BANGKOK TRAFFIC CONGESTION, STRESSED INVESTORS, AND THAI STOCK-MARKET RETURNS

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Abstract

Stress influences decision making. Stressed investors may trade in concert, driving stock market returns in a certain direction. This study examines the effect of Bangkok's traffic-induced stress on Thai stock market returns. The average Longdo traffic index during morning rush hours was used as the proxy for the level of stress. As Bangkok traffic affects only local investors, this study measures returns using the return on the Market for Alternative Investment (mai) index. Local investors have an average 96.96% share of the mai stocks' trading volume. The sample data were taken from the period beginning on January 4, 2012, and ending on April 2, 2020. A test based on the artificial Hausman regression indicates that error-in-variable and omitted-variable problems are present in the estimation. Therefore, the generalized method of moments (GMM) regression—an instrumental variable (IV) regression, together with Racicot and Théoret's (2010) two-step IVs, were chosen over the traditional ordinary least squares regression for this study. The IVs are informative and valid, with informativeness and validity R^2 values of 0.9888 and 0.0000, respectively. The slope coefficient of stock returns on the traffic index was found to be negative and significant. Traffic-induced stress can drive stock market returns. Net selling by local institutional investors explains the significant traffic-induced stress effect in the stock market.

Keywords: behavioral finance; decision making; instrumental variables

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1. INTRODUCTION

Stress is "the feeling of being overwhelmed or unable to cope with mental or emotional pressure" (Mental Health Foundation, 2021). It is a non-specific response of the body to any demand for change (Selye, 1936), and occurs when the demand exceeds the capacity of a person, especially in unpredictable and uncontrollable situations (Dickerson & Kemeny, 2004). Stress affects decision making (Starcke & Brand, 2012) due to altered risk preference (Porcelli & Delgado, 2009; Van den Bos, Harteveld, & Stoop, 2009) and attitude misattribution (Kinner, Wolf, & Merz, 2016). The brain regions underlying intact decision-making are sensitive to stress-induced changes (Starcke & Brand, 2012).

In a prior survey (Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004), traffic was found to be one of the least enjoyable experiences in people's daily lives. It is among the leading causes of stress to those who drive in congested traffic (Hennessy, Wiesenthal, & Kohn, 2000; Stokols, Navaco, Stokols, & Campbell, 1978; Thwe, Yamamoto, Sato, & Morikawa, 2017). During rush hours, drivers in cities with severe traffic congestion, such as Moscow, Mumbai, Manila, Bangkok, and New York, tend to suffer acute stress (Hennessy & Wiesenthal, 1999). These drivers are also often investors in the respective stock markets. As stress affects decision making, the trades of stressed investors are associated with morning traffic conditions. Prior studies have established the effect of morning traffic conditions on stock market returns (Imisiker, Tas, & Yildirim, 2019).

2. LITERATURE REVIEW

2.1 Traffic-Induced Stress

Traffic is an environmental stressor. It obstructs commuters in moving to their destinations (Stokols et al., 1978). The association of traffic congestion with rising stress levels has been reported by Antoun, Edwards, Sweeting, and Ding (2017), Gottholmseder, Nowotny, Pruckner, and Theurl (2009), Hennessy and Wiesenthal (1999), and Stokols et al. (1978). Drivers show significantly more stress than non-drivers do (Venkatesh & Pushpa, 2014). Moreover, traffic contributes to stress at different degrees, depending on mood states (Von Helversen & Rieskamp, 2020), time urgency and hassle exposure (Hennessy et al., 2000), predictability (Evans, Wener, & Phillips, 2002; Wener & Evans, 2011), duration in traffic and individual trait stress susceptibility to congestion (Higgins, Sweet, & Kanaroglou, 2018), road conditions (Thwe et al., 2017), control and choice (Schaeffer, Street, Singer & Baum, 1988), and days of the week (Gulian, Debney, Glendon, Davies, & Matthews, 1989).

2.2 Stress and Decision Making

Stress affects decision-making (Starcke & Brand, 2012). It can change the risk preference of an individual and induce attitude misattribution. An individual tends to experience multiple stressors in a day. However, one stressor does not exacerbate the effects of another (Bolger, DeLongis, Kessler, & Schilling, 1989)

2.2.1 Risk Preference

Acute stress increases the level of the hormone cortisol, promoting risk-taking behavior (Porcelli & Delgado, 2017; Starcke & Brand, 2016; Van den Bos et al., 2009). Starcke and Brand (2016) and Van den Bos et al. (2009) provide supporting evidence for the increase in risk-taking behavior. However, Starcke, Wolf, Markowitsch, and Brand (2008) reported an opposite result for more risk-averse behavior, while Plieger, Grünhage, Duke, and Reuter (2021) found no effect.

The time-dependent nature of stress effects may explain these inconsistent results. Hermans, Henckens, Joëls, and Fernández (2014) argued that acute stress immediately promotes fear and vigilance; however, the reaction reverses after stress subsides, to increase long-term survival. Bendahan, Goette, Thoresen, Loued-Khenissi, Hollis, and Sandi (2017) reported that participants in their study were less risk averse immediately after experiencing acute stress, but demonstrated greater risk-aversion behavior after 45 minutes. However, Starcke and Brand (2016) found no effect of time after stress.

The differing responses of alternate genders can be an alternative explanation for the inconsistent results. In many studies the results show the average effects of both male and female participants. Preston, Buchanan, Stansfield, and Bechara (2007) reported that acutely stressed males are risk-taking while females are risk-averse, while Cahlíková and Cingl (2017) and Van den Bos et al. (2009) reported that males and females are risk averse and risk taking, respectively.

2.2.2 Attitude Misattribution

Stress-induced misattribution results from the stress hormone cortisol reducing an individual's anticipation of reward (Kinner et al., 2016). The attitude misattribution effect toward pessimism in decision making was supported empirically by Gelman and Kliger (2021), Kandasamy et al. (2014), and Kinner et al. (2016). Cueva et al.'s (2015) study is among the few that have reported no misattribution.

2.2.3 Mood

Stress can influence decision-making indirectly via mood, as it decreases the expression of brain-driven neurotropic factors in limbic structures that control mood (Duman & Monteggia, 2006). Bolger et al. (1989) found that daily stress explains up to 20% of variation in mood. Bolger et al. (1989), DeLongis, Folkman, and Lazarus (1988), and Het and Wolf (2007) reported an association between stress and bad mood. Bad moods are also related to shifted risk preference (Mehra & Sah,

2002) and attitude misattribution (Hirshleifer & Shumway, 2003).

It is interesting to explore whether traffic directly affects mood. Morris and Guerra (2015) found non-significant effects. Mood during travel was approximately the same as the average.

2.2.4 Chronic Stress

Stress can be acute (e.g., being in traffic congestion) or chronic (e.g., driving in rush-hour traffic daily) (Gatersleben & Griffin, 2017). Acute and chronic stresses lead to different responses in decision making (Starcke & Brand, 2012). In Kandasamy et al. (2014), acute stress on days 0 and 1 of cortisol administration had no effect on participants' risk preference, whereas chronic stress on days 2 to 7 raises the level of risk aversion and pessimism.

2.2.4 Spillover Effect

Traffic-induced stress exhibits a spillover effect on drivers even after they arrive at their destinations (Sherrod, 1974). Marco and Suls (1993) explained that this is caused by the effect of current stress on mood during the day. Li et al. (2020), Sherrod (1974), and Wener, Evans, and Boately (2005) reported spillover that affects decision-making at work.

2.3 Stress and Financial Markets

2.3.1 Effects of Markets on Investors' Stress

Rising return volatility is a significant stressor for investors and traders. Lo and Repin (2002) monitored the cardiovascular variables of 10 professional foreign exchange and interest rate derivative traders in Boston, finding that variables rose significantly during volatile markets in comparison to average markets. Coates and Herbert (2008) studied the stress levels of 17 traders in London, whose portfolios were mostly exposed to German interest-rate futures. The researchers reported that cortisol levels of traders rose with the volatilities of the performance of their portfolios and the markets. Xie, Page, Granger, and Coates (2018) recruited 15 traders from a mid-sized hedge fund in London who bought and sold equity and bond futures. They were monitored for two weeks, and their cortisol levels were measured three times each day. The average cortisol levels strongly correlated with the volatilities of the equity and bond indexes.

Oran, Akyatan, and Hekim (2009) studied 57 investors in Turkey. Investors' cortisol levels were analyzed using the intraday volatility of the Istanbul Stock Exchange (ISE) 100 index return. The results were different. The correlation between cortisol levels and ISE-100 return volatility was non-significant.

2.3.2 Effects of Investors' Stress on Markets

Unlike the effects of behavioral factors, such as mood (Hirshleifer & Shumway, 2003) or sentiment (Nguyen & Pham, 2018), which have already been studied extensively, the effects of acute stress are few and limited to traffic-induced stress. Imisiker et al. (2019) studied the effects of traffic-induced stress in New York and London on the returns of the S&P 500 and FTSE-100 indexes, respectively. Stress was measured using the average traffic speed during the 90-minute interval before the opening of the stock markets as a proxy. The researchers found significantly negative stock returns on high-traffic days. Traffic-induced stress raises investors' risk aversion, pressuring stock prices downward.

Gelman and Kliger (2021) related stress from traffic congestion in Moscow, with the slope of the implied volatility function of options on the Russian Trading System Index futures on the left-hand side of the volatility smile. Unexpected traffic congestion, computed from the average deceleration coefficient (DC) from 8.15 a.m. to 9.45 a.m., was the stressor. DC is the time needed to cover a reference distance relative to a free traffic situation. The slope in the morning session was higher following Moscow's high unexpected DC. The results were interpreted for stressed investors assigning more weight to extreme losses.

This study examines the effect of Bangkok's traffic-induced stress on Thai stock market returns. Bangkok is chosen as the subject of the study, for its famously high traffic, which is among the heaviest in the world. For perspective, the 2020 TomTom Traffic Index (TomTom International BV, 2021a) ranks Moscow in first place, while Bangkok ranks tenth; London and New York rank 49 and 102, respectively.

The Stock Exchange of Thailand (SET) is one of the leading stock markets in emerging economies. According to an assessment by the World Federation of Exchanges (2021), the SET ranks 10th among markets in the Asia-Pacific region and is the 24th largest market in the world. In May 2021, the market capitalization of the SET was US$ 596 billion.

The SET is located in Bangkok, where most stock investors live and trade. Stock News Online (2015) reported that there were 1,134,500 open stock accounts in February 2015, and 88% of these accounts were in the Bangkok metropolitan area. Thus, Bangkok traffic affects the majority of investors.

The return is computed from the Market for Alternative Investment (mai) index. The mai index is a value-weighted index of all stocks on the mai. These stocks are mostly traded by local investors who suffer from Bangkok traffic congestion. From January 4, 2012, to April 2, 2020, the average total trading volume of local investors was 96.96%. Local institutional investors contributed 1.77%, while local individual investors contributed 95.19%.

Imisiker et al. (2019) employed the S&P 500 and FTSE-100 indexes to compute returns. Note that investors worldwide trade these two indexes. New York and London traffic do not affect investors outside the two cities. Hence, it is possible that the results are spurious.

To avoid possible spurious results, this study did not choose the SET index, which is a more popular index than the mai index. SET stocks possess a high share of foreign investor trading volume. Local and foreign investors contribute 70.73% and 29.27% to the SET stocks, respectively, compared to 96.96% and 3.04% to the mai stocks, respectively.

Traffic-induced acute stress cannot be directly observed. In previous studies (Gelman & Kliger, 2021; Imisiker et al., 2019) the DC and travel speed were used as proxies, serving as independent variables in ordinary least squares (OLS) regression. Certain variables, such as weather conditions and event dummies, were added as control variables in the OLS equations. The significant slope coefficients for these stress proxies indicate significant effects.

Using proxies and adding control variables in estimation induces error-in-variable (EIV) and omitted-variable (OV) problems. The problems lead to inconsistent coefficient estimates (Greene, 2018). Traffic variables approximate the stress level and thus, contain measurement errors. Moreover, these variables can be missing at times because of faulty equipment or missed observations. When variables are missing, researchers may choose an imputation approach and impute proxies for missing data. Measurement errors from the two sources can cause EIV problems.

Dependent stock market variables are driven by various factors, including economic, political, event, and behavioral factors. The stress and control variables cannot exhaust the set of all explanatory variables. The remainder is omitted, constituting the OV problem.

In this study, the unexpected level of the Longdo traffic index was the stressor. This index proxies for traffic-induced stress. It is the only explanatory variable for the mai return in the regression equation. Hence, the slope coefficient will be inconsistent if OLS regression is chosen for the estimation.

The EIV and OV problems can be solved using instrumental variable (IV) regressions (Greene, 2018). Among alternative IV estimators, the generalized method of moments (GMM) estimator was chosen for this study. GMM estimators give consistent, asymptotically normal, and efficient estimates in the class of all estimators that do not use any extra information aside from those contained in the moment conditions (Hansen, 1982).

The choice of IV for the traffic variables is crucial. The IV must be informative in that it must explain the traffic variable well and must be valid, in that it is not correlated with the error term in the regression equation. Owing to its informativeness and validity, the Racicot and Théoret’s (2010) two-step IV is used in the estimation in this study. For the full sample, the informativeness R^2 is 0.9888, while the validity R^2 is 0.0000.

3. RESEARCH METHOD AND DATA

3.1 The Model

Let R_t and S_t denote the stock market return and traffic-induced stress on day t, respectively. $t = 1, \dots, T$. The study assumes that the relationship is linear in regression Equation (1).

$$R_t = a_0 + a_1 S_t + e_t, \qquad (1)$$

where e_t is the regression error. Parameters a_0 and a_1 are the intercept and slope coefficients, respectively. If stress affects the return, the slope coefficient a_1 must be significantly different from 0.00.

The model in Equation (1) can be estimated using the OLS technique. If all OLS assumptions are satisfied, the OLS coefficients are the most efficient, unbiased, and consistent. However, the possible EIV and OV problems suggest that OLS regression should not be used.

3.2 Generalized Method of Moments Regression

GMM regression is an IV technique that helps solve EIV and OV problems. It has been used extensively in the literature to improve performance over OLS regression. Let $\boldsymbol{Z}_t = \left[1\ Z_{1,t}\ Z_{2,t}\ \dots\ Z_{m,t}\right]'$ be the $m+1$ instrumental variable. The GMM estimators are $\widehat{\boldsymbol{\theta}} = [\hat{a}_0\ \hat{a}_1]'$, minimizing the objective function $Q_T(\boldsymbol{\theta})$ in Equation (2).

$$Q_T(\boldsymbol{\theta}) = f_T(\boldsymbol{\theta})'\boldsymbol{W}_T f_T(\boldsymbol{\theta}), \qquad (2)$$

where $f_T(\boldsymbol{\theta}) = \frac{1}{T}\sum_{t=1}^{T} \boldsymbol{Z}_t(R_t - a_0 - a_1 S_t)$ and the matrix $\boldsymbol{W}_T$ is the weighting matrix. The continuously updating GMM was applied, as it offers better performance than the traditional two-step GMM. This method is more reliable and gives smaller mean biases (Hansen, Heaton, & Yaron, 1996).

3.3 Hypothesis Test

The slope estimate $\hat{a}_1$ was used for the hypothesis test. Under the null hypothesis, there were no effects of traffic-induced stress on stock market returns, $\hat{a}_1 = 0.00$. The test was conducted based on Newey and West's (1987) heteroskedasticity and autocorrelation consistent standard deviation.

3.4 Instrumental Variables

The study employs Racicot and Théoret's (2010) two-step technique to construct the IV (Z_t). In the first step, seven variables—$Z_I, \dots, Z_{VII}$, were constructed from the return and traffic variables as follows:

$$\boldsymbol{Z_I} = \boldsymbol{s} * \boldsymbol{s},$$
$$\boldsymbol{Z_{II}} = \boldsymbol{s} * \boldsymbol{r},$$
$$\boldsymbol{Z_{III}} = \boldsymbol{r} * \boldsymbol{r},$$
$$\boldsymbol{Z_{IV}} = \boldsymbol{s} * \boldsymbol{s} * \boldsymbol{s} - \boldsymbol{3s}\left[E\left(\frac{\boldsymbol{s'}\boldsymbol{s}}{\boldsymbol{T}}\right) * \boldsymbol{I_T}\right],$$

$$\boldsymbol{Z}_V = \boldsymbol{s} * \boldsymbol{s} * \boldsymbol{r} - 2\boldsymbol{s}\left[E\left(\frac{\boldsymbol{s}'\boldsymbol{r}}{\boldsymbol{T}}\right) * \boldsymbol{I}_T\right] - \boldsymbol{r}\left\{\boldsymbol{\iota}_T{}'\left[E\left(\frac{\boldsymbol{s}'\boldsymbol{s}}{\boldsymbol{T}}\right) * \boldsymbol{I}_T\right]\right\},$$

$$\boldsymbol{Z}_{VI} = \boldsymbol{s} * \boldsymbol{r} * \boldsymbol{r} - \boldsymbol{s}\left[E\left(\frac{\boldsymbol{r}'\boldsymbol{r}}{\boldsymbol{T}}\right)\right] - 2\boldsymbol{r}\left[E\left(\frac{\boldsymbol{r}'\boldsymbol{s}}{\boldsymbol{T}}\right)\right],$$

$$\boldsymbol{Z}_{VII} = \boldsymbol{r} * \boldsymbol{r} * \boldsymbol{r} - 3\boldsymbol{r}\left[E\left(\frac{\boldsymbol{r}'\boldsymbol{r}}{\boldsymbol{T}}\right)\right],$$

where $\boldsymbol{s}$ and $\boldsymbol{r}$ are the vectors of the deviation of the traffic variable S and stock return R from their means. $\boldsymbol{I}_T$ is the identity matrix of size T, and $*$ denotes the Hadamard element-by-element matrix multiplication operator.

In the second step, four sets of IVs are considered: Durbin's (1954) $\{\boldsymbol{\iota}_T, \boldsymbol{Z}_I\}$, Dagenais and Dagenais's (1997) $\{\boldsymbol{\iota}_T, \boldsymbol{Z}_I, \dots, \boldsymbol{Z}_{IV}\}$, Pal's (1980) $\{\boldsymbol{\iota}_T, \boldsymbol{Z}_{IV}\}$, and Racicot and Théoret's (2010) $\{\boldsymbol{\iota}_T, \boldsymbol{Z}_I, \boldsymbol{Z}_{IV}\}$. $\boldsymbol{\iota}_T$ is a unit vector of size T. It is easy to construct these IVs, and they are informative (Dagenais & Dagenais, 1997). Let $\boldsymbol{Z}^*$ be the IV choice, $\boldsymbol{Z}^a = \{\boldsymbol{\iota}_T, \boldsymbol{Z}_I\}$, $Z^b = \{\boldsymbol{\iota}_T, \boldsymbol{Z}_I, \dots, \boldsymbol{Z}_{IV}\}$, $\boldsymbol{Z}^c = \{\boldsymbol{\iota}_T, \boldsymbol{Z}_{IV}\}$, and $\boldsymbol{Z}^d = \{\boldsymbol{\iota}_T, Z_I, \boldsymbol{Z}_{IV}\}$. The second step, IV $(\boldsymbol{Z})$ is the residual from the regression of traffic variable S on the first step IV ($\boldsymbol{Z}^*$).

The informativeness R^2 for $\boldsymbol{Z}$ is the R^2 from the regression of traffic variable S on $\boldsymbol{Z}$, while the validity R^2 is the R^2 from the regression of the residual in Equation (1) on $\boldsymbol{Z}$. Informativeness performances of $\boldsymbol{Z}$'s from $\boldsymbol{Z}^a$, $\boldsymbol{Z}^b$, $\boldsymbol{Z}^c$, and $\boldsymbol{Z}^d$ were compared. The IV with the highest informativeness R^2 was chosen for the analysis.

3.5 The Data

3.5.1 Data Description

The study analyzes the effects of stress induced by Bangkok traffic during the morning rush hours on Thai stock-market returns, using daily data. The stock returns were the closing-to-opening returns computed from the log differences of the closing and opening mai indexes. The closing-to-opening return uses stress as a behavioral factor. Its effect may be short-lived, disappearing within a few minutes after the market opens (Chang, Chen, Chou, & Lin, 2008). Bangkok traffic affects local investors who live in the Bangkok metropolitan area. The mai index was chosen over the SET index because the mai stocks are traded mostly by local investors. The average trading volume of foreign investors in the mai is low (3.04%) in comparison to the SET which has much higher foreign investment (29.27%). The opening and closing mai indexes were retrieved from the SET database.

The traffic variable is the Longdo traffic index, which ranges from 0 to 10. The index level 0 means no traffic, while index level 10 indicates traffic immobility in all streets in the Bangkok metropolitan area. The index is reported every 5 minutes throughout the day. The Longdo traffic index was downloaded from the Longdo.com database (https://traffic.longdo.com/download).

Rush hours are the period of day during which traffic congestion is at its peak. For Bangkok, morning rush hours are from 6.00 a.m. to 10.00 a.m.

(TomTom International BV, 2021b). The morning rush-hour traffic value was the index averaged from the indexes for every 15 minutes from 6.00 a.m. to 10.00 a.m.

The Longdo traffic index began on January 1, 2012. Therefore, January 4, 2012, was chosen as the first sample day, as it was the first trading day of the SET in 2012. The full sample ended on April 2, 2020. This choice was to avoid the effects of the COVID-19 pandemic in the analysis. On April 3, 2020, the Thai government imposed its first curfew to contain the spread of COVID-19 (Post Reporters, 2020).

3.5.2 Data Imputation and Removal

It was noticed that the indexes for exact times during the morning rush hours were sometimes missing. For some trading days, the indexes were missing for the entire day. The study proceeded by removing the trading days on which the traffic data were missing for the entire day, from the sample.

If traffic data were available on the correct day, but not at the exact time, the index value from five minutes earlier was used, if available. If that index was also missing, the index value from ten minutes earlier was used, if available. This procedure is not able to impute all missing indexes. If unsuccessful, linear interpolated indexes were used for imputation.

The full sample period from January 4, 2012, to April 2, 2020, covered 2,020 trading days. One hundred and seventy-nine days were removed due to missing indexes; imputation was performed for 466 days of the remaining 1,841 days of the usable sample. The full sample was separated into two sub-samples to gain insight into how effects evolve over time. The first sub-sample, taken from January 4, 2012, to December 30, 2015, contained 894 usable observations, while the second sub-sample, taken from January 4, 2016, to April 2, 2020, contained 947 usable observations.

3.5.3 De-seasonalized and De-weathered Traffic Index

This study follows previous studies (Gelman & Kliger, 2021; Imisiker et al., 2019) in removing seasonal factors that may be present in the traffic index. The seasonal variables are dummies for days of the week, weeks of the year, months of the year, days before and after long holidays of three or more days, the last trading Friday of the month, and the Royal Ploughing Ceremony Day. The first three sets of dummies remove the seasonal pattern shown by TomTom analysis (TomTom Intervational BV, 2021b). The days before and after long holidays and the Royal Ploughing Ceremony Day are considered similar to those of Gelman and Kliger (2021) and Imisiker et al. (2019). The Royal Ploughing Ceremony Day is a national holiday day on which the market opens.

The traffic index was de-weathered using weather variables for two reasons. First, weather variables, such as rainfall, cause poor road conditions, reducing the predictability of arrival time, and forcing a change in transportation (Imisiker et al., 2019). Second, weather proxies for mood state (Hirshleifer & Shumway, 2003). Removing weather effects should mitigate the effect of traffic-induced mood (Morris & Guerra, 2015) in the analysis. The weather variables used were average temperature, and cloud cover, from 6.00 a.m. to 10.00 a.m. Temperature and rainfall have previously been found to affect the Thai stock- and bond-market returns (Khanthavit, 2017, 2018). Because the rainfall variable is missing for many trading days, it was substituted with cloud cover, as these two variables are highly correlated.

The de-seasonalized and de-weathered index is an unpredicted index. This is the traffic-induced stress S_t in Equation (1). Predictability determines stress levels (Evans et al., 2002; Wener & Evans, 2011), and unexpected traffic variables are traffic stressors (Gelman and Kliger, 2021; Imisiker et al., 2019).

3.5.4 Descriptive Statistics

Panel 1.1 of Table 1 reports the descriptive statistics for the mai index return for the full sample and the first and second sub-samples. The return is a closing-to-opening return. For the full and sub-samples, the returns are negatively skewed and fat-tailed. The Jarque-Bera test rejects the normality hypothesis at the 99% confidence level.

Panel 1.2, Table 1 shows the descriptive statistics for the raw, de-seasonalized and de-weathered traffic indexes. Although the distributions of the indexes are not so skewed and their tails are not as fat as those of the mai return, the normality hypothesis is rejected at the 99% confidence level.

Table 1 Descriptive Statistics
Panel 1.1 mai Index Return

Statistic	mai Index Return		
	Full Sample	First Sub-sample	Second Sub-sample
Average	0.1653	0.2332	0.1013
Standard Deviation	0.5407	0.5703	0.5031
Skewness	-3.2532	-2.1553	-5.0071
Excess Kurtosis	36.1374	15.2734	69.1679
Maximum	4.2875	3.5484	4.2875
Minimum	-7.2602	-4.5738	-7.2602
Jarque-Bera Statistic	1.03E+05***	9.38E+03***	1.93E+05***
Number of Observations	1841	894	947

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

Panel 1.2 Traffic Congestion Index

Statistic	Raw Index			De-seasonalized and De-weathered Index		
	Full Sample	First Sub-sample	Second Sub-sample	Full Sample	First Sub-sample	Second Sub-sample
Average	4.1983	3.9195	4.4615	0.0000	-0.3589	0.3388
Standard Deviation	0.8833	0.8118	0.8674	0.9978	0.8305	1.0240
Skewness	-0.6444	-1.0161	-0.6483	-0.1837	-0.8426	-0.2426
Excess Kurtosis	1.7105	3.0003	1.2135	1.0085	3.9062	-0.1986
Maximum	7.6200	5.9800	7.6200	3.6653	1.8945	3.6653
Minimum	0.0000	0.0000	0.2500	-5.1960	-5.1960	-3.6127
Jarque-Bera Statistic	.52E+02***	4.89E+02***	1.24E+02***	8.84E+01***	6.74E+02***	1.08E+01***
Number of Observations	1841	894	947	1841	894	947

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

The fact that the return and traffic variables are not normally distributed does not affect the estimation. GMM does not require normally distributed variables. Despite non-normality, GMM estimators are consistent, asymptotically normal, and efficient.

4. EMPIRICAL RESULTS

4.1 Ordinary Least Squares Regression and Estimation Problems

Possible EIV and OV problems provide motivation for the use of GMM regression in the estimation in this study. To check whether the problems exist which make OLS regressions unusable, a test based on the artificial Hausman regression model was used (Racicot & Théoret, 2008). The model in Equation (1) was modified to:

$$R_t = a_0 + a_1 S_t + \gamma \hat{u}_t + e_t. \qquad (3)$$

The variable $\hat{u}_t$ is defined as $R_t = b_0 + b_1 Z_t + \hat{u}_t$. If the EIV and OV problems do not exist, the slope coefficient $\gamma = 0.00$. The estimation of γ was performed in two steps. In the first step, the OLS regression was run for the model $R_t = b_0 + b_1 Z_t + \hat{u}_t$. The residual $\hat{u}_t$ was maintained. This was then used in the OLS regression model (3) in the second step. For the full sample and the first sub-sample, the Z_t was constructed from Durbin's (1954) IV. The Z_t for the second subsample was constructed from Pal's (1980) IV. These choices were made based on their informativeness R^2's. The artificial Hausman slope coefficient γ was 0.4737, 0.0974, and -0.1933, for the full sample, the first sub-sample, and second sub-sample, respectively. The coefficient for the full sample was significant at the 99% confidence level. The coefficients for the two subsamples were nonsignificant. The problems exist. The significant slope coefficient γ justifies the use of GMM in the estimation.

4.2 Results for Generalized Method of Moments Regression

4.2.1 Construction of Instrumental Variable

The study constructed Z_t from four versions of IV, including (a) Durbin's (1954) IV, (b) Dagenais and Dagenais's (1997) IV, (c) Pal's (1980) IV, and (d) Racicot and Théoret's (2010) IV, computing their informativeness and validity R^2's. Table 2 reports these performance statistics. The validity R^2 values were identical at zero for all IV techniques and samples. With respect to informativeness R^2, Durbin's (1954) IV was used to construct Z_t for the full sample and the first sub-sample. For the second sub-sample, Z_t was constructed from Pal's (1980) IV.

Table 2 Performance Comparison of Instrumental Variables Constructed by Alternative Techniques

Technique	Full Sample		First Sub-sample		Second Sub-sample	
	Informative-ness R^2	Validity R^2	Informative-ness R^2	Validity R^2	Informative-ness R^2	Validity R^2
(a) Durbin (1954)	**0.9888**	0.0000	**0.8596**	0.0000	0.9700	0.0000
(b) Dagenais and Dagenais (1997)	0.9009	0.0000	0.7641	0.0000	0.9268	0.0000
(c) Pal (1980)	0.9679	0.0000	0.8542	0.0000	**0.9935**	0.0000
(d) Racicot and Théoret (2010)	0.9679	0.0000	0.8453	0.0000	0.9555	0.0000

Note: The **bold** number indicates the largest informativeness R^2.

Table 3 Effects of Traffic-Induced Stress on mai-Index Return

Sample Period	Slope Coefficient for Traffic-Induced Stress	
	Main Result	Robustness Check
Full Sample	-0.0712[a,***]	-0.0693[c,***]
First Sub-sample	0.0132[a]	0.0321[c]
Second Sub-Sample	-0.0727[c,**]	-0.0718[a,***]

Note: ** and *** = Significant at the 95% and 99% confidence levels, respectively; [a] and [c] = Durbin's (1954) and Pal's (1980) instrumental variables, respectively.

4.2.2 Effects of Traffic-Induced Stress on Stock-Market Returns

Column 2 of Table 3 reports the GMM regression results. The slope coefficient for traffic-induced stress is negative and significant for the full sample and the second sub-sample. The coefficient for the first subsample was nonsignificant. This finding leads to the conclusion that traffic-induced stress significantly affects stock returns. This result is consistent with that of Imisiker et al. (2019), who studied the effects of traffic conditions in New York and London. This negative effect supports the fact that traffic-induced stress raises investors' degree of risk aversion (e.g. Bendahan et al., 2017) and enhances their pessimism (e.g. Gelman & Kliger, 2021).

5. DISCUSSION

5.1 Robustness Check

5.1.1 Alternative Specifications for Instrumental Variables

The main results in Column 2 of Table 3 are based on the IV constructed from the best-performing inputs. Checks were conducted to determine whether the results are sensitive to the manner in which the IVs are constructed. Therefore, Z_t was reconstructed from Pal's (1980) IV for the full sample and the first subsample, and Durbin's (1954) IV for the second sub-sample. Equation (1) was then estimated using the new sets of IVs. The results in Column 3 of Table 3 are very similar to those in Column 2.

5.1.2 Alternative Specifications for Traffic Index

Imisiker et al. (2019) removed the year's fixed effect from the traffic variable. The traffic variable used was the average during the 90-minute interval before the market opening; this was the dummy variable for the days in which the traffic was within the 10th worst percentile. The researchers reported that their results remained unchanged even if the traffic variable was not de-weathered.

This study considers four alternative specifications for the traffic index with respect to Imisiker et al.'s (2019) specifications. The "Closing-to-Opening" row of Table 4 presents the results. The results for the de-seasonalized but not de-weathered, and de-seasonalized and year-effect-removed index are very similar to the main results. However, when the traffic index is changed to the average index during the 90-minute interval before the market opening or to the dummy for the worst traffic days, the significant results disappear. The non-significance of the former specification may be explained by the fact that investors arrive at their destinations much earlier than 90 minutes before the market opening. The SET opens at 10.00 a.m., whereas office hours at most firms in Bangkok begin at 8.30 a.m. or 9.00 a.m. The reason for the latter specification may be the low information in the dummy variable.

Table 4 Results for Alternative Specifications for Traffic Index and Stock-Market Return

Alternative Specification		Slope Coefficient for Traffic-Induced Stress		
Return	Traffic Index	Full Sample	First Sub-sample	Second Sub-sample
Closing-to-Opening	De-seasonalized Rush-Hour Traffic	$-0.0665^{a,***}$	0.0223^{a}	$-0.0674^{c,**}$
	De-seasonalized and Year-Effect Removed Rush-Hour Traffic	$-0.0686^{a,***}$	0.0052^{a}	$-0.0638^{c,**}$
	De-seasonalized and De-weathered 90-Minute Interval Traffic before Market Opening	0.0035^{c}	0.0400^{c}	-0.0255^{a}
	Worst Traffic-Day Dummy Variable	-0.0363^{OLS}	0.0424^{OLS}	-0.0691^{OLS}
Closing-to-Closing	De-seasonalized and De-weathered Rush-Hour Traffic	$-0.0391^{a,*}$	0.0434^{a}	$-0.0813^{c,**}$
Opening-to-Closing	De-seasonalized and De-weathered Rush-Hour Traffic	0.0029^{a}	$0.0857^{a,***}$	$-0.0747^{c,**}$
Closing-to-Opening SET Return	De-seasonalized and De-weathered Rush-Hour Traffic	-0.0304^{a}	0.0278^{a}	$-0.0430^{c,*}$

Note: *, ** and *** = Significant at the 90%, 95% and 99% confidence levels, whereas ^{a} and ^{c} = Durbin (1954) and Pal (1980)'s instrumental variables, respectively. ^{OLS} = Results from ordinary least squares regression.

5.2 Spillover Effects

The main results in Column 2 of Table 3 support the spillover effect of traffic-induced stress (Sherrod, 1974). Decision-making on trades at the opening price is made minutes or hours later, after investors arrive at their destinations.

In addition to the effect at the opening time, it is possible that the spillover effect spreads over the day (Marco & Suls, 1993). This study examines the prolonged spillover effect. The estimation is repeated. The dependent variable changes to a closing-to-closing return. The "Closing-to-Closing" row of Table 4 presents the results. This is similar to the main result. This study concludes that the spillover effect extends over the day.

5.3 Trading Strategies

Investors and traders know the traffic conditions during the hours before market opening. If the condition can predict the opening-to-closing return, this information can be used to form profitable trading strategies. In this study the opening-to-closing return is regressed on the traffic index. The "Opening-to-Closing" row of Table 4 reports this result.

The slope coefficient is not significant for the full sample. Nevertheless, it is positive and significant for the first sub-sample, but negative and significant for the second sub-sample. The return can be predicted by the morning traffic for the two sub-samples. Possible trading strategies are buying (selling) at the market opening (market closing) and selling short (buying) at the market opening (market closing).

In the regression, all variables were normalized by their means and standard deviations. The significant coefficients translate to 0.0489% and -0.0376% returns for the first and second sub-samples, respectively, if the standardized traffic variable moves by one standard deviation. The minimum transaction cost possible is 0.1145%; thus, the strategies incur 0.2290% from buying and selling stocks. However, these strategies are not profitable.

5.4 Effect on the Stock Exchange of Thailand Index Return

The SET index was not chosen for the analysis as its trading volume includes a large percentage share of foreign investors. However, it is interesting to ask whether the SET index return reacts in a similar manner to that of the mai index return. To answer this question, the SET return is substituted for the mai return and Equation (1) is re-estimated. The results are shown in the row "Closing-to-Opening SET Return" in Table 4. The study did not find significant effects for the full sample and the first sub-sample. For the second sub-sample, the effect is negative and marginally significant at the 90% confidence level. This result is consistent with the fact that Bangkok traffic affects local investors rather than foreign investors.

5.5 Behaviors of Local Investors

If traffic-induced stress raises risk aversion and enhances the pessimism of local investors, local investors should be net sellers on heavy traffic days. To check for this implication, the net buying volume of local investors was regressed on the traffic variable. The net buying volume variable is the ratio of net buying volume to market capitalization.

This implies a significantly negative slope coefficient. The results are reported in the row "All Local" in Table 5. The coefficient is negative for the full sample and the two sub-samples, but significant only for the full sample and the first sub-sample. The results support significant net selling on heavy traffic days.

Local investors consist of local institutional and individual investors. To determine who drives the market due to traffic-induced stress, the net buying volumes of local institutional investors and local individual investors were regressed on the traffic variable. The results are reported in the rows "Local Institutional" and "Local Individual" of Table 5, respectively. The slope coefficient for local institutional investors is negative and significant for the full sample and the two sub-samples, while the coefficient of local individual investors is nonsignificant. This finding leads to the conclusion that local institutional investors move the market due to traffic-induced stress. A possible explanation is that local institutional investors are professionals. They stand ready and act in concert with trade stocks at market opening. Local individual investors trade conveniently.

While local institutional investors respond significantly to traffic-induced stress in the full sample and the two sub-samples, it should be considered why the coefficient for the mai return in the first sub-sample is non-significant. The average trading shares of the local institutional investors for the first and second sub-samples were computed, generating values of 1.22% and 2.29%, respectively. The difference of 1.07% is significant, explaining

Table 5 Effects of Traffic-Induced Stress on Net-Buying Behaviors of Local Investors

Investor Group	Traffic-Induced Stress Slope Coefficient		
	Full Sample	First Sub-sample	Second Sub-sample
All Local	$-0.0505^{a,*}$	$-0.1300^{a,***}$	-0.0394^{c}
Local Institutional	$-0.0783^{a,***}$	$-0.0749^{a,**}$	$-0.0936^{c,**}$
Local Individual	0.0328	-0.0216	0.0609

Note: *, **, and *** = Significant at the 90%, 95% and 99% confidence levels, whereas ^{a} and ^{c} = Durbin (1954) and Pal (1980)'s instrumental variables, respectively.

why the trading volume of local institutional investors in the first sub-sample is not large enough to drive the mai return.

6. CONCLUSION

Morning traffic congestion causes investor stress, which in turn affects decision making in stock trading. This study examines the effect of stress induced by Bangkok's morning traffic on Thai stock market returns. Stress was measured using the unexpected Longdo traffic index. This effect is reflected in the significant slope coefficient in the regression of stock returns on the traffic variable. The generalized method of moments regression was used to solve possible error-in-variable and omitted-variable problems in the estimation. Based on the daily sample from January 4, 2012, to April 2, 2020, the study finds a significantly negative coefficient. The effect exists and is explained by the net selling of local institutional investors on high-traffic days. Net selling is due to rising risk aversion and pessimism.

In this study, traffic is a proxy for stress. This is the determinant of the stock market returns. However, traffic and stock returns can be endogenous. Both variables are driven by economic and political conditions (El-Alfy, Ratrout, & Gazder, 2015; Sweet, 2011). The endogenous or causal relationship between these two variables is interesting, such that future research should examine this issue.

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