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THE RELATIONSHIP BETWEEN HUMAN BEHAVIOR AND STOCK RETURNS IN EFFICIENT STOCK MARKETS: THE MOOD-EFFECT UNDER A CULTURAL PERSPECTIVE

ZWIĄZEK POMIĘDZY LUDZKIM ZACHOWANIEM A ZWROTEM Z AKCJI NA EFEKTYWNYCH GIEŁDACH: EFEKT NASTROJÓW W PERSPEKTYWIE KULTUROWEJ

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Summary: This paper examines the relationship between stock return and human behavior in ten well-established stock exchanges, from a monthly data sample from January 1991 to December 2015. The results show that there is no sufficient evidence to generalize the impact of human behaviour on common stock return, through mood state altered by weather variables. When the substance of the underlying process (i.e. the weather alters the mood state) is established by logit regression, the results reveal that there is a bias in the variable selection as regressors, which is subject to the metrological situation of each country (or region). As such, collectivism does not appear to be an explanatory variable of the magnitude of price changes, as a variable uncontrolled for in the regression. Although the null hypothesis is accepted for four countries in the sample, the findings do not warrant researchers to generalize the effect of human behavior on stock price changes through weather variables, for a large population.

Keywords: efficient markets, stock returns, culture, weather variables, OLS regression, logit regression.

Streszczenie: W tym artykule zbadano związek między zwrotem z akcji a ludzkim zachowaniem na przykładzie dziesięciu uznanych giełd, opierając się na miesięcznej próbce danych z okresu od stycznia 1991 r. do grudnia 2015 r. Wyniki pokazują, że nie ma wystarczających dowodów, aby uogólnić wpływ ludzkich zachowań wywołanych zmiennymi warunkami pogodowymi na zwrot z akcji zwykłych. Gdy zasada leżąca u podstaw procesu (tzn. pogoda zmienia stan nastroju) jest ustalana przez regresję logitów, wyniki ujawniają, że w wyborze zmiennych jako regresorów występuje nastawienie zależne od sytuacji metrologicznej każdego z krajów (lub regionów). Kolektywizm jako taki nie wydaje się zmienną wyjaśniającą wielkość zmian cen jako zmienną niekontrolowaną w regresji. Chociaż hipoteza zerowa w badanej próbie została przyjęta dla czterech krajów, odkrycia te nie upoważniają badaczy do uogólnienia wpływu ludzkich zachowań na zmiany cen akcji przez zmienne pogodowe, dla dużej populacji.

Słowa kluczowe: efektywne rynki, zwrot z akcji, kultura, zmienne pogodowe, regresja OLS, regresja logit.

1. Introduction

The efficient market hypothesis of Fama [1965] suggests that stock price changes are independent and determined by new information available to investors at any given point in time. Studies in the section of behavioral finance demonstrate that human psychology influences the behavior of investors (see [Shleifer 2000]). Variables such as depression, aggression, anxiety, control, optimism, concentration and co-operation that determine human mood could be proxied by weather variables [Howarth, Hoffman 1984] and the relationship between weather and human behavior has been a long-established phenomenon in the literature (see eg [Allen, Fischer 1978; Bell, Baron 1976; Cunningham 1979; Howarth, Hoffman 1984; Linning et al. 2016; Mares, Moffett 2016; Moos 1975; Parsons 2001; Pilcher et al. 2002; Rind 1996; Sanders, Brizzolara 1982; Schneider et al. 1980; Watson 2000; Wyndham 1969].

Meteorological factors such as sunshine, wind, rain and temperature have been shown to provide some predictive power of stock returns. In particular, scholars such as Saunders [1993] and Hirshleifer and Shumway [2003] show that weather influences stock price changes, and sunshine has been shown to have a good correlation with common stock returns (see eg [Hirshleifer, Shumway 2003; Keef, Roush 2007]. Moturu et al. [2011] suggest that people with a lower level of social interaction tend to exhibit a poor mood state. It is therefore expected that a bad/good mood-weather relationship may be altered by cultural dimensions and the effect of a bad mood-weather relationship on human behavior may be offset in collectivist cultures.

Scholars suggest that the prominent dimension for distinguishing different national cultures is collectivism–individualism (see [Hofstede 2001; Triandis 1990]). In collective cultures, *individuals belong to 'in groups' that take care of them in exchange for loyalty and define self-image interims of "WE" instead of "I"* *whereas in individualistic societies people are supposed to look after themselves and their direct family only* [Hofstede Insights 2017]. De Jong and Semenov [2002] demonstrate that cultural elements such as uncertainty avoidance and higher levels of masculinity have an impact on equity market development. Therefore, important cultural dimensions such as individualism and collectivism must be considered in order to ascertain whether human behavior determines the magnitude of price changes. The scholars supporting the influence of weather on stock return omitted the significance of cultural influences on the mood state of individual investors. Moreover, they have disregarded the substance between the weather and the mood state of investors in establishing the relationship between human behaviour (alerted by the mood state) and common stock returns. This study therefore invokes the substance between the weather and the mood state by employing logit regression principles and considers individualism and collectivism as important cultural dimensions in examining the relationship between human behavior and stock returns. The findings and suggestions of this study will be useful for market analysts, fund managers and investment advisors to put forward their investment advisory work with justifiable reasons as to what behavioural factors need to be taken into account, in addition to quantitative assessments.

The main objective of this paper is to examine whether human behavior influences the stock returns of ten well-established stock exchanges. The conceptual model will be extended to include the most significant variables (i.e. cultural variables) that effect human behavior, through mood state, in addition to weather variables. The results show that there is no sufficient evidence to generalize the impact of human behaviour on stock returns through the mood state altered by weather variables. The results also reveal that there is a bias in metrological variable selection, when the substance of the underlying relationship between weather and mood is invoked in the regression.

The paper is organized as follows. Section 2 outlines the research model in detail and provides a brief description about the data and sample selection. Section 3 discusses the findings of the study and Section 4 provides the concluding remarks.

2. Research method

Following the basic regression idea of Hirshleifer and Shumway [2003], the return is regressed on meteorological variables in a linier relationship such that $r_i = f(Temperature, Rain)$, where the noise on all uncontrolled determinants of return is lumped into the error term, given the information set I available to investors at time t and r_i denotes return of country i. However, the empirical model is designed to consider temperature as the key variable predicting stock return. Hirshleifer and Shumway [2003] consider *Sky cover* instead of temperature, *rain* and *snow* as additional variables to conclude the regression specification with three variables. Note that the number of directly uncontrolled variables in the model specification have an impact on regression specification, for example, cultural dimensions (i.e. individualism and collectivism), if ε_i qualifies for the best linier unbiased estimate for the true population parameter σ_i^2, which is assumed to be distributed as $\varepsilon_t | I_t \sim N(0, n\sigma^2)$[1]. Zhang et al. (2013) use an intuitively appealing methodology in examining the impact of interest rate on information flow interpretation without controlling for interest rate in the regression specification. A simple Ordinary Least Square (OLS) regression to model this phenomenon could be written as;

$$r_t = \alpha_0 + \beta_1 TEMP_t + \beta_2 RAIN_t + \psi EXCH_t + \lambda INT_t + \varepsilon_t, \tag{1}$$

where ε_t error term of the regression at time t – given the information set I available to investors – such that $\varepsilon_t \geq \varepsilon_{t-1} \geq \varepsilon_{t-2}$ ...*conditional* on I at time t. Specifically, $E(r_i | I_t) \geq 0$ because the price increments conditional on information set available to investors at time t are assumed to be positive[2] and an increasing function of time t. Of course, $E(\varepsilon_i | TEMP) = 0$ and $E(\varepsilon_i | RAIN) = 0$ as mean conditional on I at any observation time is simply zero[3] and the metrological variable of interest for the proxy is the temperature. That is to say, the price increments are completely random and determined only by the firm-specific information of all listed securities of exchange (see [Roll 1988; Tobin 1984]). $EXCH$ is the exchange rate and INT is the interest rate at the respective operational time.

Under null hypothesis of human behavior impacting stock price changes, β_1 should be statistically significant and negative[4]. In addition, the countries whose coefficient β_1 is negative and statistically significant should belong to individualistic societies (see Section 1 for reasoning). However, there have been many criticisms on regressing return on meteorological variables because the coefficient estimates may be subject to spurious correlation (see [Krämer, Runde 1997]). Normally when there is rain, the temperature is lower than on sunny days on average, and the temperature is higher when there is no or little rain under usual circumstances. As such, coefficient β_2 of variable $RAIN$ is introduced to test the tradeoff between weather and mood. Coefficient β_2 is expected to be statistically insignificant when the null hypothesis is accepted.

There is a possibility that the index return can be related to temperature, although the magnitude may not be significant. Hirshleifer and Shumway [2003]

[1] See [Senarathne 2017].

[2] This study is carried out on stock markets that are assumed to be efficient as null hypothesis reads.

[3] See e.g. Senarathne and Jayasinghe [2017] for a complete exposition.

[4] Cao and Wei [2005] provide a comprehensive discussion and analysis on the relationship between temperature and stock return together with its linkage to mood.

employ the following logit regression to understand the reasonableness of their meteorological variables of interest (note that the temperature is the variable of interest of this study):

$$Y_{1t} = \alpha_1 + \beta_3 TEMP_t + u_{1t} \quad (2)$$

and the corresponding probability estimate at unit variable is given by

$$P(r_{it} > 0) = \frac{e^{\alpha_1+\beta_3}}{e^{\alpha_1+\beta_3}+1}. \quad (3)$$

If the expected relationship (e.g. negative) between index return and weather is established, coefficient β_3 should be negative and statistically significant.

This specification omits the substance of the relationship between return and weather variables, particularly under adverse weather conditions. This regression issue could not be solved just by adding weather variables into the regression specification because the role of weather variables in the regression differs from one variable to another (e.g. rain vs. temperature).

The central problem of linear probability models is that it may produce predicted probabilities with > 1 or < 0 which may cast reasonable doubt about the relationship between mood and weather. In order to be satisfied with the specification above, the following logit regression model as specified – which offers a realistic picture of how mood responds to the changing circumstances of nonlinear nature – is used:

$$Y_{2t} = \alpha_2 + \beta_4 TEMP_t + u_{2t}, \quad (4)$$

where Y_2 is a dummy variable that must establish a positive relationship between Y and $TEMP$, if $TEMP$ is the right influential candidate for the mood state of individual investors. Y takes the value 1 when the $TEMP$ at time t is greater than the average $TEMP$ for the period AND $RAIN$ at time t is less than the average $RAIN$ for the period. Coefficient β_4 should be positive and statistically significant, if the $TEMP$ is appropriate for the regression as in (1) above. Maximum likelihood estimation (MLE) is used to estimate the parameters of the logit regression model as,

$$ln\left(\frac{p}{1-p}\right) = \alpha_2 + \beta_4 TEMP_t + u_{2t} \quad (5)$$

and the corresponding probability (p) of the estimates is given by,

$$\hat{p} = \frac{e^{\alpha_1+\beta_4}}{e^{\alpha_1+\beta_4}+1}, \quad (6)$$

where α_1 and β_4 are the estimates from the regression. If regression (1) is well specified, coefficient β_4 should be positive and statistically significant with an acceptable level of probability. The variable $TEMP$ may however significantly influence the mood state of individual investors in countries with significant weather variations. To identify any influence of this selection bias on the hull hypothesis of the study, the following logit regression is employed:

$$Y_{3t} = \alpha_3 + \beta_5 TEMP_t + u_{3t,} \tag{7}$$

where Y_3 is a dummy variable that takes the value 1 when the $TEMP$ at time t is greater than the average $TEMP$ for the period AND $RAIN$ at time t is less than the average $RAIN$ for the period AND the return is less than 0 (negative). If the expected relationship (negative) between $TEMP$ and return observations is established, β_5 should be positive and statistically significant with an acceptable level of probability.

3. Data

Monthly meteorological data[5] are obtained from the Climate Change Knowledge Portal (CCKP) webpage of the World Bank Group[6] over a twenty-five-year sampling period starting from 31st January 1991 (including January 1991) to 31st December 2015. Interest rates (average of government securities including discount rates) and exchange rates are obtained from the Federal Reserve Bank of St. Louis, https://fred.stlouisfed.org and the respective central banks' websites.
Stock market index data are obtained from the Yahoo Finance[7] webpage of Oath Inc. The list of exchanges and indices used are as follows:

1. Jakarta Stock Exchange Composite Index (JKSE).
2. Karachi Stock Exchange KSE100 Index (KSE100).
3. National Stock Exchange of India (NSEI-NIFTY 50).
4. Shanghai Stock Exchange (SSE Composite Index).
5. Euronext Amsterdam (AEX Index) – formerly known as the Amsterdam Stock Exchange.
6. Australian Securities Exchange (All Ordinaries Index).
7. Frankfurt Stock Exchange (CDAX Performance-Index).
8. New York Stock Exchange (NYSE Composite Index).
9. Philippine Stock Exchange (The PSE Composite Index).
10. Colombo Stock Exchange (All Share Price Index).

Five countries are selected from the list of countries whose Hofstede Score for individualism is greater than 60 and further five countries are selected from the countries with a score range between 0 to 40. Table 1 provides some empirical properties of the data set.

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[5] Usual units of measures are used.

[6] Available at http://sdwebx.worldbank.org/climateportal/index.cfm?page=downscaled_data_downloadandmenu=historical.

[7] Available at https://finance.yahoo.com/.

Table 1. Descriptive Statistics of Sample Data

Country	JB	ADF	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
1	2	3	4	5	6	7	8	9	10
Australia									
r_i	36.24	-16.89	0.00	0.01	0.08	-0.15	0.04	-0.75	3.82
$TEMP_i$	26.52	-3.66	21.92	22.74	29.56	13.34	4.88	-0.22	1.61
$RAIN_i$	88.38	-2.77	40.37	29.45	154.07	6.71	30.48	1.26	3.84
$EXCH_i$	7.11	-1.91	0.76	0.75	1.08	0.50	0.14	0.32	2.61
INT_i	21.59	-2.35	0.06	0.06	0.12	0.02	0.02	0.65	3.13
Canada									
r_i	300.86	-14.65	0.00	0.01	0.11	-0.23	0.04	-1.21	7.28
$TEMP_i$	26.91	-2.67	-5.97	-5.30	13.02	-26.96	12.54	0.01	1.53
$RAIN_i$	22.75	-4.23	39.09	36.08	71.16	16.42	13.52	0.40	1.92
$EXCH_i$	20.81	-1.37	0.81	0.79	1.05	0.62	0.12	0.26	1.82
INT_i	15.61	-1.88	0.03	0.03	0.08	0.00	0.02	0.37	2.16
China									
r_i	3990.01	-17.64	0.01	0.01	1.02	-0.37	0.13	2.32	20.28
$TEMP_i$	26.49	-3.28	7.01	8.27	20.61	-10.82	9.71	-0.17	1.59
$RAIN_i$	80.43	-2.60	1795.66	1598.52	5954.77	113.94	1038.96	1.04	4.46
$EXCH_i$	34.22	-2.30	0.14	0.13	0.19	0.11	0.02	0.72	2.18
INT_i	56.59	-1.01	0.05	0.03	0.10	0.03	0.03	1.02	2.39
Germany									
r_i	137.23	-15.74	0.01	0.01	0.18	-0.27	0.06	-0.89	5.81
$TEMP_i$	18.37	-4.21	9.59	9.05	22.44	-3.50	6.56	-0.03	1.79
$RAIN_i$	7.94	-14.36	60.24	57.64	136.19	2.79	24.80	0.40	3.00
$EXCH_i$	11.47	-2.43	1.22	1.25	1.58	0.85	0.16	-0.47	2.85
INT_i	4.00	-1.01	0.04	0.04	0.09	0.00	0.02	0.07	2.45
Indonesia									
r_i	235.72	-13.16	0.01	0.02	0.25	-0.38	0.08	-1.14	7.50
$TEMP_i$	1.32	-3.90	26.19	26.18	27.28	25.34	0.33	0.19	3.06
$RAIN_i$	11.33	-3.88	243.15	256.90	366.32	78.45	66.23	-0.40	2.23
$EXCH_i$	5075	-5.75	1.1E-04	1.1E-04	3.1E-04	6.9E-05	3.7E-05	4.54	24.54
INT_i	3928.84	-3.47	0.13	0.10	0.71	0.06	0.10	3.68	19.13
Netherlands									
r_i	108.44	-15.30	0.00	0.01	0.15	-0.23	0.06	-0.99	5.32
$TEMP_i$	14.03	-3.81	10.32	9.93	21.78	-1.07	5.50	-0.02	1.90
$RAIN_i$	9.71	-15.37	67.95	65.83	165.94	0.66	32.04	0.46	3.02
$EXCH_i$	10.51	-2.06	0.55	0.57	0.72	0.39	0.07	-0.44	2.63
INT_i	2.88	-1.12	0.05	0.04	0.09	0.00	0.02	0.19	2.70

Table 1, cont.

1	2	3	4	5	6	7	8	9	10
Pakistan									
r_i	282.21	-14.55	0.01	0.02	0.24	-0.45	0.09	-1.18	7.99
$TEMP_i$	21.94	-3.77	20.76	22.21	30.23	6.85	7.22	-0.34	1.62
$RAIN_i$	151.49	-11.34	25.47	20.48	110.16	0.15	21.14	1.53	5.63
$EXCH_i$	44.62	-2.44	0.02	0.02	0.04	0.01	0.01	0.92	2.61
INT_i	47.77	-1.97	0.10	0.10	0.15	0.01	0.03	-0.92	3.65
Philippines									
r_i	116.56	-16.07	0.01	0.01	0.33	-0.30	0.07	-0.09	6.05
$TEMP_i$	4.16	-4.67	25.89	25.94	27.56	23.62	0.74	-0.29	2.98
$RAIN_i$	10.27	-4.04	211.31	211.64	459.70	22.03	99.78	0.03	2.10
$EXCH_i$	51.96	-1.62	0.03	0.02	0.04	0.02	0.01	1.00	2.58
INT_i	19.32	-2.43	0.09	0.07	0.28	0.00	0.06	0.62	2.84
Sri Lanka									
r_i	6.32	-14.44	0.01	0.01	0.23	-0.18	0.07	0.21	3.58
$TEMP_i$	16.82	-2.48	27.20	27.47	29.22	24.89	1.01	-0.35	2.08
$RAIN_i$	111.23	-4.38	142.98	109.64	569.36	1.42	109.37	1.29	4.50
$EXCH_i$	40.69	-4.24	0.01	0.01	0.02	0.01	0.01	0.83	2.27
INT_i	45.11	-2.61	0.11	0.10	0.19	0.07	0.04	0.94	2.75
United States									
r_i	173.26	-15.44	0.01	0.01	0.11	-0.22	0.04	-1.01	6.22
$TEMP_i$	26.64	-2.77	7.48	7.33	21.44	-6.82	9.13	0.03	1.51
$RAIN_i$	1.56	-3.74	55.75	55.97	85.12	27.40	11.20	0.04	2.65
$EXCH_i$	11.47	-2.43	1.22	1.25	1.58	0.85	0.16	-0.47	2.85
INT_i	28.75	-2.16	0.03	0.03	0.07	0.01	0.02	0.03	1.48

Note:
1. JB – Jarque–Bera test statistic for normality. Under null hypothesis for normality, critical value of $\chi 2$ (2) distribution at 5% significance level is 5.99.
2. ADF – Augmented Dickey–Fuller test statistic for stationarity of data for maximum 15 lags. Under null hypothesis for data having unit root, the critical value at 5% significance level is -2.87.

3.1. Descriptive statistics of sample

As Table 1 outlines, stock returns, meteorological variables, exchange rates and interest rate data of all countries (except temperature data for Indonesia and rain data for the United States) exhibit non-normality of their individual distributions as the JB test statistic exceeds its critical value of 5.99. Unconditional distributions of asset prices are usually highly non-normal given the form of associations with common market expectation or premium (see especially [Fama 1965] for a complete survey). The null hypothesis for meteorological variable $TEMP_i$ having unit roots is accepted only for Canada and the United States as the test statistics fall below the critical value of -2.87 at 5% significance level. Similarly, $RAIN_i$ is non-stationary for Australia, China and the United States. The exchange rate data for Australia, Canada, China, Germany, the Netherlands, Pakistan, the Philippines and the United States have shown non-stationarity of their distributions. Data pertaining to the interest rates of all countries are non-stationary except Indonesia.

3. Empirical Findings

Except for Germany, the Netherlands, Pakistan and the United States (whose coefficients are negative and statistical significant at 5% or 15%), coefficient (β_1) of variable $TEMP_i$ is statistically insignificant for all countries as reported in the regression results. Coefficient (β_2) of variable $RAIN_i$ is negative for China, Germany, the Netherlands, the Philippines and Sri Lanka, although their coefficients are statistically insignificant at 5% or 10% significance level. The

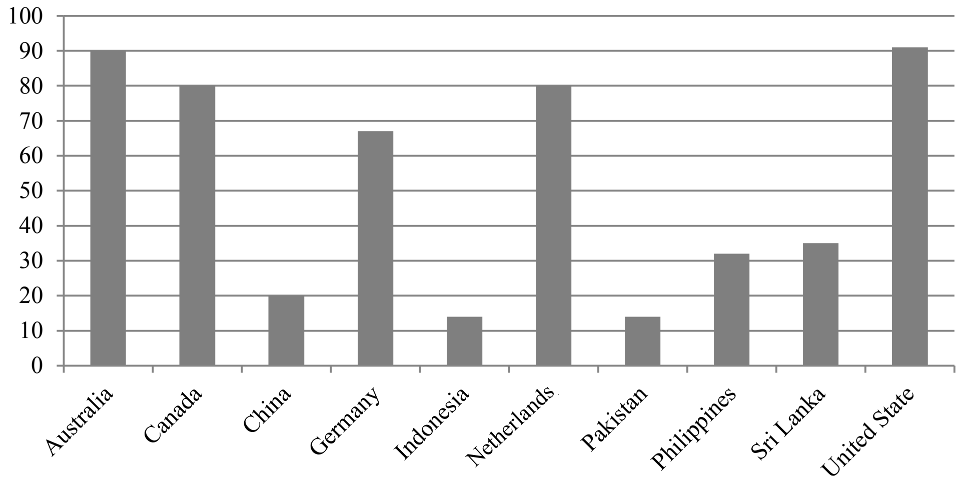

Figure 1. Hofstede Score – Individualism

Source: [Hofstede Insights 2017].

Table 2. Regression Results

Country	Australia	Canada	China	Germany	Indonesia	Netherlands	Pakistan	Philippines	Sri Lanka	United States
β_1	**5.7E-04**	**-5.1E-04**	**1.9E-04**	**-1.3E-03**	**2.8E-02**	**-1.1E-03**	**-1.5E-03**	**-5.5E-03**	**4.4E-3**	**-8.4E-04**
t-statistic	0.986	-1.391	0.104	-2.397	1.606	-1.550	-2.269	-0.844	0.897	-2.296
P-value	0.325	0.165	0.918	0.017	0.110	0.122	0.024	0.399	0.370	0.022
β_2	**-8.2E-06**	**1.0E-04**	**-3.0E-04**	**-4.8E-05**	**1.7E-04**	**4.1E-05**	**6.9E-05**	**-1.1E-05**	**-13.1E-6**	**4.8E-04**
t-statistic	-0.101	0.328	-0.515	-0.303	2.025	0.350	0.328	-0.241	-0.299	1.515
P-value	0.919	0.743	0.607	0.762	0.044	0.727	0.743	0.809	0.765	0.131
ψ	**-0.013**	**0.030**	**0.386**	**0.015**	**-261.73**	**0.044**	**-0.990**	**-0.021**	**-0.224**	**0.005**
t-statistic	-0.873	1.101	0.877	0.504	-0.970	0.649	-0.760	-0.030	-0.194	0.304
P-value	0.384	0.272	0.381	0.615	0.333	0.517	0.448	0.976	0.847	0.762
λ	**0.034**	**0.336**	**0.183**	**-0.126**	**-0.059**	**0.091**	**0.250**	**0.020**	**-0.143**	**0.287**
t-statistic	0.339	1.938	0.641	-1.153	-0.631	0.630	0.841	0.217	-1.225	2.134
P-value	0.735	0.054	0.522	0.250	0.529	0.529	0.401	0.829	0.222	0.034
β_3	**0.006**	**-0.014**	**-0.022**	**-0.028**	**0.455**	**-0.020**	**-0.019**	**-0.155**	**0.169**	**-0.021**
t-statistic	0.259	-1.429	-1.846	-1.502	1.033	-0.897	-0.963	-0.973	1.456	-1.534
P-value	0.796	0.153	0.065**	0.133	0.301	0.370	0.336	0.331	0.146	0.125
Estimated Prob.	57.34%	57.33%	57.91%	64.74%	0.00%	64.97%	71.77%	98.32%	1.42%	66.10%
β_4	**0.172***	**0.041***	**0.024***	**0.193***	**3.278***	**0.299***	**0.184***	**3.088***	**3.229***	**0.032***
t-statistic	7.886	6.582	3.078	8.848	5.239	9.734	8.884	8.428	8.878	4.846
P-value	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Estimated Prob.	0.58%	10.98%	14.24%	49.69%	0.00%	1.07%	0.83%	0.00%	0.00%	6.34%
β_5	**0.161***	**0.044***	**0.025***	**0.148***	**2.671***	**0.208***	**0.130***	**2.493***	**1.270***	**0.056***
t-statistic	5.156	6.560	2.802	5.798	4.279	6.535	5.668	7.199	7.733	4.099
P-value	0.000	0.000	0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Estimated Prob.	0.21%	3.93%	5.66%	50.02%	0.00%	0.87%	0.68%	0.00%	0.00%	2.40%
BP*(Equation 1)	**2.8521**	**1.5714**	**0.8170**	**5.5752****	**3.3087**	**7.7458***	**0.8305**	**0.7363**	**0.3699**	**2.3093**
P-value	0.2403	0.4558	0.6647	0.0616	0.1912	0.0208	0.6602	0.6920	0.8311	0.3152

Note:

1. BP is the Breusch and Pagan test (Obs*R-squared) for detecting heteroskedasticity for OLS regression as specified in Equation 1.
2. *Statistically significant at 5% significance level assuming conditional normality. **Statistically significant at 10% significance level.
3. Equation 1 is estimated NW stands for Newey and West (1987) procedures for the estimate of regression coefficients on the robust standard errors for consistent heteroskedasticity and autocorrelation.
4. Equations (2), (4) and (7) of binary logit regressions are estimated with QML (Huber/White) robust standard errors and covariances.

expected relationship between stock returns and weather variables is established by the regression for four countries (i.e. the statistically significant negative relationship between $TEMP_i$ and r_i). Furthermore, except for the Netherlands, regression residuals obey the homoscedasticity principle of OLS regression as the BP coefficient is highly statistically insignificant at 5% significance level[8]. As such, the noise on directly uncontrolled variables in the regression provides a reliable basis for the regression coefficient estimates[9]. However, the regression for Germany produces heteroskedasticity residuals at 10% significance level. As shown in the regression results of equation (1), temperature is shown to provide some predictive ability of stock returns as the corresponding variable $RAIN_i$ does not supplement for such relationship, irrespective of their cultural dimension they are expected to exhibit.

Coefficient β_3 of equation (2) under logit regression is negative for seven countries as hypothesized. The negative relationship between weather and stock return is not established for Australia, Indonesia and Sri Lanka. The corresponding probabilities of occurrence are also acceptable except for Indonesia and Sri Lanka. Specification (2) omits the impact of adverse weather conditions on regression outcome and the substance of the relationship between stock return and mood.

Coefficient β_4 of equation (4) is positive for all countries and highly statistically significant. However, the probability of observing the weather event established under Y_{2t} is acceptable only for Germany and the probability estimates are very low for other countries. This implies that the selection of weather variables as proxies for mood states of individual investors is subjective. The logit regression results of equation (7) show that coefficient β_5 is positive for all countries and is highly statistically significant. Although one unit increase in $TEMP$ increases the likelihood of the occurrence of Y, the corresponding probabilities are extremely low except for Germany. This implies that the probability of observing a negative return and an expected association between $TEMP$ and $RAIN$ as established in (Y_{3t}) above is very rare. It is highly likely that $TEMP$ is subject to a *selection bias* and the results should be interpreted carefully. However, there is a possibility of observing change in the mood state of individual investors across countries based on meteorological phenomena.

4. Conclusions

On one side of the spectrum, human behavior is certainly unpredictable although some patterns can be observed under context dependent circumstances (see e.g [Matthews 1982; Vallacher and Wegner 1987]). As such, behavioral bias is often

[8] This is apparent as returns are not drawn with reference to an active market where the regressors are a common variable in such market.

[9] It is assumed that all other assumptions of OLS regression are fulfilled.

observed particularly in the markets [Wright 2006]. On the other side of the spectrum, the human mind could shape the human actions of direct interest, for example, investment decisions. The cognitive human errors made in the market place are, however, corrected as humans learn from errors overtime (see especially [Epstein 2006]).

The results show that there is no sufficient evidence to generalize the impact of human behavior on stock returns through mood state altered by weather variables. The results also reveal that there is a bias in metrological variable selection when the substance of the underlying relationship between the weather and the mood invoked in the regression. Temperature taken as a proxy variable, that alters the mood state of individual investors, is shown to provide a logical substance over its regression form. Although the logit regression results support the use of weather variables (e.g. temperature), the probabilities of the occurrence of the true substance of weather is very low. This suggests that the selection of weather variables as proxies for the human mood is subject to a selection bias, given the metrological situation of each country. These findings question the use of regressions that omit the behavioral substance of the underlying data (i.e. variables or regressors). The coefficient estimates therefore do not provide reliable evidence for the conclusion that the human mood alters the magnitude of equity price changes. Out of the countries accepted under the null hypothesis, only Pakistan belongs to collectivist societies and other three countries are ruled by individualism.

As such, the critical cultural dimensions such as collectivism or collectivism do not matter in asset pricing. These results should, however, be interpreted with reference to context-dependent factors that may potentially affect the return estimation process, but uncontrolled for in the regression specifications, without simply generalizing to a large population. This study opens up many avenues for qualitative research in this section of finance, for example, examining the impact of the mood state of individual investors on the price change behavior of other speculative markets such as the commodity markets.

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