The Weather and Stock Returns in New Zealand

Stephen P Keef *
Victoria University of Wellington

Melvin L Roush,
Victoria University of Wellington

We examine how the daily returns of the Value-Weighted All Shares Stock Index of the New Zealand Stock Exchange are influenced by different facets of Wellington's weather. The period studied is June 1986 to October 2002. Factor analysis of eight weather variables results in the extraction of three distinct factors: CLOUD, TEMP and WIND. OLS regression and bootstrap-t methods are used to test the implied hypotheses. CLOUD has no influence on returns. TEMP has a small influence on returns. WIND has a significant influence on returns. This latter result should not come as a surprise to those who live in, or have visited, Wellington, New Zealand.

Introduction

New Zealand, like many other countries, is famous on any number of accounts. Its exports of dairy products, lamb, wool, and kiwi fruit are marketed throughout the world. The New Zealand Stock Exchange is located in Wellington, the capital city of New Zealand. Wellington is also famous for its weather. The capital is affectionately known as *Windy Wellington*. This is not a fact that the Tourism Board attempts to exploit in its advertising. The locals, however, bravely acknowledge the undeniable fact of life. A local radio station is called "The Breeze." The district's Super 12 Rugby team is called the "Hurricanes." Seagulls sometimes are seen flying upside down. There is only one wind turbine in the area, which has to be shut down occasionally due to excess wind.

* We are indebted to NIWA (National Institute of Water and Atmospheric Research Ltd) and the New Zealand Stock Exchange for the provision of the data used in this study and for their helpful advice. The paper has benefited from the comments of two reviewers of this journal. The authors are responsible for any errors in the paper.

0747-5535/02/1600/0061/$2.00

The research question addressed in this study is to what degree, if any, does the weather in Wellington affect the daily return of the shares listed on the New Zealand Stock Exchange? There are two strands to the existing literature. First, there is a body of empirical evidence from the psychology literature. This literature (Saunders, 1993; Hirshleifer and Shumway, 2003 and Loughran and Schultz, 2003) provides support for the thesis that the weather affects human behavior, mood, and attitudes. Second, there are empirical studies in the economics and finance literature (Saunders, 1993; Trombley, 1997; Kramer and Runde, 1997; Pardo and Valor, 2003; Hirshleifer and Shumway, 2003; Loughran and Schultz, 2003).

Saunders (1993) obtains six meteorological variables (wind speed, temperature, cloud cover, humidity, hours of sunshine, and rainfall) from weather stations in close proximity to the New York Stock Exchange. His assessment is that wind speed and temperature are not important in psychological research. Thus, these two variables are not used in the analysis. He finds that cloud cover is highly correlated with humidity and negatively correlated with hours of sunshine. Furthermore, he finds that high levels of rain are associated with high levels of cloud cover. As a result, he uses cloud cover as the sole explanatory variable in his analysis. The raw data are based on 10 percent increments of cloud cover; that is, eleven levels ranging from 0 percent cloud cover to 100 percent cloud cover.

Saunders (1993) focuses on the extremes of the weather data in his first analysis of three stock indices from the New York Stock Exchange. He compares the daily rates of return for those days with cloud cover in the range of 0 percent to 20 percent with the return on days with 100 percent cloud cover. This shows significant evidence that the return on the index is affected by the degree of cloud cover. In his second analysis, he classifies the cloud cover into three levels: (i) 0 percent to 20 percent; (ii) 30 percent to 90 percent; and (iii) 100 percent. This three level variable is used in conjunction with four day-of-the-week dummy variables, eleven month-of-the-year dummy variables, and the lagged return to explore variations in rates of return. Again, cloud cover is observed to influence stock returns after controlling for these effects.

Trombley (1997) replicates Saunders' (1993) study using essentially identical data, but with a different statistical methodology. His first analysis compares the rate of return across the eleven levels of cloud cover using Duncan's (1975) multiple range test. Support for a cloud cover effect is mixed and, at best, is somewhat weak. In his replication of Saunders' (1993) second analysis, he replaces the three level cloud cover variable by three (0, 1) dummy variables based on cloud cover of 0 percent, 10 percent to 20 percent, and 30 percent to 90 percent. Total cloud cover, 100 percent, is captured by the regression constant. The results are again mixed. Trombley (1997, p. 18) concludes " … 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."

Essentially similar conclusions to those of Trombley (1997) are reported by Kramer and Runde (1997) with the DAX index of the Frankfurt Stock Exchange and Pardo and Valor (2003) with the Madrid Stock Exchange Index. Hirshleifer and Shumway (2003), however, report the presence of a significant cloud cover influence, on average, across 26 international stock exchanges. In contrast, Loughran and Schultz (2003) examine portfolios of Nasdaq shares based on companies located in specific U.S. cities. They examine 26 portfolios. They find little evidence that local cloud cover affects the stock returns. Goetzmann and Zhu (2003) find that cloud cover does not affect investors' disposition to buy or sell shares. In short, prior research shows mixed evidence of the effect of cloud cover on stock returns.

The motivation for our study develops as follows. First, there is psychological evidence that cloud cover (sunshine) affects mood (Saunders, 1993; Hirshleifer and Shumway, 2003). Second, there is mixed evidence showing that cloud cover affects stock returns. Third, Saunders (1993) reports a unitary measure of cloud cover that is correlated with other weather variables. This points to the presence of what could be called a facet (or factor) of weather. Fourth, this raises the question of the degree to which weather is multifaceted. We show that Wellington's weather consists of three distinct facets. Fifth, the natural question, given the prior research, is the degree that these other facets of the weather, beside cloud cover, influence stock returns. We observe that all studies of the topic include the word weather in the title. Yet they invariably focus solely on cloud cover. As we illustrate, cloud cover is but one facet of the weather. Thus, it is hard to escape the conclusion that the existing literature has not analyzed the full effects of weather on stock returns. This is the gap in the literature we seek to fill.

This present study is based on a stock index from the New Zealand Stock Exchange. By the use of the factor analysis procedure, the study seeks to use all relevant data that are collected from two local weather stations. We find that cloud cover has no causal influence on stock returns. There is weak evidence that stock returns are negatively affected by the temperature. Furthermore, the level of the wind has a significant negative effect. This latter result is not unexpected, given the fact that Wellington is renowned for its windy conditions.

The Data

Index Data

The New Zealand Stock Exchange (NZSE) provided an electronic copy of the All Shares Gross Index for the period June 30, 1986 to October 25, 2002. As its name implies, it is a value-weighted index of all the shares of domestic companies listed on the exchange. It does not include the shares of overseas companies that have a dual listing on the NZSE as well as on their home exchange. It is a gross index that is corrected appropriately for dividends and stock issues such as rights issues and bonus issues. The daily rate of return r_t, based on close-of-business values of the index, is calculated as

$$r_t = 100 \times \ln \left(\frac{I_t}{I_{t-1}} \right), \tag{1}$$

where:

I_t = The closing value of the index on day t.

After the deletion of missing values occasioned by closures of the stock exchange, due mainly to national holidays, there are 3,993 daily rates of return available for analysis. The sample size is reduced further by the presence of missing variables in the weather data.

Weather Data

We contacted NIWA (National Institute of Water and Atmospheric Research Ltd) with a request for suitable daily weather observations that capture the essence of Wellington's climate. NIWA is one of nine New Zealand Crown Research Institutes. Its mission is to provide a scientific basis for the sustainable management and development of New Zealand's atmospheric, marine, and freshwater systems and associated resources. NIWA provided weather data from two locations. The Kelburn weather station is about a kilometer west of the city's central business district where the stock exchange is located. The Wellington Airport weather station is five kilometers to the southeast. The variables from the Kelburn station are temperature (high and low), rainfall, and hours of sunshine. The variables from the airport station are relative humidity and average wind speed (together with the speed of the maximum gust and its direction). The daily data cover the period January 1, 1980 to October 14, 2002 (n = 8,323). These data predate the stock index data by approximately six years and are 11 days shorter at the end.

The weather data we obtained in Wellington differ subtly from those obtained by Saunders (1993) in New York. The collection of maximum and minimum temperature in Wellington, compared to the mean temperature in New York, is of minor import. The fact that cloud cover is not available in our study is, at first sight, enigmatic. The Maori name for New Zealand is *Aotearoa*, which is translated as "the land of the long white cloud." On many days clouds hover over the ridges of the mountain ranges. The absence of an explicit measure of cloud cover is not of pressing concern, however, for this present study. Factor analysis of the weather variables results in a factor that proxies for cloud cover.

Compared to Saunders (1993), two extra weather variables are collected in this Wellington study: the magnitude and direction of the maximum wind gust. This information is collected for a rational reason. An important facet of Wellington's weather is the speed and direction of the wind. This suggests there is prima facie evidence for the inclusion of maximum wind speed and its direction in an investigation into the causal effects of local weather conditions on stock returns.

The factor analysis is based on the full times series of the weather data (including Saturdays and Sundays) made available to us (rather than the shorter period associated with the stock index time series). We base this decision on the premise that the more data used in the analysis, the better the precision of the estimates of the resulting factors. Weather patterns and interrelationships between weather variables are stable over a relatively short period of 22 years. Systematic climate changes, such as global warming or ice ages, are gradual.

Preliminary analysis (Figure 1) shows that the distributions of *hi_temp* (maximum temperature), *lo_temp* (minimum temperature), *humidity* (relative humidity), *wind_speed* (average daily wind speed) and *max_gust* (maximum wind gust) are reasonably bell shaped. These variables can be factor analyzed without further ado. Nature's variables, however, are not always normally distributed. The variable *sunshine* (hours of sunshine) and the variable *rainfall* (precipitation) exhibit unsatisfactory distributions. We are unable to find a suitable transformation that improves their distributional properties.

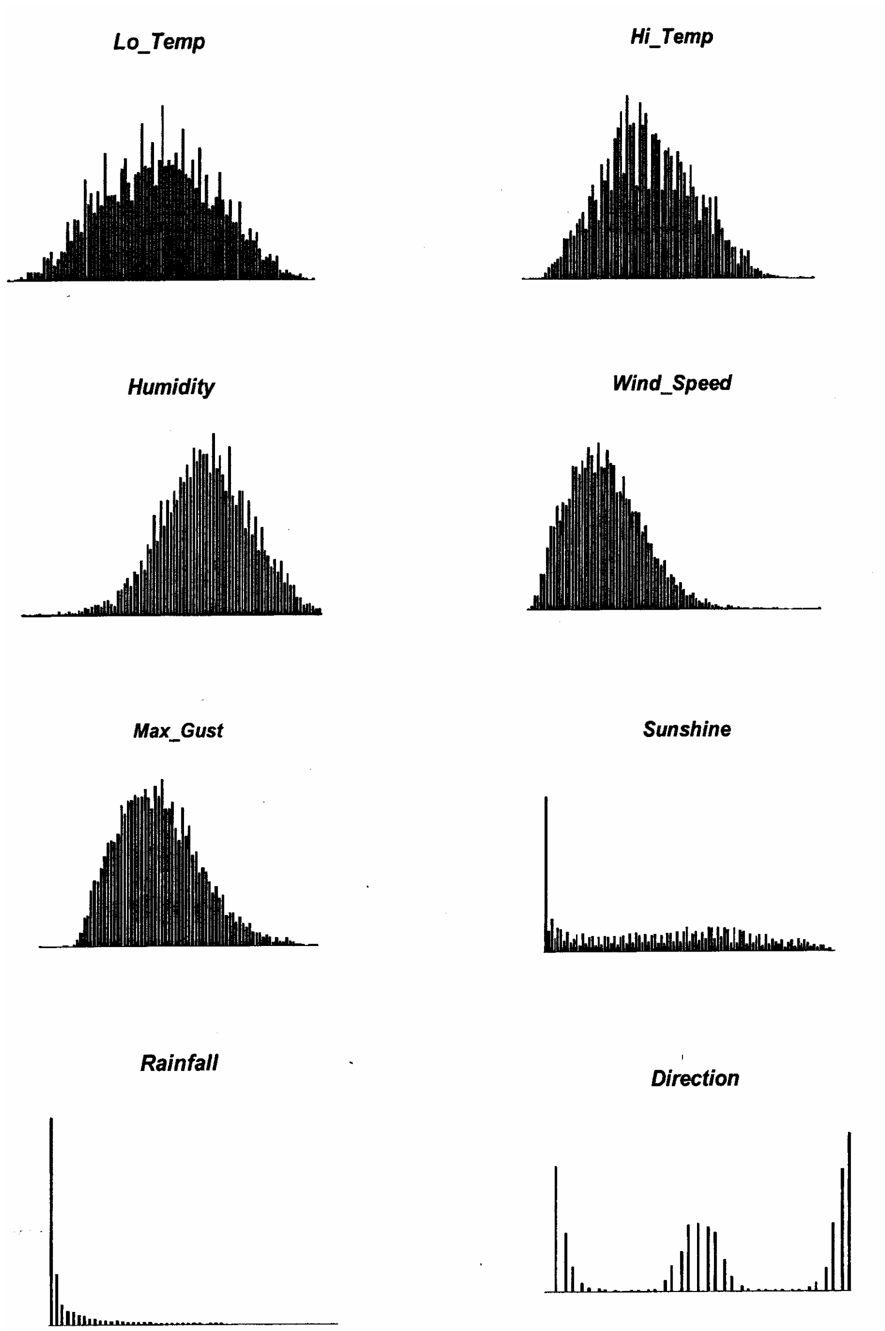
The variable direction (direction of the daily maximum wind gust, max_gust) is recorded on the 360 degree compass scale where zero and 360° represent true north. The mathematical properties of this variable are inappropriate for factor analysis. As an illustration, a wind coming from just west of north is recorded as 355°. A wind that is coming from just east of north is recorded as 5°. The difference in the direction is only 10°, yet the difference in the recorded data is 350°. Wellington's wind can be characterized as either coming from the north (this is the predominant direction) or coming from the south (Figure 1). Thus, the direction variable was recoded into a dichotomous variable based on whether the maximum gust was from the north ($270° \leq$ direction $\leq 90°$) or from the south ($90° <$ direction $< 270°$).

Factor Analyses

The weather data contain missing values for direction (503 observations) and max_gust (471 observations). Our initial thought was that a large gust of wind destroyed the anemometer! The airport weather station is operated by the Airways Corporation of New Zealand. Around May 1993, they decided that the collection of these two variables served little purpose. In July 1994 they changed their mind and recommenced the collection of these data. There are some other missing data; the occurrences are relatively small. These we attribute to equipment failure and other unavoidable circumstances.

In the context of this study, a sensible approach to the presence of missing values is to use pair-wise deletion. Factor analysis is based on the correlation matrix. Pair-wise deletion permits the correlation coefficient to be based on all days where there is not a missing value for either variable. The alternative approaches of substi-

Figure 1 - Distributions of Weather Variables



tuting the mean value of the variable or list-wise deletion are less attractive. The latter entails the deletion of all the variables on the particular day where there is one, or more, missing value(s) for any variable(s). Thus, the approach adopted achieves the best estimate of the factor loadings. Missing values in the data result in the presence of missing values in the resultant factor scores on a list-wise basis.

We conduct three factor analyses, one of which seeks to ameliorate the problem associated with the block of missing values for direction and max_gust. They are called FA-I (n = 7,820), FA-II (n = 7,852), and FA-III (n = 8,323). The preliminary factor analysis of the eight weather variables (this is called FA-I) shows that the communality for the two variables rainfall and direction are somewhat lower than those for the other six weather variables. Communality is the proportion of the variable's variance that is explained by all the factors. For this reason, the factor analysis is repeated with the omission of these two variables. This analysis with six variables is called FA-II, where the resulting communalities are a little better (Table 1). There are, however, 471 missing cases. (Max_gust is the culprit in this case.) The factor analysis is applied again (called FA-III) with the omission of max_gust. The intention is to use the most appropriate set of factors.

The two primary steps in a factor analysis are extraction and rotation. The factors are extracted using principal components analysis. In all analyses, three factors are isolated with eigenvalues greater than unity. The eigenvalue of the fourth factor is 0.79 for FA-I, 0.39 for FA-II, and 0.37 for FA-III. Oblique rotation with a delta of -2 is adopted. This allows a modest degree of correlation between the extracted factors. There is a possibility that the distinct facets of the weather are not orthogonal. The rotation is followed by Kaiser normalization. The factor scores are obtained in the conventional fashion. A consequence of factor analysis, in general, is that each factor has an approximate mean of zero and an approximate standard deviation (and variance) of unity. All factors exhibit acceptable visual approximations to a normal distribution.

The goal now is to choose the most appropriate set of factors. To achieve this end we use a number of criteria to assess the relative merits of the three sets of factors. First, there are the communalities. As mentioned earlier, with FA-I the communalities for the variables of rainfall (0.47) and direction (0.37) are poor. The most plausible reason is that nature is not normally distributed. In contrast, the communalities for the six other variables are acceptable and not dramatically different between the three factor analyses (Table 1). Second, the difference between the eigenvalue for the third factor and the eigenvalue for the fourth factor is greater for FA-II (0.93) than for FA-I (0.63) and FA-III (0.65). FA-II achieves the best discrimination between a significant factor and an insignificant factor. Third, taken at face value, the cumulative variance explained by either FA-II or FA-III (90 percent) is greater than the cumulative variance explained by FA-I (73.9 percent). This observation, however, has to be treated with caution because there are differences in the

Table 1—Summary of the Factor Analyses

Weather Variable	Communality	Extracted Factor 1	2	3
Panel A: Factor Analysis 1 (FA-I), Pattern Matrix[a, b]				
Sunshine	0.75	-0.81		
Humidity	0.74	0.86		
Rainfall	0.47	0.66		
Hi_Temp	0.92		0.91	
Lo_Temp	0.83		0.90	
Direction	0.37		-0.57	
Max_Gust	0.93			-0.95
Wind_Speed	0.92			-0.95
Summary Statistics				
Eigenvalue		2.40	2.09	1.42
Variance Explained, %		30.0	26.1	17.8
Cumulative Variance Explained, %		30.0	56.1	73.9
Name of Factor		CLOUD	TEMP	WIND
Panel B: Factor Analysis 2 (FA-II), Pattern Matrix[a, b]				
Sunshine	0.81			-0.84
Humidity	0.83			0.91
Rainfall	...			...
Hi_Temp	0.94		0.91	
Lo_Temp	0.94		0.95	
Direction	...		...	
Max_Gust	0.93	0.96		
Wind_Speed	0.93	0.96		
Summary Statistics				
Eigenvalue		2.18	1.88	1.32
Variance Explained, %		36.3	31.3	22.0
Cumulative Variance Explained, %		36.3	67.5	89.5
Name of Factor		WIND	TEMP	CLOUD
Panel C: Factor Analysis 3 (FA-III), Pattern Matrix[a, b]				
Sunshine	0.82	0.82		
Humidity	0.85	-0.93		
Rainfall	...	...		
Hi_Temp	0.95		0.91	
Lo_Temp	0.95		0.96	
Direction	...		...	
Max_Gust	...			...
Wind_Speed	0.96			0.98
Summary Statistics				
Eigenvalue		2.01	1.49	1.02
Variance Explained, %		40.2	29.8	20.3
Cumulative Variance Explained, %		40.2	70.0	90.3
Name of Factor		CLOUD	TEMP	WIND

Notes:
[a]Loadings less than 0.35 are omitted
[b]...Denotes variable not included in the analysis

number of variables in the factor models and hence differences in total variation. In all three cases, these statistics imply that the majority of the variation in the weather variables is captured by the three factors. Fourth, the Kaiser-Meyer-Olkin (KMO) statistic (Norusis, 1990, p. 317) is better for FA-I (0.53) than for FA-II (0.48) and FA-III (0.40). One should be aware, however, that the differences are relatively small, and a KMO of 0.5 is generally deemed as being miserable. This suggests that Wellington's weather is not well behaved from a statistical perspective. In addition, FA-II excludes the two variables of rainfall and direction. These are potentially important in the context of Wellington's weather. Finally, FA-III has the attraction of a larger sample size but omits three weather variables.

It is not an easy task to select the best set of factors. For these reasons we report the results of the three factor analyses (Table 1) and the corresponding regression analyses. There is minimal extra cost, but considerable benefit arises if the three sets of factors generate consistent results.

There is a small possibility that we may be overly cautious here. The corresponding factors from FA-I, FA-II, and FA-III are highly correlated. The lowest correlation coefficient is 0.9451. This suggests that unexplained variation between corresponding factors is less than 11 percent. In contrast, the highest correlation coefficient between non-corresponding factors is 0.1759, suggesting, at best, one will explain 3.1 percent of the other. This shows that the factors are essentially orthogonal. There are reasons to suspect, but we cannot be absolutely sure ex-ante, that similar results will emanate from the three sets of factors.

The results presented in Table 1 show that three, largely orthogonal, facets of Wellington's weather are clearly identified. We report the results as generated from the statistical package. There are two distractions that need to be noted at this stage. First, there is the change in the sign for the variables loading on the factors called CLOUD and WIND. The sunshine variable has a negative loading on factor cloud for FA-I and FA-II, but a positive loading for FA-III. Variable humidity exhibits a corresponding, yet reverse, effect. Variables max_gust and wind_speed exhibit negative loadings for factor wind for FA-I yet positive loadings for FA-II and FA-III. Second, there is a difference in the rankings of the factors. The rankings of the first and third factors are interchanged as we move from FA-II to FA-I (and FA-III). We believe these differences to be unimportant from an empirical perspective. The three factor analyses generate essentially similar sets of factors that measure facets that are, as we show next, intuitive from the perspective of Wellington's weather. The implication is that Wellington's weather is robust to the choice of the factor analytic method. Varimax (orthogonal) rotation achieved essentially similar results to those obtained with oblique rotation.

One factor is called *CLOUD*. Bearing in mind the changes in the signs of the factor loadings, let us initially focus on FA-I. The factor CLOUD is so named because the variable sunshine (hours of sunshine per day) has a negative loading. It goes without saying, that when the sun is not shining, then it must be cloudy. For FA-I, the three variables loading on this factor are consistent with our experiences of local weather conditions. Relative humidity (humidity) is higher when it is cloudy or raining (rainfall). Hence, both of these variables have the same loading sign. The two other factor analyses, FA-II and FA-III, do not include the variable rainfall. Their cloud factor is consistent with the counterpart from the first factor analysis FA-I. We suggest that the factor CLOUD is akin to the cloud cover variable examined by Saunders (1993) and Trombley (1997). The implied correlations outlined above are consistent with those reported by Saunders (1993, p. 1338) for New York's weather.

Another factor is called *TEMP*. The variables hi_temp (maximum temperature) and lo_temp (minimum temperature) have similar loadings for the three factor analyses. This factor can be assessed as a measure of the average daily temperature, hence the name. The negative loading of direction (see the first factor analysis FA-I) is a reflection of Wellington's climate. The southerly wind originates from near the South Pole. There is no land mass between New Zealand and the Antarctic to warm the air. Wind often is bitterly cold during a storm. As explained earlier, direction is a dichotomous variable coded with 1 = northerly wind and 2 = southerly wind. Thus, its negative loading is consistent with the local climatic conditions. To confirm this, we reversed the values of direction and repeated the factor analysis FA-I. The sign of direction became positive.

The final factor is called *WIND*. This factor is based on the variables of wind_speed (average daily wind speed) and max_gust (maximum wind speed) for FA-I and FA-II. There are essentially the same variable loadings for both factor analyses. Care must be exercised with the signs of the loadings and the ranking of the factors between FA-I and FA-II. The weather variable max_gust is not included in FA-III. The factor WIND captures the special essence of Wellington's weather.

Regression Analyses

The initial plan was to use the ordinary least squares (OLS) regression model

$$r_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i WF_{i,t} + error_t \ , \tag{2}$$

where:

WF_i = The weather factors (i = 1 ... k) obtained from the factor analysis.

As per convention, we apply a criterion of $p = 0.05$ as a gauge of statistical significance. Given the three factors outlined earlier, the three regression models applied are

$$r_t = \alpha_{\lambda,0} + \alpha_{\lambda,1} CLOUD_{\lambda,t} + \alpha_{\lambda,2} TEMP_{\lambda,t} + \alpha_{\lambda,3} WIND_{\lambda,t} + error_{\lambda,t} \ , \tag{3}$$

where the subscript λ differentiates between the factors arising from the factor analyses FA-I, FA-II, and FA-III.

These three sets of regression results are based (with the benefit of the hindsight outlined below) on the application of a Newey and West (1987) adjustment to the standard errors. Essentially similar results are obtained from the use of the three sets of factors as independent variables (Table 2). At this stage there is evidence that:

(i) The factors of CLOUD and TEMP have no significant ($p > 0.05$) causal effect on daily stock returns;

(ii) Factor WIND has a significant causal effect ($p < 0.05$) on daily stock returns. These results should be treated with caution because, as we show next, the errors of equation (3) are not well behaved.

Table 2—OLS Regression Results (r_t is dependent variable)

		t-Value with Lag [a,b]	
Independent Variable	Estimated Coefficient %	0	9
Panel A: Factor Analysis 1 (FA-I) (Sample Size 3,647)			
CLOUD[c]	0.0100	0.619	0.609
TEMP	-0.0231	-1.490	-1.367
WIND[c]	0.0440	<u>2.618</u>	<u>2.443</u>
Constant	0.0123	0.739	0.663
Panel B: Factor Analysis 2 (FA-II) (Sample Size 3,667)			
CLOUD[c]	0.0046	0.281	0.280
TEMP	-0.0243	-1.577	-1.397
WIND[c]	-0.0470	<u>-2.782</u>	<u>-2.603</u>
Constant	0.0125	0.749	0.671
Panel C: Factor Analysis 3 (FA-III) (Sample Size 3,984)			
CLOUD[c]	-0.0124	-0.775	-0.772
TEMP	-0.0255	-1.703	-1.517
WIND[c]	-0.0395	<u>-2.466</u>	<u>-2.353</u>
Constant	0.0181	1.120	1.001

Notes:
[a]Significant t-statistics ($p < 0.05$) are underlined
[b]The lag of 0 uses White's (1980) heteroskedasticity-consistent covariance matrix. The lag of 9 uses the Newey and West (1987) autocorrelation-consistent matrix with order of 9
[c]Caution that the signs of independent variables CLOUD for FA-III and WIND for FA-I are negative

Conventional diagnostic tests are applied to the errors from equation (3). The correlogram for 23 lags [from White's (1997) SHAZAM econometrics software] shows the presence of significant ($t > 1.96$) serial correlation at lags 1, 3, 5, 9, 10, and 12 for the regression errors based on the FA-I factors. The results are virtually the same for the errors arising from the use of the other sets of factors derived from FA-II and FA-III. In each case, the highest t-statistic is observed for lag 9 ($t = 6.79$, 6.73, and 6.05, respectively). Engle's (1982) ARCH test has a chi-square distribution on one degree of freedom if autoregressive conditional heteroskedasticity is absent. The critical $p = 0.05$ value is 3.84. The estimated chi-square statistics are 115.9, 115.1, and 122.1, respectively. It is clear that corrections are necessary for the presence of serial correlation and heteroskedasticity.

The conventional procedure to ameliorate these problems is to apply the Newey and West (1987) correction to the standard errors. The correlogram suggests that a lag of nine would be appropriate. This correction controls for serial correlation and heteroskedasticity. It is an enhancement on White's (1980) control for unknown forms of heteroskedasticity. This is the way that the OLS regression results (Table 2) reported earlier are obtained.

The Jarque and Bera (1980) LM test statistic has a chi-square distribution on two degrees of freedom if the distribution is normal. The critical $p = 0.05$ value is 5.99. The estimated chi-square statistics for the errors of equation (3) are 44,560, 44,781, and 41,704, respectively. The assumption of normally distributed errors is denied. Further investigation shows that the incidence of fat tails (the t of excess kurtosis is 210.9, 210.3, and 203.3, respectively) is more pressing than the negative skewness ($t = -22.5$, -22.6, and -22.5, respectively).

The inherent problem with the regression results reported in Table 2, and briefly discussed above, is that the effects of non-normality are unknown. We address the issue of non-normality by the use of the bootstrap method (Mooney and Duval, 1993; Noreen, 1989). Saunders (1993) adopts a bootstrap (Monte Carlo) approach. A bootstrap process entails two decisions. The first decision concerns the resampling process. We adopt the nonparametric method because it is devoid of assumptions relating to the distribution of the data. The data in this study form an $n \times \kappa$ matrix where n is the sample size (3,647 for the FA-I factors, 3,667 for the FA-II factors, and 3,984 for the FA-III factors) and κ (= k + 1) is the number of coefficients in the regression model (this being four). The four variables are the rate of return (or constant) and the three independent factors. A random sample, with replacement, of 3,647 (or 3,667 for FA-II or 3,984 for FA-III) full rows is generated. Regression on this resample is used to estimate the coefficients of interest. The resampling is repeated a large number of times; we chose 9,999.

The second decision in a bootstrap analysis relates to the parameter used to characterize the effect and its confidence interval. We apply the bootstrap-t (or percentile-t) method to the estimated coefficients (Mooney and Duval, 1993, p. 40). The resampling section and associated regression generates 9,999 t-statistics per independent variable. When ranked in ascending order, the 250th and 9,750th values form the basis of the lower and upper confidence intervals for a double tailed test, that is, 2.5 percent in each tail. Using $\hat{\alpha}_i$ to denote the estimate of the ith coefficient (i = 0 ... 3) with standard error given by $\hat{\sigma}_i$ obtained from the original regression (Table 2), the coefficient's $p = 0.05$ confidence interval is given by

$$\hat{\alpha}_i - \hat{\sigma}_i t^*_{i,250} \text{ to } \hat{\alpha}_i + \hat{\sigma}_i t^*_{i,9750} \ , \tag{4}$$

where

$$t^*_{i,j} = \left(\hat{\alpha}^*_{i,j} - \hat{\alpha}_i\right) / \hat{\sigma}^*_{i,j} \ , \tag{5}$$

with the superscript * denoting the estimate is obtained from the resamples and the additional subscript j represents the resample. If the confidence interval in equation (4) contains zero, then it can be concluded that there is insufficient evidence to reject the null hypothesis.

The estimate of the standard error $\hat{\sigma}_i^*$ for each of the resamples is obtained after the application of the Newey and West (1987) adjustment with a lag of 9. The random sampling process, with replacement, shuffles the temporal order of the data. This aspect is addressed by resorting the data, by temporal indicator, prior to running each of the resample regressions. For practical reasons it was not possible to determine the appropriate lag for each of the sorted resamples. Thus, the use of a lag of 9 is a pragmatic compromise. The results of the bootstrap-t exercise are presented in Table 3.

Table 3—Bootstrap-t Regression Results (r_t is dependent variable)

	Bootstrap-t, p = 0.05 Confidence Limits, %[a]		
Independent Variable	Lower	Median	Upper
Panel A: Factor Analysis 1 (FA-I)			
CLOUD[b]	-0.0132	+0.0099	+0.0330
TEMP	-0.0467	-0.0235	+0.0004
WIND[b]	+0.0180	+0.0439	+0.0686
Constant	-0.0121	+0.0126	+0.0384
Panel B: Factor Analysis 2 (FA-II)			
CLOUD[b]	-0.0189	+0.0049	+0.0283
TEMP	-0.0479	-0.0240	-0.0005
WIND[b]	-0.0618	-0.0471	-0.0315
Constant	-0.0119	+0.0127	+0.0386
Panel C: Factor Analysis 3 (FA-III)			
CLOUD[b]	-0.0352	-0.0123	+0.0111
TEMP	-0.0482	-0.0256	-0.0028
WIND[b]	-0.0621	-0.0393	-0.0143
Constant	-0.0057	+0.0181	+0.0431

Notes:
[a]Significant coefficients ($p < 0.05$) are underlined
[b]Caution that the signs of independent variables CLOUD for FA-III and WIND for FA-I are negative

Results and Discussion

There are six sets of regression results reported in this study (Tables 2 and 3). They are described by a 3 × 2 matrix. One dimension is FA-I versus FA-II versus FA-III as the source of the independent variables. The other dimension is the OLS regression method against the bootstrap-t method. A summary of the results is presented in Table 4. In this table, the emphasis is on the probability that the implied null hypothesis is accepted. The OLS method, as per convention, generates a double tailed test of significance. The results from the bootstrapping exercise are akin to single tailed tests. The probability that the null hypothesis is rejected is estimated by the proportion of resamples in the appropriate tail, delineated by zero, of the bootstrap-generated distribution. Hence, these latter probabilities are doubled to make them directly comparable with the OLS results.

Table 4—Summary of Results

	Probability (Double-Tailed Test) That the Null Hypothesis is Accepted					
	OLS Method[a]			Bootstrap-t Method[b]		
Independent Variable	FA-I	FA-II	FA-III	FA-I	FA-II	FA-III
CLOUD	0.54	0.78	0.44	0.40	0.69	0.30
TEMP	0.17	0.16	0.13	0.052	0.043	0.028
WIND	0.015	0.009	0.019	0.0002	< 0.0001	0.002
Constant	0.51	0.50	0.32	0.32	0.31	0.14

Notes:
[a]Double tailed test
[b]Area in the appropriate tail of the bootstrap-t generated distribution multiplied by 2 to convert the probability into the equivalent for a double tailed test

The orthodox finance view is that the expected return on the market index is greater than the risk-free rate. The risk-free rate always should be positive. The addition of unbiased expectations leads to the thesis that the observed return on the NZSE All Shares Index, on average, should be statistically positive. In this study, the estimate of the constant's coefficient is not statistically greater than zero in all six analyses ($p > 0.14$), which implies that returns on the index are highly variable. This also explains why the mean daily rate of return is positive yet not statistically different from zero. Thus, the intriguing question is whether a weather effect stands out against this background noise after controls are made for the observed non-normality. If it does, then this attests to the importance of the weather effect.

There is complete agreement in these six analyses that the CLOUD factor has no significant causal effect of the daily returns on the All Shares Gross Index of the New Zealand Stock Exchange. The most significant effect is $p = 0.30$ for the bootstrap-t method with the FA-III factors. This result is inconsistent with the prior research of Saunders (1993) yet consistent with the majority of research since then.

At a confidence level of $p = 0.05$, the factor TEMP generates mixed results. For the three OLS regressions there is insufficient evidence to reject the null hypothesis (most significant result is $p = 0.13$ for FA-III). For the bootstrap-t exercise, TEMP is statistically significant for FA-II ($p = 0.043$) and FA-III ($p = 0.028$), but, strictly interpreted, not for FA-I ($p = 0.052$). Notwithstanding, it is clear that these bootstrap-t results are on the cusp of statistical significance. They suggest there is a weak temperature effect on stock returns in New Zealand.

The results for the TEMP factor raise three points of interest. First, prior research has not tested for a temperature effect with the stock indices. Thus, the question of whether such an effect exists in the U.S., or elsewhere, remains unanswered.

Second, Wellington's climate, in terms of temperature, can be described as being moderate and relatively uniform. It does not experience extremes of temperature. Based on the 22 years of Wellington's weather data used in this study: (i) the lower 5 percent and upper 5 percent maximum temperatures are 9.5°C (49°F) and 22.5°C (73°F), respectively; (ii) the lower 5 percent and upper 5 percent minimum temperatures are 4.2°C (40°F) and 15.8°C (60°F), respectively; (ii) the lowest temperature was 0.2°C (32°F) and the highest temperature was 30.1°C (86°F). We suggest that these data do not illustrate dramatic variations in the temperature. Thus, the temperature effect is somewhat surprising. Consider, as a reference, New York's climate. In contrast to Wellington, New York's temperature exhibits far greater variability; blizzards and heat waves are not uncommon. A possible implication is that temperature may have a stronger effect on stock indices of the New York Stock Exchange.

Third, the negative sign of TEMP's coefficient shows that the higher the temperature, the lower the daily rate of return on the stock index and vice versa. Such an effect is understandable if the climate is, on occasions, oppressively hot (as might be experienced in Singapore or Kuala Lumpur). But as we show above, this is not the case with Wellington's climate. For the reasons outlined above, it is prudent at this stage to treat the TEMP effect with caution. It is clear, however, that further research into the effects of temperature on the returns of stock indices is warranted.

The factor WIND exhibits a negative and significant causal influence on stock returns (note the reversal of signs with the loadings of FA-I). The higher the speed of the wind is, the lower the return on the stock index and vice versa. The effect is consistent across the six analyses. The most conservative estimate (FA-III with OLS) is that the null hypothesis is rejected at $p = 0.019$. We suggest that this result would seem eminently sensible to those who have experienced Wellington's climate.

There are few psychological studies into the effect of wind on mood. Sandilands (1995) presents a review of the effects of wind on individuals. He cites the empirical studies of his students who show evidence that wind gusts affect the receipt of parking tickets (Green, 1994); motor vehicle accidents (Ponech, Williams, and Schmidt, 1994) and the number of telephone calls to a crisis line (Sandilands and Christman, 1987). These studies indicate that individuals are affected by wind. Our result is consistent with these studies.

We are aware of the possibility that the WIND factor is indirectly capturing a seasonal element in New Zealand's economy. There are two dimensions to consider. They are the seasonality of nature's produce and the seasonality of the wind. New Zealand is quintessentially a primary producer. The major exports are dairy products (cheese, butter, and milk powder), meat (lamb and beef), fruit (apples, pears, and kiwi fruit) and forestry products. These exports originate, in the main, from owner-operated farms and are marketed by single desk cooperatives. New Zealand's major imports are machinery, vehicles, mineral fuels, and consumer goods. These are essentially independent of the season. Few of the businesses involved in either exports or imports are listed on the local stock market. There is little reason to suspect that the stock market is influenced by the seasonality of agriculture. Furthermore, the winds in Wellington relentlessly blow no matter the season (Table 5). It is unlikely that the wind effect is operating through other mechanisms other than the implied mood shift.

Table 5—Seasonality of the Wind in Wellington

	Wind Speed in Knots			
Season	Mean	Maximum	Minimum	Standard Deviation
Winter	14.1	35.6	2.0	5.88
Spring	13.7	51.6	0.9	6.80
Summer	13.4	40.7	1.1	6.78
Fall	15.5	36.3	2.1	6.16
All Data	14.2	51.6	0.9	6.47

The Beaufort scale is an international measure of the force of the wind. The lower range of the scale is wind Force 0, where the wind speed is less than one knot. This is called *calm conditions*. The upper range of the scale is wind Force 12, where the wind speed exceeds 64 knots. This is known as *hurricane conditions*. Table 6 presents a summary of the wind variables wind_speed and max_gust (note the 471 missing values) converted to the Beaufort scale. Wellington's average wind speed can be summarized by the following stylized facts: (i) one third of the time the average wind speed is less than a moderate breeze (Force 4); (ii) one third of the time there is a moderate breeze (Force 4); (iii) one third of the time there is a fresh breeze (Force 5) or stronger; (iv) a strong gale (Force 9) or a storm (Force 10) lasted for more than a day on three and one occasions, respectively, in the last 22 years; (v) only on one day during this period was there a truly calm day (Force 0). The maximum gust data give a similar picture. On average, a hurricane gust (Force 12) occurs five times a year. Notwithstanding, the high winds only cause localized havoc—a tree blown over here and a roof ripped off there. We are not aware of an example of a systematic disruption to either the business community or the social life of the district.

We believe that, in lay terms, the psychology of the wind effect is relatively straightforward. When the wind blows with gusto, our outlook on life is pessimistic. When the wind is relatively still or there is a pleasant breeze, our outlook on life is optimistic. The orthodox view is that a share price is the present value of the future cash flows accruing to the owner of the share. Thus, the level of the wind affects the investor's position in the pessimism—optimism continuum. This position, in turn, subtly influences expectations about the future cash flows and the discount rate of the company. Hence, there is a negative relation between the return on the index and the strength of the wind.

Table 6—Wellington's Wind Statistics

	Wind Speed (knots)	Beaufort Scale	Wind_Speed Frequency	Wind_Speed %	Max_Gust Frequency	Max_Gust %
Calm	< 1	0	1	< 0.1	1	< 0.1
Light Air	> 1 to < 4	1	240	2.9	0	0.0
Light Breeze	> 4 to < 7	2	900	10.8	2	< 0.1
Gentle Breeze	> 7 to < 11	3	1,738	20.9	82	1.0
Moderate Breeze	> 11 to < 17	4	2,852	34.3	627	8.0
Fresh Breeze	> 17 to < 22	5	1,592	19.1	924	11.8
Strong Breeze	> 22 to < 28	6	699	8.4	1,180	15.0
Near Gale	> 28 to < 34	7	267	3.2	1,748	22.3
Gale	> 34 to < 41	8	30	0.4	1,456	18.5
Strong Gale	> 41 to < 48	9	3	< 0.1	970	12.4
Storm	> 48 to < 56	10	1	< 0.1	537	10.7
Violent Storm	> 56 to < 44	11	0	0.0	225	2.9
Hurricane	> 64	12	0	0.0	100	1.3
Total			8,323	100	7,852	100

The alternative view, from a strictly rational economic perspective, is that psychology and mood are irrelevant. Rational investors are hard hearted. Their economic decisions are not swayed by swings in mood. After all, cash is cash. Thus, the results reported in this study are susceptible to two interpretations. First, they are truly anomalous for the reason just espoused. Second, the results reflect human behavior and are not anomalous. We are content to leave the resolution of this debate to others.

The degree that the results reported in this study extend to security markets in other economies with different climates is uncertain. Further research is necessary. We incline to the view that the weather conditions in other cities where stock exchanges are located will be multifaceted. Whether the facets are identical to those observed in Wellington is a question for further research. We suspect, given the prior research, that cloud cover will be an international weather facet. (See the correlations reported by Saunders, 1993.) The degree that facets capturing temperature and windiness, or other facets, are present in the weather experienced by other cites remains to be seen.

A pressing question is whether there is an international effect, in terms of the influence of the weather facets on stock returns, that is uniform across all economies. The research into the influence of cloud cover on stock returns, clearly one of the facets of weather, provides an insight. This research can be interpreted in two ways. One proposition is that a universal effect exists. Hirshleifer and Shumway (2003) aggregate all their data (92,445 days) and show, on average, a significant negative influence. The alternative, behaviorally oriented, hypothesis is that the relation between stock returns and weather facets is specific to the location. That is, distinctive weather conditions lead to unique relationships. A strict, one by one, assessment of the results of Hirshleifer and Shumway (2003) shows that the returns for 22 of the 26 stock exchanges are not significantly (p = 0.05) influenced by cloud cover. A similar conclusion is reached by others (Trombley, 1997; Kramer and Runde, 1997; Pardo and Valor, 2003; Loughran and Schultz, 2003; Goetzmann and Zhu, 2003).

We wonder about the degree that the WIND effect we observe on stock returns is a unique reflection of the weather experienced in Wellington. Few would deny the proposition that Wellington, the capital city of New Zealand, has its own special weather features. We are, of course, making an indirect reference to its bracing and refreshing winds.

References

1. Duncan, D.B., "t-tests and Intervals for Comparisons Suggested by the Data," *Biometrics*, 31 (1975), pp. 339-359.

2. Engle, R.F., "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation," *Econometrica*, 50, no. 4 (July 1982), pp. 987-1007.

3. Goetzmann, W.N., and N. Zhu, "Rain or Shine: Where is the Weather Effect," working paper 9465, National Bureau Economic Research, Cambridge, MA (2003).

4. Green, C., "Wind Gusts and Receipt of Parking Tickets," unpublished manuscript, Department of Psychology, University of Lethbridge (1994).

5. Jarque, C.M., and A.K. Bera, "Efficient Tests for Normality, Homoskedasticity and Serial Independence of Regression Residuals," *Economics Letters*, 6 (1980), pp. 255-259.

6. Hirshleifer, D., and T. Shumway, "Good Day Sunshine, Stock Returns and the Weather," *Journal of Finance*, 58, no. 3 (June 2003), pp. 1009-1062.

7. Kramer, W., and R. Runde, "Stocks and the Weather: An Exercise in Data Mining or Yet Another Capital Market Anomaly?" *Empirical Economics*, 22, no. 4 (1997), pp. 637-641.

8. Loughran, T., and P. Schultz, "Weather, Stock Returns and the Impact of Localized Trading Behavior," *Journal of Financial and Quantitative Analysis*, forthcoming (2003).

9. Mooney, C.Z., and R.D. Duval, *Bootstrapping: A Nonparametric Approach to Statistical Inference, Sage University Papers on Quantitative Applications in the Social Sciences*, 07-095 (Newbury Park, California: Sage Publications, 1993).

10. Newey, W., and K. West, "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55, no. 3 (May 1987), pp. 703-708.

11. Noreen, E.W., *Computer Intensive Methods for Testing Hypotheses: An Introduction* (New York, New York: John Wiley and Sons, Inc., 1989).

12. Norusis, M.J., *SPSS Base System User's Guide* (Chicago, Illinois: SPSS Inc., 1990).

13. Pardo, A., and E. Valor, "Spanish Stock Returns: Where is the Weather Effect?" *European Financial Management*, 9, no. 1 (March 2003), pp. 117-126.

14. Ponech, S., S. Williams, and S. Schmidt, "Wind Gusts and Motor Vehicle Accidents," unpublished manuscript, Department of Psychology, University of Lethbridge.

15. Sandilands, M.L., "Psychology of the Wind," paper presented at the annual convention of the Canadian Psychological Association (Charlottetown, June, 1995). See, also, abstract in *Canadian Psychology/Psychologie Canadienne,* 36, no. 2a (1995), p. 138.

16. Saunders, E.M., "Stock Prices and Wall Street Weather," *American Economic Review*, 83, no. 5 (December 1993), pp. 1337-1345.

17. Sandilands, M.L., and G. Christman, "The Effect of Weather Variables and Month on Frequency of Calls to a Crisis Line and Visits to an Emergency Ward," paper presented at the Annual Convention of the Canadian Psychological Association (June 1987).

18. Trombley, M.A., "Stock Prices and Wall Street Weather: Additional Evidence," *Quarterly Journal of Business and Economics*, 36, no. 3 (Summer 1997), pp. 11-21.

19. White, H., "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity," *Econometrica*, 48, no. 4(May 1980), pp. 817-838.

20. White, K.J., *SHAZAM User's Reference Manual Version 8.0* (New York, New York: McGraw-Hill, 1997).