TO QUALITY

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Abstract

During crises, investment re-allocation from risky to safe assets, constitutes a flight to quality market environment. This study investigates the flight to quality in Thailand from risky stocks to safe government bonds. It describes returns using the modified, conditional regression model, and extracts the unobserved abnormal returns using the Kalman filtering technique. Estimates of abnormal returns were used in tests for the Granger causality of stocks to bonds, and for investigating the significance of the contributions of abnormal returns to a decreasing correlation. Flight to quality implies these test hypotheses. The data are returns representative of stocks listed on the Stock Exchange of Thailand and of bonds registered on the Thai Bond Market Association. The full period runs from August 28, 2018 to June 30, 2020, whereas the COVID-19 period covers November 18, 2019, to June 30, 2020. The return correlation in the COVID-19 period is more negative than that in the pre-(COVID-19) period. Stocks Granger cause bonds. The contribution share of COVID-19 to the falling correlation is 89.2080%. While the joint Wald-test for the non-significance of COVID-19's contributing correlations yields a p-value of 0.1144, the impulse response analyses suggest that they are all significant. Thailand has experienced flight to quality during the COVID-19 crisis.

Keywords: financial crisis; flight to safety; return correlation

1. INTRODUCTION

Flight to quality describes a market environment where, in a time of crisis, investors sell assets that they perceive as risky, while purchasing those they consider to be safe (Caballero & Kurlat, 2008). Flight to quality is interesting and important for market participants. To policy makers and regulators, a serious concern is that a massive sell-off of risky assets and a

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corresponding flight to safe assets can cause a cascading effect of downward corresponding flight to safe assets can cause a cascading effect of downward pressures on the prices of risky assets. Thus, flight to quality can deteriorate the economic environment due to increased volatility in asset prices and rapid capital outflow (Baele, Bekaert, Ingelbrecth, & Wei, 2020). Eventually, these combined adverse effects impact the real economy (Bofinger, Dullien, Felbermayr, Fuest, Hüther, Südekum, & Di Mauro, 2020). For investors, flight helps to mitigate losses that they could otherwise incur (Baur & Lucey, 2009). Investors will naturally seek to rebalance their portfolios optimally by taking into account asset correlations that may change as a result of flight to quality (Mustafa, Samsudin, Shahadan, & Yi, 2015).

Coronavirus disease 2019 (COVID-19), the most recent pandemic, is an infectious respiratory disease caused by Severe Acute Respiratory Syndrome Coronavirus 2 (Lai, Shih, Ko, Tang, & Hsueh, 2020). COVID-19 can induce flight to quality (Ozili & Arun, 2020). To limit the spread of the virus, social-distancing measures are implemented, offices are closed, and cities are locked down. Economic activities fall precipitously. As the virus continues to spread, the heightened uncertainty as to how severe the situation will get leads to a flight to safety in consumption, investment, and trade.

COVID-19 has drawn considerable attention from flight to quality studies. Chen (2020) reported on the flight of common stocks to corporate social-responsibility stocks in the Chinese market. Coibion, Gorodnichenko, and Weber (2020) found from survey data that U.S. investors raised shares of safe assets in their portfolios, thus suggesting flight to quality behavior in the time of COVID-19. Akhtaruzzaman, Boubaker, Lucey, and Sensoy (2020) found flight from stocks to gold in China, Europe, Japan, and the United States; similarly, Kristoufek (2020) and Corbet, Hou, Hu, and Oxley's (2020a) findings supported flight to gold from U.S. and Chinese stocks, respectively. However, Corbet, Larkin, and Lucey's (2020b) results did not support flight to gold for the stocks listed in China's Shanghai and Shenzhen markets.

Stocks in developed markets, bonds, and cryptocurrencies are perceived as safe assets to which risky assets are re-allocated. However, it is interesting to note that these assets have not been targeted as safe assets during the COVID-19 pandemic. Günay (2020) found that the U.S. and U.K. stocks moved in tandem with Chinese, Italian, Spanish, and Turkish stocks. According to Bouri, Cepni, Gabauer, and Gupta (2020) the degree of correlation of bonds with gold, crude oil, world equities, and currencies increased during the COVID-19 crisis. Hence, bonds cannot be considered as safe assets for the previously mentioned four asset classes to move to. Both Corbet, et al. (2020b) and Johnson (2020) found that cryptocurrencies cannot serve as safe havens while respectively studying Chinese stocks, and seven major stock index portfolios and five major currencies. The correlations are increasing instead of decreasing.

This study tests for flight to quality in Thailand's financial markets during the COVID-19 pandemic period. Thailand has been chosen as the sample country because its economic contraction, due to COVID-19, has been among the most severe in the East Asia and Pacific Region (World Bank, 2020). From a health perspective, Thailand is the first country outside China that experienced COVID-19 infections. However, the Thai government has effectively and successfully managed the situation. As of July 17, 2020, the country ranks first in Asia and second among 184 countries worldwide, to have successfully recovered from COVID-19 (PEMANDU Associates, 2020). New infections among the population within the country have not been found for more than two months since May 13, 2020. Due to the improved and controlled situation, on July 1, 2020, the Thai government ended the lockdown on all business and other activities across the country (Bangprapa, 2020).

Flight to quality studies are interested in return outcomes in the pre-crisis and crisis periods. The start of a crisis is not difficult to identify. It is typically associated with the outbreak of a major event. However, the end of a crisis is more difficult to determine as markets are slow to return to their normal conditions (Boucher & Tokpavi, 2019). Thailand is a strong candidate as the sample country for a study of (COVID-19)-induced flight to quality. Despite the spread of the virus continuing outside Thailand, the country's economic activities have gradually returned to normal after the end of the lockdown.

In this study stocks and government bonds have been chosen to represent risky and safe assets, respectively. These two asset classes, which at times are complementary to, and serve as substitutes for each other, are widely recognized in the literature (Boucher & Tokpavi, 2019). The Thai stock and bond markets are important, as they are among the leading markets in emerging economies. According to a recent assessment by the World Federation of Exchanges (2020), the SET ranks 11th among markets in the Asia-Pacific region and is the 25th largest market in the world. In June 2020, the market capitalization of the Stock Exchange of Thailand (SET) was US$ 473 billion. Thailand's bond market is also significant. The 2019 market capitalization of its government bonds was US$ 318 billion. Among the sample countries of the *Asia Bond Monitor* (Asian Development Bank, 2020), the Thai bond market ranks 5th in terms of market capitalization after Japan, India, China, and Korea.

This study recognizes the weaknesses of the testing methods used in previous studies. Flight to quality occurs in a brief burst during crises wherein returns take on extreme values. However, analyses of correlations (Brière, Chapelle, & Szafarz, 2012), rolling correlations (Bethke, Trapp, & Kempf, 2017), and conditional correlations (Akhtaruzzaman, et al., 2020) consider the whole distribution rather than the tail areas of the distribution (Soylu & Güloğlu, 2019). Tests based on conditional regressions (Baur & Lucey, 2009) are the same as tests for correlation difference. Significant slope coefficients imply significant differences. Rolling and conditional correlations may give biased results due to increasing volatilities in a time of crisis (Forbes & Rigobon, 2002). Even if certain methods, such as those of Soylu and Güloğlu (2019), consider extreme returns, such extreme returns can also occur in a pre-crisis period.

To overcome these weaknesses, this study applies the modified conditional regression approach proposed by Khanthavit (2020a) to decompose the returns into normal and abnormal components. The abnormal returns are considered to be induced by COVID-19. The decreasing correlation due to COVID-19 is based on the contribution from abnormal returns. The correlation estimates are unconditional, so they are not biased by increasing volatilities (Forbes & Rigobon, 2002). The Granger causality test (Kim & Dilts, 2011) is applied using the abnormal returns. Although the test considers the whole distribution of returns, the returns are abnormal returns in the crisis period. The concern of Soylu and Güloğlu (2019) with respect to (COVID-19)-induced extreme returns is hereby solved.

2. METHODOLOGY

2.1 The Model

Let $\tilde{r}_{i,t}$ be the random return on asset i on day t. The subscripts $i = s$ and $i = b$ denote the stock and bond returns, respectively. This study applies Khanthavit's (2020a) approach, which is a modification of the conditional regression model in event-study analyses (Thompson, 1985). It measures the unobserved abnormal return by parameterizing the return $\tilde{r}_{i,t}$ in the regression model in equation (1).

$$\tilde{r}_{i,t} = \tilde{\mu}_{i,t} + \tilde{e}_{i,t} + \delta_t \tilde{r}^a_{i,t}. \qquad (1)$$

In equation (1), $\tilde{\mu}_{i,t}$ ($\tilde{e}_{i,t}$) is the expected return (error term) on a normal day. The mean and variance of $\tilde{e}_{i,t}$ are 0.00, and $\sigma^2_{e_i}$, respectively. δ_t is the dummy variable; it identifies the COVID-19 period. δ_t is 1 if day t is in the COVID-19 period, and 0 otherwise. This study has interpreted $\tilde{\mu}_{i,t} + \tilde{e}_{i,t}$ as the normal return $\tilde{r}^n_{i,t}$; as such $\tilde{r}^n_{i,t}$ is unaffected by the COVID-19 crisis. $\tilde{r}^a_{i,t}$ is the abnormal return because it occurs only on day t in the COVID-19 period.

2.2. Model for Normal Returns

The expected return $\tilde{\mu}_{i,t}$ cannot be observed. It must be estimated. This study assumes that $\tilde{\mu}_{i,t}$ follows an autoregressive process of order 1 (AR(1)) in equation (2):

$$\tilde{\mu}_{i,t} = \alpha_{i,0} + \alpha_{i,1}\mu_{i,t-1} + \tilde{\varepsilon}_{i,t}. \quad (2)$$

$\alpha_{i,0}$ is the intercept, whereas $\alpha_{i,1}$ is the AR(1) slope coefficient. The error term $\tilde{\varepsilon}_{i,t}$ has a zero mean and a variance of $\sigma^2_{\varepsilon_i}$. This designation implies the mean-adjusted specification when $\alpha_{i,0} = \sigma^2_{\varepsilon_i} = 0.00$. The mean-adjusted specification is widely used in event-study analyses. It is simplistic and can perform as well as the alternatives (Brown & Warner, 1985).

2.3 Model for Abnormal Returns

The abnormal return $\tilde{r}^a_{i,t}$ is also unobserved. The $\tilde{r}^a_{i,t}$ movement is described by an AR(1) process in equation (3).

$$\tilde{r}^a_{i,t} = \beta_{i,0} + \beta_{i,1} r^a_{i,t-1} + \tilde{\omega}_{i,t}, \quad (3)$$

where $\beta_{i,0}$ is the intercept and $\beta_{i,1}$ is the AR(1) coefficient. $\tilde{\omega}_{i,t}$ is the error term, whose mean is 0.00, and whose variance is $\sigma^2_{\omega_i}$.

2.4. Model Estimation

Equations (1), (2), and (3) constitute a state-space model for stock and bond returns. Equation (1) is the measurement equation, in which the observed return is related to the unobserved normal and abnormal returns. Equations (2) and (3) are the transition equations. These equations describe the stochastic behaviors of the unobserved, state variables, $\tilde{\mu}_{i,t}$ and $\tilde{r}^a_{i,t}$.

It is assumed that the error terms $\tilde{\varepsilon}_{i,t}$ and $\tilde{\omega}_{i,t}$ are uncorrelated. This assumption is justified by the fact that $\tilde{r}^a_{i,t}$ is zero under the null hypothesis of no (COVID-19)-induced flight. Transition equations (2) and (3) can be rewritten as the system of equations in (4).

$$\begin{bmatrix} \tilde{\mu}_{i,t} \\ \tilde{r}^a_{i,t} \end{bmatrix} = \begin{bmatrix} \alpha_{i,0} \\ \beta_{i,0} \end{bmatrix} + \begin{bmatrix} \alpha_{i,1} & 0 \\ 0 & \beta_{i,1} \end{bmatrix} \begin{bmatrix} \mu_{i,t-1} \\ r^a_{i,t-1} \end{bmatrix} + \begin{bmatrix} \tilde{\varepsilon}_{i,t} \\ \tilde{\omega}_{i,t} \end{bmatrix}, \quad (4)$$

where the covariance matrix of $\begin{bmatrix} \tilde{\varepsilon}_{i,t} \\ \tilde{\omega}_{i,t} \end{bmatrix}$ is $\begin{bmatrix} \sigma^2_{\varepsilon_i} & 0 \\ 0 & \sigma^2_{\omega_i} \end{bmatrix}$.

This study estimates the model in equations (1) and (4), using Kalman filtering (Harvey, 1990). In addition to parameter estimates, Kalman filtering returns the estimates $\hat{\mu}_{i,t}$ and $\hat{r}^a_{i,t}$ of $\mu_{i,t}$ and $r^a_{i,t}$.

2.5 Event and Estimation Periods

2.5.1 COVID-19 Period

The beginning of a crisis can be identified by the outbreak of an event (Boucher & Tokpavi, 2019). In previous flight to quality studies for COVID-19, Corbet, et al. (2020a) determined the outbreak date as November 17, 2019, being when COVID-19 was first detected in China; while Cheema and Szulczyk (2020) preferred December 31, 2019, as the date when China informed the World Health Organization (WHO) of patients with mysterious pneumonia.

In contrast, Akhtaruzzaman, et al. (2020) studied the U.S. market, selecting March 17, 2020, as this was the date that U.S. Congress passed the Coronavirus Aid, Relief, and Economic Security Act.

In this study, the COVID-19 crisis period covers 152 daily observations. The study follows Corbet, et al. (2020a) in selecting November 17, 2019, as the crisis start date. Furthermore, previous COVID-19 studies for Thailand's financial markets likewise chose November 17, 2019, (Khanthavit, 2020a; 2020b). However, because November 17, 2019, fell on a Sunday, the start of the event period has been adjusted to the first trading day following this date, being Monday, November 18, 2019.

The last day of the crisis period in this study is June 30, 2020. Although, at the time of writing, the COVID-19 pandemic has not yet ended, June 30, 2020, represents the last day of Thailand's business lockdown. Since July 1, 2020, all business and other activities have gradually returned to normal.

2.5.2 Pre-(COVID-19) Period

Peterson (1989) reviewed event studies and concluded that typical lengths of the pre-event period range from 100 to 300 days. This study prefers the longest period of 300 days for accurate parameter estimation (Salinger, 1992). The pre-event period in this study thus begins on August 28, 2018, and ends on November 15, 2019, being the last trading day before the start of the crisis.

2.6 Hypothesis Tests

2.6.1 Granger Causality Test

The Granger causality test is performed based on the vector auto-regressive model of order p (VAR(p)) for abnormal returns $\begin{bmatrix}\tilde{r}^a_{s,t}\\ \tilde{r}^a_{b,t}\end{bmatrix}$. This study considers $\begin{bmatrix}\tilde{r}^a_{s,t}\\ \tilde{r}^a_{b,t}\end{bmatrix}$, but not raw returns $\begin{bmatrix}\tilde{r}_{s,t}\\ \tilde{r}_{b,t}\end{bmatrix}$ because flight to quality studies are interested in incremental effects (Forbes & Rigobon, 2002). The VAR(p) model is shown in equation (5).

$$\begin{bmatrix}\tilde{r}^a_{s,t}\\ \tilde{r}^a_{b,t}\end{bmatrix} = \begin{bmatrix}a_{s,0}\\ a_{b,0}\end{bmatrix} + \sum_{k=1}^{p}\begin{bmatrix}a^s_{s,k} & a^b_{s,k}\\ a^s_{b,k} & a^b_{b,k}\end{bmatrix}\begin{bmatrix}r^a_{s,t}\\ r^a_{b,t}\end{bmatrix} + \begin{bmatrix}\tilde{z}^a_{s,t}\\ \tilde{z}^a_{b,t}\end{bmatrix} \qquad (5)$$

where $\begin{bmatrix}a_{s,0}\\ a_{b,0}\end{bmatrix}$ is the vector of the intercepts, and $\begin{bmatrix}a^s_{s,k} & a^b_{s,k}\\ a^s_{b,k} & a^b_{b,k}\end{bmatrix}$ is the matrix of order k coefficients. $\begin{bmatrix}\tilde{z}^a_{s,t}\\ \tilde{z}^a_{b,t}\end{bmatrix}$ is the vector of regression errors, whose mean vector and covariance matrix are $\begin{bmatrix}0\\ 0\end{bmatrix}$ and Ω respectively. This study chooses the order p from the VAR(p^*) model that yields the minimum Bayesian information criterion (BIC) (Schwarz, 1978). This technique estimates p consistently (Zivot & Wang, 2006).

If flight to quality exists, $\tilde{r}^a_{s,t}$ Granger causes $\tilde{r}^a_{b,t}$ (Soylu & Güloğlu, 2019). The test must reject the hypothesis $a^s_{b,1} = \cdots = a^s_{b,p}$; and if so the hypothesis $a^b_{s,1} = \cdots = a^b_{s,p}$ cannot be rejected. Under the null hypothesis, the Wald statistics are chi-square variables with p degrees of freedom.

2.6.2 Equal-Correlation Tests

2.6.2.1 Analyses of Correlations

If COVID-19 induces flight to quality, $\tilde{r}^a_{s,t}$ and $\tilde{r}^a_{b,t}$ are non-zero and contribute to a decreasing, more negative return correlation. The correlation $\rho(\tilde{r}_{s,t}, \tilde{r}_{b,t})$ between $\tilde{r}_{s,t}$ and $\tilde{r}_{b,t}$ is

$$\rho(\tilde{r}_{s,t}, \tilde{r}_{b,t}) = \frac{\rho(\tilde{r}^n_{s,t}, \tilde{r}^n_{b,t})\sigma(\tilde{r}^n_{s,t})\sigma(\tilde{r}^n_{b,t})}{\sigma(\tilde{r}_{s,t},)\sigma(\tilde{r}_{b,t})} + \frac{\rho(\tilde{r}^a_{s,t}, \tilde{r}^a_{b,t})\sigma(\tilde{r}^a_{s,t})\sigma(\tilde{r}^a_{b,t})}{\sigma(\tilde{r}_{s,t},)\sigma(\tilde{r}_{b,t})} + \frac{\rho(\tilde{r}^a_{s,t}, \tilde{r}^n_{b,t})\sigma(\tilde{r}^a_{s,t})\sigma(\tilde{r}^n_{b,t})}{\sigma(\tilde{r}_{s,t},)\sigma(\tilde{r}_{b,t})} + \frac{\rho(\tilde{r}^n_{s,t}, \tilde{r}^a_{b,t})\sigma(\tilde{r}^n_{s,t})\sigma(\tilde{r}^a_{b,t})}{\sigma(\tilde{r}_{s,t},)\sigma(\tilde{r}_{b,t})} \qquad (6)$$

where $\sigma(\tilde{x})$ denotes the standard deviation of the variable $\tilde{x} = \tilde{r}_{i,t}, \ \tilde{r}^j_{i,t}$, $i = s, b$ and $j = n, a$. From equation (6), the hypothesis of no (COVID-19)-induced flight to quality is joint-zero contributing the following correlations:

$$\rho(\tilde{r}^a_{s,t}, \tilde{r}^a_{b,t}) = \rho(\tilde{r}^a_{s,t}, \tilde{r}^n_{b,t}) = \rho(\tilde{r}^n_{s,t}, \tilde{r}^a_{b,t}) = 0. \qquad (7)$$

If hypothesis (7) is correct, the Wald statistic is a chi-square variable with 3 degrees of freedom.

This study checks for the economic significance of the change. From equation (6), the aggregate percentage share due to COVID-19 is

$$\frac{\rho(\tilde{r}^a_{s,t}, \tilde{r}^a_{b,t})\sigma(\tilde{r}^a_{s,t})\sigma(\tilde{r}^a_{b,t})}{\rho(\tilde{r}_{s,t}, \tilde{r}_{b,t})\sigma(\tilde{r}_{s,t},)\sigma(\tilde{r}_{b,t})} + \frac{\rho(\tilde{r}^a_{s,t}, \tilde{r}^n_{b,t})\sigma(\tilde{r}^a_{s,t})\sigma(\tilde{r}^n_{b,t})}{\rho(\tilde{r}_{s,t}, \tilde{r}_{b,t})\sigma(\tilde{r}_{s,t},)\sigma(\tilde{r}_{b,t})} + \frac{\rho(\tilde{r}^n_{s,t}, \tilde{r}^a_{b,t})\sigma(\tilde{r}^n_{s,t})\sigma(\tilde{r}^a_{b,t})}{\rho(\tilde{r}_{s,t}, \tilde{r}_{b,t})\sigma(\tilde{r}_{s,t},)\sigma(\tilde{r}_{b,t})},$$

where

$$\frac{\rho(\tilde{r}^a_{s,t}, \tilde{r}^a_{b,t})\sigma(\tilde{r}^a_{s,t})\sigma(\tilde{r}^a_{b,t})}{\rho(\tilde{r}_{s,t}, \tilde{r}_{b,t})\sigma(\tilde{r}_{s,t},)\sigma(\tilde{r}_{b,t})},$$

$$\frac{\rho(\tilde{r}^a_{s,t}, \tilde{r}^n_{b,t})\sigma(\tilde{r}^a_{s,t})\sigma(\tilde{r}^n_{b,t})}{\rho(\tilde{r}_{s,t}, \tilde{r}_{b,t})\sigma(\tilde{r}_{s,t},)\sigma(\tilde{r}_{b,t})},$$

and

$$\frac{\rho(\tilde{r}^n_{s,t}, \tilde{r}^a_{b,t})\sigma(\tilde{r}^n_{s,t})\sigma(\tilde{r}^a_{b,t})}{\rho(\tilde{r}_{s,t}, \tilde{r}_{b,t})\sigma(\tilde{r}_{s,t},)\sigma(\tilde{r}_{b,t})}$$

are the respective percentage shares of its three underlying components. No flight to quality implies

$$\frac{\rho(\tilde{r}^a_{s,t}, \tilde{r}^a_{b,t})\sigma(\tilde{r}^a_{s,t})\sigma(\tilde{r}^a_{b,t})}{\rho(\tilde{r}_{s,t}, \tilde{r}_{b,t})\sigma(\tilde{r}_{s,t},)\sigma(\tilde{r}_{b,t})} + \frac{\rho(\tilde{r}^a_{s,t}, \tilde{r}^n_{b,t})\sigma(\tilde{r}^a_{s,t})\sigma(\tilde{r}^n_{b,t})}{\rho(\tilde{r}_{s,t}, \tilde{r}_{b,t})\sigma(\tilde{r}_{s,t},)\sigma(\tilde{r}_{b,t})} + \frac{\rho(\tilde{r}^n_{s,t}, \tilde{r}^a_{b,t})\sigma(\tilde{r}^n_{s,t})\sigma(\tilde{r}^a_{b,t})}{\rho(\tilde{r}_{s,t}, \tilde{r}_{b,t})\sigma(\tilde{r}_{s,t},)\sigma(\tilde{r}_{b,t})} = 0$$

such that the Wald statistic is a chi-square variable with 1 degree of freedom.

2.6.2.2 Impulse Responses

This study performs an additional test for $\rho(\tilde{r}^{a}_{s,t}, \tilde{r}^{a}_{b,t}) = 0$, using impulse response (IR) analyses (Enders, 1995) for day $h = 0, \dots, 20$. The hypothesis imposes that all the IRs of $\tilde{r}^{a}_{s,t}$ ($\tilde{r}^{a}_{b,t}$) to $\tilde{r}^{a}_{b,t}$ ($\tilde{r}^{a}_{s,t}$) are non-significant.

The correlations $\rho(\tilde{r}^{a}_{s,t}, \tilde{r}^{n}_{b,t})$ and $\rho(\tilde{r}^{n}_{s,t}, \tilde{r}^{a}_{b,t})$ add to the decreasing correlation $\rho(\tilde{r}_{s,t}, \tilde{r}_{b,t})$ in the COVID-19 period. The study tests for $\rho(\tilde{r}^{a}_{s,t}, \tilde{r}^{n}_{b,t}) = 0$ and $\rho(\tilde{r}^{n}_{s,t}, \tilde{r}^{a}_{b,t}) = 0$, using corresponding IRs, in a manner similar to that for $(\tilde{r}^{a}_{s,t}, \tilde{r}^{a}_{b,t}) = 0$.

3. THE DATA

The sample returns are the daily logged returns derived from the closing values of the SET index and the government bond total return index of the Thai Bond Market Association (Thai BMA). The stock and bond market data have been sourced from the SET and Thai BMA databases, respectively.

Table 1 below reports the descriptive statistics. In the full-sample period, both stock and bond returns are negatively skewed and have fat-tailed distributions; the

Table 1 Descriptive Statistics

Statistics	Full Sample (452 Observations from 08/28/18 to 06/30/20)		Pre-(COVID-19) Sample (300 Observations from 08/28/18 to 11/15/19)		COVID-19 Sample (152 Observations from 11/18/20 to 06/30/20)	
	Stock Return	Bond Return	Stock Return	Bond Return	Stock Return	Bond Return
Average	−5.50E-04	3.86E-04***	−2.31E-04	5.08E-04***	−0.0012	1.44E-04
Standard Deviation[1]	0.0138	0.0024	0.0068	0.0019	0.0218	0.0032
Skewness	−2.2512***	−1.6914***	−0.0674	2.1168***	−1.6264***	−3.0580***
Excess Kurtosis	22.3568***	21.7754***	1.1450***	13.9601***	9.0541***	16.8837***
AR(1) Coefficient	−0.1221***	0.4770***	−0.0084	0.4541***	−0.1451*	0.4891***
Optimal Number of Lags	5	1	1	3	1	1
Jarque-Bera Statistic	9.80E+03***	9.15E+03***	16.6154***	2.66E+03***	5.86E+02***	2.04E+03***
Correlation	−0.0697		−0.0695		−0.0778	

Note: [1] indicates significance tests are not performed. * and *** indicate significance at the 90% and 99% confidence levels.

Jarque-Bera tests reject the normality hypothesis. The correlation between stock and bond returns is −0.0697, but is non-significant.

For the sub-periods, the returns are not distributed normally; they are autocorrelated, except for the stock return in the pre-(COVID-19) period. The standard deviation for the COVID-19 period is much larger than that for the pre-(COVID-19) period. High volatility is associated with crises (Forbes & Rigobon, 2002). The correlations are non-significant at −0.0695 and −0.0778, respectively.

In the COVID-19 period, the stock market fell by 18.3046% and the bond market rose by 2.1731%. These market movements readily indicate that the pre-condition of a flight to quality from stocks to bonds occurred (Baur & Lucey, 2009).

The study checks for significant autocorrelation for the sample returns. All the AR(1) coefficients are significant, except for the stock return in the pre-(COVID-19) sample. The optimal numbers of autoregressive lags are 1, except for the stock return in the full sample and bond return in the pre-(COVID-19) sample. Significant AR(1) coefficients and optimal lag numbers support the AR(1) specifications for expected and abnormal returns in equations (2) and (3).

The state-space model is estimated by Kalman filtering regression, using the full sample. Despite the non-normality of the returns, the Kalman filter is optimal and produces the minimum mean square linear estimates (Kellerhals, 2001).

There is an indication of a structural change; the volatility is higher, and the correlation is more negative in the COVID-19 period. In the estimation, the possible structural change is accounted for by the abnormal returns $r_{s,t}^{a}$ and $r_{b,t}^{a}$.

4. EMPIRICAL RESULTS

4.1 Traditional Tests for Equal Correlations

Before a study proceeds to report the results for the state-space model, a traditional correlation-difference test should be performed (e.g., Brière, et al., 2012). Table 1 shows the correlation difference between the pre-(COVID-19) and COVID-19 periods is −0.0083, with a p-value of 0.9341.

The slope-coefficient test was also undertaken in the study (Baur & Lucey, 2009). It regresses the stock returns $r_{s,t}$ on the bond returns $r_{b,t}$ and the product $\delta_t r_{b,t}$ of the (COVID-19)-period dummy variable and bond returns. The slope coefficient for the $\delta_t r_{b,t}$ variable was −0.3419, with a p-value of 0.5233.

The two tests yield consistent results. The correlation is more negative during the COVID-19 crisis. There is evidence to suggest a flight to quality. However, the evidence is weak, as the resulting statistical measures are not statistically significant.

4.2 Parameter Estimates for the State-Space Model

Table 2 reports the parameter estimates for the state-space model in equations (1) and (4). In estimation, the returns are scaled by 100.

For stocks, the expected returns are not autocorrelated, but the abnormal returns are negatively autocorrelated. This result is consistent with the AR(1) coefficients for the raw stock returns in Table 1. The volatility of the abnormal stock returns is very high. It is the abnormal returns that explain the high volatility of the raw returns during the COVID-19 crisis. The volatilities of the expected returns and the normal error are not significant. This non-significance may be due to the fact that the statistics are very small when compared to those of the abnormal returns.

For bonds, the expected and abnormal returns are positively autocorrelated. This finding explains the significant and positive AR(1) coefficient of the raw returns in the pre-(COVID-19) as well as COVID-19 samples. The volatility of the abnormal returns is high. The abnormal returns contribute to the high volatility of the raw returns from bonds during the COVID-19 crisis.

4.3 Test for Flight to Quality

4.3.1 Granger Causality Test

The study estimates a VAR(p) model for $p = 1, \dots, 5$. The BIC test identified VAR($p = 1$) as the optimal model. The BIC($p = 1$) statistic is 3.6899. The parameter estimates are reported in Panel 3.1 of Table 3. The abnormal stock returns can be due to a lag in that asset class, but not due to a lag in the abnormal bond returns; whereas the abnormal bond returns can be explained by both lagged stock and bond returns.

Table 2 Parameter Estimates

Parameter	Stock Return	Bond Return
α_0	−0.0231	0.0140*
α_1	−6.02E-06	0.7278***
β_0	−0.1111	−0.0188
β_1	−0.1630*	0.4915***
σ_e	0.4048	0.1209***
σ_ε	0.5419	0.1028***
σ_ω	2.0411***	0.2241***

Note: * and *** indicate significance at the 90% and 99% confidence levels, respectively.

Table 3 The VAR($p = 1$) Model for Abnormal Stock and Bond Returns
Panel 3.1 Parameter Estimates

Regressors	Regressands	
	$\hat{r}^a_{s,t}$	$\hat{r}^a_{b,t}$
$\hat{r}^a_{s,t-1}$	-0.1852^{**}	0.0225^{***}
$\hat{r}^a_{b,t-1}$	-0.6285	0.5300^{***}
Constant	-0.1555	-0.0289^{***}

Note: ** and *** indicate significance at the 95% and 99% confidence levels, respectively.

Panel 3.2 Granger Causality Tests

Null Hypothesis	χ^2_1 Statistic
$\tilde{r}^a_{s,t}$ does not Granger cause $\tilde{r}^a_{b,t}$.	9.6958^{***}
$\tilde{r}^a_{b,t}$ does not Granger cause $\tilde{r}^a_{s,t}$.	0.6698

Note: *** indicates significance at the 99% confidence level.

In Panel 3.2 of Table 3, the hypothesis—$\tilde{r}^a_{s,t}$ does not Granger cause $\tilde{r}^a_{b,t}$, is rejected at the 99% confidence level. The hypothesis—$\tilde{r}^a_{b,t}$ does not Granger cause $\tilde{r}^a_{s,t}$—cannot be rejected. The Granger- causality condition indicates flight to quality.

4.3.2 Significant Decrease of Return Correlation

4.3.2.1 Analyses Based on Correlations

As shown in Table 4, the correlation $\rho\left(\tilde{r}^n_{s,t}, \tilde{r}^n_{b,t}\right)$ is -0.0661 with a p-value of 0.1602. Normal returns are those that are unaffected by COVID-19. The statistic is computed from the full-sample data. The series have been constructed by appending the raw-return series in the pre-(COVID-19) period with the normal-return series from the Kalman filtered data from the COVID-19 period. The -0.0661 correlation between the normal returns for the full period and the -0.0695 correlation between the raw returns for the pre-(COVID-19) period are very close. The difference of 0.0034 is small and not significant.

With respect to Philippas and Siriopoulos (2013), the choice of November 17, 2019, as the first day of the COVID-19 period is an ad-hoc choice. Some researchers (e.g. Soylu & Güloğlu, 2019) prefer a data-determined sample. The small and non-significant difference of 0.0034 provides empirical justification for the choice of November 17, 2019, made in this study.

The correlation $\rho\left(\tilde{r}^a_{s,t}, \tilde{r}^a_{b,t}\right)$ is -0.0850. The correlations $\rho\left(\tilde{r}^a_{s,t}, \tilde{r}^n_{b,t}\right)$ and $\rho\left(\tilde{r}^n_{s,t}, \tilde{r}^a_{b,t}\right)$ add to the decreasing correlation $\rho(\tilde{r}_{s,t}, \tilde{r}_{b,t})$. The statistics are −0.0681, and −0.0682, respectively. Considering whether COVID-19 induces flight to quality, the hypothesis—$\rho(\tilde{r}^a_{s,t}, \tilde{r}^a_{b,t}) = \rho(\tilde{r}^a_{s,t}, \tilde{r}^n_{b,t}) = \rho(\tilde{r}^n_{s,t}, \tilde{r}^a_{b,t}) = 0$ — is rejected by the Wald test. The test statistic, which is a chi-square variable of three degrees of freedom, is 2.4910, with a p-value of 0.1144.

As summarized in Column 3 of Table 4, $\rho(\tilde{r}^n_{s,t}, \tilde{r}^n_{b,t})$ contributes only 10.7920% to $\rho(\tilde{r}_{s,t}, \tilde{r}_{b,t})$. The remaining correlations—$\rho(\tilde{r}^a_{s,t}, \tilde{r}^a_{b,t})$, $\rho(\tilde{r}^a_{s,t}, \tilde{r}^n_{b,t})$, and $\rho(\tilde{r}^n_{s,t}, \tilde{r}^a_{b,t})$—resulting from COVID-19, jointly contribute 89.2080%, with a p-value of 0.2902. $\rho(\tilde{r}^a_{s,t}, \tilde{r}^a_{b,t})$ is dominant, with a contribution of 58.4344%. This contribution share is economically significant, although it is not statistically significant.

This study proposes two possible explanations for these non-significant results. First, as shown in Table 1, the stock and bond returns are very volatile during the COVID-19 period. Parameter estimation is imprecise, especially for the stock returns. Second, the contributing correlations are computed from Kalman filtering estimates, and these estimates are influenced by estimation errors.

4.3.2.2 Analyses Based on Impulse Responses

The results for the correlation $\rho(\tilde{r}^a_{s,t}, \tilde{r}^a_{b,t})$ are shown in Sub-figures 1.1.1 and 1.1.2, of Figure 1. The solid line represents the level of IRs. The dotted lines identify a two-S.D. band surrounding the IR. In Sub-figure 1.1.1, the IR of $\tilde{r}^a_{b,t}$ to $\tilde{r}^a_{s,t}$ is positive and significant on day 1, whereas none of the IRs in Sub-figure 1.1.2 of $\tilde{r}^a_{s,t}$ to $\tilde{r}^a_{b,t}$ are significant. The significant IR on day 1 suggests that $\rho(\tilde{r}^a_{s,t}, \tilde{r}^a_{b,t})$ is significant.

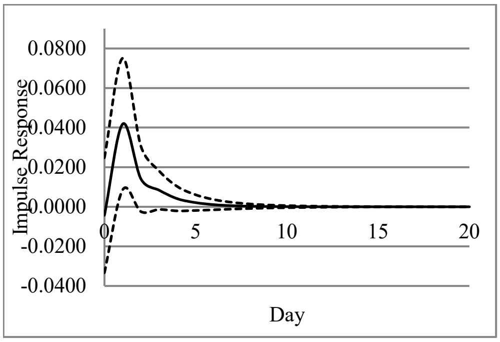
Table 4 Test for Contribution of COVID-19 to Return Correlation

Return Pair	Correlation	
	Size	% Share
$(\tilde{r}^n_{s,t}, \tilde{r}^n_{b,t})^{1,3}$	−0.0661	10.7920
$(\tilde{r}^a_{s,t}, \tilde{r}^a_{b,t})^{2}$	−0.0850	58.4344
$(\tilde{r}^a_{s,t}, \tilde{r}^n_{b,t})^{2}$	−0.0681	25.6398
$(\tilde{r}^n_{s,t}, \tilde{r}^a_{b,t})^{2}$	−0.0682	5.1339
$(\tilde{r}_{s,t}, \tilde{r}_{b,t})^{2}$	−0.0778	100.0000

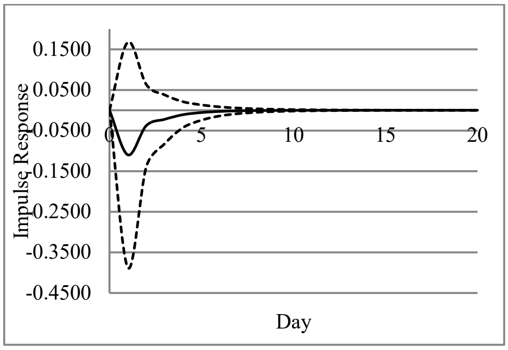
Note: ^{1} (^{2}) indicates that the statistics are computed based on the full COVID-19 sample period. ^{3} indicates that the correlation computed from the COVID-19 sample is −0.0424.

Figure 1 Impulse Responses of Stock and Bond Returns

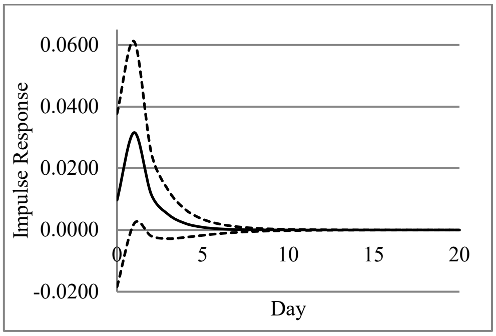
Sub-figure 1.1.1 Response of Abnormal Bond to Abnormal Stock



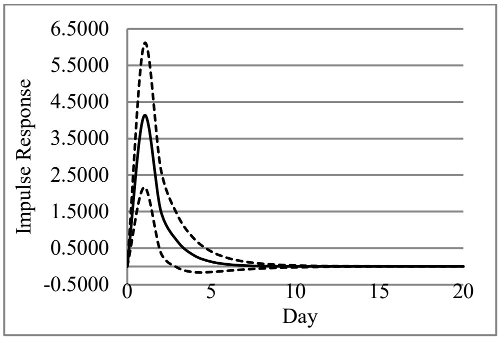
Sub-figure 1.1.2 Response of Abnormal Stock to Abnormal Bond



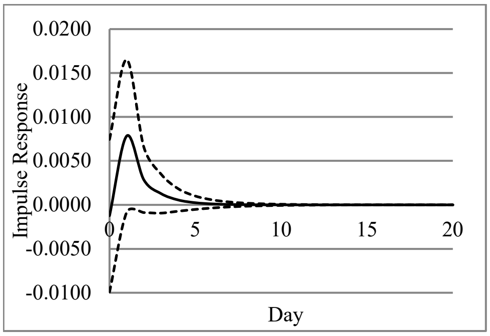
Sub-figure 1.2.1 Response of Normal Bond to Abnormal Stock



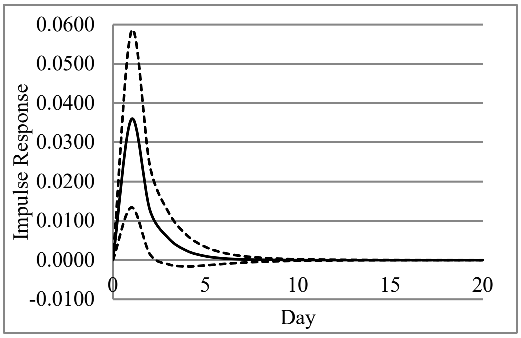
Sub-figure 1.2.2 Response of Abnormal Stock to Normal Bond



Sub-figure 1.3.1 Response of Abnormal Bond to Normal Stock



Sub-figure 1.3.2 Response of Normal Stock to Abnormal Bond



In Sub-figure 1.2.1 of Figure 1, the IR of $\tilde{r}_{b,t}^{n}$ to $\tilde{r}_{b,t}^{a}$ is significant on day 1; and in Sub-figure 1.2.2 of Figure 1, the IRs of $\tilde{r}_{s,t}^{a}$ to $\tilde{r}_{b,t}^{n}$ are significant on days 1 and 2. The significant IRs lead this study to conclude that $\rho(\tilde{r}_{s,t}^{a}, \tilde{r}_{b,t}^{n})$ is significant.

Finally, there is evidence to suggest that $\rho(\tilde{r}_{s,t}^{n}, \tilde{r}_{b,t}^{a})$ is also significant. In Sub-figures 1.3.1 and 1.3.2 of Figure 1, although none of the IRs of $\tilde{r}_{b,t}^{a}$ to $\tilde{r}_{s,t}^{n}$ are significant, the IRs of $\tilde{r}_{s,t}^{n}$ to $\tilde{r}_{b,t}^{a}$ are significant on days 1 and 2.

5. DISCUSSION

5.1 Alternative Choice for the Start of the COVID-19 Period

This study examines how the results may change based on an alternative start date for the COVID-19 crisis. Khanthavit (2020b) reported that the first time the SET reacted to COVID-19 was January 27, 2020, being the first time that COVID-19 was extensively covered by the media. For this reason, this study has selected January 27, 2020, as an alternative start date for the crisis. The date of December 31, 2019, selected by Cheema & Szulczyk (2020) has not been considered because of its proximity to November 17, 2019. Lastly, while March 17, 2020, is important for the United States (Akhtaruzzaman, et al., 2020), it is irrelevant to Thailand.

The tests find that $\tilde{r}_{s,t}^{a}$ Granger causes $\tilde{r}_{b,t}^{a}$, but not vice versa. The contribution analysis of COVID-19 to the falling correlation is reported in Columns 2 and 3 of Table 5. The correlation $\rho(\tilde{r}_{s,t}^{n}, \tilde{r}_{b,t}^{n})$ is −0.1113 and significant. The test cannot reject the hypothesis: $\rho(\tilde{r}_{s,t}^{a}, \tilde{r}_{b,t}^{a}) = \rho(\tilde{r}_{s,t}^{a}, \tilde{r}_{b,t}^{n}) = \rho(\tilde{r}_{s,t}^{n}, \tilde{r}_{b,t}^{a}) = 0$. The p-value is 0.2645. The contribution share of COVID-19 $\rho(\tilde{r}_{s,t}, \tilde{r}_{b,t})$ is 85.3832%. The share is statistically non-significant, with a p-value of 0.3653.

The correlation $\rho(\tilde{r}_{s,t}^{n}, \tilde{r}_{b,t}^{n})$ decreases to −0.1113 for January 27, 2020, from −0.0661 on November 18, 2019. It is likely that the more negative correlation results from the fact that the alternative pre-(COVID-19) period incorporates crisis days. Kalman filtering interprets the raw returns on normal and crisis days in the pre-(COVID-19) period as normal returns, thus causing a more negative correlation. It is consequently concluded that November 18, 2019, is a better choice.

5.2 Alternative Pre-(COVID-19) Period

If the correlation is not constant, a short pre-(COVID-19) period is preferred (Baur & Lucey, 2009). This study verifies the robustness of the results in relation to the length of the pre-crisis period. The alternative specification is 200 days, whereby the pre-(COVID-19) period begins January 23, 2019, and ends, November 15, 2019. Columns 4 and 5

Table 5 Results for Alternative Specifications

Return Pair	Alternative COVID-19 Period		Alternative Pre-(COVID-19) Period		Infections	
	Correlation	% Share	Correlation	% Share	Correlation	% Share
$(\tilde{r}^n_{s,t}, \tilde{r}^n_{b,t})^1$	$-0.1113^{3,**}$	14.6168	-0.0617^4	5.6864	-0.0626^5	10.1161
$(\tilde{r}^a_{s,t}, \tilde{r}^a_{b,t})^2$	−0.0683	59.9300	−0.0856	53.3338	−0.0927	63.8778
$(\tilde{r}^a_{s,t}, \tilde{r}^n_{b,t})^2$	−0.0693	22.5096	−0.0686	35.9385	−0.0560	20.6713
$(\tilde{r}^n_{s,t}, \tilde{r}^a_{b,t})^2$	−0.0495	2.9436	−0.0704	5.0413	−0.0691	5.3348
$(\tilde{r}_{s,t}, \tilde{r}_{b,t})^2$	−0.0679	100.0000	−0.0778	100.0000	−0.0778	100.0000

Note: ^{1} and ^{2} indicate that the statistics are computed based on the full COVID-19 and COVID-19 sample periods, respectively. ^{3}, ^{4}, and ^{5} indicate that the correlations computed from the COVID-19 sample are −0.0449, −0.0433, and −0.0014, respectively. ** indicates significance at the 95% confidence level.

of Table 5, report the results for the contribution of COVID-19 to the correlation. The results are similar to those for the 300-day specification.

5.3. The Role of Infections in Thailand and Worldwide

Liu, Manzoor, Wang, Zhang, and Manzoor (2020) reported that the number of COVID-19 infections explain abnormal returns in the stock markets of 21 affected countries. To account for the possible roles of infections in abnormal returns, this study modifies equation (3) as follows:

$$\tilde{r}^a_{i,t} = \beta_{i,0} + \beta_{i,1} r^a_{i,t-1} + \beta_{i,2}\tau_t + \beta_{i,3} I^{TH}_t + \beta_{i,4} I^{WO}_t + \tilde{\omega}_{i,t}. \tag{10}$$

The notations I^{TH}_t and I^{WO}_t denote the numbers of COVID-19 infections in Thailand and the world on day t, respectively. τ_t is a dummy variable. It takes the value of 1 for the period from November 18, 2019, to December 30, 2019, the latter date being one day before Thailand's Department of Disease Control and the WHO started to report COVID-19 daily statistics, and 0 otherwise. The study sourced the numbers of infections for Thailand and the world from Thailand's Department of Disease Control (https://covid19.ddc.moph.go.th/th) and the Global Change Data Lab (https://ourworldindata.org/coronavirus-source-data), respectively.

The coefficients $\beta_{i,2}$, $\beta_{i,3}$, and $\beta_{i,4}$ are the response coefficients of the abnormal returns $\tilde{r}^a_{i,t}$ to exogenous variables τ_t, C^{TH}_t, and C^{WO}_t, respectively. Since the infection data are missing from November 18, 2019, to December 30, 2019, the coefficient $\beta_{i,2}$ is the average response of abnormal returns $\tilde{r}_{i,t}^{a}$ to the missing COVID-19 data. The response $\beta_{s,4}$ of abnormal stock returns to the number of world infections is significant at the 95% confidence level, whereas the remaining responses $\beta_{s,1}, \dots, \beta_{s,3}, \beta_{b,1}, \dots, \beta_{b,4}$ are not significant.

The study repeats the hypothesis tests for flight to quality, based on the modified state-space model. $\tilde{r}_{s,t}^{a}$ Granger causes $\tilde{r}_{b,t}^{n}$. The results for COVID-19's contributions to $\rho(\tilde{r}_{s,t}, \tilde{r}_{b,t})$ are reported in Columns 6 and 7 of Table 5. The results are similar to those in Table 4. The hypothesis—$\rho(\tilde{r}_{s,t}^{a}, \tilde{r}_{b,t}^{a}) = \rho(\tilde{r}_{s,t}^{a}, \tilde{r}_{b,t}^{n}) = \rho(\tilde{r}_{s,t}^{n}, \tilde{r}_{b,t}^{a}) = 0$—has a p-value of 0.1145; the contribution of COVID-19 is 89.8839% with a p-value of 0.2750.

6. CONCLUSION

This study investigated flight to quality in Thailand's stock and bond markets during the COVID-19 crisis. The tests are based on abnormal returns induced by COVID-19. The raw return correlation is more negative in the COVID-19 period than in the pre-(COVID-19) period. The contribution of abnormal returns to the falling correlation in the COVID-19 period is economically significant at the 89.2080% level. The joint Wald-test for no effects from COVID-19, using the COVID-19 induced correlations, yielded a p-value of 0.1144, whereas the impulse response analyses suggest that all the correlations are significant. Flight to quality exists in Thailand's financial markets in the time of COVID-19.

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