CAUSALITY OF WEATHER CONDITIONS IN AUSTRALIAN STOCK EQUITY RETURNS

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Abstract: This study investigates causality of weather and its impact on the The S&P/ASX All Australian 200 Index has been selected as a proxy for the Australian capital market. The index consists exclusively of Australian domiciled companies. Following previous research in behaviour finance in the area of environmental psychology, the data set covers temperature, quality temperature, wet bulb temperature, quality wet bulb temperature, humidity, pressure and vapour pressure variables. The data set is a daily return time series and covers the period between 01.06.1992 and 07.07.2006, and was provided by the Australian Bureau of Meteorology. Sydney's meteorological data was selected to match the stocks that were traded on the Australian Stock Exchange, because Sydney is generally accepted as the financial centre of Australia. Capital market data is of daily–end closing share prices traded on the Australian Stock Exchange and was collected from DataStreem's database.

JEL classification: G14, G10.

Key words: Weather Effect, Granger Causality Test, Australian Stock Exchange, ARCH and GARCH Tests

1. INTRODUCTION

An acceptance of investors' rationality causes a deep divide in opinions between the Efficient Market Hypothesis (EMH) and Behavioural Finance (BF). EMH was developed by Nobel Laureate *Samuelson* (1965) and *Fama (1970),* and formed the term 'efficient market' in economical and financial literature. An efficient market was defined as a market which 'adjusts rapidly to new information' (*Fama et al*, *1969).* Fama assumes that in an active market of a large number of well-informed and intelligent investors, stocks will be appropriately priced and will reflect all available information. EMH assumes that investors behave rationally and predictably.

In contrast, Behavioural Finance assumes that investors may be irrational, and takes into account human psychology to explain security prices valuation and market anomalies. There are many instances where emotion and psychology influence investors, causing them to behave in unpredictably or irrational ways. The capital market's 'mood' can turn from irritable to euphoric and it can react hastily one day and make amends the next (*McClure, 2009)*. Investors are subject to various psychological and behaviour biases including overconfidence, loss aversion and mood fluctuation, and they can also be affected by factors such as culture, weather, religion and others.

There is significant scientific evidence showing that human psychology is affected by weather-related factors including sunny or cloudy days, as well as rainy or windy days, and therefore, that these factors influence people's moods, thinking and judgement. After a period of heavy rain, people tend to have a greater sense of well being. Conversely, during periods of strong wind, people's moods tend to be more negative. In addition, there are a variety of weather related factors which can influence human mental activity, such as atmospheric pressure, temperature, humidity and other factors. For example, a negative mood can be caused by a change in atmospheric pressure and high humidity. These alterations irritate human nerve endings and lead to general irritability, anxiety, fatigue and a lack of concentration *(DiVito et al, 2005),* and there is even more evidence to show how climatic factors affect the chemical balance of the human brain, consequently psychology and behaviour.

There is a relation between human behaviour and environmental factors. Even though we cannot claim that environmental factors are unique in influencing human behavioural disorders, there is some evidence in the literature. Numerous studies in the area of environmental psychology have investigated the influence of exposure to sunlight on suicidal behaviour *(Petridou et al, 2002; Preti, 1998),* correlation between genetic and environmental factors (Jang et al, 1998), lunar effects on the human body and mind, and consequently human psychology and behaviour *(Yuan, Zheng and Zhu, 2005).*

If this information is considered to be accurate, it could be meaningful to investigate climate and weather effects on stock exchanges. Research in this area is rapidly expanding with very surprising results. Researchers reported that seasonal disorders, lunar phases, geomagnetic storms and other climate–related events show the greatest relationship to equity pricing *(Dowling and Lucey, 2008; Kliger and Levy, 2008; Yuan et al, 2006).* Some researchers believe that sunshine puts people in a good mood *(Saunders, 1993),* consequently that people in a good mood are happier and make more optimistic choices.

Recently, an increasing number of researchers in behavioral finance have empirically investigated the weather effect on an individual's emotional state and mood, and hence, on investment decisions, by testing the different capital market indexes and stocks in different countries, regions and cities *(Pardo and Valor, 2003; Loughran and Schultz, 2003; Dowling and Lucey, 2005; Tufan and Hamarat, 2004, 2006; Borghesi, 2007; Chang et al, 2006, 2008; Forgas et al, 2008; Levy and Galili, 2008, and others).* While some research found a significant association between weather effect and returns, other research found an insignificant relationship.

A limited number of empirical studies investigated the effect of weather related moods and feelings on Australian stock returns *(Worthington, 2006),* and weather effects on the Australian capital market *(Cao and Wei, 2005). Cao and Wei's (2005)* and Worthington's (2006) results indicate no significant relationship between the weather and Australian market returns.

However, there is no research that focuses on the causal direction between weather and stock returns, thus the present research attempts to fill this gap. The purpose of this paper is to investigate whether or not the weather affects Australian share prices. This study contributes empirical findings on weather causality in Australian securities returns and discusses it from the Efficient Market Hypothesis and Behavioural Finance perspectives. The ARCH and GARCH time-series models and Granger Causality test relies on temporal predictability as evidence of causality have been applied, for more informative results.

The remainder of the paper is organized as follows. Section 2 discusses the literature on how weather conditions affect human mood and behavior, and consequently stock returns. Section 3 describes the data and discusses the methodology. Section 4 gives empirical results, Section 5 discusses results, and the final section delivers conclusions and provides suggestions for future research.

2. LITERATURE REVIEW

EMH is based on the assumption that individuals act rationally and consider all available information in the decision-making process. However, many examples of irrational behaviour and repeated errors in judgment have been documented in academic studies. The weather effect on the human body and mind, and consequently on psychology and behavior is suggested empirically in psychological and biological literature. For example, *Petridou et al, (2001)* investigated whether exposure to sunshine can trigger suicidal behaviour. They applied data from 29 OECD countries and reported a remarkably consistent pattern of seasonality, with peak incidence around June in the northern hemisphere and December in the southern hemisphere.

Preti (1998) conducted research into the direct influence of climate on suicidal behaviour, focussing on Italy. The researcher reported that the distribution of deaths by suicide shows a negative relationship to mean yearly temperature values, maximum and minimum, and with sun exposure indicators, and a positive, but less significant relationship to rainfall values. Considering climatic variables as a whole, stepwise regression identifies three relevant factors, with significant relationships to suicide rates, humidity grade, rainfall mean and sunlight exposure.

Numerous psychological studies suggest that mood can affect human judgment and behavior *(Frijda, 1988; Schwarz and Bless, 1991)*. Research undertaken by *Forgas et al, (2008)* examined the relationship between mood and weather, and found that weather-induced negative mood improved memory accuracy.

Borghesi (2007) tested price efficiency in the National Football League (NFL) point spread betting market by examining the relationship between betting line forecast errors and game day temperatures for 5463 NFL games from 1981 to 2004. As a result, they reported that game day temperature significantly affects team performance and that this information is not efficiently incorporated into betting prices.

Behaviour finance literature documents evidence on the effects of mood on assets prices *(Avery and Chevalier, 1999, Kamstra et al, 2000)*. Recently, an increasing number of researchers in behavioural finance have investigated weather and its impact on the equity markets. *Saunders (1993)* was the first to examine the influence of the weather on asset returns. He examined the Dow-Jones Industrial Average (DJIA), the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX). He found that the weather in New York City is significantly correlated to the daily returns of the three major stock indices.

Kramer and Runde (1997) also replicated Saunders' study in the German stock market and found that the level of cloud cover over Frankfurt did not influence the shares of the Deutscher Aktien Index. The same result has been reported by *Pardo and Valor (2003)* for the Madrid Stock Exchange, and *Loughran and Schultz (2003)* for portfolios of the Nasdaq share index, based on companies located in 26 U.S. cities. *Keef and Roush (2003)* found the absence of a cloud-cover effect but reported a marginal negative temperature effect and strong negative wind effect.

Later, *Keef and Roush (2003; 2005)* again confirmed that prices of stock indices are negatively influenced by wind factor. They are 'inclined to the view that the evidence of the influence of cloud cover on stock return remains mixed' (p.436). *Dowling and Lucey (2005)* examined weather influence for the Irish Stock Exchange and concluded that rain was a minor, but significant, influence.

Chang, Nieh, Yang and Yang (2005) investigated the effect of economically neutral behaviour variables on equity returns in Taiwan. They found that temperature and cloud cover are two important weather factors that affect stock returns. They suggested that weather factors should be included in assets pricing models.

Tufan and Hamarat (2004, 2006) delivered Turkish case evidence regarding the weather effect on the Turkish stock exchange (ISE) and reported evidence favouring the effects of days when snow fell. Their research results claimed that cloudy and rainy days do not have any affect on ISE 100 Index returns, whilst snowy days do have an effect.

Kamstra et al, (2003), Garrett et al, (2005) and Kliger and Levy (2008) investigated the effect of seasonal affective disorders on capital market returns. *Kamstra et al, (2003)* studied the number of hours of potential daylight, which is less in winter, and found that it is significantly related to returns on international equity indices. *Garrett et al, (2005)* applied a conditional CAPM to investigate the U.S., Sweden, New Zealand, the U.K., Japan and Australia. They concluded that seasonal affective disorders come with seasonal depression, which was reflected by changing risk premiums. Moreover, *Hirshlefer and Shumway (2003)* attempted to examine weather-equity returns' relationship in 26 international markets and found a negative relationship for Milan, Rio de Janeiro and Vienna.

Dowling and Lucey (2008) investigated the relationship between seven mood-proxy variables which are constructed from weather data (precipitation, temperature, wind, geomagnetic storms) and biorhythm data (seasonal affective disorders, daylight savings time changes, lunar phases) and a global equity dataset using a variety of group tests. The researchers reported that seasonal affective disorders and low temperatures show the greatest relationship to equity pricing. *Levy and Galili (2008)* investigated the effect of cloudy days on 3000 individual investors. In this study, the degree of cloud cover has been used as a proxy for mood, and the study found that three subgroups of investors (male, young and poor) are more likely to be net buyers of equity on cloudy days.

Cao and Wei (2005) examined the international weather effect in six markets including Australia, and found that the temperature was not a significant factor for the Australian market. However, they suggested that extreme temperatures could increase risk-taking, and hence, cause higher returns. *Worthington (2006)* examined the impact of weather-related moods and feelings on the Australian stock market over 47 years from 1958 to 2005. He used a wide range of weather indicators and proxies for mood and feeling factors. His results indicate that there is no statistically significant relationship between the weather and Australian market returns, however, he is concerned about the inadequacies of the empirical techniques employed in this area. Following *Loughran and Schultz (2004), and Goetzmann and Zhu (2005), Worthington* suggested direct modeling investor decision making.

Research in this area has been mainly undertaken in the United States and Europe, where data are more available. A limited amount of research has been conducted examining the weather effect on the Australian capital market; moreover, none of the studies address causation.

3. DATA AND METHODOLOGY

3.1 Data

This study attempts to confirm or reject a causality of weather and its impact on the Australian capital market. The S&P/ASX All Australian 200 Index has been selected as a proxy for the Australian capital market. The S&P/ASX All Australian 200 is a broad market index that consists exclusively of Australian domiciled companies.

Following previous research in behaviour finance in the area of environmental psychology, the data set covers temperature, quality temperature, wet bulb temperature, quality wet bulb temperature, humidity, pressure and vapour pressure variables. The data set is a daily return time series and covers the period June 1, 1992 to July 7, 2006, and was provided by the Australian Bureau of Meteorology. Sydney's meteorological data was selected to match the stocks that were traded on the Australian Stock Exchange, because Sydney is generally accepted as the financial centre of Australia. All missing (Sydney city) data has been replaced by data from Sydney airport's meteorological station.

capital market data is of daily–end closing share prices traded on the Australian Stock Exchange and was collected from DataStreem's database. Daily stock returns are calculated with the formula; $R_t = (V_t - V_{t-1})/V_{t-1}$. Here, R_t; indicates return in day t, V_t indicates closing price of day t while V_{t-1} indicates closing price of day t-1.

3.2. Methodology

To examine a long term relationship between weather variables and S&P/ASX All Australian 200 Index returns and how this relationship has been formed, the following empirical model has been applied:

$$Y_t = \beta_0 + \beta_1 T_t + \varepsilon_1 \qquad (1)$$

Where, Y indicates return in time t, T indicates weather variables, ε indicates error term while β indicates parameters, respectively.

To estimate the model, the following procedure has been applied:

1. Jarque-Bera statistics have been used to test the null hypothesis that the residuals are normally distributed.
2. Augmented Dickey-Fuller (ADF) statistics have been applied to test that time-series data are stationary and co-integrated.
3. ARCH and GARCH models have been used to identify the volatility of stock returns.
4. The Granger Causality test has been employed to determine the causal relationship between weather and return on investment.

3.2.1. Jarque-Bera statistics

The Jarque-Bera test is a two-sided goodness-of-fit test suitable for use when a fully-specified null distribution is unknown and its parameters must be estimated. The test statistic is

$$JB = \frac{n}{6}\left(s^2 + \frac{(k-3)^2}{4}\right) \qquad (2)$$

where *n* is the sample size, *s* is the sample skewness, and *k* is the sample kurtosis
If the *p*-value is below the default significance level of 5%, and the test rejects the null hypothesis, then the distribution is normal.

3.2.2.ADF Unit Root Test

ADF Unit Root Test and regression model below (Gujarati 1995):

$$Y_t = \rho Y_{t-1} + u_t \qquad (3)$$

Where, Y_t indicates index return in time t, Y_{t-1} indicates index return in time t-1 while u_t indicates stochastic error term. The same model has been applied to weather variables. In this model, ρ=1 indicates that the stochastic variable Y_t has a unit root, so the series is known as a random walk.

If the null hypothesis is rejected and series are stationary (or have been transformed to stationary), the assumption is that the series is integrated of order one. The degree of co-integration will be used as a lag coefficient in causality test.

3.2.3.GARCH and ARCH Models

The long-term relationship between weather and capital market return has been modelled as ARCH (1) and GARCH (1) processes. These processes maintain the essential characteristics of the ARCH (GARCH) effect, including an important persistence effect in volatility. Financial time series often exhibit volatility clustering or persistence, where large changes tend to follow large changes, and small changes tend to follow small changes. Volatility clustering, which is a type of heteroskedasticity, accounts for the excess kurtosis typically observed in financial data.

ARCH(1) has been used since the conditional variance depends on only one lagged squared error. In the ARCH (1) model conditional variance of a shock at time *t* is a function of the squares of past shocks:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 \qquad (4)$$

Where, *h* is the variance and ε is a 'shock,' 'news' or 'error'.

GARCH model is useful to examine the volatility of the series over time:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad (5)$$

Where, the variance (h_t) is a function of an intercept (ω), a shock from the prior period (α) and the variance from last period (β).

If the S&P/ASX 200 Index has a variable variance, this could stem from weather variables and the weather factors could be Granger-cause stock returns.

3.2.4.Granger Causality Test

The existence of a co-integrating relationship among variables suggests that there must be Granger causality in at least one direction. It is not rational to expect that returns on investment of the S&P/ASX200 Index could affect weather conditions. Thus, the one way relationship between weather variables and return on investment of the S&P/ASX200 Index has been determined:

$$ASX\ 200_t = \sum_{i=1}^{n} \alpha_i TE_{t-1} + \sum_{j=1}^{n} \beta_j ASX_{t-j} + u_{1t} \tag{6}$$

$$ASX\ 200_{tS} = \sum_{i=1}^{n} \alpha_i QTE_{t-1} + \sum_{j=1}^{n} \beta_j ASX_{t-j} + u_{1t} \tag{7}$$

$$ASX\ 200_t = \sum_{i=1}^{n} \alpha_i WBTE_{t-1} + \sum_{j=1}^{n} \beta_j ASX_{t-j} + u_{1t} \tag{8}$$

$$ASX\ 200_t = \sum_{i=1}^{n} \alpha_i QWBTE_{t-1} + \sum_{j=1}^{n} \beta_j ASX_{t-j} + u_{1t} \tag{9}$$

$$ASX\ 200_t = \sum_{i=1}^{n} \alpha_i HU_{t-1} + \sum_{j=1}^{n} \beta_j ASX_{t-j} + u_{1t} \tag{10}$$

$$ASX\ 200_t = \sum_{i=1}^{n} \alpha_i PRE_{t-1} + \sum_{j=1}^{n} \beta_j ASX_{t-j} + u_{1t} \tag{11}$$

$$ASX\ 200_t = \sum_{i=1}^{n} \alpha_i VPRE_{t-1} + \sum_{j=1}^{n} \beta_j ASX_{t-j} + u_{1t} \tag{12}$$

Where, n indicates lags and it is being assumed no relationship (white noise) between u_{1t} and weather variables series error terms (which has not been given in the equation) u_{2t} (Granger 1969). Granger Causality Test is based on *F* statistics which were proven by Wald (Işığıçok, 1994):

$$F_{n;m-2n} = \frac{(ESS_r - ESS_{ur})/n}{ESS_{ur}/(m-2n)} \tag{13}$$

Where, ESS indicates the sum of error terms squares, *ur* indicates the model which is unrestricted, while *r* indicates the model which is restricted.

If the computed *F* value exceeds the critical *F* value at the chosen level of significance (α) with (*n;m-2n*) degrees of freedom, the null hypothesis (H_0) that there is no causality between the two series should be rejected. So, coefficients (or coefficient) in the model are statistically significant.

4. EMPIRICAL ANALYSIS

4.1 Descriptive Statistics and Pre-estimation Analysis

The descriptive statistics of the weather variables and S&P/ASX200 Index returns are presented in Table 1. The descriptive statistics for weather-related variables indicates that the average temperature in Australia is around 21oC, maximum is around 39oC and minimum is 8.5oC. The minimum of 2.2mb (millibars) and maximum of 62.0mb indicate high changes in atmospheric pressure, but moderate fluctuation in humidity.

The minimum of -6.78 per cent and maximum of 5.89 per cent show that daily losses on return on investment are slightly higher than gains, on a daily basis. Also, a positive mean and median indicate a positive return on average. The high positive kurtosis indicates the possibility of a severe market reaction to events.

Table 1. Descriptive Statistics

	Temperature	Quality Temperature	Wet Bulb Temperature (WBT)	Quality WBT	Humidity	Pressure	Vapour Pressure	ASX200 Return
Mean	21.21	11.31	15.90	55.76	1010.77	14.24	25.96	0.0033
Median	21.00	12.00	15.90	56.00	1011.00	14.00	24.90	0.0002
Maximum	38.70	24.00	26.10	99.00	1031.80	62.00	68.80	0.0589
Minimum	8.50	-13.40	6.00	9.00	986.10	2.200	11.10	-0.0678
Std. Dev.	4.23	5.71	3.71	16.49	7.34	5.01	7.04	0.0077
Skewness	0.34	-0.51	0.03	-0.00	-0.25	0.40	1.13	-0.3369
Kurtosis	3.13	2.84	2.23	2.99	2.97	4.50	5.61	7.3037
Jarque-Bera	74.30	166.40	91.53	0.001	39.69	451.93	1836.17	2909.73
Probability	0.00	0.00	0.00	0.99	0.00	0.00	0.00	0.00
Sum	78074.3	41656.4	58536.8	205218	3719641.	52412.8	95557.7	1.2127
Sum Sq. Dev.	65896.2	120015.6	50765.9	1000850	198658.3	92355.3	182559.8	0.2209

Jarque-Bera (J-B) statistics have been used to test the null hypothesis that the data are from normal distribution. All J-B statistics are greater than the critical value 5.99. Thus, the null hypothesis of normality is rejected. The return's kurtosis of 7.30 exceeds the value 3 of normal distribution, but skewness is less than $\pm$1.00 due to the large sample size.

4.2.Augment Dickey-Fuller Test (ADF)

The ADF test has been used to test if the data are stationary and co-integrated. Augment Dickey-Fuller Test Statistics results are presented in Table 2.

Table 2. Augmented Dickey-Fuller Test Statistics for all variables

	Temperature				
Exogenous	1% level	5% level	10% level	t-Statistic	Prob.*
Constant	-3.431947	-2.862131	-2.567128	-5.840922	0.0000
Constant, Linear Trend	-3.960542	-3.411031	-3.127332	-5.854211	0.0000
None	-2.565593	-1.940910	-1.616641	-0.726992	0.4019
	Quality Temperature				
Exogenous	1% level	5% level	10% level	t-Statistic	Prob.*
Constant	-3.431946	-2.862130	-2.567128	-6.948791	0.0000
Constant, Linear Trend	-3.960541	-3.411030	-3.127331	-6.979036	0.0000
None	-2.565593	-1.940910	-1.616642	-2.364890	0.0175
	Wet bulb Temperature				
Exogenous	1% level	5% level	10% level	t-Statistic	Prob.*
Constant	-3.431946	-2.862131	-2.567128	-5.295731	0.0000
Constant, Linear Trend	-3.960542	-3.411031	-3.127332	-5.294090	0.0000
None	-2.565593	-1.940910	-1.616642	-0.984942	0.2912

Exogenous	Quality Wet bulb				
	1% level	5% level	10% level	t-Statistic	Prob.*
Constant	-3.431942	-2.862129	-2.567127	-30.13833	0.0000
Constant, Linear Trend	-3.960535	-3.411027	-3.127330	-30.15889	0.0000
None	-2.565593	-1.940910	-1.616641	-1.654385	0.0927
Exogenous	Humidity				
	1% level	5% level	10% level	t-Statistic	Prob.*
Constant	-3.431943	-2.862129	-2.567127	-17.57673	0.0000
Constant, Linear Trend	-3.960537	-3.411028	-3.127330	-17.75911	0.0000
None	-2.565595	-1.940911	-1.616641	0.255220	0.7601
Exogenous	Pressure				
	1% level	5% level	10% level	t-Statistic	Prob.*
Constant	-3.431946	-2.862130	-2.567128	-6.762404	0.0000
Constant, Linear Trend	-3.960541	-3.411030	-3.127331	-6.788669	0.0000
None	-2.565593	-1.940910	-1.616641	-1.578393	0.1078
Exogenous	Vapour Pressure				
	1% level	5% level	10% level	t-Statistic	Prob.*
Constant	-3.431947	-2.862131	-2.567128	-6.085786	0.0000
Constant, Linear Trend	-3.960542	-3.411031	-3.127332	-6.107463	0.0000
None	-2.565593	-1.940910	-1.616641	-1.152124	0.2278
Exogenous	ASX Return				
	1% level	5% level	10% level	t-Statistic	Prob.*
Constant	-3.431941	-2.862128	-2.567127	-58.98151	0.0001
Constant, Linear Trend	-3.960534	-3.411027	-3.127329	-58.97828	0.0000
None	-2.565591	-1.940910	-1.616642	-58.88553	0.0001

*MacKinnon (1996) one-sided p-values.

The returns could in general be affected by a time trend, a constant and a unit root. The ADF test has also been used to test for these possibilities and has been performed with a linear trend and constant, constant alone and with no constant/trend. The null hypothesis of a unit root has been applied to the S&P/ASX200 Index return:

H_0: ASX2000 returns have a unit root and are nonstationary, or H_0: $\delta_i = 0, \quad \rho = 1$.

H_1: ASX2000 returns have no unit root and are stationary, or H_1: $\delta_i \neq 0$.

The null hypothesis of a unit root and nonstationary data has been tested for all weather variables separately:

H_0: Weather variables have a unit root and are stationary, or H_0: $\delta_i = 0, \quad \rho = 1$.

H_1: Weather variables have no unit root and are stationary, or H_1: $\delta_i \neq 0$.

The absolute value of the τ statistic exceeds the DF absolute 1% (-3.95), 5% (-3.41) and 10% (-3.127) critical τ values. However, except temperature, quality wet bulb (10% significance) all series are not stationary in 'none' conditions. The S&P/ASX200

Index returns series have been found stationary for all conditions after taking first differences into account.

The null hypothesis of a unit root has been rejected and that means that all the variables do not have the unit root problem and the series are stationary. Moreover, since all time series are stationary, the assumption is that the series is integrated in the order of one. The degree of co-integration 1 will be used as a lag coefficient in the causality test.

4.3 ARCH/ GARCH Effects and Granger Causality Test

The volatility of the return has been tested by applying ARCH (1) and GARCH (1) models. Results from Table 3 indicate that intercept is statistically significant (t =5.11, p = .000) and represents the fact that an average daily return on the S&P/ASX200 Index is 1.33 per cent. ARCH (1), up to 1 lag, is statistically significant (t =13.59, p =.000). This indicates that the current square of error term is statistically correlated with the previous day squared of error terms. GARCH (1) up to one lag variance of error term is also statistically significant and indicates volatility clustering. Variation in the returns today is dependent upon variation and squared error term of the preceding trading day.

Table 3. The Results of ARCH and GARCH Tests

Dependent Variable: ASX2000 return				
Method: ML - ARCH (Marquardt)				
Sample: 1 3680				
Included observations: 3680				
Convergence achieved after 12 iterations				
Variance backcast: ON				
	Coefficient	**Std. Error**	**z-Statistic**	**Prob.**
	Variance Equation			
C	1.33E-06	2.61E-07	5.107223	0.0000
ARCH(1)	0.070750	0.005206	13.59129	0.0000
GARCH(1)	0.908652	0.008358	108.7152	0.0000
R-squared	-0.001808	Mean dependent var		0.000330
Adjusted R-squared	-0.002353	S.D. dependent var		0.007750
S.E. of regression	0.007759	Akaike info criterion		-6.995989
Sum squared resid	0.221381	Schwarz criterion		-6.990926
Log likelihood	12875.62	Durbin-Watson stat		1.941033

Thus, ARCH has been found to be significant and has been interpreted to show that today's volatility (squared error term) has impact over the next trading day's volatility. GARCH can be interpreted as today's volatility (variance of error term) is correlated with the previous trading day's volatility (with both squared error term and variance). The sum of ARCH (1) and GARCH (1) coefficient nearby 1 (0.97) which is statistically significant, indicates that the S&P/ASX200 Index has persistent volatility and variable variance. The Granger Causality test could reveal whether the variance stems from weather variables and Granger cause S&P/ASX200 Index returns.

One way direction of causality should be present from weather variables to S&P/ASX200 Index returns, and a one day lag for stationary related daily variables should be used. Testing causality involves using *F*-tests to determine whether lagged information on weather-related variables provides any statistically significant information about returns. It is assumed that the estimated coefficients on the lagged weather-related variables are statistically indifferent from zero, as a group indicates there is no causality between two series (Gujarati 2001; 621).

The values of *F* statistics suggest that, with the exception of humidity, weather variables do not cause S&P/ASX200 Index returns. The results in Table 4 indicate that only humidity affects S&P/ASX200 Index returns at a 10 per cent level of significance.

Table 4. Granger Causality Test Results (1 Lag)

Null Hypothesis:	Obs	F-Statistic	Probability
TEMPERATURE does not Granger Cause ASX200 RETURN	3679	0.19142	0.66177
QUALITY TEMPERATURE does not Granger Cause ASX2000 RETURN	3679	1.50619	0.21980
WET BULB T does not Granger Cause ASX200 RETURN	3679	1.06009	0.30326
QUAL.WET B does not Granger Cause ASX200 RETURN	3679	1.10131	0.29405
HUMIDITY does not Granger Cause ASX200 RETURN	3679	2.97973	0.08440*
PRESSURE does not Granger Cause ASX2000 RETURN	3679	1.22423	0.26860
VAPOUR PRESSURE does not Granger Cause ASX2000 RETURN	3679	0.18178	0.66987

* There is one way Granger causality from the humidity variable to ASX200 return series (10%).

In other words, unidirectional causality from humidity H_t to S&P/ASX200 Index returns is indicated if the estimated coefficients on the lagged H_t are statistically different from zero as a group (i.e. $\sum \alpha_i \neq 0$) and there is causality between the two series, at least from H_t to S&P/ASX200 Index returns.

5. DISCUSSION

Thus, the results from one way Granger causality suggest that past values of weather- related variables do not lead market behaviour, with the exception of humidity. Australia experiences high humidity all year round, but has an extremely humid wet season from December to April. Under conditions of high humidity, the body's efforts to maintain an acceptable body temperature may be significantly impaired. Blood circulation at the body's surface cannot shed heat by conduction to the air and a condition called hyperpyrexia can result. With so much blood going to the external surface of the body, relatively less goes to active muscles, the brain and other internal organs. Physical strength declines and fatigue occurs sooner than it would otherwise. Alertness and mental capacity may also be affected. The resulting condition is called heat stroke or hyperthermia. Therefore, high humidity could have a negative impact on physical and psychological conditions and consequently, could influence investors' decision-making processes.

However, humidity is an important metric used in forecasting weather. Weather has always played an important role in the economy and could have a significant impact on business activities. Every sector of the economy has some sort of weather sensitivity. Extreme weather events like heat-waves, torrential rain and freezing cold are bad for business, and bad weather can decrease productivity, lower profits, and increase the costs of running businesses. However for some companies, bad weather in the traditional sense of cold, grey and rainy days can be actually be good for business.

The Australian economy is also exposed to weather conditions and its variability. The Australian S&P/ASX200 Index includes companies from the major weather sensitive sectors of the economy such as energy suppliers, transportation systems and others that are heavily dependent on weather and weather forecasting. Thus, there is a high possibility that investors do actually incorporate weather-related information in their decision-making processes.

Thus, on one hand, capital markets could respond to new weather-related information and incorporate this information in the stock valuation process. On other hand, stock prices could be affected by the mental or physical state of investors caused by weather conditions. People are 'rational' in standard finance and they are 'normal' in behavioral finance. Rational people have perfect self-control, and they are always averse to risk and never averse to regret. However, normal people do not always follow that pattern (Statman, 1999).

The Efficient Market Hypothesis is associated with idea of 'random walk', which is used in financial literature to characterise the price series where all subsequent price changes represent random departures from previous prices. The logic of the random walk is that the information is immediately reflected in stock prices. The news is unpredictable, and thus price changes must be unpredictable and random. The importance of the EMH is that it justifies the use of movement in stock prices as the test of usefulness of financial and non-financial information. However, behavioural finance points to the existence of market bubbles and manias as examples of cases where human behavior may be the missing link that explains such market anomalies. This study suggests that Australian stock market returns are affected by weather; however, the way in which weather affects stock prices remains the question.

6. CONCLUSION

If modern finance relies on two key assumptions: rational people and a 'fair price' being determined by financial markets, behavioural finance examines the psychology underlying investors' decisions to explain irrational behavior. Recent literature in behavioural finance investigated the effects of weather conditions on the emotional state of investors. This study investigated the hypothesis that the weather causes changes in Australian stock market returns. But contrary to previous research, this study found that the weather effect of humidity causes significant changes in Australian stock returns.

Australia experiences high humidity throughout the year. High humidity could significantly affect physical and mental capacity and, consequently, could have an effect on financial trading activities and investment decision-making processes. Moreover, humidity is an important metric in weather forecasting. Weather has always played an important role in the economy and could significantly impact on business activities. The S&P/ASX 200 All Australian Index is a broad market index that includes Australian domicile companies as well as companies that depend on weather for their business.

On one hand, the capital market could respond to new weather-related information and could incorporate this information in the stock valuation process. Alternatively, stock prices could be affected by the mental or physical changes in investors, caused by weather conditions. Does weather-related information have an effect on stock prices? The answer is yes, it does. However, how weather–related information actually impacts on stock prices is a question for future research.

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