Does Weather Contribute to Stock Price Variation?
A Cointegration Analysis

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Abstract

The objectives of this study are to investigate whether there is a long term relationship between stock returns and weather factors and to examine whether the weather factors have an outperforming effect over macroeconomic variables when explaining the stock price variation. This study is motivated by the emergence of behavioral branch of asset pricing which pays attention towards the irrationality of investors who are influenced by the mood and the sentiment. This study investigates this phenomenon taking evidence from an emerging market, Colombo Stock Exchange. The study uses Johansen Cointegration Test with VAR - Vector Error Correction Estimates and Variance Decomposition. The results confirm that weather factors are related with the stock prices in the long run and reveal that temperature has an outperforming contribution to the stock price variation whiles supporting the Temperature Anomaly which is widely tested in this background.

Keywords: Stock Returns, Weather, Mood, Temperature Anomaly, Cointegration.

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Introduction

The behavioural branch of asset pricing plays an important role in asset pricing addressing the gaps in traditional finance theory which fails to sufficiently explain the asset prices when market anomalies are present (Prosad et al, 2015). The behavioural finance theory has evolved over the past decades and has reduced the gaps in traditional finance theory taking more realistic factors which capture the investor irrationality. For example, the Nobel Prize winning Prospect Theory (Kahneman and Tversky, 1979) marks a milestone in academic debate introducing loss aversion bias whiles the traditional finance theory is based on risk aversion of rational investors. The core assumptions of behavioral asset pricing are investors are not always rational and there are limits to arbitrage (Nanayakkara et al, 2019). Accordingly, the investor mood and sentiment have an impact on asset returns (Gunathilaka and Jais, 2019). In this background, it is interesting to study whether there is a long run relationship between weather factors and stock prices and to study whether the weather factors contribute to the stock price variation as the weather can change the mood of a normal investor.

The empirical evidence can be found on the topic and the investigations have been carried out taking various weather variables into account. These include temperature, wind speed, humidity, sunshine hours and cloud cover among others. Some studies have only focused on the weather variables, but we can find recent studies which also consider other factors as control variables to isolate the impact of weather variables on stock returns (Sariannidis et al, 2016). Besides, finance literature provides plenty of international and local empirical evidence that macroeconomic variables have an impact on stock returns.

This research is motivated by the lack of research carried out combining both macroeconomic variables and weather variables to find a long term relationship between stock prices and weather variables. It is interesting to study this phenomenon in Sri Lanka because, unlike other counties, there is less variation in weather conditions and people do not experience distinct seasons such as winter, summer, etc.

The objectives of this study are to investigate whether there is a long term relationship between stock prices and weather factors and to examine whether the weather factors outperform macroeconomic variables when explaining the variation in stock prices.

Further, if foreign investors create a large part of the investor community who invest in a local stock exchange, a local exchange focused study becomes less useful, because the local weather conditions will not impact on their mood or the sentiment but the conditions of their home country. Thus, the weather conditions of that local context explain the price variation of that local market inadequately. When looking at the local stock exchange, Colombo Stock Exchange (CSE), by second quarter of 2018, the local individuals account for 74% of the total registered security accounts. The domestic clients account for 76% of the total number of shares in custody.

The remainder of this paper has organized as follows. The section 02 discusses the literature related to the topic, the section 03 explains the methodology of the study, section 04 discusses the results of the study and finally, section 05 provides the conclusion.

Literature Review

The documented literature on this background can mainly be classified into two branches as psychological branch and investor's financial behavioural branch. The psychological branch provides evidence on weather impacts mood. The investor's financial behavioural branch provides evidence on weather impacts stock prices.

Weather and Mood

The Mood impacts on the decision making. The mood effects can influence on financial analysis tasks (Wright and Bower, 1992). The positive mood could increase the risk taking and negative mood is more likely to result careful information processing to avoid potential loss (Yuen and Lee, 2003). There are plenty of empirical studies that tested whether the weather can influence the mood. Keller et al (2005) found, in two correlational studies, that pleasant weather was related to higher mood. Howarth and Hoffman (1984) investigated the relationship between mood and weather taking ten mood variables and eight weather variables and the study revealed that rising temperature lowered anxiety and scepticism mood scores. However, Cao and Wei (2005) argue that both lower and higher temperature can cause aggression and at higher temperature levels people may experience apathy. Besides, Dowling and Lucey (2005) investigated a relationship between investor mood and equity returns taking eight proxy variables such as cloud cover and rainfall for mood and found that rain and other variables have a minor but significant impact on equity returns.

Weather and Equity Returns

Plenty of empirical support can be found for the argument that weather impacts on the equity returns. Number of investigations has been carried out considering different weather factors such as number of sunshine hours (Shu and Hung, 2009), cloud cover, humidity levels (Shim et al, 2015), wind speed (Shu and Hung, 2009; Shim et al, 2015), raininess (Hirshleifer and Shumway, 2003) and temperature (Cao and Wei, 2005; Floros, 2008, 2011; Shim et al, 2015)

Cao and Wei (2005) examined the temperature anomaly in nine stock indices in eight equity markets in USA, Canada, Britain, Germany, Sweden, Australia, Japan and Taiwan using bin-test and regression. The study revealed that there is a negative relationship between temperature and stock market returns.

Keef and Roush (2007a) investigated whether the daily stock returns of two Australian stock market indices, namely, S&P/ASX 20 and S&P/ASX 300, are impacted by the temperature, cloud cover and wind speed. The study revealed that the temperature has a negative impact on equity returns, but the equity returns are not impacted by wind speed and cloud cover.

Keef and Roush (2007b) investigated the impact of cloud cover on equity index returns for twenty six international exchanges. The study examined whether there is an influence by the location of the stock exchange (latitude) and the economic development (per capita GDP of the country) employing Fisher Z correlation coefficient. The study revealed that there is a more negative impact of cloud cover on equity returns as latitude increases and as per capita GDP increases.

This phenomenon has widely tested employing volatility models.

Floros (2008) examined five European equity markets (Austria, Belgium, France, Greece and UK) to identify whether the market returns are related to temperature, employing GARCH method taking daily data. The study revealed that there is a negative relationship between temperature and equity market returns for Austria, Belgium and France. The results for Greece and UK were not significant.

Shu and Hung (2009) investigated whether there is a relationship between daily equity market returns of eighteen sample European countries (Czech Republic, Belgium, Finland, France, Hungary, Greece, Ireland, Luxemburg, Italy, Norway, Portugal, Poland, Russia, Sweden, Spain, Switzerland, UK and Turkey) and weather factors employing GARCH model. The study revealed that there is a negative impact of temperature on stock returns. Further, the study revealed that the wind has a greater impact on mood than sunshine.

The past empirical studies have also linked the weather factors with calendar anomalies to examine whether the stock returns are influenced by weather factors. Floros (2011) investigated Portugal stock market employing AR(1)-TGARCH(1,1) model to identify a relationship between temperature and stock returns using PSI 20 index of the Lisbon Stock Exchange. The study also takes calendar anomalies into consideration to examine whether the temperature is driven by them. Empirical results showed that the influence of temperature is negative on the index returns. Further the study found that the temperature depended on January and trading month effects.

Shim et al (2015) investigated how weather impacts on the volatility of Korean KOSPI200 options, employing GJR-GARCH. The study revealed that volatility tends to increase in windless,

cloudy and wet weather. Further, they found that when the weather conditions are extremely high, the investors comparatively asymmetrically react to them than in extremely low conditions of weather.

The studies that have investigated the relationship between weather variables and stock returns taking macroeconomic variables as control variables are lacking.

Sariannidis et al (2016) investigated whether the weather factors can explain the stock return reactions on the Dow Jones Sustainability Europe Index using a number of macroeconomic variables as control variables, employing GJR-GARCH (1, 1) model. The results of the study revealed that humidity and wind impact positively on the stock market. Further, the empirical results reveal that oil and gold prices also impact on the market positively. Moreover, the US dollar/Yen exchange rate volatility and ten-year bond value have a significant negative impact on stock returns.

The literature has documented few latest investigations which takes evidence from Sri Lanka.

Sheikh et al (2017) examined the effect of six weather mood-proxy variables (temperature, humidity, cloud cover, air pressure, visibility and wind speed), three weather indicators (fog, thunder storm and rain or drizzle) and two biorhythmic variables on index return volatility in six South Asian markets in four countries, namely, Sri Lanka, India, Pakistan and Bangladesh. The findings of the study suggested that mood-proxy variables have influences in South Asian capital markets.

Kathiravan et al (2018) examined the impact of weather factors (temperature, humidity and wind speed), on the returns

of the stock market of Sri Lanka, Colombo Stock Exchange, employing OLS regression, taking weather data from the Colombo city, covering a period of ten years from 1st April 2008 to 31st March 2017. The study revealed that wind speed has an impact on stock market returns in Sri Lanka.

The documented literature leaves a gap which can be addressed by investigating whether the stock price variation is explained by weather factors through a long run equilibrium model taking macroeconomic variables as control variables.

Methodology

Data and Variables

This study utilizes equity market index, weather and macroeconomic data, taking macroeconomic variables as control variables, with the aim of isolating the impact of weather factors on market index price variation. The All Share Price Index (ASPI) of Colombo Stock Exchange is used as the market index. The Rainfall (RAIN) and Temperature (TEMP) are used as the weather variables. Money Supply (M2B), Treasury Bill Rate (TB) (Gunasekarage et al, 2004; Menike, 2006) and Exchange Rate (USD) (Menike, 2006) are used as macroeconomic Variables. The issues such as seasonality do not arise as Sri Lanka does not experience distinct seasons such as winter, summer etc., unless the data series has to be deseasonalised (Shim et al, 2015).

CSE Data Library and Economic Data Library of Central Bank of Sri Lanka are used to collect data ASPI and macroeconomic data. The weather data are gathered from the World Bank. The sample consists of monthly data from January 2009 to December 2016.

Econometric Model and Estimates

The all the variables are in log form in order to partially address the problem of skewness and to get the sensitivity (elasticity) of each variable to the stock price index.

To investigate the relationship between stock returns, weather and macroeconomic variables, the following model is specified.

$$LASPI_t = \mu_t + \beta_1 LM2B_t + \beta_2 LTB_t + \beta_3 LUSD_t + \beta_4 LRAIN_t + \beta_5 LTEMP_t + \varepsilon_t$$

Where, μ_t is the intercept and β_1 to β_5 are the coefficients.

If some series are cointegrated they have a long term relationship (Brooks, 2008). In this study, if the variables are integrated of I(1) order, Johansen Cointegration Test with Vector Error Correction Estimates (VECM) employed opting linear intercept and no trend.

Johansen Cointegration Test

Brooks (2008) argues that, most of the time, the linear combination of two variables that have one unit root, I(1), will also has one unit root. Thus, the linear combination is Non-Stationary. The variables are said to be Cointegrated if the linear combination of them is stationary. As cointegrating variables can have an association in the long run although a significant short run association absent, cointegrating relationship can be seen as equilibrium or as a long term case.

In this study, we use Normalized Cointegrating Coefficients for the interpretation purpose. The coefficient signs are reversed when interpreting the

Normalized Cointegrating Coefficients. Cheung and Thomson (2004) have used similar interpretations.

Error Correction Model

Series with one unit root can turn into stationary by taking the first difference of them. But, the problem is that pure first difference models would not have a long run solution (Brooks, 2008). The long run relationship can be defined as a situation where the variables are not changing as they have converged upon certain long term values.

$$\Delta y_t = \beta \Delta x_t + u_t$$

If variables converged upon certain long term values, $y_t = y_{t-1}$ and $x_t = x_{t-1}$, then, $\Delta y_t = 0$ and $\Delta x_t = 0$. Thus, a relationship cannot be identified.

However, this problem can be solved using Error Correction Model which uses combinations of first differenced and lags of variables that are cointegrated. The model is as follows.

$$\Delta y_t = \beta_1 \Delta x_t + \alpha_i (y_{t-1} - \gamma x_{t-1}) + u_t$$

The Error Correction Term (ECT) is $y_{t-1} - \gamma x_{t-1}$. The ECT is zero in the long run equilibrium. The ECT will take some value if the variables in the model are deviating from the long run equilibrium and the variables will adjust to restore the long run equilibrium relationship partially. Coefficient α_i indicates the speed of adjustment towards the equilibrium of the ith endogenous variable. A negative sign for α_i confirms that any deviation from the equilibrium is corrected. The percentage of the corrected disequilibrium from each period will be larger if α_i closer to -1 and the adjustment will be slow if it takes a value closer to zero. If the sign is positive, the system diverges from the equilibrium path.

It is possible to have an intercept in the Error Correction Model and also can be estimated when there are more than two variables (Brooks, 2008).

The Error Correction Model in this study can be specified as follows. Pojanavatee (2014) has used a similar model in a different study.

$$\Delta LASPI_t = \mu_t + \sum_{k=1}^{r} \alpha_{1,k} ECT_{k,t-1}$$
$$+ \sum_{s=1}^{p} \gamma_{1,s} \Delta LASPI_{t-s}$$
$$+ \sum_{s=1}^{p} \gamma_{2,s} \Delta LM2B_{t-s}$$
$$+ \sum_{s=1}^{p} \gamma_{3,s} \Delta LTB_{t-s}$$
$$+ \sum_{s=1}^{p} \gamma_{4,s} \Delta LUSD_{t-s}$$
$$+ \sum_{s=1}^{p} \gamma_{5,s} \Delta LRAIN_{t-s}$$
$$+ \sum_{s=1}^{p} \gamma_{6,s} \Delta LTEMP_{t-s} + \varepsilon_t$$

Unit Root Test

Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test are used to test the stationarity of variables. A series is categorized as Stationary in first difference and Non-Stationary in levels if any of the tests shows that a series is Stationary in first difference and Non-Stationary in level form. The unit root tests are performed allowing both intercept and trend at levels and at first difference.

The first step is to test variables for stationarity and decide the variables are I(1). Then, Johansen Cointegration Test is used to identify whether at least one Cointegration Relationship is present. If so, VECM is employed. The optimum lag length is identified based on AIC. The variance decomposition will reveal to what extent the variation in ASPI is

explained by each variable in the model. Finally, the model checking is carried out through residual diagnostics to determine whether the model specified and estimated is adequate.

Results and Discussion

Unit Root Test

The results of ADF Test and PP Test are presented in the Table 1. Both of the tests confirm that all variables are Non-Stationary in level form except for LUSD, LRAIN and LTEMP.

LUSD in level form is Stationary according to the ADF Test. However, the PP test confirms that LUSD is Non-Stationary. Thus, LUSD is categorized as Non-Stationary in level form. LRAIN and LTEMP in level form are Stationary according to the PP Test but Non-Stationary according to the ADF Test. Thus, LRAIN and LTEMP are also categorized as Non-Stationary in level form. All the variables are Stationary in first difference. Thus, all variables are I(1).

Johansen Cointegration Test

Table 2 shows the results of Cointegration Rank Test. The test is performed allowing linear relationship with intercept and no trend and with three lags as given by AIC taking level variables. The results presented in Table 02 strongly reject the hypothesis that there is no cointegrating equation. Further, the Cointegration Rank Test confirms that there are three cointegrating equations at 5% level.

Table 1 Unit Root Test
(t-stat and P Values [within parentheses])

	Level		First Difference	
	ADF test	**PP test**	**ADF test**	**PP test**
LASPI	-2.4110 (0.3716)	-2.3966 (0.3790)	-8.7337 (0.0000)**	-8.7115 (0.0000) **
LM2B	-1.8208 (0.6870)	-1.9662 (0.6118)	-9.0909 (0.0000)**	-9.1434 (0.0000) **
LTB	-2.3531 (0.4015)	-2.0788 (0.5506)	-6.4768 (0.0000)**	-6.4831 (0.0000) **
LUSD	-3.5890 (0.0363)*	-2.2578 (0.4523)	-8.0855 (0.0000) **	-8.2342 (0.0000) **
LRAIN	-2.2169 (0.4739)	-7.7391 (0.0000)**	-7.0645 (0.0000) **	-29.7896 (0.0001) **
LTEMP	-1.9113 (0.6400)	-4.2249** (0.0061)	-10.3032 (0.0000) **	-5.5458 (0.0001) **

Significant at 5% level,
*** Significant at 1% level*
Source: Authors Compiled

Table 2 Cointegration Rank Test

Hypothesized No. of CE(s)	Cointegration Rank Test			
	Trace Statistic	Prob.**	Max-Eigen Statistic	Prob.**
None *	140.6229	0.0000	46.63335	0.0080
At most 1 *	93.98958	0.0002	42.21187	0.0040
At most 2 *	51.77771	0.0205	30.87750	0.0182
At most 3	20.90020	0.3639	15.18682	0.2760

* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values
Source: Authors Compiled

The Table 3 presents the long run estimated coefficients of cointegration. The weather variables introduced to the model are highly significant and the results indicate that the relationship between ASPI and the temperature is positive. This result is contradictory to the international evidences. The long run sensitivities indicate that the relationship between M2B and ASPI is negative whiles the relationship between USD and ASPI is positive. These results are contradictory to Gunasekarage et al (2004) and Menike (2006) when considering weather factors in the model that use different sample.

VAR - Error Correction Terms

The estimated results of the ECTs are presented in Table 4 below. The ECT is negative, when ASPI is considered endogenously.

This indicates that if the ASPI price is too high in the short term, it will decrease by 2.05% per period to eliminate the deviation caused by their own shocks as well as the shocks from weather and macroeconomic variables in the model.

The ECT is positive, when USD is considered endogenously. This indicates that USD is deviating from the equilibrium path. The other ECTs are not statistically significant at 5%. This indicates that none of the variables in the model significantly contribute to variation of those variables when they considered endogenously.

Table 3 Normalized Cointegrating Coefficients

Cointegrating Equation(s):   Log likelihood   1113.867

Normalized cointegrating coefficients (standard error in () t-stat in [])

LNASPI	LM2B	LTB	LUSD	LRAIN	LTEMP
1.000000	8.625911	2.125329	-23.64422	-2.821941	-57.50129
	(2.52339)	(1.26233)	(8.48914)	(0.58683)	(12.7722)
	[3.4184]	[1.6837]	[-2.7852]	[-4.8088]	[-4.5021]

Source: EVIEWS Output

Table 4 Error Correction Terms

Error Correction:	D(LASPI)	D(LM2B)	D(LTB)	D(LUSD)	D(LRAIN)	D(LTEMP)
Standard errors in ( ) & t-stat in [ ]						
CointEq1	-0.020533	0.000229	0.001232	0.002515	0.156449	0.001642
	(0.00473)	(0.00059)	(0.00451)	(0.00117)	(0.08099)	(0.00169)
	[-4.34477]	[0.39017]	[0.27331]	[2.14507]	[1.93169]	[0.97066]

Source: EVIEWS Output

Variance Decomposition

The Table 5 presents the Variance Decomposition of LASPI. The LASPI contributed 100% of the variation in LASPI in the first period and the other variables contributed 0%. The results reveal that the LTEMP is the biggest contributor of the variation in LASPI among others. It contributes 12% and 27% of the variation in LASPI in the third and sixth period. This confirms that the contribution of LTEMP to LASPI keep increasing as time passes.

Residual Diagnostics

The model assumption violation can result wrong coefficient estimates, wrong standard errors and the distribution for test statistics will be inappropriate.

The residual normality test fails to reject the null hypotheses that residuals are multivariate normal at 1% level. The White Heteroskedasticity Test also fails to reject the null hypotheses that residuals are not heteroskedastic at 5% level. These results are summarized in the Table 6. The residual serial correlation is tested using VEC Residual Serial Correlation LM Tests taking 12 lags and confirms that there is no serial correlation in residuals at any lag from 1 to 12, at 5% level. The results are presented in the Table 07.

Table 5 Variance Decomposition of LASPI

Period	S.E.	LASPI	LM2B	LTB	LUSD	LRAIN	LTEMP
1	0.0514	100.00	0.0000	0.0000	0.0000	0.0000	0.0000
3	0.0933	85.762	0.8739	0.6998	0.1642	0.4132	12.086
6	0.1726	67.587	4.2483	0.8593	0.2405	0.2252	26.839

Source: EVIEWS Output

Table 6 Summary Residual Normality and Heteroskedasticity

Test	Chi-Sq	P-Value
Normality Test		
Skewness (Joint)	16.4088	0.0117
Kurtosis (Joint)	16.3833	0.0118
White Heteroskedasticity -No Cross Terms (Joint)	788.8151	0.5848

Source: Authors Compiled

Table 7 VEC Residual Serial Correlation LM Tests

Lags	LM-Stat	Prob
1	37.31739	0.4083
2	48.81987	0.0752
3	33.56561	0.5849
4	41.32797	0.2492
5	32.32923	0.6439
6	38.67224	0.3499
7	36.27005	0.4561
8	35.59387	0.4878
9	24.72301	0.9221
10	28.16470	0.8213
11	48.38875	0.0813
12	28.96992	0.7909

Source: EVIEWS Output

Conclusion

The emergence of behavioural finance branch of asset pricing directed the attention of researchers to investigate irrational behaviours and cognitive biases of investors. There is plenty of empirical evidence that investor decisions are impacted by the mood, and the weather is a major factor that determines the mood of investors. Thus, arguments are being made and being tested in the finance literature, searching whether the weather impacts on the stock market returns and evidence were generated such as Temperature Anomaly supporting this debate.

This study aimed to investigate whether there is a long term relationship among stock returns and the weather factors and to examine whether the weather factors outperform macroeconomic variables when explaining the variation in stock price. This study used Johansen Cointegration Test with Vector Error

Correction Estimates to test this phenomenon. The results confirmed that there is a statistically significant long run relationship between stock price and weather factors and weather factors are highly significant in the model. Further, this study confirms that Temperature has an outperforming contribution for the variation in stock prices over macroeconomic variables.

However, Floros (2011) argues that the stock exchanges around the world are electronic markets, thus anybody can access the market from anywhere in the world. Therefore, even a local investor can buy and sell equities siting in a foreign country. Thus, this is a limitation of this type of study. Besides, we can opine that such a study will be less useful in an equity exchange where the local investors predominantly follow foreign investors.

This phenomenon should be further tested employing econometrics models such as ARDL taking latest data covering at least 17 years. ARDL is a more flexible model that can accommodate both I(0) and I(1) variables in a one model.

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