THE RELATIONSHIP BETWEEN TRAFFIC CONGESTION AND STOCK MARKET RETURNS

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Abstract

Traffic congestion and stock market returns are related, and these variables affect—and are affected by—economic conditions. Moreover, traffic congestion induces investor stress, thereby altering decision-making. Stock market returns are depressed on high traffic days owing to behavioral reasons. This study analyzes the relationship between Bangkok traffic and Thai stock market returns. A directed acyclic graph and Granger causality tests were used to identify the contemporaneous and time-sequence causalities between the variables. The sample data were collected from January 4, 2012 to April 2, 2020, making a total of 2,020 trading days. The average Longdo traffic index during morning rush hours and the closing-to-closing return on the Market for Alternative Investment (mai) index portfolio represent the traffic congestion and stock market return, respectively. The mai return was chosen as mai stocks are mostly traded by local investors, which is the only investor group affected by Bangkok traffic. The traffic index was missing for 179 of the trading days, making the vector-autoregressive model estimation which accompanies the Granger causality tests, not possible. The missing-data problem was resolved by using imputation data constructed from the vector autoregressive model-imputation algorithm. It was found that the Bangkok traffic contemporaneously, and Granger causes, the mai return. The effect on the mai return was found to be negative and permanent.

Keywords: directed acyclic graph; Granger causality; missing data; stress; vector autoregression

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1. INTRODUCTION

Traffic congestion refers to the manner in which the movement of vehicles is delayed by one another (Rahane & Saharkar, 2014), resulting from high traffic volume beyond the service ability of a transportation system (Sweet, 2011). It is among the least enjoyable daily experiences (Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004) and ranks as a leading cause of the stress a person may experience during a day (Hennessy, Wiesenthal, & Kohn, 2000; Stokols, Navaco, Stokols, & Campbell, 1978). Stress affects decision-making (Starcke & Brand, 2012), thus establishing the effect of traffic congestion on stock market returns.

Traffic congestion is a major economic issue worldwide (Russo, Adler, Liberini, & van Ommeren, 2021; Struyf, Sys, Van de Voorde, & Vanelslander, 2020). It contributes to a reduction in employment growth (Hymel, 2009; Jin & Rafferty, 2017), income growth (Jin & Rafferty, 2017), work productivity (McLennan & Bennetts, 2003), efficiency (Ministry of Economic Planning and Budget, 2013), growth of the real gross domestic product, and wage growth (Winston & Karpilow, 2017). As macroeconomic variables influence stock market returns (Flannery & Protopapadakis, 2002; Sousa, 2015), the effect of traffic congestion on stock market returns should be significant.

In contrast, Kutzbach (2010) argued that traffic congestion results from economic growth. As income rises, people demand faster and more comfortable means of travel, leading to increased car use and more traffic congestion. El-Alfy, Ratrout, and Gazder (2015) linked traffic congestion to stock market returns via wealth effects and consumption. This linkage is supported by Ludvigson and Steindel (1999), who reported the significant effect of stock market returns on consumption in the US. Milani (2017) proposed a theoretical model that explains the effect of stock market returns on outputs by increasing wealth and changing the expectations of economic agents. In the context of the US market, the contribution of rising wealth is smaller, while that of changing expectations is larger.

The relationship between traffic congestion and stock market returns is not necessarily unidirectional. Jin and Rafferty (2017) modeled traffic congestion, income, and employment as interrelated variables. In the case of the US, an interrelationship was found for the three variables. As stock market returns are related to macroeconomic variables, it is possible that the relationship between traffic congestion and stock market returns is also an interrelationship.

The relationship between traffic congestion and stock market returns is interesting in terms of causality, its mechanism, and policy implications. Nonetheless, only a few empirical studies have analyzed traffic congestion and stock market returns. In a forecasting study, El-Alfy et al. (2015) improved the forecasting performance for traffic congestion in the Saudi–Bahrain corridor using the Saudi and Bahrain stock indexes. Stock indexes served as surrogate measures of political and economic conditions. In the realm of behavioral studies, Imisiker, Tas, and Yildirim (2019) studied the effect of traffic congestion in New York and London on the US and UK stock returns, respectively, while Khanthavit (2021) studied the effect of Bangkok traffic on the Thai stock market returns. The traffic variables proxied investor stress induced by morning traffic congestion. These effects were negative and significant.

This study examines the contemporaneous and time-sequence relationships of Bangkok traffic congestion and Thai stock market returns. Granger causality tests (Granger, 1969) and directed acyclic graph (DAG) contemporaneous causality tests (Swanson & Granger, 1997) were conducted for the time-sequence and contemporaneous relationships, respectively. These two variables were chosen because Bangkok traffic is among the busiest in the world, while the Stock Exchange of Thailand (SET) is also one of the largest markets. Bangkok ranks 10th in terms of traffic congestion (TomTom International BV, 2021), while the SET is the 24th largest stock market in terms of market capitalization (World Federation of Exchanges, 2021).

This study used the Longdo traffic index to measure traffic congestion. The full sample encompassed data from January 4, 2012, to April 2, 2020, generating a total of 2,020 trading days. Due to faulty equipment, missed observations, or disrupted systems, the traffic index was missing for the whole day on 179 trading days. Missing observations prohibit testing of the time-sequence relationship. Reliable imputation of missing data for 179 days is a challenging task. This challenge was overcome by applying a vector autoregressive model-imputation (VAR-IM) algorithm (Bashir & Wei, 2018) to construct imputation observations of traffic. The algorithm is based on a vector autoregressive model (VAR) that combines an expectation and minimization algorithm with the prediction error minimization method. Bashir and Wei (2018) reported improved performance of the VAR-IM imputation method compared to traditional methods.

2. THE MODELS

2.1 DAG Contemporaneous Causality

This study identifies the contemporaneous causal structure of traffic congestion and stock market returns using the data-determined DAG approach. Let T_t and R_t be the traffic congestion and stock return variables at time t, respectively. Next, $Pr(T_t, R_t)$ represents the joint density of variables $[T_t, R_t]$. Equation (1) describes the density of the product decomposition (Pearl, 2000).

$Pr(T_t, R_t) = \prod_{k=T,R} Pr(T_t|pa^k) \times Pr(R_t|pa^k)$, (1)

where pa^k is the subset of $[T_t, R_t]$ which causes the variable $k = T_t, R_t$. The densities $Pr(T_t|pa^k)$ and $Pr(R_t|pa^k)$ are the densities of T_t and R_t, conditioned on pa^k.

Five DAG relationships between each $[T_t, R_t]$ pair are possible.

(1) No edge ($T_t \quad R_t$) indicates independent T_t and R_t.
(2) An undirected edge ($T_t — R_t$) indicates their correlation, but not causation.
(3) A uni-directed edge ($T_t \rightarrow R_t$) indicates causality from T_t to R_t.
(4) A uni-directed edge ($T_t \leftarrow R_t$) indicates causality from R_t to T_t.
(5) A bi-directed edge ($T_t \leftrightarrow R_t$) indicates bidirectional causality between T_t and R_t.

In this study, the DAG is estimated using the PC causal search algorithm (Spirtes & Glymour, 1991) from the relationship in Equation (1). The algorithm relies on hypothesis testing for significant correlations and partial correlations between variables T_t and R_t. The significance level was set to 10%. Correlations were estimated using the adjusted Spearman rank correlation. This statistic is preferred to the Pearson correlation when the variables are not normally distributed (Teramoto, Saito, & Funahashi, 2014).

2.2 Time-Sequence, Granger Causality

This study models the dynamics of T_t and R_t using bivariate vector autoregression of order $(VAR(p))$. The model is shown in equation (1).

$$\boldsymbol{Y}_t = \sum_{i=1}^{p} B_i \boldsymbol{Y}_{t-i} + \boldsymbol{e}_t, \quad (2)$$

where the variable vector $\boldsymbol{Y}'_{t-i} = [T_{t-i}, R_{t-i}]$ and the residual vector $\boldsymbol{e}'_t = [e^T_t, \varepsilon^R_t]$. $\boldsymbol{e}_t$ has a zero-mean vector and Ω covariance matrix. The (2×2) matrix B_i, $\begin{bmatrix} b_i^{TT} & b_i^{TR} \\ b_i^{RT} & b_i^{RR} \end{bmatrix}$ is the slope coefficient matrix. The intercept vector does not appear in equation (2); the study uses $[T_{t-i}, R_{t-i}]$ standardized by their means and standard deviations in the analysis.

The study is aware that the Granger causality test is a statistical test for predictive causality (Diebold, 2007). However, the test is still useful. If traffic congestion causes stock market returns, it necessarily leads to returns. Additionally, if stock market returns cause traffic congestion, they necessarily lead to congestion. Rejection of the joint hypotheses $b_1^{RT} = \cdots = b_p^{RT} = 0.00$ and $b_1^{TR} = \cdots = b_p^{TR} = 0.00$ suggest that traffic congestion Granger causes stock market returns and that stock market returns Granger cause traffic congestion. Under the null hypothesis of Granger non-causality, the F-statistic is distributed as an F variable with $(p, N - p)$ degrees of freedom, where N is the number of observations.

2.3 Missing Data and Imputation

The study requires a complete set of time-series data for $[T_t, R_t\ ]$ from $t = 1$ to $t = N$ to estimate the $VAR(p)$ model in equation (2). No missing data were available. The full sample was checked for missing data, revealing that the traffic index was missing for 179 days out of the total 2,020 trading days. Imputation was thus required to fulfill the missing observations. As the relationship between $[T_t, R_t\ ]$ in equation (2) is dynamic, the study chose the (VAR-IM) algorithm (Bashir & Wei, 2018) to construct the imputation data. The study sets a lag number p equal to 1 for the $VAR(p)$ model and for the VAR-IM algorithm. The VAR-IM algorithm is complicated; a large lag number p overfits the data, reduces the degrees of freedom, and induces large estimation errors (Karlsson, 2013). The $VAR(p = 1)$ model was $\boldsymbol{Y}_t = B_1\boldsymbol{Y}_{t-1} + \boldsymbol{e}_t$. The hypothesis is $b_1^{RT} = 0.00$ $(b_1^{TR} = 0.00)$ for the Granger causality of traffic congestion on returns (returns to traffic congestion). Under the null hypothesis, the F-statistic is distributed as an F variable with $(1{,}2017)$ degrees of freedom.

3. THE DATA

3.1 Data Sources, Data Construction, and Imputation

The study uses daily data. Traffic congestion was measured using the Longdo traffic index, while the stock market return was the logged return on the Market of Alternative Investment (mai) index portfolio. The Longdo traffic index was retrieved from the Longdo.com database (https://traffic.longdo.com/download) An index level of 0 indicates no traffic, while level 10 indicates traffic immobility on all streets of the Bangkok metropolitan area. The index is reported every five minutes throughout the day. This study considers the average index during morning rush hours. Morning rush hours were chosen because they are popular among traffic studies (Novaco & Gonzalez, 2009). Following Khanthavit (2021), the morning rush-hour traffic is the index averaged from the indexes for every 15 minutes from 6.00 a.m. to 10.00 a.m.

If the index was missing for the entire day, the index was considered to be missing for the day. If the traffic data are available on the day, but not at the exact time, the index available five minutes earlier was used. If that index was still missing, the one available ten minutes earlier was used. Finally, if this procedure was not successful, linear interpolated indexes were used for imputation.

The mai index was the closing index available in the SET database. This value is the market-capitalization-weighted average index for all stocks traded on the mai. The average trading shares of local investors accounted for 96.96% of the total trading volume of the mai, and 70.73% of the total trading volumes of the SET. As Bangkok traffic affects only local investors, the mai index was chosen over the SET index due to its higher proportion of local investors.

The Longdo traffic index began on January 1, 2012. Thus, the first day of the sample period was January 4, 2012, the first trading day of 2012. The sample ended on April 2, 2020, to avoid spurious results owing to the COVID-19 pandemic's effect on traffic. On April 3, 2020, the Thai government imposed the first curfew to contain the spread of the virus. The full sample covers 2,020 trading days, with missing average traffic indexes for 179 days.

Khanthavit's (2021) method was applied to remove seasonality and weather effects on the available 1,841 average traffic indexes. The VAR-IM algorithm was then employed to construct imputation indexes from the de-seasonalized and de-weathered indexes to complete the missing observations.

3.2 Descriptive Statistics

Table 1 reports the descriptive statistics for the mai returns and the de-seasonalized and de-weathered traffic index. The return distribution was negatively skewed. The tail areas were much larger than those of a normal distribution. The Jarque-Bera statistic rejects the normality hypothesis at the 99% confidence level.

The distribution of the 1,841 de-seasonalized and de-weathered traffic indexes was also negatively skewed and fat tailed. The Jarque-Bera statistic suggests that it is non-normal.

Table 1 Descriptive Statistics

Statistic	Return	Traffic Index	
		De-seasonalized and De-weathered	Standardized Imputation
Average	-0.0097	0.1653	0.0000
Standard Deviation	1.1832	0.5407	1.0000
Skewness	-0.9338	-3.2532	-0.1945
Excess Kurtosis	8.2248	36.1374	1.3620
Maximum	8.0512	4.2875	3.8480
Minimum	-8.0014	-7.2602	-5.4550
Jarque-Bera Statistic	5.99E+03***	1.03E+05***	1.69E+02***
Number of Observations	2020	1841	2020

NOTE: *** = Significant at the 99% confidence level.

After imputation, the traffic index had 2,020 observations. The imputation sample has a distribution similar to that of the de-seasonalized and de-weathered samples. The normality hypothesis is therefore rejected. The non-normality of the mai return and the Longdo traffic index did not significantly influence the DAG result. The adjusted Spearman rank correlation was applied in the DAG analysis (Teramoto et al., 2014). While it was noted that the non-normal mai return and the Longdo traffic index violate the variance properties of a VAR regression, this violation does not necessarily invalidate the VAR results (Kunst, 2007).

4. EMPIRICAL RESULTS

4.1 DAG Contemporaneous Causality

At the 10% significance level, the PC algorithm can identify a DAG contemporaneous relationship between the Bangkok traffic index and mai return of the edge "$T_t \rightarrow R_t$." The evidence leads to the conclusion that traffic congestion contemporaneously causes stock market returns. In order to understand whether the causal relationship was positive or negative, the Spearman rank and Pearson correlations between the two variables were estimated. The calculated statistics were -0.0531 and -0.0381 respectively, and were found to be significant at the 95% and 90% confidence levels, respectively. The contemporaneous causal relationship was negative.

4.2 Time-Sequence, Granger Causality

The results for the $VAR(1)$ model for Bangkok traffic and mai returns are reported in Table 2. In Panel 2.1 of Table 2, the mai return can be predicted using its first lag and the traffic's first lag, while the traffic can be predicted using its first lag alone. In Panel 2.2 of Table 2, the causality test suggests that Bangkok traffic Granger causes the mai returns. The test does not support the Granger causality of mai returns to Bangkok traffic.

Table 2 Tests for Granger Causality of the mai returns and Bangkok traffic
Panel 2.1 Vector Autoregression Model of Order One

Lagged Variable	Variable	
	Return	Traffic
First-Lagged Return	0.0860***	-0.0036
First-Lagged Traffic	-0.0397*	0.7325***

NOTE: ** and *** denote significance at the 90% and 99% confidence levels, respectively.

Panel 2.2 Granger Causality Tests

Test	$F\ (1, 2017)$
Traffic does not Granger cause the return.	3.2493*
The return does not Granger cause traffic.	0.0554

NOTE: * denotes significance at the 90% confidence level.

5. DISCUSSION

5.1 Effects of Traffic-Induced Stress on Stock Market Returns

Imisiker et al. (2019) and Khanthavit (2021) reported significant negative effects of traffic-induced stress on stock market returns. Measures of traffic congestion-average travel speeds in Imisiker et al. (2019) and the average Longdo traffic index in Khanthavit (2021)-were used as proxies for stress levels. However, the estimation methods of the two studies could only establish associations between the variables, and not their causal relationships. The significant contemporaneous causal relationship in this study supports the conclusions of Imisiker et al. (2019) and Khanthavit (2021), even though they were inferred from the association relationships. The negative effects of traffic-induced stress were significant.

5.2 Forecasting Ability of Stock Market Returns

El-Alfy et al. (2015) reported that the Saudi and Bahrain stock indexes could improve the forecasting performance of artificial neural-network models for traffic in the Saudi–Bahrain corridor. However, the Granger causality test in Panel 2.2 of Table 2 indicates that the stock market variable cannot predict Bangkok traffic. The $VAR(1)$ model used in this study was linear and simplistic. It is likely that the model's forecasting ability is not as high as that of a machine-learning neural network model.

5.3 Results Based on the SET Index Return

The study did not consider the SET return because of its high trading share from foreign investors. From a behavioral perspective, Bangkok traffic influences local investors. Based on closing-to-opening returns, Khanthavit (2021) reported that traffic-induced stress affected the mai stocks, but not the SET stocks.

It is important to note that traffic congestion bundles both behavioral (Starcke & Brand, 2012) and economic (Kutzbach, 2010) components. This study employed closing-to-closing returns for the analysis. Although the behavioral effect is non-significant, the Bangkok traffic and the SET return may be linked via economic factors.

DAG and $VAR(1)$ models were estimated for Bangkok traffic and the

SET return. At the 10% significance level, the DAG contemporaneous causal relationship is "$T_t \rightarrow R_t$." The Spearman rank and Pearson correlations were -0.0267 and -0.0398, respectively. The Spearman rank correlation was non-significant, while the Pearson correlation was significant at the 90% confidence level. The contemporaneous effects were negative. The Granger causality tests based on the $VAR(1)$ model could not find significant Granger causality in either direction.

5.4 Permanent Effects of Traffic Congestion

The study computes impulse response functions (IRFs) from the $VAR(1)$ models for the mai return - Bangkok traffic and SET return - Bangkok traffic pairs. The IRFs describe the reaction of current and future stock returns (traffic congestion) to current shock of traffic congestion (stock return's current shock). With respect to the significant uni-directed edge $(T_t \rightarrow R_t)$, the structural factorization for contemporaneous causation between the shocks is set from traffic congestion to return. The results are presented in Table 3.

In Panel 3.1 of Table 3, the IRFs of the mai return to Bangkok traffic are significant for days 1–10, while the cumulative IRFs are negative and significant for days 2–20. The study concludes that the traffic congestion effect is permanent. The IRFs of the Bangkok traffic to mai returns were non-significant. This result is explained by the non-significant Granger causality of the mai returns on traffic congestion.

In Panel 3.2 of Table 3, the IRFs of the SET return to Bangkok traffic are negative for all days; none are significant. The cumulative IRFs were significant for days 7–20. The effect of Bangkok traffic on the SET return is permanent. As the daily effects are small but consistently negative, the SET return is taken for seven days to show cumulative significance. The IRF result for the SET return was similar to that of the mai return. The IRFs and cumulative IRFs were non-significant for all days.

The results for the mai and SET returns, in Panels 3.1 and 3.2 of Table 3 respectively, suggest permanent effects of traffic congestion on stock returns. This result was stronger for the mai case. In order to understand the different levels of significance, it should be noted that traffic congestion consists of behavioral and economic components. The results in this study and in Khanthavit (2021) jointly imply that only the economic component of traffic congestion affects the SET return, while the mai return is affected by both the behavioral and economic components. Consequently, the significance levels for the SET return are lower than those for the mai return. Finally, the study concludes that the behavioral and economic components of traffic congestion have negative and permanent effects on stock market returns.

Table 3 Impulse Response Functions

Panel 3.1 The mai Index and Bangkok Traffic

Day	Response of Return to Traffic		Response of Traffic to Return	
	Level	Cumulative Level	Level	Cumulative Level
0	-0.0099	-0.0099	0.0000	0.0000
1	-0.0281*	-0.0380	-0.0036	-0.0036
2	-0.0224*	-0.0604*	-0.0029	-0.0029
3	-0.0165*	-0.0769**	-0.0022	-0.0022
4	-0.0121*	-0.0890**	-0.0016	-0.0016
5	-0.0089*	-0.0979**	-0.0012	-0.0012
6	-0.0065*	-0.1045***	-0.0009	-0.0009
7	-0.0048*	-0.1092***	-0.0006	-0.0006
8	-0.0035*	-0.1127***	-0.0005	-0.0005
9	-0.0026*	-0.1153***	-0.0003	-0.0003
10	-0.0019*	-0.1172***	-0.0002	-0.0002
11	-0.0014	-0.1185***	-0.0002	-0.0002
12	-0.0010	-0.1195***	-0.0001	-0.0001
13	-0.0007	-0.1203***	-0.0001	-0.0001
14	-0.0005	-0.1208***	-0.0001	-0.0001
15	-0.0004	-0.1212***	-0.0001	-0.0001
16	-0.0003	-0.1215***	0.0000	0.0000
17	-0.0002	-0.1217***	0.0000	0.0000
18	-0.0002	-0.1219***	0.0000	0.0000
19	-0.0001	-0.1220***	0.0000	0.0000
20	-0.0001	-0.1221***	0.0000	0.0000

NOTE: *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

Panel 3.2 The SET Index and Bangkok Traffic

Day	Response of Return to Traffic		Response of Traffic to Return	
	Level	Cumulative Level	Level	Cumulative Level
0	-0.0296	-0.0296	0.0000	0.0000
1	-0.0189	-0.0485	-0.0033	-0.0033
2	-0.0139	-0.0624	-0.0023	-0.0056
3	-0.0102	-0.0726	-0.0017	-0.0073
4	-0.0075	-0.0801	-0.0012	-0.0085
5	-0.0055	-0.0856	-0.0009	-0.0095
6	-0.0040	-0.0896	-0.0007	-0.0101
7	-0.0029	-0.0926*	-0.0005	-0.0106
8	-0.0022	-0.0947*	-0.0004	-0.0110

Table 3 Impulse Response Functions (Continued)

Day	Response of Return to Traffic		Response of Traffic to Return	
	Level	Cumulative Level	Level	Cumulative Level
9	-0.0016	-0.0963*	-0.0003	-0.0112
10	-0.0012	-0.0975*	-0.0002	-0.0114
11	-0.0008	-0.0983*	-0.0001	-0.0116
12	-0.0006	-0.0989*	-0.0001	-0.0117
13	-0.0005	-0.0994*	-0.0001	-0.0117
14	-0.0003	-0.0997*	-0.0001	-0.0118
15	-0.0002	-0.1000*	0.0000	-0.0118
16	-0.0002	-0.1001*	0.0000	-0.0119
17	-0.0001	-0.1003*	0.0000	-0.0119
18	-0.0001	-0.1004*	0.0000	-0.0119
19	-0.0001	-0.1004*	0.0000	-0.0119
20	-0.0001	-0.1005*	0.0000	-0.0119

NOTE: * denotes significance at the 90% confidence level.

6. CONCLUSION

The relationships between traffic congestion and stock market returns are possible due to behavioral factors such as traffic-induced stress on investors' decision making and economic factors such as stock-induced wealth effects on vehicle sales. Previous studies (Imisiker et al., 2019; Khanthavit, 2021) investigated the relationship between the two variables from a behavioral-finance perspective, finding negative relationships between them. The researchers relied on these significant relationships to conclude the significant effects of traffic-induced stress on stock market returns. In a forecasting study, El-Alfy et al. (2015) employed stock indexes to improve the accuracy of traffic forecasts. Stock indexes serve as surrogates for economic and political conditions.

The study found that significant relationships between the variables do not necessarily imply one variable's causality or effect on the other. Therefore, the current study examined the contemporaneous and time-sequence causal relationships between traffic congestion and stock market returns. Focusing on the Thai stock market, the study found contemporaneous and Granger causalities of traffic congestion on stock returns. The findings are based on a sample of daily data, from January 4, 2012, to April 2, 2020, taking the average Longdo traffic index during morning rush hours and the closing-to-closing mai index returns. Traffic congestion consists of both behavioral and economic components. The additional result for the SET index return helps this study to infer that the two components have permanent negative effects. The effect of the behavioral component is stronger than that of the economic component.

The relationships between behavioral and economic components and stock market returns are important and interesting. In this study, the relationships were inferred from the estimation results. However, they were not directly tested. The study provides direct tests for future research.

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