Does Weather Matter?

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Abstract

We use semi-parametric bin tests, regression analyses and copula modeling techniques to identify the relationship between temperature and stock market returns. After examining 25 international stock markets, we find that the negative correlation is statistically significant in individual countries, i.e. the higher is the temperature, the lower the stock returns. However, we fail to find joint significance of temperature effects across markets after correcting for market comovement by seemingly unrelated regression. We also find negative temperature effects on returns are robust to different measures of daily temperature. Both constant-dependence and time-varying-dependence conditional copula models are employed to analyze the general dependence between temperature and stock market returns. The copula results show that the negative relation remains after controlling for autocorrelations, GARCH effects and non-normality and the dependence between temperature and stock market returns is relatively stable over time.

JEL Classifications: G10, G11, G14, G15
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1 Introduction

Does weather affect stock market returns? This is an interdisciplinary question in both economics and psychology. Psychological evidence shows that some economically neutral variables, such as temperature, cloud cover, raininess, snowiness, seasonal affective disorder and lunar cycle, do affect people's mood, which in turn influences investment behavior and subsequently affect stock market returns (Jacobsen and Marquering, 2004). The literature is still growing in the field of behavioral finance that investigates the effect of human being's mood and feeling on stock market returns.

Saunders (1993) is the first researcher who relates investment behavior to weather conditions. He finds that cloud cover is negatively correlated with stock returns in the U.S. from 1927 to 1989. He concludes that less cloud cover (or more sunshine) is associated with higher returns and the return difference between the bins with the most cloud cover and that with the least cloud cover is statistically significant. He also indicates that all results are robust with respect to market anomalies including the January, weekend, and small firm effects.

Hirshleifer and Shumway (2003) confirm Saunders' findings by focusing on 26 international stock markets from 1982 to 1997. Using OLS and logit regressions they show that the results remain consistent even after controlling for adverse weather conditions such as snow and rain. Cao and Wei (2004, 2005) extend this research by considering temperature as the main economically neutral variable. They find that there exists a statistically significant and negative correlation between temperature and stock market returns. They further show that the results remain consistent after controlling for the geographical dispersion of investors relative to the city.

Kamstra, Kramer and Levi (2000) argue that stock returns following daylight savings time changes are significantly more negative due to sleep disruptions. Furthermore, Kamstra, Kramer and Levi (2003) indicate that stock markets experience the highest returns during the short, dark days in winter and the lowest returns during the long bright days in summer due to Seasonal Affective Disorder (SAD). They also report both positive and negative effects of temperature on stock market returns in their individual country regressions using SAD, cloud cover, precipitation, and temperature as independent variables. Dichev and Janes (2003) and Yuan, Zheng and Zhu (2001) report the negative relationship between stock market returns and lunar phases.

To my best knowledge, all the previous research is based on regression analysis, either OLS or logit regressions. This is implicitly assumed that the residuals follow normal distribution. However, it is widely accepted that the stock index returns actually follow Students' t distribution instead of normal distribution in most situations. A relatively advanced technique in economics, which is called copula, will be very powerful in modeling dependence between temperature and stock market returns without requiring normality. In this paper, apart from regression analyses, we use time-varying normal copula model to examine the general dependence between temperature and stock market returns. The contributions of this paper is threefolders: Firstly, to my best knowledge, this paper is the first one to examine the dependence between weather variables and stock market returns using copula models. Secondly, we confirm the previous results in this field of behavioral finance by examining more current data. Thirdly, we give the guidance for trading strategy using these techniques. The paper is organized as follows: Section 2 presents the data description. Section 3 reports our empirical results and analysis. The last section concludes and gives further research suggestions.

2 Data Description

To be consistent with previous work, we use weather data and international stock indices from 25 financial markets[1] (i.e. financial centers in 25 countries). Weather data are obtained from National Climate Data Center (NCDC). If there exist several stations within one city, then we will choose the one that is closest to the financial market location in terms of the accurate latitude within the city. Also, we find there is no remarkable differences in temperature, rain, snow indicators across stations within one city. This choice of station doesn't matter much. The stock market data is retrieved from Datastream electronic database. They are Datastream Global Indices (Datastream calculated indices), or local market indices (if Datastream Global Index is not available). Following the definitions of NCDC, TEMP is defined as mean temperature for the day in degrees Fahrenheit to tenths. HIGH is highest temperature reported during the day in Fahrenheit to tenths. LOW is defined as lowest temperature reported during the day in Fahrenheit to tenths. Percentage return is defined as 100 times log-difference of index. (i.e. $r_t = 100 \times (\ln P_t - \ln P_{t-1})$)

The stock market data covers only trading days while weather data covers everyday. Note that the weather data from NCDC are usually incomplete. We have missing observations in our dataset. The final dataset is return and weather variable series that are matched each other, meaning the weather observations for non-trading days have to be removed. After matching for 25 financial markets, Argentina has the smallest sample size of 1109 while Austria and Switzerland have the largest sample size of 9257. All data

[1]This sample is 2 cities less than the data in Cao and Wei (2005), which contains 27 international markets, since the sample size of these 2 missing cities is not large enough to perform formal econometric analysis. The excluded markets are Canada and Chile.

ends at June 27th, 2008 except that Argentina sample ends in 1997 (which also carries the smallest sample size) and Germany sample ends in 1998. Some markets have starting dates as early as January 1st, 1973 while Brazil has starting data as late as July 4th, 1994. Obviously this is an unbalanced panel data.

Table 1 presents financial center locations, latitude, countries, sample periods and descriptive statistics of daily percentage returns. Return mean ranges from 0.002% in Argentina to 0.070% in Turkey. As for standard deviation, Austria has the least volatile index at 0.351% while Turkey has the most volatile index at 1.17%. The largest single-day loss was -9.158%, experienced in Norway, while the largest single-day gain was 8.615%, experienced in Malaysia. Most of the index returns exhibit negative skewness and strong kurtosis. Malaysia has the most negative skewness at –0.978 while Brazil exhibits the most positive skewness at 0.451. Taiwan has the lowest kurtosis at 5.890 while Denmark has the highest kurtosis at 44.327.

In Table 2, we report financial center locations, latitude, countries, sample periods and descriptive statistics of daily temperature. Average temperature ranges from $40.598°F$ in Oslo, Norway to $83.217°F$ in Manila, Philippines. The standard deviation of daily temperature varies from $2.044°F$ in Kuala Lumpur, Malaysia and $17.228°F$ in New York, United States. The lowest temperature was -$19.4°F$ in Oslo, Norway while the highest temperature was $94.2°F$ in Madrid, Spain. 20 out of 25 temperature series reflect a negative skewness, meaning that it is more likely to have extremely cold days than extremely hot days. Madrid, Spain has the most positive skewness at 0.261 while Oslo, Norway has the most negative skewness at -0.342. Kuala Lumpur, Malaysia has the highest kurtosis at 2.912 while Tokyo, Japan has the lowest kurtosis at 1.840. All temperature series are less peaked than normal distribution.

[Table 1 and 2]

3 Empirical Evidence

3.1 Bin Tests

We follow previous study by Cao and Wei (2005) to perform bin tests in individual countries. After grouping returns according to temperature ordering, the semi-parametric "Bin Test" aims to calculate z-score in order to investigate the statistical difference between return-groups. Specifically, we sort the final matched return and temperature series by temperature in ascending order, and then divide the sorted series into bins (or groups). For each temperature bin, we compute the mean return, compare the mean returns associated with the lowest bin covering the lowest spectrum of the temperature range and the highest bin covering the highest spectrum of the temperature range, and then examine the statistical significance of the difference in mean returns. Moreover, we perform comparison and tests for the percentage of positive returns of the two extreme bins. The purpose of this frequency test is to avoid the possible bias driven by outlier in mean return test.

Now we briefly describe the testing procedure. Firstly, we compute the difference between the maximum and minimum of the temperature series in each country. Then we divide the difference by the number of bins, say k, to obtain the temperature range of each bin. More explicitly, $\Delta_k = (TEMP_{MAX} - TEMP_{MIN})/k$. Consequently the lowest bin contains temperatures in range of $[TEMP_{MIN}, TEMP_{MIN} + \Delta_k)$, the second lowest bin contains temperature in the range of $[TEMP_{MIN} + \Delta_k, TEMP_{MIN} + 2\Delta_k)$, and so on so forth. To determine whether the difference in mean returns of the two extreme bins (lowest and highest bins) is statistically significant, we compute the following z-score:

$$z_{1,k}^{mean} = \frac{\mu_k - \mu_1}{\sqrt{\frac{\sigma_k^2}{n_k} + \frac{\sigma_1^2}{n_1}}} \tag{1}$$

where μ_i, σ_i, n_i represent the mean return, the standard deviation of the return and the number of observations in bin i. Another similar z score is computed to examine the significance of the difference in the frequencies of positive returns between two extreme bins:

$$z_{1,k}^{frequency} = \frac{p_k - p_1}{\sqrt{\frac{p_k(1-p_k)}{n_k} + \frac{p_1(1-p_1)}{n_1}}} \tag{2}$$

where p_i stands for the percentage of positive returns in bin i. Also, as Cao and Wei (2005b) point out, the potential heteroscedesticity in the variance estimators used to construct the z-score is largely absent because the heteroscedesticity in the variance for the frequency of positive returns is ruled out since the variable measures a binomial outcome and the variance of daily returns is not heteroscedastic since the returns are grouped according to temperature, an entirely exogenous factor. However, the daily return series is very likely to be heteroscedastic as documented by French, Schwert and Stambaugh (1987) and Schwert (1989).

We perform both 3-bin and 4-bin tests. Keller et al. (2005) report that people tend to have aggression when temperature is either very high or very low and have clear minds when temperature is in the middle range. This suggests that we may divide temperature into 3 bins to differentiate changes in people's mood. We also conduct 4-bin test to make our work consistent with previous research by Cao and Wei (2005a). The results are presented in Table 3. In Panel A, 20 of 25 mean returns of bin 1 are greater than those of bin 4, and the z-scores for mean are statistically significant at 10% in 7 locations. The z-scores for mean in the rest 5 cities are not significant at all.

Furthermore, 16 of 25 frequencies of positive return in bin 1 are higher than those of bin 4, among which one of them is statistically significant at the 10% level. The z-scores for frequency in the rest 9 cities are not significant.

The results in 3-bin tests are stronger than those in 4-bin tests, which is consistent with Cao and Wei (2005b). For example, for Amsterdam, Netherlands, the z-score for the mean return has changed from insignificance in 4-bin case to 5% significance level in 3-bin case. Similar changes apply to Britain, France, Austria and Switzerland, too. In particular, the improvement for France is even stronger, which changes from insignificance in 4-bin case to 1% significance in 3-bin case. The z-score for the frequency of positive returns is stronger in 3-bin case as well, but improvement is not as much as that of z-score for mean returns. The test results show that there exists a negative correlation between temperature and stock market returns, meaning that the lower the temperature, the more likely the stocks will experience a positive price change.

[Table 3]

3.2 Regression Analyses

3.2.1 Individual OLS Regressions

In the bin tests, we didn't correct for any other stock market anomalies, such as Monday effect and tax loss effect. Therefore, it is just a preliminary check for the negative correlation between temperature and stock market returns. We need further econometric analysis to confirm our finding. To formally examine the relationship between temperature and returns, we perform regression analysis with controlling for some known anomalies such as the Monday effect and tax-loss selling effect. The regression equation is:

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 MON_t + \alpha_4 TAX_t + \alpha_4 TEMP_t + \varepsilon_t \tag{3}$$

where r_t is the daily return at time t for a given index, MON is a dummy variable which equals 1 for Monday and 0 otherwise, TAX is a dummy variable which equals 1 for the first 10 days of the taxation year and 0 otherwise, $TEMP$ is the daily temperature at time t. The tax year for most countries starts on January 1. However, the tax year starts on March 1 in South Africa, April 1 in New Zealand, April 6 in Britain and Ireland, and July 1 in Australia.

We actually use temperature as the sole variable of nature in our regressions for two reasons: Firstly, most of variables of nature are highly correlated in our sample, such as precipitation and temperature, wind speed and temperature, etc. To avoid multicollinearity trap, we have to use only one variable of nature. Secondly, temperature is the most significant weather condition, which attracts people's attention and affects people's mood in our daily life. Therefore, temperature is a good proxy variable for all weather conditions in general. Additionally, although we know that the causality is not quite clear in some research in social science, fortunately we can avoid causality problem in our analysis because temperature is an exogenous variable of nature, which will apparently not be affected by stock market returns. Hence, the one-way causality from temperature to stock market returns is clearly established.

We run the regression for each individual country. The results are reported in Panel A of Table 4. After controlling for first-order autocorrelations as well as Monday and tax year effects, we got very signnificant coefficients on temperature. 14 out of 25 markets have significant coefficients on temperature, among which 13 out of 14 markets get significant negative coefficients at the 10% level with exception of South Africa. Some markets are significant at the 5% or even the 1% levels. Considering all markets, 22 out of 25 markets have negative coefficients on temperature with exception of Argentina, South Africa, and Australia. Interestingly, they are all from South Hemisphere. It seems that the negative association between temperature and stock market returns is common. These reuslts are stronger than bin tests because we take into account the known anomalies, including Monday and tax year effects. This result is also consistent with Cao and Wei (2005b). As a stylized fact, most of negative coefficients are close to 0.001 in terms of magnitude. Hence we may conjecture that the investors react to the temperature change by similar degree. However, we need to perform formal test to confirm our conjecture.

Additionally, returns on Mondays are lower for all markets except Finland, US and Canada. This effect is significant at 1% level in Greece, New Zealand, Turkey, Malaysia, Britain, Italy, France, Brazil and Switzerland, and it is significant at 5% in Netherlands, South Africa. In contrast, the tax loss effect is only significant in New Zealand, Turkey, Norway, Brazil, Japan, Canada and Switzerland. Among these 7 markets, most of them get positive signs with exception of Brazil and Japan.

[Table 4]

3.2.2 Seemingly Unrelated Regression

As Cao and Wei (2005b) argued, there are several drawbacks in individual OLS regressions. Firstly, it is hard to make valid comparisons among international stock markets with different sample periods. Secondly, stock index returns are correlated across markets due to financial contagion. For geographically close cities, temperatures are correlated with each other too. In OLS regressions, we do not take into account these cross-market effects in individual country regressions. Last, there is no way to perform joint tests of the temperature variables' significance across markets in individual regressions. To overcome these shortcomings of individual OLS estimation, we will employ seemingly unrelated regression (SUR) in order to test the joint significance of temperature coefficients and correct for market comovement. We will implement two χ^2 tests. One test aims to determine if all the coefficients of temperature are jointly different from zero. The test results will tell us whether the negative correlations in individual countries are jointly significant after taking into account cross-market correlations. The other one is to test whether all temperature coefficients are equal. We want to see if investors in different markets response to the same temperature change by the same extent.

To get long enough common sample period and include more current data, we exclude Argentina and Germany for the SUR regression. Eventually, the equal-sized sample for this SUR regression contains 1953 observations from January 2000 to June 2008 in 23 stock markets. The results are reported in Panel B of Table 4. Surprisingly, only two markets got significant temperature coefficients and both are negative. Considering all markets, 14 out of 23 markets got negative coefficients. Although the negative correlation still dominates, the result is apparently much less significant than that of OLS regressions. Some coefficients have changed their signs from negative to positive or at least less significant. This may be due to the positive cross-market correlations. However, we also observe that the coefficients have chnaged from positive in individual regressions to negative in Argentina and Australia in SUR regression.

Also, the first χ^2 test statistic is insignificant at all. This implies that after controlling for cross-market correlations, it is hard to say that the temperature coefficients are jointly significant across these 23 markets. This result is not consistent with Cao and Wei (2005b). Cao and Wei (2005b) examine the common sample period data from 1988 to 1997 while we have the common sample period data from 2000 to 2008. One explanation would be the increased market comovement over last decade, which dominates the temperature effects. The second χ^2 test statistic is also insignificant (the null of equal effect in the second χ^2 test is not rejected.), meaning that the investors' reactions to the temperature changes in different markets are equal. People in different countries react to temperature fluctuations by similar extent.

3.2.3 Robustness Check and Extensions

Firstly, we conduct regression analysis for full samples using high/low temperature as key explanatory variables, where high temperature means the highest temperature reported during the day in Fahrenheit to tenths while low temperature represents the lowest temperature. Table 5 presents the estimation results. In general, the results show that the high and low temperature have negative effects on stock market returns just like average temperature does. Panel A reports the results of regressions with high temperature. Most of markets show negative coefficients on temperature with only two exceptions of South Africa and Australia in South Hemisphere. In Argentina, it shows negative sign in this set of regressions while it is positive in average temperature regression. This result indicates that the high and low temperature may negatively affect stock market returns through human being's investment behavior while the average temperature shows positive effects. Panel B reports similar results as Panel A. Again, it shows negative coefficient in Argentina. These results indicate that the negative association between temperature and stock market returns does exist when using high and low temperature as the explanatory variables.

[Table 5]

Secondly, in another set of regressions, historical moving average temperature and forward moving average temperature are employed to examine the impact on stock market returns in full samples. We follow Cao and Wei (2005b) to calculate the historical moving average temperature using moving window sizes of 3, 7, 15, and 31 days, where the current day is placed at the end of the moving window. As the moving window size expands, the moving averages of temperature become more and more smooth. These moving averages represent the average temperature in the recent past. We also calculate the forward moving average temperature using moving window sizes of 3, 7, 15, and 31 days, where the current day is placed at the beginning of the moving window. These moving averages measure the average temperature in the near future. This is to test the conjecture that stock market participants are forward-looking so that future weather conditions may affect their investment decisions. Table 6 reports the regression results. For simplicity, we report only the temperature coefficients and their standard errors in individual OLS regressions. In general, the negative correlation results are not sensitive to the smoothing of daily temperature. The negative effect on returns still dominates in both historical moving average regressions and forward moving average regressions. Most of the markets exhibit negative relationship between moving average temperature and stock market returns with exception of 3 southern countries. Panel A presents results of regressions with historical moving average temperature. The dominant negative relation in window size of 31 days indicates that the negative effect on stock market returns is robust to 31-days smoothing. Investors' mood may be affected by the general weather conditions in recent past, not just today's temperature, hence these behavior fluctuations will be indirectly reflected on the stock markets. Panel B presents results of regressions with forward moving average temperature. The negative effects on stock returns still dominate. Investors may be forward-looking on weather and form their expectations on the temperature in the near future and response accordingly. This leads to changes in investors' behavior and hence changes in stock market returns. To sum up, these results imply that the weather in recent past and near future will also affect stock market participants' mood and subsequently stock market returns.

[Table 6]

3.3 Copula-based Analyses

We implicitly assume normal distribution in our regression analyses. However, financial returns are generally non-normal and temperature series is not necessarily normal. Moreover, GARCH effects are widely reported in financial returns. We do not take care of GARCH effects in our regression analyses. All these will cast doubts on the validity of regression results. Hence it is good to take advantage of conditional copula to model joint distribution in order to avoid these shortcomings of regression analysis. Therefore, we use conditional copula models to investigate the general dependence between temperature and stock market returns. Furthermore, we allow the dependence to be time-varying over time in order to check whether the dependence changes over time or not.

3.3.1 Marginal Model

As Hu (2008) pointed out, to estimate bivariate distribution, we need to make assumption about each univariate marginal distribution. As for the return series, in Table 7, we can see that all series in 25 markets very strongly rejects the Jarque-Bera test, showing non-normality of unconditional distribution of each series. This is one of the reasons why multivariate normal distribution would be inappropriate. We perform LM test to examine whether the squared return is serially correlated up to lag 1, 5 and 10. The significant statistics clearly indicate that ARCH effects in return series are very likely to be found in all markets. Ljung-Box autocorrelation test with correction for heteroskedesticity is also implemented at lag 1, 5 and 10, implying most of return series are serially correlated. As for the temperature series, we perform the same tests as we do on stock market return series. Table 8 presents the test results. We can see that all series in 25 markets strongly rejects the Jarque-Bera tests with exception of Malaysia, indicating temperature is not normally distributed. There exist very strong ARCH effects (stronger than return series) in temperature series in all markets. And all temperature series are highly autocorrelated (stronger than return series). Therefore, we can use similar marginal models on temperature series as those on return series.

[Table 7 and 8]

Given the test results we have, we assume the marginal distributions of both stock market returns and temperature series follow $AR(1) - GARCH(1,1) - t$ process. This is standard model for financial returns introduced by Bollerslev (1987), which is widely used in the literature; see Patton (2002, 2006a) Jondeau and Rockinger (2006) among others. We use exactly the same model on temperature as that on returns for two reasons: First, we get similar test results on temperature as compared to those on return series. Second, it is easy to make two marginal distributions comparable and apply conditional copula theory without requiring further assumptions. More explicitly,

$$
\begin{aligned}
y_{i,t} &= \alpha_i + \sum_{j=1}^{p} \beta_j y_{i,t-j} + \varepsilon_{i,t} \text{ for i=1,2} &(4)\\
\sqrt{\frac{\nu}{\sigma_{i,t}^2(\nu-2)}} \cdot \varepsilon_{i,t}|I_{t-1} &\sim t(\nu) &(5)\\
\sigma_{i,t}^2 &= a_i + b_i\sigma_{i,t-1}^2 + c_i\varepsilon_{i,t-1}^2 &(6)
\end{aligned}
$$

3.3.2 Copula Model

Conditional Copula Review We provide a very brief review on conditional copula. For simplicity, we focus on bivariate copulas. Given two random variables Y_1 and Y_2, the joint distribution function can be written as:

$$F(y_1, y_2) = \Pr(Y_1 \leq y_1, Y_2 \leq y_2) \tag{7}$$

where y_1 and y_2 denote the realizations of random variables Y_1 and Y_2, respectively.

A copula is virtually a multivariate joint distribution. We can decompose a joint distribution into its marginal distribution and its dependence function, i.e. copula. We may construct the copula function by transforming the random variables Y_1 and Y_2 to uniform marginal distribution (CDF), i.e. F_1, F_2. Specifically,

$$
\begin{aligned}
F(y_1, y_2) &= \Pr(F_1(Y_1) \leq F_1(y_1), F_2(Y_2) \leq F_2(y_2)) \qquad (8) \\
&= C(F_1(y_1), F_2(y_2))
\end{aligned}
$$

A complete and formal definition of copulas can be found in Nelsen (2006). Also, Joe(1997) provided many nice properties of various copula families. Patton (2006a) summarizes the conditional copula theory. Similar to unconditional case, we have two random variables Y_1 and Y_2. We introduce conditioning vector W. Let $F_{Y_1Y_2|W}$ denote the conditional distribution of (Y_1, Y_2) given W, and let the conditional marginal distributions of $Y_1|W$ and $Y_2|W$ be denoted $F_{Y_1|W}$ and $F_{Y_2|W}$, respectively. We assume that $F_{Y_1|W}$, $F_{Y_2|W}$ and $F_{Y_1Y_2|W}$ are all continuous for simplicity.[2] Let $F_{Y_1|W}(\cdot|w)$, $F_{Y_2|W}(\cdot|w)$ be the conditional distribution of $Y_1|W = w$ and $Y_2|W = w$, respectively, $F_{Y_1Y_2|W}(\cdot|\omega)$ be the joint conditional distribution of $(Y_1, Y_2)|W = w$ and ω be the support of W. Assume that $F_{Y_1|W}(\cdot|w)$ and $F_{Y_2|W}(\cdot|w)$ are continuous in y_1 and y_2 for all $w \in \omega$. Then there exists a unique conditional copula $C(\cdot|\omega)$ such that

$$
\begin{aligned}
F_{Y_1Y_2|W}(y_{1,}y_2|\omega) &= C(F_{Y_1|W|}(y_1|w), F_{Y_2|W}(y_2|w)|w) \\
&= C(u, v) \qquad (9) \\
\forall(y_{1,}y_2) &\in \bar{R} \times \bar{R} \text{ and } w \in \omega \qquad (10)
\end{aligned}
$$

where $u = F_{Y_1|W}(y_1|w)$ and $v = F_{Y_2|W}(y_2|w)$ are realizations of $U \equiv F_{Y_1|W}(Y_1|w)$ and $V \equiv F_{Y_2|W}(Y_2|w)$ given $W = w$.

This conditional copula is just an extension of Sklar's Theorem (1959). U and V

[2]This assumption is not necessary for the properties of copulas to hold. See Nelsen (2006).

are the conditional "probability integral transforms" of Y_1 and Y_2. Fisher (1932) and Rosenblatt (1952) prove that U and V follow the $Unif(0,1)$ distribution, regardless of the original distributions. This is where the nice properties of copulas come from. Patton (2002) shows that a conditional copula has all the properties of an unconditional copula.

Normal Copula Function In our study, we will use both constant-dependence and time-varying-dependence normal copulas to examine the general dependence between temperature and stock returns, where normal copula is the dependence function associated with bivariate normality, and can be written as:

$$C^N(u,v;\rho) = \int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi\sqrt{(1-\rho^2)}} \exp\left\{ \frac{-(r^2 - 2\rho rs + s^2)}{2(1-\rho^2)} \right\} dr\ ds \qquad (11)$$

where Φ^{-1} is the inverse of the standard normal CDF, ρ is the correlation coefficient.

Throughout this paper, we assume that the functional form of copula is fixed throughout the sample period while the dependence parameter can be time-varying following some evolution equation. We follow Patton (2006a) 's work to assume the following evolution dynamics for ρ_t:

$$\rho_t = \Lambda\left(\omega_\rho + \beta_\rho \cdot \rho_{t-1} + \alpha_\rho \cdot \frac{1}{10}\sum_{j=1}^{10}[\Phi^{-1}(u_{t-j}) \cdot \Phi^{-1}(v_{t-j})]\right) \qquad (12)$$

where $\Lambda(x) = \dfrac{(1-e^{-x})}{(1+e^{-x})}$ is the modified logistic transformation, aiming to keep ρ_t within $(-1,1)$ interval. Here we assume that the copula dependence parameter follows an $ARMA(1,10)$-type process, in which the autoregressive term $(\beta_\rho \cdot \rho_{t-1})$ captures persistence effect and the last term $(\alpha_\rho \cdot \frac{1}{10}\sum_{j=1}^{10}[\Phi^{-1}(u_{t-j}) \cdot \Phi^{-1}(v_{t-j})])$ captures variation effect in dependence. Here constant-dependence implies that β_ρ and α_ρ will be zero. At this point, the constant-dependence model is nested in the time-varying-dependence model. Therefore, we can perform likelihood ratio test to compare these two models.

3.3.3 Estimation Results

We present the normal copula estimation results of equal-sized sample in Table 9. We report the constant-dependence copula results in Panel A in Table 9. Apart from the dependence estimates, log-likelihood and Akaike Information Criteria (AIC) are also reported for comparison purpose. 19 out of 23 markets get negative dependence estimates. It seems that negative association is robust in most countries when the dependence is assumed to be constant. Therefore, after taking into account autocorrelations, GARCH effects and non-normality, there still exists a very strong negative correlation between temperature and returns in most markets with exception of Turkey, South Africa, Spain, and Norway. In Australia, the dependence becomes negative while it is positive in individual regression analysis.

We also report time-varying-dependence copula estimates in Panel B in Table 9. In terms of magnitude, the AR coefficients ($\beta' s$) are higher than MA coefficients ($\alpha' s$) with only 5 exceptions. This fact implies that persistence effects dominates in our models. Put differently, the dependence between temperature and stock market returns are very consistent over time. In absolute terms, all AICs of constant-dependence models are obviously lower than those of time-varying-dependence models with exception of Oslo, Norway, indicating a better fit in constant-dependence models in most markets. More importantly, we perform likelihood-ratio tests to compare constant-dependence models and time-varying-dependence models, all markets have a better fit in the constant-dependence models with exception of London, Britain. Unlike the time-varying dependence between stock markets, the depndence between stock market returns and temperature are relatively stable. This is because the temperature comes from nature, which will not affected by the volatility of stock market returns. We can also confirm our causality argument that the fluctuations in stock market returns depends upon the changes in temperature but not the other way around.

We report the time-varying dependence path in all markets in Figure 1. We observe relatively smoothing path in Finland (Country 3), Ireland (Country 5), Austria (Country 11), Italy (Country 12), Turkey (Country 14) while we see volatile or white noise-type pathes in other markets. All these 5 markets exhibit positive dependence during some time periods. This shows that the dependence could be positive in a few short periods, although it is negative in the long-run. For other markets, we observe similar phenomena. For example, in Britain (Country 4) where time-varying-dependence copula model fits better, we can see a lot of positive dependence thoughout the sample period, but on average the dependence is negative. We conclude that the dependence between temperature and stock market returns on average is negative in the long-run in most of markets, though it could be positive in some time periods.

[Table 9]

4 Concluding Remarks

This line of research is parallel to studies which relate stock market returns to a set of variables of nature, such as the amount of sunshine by Sanders (1993) and Hirshleifer and Shuway (2003), the length of day light by Kamstra, Kramer and Levi (2003), temperature by Cao and Wei (2005b). This line of work are based on the following reasoning: The variables of nature, such as temperature, the amount of sunshine, the length of day light, affect human being's mood and mood in turn will influence investors' behavior. Research evidence shows that low temperature tends to cause aggression while high temperature tends to cause aggression, hysteria, and apathy. These fluctuations in mood, feelings and emotions have impact on people's decision-making, for example, risk-aversion level, which in turn affects their investment decision. This intuition is supported by psychological literature on the relation between people's mood and decision-making. For example, Mehra and Sah (2002) show that the emotional state of investors will influence stock prices when investors' subjective parameters such as risk-aversion change in response to mood fluctuations.

In our study, we use semi-parametric bin tests, regression analyses and copula modeling techniques to identify the linkage between temperature and stock returns. Since psychological literature suggests that low temperature causes aggression while high temperature causes apathy and aggression, we argue that lower temperature leads to higher stock market returns due to investors' aggressive risk-taking, i.e. less risk-averse, and higher temperature leads to higher or lower stock market returns due to net effects of apathy and aggression. We have 25 international stock markets in our matched dataset and find that the negative correlation between temperature and stock market returns is statistically significant in individual countries around the world, especially in North Hemisphere. We conclude that weather does matter and in general the higher the temperature, the lower the stock market returns. However, there is no joint significance of temperature effects across markets after correcting for market comovement. We also test the results by using high and low daily temperature as well as historical and forward moving average temperature as explanatory variables and get similar negative effects on stock market returns. Copula models are used to examine the general dependence between temperature and stock market returns. This shows that the negative relationship remains after controlling for autocorrelations, GARCH effects and non-normality. Time-varying-dependence copula models are employed to estimate dynamic dependence. Unlike the time-varying dependence among stock markets, the results indicate that the dependence between temperature and stock market returns is relatively stable over time, though it could be positive in some short periods.

Regarding trading strategy, based on our findings in this paper, it is natural to recommend investors to hold more long positions in their domestic portfolio when temperature is below average (associated with higher returns) and hold more short positions when temperature is above average (associated with lower returns) on a daily basis. This trading strategy should be less effective when dealing with international portfolio since we can not find joint significance after correcting for cross-markets correlation. We conclude that this trading strategy on average will assist investors to outperform their domestic stock markets in a fairly long time period keeping other factors constant. However, we understand that the extra return obtained by following temperature-based trading strategy will be nominal after taking into account the transaction costs and market co-movement. Therefore, we are not saying that temperature-based trading strategy will have significant effects on portfolio returns (even domestic portfolio), rather, we believe that temperature is an easy-to-use investors' mood indicator that should not be ignored when making investment decisions.

References

[1] Bollerslev, T. (1987), A conditional heteroskedastic time series model for speculative prices and rates of return, *Review of Economics and Statistics* 69, 542-547.

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

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

[4] Dichev, I.D., & Janes, T.D. (2003), Lunar cycle effects in stock returns, *The Journal of Private Equity* Fall 2003, 8-29.

[5] French, K. R., Schwert, G. W. and R. F. Stambaugh (1987), Expected Stock Returns and Volatility, *Journal of Financial Economics*, 19, 3-29.

[6] Hirshleifer, D. and Shumway, T., (2003), Good Day Sunshine: Stock Returns and the Weather, *Journal of Finance*, 58 (3), 1009-1032.

[7] Hu, J. (2008), Dependence Structures in Chinese and U.S. Financial Markets: A Time-varying Conditional Copula Approach, Departmental Working Paper Series, Southern Methodist University Department of Economics.

[8] Jacobsen, Ben and Marquering, Wessel A. (2004), Is it the Weather?, ERIM Report Series Reference No. ERS-2004-100-F&A Available at SSRN: http://ssrn.com/abstract=636811

[9] Jondeau, E. and Rockinger, M. (2006), The Copula-GARCH model of conditional dependencies: An international stock market application, *Journal of International Money and Finance* 25 827-853.

[10] Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2000), Losing sleep at the market: The daylight-savings anomaly, *American Economic Review*, 90(4), 1005-1011.

[11] Kamstra, M. J., Kramer, L. A. & Levi, M. D. (2003). Winter blues: A SAD stock market cycle, *American Economic Review*, 93(1), 324-343.

[12] Keller, M. C., Fredrickson, B. L., Ybarra, O., Cote, S., Johnson, K., Mikels, J., Conway, A., & Wager, T. (2005), A warm heart and a clear head: The contingent effects of weather on human mood and cognition, *Psychological Science*, 16, 724-731.

[13] Patton, A. J., (2002), Applications of Copula Theory in Financial Econometrics, Unpublished Ph.D. dissertation, University of California, San Diego.

[14] Patton, A.J., (2006a), Modelling Asymmetric Exchange Rate Dependence, *International Economics Review* 47 (2), 527-556

[15] Patton, A.J., (2006b), Estimation of copula models for time series of possibly different lengths, *Journal of Applied Econometrics* 21 (2), 147-173.

[16] Saunders, E. M. (1993), Stock prices and Wall Street weather, *American Economic Review*, 83(5), 1337-1345.

[17] Schwert, G. W. (1989), Why Does Stock Market Volatility Change Over Time?, *Journal of Finance*, 44, 1115-1153.

[18] Yuan, K., Zheng, L., & Zhu, Q. (2001), Are investors moonstruck? Lunar phases and stock returns, Working Paper, Retrieved October 11, 2008, from http://www.ssrn.com.

Table 1 Summary Statistics of Daily Returns.

City and Country	Latitude	Period	Obs. #	Mean	Std. Dev.	Min	Max	Skew.	Kurt.
Amsterdam, Netherlands	52°18′N	73-08	8731	.011	.451	-4.791	3.446	-.300	9.432
Athens, Greece	37°54′N	88-08	5338	.024	.716	-6.355	6.650	.029	11.240
Auckland, New Zealand	37°01′S	88-08	5318	.007	.426	-5.554	3.975	-.267	18.645
Buenos Aires, Argentina	34°49′S	88-97	1109	.002	.876	-4.139	4.830	-.045	6.041
Copenhagen, Denmark	55°38′N	73-08	9252	.017	.468	-7.556	7.594	-.173	44.327
Dublin, Ireland	53°26′N	73-08	9163	.013	.518	-7.311	6.405	-.333	14.148
Frankfurt, Germany	50°03′N	73-98	6776	.016	.465	-5.421	3.295	-.470	10.224
Helsinki, Finland	60°19′N	92-08	2573	.008	.954	-7.924	6.664	-.382	9.712
Istanbul, Turkey	40°58′N	88-08	5342	.070	1.170	-8.451	7.394	-.004	6.915
Johannesburg, South Africa	26°08′S	73-08	8206	.018	.678	-7.056	7.243	-.567	11.366
Kuala Lumpur, Malaysia	03°07′N	86-08	5739	.010	.596	-9.890	8.615	-.978	39.443
London, Britain	51°29′N	73-08	9256	.013	.447	-5.649	3.960	-.244	11.008
Madrid, Spain	40°27′N	87-08	5366	.014	.467	-4.093	3.038	-.494	9.083
Manila, Philippines	14°31′N	87-08	4699	.012	.640	-4.260	7.026	.375	10.544
Milan, Italy	45°26′N	73-08	9256	.015	.562	-4.275	3.989	-.287	7.881
New York, United States	41°46′N	76-08	2715	-.001	.455	-2.952	2.331	.052	6.289
Oslo, Norway	60°12′N	80-08	7429	.018	.595	-9.158	4.482	-.663	16.253
Paris, France	49°01′N	74-08	8894	.015	.490	-4.297	3.460	-.372	7.963
Rio de Janeiro, Brazil	22°54′S	94-08	3572	.036	.684	-4.552	8.480	.451	14.749
Stockholm, Sweden	50°21′N	82-08	6895	.020	.579	-3.690	4.718	-.053	7.830
Sydney, Australia	33°57′S	90-08	4557	.015	.363	-3.212	2.503	-.351	8.576
Taipei, Taiwan	25°02′N	87-08	5366	.009	.832	-4.206	5.531	.029	5.890
Tokyo, Japan	35°41′N	73-08	9254	.007	.453	-6.836	4.080	-.379	13.985
Vienna, Austria	48°07′N	73-08	9257	.012	.351	-4.017	3.345	-.393	17.551
Zurich, Switzerland	47°23′N	73-08	9257	.010	.387	-5.346	2.875	-.929	17.547

Notes: This table presents summary statistics of each stock return series. Daily returns are in percentage forms, i.e. 100 times the log-differences of daily index returns. Latitude means the latitude of the financial market location where N represents North Hemisphere and S represents South Hemisphere. The sample period varies across countries, yielding 1109 observations for the smallest sample in Argentina and 9257 observations for the largest sample in Austria and Switzerland. The latest observation occurs at June 27, 2008.

Table 2 Summary Statistics of Daily Temperature (Fahrenheit).

City and Country	Latitude	Period	Obs. #	Mean	Std. Dev.	Min	Max	Skew.	Kurt.
Amsterdam, Netherlands	$52^{0}18'N$	73-08	8731	50.242	10.901	9.5	80.2	-.179	2.625
Athens, Greece	$37^{0}54'N$	88-08	5338	64.738	12.855	28.4	93.9	.049	1.944
Auckland, New Zealand	$37^{0}01'S$	88-08	5318	59.251	6.955	35.4	75.4	-.323	2.896
Buenos Aires, Argentina	$34^{0}49'S$	88-97	1109	64.157	10.558	39	91.4	-.148	2.056
Copenhagen, Denmark	$55^{0}38'N$	73-08	9252	47.190	12.004	6.4	76.2	-.039	2.182
Dublin, Ireland	$53^{0}26'N$	73-08	9163	49.611	7.890	22	71.4	-.082	2.320
Frankfurt, Germany	$50^{0}03'N$	73-98	6776	50.037	13.302	7.2	82.4	-.110	2.378
Helsinki, Finland	$60^{0}19'N$	92-08	2573	43.481	16.452	-11.7	78.3	-.0289	2.636
Istanbul, Turkey	$40^{0}58'N$	88-08	5342	58.570	13.526	24.3	88	-.032	1.883
Johannesburg, South Africa	$26^{0}08'S$	73-08	8206	60.615	7.749	31.9	79.6	-.429	2.630
Kuala Lumpur, Malaysia	$03^{0}07'N$	86-08	5739	81.473	2.044	73.2	88.9	-.013	2.912
London, Britain	$51^{0}29'N$	73-08	9256	50.433	9.771	16.5	79.8	-.078	2.413
Madrid, Spain	$40^{0}27'N$	87-08	5366	60.972	14.274	29	94.2	.261	1.972
Manila, Philippines	$14^{0}31'N$	87-08	4699	83.217	2.801	73	93.4	.006	2.821
Milan, Italy	$45^{0}26'N$	73-08	9256	55.790	14.698	14	88.5	-.031	1.898
New York, United States	$41^{0}46'N$	76-08	2715	54.400	17.228	5.7	91.9	-.205	2.132
Oslo, Norway	$60^{0}12'N$	80-08	7429	40.598	15.973	-19.4	76.6	-.342	2.658
Paris, France	$49^{0}01'N$	74-08	8894	52.237	11.770	8.2	88.8	-.118	2.526
Rio de Janeiro, Brazil	$22^{0}54'S$	94-08	3572	75.744	5.093	60.9	93.4	.023	2.512
Stockholm, Sweden	$50^{0}21'N$	82-08	6895	45.040	14.775	-7.8	81.5	-.147	2.500
Sydney, Australia	$33^{0}57'S$	90-08	4557	64.593	7.417	46.4	88.1	-.010	2.161
Taipei, Taiwan	$25^{0}02'N$	87-08	5366	73.682	9.593	41.9	91.5	-.304	2.110
Tokyo, Japan	$35^{0}41'N$	73-08	9254	60.509	13.758	30.9	90.6	.019	1.840
Vienna, Austria	$48^{0}07'N$	73-08	9257	50.336	14.890	-3.7	85.4	-.203	2.187
Zurich, Switzerland	$47^{0}23'N$	73-08	9257	48.784	13.545	-4	80.5	-.111	2.225

Note: This table presents summary statistics of each daily temperature series. Daily temperature is the mean temperature for the day in degrees Fahrenheit to tenths. Latitude means the latitude of the financial market location where N represents North Hemisphere and S represents South Hemisphere. The sample period varies across countries, yielding 1109 observations for the smallest sample in Argentina and 9257 observations for the largest sample in Austria and Switzerland. The latest observation occurs at June 27, 2008.

Table 3 Bin Test Results of Daily Returns across Temperature Groups using Full-sized Sample

		Panel A: 4 Bins					***Panel B: 3 Bins***			
City and Country	**Return Statistics**	**Bin 1**	**Bin 2**	**Bin 3**	**Bin 4**	**z-score (4,1)**	**Bin 1**	**Bin 2**	**Bin 3**	**z-score (3,1)**
Amsterdam,	mean	.032	.035	-.001	.004	-.895	.035	.018	-.005	-2.096**
Netherlands	% of +returns	.279	.319	.317	.304	.161	.292	.326	.300	-2.018**
Athens,	mean	.066	.048	-.005	.013	-1.077	.041	.029	.008	-1.119
Greece	% of +returns	.589	.515	.518	.454	.687	.508	.528	.471	.362
Auckland,	mean	.069	.001	.010	-.001	-1.795*	.058	.002	.007	-2.159**
New Zealand	% of +returns	.352	.274	.291	.313	-1.873*	.319	.281	.308	-1.901*
Buenos Aires,	mean	-.061	.052	-.019	.010	.704	.003	-.0004	.008	.073
Argentina	% of +returns	.572	.604	.643	.557	.660	.587	.626	.600	.088
Copenhagen,	mean	.005	.023	.014	.015	.192	.052	.017	.012	-1.956*
Denmark	% of +returns	.315	.346	.315	.343	-1.535	.336	.338	.320	-1.483
Dublin,	mean	.063	.032	-.000	.006	-1.391	.043	.011	.011	-1.574
Ireland	% of +returns	.440	.385	.358	.359	.470	.400	.371	.356	.056
Frankfurt,	mean	.032	.027	.009	.012	-.593	.045	.013	.015	-1.399
Germany	% of +returns	.372	.350	.337	.327	1.018	.395	.340	.329	.839
Helsinki,	mean	-.024	.063	.020	-.059	-.389	.040	.037	-.033	-1.180
Finland	% of +returns	.453	.671	.700	.571	-.087	.490	.694	.619	-.969
Istanbul,	mean	.108	.072	.093	.016	-1.378	.079	.087	.039	-.867
Turkey	% of +returns	1.024	.937	.885	.775	-.550	.983	.922	.795	-.330
Johannesburg,	mean	.079	-.004	.010	.061	-.393	.042	-.004	.043	.034
South Africa	% of +returns	.464	.442	.481	.500	-.239	.457	.457	.499	.108
Kuala Lumpur,	mean	.011	.006	.016	-.029	-.543	-.022	.015	-.001	.484
Malaysia	% of +returns	.380	.377	.356	.434	-.482	.387	.367	.364	.564
London,	mean	.056	.034	-.006	.013	-1.579	.054	.013	-.005	-3.777***
Britain	% of +returns	.316	.343	.310	.278	-.020	.314	.335	.285	-1.634
Madrid,	mean	.033	.023	.001	-.004	-1.695*	.027	.019	-.011	-2.273**
Spain	% of +returns	.324	.339	.323	.325	.050	.323	.344	.313	-.462
Manila,	mean	.147	.011	.002	.041	-1.773*	.095	-.003	.027	-1.780*
Philippines	% of +returns	.440	.460	.477	.502	-1.452	.476	.462	.500	-1.703*
Milan,	mean	.112	.037	-.006	-.008	-4.433***	.058	.016	-.006	-3.787***
Italy	% of +returns	.423	.417	.403	.396	-1.507	.411	.414	.399	-1.287
New York,	mean	-.019	-.001	.010	-.013	.169	-.003	.012	-.017	-.534
United States	% of +returns	.306	.322	.334	.295	1.066	.308	.333	.302	.532
Oslo,	mean	.068	.029	.020	.004	-1.230	.035	.024	.009	-.848
Norway	% of +returns	.475	.424	.441	.393	-.262	.443	.445	.398	.319
Paris,	mean	.053	.043	-.008	.034	-.496	.045	.021	-.012	-3.019***
France	% of +returns	.344	.367	.355	.327	-.548	.319	.370	.330	-3.326***
Rio de Janeiro,	mean	.061	.039	.025	.016	-.477	.039	.038	.013	-.532
Brazil	% of +returns	.468	.481	.513	.480	.217	.475	.491	.530	-.827
Stockholm,	mean	.071	.052	.010	-.009	-1.659*	.087	.028	-.003	-2.786***
Sweden	% of +returns	.441	.439	.425	.369	-.739	.467	.437	.380	-2.025**
Sydney,	mean	.023	.010	.013	.040	.527	.012	.013	.031	.968
Australia	% of +returns	.245	.274	.285	.233	.756	.247	.282	.291	-.388

Taipei, Taiwan	mean	.146	.051	.012	-.031	-2.449**	.086	.023	-.014	-2.038**
	% of +returns	.630	.663	.612	.609	-1.043	.692	.625	.613	-.515
Tokyo, Japan	mean	.024	.016	.003	-.022	-2.977***	.028	.001	-.008	-2.962***
	% of +returns	.304	.340	.299	.306	-1.374	.316	.321	.299	-.361
Vienna, Austria	mean	.016	.029	.006	.004	-.324	.045	.018	.001	-2.386**
	% of +returns	.262	.245	.238	.239	-.106	.281	.237	.239	-.982
Zurich, Switzerland	mean	-.003	.027	.009	-.004	-.016	.043	.015	.002	-2.172**
	% of +returns	.244	.248	.263	.238	.724	.229	.263	.240	-.370

Notes: This table presents bin test results of daily returns across temperature groups using full sample. The sample period varies across countries. Panel A reports 4-bin test results while Panel B presents 3-bin test results. Bin 1 contains returns in the lowest temperature group while bin3 (or bin 4) contains returns in the highest temperature group. Both the mean return and the percentage of positive returns for each bin are reported. The z-scores are calculated for both measures. The null hypothesis is there is no difference between the mean returns (or frequencies of positive returns) of bin 1 and bin 3 (or bin 4). The asterisks, (*) (**) and (***) indicate a rejection of the null hypothesis at the 1%, 5% and 10% levels, respectively.

Table 4 Results of Individual OLS Regressions and SUR Regression with Daily Temperature

City	Panel A: Individual Regression with Full-sized Sample					Panel B: SUR with Equal-sized Sample				
	$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 MON_t + \alpha_4 TAX_t + \alpha_5 TEMP_t + \varepsilon_t$					$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 MON_t + \alpha_4 TAX_t + \alpha_5 TEMP_t + \varepsilon_t$				
Country	r(t-1)	MON	TAX	TEMP	R^2	r(t-1)	MON	TAX	TEMP	R^2
Amsterdam	.014	-.025**	.029	-.001***	0.002	-.071***	-.039	.043	.0003	-.005
Netherlands	(.011)	(.012)	(.012)	(.0005)		(.011)	(.030)	(.039)	(.001)	
Athens	.138***	-.080***	.080	-.001	0.022	.097***	-.138***	-.002	-.0001	.024
Greece	(.014)	(.024)	(.060)	(.001)		(.019)	(.030)	(.068)	(.001)	
Auckland	.036***	-.055***	.058*	-.001	0.005	.064	-.011	.050	-.0003	.008
New Zealand	(.014)	(.015)	(.036)	(.001)		(.020)	(.015)	(.033)	(.001)	
Buenos Aires	.139***	-.092	-.130	.001	0.022	N/A	N/A	N/A	N/A	N/A
Argentina	(.030)	(.066)	(.175)	(.003)						
Copenhagen	.064***	-.004	.026	-.0003	0.004	.001	-.013	.046	.001	-.0004
Denmark	(.010)	(.012)	(.030)	(.0004)		(.016)	(.027)	(.052)	(.001)	
Dublin	.110***	-.008	.029	-.001*	0.013	.018	-.063**	-.025	-.001	.005
Ireland	(.010)	(.013)	(.033)	(.0007)		(.018)	(.029)	(.056)	(.001)	
Frankfurt	.034***	-.026*	-.019	-.001	0.002	N/A	N/A	N/A	N/A	N/A
Germany	(.012)	(.014)	(.035)	(.0004)						
Helsinki	.005	.008	-.112	-.002**	0.002	-.058***	-.024	-.014	-.001	-0.0041
Finland	(.020)	(.047)	(.116)	(.001)		(.016)	(.051)	(.101)	(.001)	
Istanbul	.085***	-.148***	.236**	-.001	0.011	.001	-.241***	.197	.001	.010
Turkey	(.014)	(.040)	(.099)	(.001)		(.021)	(.057)	(.137)	(.002)	
Johannesburg	.078***	-.046**	-.036	.002**	0.008	.005	.002	-.097	.001	.003
South Africa	(.011)	(.019)	(.046)	(.001)		(.019)	(.038)	(.071)	(.002)	
Kuala Lumpur	.150***	-.111***	-.012	-.0004	0.027	.125***	-.093***	.070	-.005	.029
Malaysia	(.013)	(.019)	(.047)	(.004)		(.020)	(.022)	(.050)	(.004)	
London	.086***	-.066***	.015	-.002***	0.012	-.120***	-.036	.012	.0003	-.001
Britain	(.010)	(.012)	(.028)	(.0005)		(.011)	(.026)	(.027)	(.001)	
Madrid	.083***	-.003	-.011	-.001**	0.008	-.066	-.057	.002	.0004	.004
Spain	(.014)	(.016)	(.039)	(.0005)		(.013)	(.025)	(.039)	(.0004)	
Manila	.189***	-.034	-.065	-.006*	0.037	.109***	-.062**	.057	-.005	.018
Philippines	(.014)	(.022)	(.058)	(.003)		(.021)	(.032)	(.076)	(.004)	
Milan	.124***	-.064***	-.007	-.002***	0.019	-.063***	-.057**	.006	-.0003	.002
Italy	(.010)	(.014)	(.036)	(.0004)		(.012)	(.026)	(.039)	(.0004)	
New York	-.015	.001	.031	-.0000	0.0004	-.137***	-.030	.078	.0003	-.006
United States	(.019)	(.022)	(.053)	(.0005)		(.018)	(.026)	(.059)	(.001)	
Oslo	.081***	-.032*	.093**	-.0003	0.008	-.022	-.037	.004	4.75e-08	-0.0001
Norway	(.012)	(.017)	(.043)	(.0004)		(.016)	(.031)	(.059)	(.001)	
Paris	.089***	-.059***	.040	-.001***	0.012	-.059	-.036	.031	-.0002	-.0024
France	(.011)	(.013)	(.032)	(.0004)		(.010)	(.030)	(.038)	(.001)	
Rio de Janeiro	.092***	-.120***	-.115*	-.0005	0.014	-.037**	-.088***	.114	-.005**	.002
Brazil	(.017)	(.029)	(.069)	(.002)		(.019)	(.031)	(.071)	(.002)	
Stockholm	.080***	-.005	.043	-.001***	0.008	-.068***	-.011	.025	-.001	-0.004
Sweden	(.012)	(.017)	(.043)	(.0005)		(.013)	(.036)	(.062)	(.001)	
Sydney	.015	-.009	.030	.001	0.001	-.084***	-.003	-.044	-.001	.002
Australia	(.015)	(.013)	(.035)	(.001)		(.017)	(.020)	(.039)	(.001)	

Taipei	.060***	-.005	.019	-.003**	0.005	-.012	-.072**	.256***	-.003*	.007
Taiwan	(.014)	(.028)	(.072)	(.090)		(.020)	(.036)	(.085)	(.001)	
Tokyo	.083***	-.028**	-.063**	-.001***	0.009	.040**	-.050*	-.132**	-.001	.007
Japan	(.010)	(.012)	(.029)	(.0003)		(.018)	(.030)	(.064)	(.001)	
Vienna	.205***	-.004	.008	-.001*	0.044	.010	-.036*	.009	-.001	.004
Austria	(.010)	(.009)	(.022)	(.0003)		(.017)	(.021)	(.043)	(.0005)	
Zurich	.072***	-.046***	.051**	-.001**	0.009	-.045***	-.048*	.072*	.0002	-.004
Switzerland	(.010)	(.010)	(.025)	(.0003)		(.013)	(.025)	(.039)	(.0005)	
Chi-square (8)						TEMP^i's=	zero	25.84		
Chi-square (7)						TEMP^i's=	equal	23.36		

Notes: This table presents results of both the full-sized sample individual OLS regressions and the equal-sized sample seemingly unrelated regression (SUR) after controlling for first-order autocorrelation (r(t-1)), Monday effect (MON) and tax loss effect (TAX). The equal-sized sample period runs from January 2000 to June 2008. Monday dummy variable is 1 if it is Monday, and 0 otherwise. Tax dummy variable is 1 if it is the first 10 trading days of the tax year, and 0 otherwise. The tax year starts on March 1 in South Africa, April 1 in New Zealand, April 6 in Britain and Ireland, July 1 in Australia, and January 1 in all other countries. We report coefficients of the lagged return (r(t-1)), Monday dummy (MON), Tax loss dummy (TAX), and Temperature (TEMP). The standard errors are reported under coefficient estimates. We also report the R-squares of individual OLS regressions and system-wide R-square of SUR. The Chi-square statistic with 8 degree of freedom is to test joint significance of the temperature coefficients. The other Chi-square statistic with 7 degree of freedom is to test if all temperature coefficients are equal. The asterisks, (*) (**) and (***) indicate two-sided statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5 Results of Individual Regressions with Daily High/Low Temperature using Full-sized Sample

	Panel A: Individual Regression with Max Temperature					*Panel B: Individual Regression with Min Temperature*				
City	$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 MON_t + \alpha_4 TAX_t + \alpha_5 TEMP_t + \varepsilon_t$					$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 MON_t + \alpha_4 TAX_t + \alpha_5 TEMP_t + \varepsilon_t$				
Country	**r(t-1)**	**MON**	**TAX**	**HIGH**	**R^2**	**r(t-1)**	**MON**	**TAX**	**LOW**	**R^2**
Amsterdam	.014	-.025**	.031	-.001***	.002	.014	-.026**	.027	-.002***	.002
Netherlands	(.011)	(.012)	(.030)	(.0004)		(.011)	(.012)	(.030)	(.0004)	
Athens	.138***	-.080***	.079	-.001	.022	.138***	-.080***	.081	-.001	.022
Greece	(.014)	(.024)	(.060)	(.001)		(.014)	(.024)	(.060)	(.001)	
Auckland	.040***	-.054***	.058	-.001	.005	.036***	-.056***	.057	-.001	.005
New Zealand	(.014)	(.015)	(.035)	(.001)		(.014)	(.015)	(.035)	(.001)	
Buenos Aires	.138***	-.093	-.151	-.002	.022	.140***	-.093	-.108	-.001	.022
Argentina	(.030)	(.066)	(.175)	(.002)		(.029)	(.066)	(.175)	(.003)	
Copenhagen	.064***	-.004	.026	-.0002	.004	.064***	-.004	.026	-.0003	.004
Denmark	(.010)	(.012)	(.030)	(.0004)		(.010)	(.012)	(.030)	(.0004)	
Dublin	.111***	-.008	.030	-.001*	.013	.111***	-.008	.028	-.001*	.013
Ireland	(.010)	(.013)	(.033)	(.001)		(.010)	(.013)	(.033)	(.001)	
Frankfurt	.034***	-.026*	-.020	-.001	.002	.034***	-.026*	-.018	-.001	.002
Germany	(.012)	(.014)	(.035)	(.0004)		(.012)	(.014)	(.035)	(.0005)	
Helsinki	.005	.013	-.120	-.003**	.002	.006	.014	-.127	-.002	.001
Finland	(.020)	(.047)	(.116)	(.001)		(.020)	(.047)	(.116)	(.001)	
Istanbul	.085***	-.148***	.229**	-.001	.011	.085***	-.148***	.238**	-.001	.011
Turkey	(.014)	(.040)	(.099)	(.001)		(.014)	(.040)	(.099)	(.001)	
Johannesburg	.079***	-.046**	-.030	.001	.007	.078***	-.046**	-.036	.002**	.007
South Africa	(.011)	(.019)	(.046)	(.001)		(.011)	(.0189)	(.046)	(.001)	
Kuala Lumpur	.150***	-.111***	-.010	-.001	.027	.149***	-.111***	-.019	-.007	.028
Malaysia	(.013)	(.019)	(.047)	(.003)		(.013)	(.019)	(.047)	(.005)	
London	.086***	-.066***	.020	-.001**	.011	.086***	-.066***	.012	-.002***	.013
Britain	(.010)	(.012)	(.028)	(.0004)		(.010)	(.012)	(.028)	(.0004)	
Madrid	.082***	-.003	-.009	-.001**	.008	.083***	-.003	-.010	-.001**	.008
Spain	(.014)	(.016)	(.039)	(.0004)		(.014)	(.016)	(.039)	(.001)	
Manila	.188***	-.033	-.068	-.006**	.038	.189***	-.034	-.058	-.004	.036
Philippines	(.014)	(.023)	(.057)	(.003)		(.014)	(.023)	(.058)	(.003)	
Milan	.124***	-.064***	-.003	-.001***	.019	.123***	-.064***	-.009	-.002***	.020
Italy	(.010)	(.014)	(.036)	(.0004)		(.010)	(.014)	(.036)	(.0004)	
New York	-.015	.001	.030	-.0001	.0004	-.015	.001	.028	-.0002	.0004
United States	(.019)	(.022)	(.053)	(.0005)		(.019)	(.022)	(.053)	(.001)	
Oslo	.081***	-.032*	.098**	-.0001	.008	.081***	-.032*	.090	-.0005	.008
Norway	(.012)	(.017)	(.043)	(.0004)		(.012)	(.017)	(.043)	(.0005)	
Paris	.089***	-.059***	.041	-.001***	.012	.089***	-.059***	.040	-.002***	.012
France	(.011)	(.013)	(.032)	(.004)		(.011)	(.013)	(.032)	(.001)	
Rio de Janeiro	.092***	-.121***	-.112*	-.001	.014	.091***	-.120***	-.114*	-.001	.014
Brazil	(.017)	(.029)	(.069)	(.002)		(.017)	(.029)	(.069)	(.002)	
Stockholm	.081***	-.005	.046	-.001**	.008	.080***	-.005	.041	-.002***	.009
Sweden	(.012)	(.017)	(.043)	(.0004)		(.012)	(.017)	(.043)	(.001)	
Sydney	.015	-.009	.028	.0005	.001	.015	-.009	.027	.0003	.001
Australia	(.015)	(.013)	(.035)	(.001)		(.015)	(.013)	(.035)	(.001)	

Taipei Taiwan	.060*** (.014)	-.006 (.028)	.023 (.071)	-.002** (.001)	.005	.060*** (.014)	-.005 (.028)	.019 (.072)	-.003** (.001)	.005
Tokyo Japan	.084*** (.010)	-.028** (.012)	-.059** (.029)	-.001*** (.0003)	.009	.084*** (.010)	-.028** (.012)	-.063** (.029)	-.001*** (.0003)	.009
Vienna Austria	.206*** (.010)	-.004 (.009)	.009 (.022)	-.001* (.0002)	.043	.205*** (.010)	-.004 (.009)	.008 (.022)	-.001* (.0003)	.044
Zurich Switzerland	.072*** (.010)	-.046*** (.010)	.054** (.025)	-.001** (.0003)	.009	.071*** (.010)	-.047*** (.010)	.050** (.025)	-.001*** (.0003)	.009

Notes: This table presents results of the full-sized sample individual OLS regressions using Max or Min temperature after controlling for first-order autocorrelation (r(t-1)), Monday effect (MON) and tax loss effect (TAX). Monday dummy variable is 1 if it is Monday, and 0 otherwise. Tax dummy variable is 1 if it is the first 10 trading days of the tax year, and 0 otherwise. The tax year starts on March 1 in South Africa, April 1 in New Zealand, April 6 in Britain and Ireland, July 1 in Australia, and January 1 in all other countries. The standard errors are reported under coefficient estimates. The asterisks, (*) (**) and (***) indicate two-sided statistical significance at the 1%, 5% and 10% levels, respectively.

Table 6 Results of Individual Regressions with Historical/Forward Moving Average Temperature using Full-sized Sample

	Panel A: Individual Regression with Historical MA TEMP				***Panel B: Individual Regression with Forward MA TEMP***			
City	$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 MON_t + \alpha_4 TAX_t + \alpha_5 TEMP_t + \varepsilon_t$				$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 MON_t + \alpha_4 TAX_t + \alpha_5 TEMP_t + \varepsilon_t$			
Country	HMA3	HMA7	HMA15	HMA31	FMA3	FMA7	FMA15	FMA31
Amsterdam	-.00148***	-.00166***	-.00170***	-.00178***	-.00121***	-.00129***	-.00134***	-.00122***
Netherlands	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)
Athens	-.00091	-.00111	-.00105	-.00128	-.00114	-.00117	-.00110	-.00109
Greece	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Auckland	-.00089	-.00088	-.00048	-.00037	-.00093	-.00072	-.00073	-.00105
New Zealand	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Buenos Aires	.00156	.00155	.00213	.00227	.00138	.00207	.00170	.00206
Argentina	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Copenhagen	-.00036	-.00030	-.00047	-.00057	-.00023	-.00013	-.00017	-.00011
Denmark	(.0004)	(.0004)	(.0004)	(.0004)	(.0004)	(.0004)	(.0004)	(.0004)
Dublin	-.00134*	-.00150**	-.00196**	-.00200**	-.00146**	-.00180**	-.00206**	-.00200**
Ireland	(.0007)	(.0007)	(.0007)	(.0007)	(.0007)	(.0007)	(.0007)	(.0008)
Frankfurt	-.00076*	-.00091**	-.00093**	-.00094*	-.00060*	-.00062**	-.00079**	-.00074*
Germany	(.0004)	(.0004)	(.0004)	(.0004)	(.0004)	(.0005)	(.0004)	(.0005)
Helsinki	-.00216*	-.00192	-.00204	-.00136	-.00230*	-.00180	-.00223*	-.00284*
Finland	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Istanbul	-.00097	-.00119	-.00098	-.00083	-.00083	-.00111	-.00166	-.00239
Turkey	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Johannesburg	.00186*	.00234**	.00232**	.00214*	.00213**	.00220**	.00225**	.00216*
South Africa	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Kuala Lumpur	-.00367	-.00611	-.00708	-.01405**	-.00073	-.00063	-.00240	-.00391**
Malaysia	(.004)	(.005)	(.006)	(.006)	(.004)	(.005)	(.006)	(.006)
London	-.00172***	-.00172***	-.00178***	-.00181***	-.00131***	-.00142***	-.00148***	-.00163***
Britain	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)
Madrid	-.00112**	-.00114**	-.00112**	-.00124**	-.00096**	-.00100**	-.00103**	-.00104**
Spain	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)
Manila	-.00552	-.00464	-.00548	-.00606	-.00646	-.00697	-.00635	-.00365
Philippines	(.004)	(.004)	(.003)	(.003)	(.004)	(.004)	(.003)	(.003)
Milan	-.00156***	-.00169***	-.00170***	-.00183***	-.00158***	-.00156***	-.00155***	-.00153***
Italy	(.0004)	(.0004)	(.0004)	(.0004)	(.0004)	(.0004)	(.0004)	(.0004)
New York	-.00002	-.00005	-.00028	-.00027	-.00005	-.00022	-.00016	-.00015
United States	(.0005)	(.0005)	(.0006)	(.0006)	(.0005)	(.0005)	(.0006)	(.0006)
Oslo	-.00034	-.00046	-.00048	-.00046	-.00020	-.00017	-.00010	-.00011
Norway	(.0004)	(.0004)	(.0004)	(.0005)	(.0004)	(.0005)	(.0005)	(.0005)
Paris	-.00155***	-.00170***	-.00179***	-.00183***	-.00152***	-.00163***	-.00155***	-.00144***
France	(.0004)	(.0004)	(.0004)	(.0004)	(.0005)	(.0005)	(.0005)	(.0004)
Rio de Janeiro	-.00087	-.00074	-.00082	-.00145	-.00022	-.00063	-.00157	-.00227
Brazil	(.002)	(.003)	(.003)	(.003)	(.002)	(.003)	(.003)	(.003)
Stockholm	-.00134***	-.00138***	-.00151***	-.00144***	-.00122**	-.00115**	-.00119**	-.00115**
Sweden	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)
Sydney	.00046	.00092	.00110	.00154	.00052	.00092	.00088	.00087
Australia	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)

Taipei Taiwan	-.00339*** (.090)	-.00355*** (.090)	-.00378*** (.090)	-.00360*** (.090)	-.00341*** (.001)	-.00354*** (.001)	-.00392*** (.090)	-.00386*** (.090)
Tokyo Japan	-.00111*** (.0003)	-.00121*** (.0003)	-.00126*** (.0003)	-.00124*** (.0003)	-.00116*** (.0003)	-.00117*** (.0004)	-.00108*** (.0004)	-.00106*** (.0003)
Vienna Austria	-.00064*** (.0003)	-.00071*** (.0003)	-.00075*** (.0003)	-.00093*** (.0003)	-.00069 *** (.0002)	-.00067*** (.0003)	-.00071*** (.0003)	-.00058** (.0003)
Zurich Switzerland	-.00072** (.0003)	-.00072** (.0003)	-.00072** (.0003)	-.00084** (.0003)	-.00067** (.0003)	-.00074** (.0003)	-.00079** (.0003)	-.00073** (.0003)

Notes: This table presents results of the full-sized sample individual OLS regressions using historical moving average or forward moving average temperature after controlling for first-order autocorrelation (r(t-1)), Monday effect (MON) and tax loss effect (TAX). Monday dummy variable is 1 if it is Monday, and 0 otherwise. Tax dummy variable is 1 if it is the first 10 trading days of the tax year, and 0 otherwise. The tax year starts on March 1 in South Africa, April 1 in New Zealand, April 6 in Britain and Ireland, July 1 in Australia, and January 1 in all other countries. The standard errors are reported under coefficient estimates. The asterisks, (*) (**) and (***) indicate two-sided statistical significance at the 1%, 5% and 10% levels, respectively.

Table 7 Results of Statistical Tests for Daily Return

		Normality	*Autocorrelation Effect*			*ARCH Effect*		
City Country	**N**	**Jarque-Bera Stat.**	**QW Stat. (1)**	**QW Stat. (5)**	**QW Stat. (10)**	**ARCH LM Stat. (1)**	**ARCH LM Stat. (5)**	**ARCH LM Stat. (10)**
Amsterdam,	8731	15182.59***	1.932	10.208*	35.051***	778.898***	1691.474***	1755.737***
Netherlands		(0.000)	(0.165)	(0.070)	(0.0001)	(0.000)	(0.000)	(0.000)
Athens	5338	15101.77***	100.945***	105.849***	113.156***	224.641***	321.109***	403.451***
Greece		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Auckland,	5318	54295.91***	6.802***	7.758	28.576***	365.726***	499.028***	546.785***
New Zealand		(0.000)	(0.009)	(0.170)	(0.002)	(0.000)	(0.000)	(0.000)
Buenos Aires,	1108	430.168***	21.658***	30.979***	33.505***	46.988***	108.134***	161.351***
Argentina		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Copenhagen,	9252	658447.1 ***	38.060***	42.923***	49.839***	4.129**	69.095***	183.822***
Denmark		(0.000)	(0.000)	(0.000)	(0.000)	(0.042)	(0.000)	(0.000)
Dublin,	9163	47617.22***	112.292***	162.308***	173.423***	97.469***	355.053***	595.971***
Ireland		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	0.000)
Frankfurt,	6776	14981.37***	7.955***	20.177***	26.581***	159.032***	296.453***	324.869***
Germany		(0.000)	(0.005)	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)
Helsinki,	2572	4894.778***	0.063	4.141	14.128	25.551***	75.761***	108.440***
Finland		(0.000)	(0.803)	(0.530)	(0.167)	(0.000)	(0.000)	(0.000)
Istanbul,	5342	3411.123***	37.955***	48.154***	60.270***	350.886***	549.997***	570.851***
Turkey		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Johannesburg,	8205	24367.88***	51.380***	54.608***	75.914***	245.921***	509.252***	561.243***
South Africa		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Kuala Lumpur,	5739	318501***	124.008***	140.414***	149.472***	210.954***	361.779***	390.225***
Malaysia		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
London,	9255	24811.45***	67.046***	83.423***	118.199***	1589.967***	1885.337***	1989.785***
Britain		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Madrid,	5366	8490.134***	37.421***	42.469***	63.928***	250.712***	604.912***	662.302***
Spain		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Manila,	4698	11274.11***	166.374***	177.000***	198.939***	94.276***	190.848***	213.966***
Philippines		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Milan,	9256	9317.008***	142.569***	167.170***	185.079***	441.411***	1179.906***	1295.120***
Italy		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
New York,	2714	1222.468***	0.578	5.472	10.614	77.958***	308.477***	360.521***
United States		(0.000)	(0.447)	(0.361)	(0.388)	(0.000)	(0.000)	(0.000)
Oslo,	7429	54909.75***	48.738***	52.133***	70.958***	623.187***	679.340***	734.017***
Norway		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Paris,	8893	9327.204***	70.484***	73.639***	94.965***	268.572***	1065.323***	1242.381***
France		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rio de Janeiro,	3572	20665.970***	28.264***	44.596***	56.916***	137.063***	237.698***	256.064***
Brazil		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stockholm,	6895	6705.065***	46.201***	48.008***	59.359***	378.805***	727.363***	849.821***
Sweden		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sydney,	4556	5992.409***	1.097	6.460	11.036	364.518***	523.967***	546.973***
Australia		(0.000)	(0.295)	(0.264)	(0.355)	(0.000)	(0.000)	(0.000)

Taipei, Taiwan	5366	1868.186*** (0.000)	20.176*** (0.000)	50.350*** (0.000)	61.547*** (0.000)	191.055*** (0.000)	813.259*** (0.000)	1088.565*** (0.000)
Tokyo, Japan	9254	46751.570*** (0.000)	65.942*** (0.000)	78.429*** (0.000)	98.697*** (0.000)	493.144*** (0.000)	649.933*** (0.000)	684.005*** (0.000)
Vienna, Austria	9257	81901.03*** (0.000)	394.616*** (0.000)	489.481*** (0.000)	533.186*** (0.000)	506.135*** (0.000)	1030.795*** (0.000)	1101.718*** (0.000)
Zurich, Switzerland	9257	82952.440*** (0.000)	47.517*** (0.000)	58.040*** (0.000)	72.372*** (0.000)	404.386*** (0.000)	1491.505*** (0.000)	1498.046*** (0.000)

Notes: This table presents results of the Jarque-Bera normality tests, autocorrelation tests (lag 1, 5 and 10) and ARCH effect tests (lag 1,5 and 10) for daily returns. The p-values are reported in the parentheses under coefficient estimates. The asterisks, (*) (**) and (***) indicate two-sided statistical significance at the 1%, 5% and 10% levels, respectively.

Table 8 Results of Statistical Tests for Daily Temperature

		Normality	*Autocorrelation Effect*			*ARCH Effect*		
City Country	**N**	**Jarque-Bera Stat.**	**QW Stat. (1)**	**QW Stat. (5)**	**QW Stat. (10)**	**ARCH LM Stat. (1)**	**ARCH LM Stat. (5)**	**ARCH LM Stat. (10)**
Amsterdam, Netherlands	8731	97.486*** (0.000)	7573.435*** (0.000)	31144.67*** (0.000)	55699.08*** (0.000)	7549.933*** (0.000)	7598.798*** (0.000)	7614.166*** (0.000)
Athens Greece	5338	250.166*** (0.000)	4966.268*** (0.000)	22518.01*** (0.000)	42600.13*** (0.000)	5009.339*** (0.000)	5019.154*** (0.000)	5017.789*** (0.000)
Auckland, New Zealand	5318	94.420*** (0.000)	3973.732*** (0.000)	16116.73*** (0.000)	29937.94*** (0.000)	4070.178*** (0.000)	4183.994*** (0.000)	4221.97*** (0.000)
Buenos Aires, Argentina	1108	45.373*** (0.000)	808.520*** (0.000)	3000.926*** (0.000)	5382.632*** (0.000)	801.366*** (0.000)	819.090*** (0.000)	824.172*** (0.000)
Copenhagen, Denmark	9252	260.455*** (0.000)	8453.513*** (0.000)	38143.77*** (0.000)	71748.38*** (0.000)	8489.753*** (0.000)	8524.209*** (0.000)	8528.211*** (0.000)
Dublin, Ireland	9163	187.096*** (0.000)	7016.224*** (0.000)	27975.42*** (0.000)	50113.5*** (0.000)	7109.673*** (0.000)	7266.232*** (0.000)	7297.377*** (0.000)
Frankfurt, Germany	6776	122.988*** (0.000)	5972.36*** (0.000)	25009.03*** (0.000)	45429.51*** (0.000)	5950.933*** (0.000)	5987.067*** (0.000)	5995.827*** (0.000)
Helsinki, Finland	2572	49.715*** (0.000)	2273.271*** (0.000)	9808.003*** (0.000)	18079.74*** (0.000)	2316.813*** (0.000)	2327.254*** (0.000)	2326.779*** (0.000)
Istanbul, Turkey	5342	278.761*** (0.000)	4888.64*** (0.000)	21791.77*** (0.000)	41145.71*** (0.000)	4926.899*** (0.000)	4946.069*** (0.000)	4947.768*** (0.000)
Johannesburg, South Africa	8205	298.442*** (0.000)	5782.806*** (0.000)	20429.03*** (0.000)	36252.11*** (0.000)	5740.592*** (0.000)	5894.828*** (0.000)	5955.386*** (0.000)
Kuala Lumpur, Malaysia	5739	1.9714 (0.373)	1601.042*** (0.000)	5176.986*** (0.000)	8263.712*** (0.000)	1621.775*** (0.000)	1990.641*** (0.000)	2045.496*** (0.000)
London, Britain	9255	142.143*** (0.000)	7634.603*** (0.000)	31019.7*** (0.000)	55599.89*** (0.000)	7726.713*** (0.000)	7804.728*** (0.000)	7826.044*** (0.000)
Madrid, Spain	5366	297.330*** (0.000)	4845.197*** (0.000)	21680.58*** (0.000)	40798.74*** (0.000)	4839.538*** (0.000)	4864.93*** (0.000)	4868.511*** (0.000)
Manila, Philippines	4698	6.355*** (0.042)	2579.65*** (0.000)	8746.783*** (0.000)	13619.26*** (0.000)	2598.942*** (0.000)	2749.063*** (0.000)	2757.031*** (0.000)
Milan, Italy	9256	469.384*** (0.000)	8753.038*** (0.000)	40586.98*** (0.000)	77120.37*** (0.000)	8748.66*** (0.000)	8760.73*** (0.000)	8760.672*** (0.000)
New York, United States	2714	104.298*** (0.000)	2303.358*** (0.000)	9816.171*** (0.000)	18437.19*** (0.000)	2334.269*** (0.000)	2361.235*** (0.000)	2366.707*** (0.000)
Oslo, Norway	7429	181.26*** (0.000)	6585.970*** (0.000)	28536.23*** (0.00)	52873.45*** (0.000)	6765.179*** (0.000)	6786.046*** (0.000)	6794.559*** (0.000)
Paris, France	8893	103.9348*** (0.000)	7623.788*** (0.000)	30644.86*** (0.000)	54058.23*** (0.000)	7579.871*** (0.000)	7634.439*** (0.000)	7649.883*** (0.000)
Rio de Janeiro, Brazil	3572	35.798*** (0.000)	2326.878*** (0.000)	7488.837*** (0.000)	12530.71*** (0.000)	2320.444*** (0.000)	2409.203*** (0.000)	2422.845*** (0.000)
Stockholm, Sweden	6895	96.894*** (0.000)	6105.593*** (0.000)	26791.36*** (0.000)	49908.85*** (0.000)	6222.591*** (0.000)	6249.586*** (0.000)	6256.652*** (0.000)
Sydney, Australia	4556	133.489*** (0.000)	3343.836*** (0.000)	13531.82*** (0.000)	25213.19*** (0.000)	3288.967*** (0.000)	3417.845*** (0.000)	3452.661*** (0.000)

Taipei, Taiwan	5366	259.031*** (0.000)	4418.212*** (0.000)	18429.96*** (0.000)	34395.4*** (0.000)	4461.546*** (0.000)	4533.969*** (0.000)	4551.441*** (0.000)
Tokyo, Japan	9254	519.626*** (0.000)	8354.063*** (0.000)	39106.42*** (0.000)	75745.01*** (0.000)	8387.725*** (0.000)	8482.82*** (0.000)	8491.309*** (0.000)
Vienna, Austria	9257	318.051*** (0.000)	8275.814*** (0.000)	35714.81*** (0.000)	65701.26*** (0.000)	8251.8*** (0.000)	8296.958*** (0.000)	8306.469*** (0.000)
Zurich, Switzerland	9257	250.262*** (0.000)	8240.499*** (0.000)	34878.52*** (0.000)	63622.71*** (0.000)	8221.013*** (0.000)	8261.917*** (0.000)	8272.896*** (0.000)

Notes: This table presents results of the Jarque-Bera normality tests, autocorrelation tests (lag 1, 5 and 10) and ARCH effect tests (lag 1,5 and 10) for daily temperature. The p-values are reported in the parentheses under coefficient estimates. The asterisks, (*) (**) and (***) indicate two-sided statistical significance at the 1%, 5% and 10% levels, respectively.

Table 9 Results of Copula Models for Daily Temperature and Daily Return with Equal-sized Sample

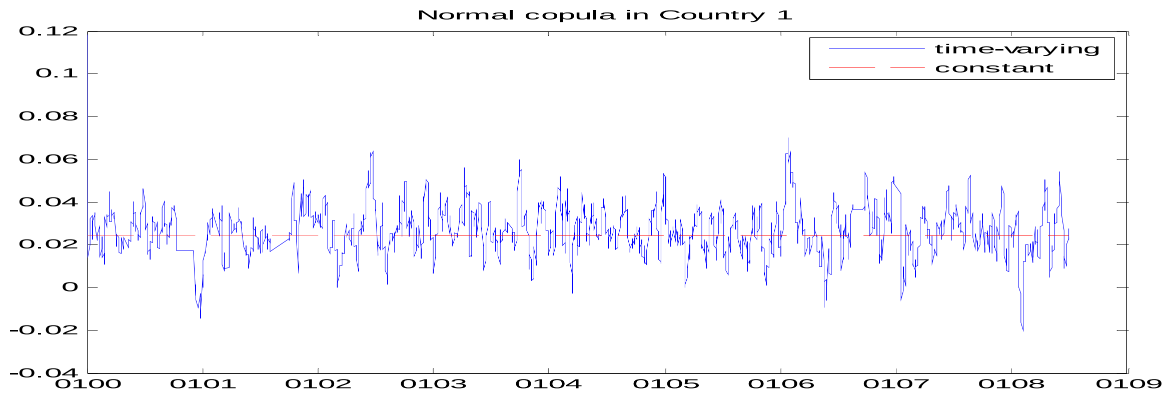
	Panel A: Constant-Dependence Copula			*Panel B: Time-Varying-Dependence Copula*					*Likelihood Ratio Test*	
City Country	**ρ**	**LL**	**AIC**	**Constant**	**MA(α)**	**AR(β)**	**LL**	**AIC**	**LR Stat.**	**P-value**
Amsterdam Netherlands	-0.012	-0.135	-0.268	-0.026	-0.207	0.224	-1.179	-2.354	-2.088	0.352
Athens Greece	-0.046	-2.101	-4.201	-0.168	-0.101	-1.764	-2.672	-5.342	-1.142	0.565
Auckland New Zealand	-0.024	-0.550	-1.099	-0.049	-0.003	0.001	-0.551	-1.099	-0.002	0.999
Copenhagen Denmark	-0.016	-0.257	-0.512	-0.033	-0.065	-0.001	-0.339	-0.676	-0.164	0.921
Dublin Ireland	-0.001	-0.002	-0.002	-0.001	-0.056	1.415	-0.515	-1.028	-1.026	0.599
Helsinki Finland	-0.032	-1.017	-2.032	-0.015	-0.046	1.551	-1.641	-3.278	-1.248	0.536
Istanbul Turkey	0.015	-0.223	-0.445	0.011	-0.055	1.317	-0.631	-1.258	-0.816	0.665
Johannesburg South Africa	0.034	-1.101	-2.200	0.070	-0.010	0.012	-1.105	-2.206	-0.008	0.996
Kuala Lumpur Malaysia	-0.012	-0.146	-0.291	-0.023	-0.006	0.003	-0.148	-0.293	-0.004	0.998
London Britain	-0.029	-0.816	-1.630	-0.094	-0.503	-0.893	-3.185	-6.368	-4.738*	0.094
Madrid Spain	0.019	-0.338	-0.676	0.053	-0.052	-0.858	-0.382	-0.761	-0.088	0.957
Manila Philippines	-0.029	-0.839	-1.677	-0.110	-0.432	-1.216	-2.649	-5.295	-3.62	0.164
Milan Italy	-0.002	-0.002	-0.004	-0.002	0.040	1.673	-0.965	-1.927	-1.926	0.382
New York United States	-0.008	-0.0562	-0.1113	-0.015	-0.003	0.004	-0.0564	-0.1097	-0.0004	0.999
Oslo Norway	0.024	-0.586	-1.171	0.056	-0.079	-0.013	-0.733	-1.464	-0.294	0.863
Paris France	-0.016	-0.243	-0.484	-0.059	0.448	-0.951	-2.272	-4.540	-4.058	0.131
Rio de Janeiro Brazil	-0.004	-0.019	-0.037	-0.012	-0.198	-0.305	-0.721	-1.439	-1.404	0.496
Stockholm Sweden	-0.020	-0.381	-0.762	-0.055	0.251	-0.914	-1.069	-2.134	-1.376	0.503
Sydney Australia	-0.005	-0.023	-0.045	-0.010	-0.033	-0.017	-0.047	-0.091	-0.048	0.976
Taipei Taiwan	-0.025	-0.633	-1.264	-0.077	-0.246	-0.484	-1.401	-2.800	-1.536	0.464
Tokyo Japan	-0.043	-1.769	-3.537	-0.067	0.024	0.467	-1.790	-3.577	-0.042	0.980

Vienna Austria	-0.001	-0.0004	0.0002	-0.0001	-0.043	1.825	-1.326	-2.648	-2.6512	0.266
Zurich Switzerland	-0.005	-0.029	-0.057	-0.011	0.009	-0.011	-0.031	-0.059	-0.004	0.998

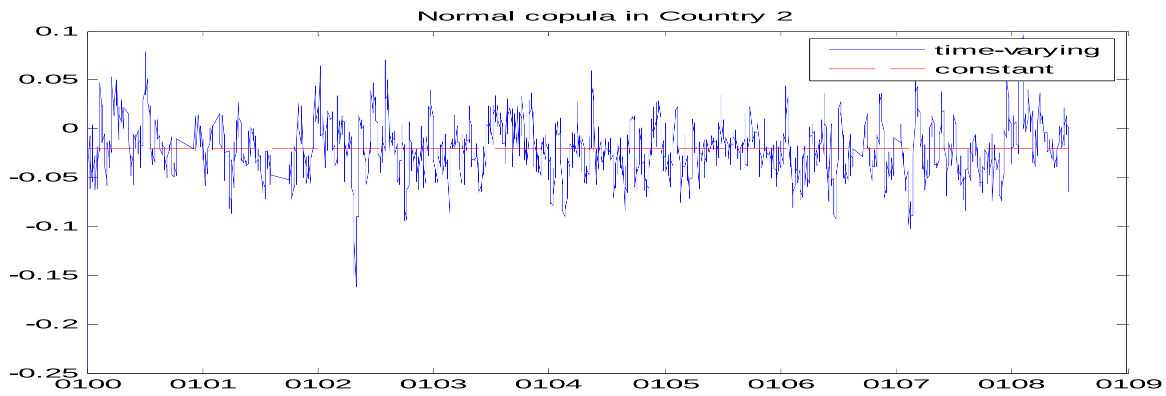
Notes: The table presents copula estimates for both constant-dependence and time-varying-dependence models. We also report log-likelihood and AIC. The Likelihood Ratio (p) Statistic test the null hypothesis that the restricted version (with constant dependence) of a model is not rejected as one moves from restricted model to unrestricted model (with time-varying dependence) where the parameter p is the number of restrictions under the null. So we have two restrictions in Normal copula. P-values are reported in parentheses. The asterisks, (*) (**) and (***) indicate a rejection of the null hypothesis at the 1%, 5% and 10% levels, respectively.

Figure 1 Plot of Time Path of Dependence between Temperature and Return using Normal Copula Models

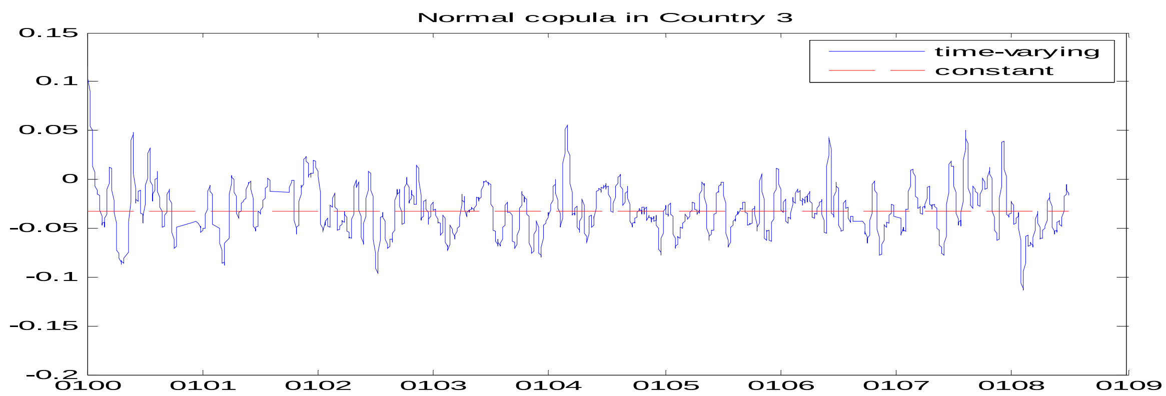
Oslo, Norway



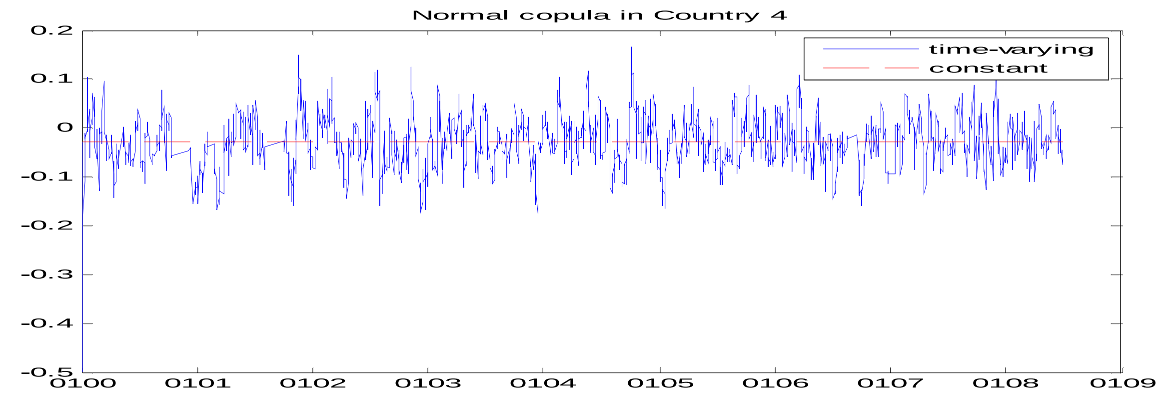
Stockholm, Sweden



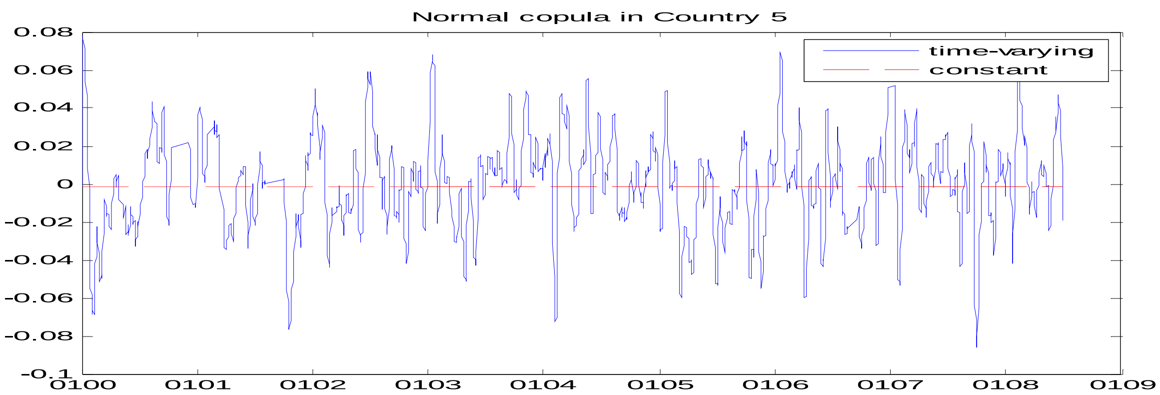
Helsinki, Finland



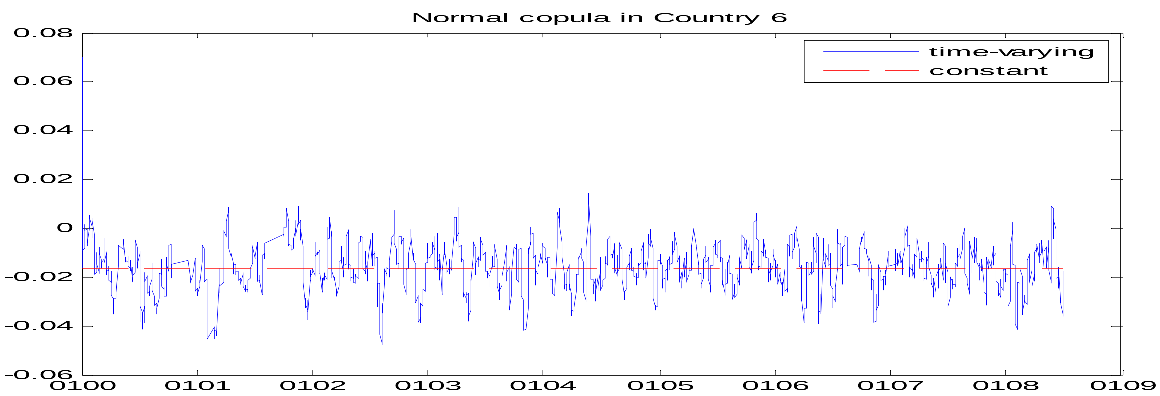
London, Britain



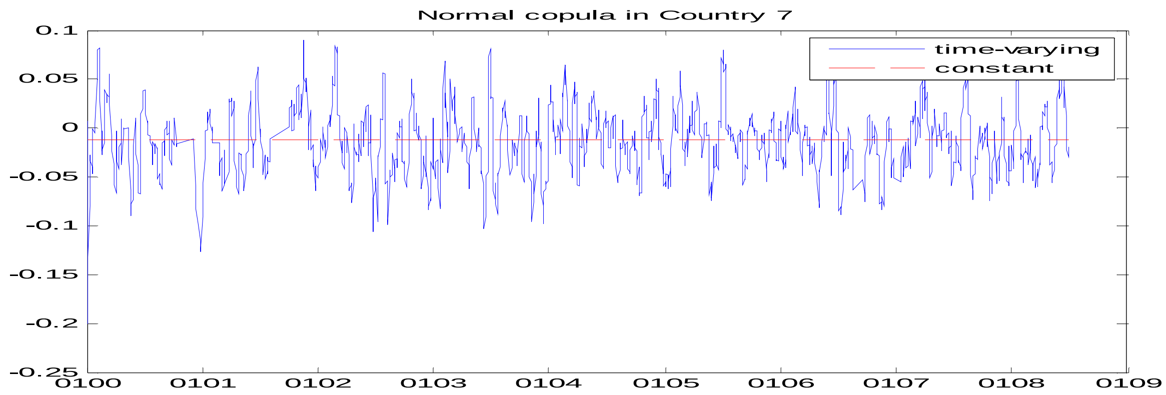
Dublin, Ireland



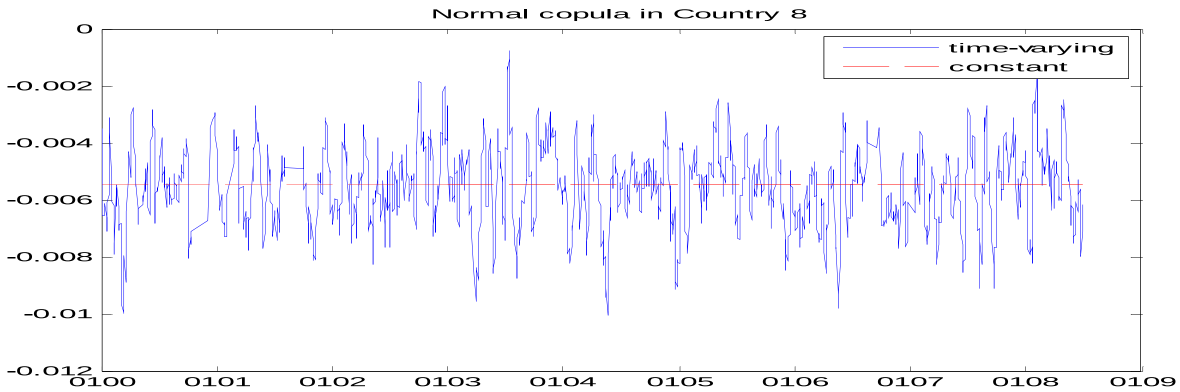
Copenhagen, Denmark



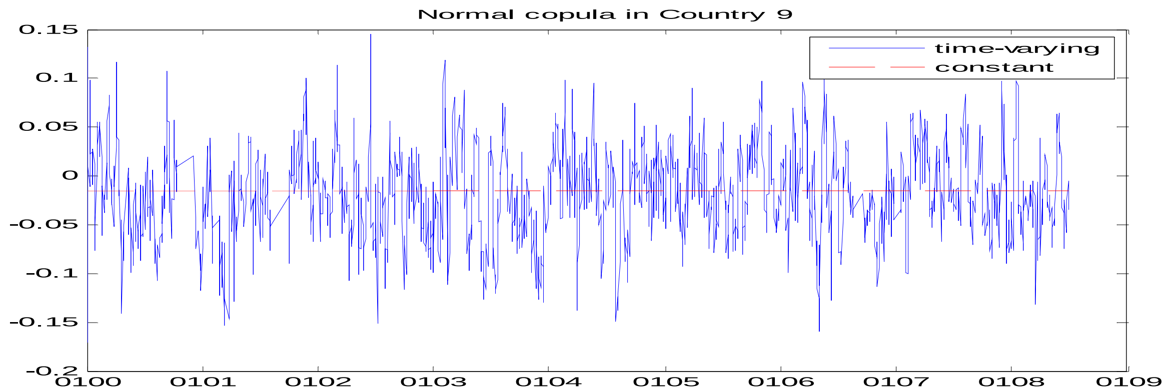
Amsterdam, Netherlands



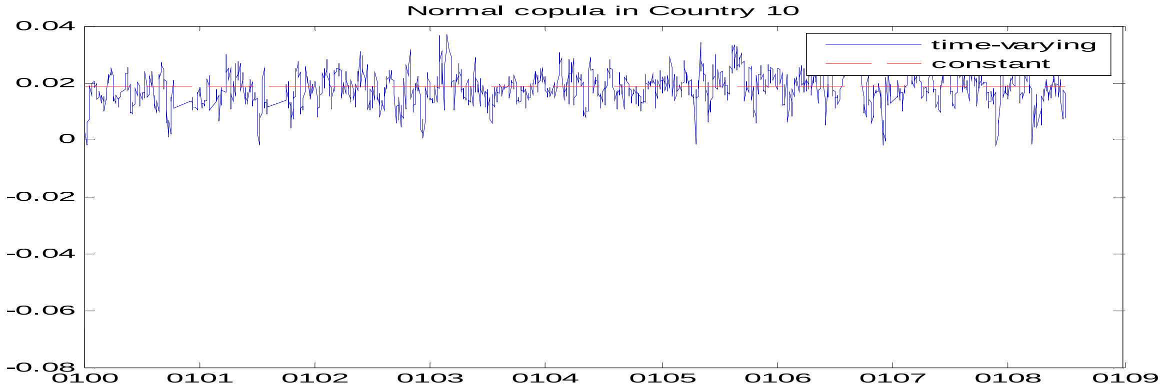
Zurich, Switzerland



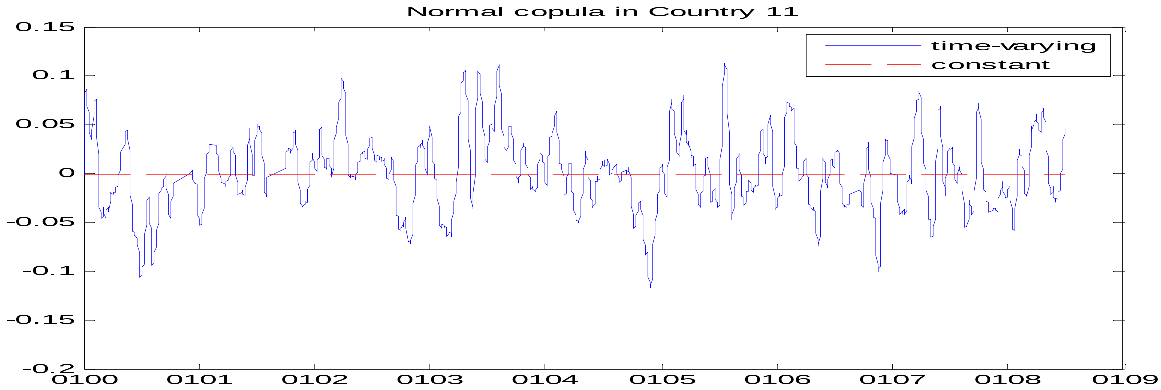
Paris, France



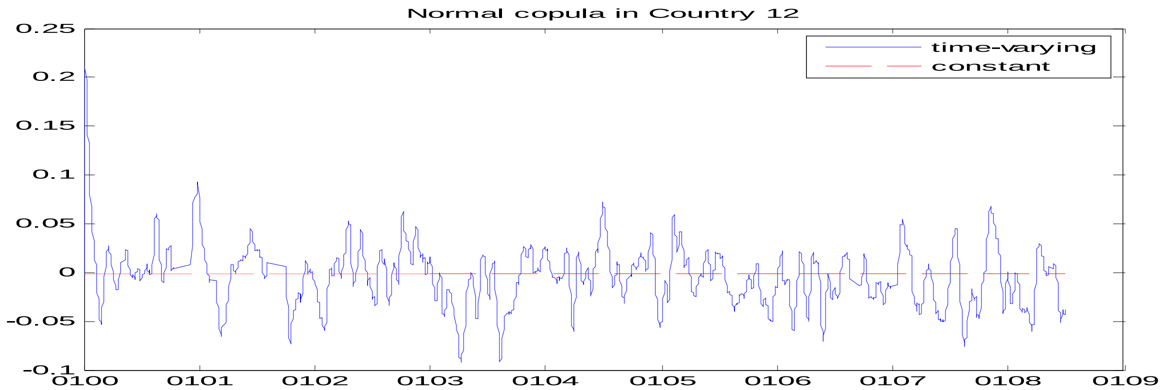
Madrid, Spain



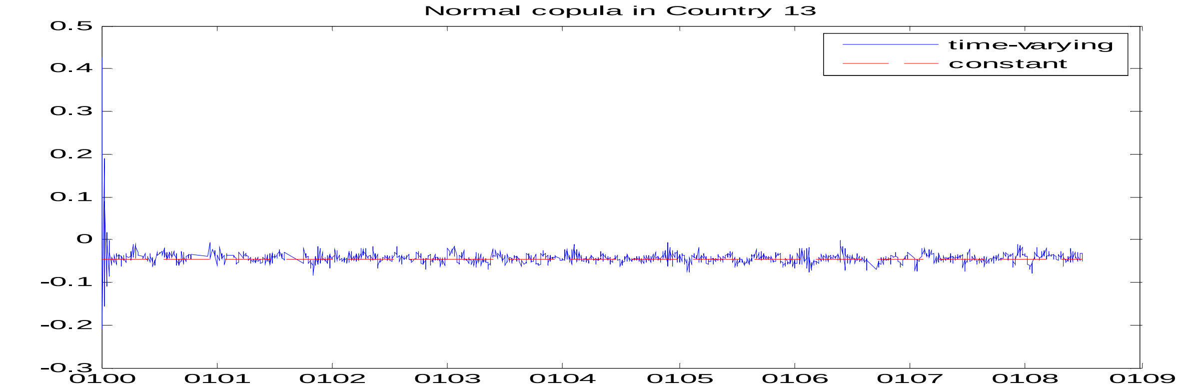
Vienna, Austria



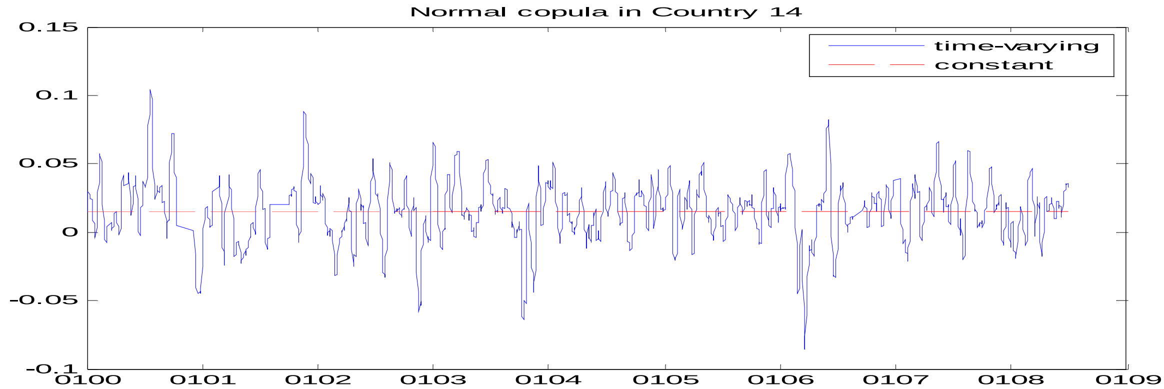
Milan, Italy



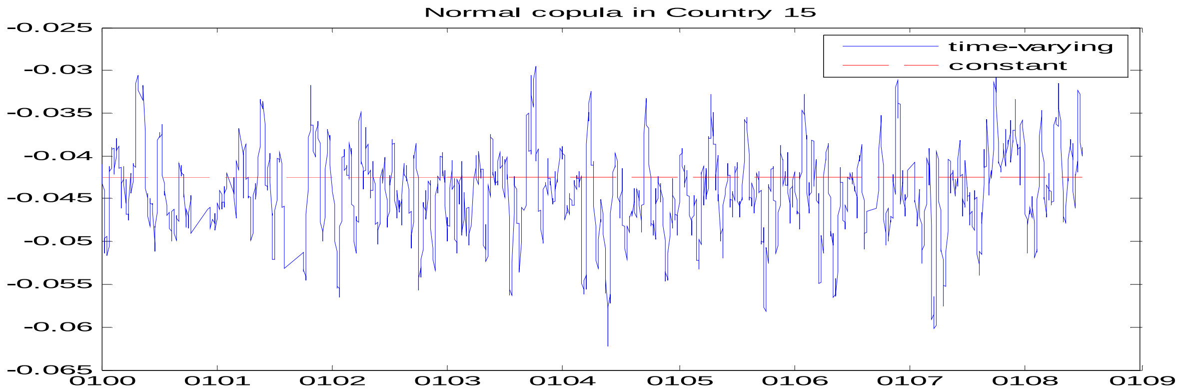
Athens, Greece



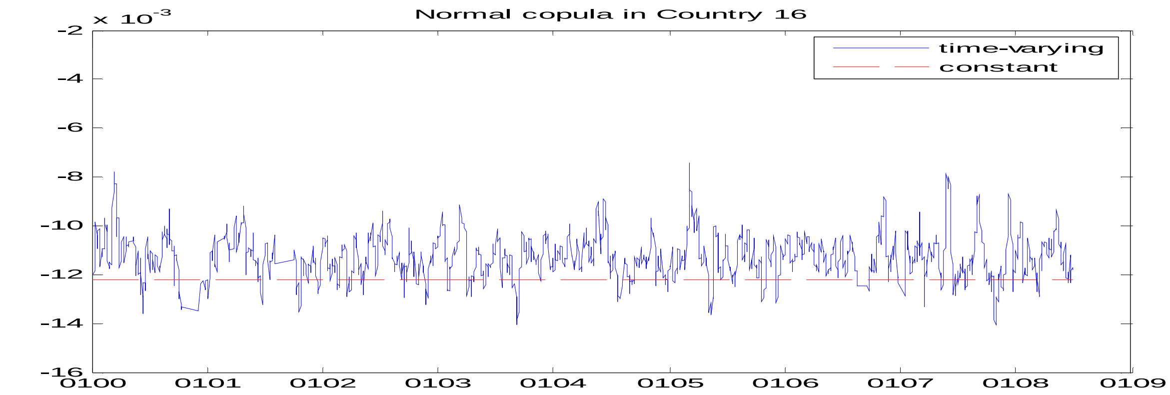
Istanbul, Turkey



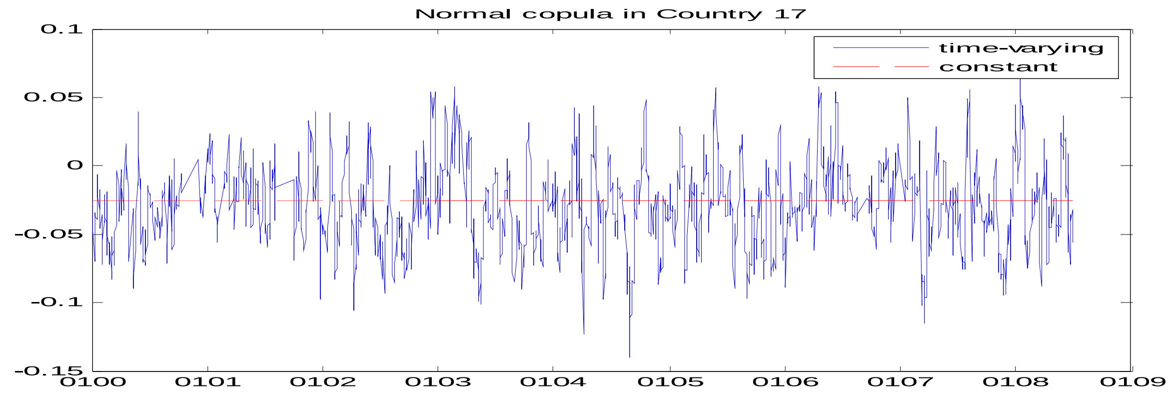
Tokyo, Japan



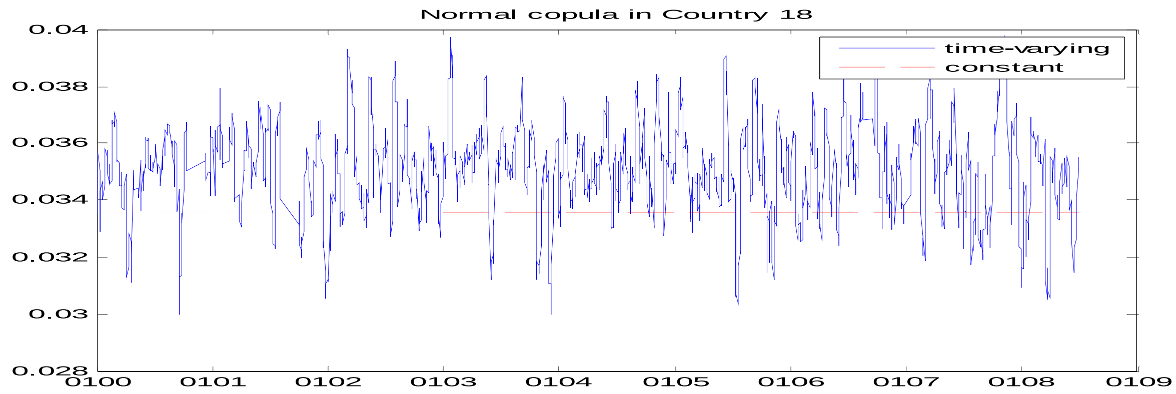
Kuala Lumpur, Malaysia



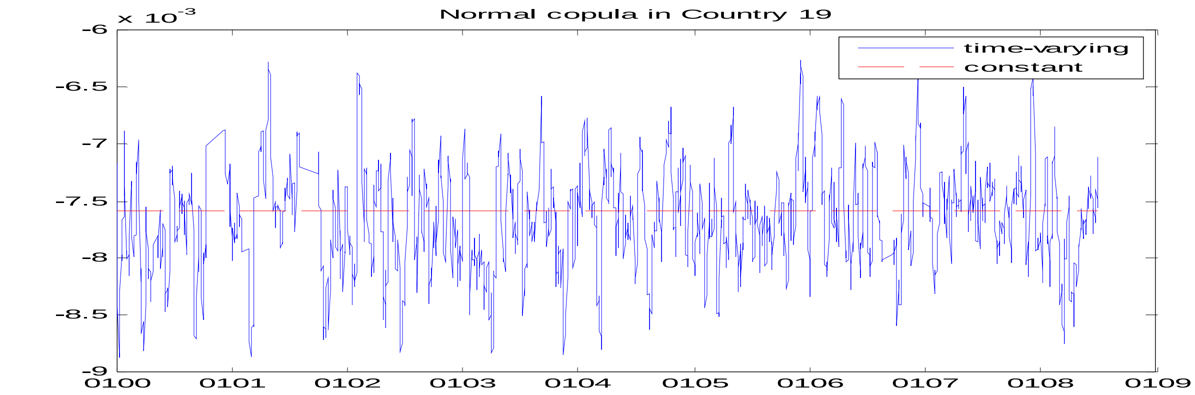
Taipei, Taiwan



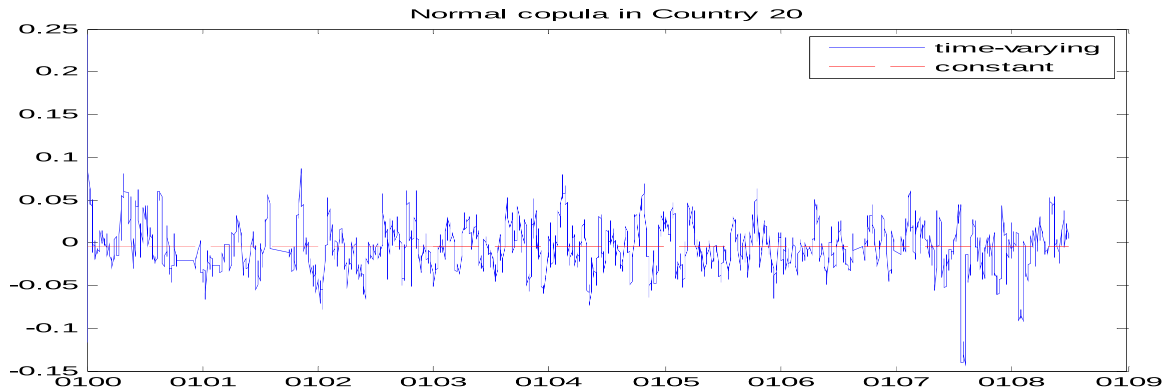
Johannesburg, South Africa



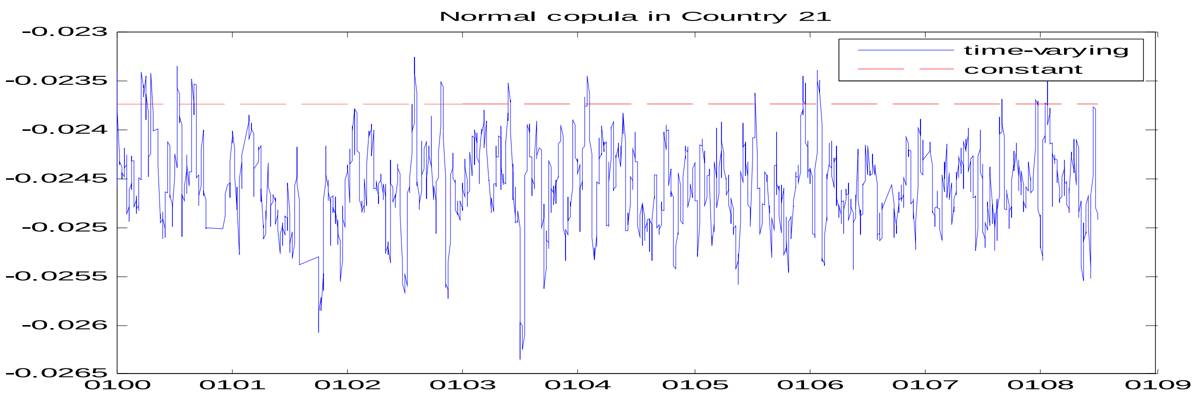
New York, United States



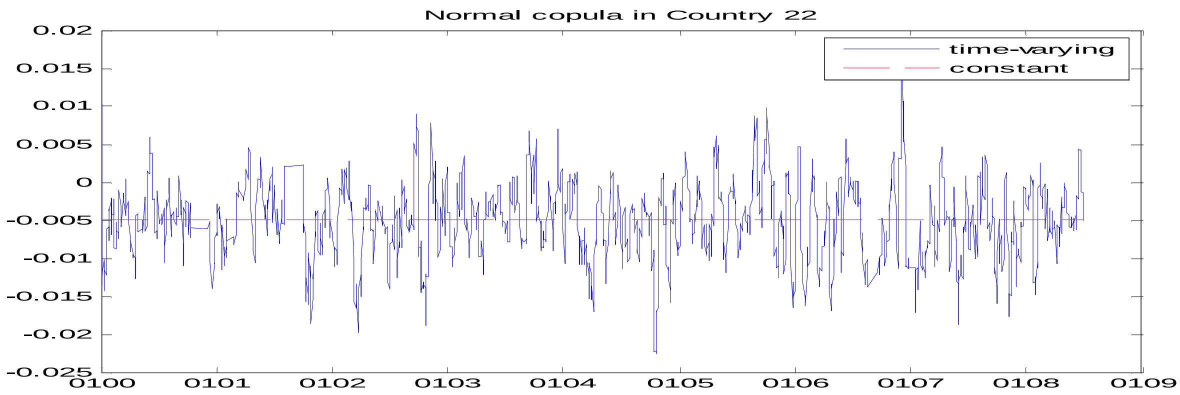
Rio de Janeiro, Brazil



Auckland, New Zealand



Sydney, Australia



Manila, Philippines