University of Pretoria
Department of Economics Working Paper Series

Can Weather Conditions in New York Predict South African Stock Returns?

Nicholas Apergis
University of Piraeus
Rangan Gupta
University of Pretoria
Working Paper: 2016-34
April 2016

Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

Can weather conditions in New York predict South African stock returns?

Nicholas Apergis
Department of Banking and Financial Management, University of Piraeus
napergis@unipi.gr

Rangan Gupta
Department of Economics, University of Pretoria
Rangan.Gupta@up.ac.za

Can weather conditions in New York predict South African stock returns?

ABSTRACT

This paper investigates the explanatory power of certain weather variables, measured as deviations from their monthly averages, in a leading international financial trading centre, i.e., New York, for South African stock returns, over the daily period January 2nd, 1973 to December, 31, 2015. The empirical results highlight that these unusual deviations of weather variables have a statistically significant negative effect on the stock returns in South Africa, indicating that unusual weather conditions in New York can be used to predict South African stock returns, which otherwise seems to be highly unpredictable.

Keywords: Unusual weather conditions; New York weather; South African stock market

JEL Classification: C22; G10; G15

1. Introduction

Predictability of stock returns is important for practitioners in finance for asset allocation, while academics in finance are also interested in stock return predictability, since it has important implications for market efficiency, which in turn, helps to produce more realistic asset pricing models (Rapach et al., 2013; Rapach and Zhou, 2013; Neely et al., 2014). However, stock returns prediction is highly challenging, given that it inherently contains a sizable unpredictable component (Rapach and Zhou, 2013). Not surprisingly, the international evidence of predicting stock returns is highly varied, with results contingent on models, variables, sample periods and countries under consideration (see, Aye et al., (forthcoming) for a detailed literature review). In light of this, the evidence for South African stock returns predictability, based on domestic and international macroeconomic and financial variables, is mixed as well. While studies like Gupta and Modise (2012a,b, 2013),

Aye et al., (2013), Wen et al., (2015), and Sousa et al., (2016) find very limited evidence of stock returns predictability, Gupta et al. (forthcoming) and Balcilar et al. (forthcoming), respectively, find that stock returns are predictable only to a certain degree, when Bayesian predictive regressions (which use many predictors simultaneously in the predictive regression model) and nonparametric quantile methodologies are employed. However, more recently, Balcilar et al. (2015) have challenged the positive results of these studies by using Bayesian graphical models, which allow not only the employment of many predictors in the modelling approach, but also to analyze the role of contemporaneous, as well as lagged predictors.

Against this backdrop of mixed evidence, the objective of this paper is to analyse the ability of weather variables, such as temperature, cloud coverage, and rain precipitation, in a leading international financial trading centre, namely New York (NY), in explaining movements in South African daily stock returns, spanning the period January 2nd, 1973 to December, 31st, 2015. There exists a voluminous international literature, which has primarily analysed the impact of weather conditions in a specific country on its own stock returns (see, Apergis et al., 2016 for a literature review). This literature has grown in recent years with advances in the identification of weather variables that affect financial market performance. Additionally, some studies for the US economy, among others, are: Saunders (1993); Hirsshleifer and Shumway (2003); Kamstra et al., (2000, 2003); Kliger and Levy (2003); Cao and Wei, (2005a); and Garrett et al., (2005). Moreover, there is also an extant literature which extends to markets outside the US, covering both European and Asian markets (Krämer and Runde, 1997; Hirshleifer and Shumway, 2003; Keef and Roush, 2003, 2005; Pardo and Valor, 2003; Cao and Wei, 2004, 2005b; Loughran and Schultz, 2004; Tufan and Hamarat, 2004; Chang et al., 2006; Dowling and Lucey, 2008; Kang et al., 2009; Zahorozhna, 2009; Floros, 2011; Lee and Wang, 2011; Kaustia and Rantapuska, 2012). Goetzmann and Zhu (2005) extended the analysis of weather effects to multiple regional trading centres in the US economy. In general, these studies conclude that unusual weather conditions, i.e., measured as deviations from a number of average conditions, have a significant negative impact on stock returns.

In a recent paper, Apergis et al. (2016) add to this intriguing body of work by analysing the impact of (unusual) weather conditions in two of the major equity market centres, i.e. New York and London, on 58 international equity market indexes.

Using a wide range of weather indicators, their paper confirms that (unusual) weather conditions can affect global stock markets. The goal of this paper is to conduct the analysis for South Africa – a country for which the evidence in favour of stock returns predictability based on standard macroeconomic and financial variables is weak. The analysis primarily aims to explore whether weather variables can play a role in explaining South African stock returns. However, unlike Apergis et al. (2016), this paper only concentrates on the New York weather, since unusual weather condition in London did not seem to have any significant impact on South African stock returns.[1]

At this stage, the question which arises is on what are the theoretical channels through which unusual weather conditions in a major international trading centre can affect overseas stock returns? The link between weather variables and stock markets is primarily based either on mood-related mechanisms, whereby a good mood implies increased trading, or on 'leverage effects' (Apergis et al., 2016). However, Apergis et al., (2016) also point out two other important channels to explain the interconnection between these two variables: (a) retail sales, and (b) energy prices.

Unusual weather has an impact on energy prices, which in turn, may affect the demand for energy, leading to changes in oil, natural gas or coal prices, and consequently, to fluctuating electricity prices. Eksi et al. (2012) argue that since oil constitutes a substantial input for many industries, increases in oil prices lead to economic crises by creating significant cost-push inflation and higher unemployment. These effects tend to undermine the willingness of both investors and portfolio managers to invest in excessively risky (in a sense of buying overvalued) assets, such as stocks. An energy importer like South Africa would in this case naturally suffer. In particular, both mining and agriculture are the most affected since production patterns cannot be shifted. Therefore, one might expect that the South African equity market with a lot of strength in these two areas might be susceptible to international weather variations. As far as the negative impact of extreme weather on retail sales channel is concerned, as it was put forward by Starr-McCluer (2000), this route discusses the effects on income and the wealth of potential investors, as well as on the investment decisions of portfolio managers who try to avoid investing in excessively risky assets across the globe.

[1] Complete details of the effect of the weather condition in London on South African stock returns is available upon request from the authors.

Hence, whether it is the mood related channel or the channels of energy prices and retail sales, theoretical arguments suggest that extreme weather conditions in an international well-established financial centre are likely to negatively impact the South African stock returns, given that this particular capital market is considered to be a good portfolio diversification option, along with other emerging markets, such as Brazil, Russia, India, and China (Mensi et al., 2014; forthcoming).

The remainder of the paper is organised as follows: Section 2 describes the data used in the empirical study, while Section 3 provides the empirical findings. Finally, Section 4 concludes the paper.

2. Data

The analysis makes use of the South African stock market price index to identify the impact of weather conditions observed in New York on stock market returns as they are derived through the South African stock market index. The data set provides daily closing price levels (P), while a time-series of stock returns (*r*) is calculated as: $r_t = 100 \times [lnP_t - lnP_{t-1}]$, with P_t being the index level at the end of day *t*, spanning the daily sample period from January 2nd, 1973 to December, 31st, 2015. Data on the price index were obtained from Datastream.

The Accuweather.com site provides daily weather observations, including daily temperatures, humidity, wind speed, rainfall/precipitation and cloud cover, obtained from 75 meteorological stations in New York City, installed within and in the neighboring areas of the metropolitan city. The primary explanatory variables are in relevance to the following weather elements extracted on a daily basis: precipitation (mm), relative humidity (%), average daytime temperature (˚C), the percentage covered by clouds (n), and the average daytime wind speed (km/h). As in Dowling and Lucey (2008) and Symeonidis et al. (2010), due to the highly seasonal nature of the weather variables, the analysis deseasonalises the weather variables under consideration by subtracting from each observation its weekly average. Magnitudes of deviations are then calculated as the absolute deseasonalised values for these weather variables from their (normal) monthly average.

3. Empirical analysis

A model for the stock (returns) index yields:

$$r_t = b_o + b_1 dt_t^{NY} + b_2 r_{t-1} + b_3 r_{t-1}^{NY} + b_4 dpr_t^{NY} + b_5 dh_t^{NY} + b_6 dcl_t^{NY} + \\ + b_7 dw_t^{NY} + b_8 MON_t + b_9 JAN_t + b_{10} HAL_t + b_{11} SAD_t + e_t \quad (1)$$

where r indicates the returns series in the South African market, dt^{NY} denotes the deviations of the NY temperature from its (normal) average monthly value, r^{NY} is the return series in the NY market, dpr^{NY} is the deviations of the NY rain precipitation from its (normal) average monthly value, dh^{NY} denotes the deviations of the humidity in NY from its (normal) average monthly value, dcl^{NY} is the deviations of the cloudiness cover hours in NY from its (normal) average monthly value, dw^{NY} is the deviations of the wind speed in NY from its (normal) average monthly value, and e is the error term. We have also explicitly introduced NY returns as explanatory variables in (1) based on Lee and Rui (2002) arguments, which provide solid evidence that the NY stock market contains extensive explanatory strength to generate spillover effects on other capital markets. MON denotes the Monday effect, JAN describes the January effect, HAL denotes the Halloween effect, and, finally, SAD denotes the seasonal affective disorder effect.

According to the related literature, the expected signs on the estimated coefficients are: precipitation (-), humidity (-), average daytime temperature (-), cloudiness cover (-), and, average daytime wind speed (-). Moreover, when it comes to deviations from average values (i.e., unusual weather conditions), we hypothesise that the signs would be negative, proxying higher uncertainty.

The model also controls for potential calendar effects, which are changes, or trends, in security prices occurring at a regular interval or at a specific time in the calendar year. The presence of such anomalies may enable market participants to beat the market by observing such patterns; Bowman and Buchanan (1995) suggest evidence against market efficiency. Some studies (Cooper et al., 2006) have documented a January effect, whereby stocks exhibit an unusually large positive return during the first few trading days of the year. Poterba and Weisbenner (2001) attribute the January effect to the tax-loss selling hypothesis, whereby investors sell stocks at the end of the year for tax purposes, which leads to lower year-end stock

prices and subsequent higher returns in January. In our case, we control for the documented end of tax-year effect by introducing a dummy-variable, which takes a value of one for the first ten days of the taxation year and zero otherwise; the tax year in the South African economy starts on January 1.

In addition, a particular calendar anomaly, known as the Halloween effect, which was identified by Bouman and Jacobsen (2002) who label this anomaly the Halloween effect, as October 31 marks the end of the 'scary period' for investors, is also introduced in model (1). In particular, the authors conclude that stock returns are significantly lower during the May-October periods versus the November-April period, while they propose a trading strategy to exploit this anomaly. The Halloween effect amounts to a 'Sell in May and go away' strategy. The strategy is described as investing in a value-weighted index over the November-April period and in a risk-free investment over the May-October period. According to the Halloween Indicator (HI), the month of May signals the start of a bear market, so that investors are better off with their stocks. The Halloween effect takes the value of 1 if the daily observation falls within the November-April period, and 0 if it falls within the May-October period.

In addition, the extant literature has also identified a day-of-the-week effect, with Monday as the only day of the week consistently averaging negative rates of return. There is some evidence though that the effect has disappeared. Hansen et al. (2005) find that the Monday effect, albeit statistically weakened, is still there, with their explanation involving issues around settlement, dividends, and taxes. In order to control for the Monday effect, a dummy variable is defined, which takes a value of one if the trading day is a Monday, and zero otherwise. Finally, Kamstra et al. (2003) argue that a psychological condition, called Seasonal Affective Disorder (SAD), drives changes in the risk aversion of the marginal investor. SAD is a mood disorder in which individuals suffer from depression as a result of fewer daylight hours in fall and winter. The authors argue that the onset of seasonal depression results in greater risk aversion in the affected subset of investors, who therefore sell stocks, decreasing prices in the fall as the days get shorter. As the days lengthen and the mood of these seasonally depressed investors improves in winter, they buy stocks, driving up their prices. The SAD index is measured as [Dfall-winter] x len_{it}, where Dfall-winter is a

fall-winter dummy and len is the normalized number of hours of night, which depends on the latitude δ of a country's stock exchange.

The first step of the empirical analysis investigates the correlation coefficients in order to assess whether the weather variables are highly correlated to one another, which could generate invalid estimations. The results are reported in Table 1 and they highlight that the size of such correlation coefficients never exceeds 0.27, which does not impose any restriction to the model equation (1) not to include all weather variables simultaneously.

[Insert Table 1 about here]

The estimations of equation (1) are reported in Table 2. The table reports two variants of estimations for equation (1), the first without the stock market calendar effects, and the second that includes those effects. The empirical findings indicate that the weather variables exert a statistical significant effect on stock returns. In terms of the temperature deviations variables, the relationship turns out to be negative; similarly, in terms of the precipitation variables, the findings indicate that the deviations of that weather metric from its monthly average also exert a negative and statistically significant effect on stock returns. In terms of the humidity weather variables, the effect also turns out to be negative and statistically significant; finally, the cloud cover variable has also a negative, and statistically significant, impact on stock returns. The same findings also hold for the wind variable, illustrating the presence of a negative effect on equity returns.

All calendar-effect variables carry the expected signs, albeit they turn to be statistically insignificant in the cases related to the Halloween effect and the SAD effect. The own stock returns variable is positive and statistically significant, indicating high persistent effects, while NY stock returns exert a positive and statistically significant effect on local stock returns, highlighting strong spillovers from the NY financial center onto local stock returns, and, thus, supporting the presence of a strong association between the NY and the South African stock markets (Li, 2007; Chan et al., 2008).

[Insert Table 2 about here]

We could also argue that there could be a temperature effect on both ends. In other words, not only do lower than usual temperatures require more heating, but also higher than usual temperatures also require more cooling (i.e., A/C, cooling of perishable goods etc). To this end, we re-estimate equation (1) by decomposing the distribution of the weather variables at their various respective quantiles to identify which part of the range of weather variables has a stronger impact on stock returns.

These robustness results are reported in Table 3 for three regions of quantiles, where the first one (i.e., 0-0.20) and the third one (i.e., 0.80-1) represent the extreme regions of the distribution. The findings highlight that the weather variables in New York do impact South African stock returns at the lower and the upper ends of their distribution stronger than the medium (normal) quantile region, indicating that not only deviations of weather conditions from their monthly mean do seem to affect stock returns, but also that extreme weather deviations can affect stock returns in a stronger manner.

[Table 3 about here]

In addition, the investigated weather effects could be different during the year. Therefore, we can also check out for this seasonal pattern by including interaction terms of the weather and seasonal dummies (winter/spring/summer). The new results, reported in Table 4, point out that the weather effect turns out to be significant only during the winter and the summer season time in which the likelihood of extreme deviations can be potentially and frequently occurred. The only exception is in relevance to the wind variable over the summer season, which seems to be statistical significant only at 10%.

[Table 4 about here]

3. Conclusion

This study identified the relationship between deviations of a number of weather variables from their normal/average conditions in a leading global financial centre, i.e., New York (NY), and stock market returns in South Africa. The empirical findings indicated that unusual weather conditions in NY had a statistically significant

negative effect on South African stock market returns. In other words, the results indicated that the link between stock returns and unusual weather conditions contained significant information on the cross-country risk premium.

This result has potentially important implications in the context of the South African stock returns predictability literature. With the existing evidence suggesting that domestic and global macroeconomic and financial variables generally do not contain any ability to predict South African stock returns, earlier studies have concluded that the market is possibly characterized by a random walk process. However, with weather conditions in New York affecting (predicting) stock returns in the South African capital market, we may conclude that the market in South Africa is probably not as efficient as deemed by the existing literature. In this regard, future research should investigate whether (unusual) weather variables, can be used to forecast South African (and other international) stock returns, since in-sample predictability does not guarantee the same over an out-of-sample horizon (Rapach and Zhou, 2013).

References

Apergis, N., Gabrielsen, A., & Smales, L.A. (2016). (Unusual) weather and stock returns—I am not in the mood for mood: further evidence from international markets. *Financial Markets and Portfolio Management*, 30, 63-94.

Aye, G.C., Gupta, R., & Modise, M.P. (2013). Structural breaks and predictive regressions models of South African equity premium. *Frontiers in Finance and Economics*, 10, 49-86.

Aye, G.C., Deale, F.W., & Gupta, R. (forthcoming). Does debt ceiling and government shutdown help in forecasting the US equity risk premium? *Panoeconomicus*.

Balcilar, M., Gupta, R., Modise, M.P, & Muteba Mwamba, J.W. (2015). Predicting South African equity premium using domestic and global economic policy uncertainty indices: Evidence from a Bayesian graphical model. Working Paper, No. 201596, Department of Economics, University of Pretoria.

Balcilar, M., Gupta, R., & Kyei, C. (forthcoming). South African stock returns predictability using domestic and global economic policy uncertainty: Evidence from a nonparametric causality-in-quantiles approach. *Frontiers in Finance and Economics*.

Bouman, S., & Jacobsen, B. (2002). The Halloween indicator, 'sell in May and go away: Another puzzle. *American Economic Review*, 92, 1618-1635.

Bowman, R., & Buchanan, J. (1995). The efficient market hypothesis-a discussion of institutional, agency and behavioural issues. *Australian Journal of Management*, 20, 2-19.

Cao, M., & Wei, J. (2004). Weather derivatives valuation and market price of weather risk. *Journal of Futures Markets*, 24, 1065-1089.

Cao, M., & Wei, J. (2005a). Stock market returns: A note on temperature anomaly. *Journal of Banking & Finance*, 29, 1559-1573.

Cao, M., & Wei, J. (2005b). An expanded study on the stock market temperature anomaly. *Research in Finance*, 22, 73-112.

Chan, L., Lien, D., & Weng, W. (2008). Financial interdependence between Hong Kong and the US: A band spectrum approach. *International Review of Economics and Finance*, 17, 507-516.

Chang, T., Nieh, C.C., Yang, M.J., & Yang, T.Y. (2006). Are stock market returns related to the weather effects? Empirical evidence from Taiwan. *Physica A: Statistical Mechanics and its Applications*, 364, 343-354.

Cooper, M., McConnell, J., & Ovtchinnikov, A. (2006). The other January effect. *Journal of Financial Economics*, 82, 315-341.

Dowling, M., & Lucey, B.M. (2008). Robust global mood influences in equity pricing. *Journal of Multinational Financial Management*, 18, 145-164.

Eksi, H.I., Senturk, M., & Yildirim, S.H. (2012). Sensitivity of stock market indices to oil prices: Evidence from manufacturing sub-sectors in Turkey. *Panoeconomicus*, 59, 463-474.

Floros, C. (2011). On the relationship between weather and stock market returns. *Studies in Economics and Finance*, 28, 5-13.

Garrett, I., Kamstra, M.J., & Kramer, L.A. (2005). Winter blues and time variation in the price of risk. *Journal of Empirical Finance*, 12, 291-316.

Goetzmann, W.N., & Zhu, N. (2005). Rain or shine: where is the weather effect?. *European Financial Management*, 11, 559-578.

Gupta. R., & Modise M.P. (2012a). Valuation ratios and stock price predictability in South Africa: Is it there? *Emerging Markets Finance and Trade*, 48, 70-82.

Gupta. R., & Modise M.P. (2012b). South African stock return predictability in the context of data mining: The role of financial variables and international stock returns. *Economic Modelling*, 29, 908-916.

Gupta. R., & Modise M.P. (2013). Macroeconomic variables and South African stock return predictability. *Economic Modelling*, 30, 612-622.

Gupta. R., Modise. M. P., & Uwilingiye. J. (forthcoming). Out-of-sample equity premium predictability in South Africa: Evidence from a large number of predictors. *Emerging Markets Finance and Trade*.

Hansen, P.R., Lunde, A., & Nason, J.M. (2005). Testing the significance of calendar effects. Federal Reserve Bank of Atlanta, Working Paper, No. 2005-2.

Hirsshleifer, D., & Shumway, T. (2003) Good day sunshine: Stock returns and the weather. *Journal of Finance*, 58, 1009-1032.

Kamstra, M.J., Kramer, L.A., & Levi, M.D. (2003). Winter blues: A SAD stock market cycle. *American Economic Review*, 93, 324-333.

Kamstra, M.J., Kramer, L.A., & Levi, M.D. (2000). Losing sleep at the market: The daylight saving anomaly. *The American Economic Review*, 90, 1005-1011.

Kang, S.H., Jiang, Z., & Yoon, S.M. (2009). Weather effects on the returns and volatility of Hong Kong and Shenzhen stock markets. Working Paper, Korea Research Foundation.

Kaustia, M., & Rantapuska, E. (2013). Does mood affect trading behavior? Working Paper, No. 4. SAFE Working Paper Series.

Keef, S.P., & Roush, M.L. (2005). Influence of weather on New Zealand financial securities. *Accounting & Finance*, 45, 415-437.

Keef, S.P., Roush, M.L. (2002). The weather and stock returns in New Zealand. *Quarterly Journal of Business and Economics*, 61-79.

Kliger, D., Levy, O. (2003). Mood and judgment of subjective probabilities: evidence from the US index option market. *European Finance Review*, 7, 235-248.

Krämer, W., & Runde, R. (1997). Stocks and the weather: An exercise in data mining or yet another capital market anomaly? *Empirical Economics*, 22, 637-641.

Lee, B.S., & Rui, O.M. (2002). The dynamic relationship between stock returns and trading volume: Domestic and cross-country evidence. *Journal of Banking and Finance*, 26, 51-78.

Lee, Y.M., & Wang, K.M. (2011). The effectiveness of the sunshine effect in Taiwan's stock market before and after the 1997 financial crisis. *Economic Modelling*, 28, 710-727.

Li, H. (2007). International linkages of the Chinese stock exchanges: A multivariate GARCH analysis. *Applied Financial Economics*, 17, 285-297.

Loughran, T., & Schultz, P. (2004). Weather, stock returns, and the impact of localized trading behaviour. *Journal of Financial and Quantitative Analysis*, 39, 343–360.

Mensi, W., Hammoudeh, S., Reboredo, J.C., & Nguyen, D.K. (2014). Do global factors impact BRICS stock markets? A quantile regression approach. *Emerging Markets Review*, 19, 1-17.

Mensi, W., Hammoudeh, S., Yoon, S-M, & Nguyen, D.K. (forthcoming). Asymmetric linkages between BRICS stock returns and country risk ratings: Evidence from dynamic panel Threshold models. *Review of International Economics*.

Neely. C., Rapach D., Tu. J., & Zhou. G. (2014). Forecasting the equity risk premium: The role of technical indicators. *Management Science*, 60, 1772–1791.

Pardo, A., & Valor, E. (2003). Spanish stock returns: Rational or weather-influenced? *European Financial Management*, 9, 117-126.

Poterba, J.M., & Weisbenner, S.J. (2001). Capital gains, tax rules, tax-loss trading, and turn-of- the-year returns. *The Journal of Finance*, 56, 353-368.

Rapach. D., Strauss. J., & Zhou. G. (2013). International stock return predictability: What is the role of the United States? *Journal of Finance*, 68, 1633–1662.

Rapach, D., & Zhou, G. (2013). Forecasting stock returns. In Rapach, D.E, & Zhou, G. *Handbook of Economic Forecasting, Volume 2A*. Graham Elliott and Allan Timmermann (Eds.) Amsterdam: Elsevier, 328-383.

Saunders, E.M. (1993). Stock prices and Wall Street weather. *American Economic Review*, 83, 1337-1345.

Sousa, R.M., Vivian, A., & Wohar, M.E. (2016). Predicting asset returns in the BRICS: The role of macroeconomic and fundamental predictors. *International Review of Economics & Finance*, 41, 122-143.

Starr-McCluer, M. (2000). The effects of weather on retail sales. Divisions of Research & Statistics and Monetary Affairs, Federal Reserve Board.

Symeonidis, L., Daskalakis, G., & Markellos, R.N. (2010). Does the weather affect stock market volatility? *Finance Research Letters*, 7, 214-223.

Tufan, E., & Hamarat, B. (2004). Do cloudy days affect stock exchange returns: Evidence from Istanbul stock exchange. *Journal of Naval Science and Engineering*, *2*, 117-126.

Wen, Y.C., Lin, P.T., Li, B., & Roca, E. (2015). Stock return predictability in South Africa: The role of major developed markets. *Finance Research Letters*, 15, 257-265.

Zadorozhna, O. (2009). Does weather affect stock returns across emerging markets? Doctoral dissertation, Kyiv School of Economics, Kyiv, Ukraine.

Table 1

Pearson correlation coefficients for the weather variables

	dtNY	dprNY	dhNY	dwNY	dsunNY
dtNY	1	0.16	0.24	0.27	0.21
		[0.09]	[0.05]	[0.05]	[0.07]
dprNY		1	0.26	0.22	0.23
			[0.04]	[0.06]	[0.05]
dhNY			1	0.20	0.19
				[0.05]	[0.05]
dwNY				1	0.14
					[0.11]
dsunNY					1

Note: Figures in brackets denote p-values.

Table 2

Estimates of returns regressions-equation (1)

Variables	Model without calendar dummies	Model with calendar dummies
dt_t^{NY}	-0.164***	-0.142***
	[0.00]	[0.00]
r_{t-1}	0.564***	0.516***
	[0.00]	[0.00]
r_{t-1}^{NY}	0.352***	0.319***
	[0.00]	[0.01]
dpr_t^{NY}	-0.039**	-0.030**
	[0.04]	[0.05]
dh_t^{NY}	-0.034**	-0.028**
	[0.05]	[0.05]
dcl_t^{NY}	-0.134***	-0.109***
	[0.00]	[0.00]
dw_t^{NY}	-0.055**	-0.046**
	[0.04]	[0.05]
MON		-0.039**
		[0.05]
JAN		-0.049***
		[0.00]

Table 2 continued

HAL		0.011
		[0.40]
SAD		0.018
		[0.29]
R^2-adjusted	0.31	0.39

Notes: Dependent variable = r_t. r = the return series, dt^{NY} = the deviations of the temperature values from the monthly average in NY, dpr^{NY} = the deviations of the precipitation values from the monthly average in NY, dh^{NY} = the deviations of the humidity values from the monthly average in NY, dw^{NY} = the deviations of the wind speed values from the monthly average in NY, $dsun^{NY}$ = the deviations of the percentage covered by clouds from the monthly average in NY, MON, JAN, HAL, SAD = the dummies capturing the Monday, the January, the Halloween effect and the SAD effect, respectively. Figures in brackets denote p-values. ***, ** denote statistical significance at 1% and 5%, respectively.

Table 3

Quantile estimates of the weather variables

Quantiles	dt^{NY}	dpr^{NY}	dh^{NY}	dw^{NY}	dcl^{NY}
0.10-0.19	-0.171***	-0.056**	-0.049**	-0.062**	-0.147***
	[0.00]	[0.03]	[0.04]	[0.03]	[0.00]
0.20-0.79	-0.106***	-0.038**	-0.031**	-0.040**	-0.123***
	[0.01]	[0.05]	[0.05]	[0.05]	[0.00]
0.80-0.99	-0.168***	-0.063**	-0.038**	-0.059**	-0.159***
	[0.00]	[0.03]	[0.05]	[0.03]	[0.00]

Notes: Figures in brackets denote p-values. S, W and SU denote seasonal dummies related to spring, winter and summer seasons, respectively. **, *** denote statistical significance at 5% and 1%, respectively.

Table 4

Estimates of returns regressions-equation (1) [with interaction terms]

Variables	Coefficients	p-values
dt_t^{NY}	-0.138***	[0.00]
r_{t-1}	0.485***	[0.00]
r_{t-1}^{NY}	0.306***	[0.01]
dpr_t^{NY}	-0.027**	[0.05]
dh_t^{NY}	-0.024**	[0.05]
dcl_t^{NY}	-0.094***	[0.00]
dw_t^{NY}	-0.041**	[0.05]
MON	-0.035**	[0.05]
JAN	-0.044***	[0.00]
HAL	0.006	[0.49]
SAD	0.013	[0.38]
dt_t^{NY}xDwinter	-0.189***	[0.00]
dt_t^{NY}xDspring	-0.061*	[0.09]
dt_t^{NY}xDsummer	-0.156***	[0.00]
dpr_t^{NY}xDwinter	-0.049***	[0.01]
dpr_t^{NY}xDspring	-0.008	[0.29]
dpr_t^{NY}xDsummer	-0.037***	[0.00]
dh_t^{NY}xDwinter	-0.052***	[0.01]

Table 4 continued

dh_t^{NY}xDspring	-0.028**	[0.05]
dh_t^{NY}xDsummer	-0.040***	[0.01]
dcl_t^{NY}xDwinter	-0.128***	[0.00]
dcl_t^{NY}xDspring	-0.055*	[0.10]
dcl_t^{NY}xDsummer	-0.074**	[0.04]
dw_t^{NY}xDwinter	-0.070***	[0.01]
dw_t^{NY}xDspring	-0.026**	[0.05]
dw_t^{NY}xDsummer	-0.021*	[0.09]
R^2-adjusted	0.44	

Notes: Dwinter, Dspring and Dsummer denote the seasonal dummies (i.e., winter, spring and summer, respectively), while * denotes statisticl significance at 10%. The remaining notes are similar to those in Table 2.