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# Whether the weather: A comprehensive assessment of climate effects in the Australian stock market

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## Abstract

The paper examines the impact of weather-related moods and feelings on the Australian stock market over the period 1958 to 2005. Eleven daily weather elements (precipitation, evaporation, relative humidity, maximum and minimum temperature, average daytime temperature, hours of bright sunshine, and the speed and direction of the maximum wind gust and the average daytime wind) are included in the analysis, along with daily nominal and real market returns. Non-parametric correlation analysis and autoregressive moving average (ARMA) models are employed, supplying strong evidence of sustained inertia and overreaction in market returns, and non-normally distributed, highly interrelated, but stationary, weather conditions. But contrary to earlier findings, the results indicate that the weather has no influence on market returns confirming that Australian investors weather the weather, whether they like it or not.

*JEL classification:* C32; G12; G14

*Keywords:* weather effects; market efficiency; investor moods

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Whether the weather be fine  
Or whether the weather be not,  
Whether the weather be cold  
Or whether the weather be hot,  
We'll weather the weather  
Whatever the weather,  
Whether we like it or not.

English Nursery Rhyme

## 1. Introduction

A well-established and diverse literature, primarily in the field of psychology, has investigated the premise that "...weather variables affect an individual's emotional state or mood, which creates a predisposition to engage in particular behaviours" (Howarth and Hoffman 1984: 15). Howarth and Hoffman (1984), for instance, found that positive human performance was negatively correlated with humidity and positively correlated with the hours of sunshine; Bell (1981) and Pilcher et al. (2002) analysed the negative relationship between individual performance and temperature; Cohen et al. (1992), Eagles (1994), Young et al. (1997) and Rosenthal (1998) examined the role of poor weather and low sunlight in heightened mental illness; and Palinkas and Houseal (2000) assessed the changing moods associated with an Antarctic winter. The behavioural impacts of these changes in moods and

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emotions are equally diverse, with Parsons (2001) linking weather and shopping patterns, Rind (1996) with the predisposition to tip generously, Schwarz (1990) with the rating of life satisfaction, and Schneider et al. (1980) with aggression and helping behaviour.

An almost equally well-known theoretical extension of this literature has examined the importance of emotions, moods and feelings (including those related to weather) in economic decision-making [see, for instance, Elster (1998), Loewenstein (2000), Romer (2000), Loewenstein et al. (2001) and Hanock (2002)]. One strand of this suggests that the feelings, emotions or moods of investors may affect equity prices if investor's subjective preferences (including the level of risk aversion and their judgement of the appropriate discount rate) fluctuate over time, if the effects of these fluctuations are widely and uniformly experienced, and if investors do not realise their decisions are influenced by fluctuations in their moods (Mehra and Sah 2002) [Lucey and Dowling (2005) provide a useful survey of the role of emotions, moods and feelings in investor decision-making]. Critically, this complements recent empirical work that has sought to investigate whether the positive (negative) moods induced by good (bad) weather cause a mood misattribution that results in marginal investors pricing stocks more optimistically (pessimistically) [see, for instance, Saunders (1993), Keef and Roush (2003), Hirshshleifer and Shumway (2003), Pardo and Valor (2003), Garrett et al. (2003), Goetzmann and Zhu (2005) and Cao and Wei (2005)].

The purpose of this paper is to add to this intriguing body of work the results of an analysis of weather and its impact on the Australian equity market. Although the Australian market has been partially addressed in studies of international weather effects by Hirshleifer and Shumway (2003), Cao and Wei (2005) and Garrett et al. (2005), a comprehensive analysis remains, as yet, undone. Using daily data over a long time period, and a wide range of weather indicators as proxies for mood factors, this paper confirms that there is no evidence to support the presence of a weather effect. It is argued that the limited evidence of a weather effect, at least in the Australian market, may be the result of seasonality in market returns unrelated, but contemporaneous with, seasonality in the weather. Moreover, the strong inertia found in both weather and stock markets, and unaccounted for in many other studies, may provide spurious evidence of the purported causal relationship.

The remainder of the paper is organised as follows. Section 2 reviews the literature on weather-related moods and its influence on investor decision making. Section 3 explains the empirical methodology and data employed in the study and provides a brief descriptive

analysis. The empirical findings are presented and analysed in Section 4. The paper ends with a brief conclusion in the final section.

## **2. Literature review**

The seminal paper on the relationship between weather-induced mood and equity returns is by Saunders (1993). Using daily returns from the Dow-Jones Industrial Average (DJIA) from 1927 to 1989 and daily returns on the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) from 1962 to 1989, Saunders (1993) examined whether any systematic variation in these markets could be associated with local weather patterns (as observed at New York Central Park from 1927 to 1960 and New York LaGuardia Field from 1961 to 1989). Weather, in the form of cloud cover, was grouped into three equally-sized categories. The results indicated that two categories of cloud cover were instrumental in influencing market returns: when cloud cover was 100 percent (85 percent of rain occurring at the same time) returns were significantly below average, and when cloud cover was below 20 percent, returns were significantly above average.

Following from these remarkable and rather well-publicised findings [see, for instance, Stecklow (1993) and Koretz (1994)] a number of other studies also examined the relationship between weather and stock returns. Trombley (1997), for example, re-examined the DJIA over the period 1927 to 1989, but re-categorised cloud cover in ten unequal groups based on an objective scientific criterion. Trombley (1997: 18) concluded that "...the relationship between security returns and Wall Street weather is neither as clear nor as strong as Saunders (1993) suggests. There is no difference between returns on clear sunny days and on cloudy or rainy days". Krämer and Runde (1997) also investigated cloud cover, though in the context of the German stock index (DAX) and with three additional weather indicators observed at Frankfurt – humidity, atmospheric pressure and rainfall. Krämer and Runde (1997: 637) concluded that no systematic relationship seemed to exist and that "...whether or not the null hypothesis of no relationship can be rejected depends mostly on the way the null hypothesis is phrased...".

Similar results were quickly confirmed in Turkey (Tufan and Hamarat 2004), New Zealand (Keef and Roush 2003) and Spain (Pardo and Valor 2003). However, Keef and Roush (2003) did find some evidence of a negative temperature and wind effect (as measured at Wellington) on New Zealand stock returns over the period from 1986 to 2002. Dowling and Lucey (2005) also examined a range of weather indicators for the Irish Stock Exchange (Dublin Airport),

including cloud, precipitation, humidity and the presence of geomagnetic storms, concluding that rain was a minor but significant market influence.

Several studies have also attempted to extend the analysis of weather-induced mood effects to multiple regional trading centres or internationally. For example, Goetzmann and Zhu (2005) obtained trading data from a large brokerage firm and examined the buying and selling behaviour of investors in five metropolitan areas (New York, Los Angeles, San Francisco, Chicago and Philadelphia). With weather specified as total sky cover (the proportion of the sky covered by clouds standardised by the average cover in the month) in each of these cities, Goetzmann and Zhu (2005: 559) found "...virtually no difference in individual's propensity to buy or sell equities on cloudy days as opposed to sunny days". However, they conceded that it was perhaps the behaviour of market-makers, rather than individual investors, who were responsible for the relation between returns and weather [see Anonymous (2004) for media coverage of this study]. Loughran and Schultz (2004) also analysed the impact of weather on local trading behaviour.

Internationally, Hirshleifer and Shumway (2003) examined the relationship between cloud cover and equity returns in twenty-six markets. As with Saunders (1993), a negative relationship between cloud cover and returns was found, but only in three cases of cloud cover (Milan, Rio de Janeiro and Vienna) and two cases of precipitation (Brussels and New York) were the estimated coefficients significant. Cao and Wei (2005) re-examined the international weather effect, though with temperature, concluding a negative correlation between temperature and returns across the entire range using least squares and seemingly unrelated regression techniques after controlling for first-order autocorrelation. However, the effect was not ubiquitous in that of the eight markets examined (including two US markets), temperature was not a significant factor in Canada and Australia. Interestingly, Cao and Wei (2005) suggested that the causal relationship between temperature and returns was not unidirectional, rather that extremes of temperatures (both hot and cold) lead to aggression, increased risk-taking, and hence, higher returns.

Finally, Kamstra et al. (2003) and later Garrett et al. (2005) examined the role of seasonal affective disorder (or SAD) in influencing market returns. More properly linked with the length of day, which depends on season and latitude rather than sunlight, these built on earlier work by Kamstra et al. (2000) of a daylight-savings effect in the United States, Canada, the United Kingdom and Germany [see Pinegar (2002) and Worthington (2003) for a rebuttal].

Kamstra et al. (2003: 14) concluded that the results, at least in the US, "...were consistent with a sad-induced pattern in returns as depressed and risk-averse investors shun risky assets in the fall and resume their risky holdings in the winter, leading to returns in the fall which are lower than average and returns following the longest night of the year which are higher than average". Likewise, employing a conditional CAPM for the US, Sweden, New Zealand, the UK, Japan and Australia, Garrett et al. (2005) found that the SAD effect arose due to the heightened risk aversion that came with seasonal depression, as reflected by a changing risk premium.

### **3. Empirical methodology**

#### *3.1 Data and variable specification*

The weather data used in the study are sourced from the NSW Climate & Consultancy Section of the Australian Bureau of Meteorology (2006). The Bureau of Meteorology provides daily weather observations, including daily minimum and maximum temperatures, 9:00 a.m. and 3:00 p.m. temperatures, humidity, wind speed and wind direction, rainfall, evaporation and sunshine, gathered from nearly 5,000 stations in New South Wales and 17,743 stations in Australia.

The weather stations selected for this analysis (latitude and longitude in brackets) are #066062 Sydney Observatory Hill (-33.8607, 151.2050) and #066037 Sydney Airport (-33.9411, 151.1725). The former has operated continuously since July 1858 and the latter since September 1929. Sydney is selected over other possible market locations (Melbourne, Brisbane, Adelaide and Perth) because the early market data in this analysis is largely compiled from old Sydney stock exchange indices. Moreover, Sydney is well accepted as Australia's financial capital, with existing international work on the weather effect, including Hirshleifer and Shumway (2003), Cao and Wei (2005) and Garrett et al. (2005), also specifying weather conditions at Sydney. Most of the observations are from Sydney Observatory Hill as it is the closest station to the CBD and offers the most complete record. Any missing data are extracted from the nearby Sydney Airport. But other than some missing data owing to faulty equipment or missed observations, the only systematic variation is that sunshine and evaporation observations originally taken at Sydney Observatory Hill have more recently been gathered at Sydney Airport.

Eleven weather elements are extracted on a daily basis. These are: precipitation (mm), evaporation (mm), relative humidity (%), maximum temperature (°C), minimum temperature (°C), average daytime temperature (°C), hours of bright sunshine (n), speed of maximum wind gust (km/h), direction of maximum wind gust (°), average daytime wind speed (km/h) and direction of average daytime wind (°). While these represent, for the most part, a substantially broader conceptualisation of weather than existing work, the specification of the individual elements draws heavily on the extant literature. For example, Krämer and Runde (1997) and Hirshleifer and Shumway (2003) specify total sky cover (i.e. cloudiness), Cao and Wei (2005) include daily temperature, Keef and Roush (2003) measure sunshine, humidity, rainfall, high and low temperature and wind gust speed and direction, and Dowling and Lucey (2005) specify cloudiness, rain and humidity. By way of comparison, in similar studies of weather effects that included Australia (read Sydney), Hirshleifer and Shumway (2003) specified morning sunshine after controlling for precipitation, Cao and Wei (2005) included temperature only, and Garrett et al. (2005) specified the length of day based on latitude and longitude and season.

The market data employed in the study are day-end closing prices from the Australian Stock Exchange (ASX) and its predecessors from Monday 6 January 1958 to Friday 30 December 2005. This sample encompasses 12,067 trading days and represents the most complete set of daily data available for the Australian market. The capitalization-weighted All Ordinaries Price Index is used. Currently, the index includes the top ASX-listed stocks by capitalization, covering about 92 percent of domestic companies by market value. To be included in the index, stocks must have an aggregate market value of at least 0.02 percent of all domestic equities, and maintain an average turnover in excess of 0.5 percent of quoted shares each month. The long-term index includes base recalculations by Global Financial Data (2006).

<FIGURE 1 HERE>

A series of nominal market returns are first calculated where  $R_t = 100\ln(P_t/P_{t-1})$  where  $P_t$  is the index level at the end of day  $t$ . The daily market index and returns for the sample period are presented in Figure 1. A measure of excess return over inflation (or the real return) is also calculated. This represents the difference between the daily market return and the daily inflation rate (calculated from monthly data) as represented by the Australian consumer price



index. The long-term series on the market index and inflation rates are obtained from Global Financial Data (2006).

### 3.2 Descriptive analysis

Table 1 includes descriptive statistics for daily nominal and real returns, precipitation, evaporation, relative humidity, maximum temperature, minimum temperature, average daytime temperature, hours of bright sunshine, speed of maximum wind gust, direction of maximum wind gust, average daytime wind speed and direction of average daytime wind. As shown, the mean nominal daily return is 0.0295 percent and the mean real return is 0.0155 percent. In terms of weather, a typical Sydney day comprises precipitation of 3.43 mm, evaporation of 4.48 mm, humidity of 63.01 percent, a maximum temperature of 22.18 degrees and a minimum of 14.20 degrees, with 6.89 hours of bright sunshine and a maximum wind gust of 44.91 km/h blowing from the south. However, all of the market and weather variables are highly volatile (as measured by the coefficient of variation). In terms of market returns, nominal returns (28.5186) are substantially less volatile than real returns (54.2903). Of the weather variables, precipitation (3.2868) and hours of bright sunshine (0.5535) are more variable, while maximum temperatures (0.1991) and humidity (0.2241) are least variable.

<TABLE 1 HERE>

By and large, the distributional properties of both the market and weather series appear non-normal. Given that the sampling distribution of skewness is normal with mean 0 and standard deviation of  $\sqrt{6/T}$  where T is the sample size, then nominal returns, real returns, humidity, minimum temperature, sunshine and the average direction of daytime wind are significantly negatively skewed (extending towards lower values), while the remaining variables are all significantly positively skewed (extending towards higher values). The kurtosis or degree of excess in all series is also large, indicating leptokurtic distributions with many extreme observations, especially for nominal returns (124.1422), real returns (124.1981) and precipitation (117.8212). Given the sampling distribution of kurtosis is normal with mean 0 and standard deviation of  $\sqrt{24/T}$  where T is the sample size, then all estimates are once again statistically significant at any conventional level. The Jarque-Bera statistics reject the null hypotheses of normality at the .01 level for all series and the first-order autoregressive coefficients are significantly positive for all series, indicating that both market returns and weather observations are positively correlated with their own lagged values.

The seasonal decomposition of each of the variables indicates, of course, that weather elements vary across the year in some systematic manner (see Figure 2). All other things being equal, Sydney is wetter and more humid in autumn, evaporation, maximum, minimum and average temperatures are higher in summer; there are stronger wind gusts and average winds and more sunshine in spring, while the winds themselves are predominately from the southwest in winter swinging around to the southeast in summer. Interestingly, returns are also apparently seasonal, with returns being lower and negative in spring, and higher and positive in summer. A simple linear time trend is also included in Table 1, and while the magnitudes are very small, there is the suggestion that precipitation, humidity and maximum wind gusts have trended down over the sample period, while evaporation, temperatures, sunshine and daytime winds have trended upwards. However, none of the least squares trend coefficients are significant at any conventional level.

<FIGURE 2 HERE>

Augmented Dickey-Fuller and Phillips-Peron (with allowance for serial correlation) tests are conducted to test the null hypothesis of a unit root (non-stationarity) in each series. In all cases, the null hypotheses are rejected at the .01 level and we conclude that all the market and weather series are stationary and suitable for regression-based analysis. As a collateral research outcome, since there is no significant trend in any of the weather elements, there is also no evidence that the adverse outcomes most associated with global warming arising from greenhouse gas emissions, including higher temperatures and falling precipitation rates, are present in Sydney, at least over the past forty-seven years.

To examine the relationships between these variables, and given the non-normality of the market returns and weather elements, non-parametric correlation coefficients are calculated and presented in Table 2. Variance inflation factors (VIF) are also included as a simple test of multicollinearity. In terms of the relationships between the market variables and the weather elements, there are significantly positive relationships between evaporation, maximum temperature and sunshine and market returns, and a negative relationship between humidity and markets returns. Many more significant negative and positive relationships are found among the weather elements (in fact, only the pairwise coefficient between average daytime temperature and evaporation is insignificant at the .05 level or higher). As an example, and all other things being equal, rainier days are characterised by lower evaporation, temperatures, sunshine hours and winds and higher humidity and winds. Clearly, the eleven weather

elements specified are strongly interrelated.

<TABLE 2 HERE>

Now consider the potential for multicollinearity. As a general rule of thumb, a VIF greater than ten is an indicator of potentially harmful multicollinearity, with the highest VIFs for average daytime temperature (25.9014), maximum temperatures (12.5229) and minimum temperatures (10.4367). Accordingly, only a single measure of temperature (maximum daily temperature) is subsequently employed. While the collinearity between (maximum and average) wind speed and (maximum and average) wind direction appear not to be excessive, only the maximums are included to maintain consistency with the specification of temperature and to reduce the total number of weather-related parameters estimated.

### 3.3 Model specification

Since the time series data on returns are available in regularly spaced intervals, and given past weather conditions are known with certainty, an autoregressive moving average (ARMA) model is constructed to evaluate the effect of weather on Australian stock returns. The structural ARMA model (including exogenous parameters) is useful in this instance because it allows a focus on the variables of most interest (i.e. the weather effects) without the need to define additional variables that are unobservable (i.e. investor risk preferences), difficult to measure (i.e. yields on alternative investments), observed at a lower frequency (i.e. macroeconomic indicators), or the requirement to specify a particular asset pricing model. Moreover, the ARMA parameters can appropriately model the higher-order autocorrelation and seasonal autoregressive factors that exist in daily returns that may not be fully captured in structural multivariate models.

The following ARMA process of order  $(k, q)$  is specified (assuming stationary daily returns):

$$\Phi_k(L)(1 - \phi L^r)y_t = \mu + \Theta_q(L)\varepsilon_t + \beta W_t \quad (1)$$

where  $\Phi_k(L)$  represents a  $k$ -order polynomial lag operator,  $\phi$  is a seasonal parameter,  $r$  is the seasonal lag term,  $y$  represents the market return in nominal or real terms,  $\mu$  is a constant,  $\Theta_q(L)$  denotes a  $q$ -order polynomial lag operator,  $\varepsilon$  is a white noise process,  $k$  is the number of autoregressive (AR) terms,  $q$  is the number of moving-average (MA) terms and  $W_t$  are weather-related variables.

Three important specification issues arise in this model. First, as part of the modeling process one first needs to choose accurate values for  $k$ ,  $r$  and  $q$  in the ARMA specification. While the identification of an appropriate ARMA model is not exact, as a rule of thumb the autocorrelation (AC) and partial autocorrelation (PAC) functions, as well as the Akaike and Schwartz information

criteria, determine  $q$  and  $k$ , respectively. The estimated model is then subjected to a range of diagnostic checks on the residuals to ensure that the model has properly accounted for all systematic variation in the time series. Second, the ARMA model specified should also capture any systematic underlying time series patterns in the data (of which seasonality is the most obvious). This is important since systematic time series patterns need to be accounted for so as to accurately gauge the impact of weather. In order to address this possibility, Equation (1) is augmented by a seasonal autoregressive term. Lastly, it is also important under ARMA theory that the series being modeled is stationary. As shown in Table 2, unit root tests of the nominal and real market return series indicate stationarity. The general form of the equation used to model market returns is then as follows:

$$(1 - \rho_1 L - \rho_2 L^2 - \dots - \rho_k L^k)(1 - \phi L^s) y_t = \mu_0 + \Theta_q(L) \varepsilon_t + \gamma_1 M_{1t} + \sum_{i=1}^{n=7} \beta_i W_{it} + w_t \quad (2)$$

where  $\rho_s$  are autoregressive parameters,  $\gamma_1$  is a market outlier parameter to be estimated (defined below), and all other variables are as previously defined.

Two sets of structural variables are included in Equation (2). First, a visual inspection of the plot of the return series in Figure 1 indicates the presence of a large number of outliers, all of which appear to relate to market incidents (predominately downturns) unconnected with weather conditions. The most significant event corresponds to 20 October 1987 when the All Ordinaries fell by a one-day record 29 percent. However, another 122 return outliers, defined as being more than three standard deviations from the sample mean ( $0.0295 \pm 3 \times 0.8413$  for nominal returns,  $0.0155 \pm 3 \times 0.8415$  for real returns) are also found. A dummy variable is used to capture these outliers in daily returns as a means of preventing possible misspecification. As an alternative, these observations (about one percent of the sample) could be excluded - this would, however, lead to a loss of continuity in the time series.

The second set of structural variables relate to the weather effect factors presented in Table 1. The sign on the estimated coefficients will, of course, depend on the net impact of each type of weather effect upon investors in the market. Generally, the literature suggests the following (ex ante sign in brackets): precipitation (-), evaporation (+ or -), relative humidity (-), maximum temperature (-), minimum temperature (-), average daytime temperature (-), hours of bright sunshine (+), speed of maximum wind gust (-), direction of maximum wind gust (+ or -), average daytime wind speed (-) and direction of average daytime wind (+ or -).

#### 4. Empirical results

The estimated coefficients, standard errors and  $p$ -values of the parameters for the ARMA regression models are provided in Table 3. The estimated coefficients and standard errors of a model incorporating only weather factors where market returns are specified in nominal terms is shown in Table 3 columns 1 to 3. A fuller version of this specification is detailed in columns 4 to 6 following the Box-Jenkins approach. The next two sets of estimated coefficients and standard errors in Table 3 relate to additional models where the dependent variable is real returns: a weather-only specification in columns 7 to 9 and a fuller specification in columns 10 to 12. Also included in Table 3 are statistics for  $R^2$  and adjusted  $R^2$ , the Akaike (AIC) and Schwartz (SC) information criteria as guides for model specification, and the Durbin-Watson (DW), Ljung-Box (Q) and Breusch-Godfrey Lagrange multiplier (LM) test statistics for first and higher-order serial correlation in the residuals.

<TABLE 3 HERE>

The basic weather models presented in Table 3 (columns 1 to 3 and 7 to 9) (in the absence of ARMA terms amounting to simple OLS) are clearly inferior. Only the coefficients for the market outlier variable and the direction of the maximum wind gust are significant, though the  $F$ -statistics reject the null hypotheses that all slope coefficients are jointly equal at the .01 level. The DW statistic, especially in the absence of lagged dependent variables in the regression model, is strongly suggestive of first-order serial correlation. The  $Q$ -statistics (10, 15 and 20 lags) and the  $LM$ -statistic (20 lags) reject the null hypotheses of no higher-order serial correlation at the .01 level. These are a clear indication of inertia and overreaction in the dynamic structure of stock market returns, especially with higher frequency observations. White's heteroskedasticity tests are used to test for heteroskedasticity in the least squares residuals. The null hypothesis of no heteroskedasticity is rejected for both nominal (statistic = 73.0586,  $p$ -value = 0.0000) and real (statistic = 72.9889,  $p$ -value = 0.0000) returns and we conclude the presence of heteroskedasticity.

As a result, both models are re-estimated and the results presented in columns 4 to 6 and 10 to 12. The standard errors and  $p$ -values shown in columns 4 to 6 and 10 to 12 incorporate White's corrections for heteroskedasticity of unknown form. The results in these models appear sensible in terms of both the precision of the estimates and the signs on the coefficients. The ARMA error process presented in Table 3 is found to generate a statistically acceptable model: that is, an autoregressive and moving average error process based on 1-3, 7,

9-13, 16-18 and 20 and 1-2, 5 and 10 day lagged residuals respectively sufficiently account for systematic variation in returns. The ARMA intervention models also pass the conventional diagnostic tests with the *LM*-statistic failing to reject the null hypothesis of no higher-order serial correlation at the .05 level or higher. The autocorrelations and partial autocorrelations of the innovations in the ARMA models (not shown) are nearly all zero with small *Q*-statistics and large *p*-values. All estimated coefficients for the seasonal  $\phi$ , autoregressive  $\rho$  and moving average  $\theta$  terms are also statistically significant (before the adjustment to the standard errors and *p*-values for heteroskedasticity) and the inverted AR and MA roots (not shown) have modulus less than one, indicating that the estimated ARMA models are stationary. Combined together, these tests and corrections indicate that no important forecasting power has been overlooked and the estimated coefficients are statistically sound.

In neither specification are the estimated coefficients for the weather effects significant [additional regressions without ARMA terms, but with adjustments for heteroskedasticity and autocorrelation, yield similar results]. A redundant variables test is conducted for the seven weather factors (precipitation, evaporation, humidity, maximum temperature, sunshine, maximum wind gust and direction of maximum wind gust) with *F*-statistics and *p*-values of the joint null hypotheses that all coefficients are zero failing to be rejected for both nominal (statistic = 1.1270, *p*-value = 0.3425) and real (statistic = 1.1186, *p*-value = 0.3464) returns. We may conclude that weather effects have no impact on Australian stock market returns. The *F*-statistics reject the null hypotheses that all slope coefficients (including the ARMA terms) are jointly equal at the .01 level and the values of the AIC and SC representing the trade-off between model complexity and goodness-of-fit are smaller than the earlier model incorporating fewer parameters in the form of weather effects. Clearly, the purported weather effects offer no significant incremental explanatory power for market returns over a simple univariate time-series model.

## **5. Concluding remarks**

A small but increasing volume of work has been concerned with the relationship between weather-induced moods, emotions or feelings and equity market behaviour. This follows psychological evidence that some weather variables affect individual emotions, moods and feelings, and potentially, actual behaviour. Building upon limited evidence concerning the Australian market, this study explores the link between a range of weather indicators and

nominal and real market returns over the last forty-seven years. The results indicate that there is no statistically significant relationship between the weather and market returns. This does not mean, of course, that individual investors are unaffected by the weather, merely that at the market level the effect is unsystematic. It also confirms evidence by Hirshleifer and Shumway (2003) and Cao and Wei (2005) concerning the Australian market individually, though both came out in favour of a weather effect on the balance of international evidence.

While it is not possible to comment directly on other contexts, it is the contention of this analysis that empirical work of this type is complicated by the strong seasonality and inertia of both equity markets and weather conditions. For example, in Australia humidity and temperature are higher and the hours of sunshine longer in summer and this aligns with higher market returns. This is unlikely, however, to be purely the result of the weather. Unless correctly modelled, the sustained seasonal autoregressivity and inertia in equity markets is then matched by similar conditions in weather yielding spurious regression results. This is highlighted by the contradiction in results between zero-order correlation analysis and the ARMA models in this study.

At the same time, and as shown in this study, weather indicators are highly and significantly correlated. While the focus of attention in the literature has often been on sunshine and temperature, other indicators or combinations of indicators, could potentially yield similar results. Because of this, and given the inadequacies of the empirical techniques employed in this area, it may never be possible to confirm the influence of a specific indicator as against a generic weather effect, if any. One solution would be to follow the work of Loughran and Schultz (2004) and Goetzmann and Zhu (2005) by directly modelling investor decision making, rather than attempting to detect actual market outcomes only possible through ubiquity.

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Figure 1  
All Ordinaries index and returns, Monday 6 January 1958 to Friday 30 December 2005

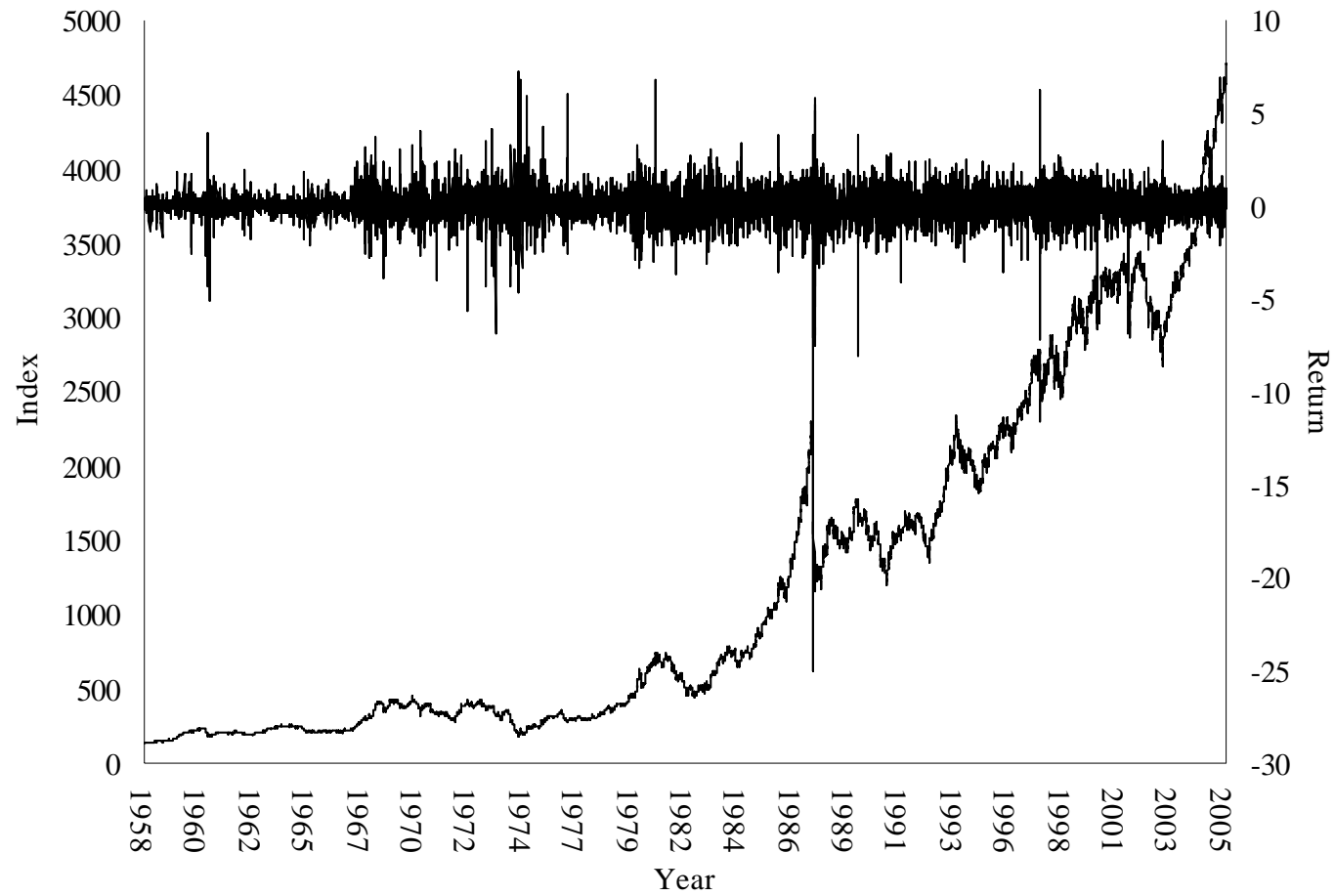


Table 1  
Descriptive analysis of returns and weather observations

		Nominal returns (%)	Real returns (%)	Precipitation (mm)	Evaporation (mm)	Relative humidity (%)	Maximum temperature (°C)	Minimum temperature (°C)	Daytime temperature (°C)	Hours of bright sunshine (n)	Speed of maximum wind gust (km/h)	Direction of maximum wind gust (°)	Daytime wind speed (km/h)	Direction of daytime wind (°)
Dispersion	Mean	0.0295	0.0155	3.4381	4.4839	63.0171	22.1838	14.2044	19.1350	6.8952	44.9069	167.5908	15.5346	174.8789
	Median	0.0431	0.0323	0.0000	4.4839	64.0000	22.0000	14.4000	19.2000	7.9000	42.5000	180.0000	13.9000	180.0000
	Maximum	7.0162	6.9777	327.6000	17.8000	99.0000	42.4000	26.6000	37.0000	13.7000	135.4000	360.0000	64.8000	360.0000
	Minimum	-28.7611	-28.7836	0.0000	0.0000	12.0000	9.3000	2.7000	7.3000	0.0000	5.4000	15.0000	0.0000	0.0000
	Std. Dev.	0.8413	0.8415	11.3004	2.4177	14.1257	4.4172	4.3908	4.2794	3.8171	15.8693	89.9621	8.3761	79.2799
	CV	28.5186	54.2903	3.2868	0.5391	0.2241	0.1991	0.3091	0.2236	0.5535	0.3533	0.5367	0.5391	0.4533
Distribution	Skewness	-3.6985	-3.7110	8.0013	0.8123	-0.1904	0.4868	-0.0490	0.1526	-0.4682	0.7320	0.0504	0.9943	-0.1873
	Kurtosis	124.1422	124.1981	117.8212	4.0655	2.8593	3.4458	1.9933	2.4637	1.9852	3.7233	1.8296	4.3980	2.3982
	J-B statistic	7.41E+06	7.41E+06	6.76E+06	1.90E+03	8.21E+01	5.76E+02	5.14E+02	1.90E+02	9.56E+02	1.33E+03	6.90E+02	2.92E+03	2.48E+02
	J-B <i>p</i> -value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	AR coefficient	0.1687	0.1690	0.2670	0.5725	0.4907	0.6838	0.8754	0.8052	0.3049	0.3313	0.3506	0.4322	0.3860
AR <i>p</i> -value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	
Decomposition	Spring	-0.0256	-0.0410	3.2607	3.9960	59.3928	21.8110	13.5372	19.1829	6.9487	49.0587	159.7276	14.1752	162.8353
	Summer	0.0621	0.0466	4.0471	5.0576	66.5299	25.4429	18.4907	23.1272	6.7458	47.0608	127.6480	12.5176	129.9260
	Autumn	0.0387	0.0233	4.2646	2.8006	66.7031	22.4445	14.7415	19.7377	5.9245	39.7127	165.3820	10.2916	172.9285
	Winter	0.0262	0.0108	3.6365	1.8597	61.7568	17.3696	8.8467	14.1991	6.0473	42.8010	218.9518	12.0619	219.6610
	Time trend	0.0000	0.0000	-0.0001	0.0002	-0.0001	0.0001	0.0001	0.0000	0.0001	0.0000	-0.0002	0.0005	0.0004
Unit roots	ADF statistic	-37.0793	-37.0470	-83.5640	-9.6693	-23.7095	-9.5704	-13.4704	-8.6162	-80.4970	-15.2961	-13.5376	-10.4251	-11.5235
	ADF <i>p</i> -value	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000
	PP statistic	-96.4845	-96.5626	-83.7792	-134.9710	-86.0599	-98.3178	-45.8976	-67.9648	-86.6443	-109.7303	-131.3908	-141.0779	-138.9411
	PP <i>p</i> -value	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0000	0.0000	0.0001	0.0001	0.0001	0.0001	0.0001

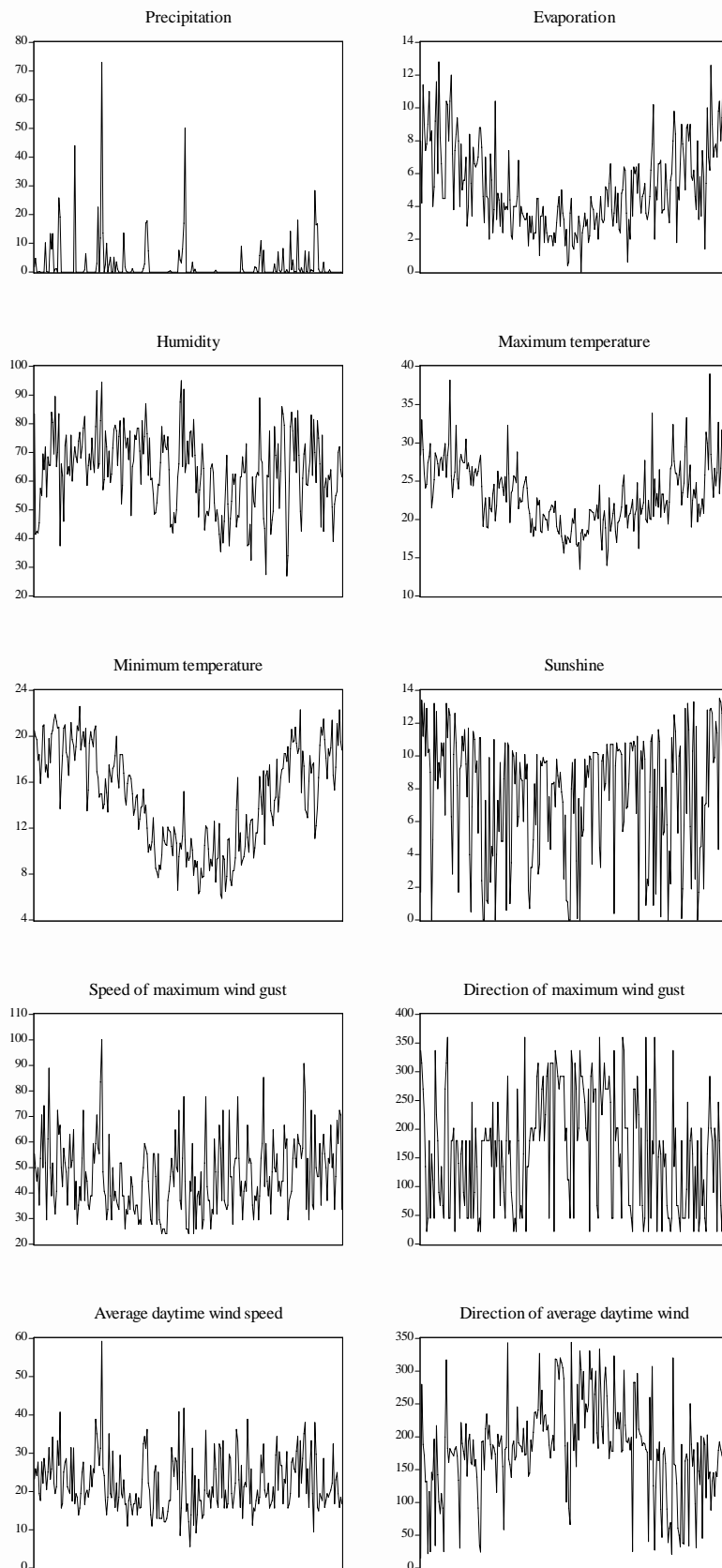
Notes: Sample period comprises 12,067 trading days from Monday 6 January 1958 to Friday 30 December 2005. All weather observations are compiled from Sydney Observatory Hill # 66062 with missing data and recent evaporation and sunshine observations from Sydney Airport #66037. Unless stated otherwise, all observations are in the 24 hours before 0900 (local time). Daytime temperature, daytime wind speed and direction are averages of observations taken at 0900 hours and 1500 hours (local time). Wind directions are from compass directions in degrees, i.e. 360 (N), 45 (NE), 90 (E), 135 (SE), 180 (S), 225 (SW), 270 (W), 315 (NW). CV – coefficient of variation, J-B – Jarque-Bera, AR – first-order autoregressive coefficient, ADF – Augmented Dickey-Fuller, PP – Phillips-Peron. Unit root tests include intercept and trend. Spring (Sep-Nov), summer (Dec-Feb), autumn (Mar-May) and winter (Jun-Aug) are seasonal decompositions of observations including linear trend. The critical value for significance for 12,067 observations is 0.0223 for skewness and 0.0446 for kurtosis.

Table 2  
Non-parametric correlation coefficients and variance inflation factors

	Nominal returns (%)	Real returns (%)	Precipitation (mm)	Evaporation (mm)	Relative humidity (%)	Maximum temperature (°C)	Minimum temperature (°C)	Daytime temperature (°C)	Hours of bright sunshine (h)	Speed of maximum wind gust (km/h)	Direction of maximum wind gust (°)	Daytime wind speed (km/h)	Direction of daytime wind (°)	Variance inflation factor
Nominal returns (%)	1.0000	0.0000	0.1090	0.0333	0.0239	0.0325	0.0940	0.0579	0.0038	0.4137	0.0690	0.1483	0.3337	–
Real returns (%)	0.9903	1.0000	0.1141	0.0530	0.0219	0.0326	0.0968	0.0561	0.0046	0.3786	0.0613	0.0779	0.3594	–
Precipitation (mm)	-0.0083	-0.0082	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0087	0.0025	0.0000	1.1837
Evaporation (mm)	0.0113	0.0100	<i>-0.1401</i>	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.5243
Relative humidity (%)	<i>-0.0121</i>	<i>-0.0124</i>	<i>0.3203</i>	<i>-0.1332</i>	1.0000	0.0001	0.0000	0.2075	0.0000	0.0000	0.0000	0.0000	0.0000	2.7295
Maximum temperature (°C)	<i>0.0112</i>	<i>0.0112</i>	<i>-0.1240</i>	<i>0.2956</i>	<i>-0.0233</i>	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0010	0.0000	12.5229
Minimum temperature (°C)	0.0080	0.0079	<i>0.0677</i>	<i>0.3197</i>	<i>0.1652</i>	<i>0.5967</i>	1.0000	0.0000	0.0134	0.0000	0.0000	0.0006	0.0000	10.4367
Average daytime temperature (°C)	0.0096	0.0097	<i>-0.0663</i>	0.3233	<i>0.0050</i>	<i>0.8149</i>	<i>0.7184</i>	1.0000	0.0000	0.0000	0.0000	0.0851	0.0000	25.9014
Hours of bright sunshine (h)	<i>0.0163</i>	<i>0.0159</i>	<i>-0.3120</i>	<i>0.1642</i>	<i>-0.3924</i>	<i>0.2296</i>	<i>-0.0136</i>	<i>0.1727</i>	1.0000	0.0000	0.0000	0.0000	0.0000	2.1379
Speed of maximum wind gust (km/h)	0.0013	0.0019	<i>0.0453</i>	<i>0.1693</i>	<i>-0.1674</i>	<i>0.0614</i>	<i>0.1100</i>	<i>0.1002</i>	<i>0.0355</i>	1.0000	0.0000	0.0000	0.0000	2.0420
Direction of maximum wind gust (°)	-0.0094	-0.0098	<i>-0.0168</i>	<i>-0.1160</i>	<i>-0.2293</i>	<i>-0.2005</i>	<i>-0.2562</i>	<i>-0.2433</i>	<i>-0.0461</i>	<i>0.1057</i>	1.0000	0.0000	0.0000	1.7990
Average daytime wind speed (km/h)	0.0064	0.0088	<i>0.0194</i>	<i>0.1354</i>	<i>-0.2065</i>	<i>-0.0192</i>	<i>0.0199</i>	<i>0.0085</i>	<i>0.0826</i>	<i>0.4965</i>	<i>0.0715</i>	1.0000	0.0000	2.1342
Direction of average daytime wind (°)	-0.0027	-0.0022	<i>-0.0557</i>	<i>-0.1335</i>	<i>-0.2422</i>	<i>-0.2225</i>	<i>-0.3191</i>	<i>-0.2772</i>	<i>0.0311</i>	<i>0.1077</i>	<i>0.4537</i>	<i>0.1773</i>	1.0000	1.8872

Notes: Kendall's tau-b coefficients are below the diagonal with  $p$ -values of one-sided tests of significance above the diagonal. Coefficients significant at the .05 level or above are in italics.

Figure 2  
Daily weather indicators at Sydney, 4 January to 30 December 2005



All indicators compiled from #66062 Sydney Observatory Hill with missing data and recent evaporation and sunshine observations from #66037 Sydney Airport.

Table 3  
 Estimated coefficients and standard errors of weather effect models

	Nominal returns						Real returns					
	Coef.	Std. err.	<i>p</i> -value	Coef.	Std. err.	<i>p</i> -value	Coef.	Std. err.	<i>p</i> -value	Coef.	Std. err.	<i>p</i> -value
$\mu_0$	0.0953	0.0866	0.2711	0.0568	0.0794	0.4745	0.0876	0.0866	0.3116	0.0461	0.0795	0.5620
$\gamma_1$	-0.9836	0.0758	0.0000	-0.9932	0.3838	0.0097	-0.9906	0.0758	0.0000	-0.9963	0.3839	0.0095
$\beta_1$	0.0002	0.0007	0.7458	0.0003	0.0006	0.5539	0.0002	0.0007	0.7641	0.0003	0.0006	0.5625
$\beta_2$	0.0034	0.0036	0.3472	0.0019	0.0037	0.6117	0.0027	0.0036	0.4570	0.0016	0.0037	0.6662
$\beta_3$	-0.0009	0.0008	0.2469	-0.0008	0.0007	0.2292	-0.0010	0.0008	0.2118	-0.0009	0.0007	0.2140
$\beta_4$	0.0013	0.0020	0.5336	0.0028	0.0021	0.1674	0.0014	0.0020	0.4972	0.0028	0.0021	0.1654
$\beta_5$	0.0009	0.0027	0.7284	0.0002	0.0024	0.9467	0.0007	0.0027	0.7877	0.0001	0.0024	0.9753
$\beta_6$	-0.0005	0.0005	0.3827	-0.0003	0.0005	0.5527	-0.0004	0.0005	0.4288	-0.0003	0.0005	0.5727
$\beta_7$	-0.0002	0.0001	0.0984	-0.0001	0.0001	0.1303	-0.0002	0.0001	0.0814	-0.0001	0.0001	0.1234
$\rho_1$	–	–	–	0.1143	0.1358	0.3996	–	–	–	0.1139	0.1357	0.4013
$\rho_2$	–	–	–	-0.5038	0.1300	0.0001	–	–	–	-0.5034	0.1297	0.0001
$\rho_3$	–	–	–	0.1240	0.0320	0.0001	–	–	–	0.1240	0.0320	0.0001
$\rho_7$	–	–	–	0.0529	0.0262	0.0435	–	–	–	0.0529	0.0262	0.0434
$\rho_9$	–	–	–	0.0294	0.0237	0.2146	–	–	–	0.0294	0.0237	0.2141
$\rho_{10}$	–	–	–	0.0592	0.0722	0.4122	–	–	–	0.0578	0.0721	0.4226
$\rho_{11}$	–	–	–	0.0147	0.0266	0.5814	–	–	–	0.0150	0.0266	0.5735
$\rho_{12}$	–	–	–	0.0315	0.0157	0.0443	–	–	–	0.0314	0.0157	0.0446
$\rho_{13}$	–	–	–	0.0102	0.0151	0.4994	–	–	–	0.0103	0.0151	0.4947
$\rho_{16}$	–	–	–	0.0268	0.0116	0.0205	–	–	–	0.0268	0.0116	0.0203
$\rho_{17}$	–	–	–	-0.0208	0.0173	0.2309	–	–	–	-0.0207	0.0173	0.2332
$\rho_{18}$	–	–	–	-0.0155	0.0182	0.3954	–	–	–	-0.0154	0.0182	0.3981
$\rho_{20}$	–	–	–	-0.0208	0.0195	0.2849	–	–	–	-0.0209	0.0195	0.2817
$\phi_{20}$	–	–	–	0.0076	0.0187	0.6862	–	–	–	0.0078	0.0188	0.6760
$\theta_1$	–	–	–	0.0555	0.1264	0.6605	–	–	–	0.0560	0.1263	0.6573
$\theta_2$	–	–	–	0.4813	0.1348	0.0004	–	–	–	0.4809	0.1345	0.0003
$\theta_5$	–	–	–	0.0428	0.0228	0.0604	–	–	–	0.0429	0.0228	0.0602
$\theta_{10}$	–	–	–	-0.0343	0.0691	0.6194	–	–	–	-0.0329	0.0690	0.6335
$R^2$	0.0146	–	–	0.0558	–	–	0.0147	–	–	0.0560	–	–
Adj. $R^2$	0.0139	–	–	0.0538	–	–	0.0141	–	–	0.0540	–	–
F-stat.	22.264	–	0.0000	27.282	–	0.0000	22.545	–	0.0000	27.403	–	0.0000
DW	1.6707	–	–	2.0014	–	–	1.6705	–	–	2.0014	–	–
AIC	2.4791	–	–	2.4423	–	–	2.4792	–	–	2.4423	–	–
SC	2.4846	–	–	2.4589	–	–	2.4847	–	–	2.4589	–	–
Q(10)	431.6	–	0.0000	5.7614	–	0.3300	432.57	–	0.0000	5.7709	–	0.3290
Q(15)	462.05	–	0.0000	9.8239	–	0.4560	463.23	–	0.0000	9.8554	–	0.4530
Q(20)	491.82	–	0.0000	10.514	–	0.7860	492.97	–	0.0000	10.536	–	0.7850
LM(20)	24.067	–	0.0000	1.4605	–	0.0840	24.102	–	0.0000	1.4899	–	0.0734

Notes: Dependent variables are nominal (columns 1-3 and 7-9) and real (columns 4-6 and 9-12) returns. Sample period Monday 6 January 1958 to Friday 30 December 2005. Standard errors and *p*-values in columns 5-7 and 11-12) incorporate White's corrections for heteroskedasticity of unknown form,  $\mu_0$  is the equation constant;  $\gamma_1$  is the estimated coefficient for the market outlier equation term, weather effect equation terms are denoted  $\beta_i$  where  $i = 1$  (precipitation), 2 (evaporation), 3 (humidity), 4 (maximum temperature), 5 (sunshine), 6 (maximum wind gust) and 7 (direction of maximum wind gust),  $\rho_k$  are autoregressive terms where  $k =$  number of lags,  $\phi$  is the seasonal lag term where  $r =$  the number of seasonal lags,  $\theta_l$  are moving average terms where  $q =$  moving average order, the *F*-statistic is a test of the null hypothesis that all slope coefficients are zero, DW – Durbin-Watson statistic, AIC – Akaike Information Criterion, SC - Schwartz Criterion, Q(*l*) is the Ljung-Box Q-statistic where *l* is the number of lags in days, LM(*l*) is the Breusch-Godfrey Lagrange multiplier statistic where *l* is the number of lags in days.