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Effects of Economic and Behavioral Components of Traffic Congestion on Stock Market Returns

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Abstract

Traffic congestion generates economic losses within and beyond the confines of transportation systems. In addition, traffic congestion induces stress, which alters investors' risk preferences and attitude misattribution. As economic losses and investor behavior affect stock market returns, traffic congestion has significant economic and behavioral effects on the returns. This study applies the state-space model to decompose the traffic variable into economic and behavioral components so that their effects can be measured separately. The model is estimated using Kalman filtering. Using the daily Longdo traffic index, the returns on the Stock Exchange of Thailand (SET), and the Market for Alternative Investment (mai) Index portfolios from January 4, 2012 to April 2, 2020, the study finds that the economic and behavioral effects are negative and significant. The economic component Granger causes a behavioral component; however, their joint explanatory power on the SET and mai returns is low at 0.29% and 0.15%, respectively.

Keywords: Behavioral finance, stock return behavior, traffic-induced stress

1. Introduction

Traffic congestion is a chronic and growing problem in metropolises worldwide. Recurrent congestion results from an increase in traffic volume beyond the capacity of a transportation system (Sweet, 2011) and generates economic losses within and beyond the confines of transportation systems. The former includes workforce productivity time loss, excess fuel energy consumption, increasing vehicle maintenance costs, and higher vehicle emissions (Jayasoosriya & Bandara, 2017; Munerra & Karuppanagounder, 2018; Sweet, 2011; Vencataya et al., 2018). Beyond the transportation systems, the losses result from the economic activities affected by hampered accessibility and mobility (Sweet, 2011), such as employment growth (Hymel, 2009; Jin & Rafferty, 2017), income growth (Jin & Rafferty, 2017), efficiency (Ministry of Economic Planning and Budget, 2013), and real gross domestic product (GDP) and wage growth (Winston & Karpilow, 2017). As economic losses adversely affect stock market returns (Flannery & Protopapadakis, 2002; Sousa, 2015), the effect of traffic congestion on stock market returns should be negative and significant.

Traffic congestion also has behavioral effects on stock market returns. It is among the least enjoyable daily experiences (Kahneman et al., 2004) and among the leading causes of daily stress (Hennessy et al., 2000). Stress affects decision-making (Starcke & Brand, 2012) due to altered risk preference (Porcelli & Delgado, 2009; Van den Bos et al., 2009) and attitude misattribution (Kinner et al., 2016). Stock market returns change due to investors' changing behavior from traffic-induced stress.

The relationship between the traffic congestion in New York and London and stock market returns in the US and the UK, respectively, was examined empirically by Imisiker et al. (2019); further, Khanthavit (2021) observed the effect of Bangkok traffic congestion on Thai stock market returns. Traffic variables serve as proxies for investor stress levels. The two studies consistently found negative and significant relationships, thus concluding that the behavioral effects of traffic congestion on stock market returns are significant. Khanthavit (2022) found the significant relationship between the Bangkok traffic and Thai stock market returns to be a causal relationship, such that the significant effects were not necessarily limited to behavioral effects. Economic effects may help explain the significant causality. As economic and behavioral effects are bundled in traffic variables, it is difficult to identify and measure the role of economic and behavioral effects in explaining the significant relationship between traffic congestion and stock market returns.

This study proposes a state-space model for determining the impact of the economic and behavioral effects of traffic congestion on stock market returns. In the model, the traffic variable is decomposed into economic and behavioral components. In the measurement equation, the components are Kalman filtered from their relationship with the returns. The slope coefficients and explanatory power can be tested to determine how significant and in what ways the components affect stock returns. The time-series behaviors of the components are described by the transition equations. The decomposition is important as it offers insights into the exact roles of economic and behavioral components in driving stock market returns. Imisiker et al. (2019) and Khanthavit (2021) explained significant relationships via behavioral effects; the explanations were conjectured and not tested. A significance test observing such behavioral and economic effects was conducted separately in this study.

This study analyzes the traffic congestion in Bangkok, among the heaviest traffic in the world, and the Thai stock market returns. TomTom International BV (2021a) ranked Bangkok in the 10th place for traffic in 2020. The additional hours spent driving in Bangkok during rush hours in a year were 220, 207, 207, and 179 in 2017, 2018, 2019, and 2020, respectively (TomTom International BV, 2021b). The annual economic loss from Bangkok traffic congestion is large, approximately US$ 350 million (Kasikorn Research Center, 2016).

The Stock Exchange of Thailand (SET) ranks 10th among the markets in the Asia-Pacific region and 24th in the world (World Federation of Exchanges, 2021). In September 2021, its market capitalization was US$ 559 billion. The SET is located in Bangkok, Thailand's capital, largest city, and economic center; therefore, Bangkok traffic congestion should have significant effects on the country and its stock market. Most local stock investors live in the metropolitan areas of Bangkok. In 2015, there were 1,134,500 open stock accounts, out of which 88% were in Bangkok (Stock News Online, 2015). Therefore, from a behavioral perspective, Bangkok traffic affects most stock investors' stress levels.

The listed stocks on the SET are traded on two boards, the main board (SET stocks) and the Market of Alternative Investment (mai stocks), which have different listing criteria (SET, 2021). SET stocks require a larger minimum equity value and combined net profit from operations prior to listing than mai stocks. In terms of trading volume, SET stocks are more popular and possess a high share of foreign investors. From January 4, 2012 to April 2, 2020, local and foreign investors contributed 70.73% and 29.27% to SET stocks, compared to 96.96% and 3.04% to mai stocks, respectively.

The fact that the SET has stock trading on the two boards enables this study to decompose and identify economic and behavioral effects with precision. Bangkok traffic does not influence the stress levels of foreign investors. Hence, the behavioral effects on the SET stock should be small or non-existent (Khanthavit, 2022). For this reason, this study suggests that SET stocks are affected by the economic component only, whereas mai stocks are affected by both the economic and behavioral components.

2. Methodology

2.1 State-space Model

This study applies the state-space model to analyze the economic and behavioral effects of traffic congestion. The economic and behavioral components are unobserved, bundled, and embedded in the traffic variable. Let $[T_t \ r_t^S \ r_t^m]'$ be the vector of the traffic variable, the returns on the SET, and mai stocks, respectively. The three variables are linearly linked with the economic component (E_t) and behavioral component (B_t) as in the measurement equation (1).

$$\begin{bmatrix} T_t \\ r_t^S \\ r_t^m \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ \alpha_E^S & 0 \\ \alpha_E^m & \alpha_B^m \end{bmatrix} \begin{bmatrix} E_t \\ B_t \end{bmatrix} + \begin{bmatrix} \varepsilon_t^T \\ \varepsilon_t^S \\ \varepsilon_t^m \end{bmatrix} \qquad (1)$$

The variables ε_t^T, ε_t^S and ε_t^m are the error terms, whose expected values are zero, and the covariance matrix is $\Omega = \begin{bmatrix} \sigma_T^2 & 0 & 0 \\ 0 & \sigma_S^2 & \rho\sigma_S\sigma_m \\ 0 & \rho\sigma_S\sigma_m & \sigma_m^2 \end{bmatrix}$. The equation $T_t = E_t + B_t + \varepsilon_t^T$ decomposes the traffic variables T_t into economic (E_t) and behavioral (B_t) variables and an error term ε_t^T. The equation $r_t^S = \alpha_E^S E_t + \varepsilon_t^S$ restricts the SET return to be affected only by the economic component. This specification was imposed for identification purposes. Finally, the equation $r_t^m = \alpha_E^m E_t + \alpha_B^m B_t + \varepsilon_t^m$ models the mai return as being influenced by economic and behavioral components. The slope coefficients α_E^S and α_E^m indicate the economic effects on the SET and mai returns, respectively. The coefficient α_B^m shows the behavioral effects on mai returns. This study considers standardized $[T_t \ r_t^S \ r_t^m]'$ on their averages and standard deviations. The intercept vector is a zero vector and not included in equation (1).

Only the economic E_t and behavioral B_t components of the traffic variable T_t affect stock returns. Thus, the correlations of ε_t^T with ε_t^S and ε_t^m are zero. Finally, a non-zero correlation ρ between ε_t^S and ε_t^m suggests that the returns r_t^S and r_t^m are explained by factors other than the traffic variable T_t.

The dynamics of E_t and B_t are described by a vector autoregressive model of order 1 $(VAR(1))$ in transition equation (2). A VAR model is flexible and easy to use for analyzing multivariate time-series variables (Zivot & Wang, 2004). This study chose lag . A large lag number overfits the data, reduces the degrees of freedom, and induces large estimation errors (Karlsson, 2013).

$$\begin{bmatrix} E_t \\ B_t \end{bmatrix} = \begin{bmatrix} \beta_E^E & \beta_B^E \\ \beta_E^B & \beta_B^B \end{bmatrix} \begin{bmatrix} E_{t-1} \\ B_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_t^E \\ \varepsilon_t^B \end{bmatrix} \tag{2}$$

where $\begin{bmatrix} \beta_E^E & \beta_B^E \\ \beta_E^B & \beta_B^B \end{bmatrix}$ is the matrix of $VAR(1)$ coefficients. The error terms ε_t^E and ε_t^B have zero expected values. The covariance matrix is a diagonal square matrix $Q = \begin{bmatrix} \sigma_E^2 & 0 \\ 0 & \sigma_B^2 \end{bmatrix}$. The study assumes uncorrelated errors ε_t^E and ε_t^B. As traffic congestion causes stress, which in turn leads to productivity losses (Sweet, 2014), the losses are classified as an economic component.

2.2 Model Estimation

This study estimates the state-space model in equations (1) and (2) using Kalman filtering. The technique is a recursive procedure for computing the optimal estimators for unobserved economic E_t and behavioral B_t components based on the observed traffic variable T_t and the stock returns r_t^S and r_t^m available up to and including period t (Harvey, 1990). The unobserved E_t and B_t and prediction error variance are estimated using the optimum estimates $\hat{E}_{t-1}$ and $\hat{B}_{t-1}$ obtained from the previous period. The predicted E_t^p and B_t^p are updated by new information in the observed variables T_t, r_t^S, and r_t^m for the optimum estimates $\hat{E}_t$ and $\hat{B}_t$. The procedure was repeated until it reached the last observation, $t=T$.

2.3 Hypothesis Testing

2.3.1 Economic and Behavioral Effects

From equation (1), the direction and significance of the economic effect of E_t on returns r_t^S and r_t^m can be determined from the sign and significance of α_E^S and α_E^m, respectively. The sign and significance of α_B^m suggest in what way and how significantly the behavioral effect of B_t

is related to return r_t^m. This study tests the significance of the slope coefficients α_E^S, α_E^m, and α_B^m using their Newey-West (1987) heteroscedasticity and autocorrelation consistent (HAC) standard deviations.

2.3.2 Explanatory Power

This study analyzes the explanatory power of E_t and B_t, jointly and separately, on the observed variables T_t, r_t^S, and r_t^m. Although E_t and B_t are not observed, Kalman filtering returns the filtered and smoothed estimates. This study chooses the smoothed estimates in the analyses because they are conditioned on all the observations in the sample period (Harvey, 1990).

The joint explanatory power of E_t and B_t on T_t and r_t^m is measured by the coefficient of determination (R^2) from the regressions of T_t and r_t^m on smoothed E_t and B_t. The R^2 obtained from the univariate regressions of T_t, r_t^S, and r_t^m on smoothed E_t and B_t indicates the separate explanatory power.

2.3.3 Causality Relationships

As economic growth leads to traffic congestion (Kutzbach, 2010), inducing stress (Hennessy et al., 2000) and stress-induced productivity loss (Sweet, 2014), it is pertinent to observe whether the economic component triggers the behavioral component or vice versa. Transition equation (2) allows this study to address this question through Granger causality tests. If the economic component causes the behavioral component, it must lead the behavioral component, such that the slope coefficient β_E^B is significant. The causality of the behavioral component on the economic component is represented by the significant slope coefficient β_B^E. Significant tests are performed based on the Newey-West (1987) HAC standard deviations for the coefficients.

3. Data

3.1 Data Sources, Construction, and Imputation

This study measures traffic congestion using the Longdo traffic index. The stock returns are the logged returns computed from the closing indexes of the SET and mai index portfolios, scaled to 100. The traffic index was retrieved from the Longdo.com database (https://traffic.longdo.com/download), whereas the stock indexes were retrieved from the SET database.

The Longdo traffic index indicates traffic mobility on all the streets of Bangkok. An index level of 0 indicates no traffic, and level 10 indicates traffic immobility. As morning indexes are mostly used in the literature (Novaco & Gonzalez, 2009), the traffic index in this study is the average of every 15-minute indexes during the morning rush hour from 6 am to 10 am.

However, the index can be found missing during the morning rush hours or for the entire day. If the index was missing for the entire day, that day was excluded from the sample. If the index was available on the observed day but not at the exact time, the index available five or ten minutes earlier was used. If that index was still missing, the indexes from linear interpolation were imputed.

Khanthavit's (2021) method was applied to remove seasonal and weather factors from the traffic index. The seasonal dummy variables considered were days of the week, weeks of the year, months of the year, days before and after long holidays of three days or more, the last trading Friday of the month, and the Royal Ploughing Ceremony Day, whereas the weather variables were the average temperature and cloud cover from 6 am to 10 am. The de-seasonalized and de-weathered index is an unexpected component of the index and, according to Imisiker et al. (2019), a traffic stressor.

The sample time ranges from January 4, 2012 to April 2, 2020. The Longdo traffic index was first available on January 1, 2012, and January 4, 2012 was the first trading day following index availability. The study does not include the data observed post April 3, 2020 to avoid the spurious results arising from the effect of the COVID-19 pandemic on traffic. On April 3, 2020, the Thai government imposed the first curfew in its attempt to contain the pandemic. As a result, the Bangkok traffic congestion reduced significantly.

There are 2,020 trading days in the full sample, in which the average traffic index is missing for 179 days. The estimation of the state-space model in equations (1) and (2) is not possible. Imputation is required for the index-missing days. The study applied the vector autoregressive model-imputation (VAR-IM) algorithm (Bashir & Wei, 2018) to construct imputation indexes from the de-seasonalized and de-weathered indexes to complete the missing observations. The algorithm is based on a vector autoregressive model (VAR) for the variables $[T_t \ r_t^S \ r_t^m]'$, which combines an expectation and minimization algorithm with the prediction error minimization method. The study chose a one-lag specification for the VAR to reduce overfitting and estimation-error problems (Karlsson, 2013).

3.2 Descriptive Statistics

Table 1 reports the descriptive statistics for the stock returns and traffic variables. The SET and mai returns are both negatively skewed and fat-tailed. The Jarque-Bera test rejects the normality hypothesis for both the return series at the 99% confidence level. The first-order autocorrelation ($AR(1)$) coefficient for the SET return is -0.0284 and non-significant, whereas that for the mai return is 0.0876 and significant at the 99% confidence level.

Table 1. Descriptive Statistics

Statistic	Return		Traffic	
	SET	mai	Raw	Standardized Imputation
Average	0.0052	-0.0097	4.1983	0.0000
Standard Deviation	0.9877	1.1832	0.8833	1.0000
Skewness	-1.7713	-0.9338	-0.6444	-0.1945
Excess Kurtosis	21.0804	8.2248	1.7105	1.3621
Maximum	7.6531	8.0512	7.6200	3.8238
Minimum	-11.4282	-8.0014	0.0000	-5.3966
First-Order Autocorrelation	-0.0284	0.0876***	N.A.	0.7324***
Jarque-Bera Statistic	3.85E+04***	5.99E+03***	3.52E+02***	1.69E+02***
Number of Observations	2,020	2,020	1841	2,020

Note: *** = significant at the 99% confidence level, whereas N.A. = not applicable.
Source: Author's calculations.

Descriptive statistics were estimated for the raw, de-seasonalized, and de-weathered index series and the standardized imputation index series, reported in Columns 4 and 5 of Table 1. The behavior of both the series was similar. The variables were negatively skewed and fat-tailed, and their distributions were not normal. The imputation traffic variable was positively autocorrelated. The significant autocorrelation of the mai return and imputation traffic variable supports the $VAR(1)$ specification for E_t and B_t in equation (2).

4. Empirical Results

The study estimates the state-space model presented in equations (1) and (2) using the closing-to-closing SET and mai returns and standardized imputation traffic variables, as reported in Column 2 of Table 2.

Table 2. Parameter Estimates

Parameter Estimates	Return Samples	
	Closing-to-Closing	Closing-to-Opening
α_E^S	-0.0918***	-0.0565
α_E^m	-0.0464***	0.0455
α_B^m	-0.0271***	-0.1654*
σ_T	6.97E-07	0.1200
σ_S	0.5764***	0.5767***
σ_m	0.5768***	0.5740***
ρ	0.7303***	0.7728***
β_E^E	0.2893***	0.3339***
β_B^E	0.0555	0.1922
β_E^B	-0.0921*	-0.0145
β_B^B	1.0027***	0.9996***
σ_E	0.3233***	0.3124***
σ_B	5.44E-09	0.0336***

Note: * and *** = significant at the 90% and 99% confidence levels respectively.
Source: Author's calculations.

4.1 Significant Economic and Behavioral Effects

The way in which the economic component E_t affects the SET and mai returns reflect the significance and signs of α_E^S and α_E^m, respectively. The coefficients are negative and significant at the 99% confidence level.

Bangkok traffic causes stress to investors only in the Bangkok metropolitan area; foreign investors, who had a 29.27% share of the SET trading volume and 3.04% of the mai trading volume, remain unaffected. This study models the behavioral component B_t by its effect on the mai return but not on the SET return. The behavioral effect is the coefficient α_B^m, which is negative and significant.

Based on the negative and significant coefficients α_E^S and α_E^m for the economic component and α_B^m for the behavioral component, the study concludes that Bangkok traffic congestion has negative economic and behavioral effects on Thai stock returns.

4.2 Explanatory Power

This study decomposed the traffic variable into economic and behavioral components. This structure implies that E_t and B_t should exhaustively explain the movement of T_t. The study regresses T_t on E_t and B_t, and on E_t and B_t in separate regressions. The R^2 coefficient from the multiple regression measures the joint explanatory power of E_t and B_t, whereas the R^2 coefficients from the univariate regressions show the power of individual E_t and B_t. In Row 3 of Table 2, the R^2 coefficient for multiple regression is 100%. Economic and behavioral components jointly constitute the traffic variables. This result is consistent with the small value of σ_T in 6.97E-07 for T_t in Table 2. The R^2's in Row 3 and Columns 3 and 4 of Table 3 reveal that the traffic variable is explained less by the economic component at 41.46% but more by the behavioral component at 65.67%.

Table 3. Explanatory Power of Economic and Behavioral Components

Variable	Coefficient of Determination (R^2)		
	Economic and Behavioral Components	Economic Component	Behavioral Component
Traffic	1.0000	0.4146	0.6567
SET Return	N.A.	0.0029	N.A.
mai Return	0.0015	8.28E-04	7.64E-04

Source: Author's calculations.

The R^2 coefficients obtained from the multivariate and univariate regressions for r_t^S and r_t^m are reported in Rows 4 and 5 of Table 3. Although the effects of the economic component are highly significant, the component can explain the SET return by 0.29%. The multiple regression on both the economic and behavioral components and the univariate regression on the behavioral component were not estimated for the SET return. From equation (1), the SET return is explained only by the economic component.

The results of the explanatory power of E_t and B_t on mai returns are similar: the power is very low. The joint explanatory power was 0.15%. The components E_t and B_t can individually explain the mai return by 0.08% and 0.07%, respectively.

4.3 Granger Causality Relationship between the Economic and Behavioral Components

The slope coefficient β_B^E for testing the Granger causality of the behavioral component on the economic component is reported in Table 2. The statistic was 0.0555 and non-significant. The hypothesis that the behavioral component does not Granger cause the economic component cannot be rejected.

The coefficient β_E^B is negative and significant, suggesting that the economic component Granger causes the behavioral component. A possible explanation is the inverse relationship between stress and happiness (Schiffrin & Nelson, 2010). Although it is stressful, heavy morning traffic congestion should predict higher economic or social activities during the day and evening. Good business and recreation should make commuters happier, such that the stress level impact on the next day is lower.

5. Discussion

5.1 Closing-to-Opening Returns

The results in Khanthavit (2021; 2022) suggest that the economic effect only appears in stock returns from the investors trading during the day and not at the market opening. At the market opening, only the behavioral component plays a significant role. This study checks for this observation using closing-to-opening SET and mai returns. If the observation is correct, the coefficients α_E^S and α_E^m for the economic component on the SET and mai returns must be non-significant, whereas the coefficient α_B^m must be significant. The parameter estimates are reported in Column 3 of Table 2. The coefficients α_E^S and α_E^m are -0.0555 and 0.0455, respectively, and not significant. The coefficient α_B^m is -0.1654 and significant. The observation by Khanthavit (2021; 2022) is supported by the data. The significantly negative behavioral effect was consistent with the pattern found during the day.

5.2 Non-stationary Behavior of the Behavioral Component

The coefficient β_B^B is the $AR(1)$ coefficient of the behavioral component in $VAR(1)$ equation (2). The statistics are 1.0027 and 0.9996 for the closing-to-closing and closing-to-opening return samples, respectively. A unit coefficient suggests a non-stationary, persistent behavior of the behavioral component, which can be explained by Bangkok's chronic traffic problem (TomTom International BV, 2021b). Chronic traffic problems induce chronic stress to local investors (Gatersleben & Griffin, 2017), leading to a higher level of risk aversion and pessimism (Kandasamy et al., 2014) and negative stock returns (Imisiker et al., 2019; Khanthavit, 2021). This explanation is supported by the negative and significant coefficients, α_B^m, in Table 2.

It is not uncommon to model the unobserved components of stock returns and other economic variables using non-stationary processes (Zalewska-Mitura & Hall, 1999). However, using non-stationary variables, such as the non-stationary behavioral component B_t in the analyses, may result in spurious and unreliable statistical inferences (Lin & Brannigan, 2003). In this study, the non-stationarity effect was small. From Table 1, the $AR(1)$ coefficients suggest that the observed stock returns and traffic variables are stationary. Moreover, the movement of B_t is not significant. Its standard deviations σ_B are 5.44E-09 and 0.0336 for the closing-to-closing and closing-to-opening return samples, respectively.

5.3 Endogeneity Problems

5.3.1 Error-in-Variable Problems

The traffic index contains measurement errors. The index is the average index from every 15-minute index during morning rush hours. As some indexes were not available at the exact time, the study used the nearby or interpolated indexes as the substitutes for averaging. Furthermore, the index may be missing on certain days, for which imputation indexes from the *VAR-IM* algorithm were used.

In this study, the measurement errors in the traffic index did not cause error-in-variable problems in the estimation. In equation (1), the traffic index T_t is the dependent variable. The measurement errors are absorbed in the error term ε_t^T and can be ignored (Greene, 2018).

5.3.2 Omitted-Variable Problems

The SET and mai returns are explained by the economic and behavioral components of the traffic variable. The two components are unlikely to be the only explanatory variables for returns, which constitutes omitted-variable problems. However, the estimates are inconsistent (Greene, 2018). The omitted variable problem can be mitigated by modeling the error terms ε_t^S and ε_t^m by autoregressive processes (Ero˜glu et al., 2021). The absolute size $|\theta|$ of the $AR(1)$ coefficient must be less than 1.00.

This study does not follow Ero˜glu et al. (2021). Instead, it regressed the estimates of ε_t^S and ε_t^m on their first lags. The $AR(1)$ coefficients for the SET and mai errors were 0.2752 and 0.5104, respectively. The statistics were not significant; hence, the omitted variable problem should be small.

5.4 Endogenous Stock returns and Traffic Congestion

In equation (1), traffic congestion is the determinant of the SET and mai returns. However, the relationship can be opposite or bidirectional. For example, Milani (2017) explained the effect of stock market returns on outputs by increasing wealth and changing the expectations of the economic agents. Therefore, stock returns can explain traffic congestion. A possible bilateral relationship between traffic congestion and stock returns can be found in Jin and Rafferty (2017). In their model, traffic congestion, income, and employment are interrelated. As stock market returns are related to macroeconomic variables, the relationship between traffic congestion and stock market returns can exist.

If stock market returns explain traffic congestion or if the relationship is bidirectional, the model in equation (1) is mis-specified. Khanthavit (2022) reported that traffic congestion Granger and contemporaneously cause stock returns. Therefore, the model in equation (1) is well specified.

6. Conclusion

Traffic congestion affects stock market returns due to economic and behavioral factors. Previous studies found significant effects but aggregate effects in this regard, with the economic and behavioral effects bundled together. This study attempted to unbundle and separately measure the economic and behavioral effects of Bangkok traffic congestion on Thai stock market returns. It proposed decomposing the traffic variable into economic and behavioral components by analyzing the traffic variable and stock market returns in the state-space framework. The study estimated the state-space model via Kalman filtering using the daily samples of the Longdo traffic index and the SET and mai returns from January 4, 2012 to April 2, 2020 to find that the economic and behavioral effects of Bangkok traffic on both the market returns are negative and significant. The economic component Granger causes a behavioral component, although their joint explanatory power is small at 0.29% and 0.15% for the SET and mai returns, respectively.

Bolger et al. (1989) found that daily stress explained up to 20% of the variation in investors' moods, whereas bad moods were associated with shifted risk preference (Mehra & Sah, 2002) and attitude misattribution (Hirshleifer & Shumway, 2003). Therefore, the behavioral component can be emanating directly via traffic-induced stress or indirectly via bad moods. Further decomposition of the behavioral component into direct and indirect parts poses as a methodological challenge in behavioral finance studies and is a topic of future research.

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