Weather Effects on Stock Returns and Volatility in South Asian Markets

Abstract

We study the effect of mood-proxy variables on index returns and volatility in six South Asian markets. Our mood-proxy variables include six weather (temperature, humidity, cloud cover, air pressure, visibility, and wind speed), three weather indicator variables (Fog, Thunder storm and Rain or Drizzle) and two biorhythmic variables (SAD and Lunar phases). We adopt a robust approach and attempt to select the best parsimonious econometric model for each market. Our findings suggest that mood-proxy variables have some convincing influences in South Asian capital markets. In some instances, these variables are influencing returns while in other instances they are influencing volatility.

Key Words: Anomaly, GARCH Models, Investor Sentiments, SAD, Stock Returns, Temperature

JEL Classification: G10, G11, G12, G14, G02

1. Introduction

The Efficient Market Hypothesis (EMH) holds the premise that stock markets are fundamentally rational. These rational stock markets reflect only economic information relevant to security prices. The portfolio theory of Harry Markowitz and the Capital Asset Pricing Model (CAPM) assume that investors behave rationally when making their investment decisions. They choose optimal portfolio weightings by analyzing the risk-return trade-off in a mean-variance efficient framework. Contrary to these traditional finance theories, supporters of limited investor rationality argue that it is not always possible for investors to make rational investment decisions since there are a number of factors that affect the market. Thus, participants involved in the stock markets certainly have only a limited rationality (Simon, 1997). Lucey and Dowling (2005) argue that investor rationality appears to be inconsistent with reality due to the reason that it overlooks the effect of investor sentiments on the process of decision making.

Over the recent years, many researchers in behavioral finance have put their efforts to investigate the influence of psychological factors influencing the investors' evaluation of securities. Generally, these psychological factors are related to mood fluctuations induced by weather. Several studies (e.g., Cao & Wei, 2005; Dowling & Lucey, 2008; Kamstra, Kramer, & Levi, 2003; Lu & Chou, 2012; Saunders, 1993) have attempted to investigate in depth the relations between stock market returns and current weather conditions. One of the empirical findings is the 'sunshine effect' - a negative correlation between cloudiness, as measured by cloud cover, and daily equity index returns (S.-C. Chang, Chen, Chou, & Lin, 2008; Hirshleifer & Shumway, 2003 ; Saunders, 1993). This sunshine effect in the New York Stock Exchange (NYSE), first found by Saunders (1993), was immediately noticed by the Wall Street. In fact, Stecklow (1993) writes in the Wall Street Journal; "Forget the January effect. A professor at the University of Massachusetts has come up with what he believes is a better indicator of when the stock market will rise or fall. Check the weather on Wall Street".

The sunshine effect has been explained using psychological arguments related to 'mood misattribution'. Simply put, sunny weather is thought to make some investors more optimistic, leading them to be willing to enter into long positions, thus leading to higher returns.

Besides sunshine, there are other environmental and weather variables that are thought to have impact on financial markets. These mood proxy variables include, among others, temperature (e.g., Cao & Wei, 2005; T. Chang, Nieh, Yang, & Yang, 2006; Kang, Jiang, Lee, & Yoon, 2010; Lu & Chou, 2012), daylight savings time changes (e.g., Dowling & Lucey, 2008; Kamstra, Kramer, & Levi, 2000), humidity, wind speed, visibility (e.g., Kang et al., 2010; Lu & Chou, 2012; Yoon & Kang, 2009) and the 'Seasonal Affective Disorder', SAD, (e.g., Garrett, Kamstra, & Kramer, 2005; Kamstra et al., 2003). Kamstra et al. (2003) contend that people become less tolerant to risk when days shorten - SAD effect.

While many studies report a significant influence of mood-proxy variables on stock markets, others report negligible or no such influence. For instance, Jacobsen and Marquering (2008) find little evidence for SAD effect. Trombley (1997) re-investigated work of Saunders (1993) and report no sunshine effect on NYSE. Goetzmann and Zhu (2005) also find limited impact of cloud cover after controlling for liquidity in NYSE.

Kamstra et al. (2003) report that precipitation and cloud cover do not affect NYSE stock returns. Dowling and Lucey (2008), after analyzing 37 stock indices and 21 MSCI small capitalization indices around the world, conclude that it is SAD not the weather which mostly influence the stock returns. Lu and Chou (2012), using Chinese market data, show that changes in mood induced by factors such as weather and SAD do not affect asset returns in an order-driven market. Some studies report similar results for other markets. For example, Krämer and Runde (1997) for the DAX stock index Germany, Pardo and Valor (2003) for the Madrid stock index and Tufan and Hamarat (2004) for the Istanbul stock exchange.

Most of the existing studies appear to focus on developed world when investigating the relation between stock markets and the mood-proxy variables with relatively less evidence from emerging markets.[1] This paper focuses on the equity markets of four countries of South Asia (India, Pakistan, Bangladesh and Sri Lanka). The stock markets of this region are considered to be emerging. The performance of these markets over the past decade has been promising and admired by various international institutions (see, Figure 1). There have been number of reforms in these markets over the last decade. Findings of Dowling and Lucey (2005), when analyzing Irish stock market, suggest that the relations between stock returns and the mood-proxy variables are considerably stronger for the markets with recent promising performance. Therefore, we may expect that such relationships are more pronounced in South Asian stock markets. Further, these sample countries have a hot summer due to their geographical locations therefore markets in these countries may be more prone to "long and hot summer effect"- a phenomenon refers to as aggressive and violent behavior in society when it is very hot (Bell, Greene, Fisher, & Baum, 2005).

FIGURE 1 HERE

Our study contributes in a number of ways. First, we investigate six weather and two biorhythmic variables, and also include various indicator variables in our analysis. Second, unlike many previous studies focusing on returns or volatility separately, we examine the impact of mood-proxy variables on both returns and volatility simultaneously using ARCH models. Third, we also account for the econometric robustness issues existing in previous studies as pointed out by Dowling and Lucey (2008) and attempt to select the best parsimonious econometric model for each market representing the unique data generating process of that market. Finally, we work on both basic and deseasonalized mood proxy variables, leading to more robust analysis.

Rest of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 discusses the data and methodology. Section 4 presents the empirical results and conclusions are presented in section 5.

2. Literature Review

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[1] Yuksel and Yuksel (2009) for instance, who include Indian market, among others, in their sample and test the effect of temperature. Similarly, Mirza, Asghar, and Mushtaq (2012) examine Pakistani markets for the temperature effects. Other studies that include Indian and Pakistani markets among others, test the impact of lunar phase Yuan, Zheng, and Zhu (2006), temperature and Sad effect Jacobsen and Marquering (2008).

Roll (1992) contends that “Weather is a genuinely exogenous economic factor. It was a favorite example of an exogenous identifying variable in the early econometric literature … because weather is both exogenous and unambiguously … weather data should be useful in assessing the information processing ability of financial markets”.

Weather is considered to be a source of misattributed mood in capital market research studies. Many weather variables have been focused to examine their effects on equity returns and volatility. Saunders (1993) examines the effect of cloud cover on stocks traded in NYSE and finds that below average returns are correlated with 100 percent cloud cover ratio, whereas above average returns are correlated with low levels or cloud cover ratio (0-20 percent). Hirshleifer and Shumway (2003) use deseasonalized cloud cover ratio and replicate the study of Saunders (1993) for index returns of 26 international capital markets for period 1982 to 1997. They find that 9 out of 25 negative relationships between cloud cover and index returns are significant while only 1 relationship has a positive sign. A large number of studies, attempting to confirm the findings of Saunders (1993) and Hirshleifer and Shumway (2003) using different markets show mixed but generally supporting results.

Wyndham (1969) and Allen and Fischer (1978) note that ability of people to complete tasks is greatly reduced when they are exposed to extreme cold or hot conditions. People may become either aggressive or unusually apathetic in very hot environment. Cunningham (1979) states that people show reluctance in helping others in hot and cold weather. Increased aggressiveness may induce more risk taking on the other hand, apathy leads to risk avoidance. Motivated by such arguments Cao and Wei (2005) test 27 national equity indices using high and low temperature relative to comfortable temperature of 18.33 degree Celsius. They get support for their hypothesis that low temperatures being related to aggression lead to higher bids for equities, whereas high temperatures are related to both apathy and aggression leading to weak prospects for the relation in any direction. They find that high returns are related to low temperature whereas lower returns are weakly related to high temperature. However, they make no adjustment for well-known ARCH effect in stock returns and include both variables temperature and amount of daylight, in the same regression ignoring the possibility of multicollinearity due to close relation between these two variables (Jacobsen & Marquering, 2008). Keef and Roush (2007) find that temperature has negative relationship with stock index. Using data from 42 markets Yuksel and Yuksel (2009) show that seasonal component of temperature has more influence on the stock returns than the deseasonalized temperature has. In their analysis Indian market is significantly affected by raw temperature and deseasonalized temperature. However, they use one model for all the markets assuming the generalized error distribution (GED) which may not be the case for every market. Mirza et al. (2012) investigate the two Pakistani markets and find that temperature is negatively related to index returns. However, they used raw temperature data only. Yoon and Kang (2009) argue that, before financial crisis 1997, extremely low temperatures positively influenced the returns, while extremely high humidity negatively affected the returns.

Keef and Roush (2002) study the relationship of stock market returns with wind speed and direction. They find that both wind speed and direction affect the stock returns. High wind speed reduces the markets returns, and vice versa. Limpaphayom, Locke, and

Sarajoti (2005) find that bid-ask spread has a positive association with windy day, while high wind speed in the morning is related to trade imbalance.

Kamstra et al. (2003) examine the SAD effects on security prices. They work on the premise that reduced hours of daylight from autumn equinox induce depression in investors leading to risk avoidance and hence lower returns. Similarly, investors become more willing to take risk when daylight hours increase from winter solstice to spring equinox and hence tend to earn higher returns. They find support for the influence of SAD on the market returns. Kelly and Meschke (2005) disapprove the SAD effect advocated by Kamstra et al. (2003) and others due to extra reliance on the high returns during December 21st till January 20th – a period of already well-known high returns anomaly (January effect).

Dichev and Janes (2003) and Yuan et al. (2006) investigate the security returns during the days close to new moon against the days close to full moon. These studies find high returns being more related to new moon dates than to full moon dates however, tend to rely on basic OLS testing technique.

Any mood misattribution induced by weather may induce disagreement among investors, leading to change in risk preferences and hence volatility. However, empirical evidence of weather induced volatility is scarce. S.-C. Chang et al. (2008) find significant positive influence of cloud cover on intraday volatility of NYSE firms. Dowling and Lucey (2008) show that SAD and different other mood proxy variables are positively related to conditional variance for most of the equity indices considered. Kaplanski and Levy (2009) show that the temperature (number of daylight hours) is positively (negatively) associated only with the 'perceived' volatility but not with the actual (historical) volatility. Using S&P 500 index options, Kliger and Levy (2003) find a positive relationship between bad weather (total cloud cover and precipitation) and volatility. Recently, Shim, Kim, Kimc, and Ryu (2015) find that historical volatility better captures the weather effects than implied volatility in an emerging market of Korea. They further find that wet, windless and cloudy weather tends to increase the volatilities. Moreover, investors' reaction is more pronounced to extreme high weather conditions than to extreme low weather conditions.

3. Data and Methodology

3.1. Stock Market Data

We collect daily index price data for South Asian markets from their respective websites. We focus on six equity market indices which include: two indices from India, BSE500 index (Bombay Stock Exchange, BSE) and NSE500 index (National Stock Exchange, NSE), two indices from Pakistan, KSE100 index (Karachi Stock Exchange, KSE) and LSE30 index (Lahore Stock Exchange, LSE), one from Bangladesh, CASP index (Chittagong Stock Exchange, CSE) and one from Sri Lanka, all-share-price index (Colombo Stock Exchange). The data period is from April 1, 2000 to March 31, 2012 (12 years) for all indices except CASP index for which it is from January 1, 2004 to March 31, 2012 (8 years and 3 months). The returns are calculated as:

$$R_t = L_n(P_t) - L_n(P_{t-1}) \tag{1}$$

Where R_t is daily index return, P_t and P_{t-1} are closing index values at time t and t-1 respectively.

3.2. Weather Data

The weather variables we focus on include temperature, cloud cover, relative humidity, air pressure, visibility and wind speed. We also use indicator variables for rain or drizzle, fog and thunder storm.

The whole weather data is compiled from National Climate Data Center website i.e. http://www.ncdc.noaa.gov/oa/climate/isd/index.php. We use ISD-Lite hourly database for temperature, cloud cover, dew point, air pressure and wind speed. Daily observations are constructed by averaging the observations reported between 0700 hours and 1800 hours. We consider the observations during the day only, ignoring the weather variations during the night. The variable visibility and indicator variables are extracted from Global Surface Summary of Day database as ISD-Lite has incomplete hourly data related to visibility for our markets. The relative humidity is estimated using temperature and dew point.

Measurement units are: temperature in Celsius degrees, relative humidity in percentage, air pressure in Hectopascals, visibility in kilometers and wind speed in meters per second. ISD-Lite database reports the sky conditions (cloud cover) as the fraction of the total celestial dome covered by clouds or other obscuring phenomena. Cloud cover is recorded as zero okta - ratio 0/10 (clear sky), one okta – ratio 1/10 (less but not zero), two oktas - ratio 2/10 - 3/10 (Few), three oktas - ratio 4/10, four oktas – ratio 5/10 (Scattered), five oktas – ratio 6/10, six oktas – ratio 7/10 - 8/10, seven oktas – ratio 9/10 (Broken), eight oktas – ratio 10/10 (Overcast). We use this okta-classification (from 0 to 8) for our analysis. Indicator variables rain or drizzle, fog and thunder storm represent the occurrence as Yes = 1 and No = 0.

We follow Hirshleifer and Shumway (2003) to deseasonalize the weather data. We first calculate an average value for each week in a year for each weather variable over the whole dataset for a particular market. This average value is then subtracted from the actual observations to get deseasonalized values of that week. For example, to calculate the average for week 1, there are 84 (12x7) values as we have 12-year data. This average is then subtracted from each day-value of the first week for all years.

From each variable, basic and deseasonalized, we create two dummy variables for extreme weather conditions. One dummy equals 1 for top 10% values while other dummy equals 1 for bottom 10% values.

3.3. Biorhythmic Data

We compute SAD variable based on the method proposed by Kamstra et al. (2003). We create a dummy taking the value 1 for the dates from September 21 to March 20 (Autumn Equinox to Spring Equinox) and 0 otherwise. This dummy is multiplied by length of night minus 12 to form 'SAD Winter' variable, i.e. dummy x (length of night -12). Data for length of night is collected from U.S. Naval Observatory website i.e. http://aa.usno.navy.mil/data/. This website explicitly provides data on daylight and darkness (length of night). To account for asymmetric effects of SAD between autumn and winter, we create a dummy variable (‘SAD Fall’) taking the value 1 for the dates from September 21 to December 20 (Autumn Equinox to Winter Solstice) and 0 otherwise.

Data for lunar phases is also collected from U.S. Naval Observatory website. The website reports the full moon dates among other dates such as new moon, and quarter dates. Following Yuan et al. (2006) we give value to each day based on how close the day is to the full moon using the formula:

$$lunarphase = cosine\left(\frac{2\pi d}{29.53}\right) \quad (2)$$

Where *d* is the number of days since the last full moon. This variable takes the value from -1 (new moon) to 1 (full moon) based on gap between the day and a full moon.

3.4. Methodology

For each index return series, we start with fitting the autoregressive moving average (ARMA) models using Box-Jenkins approach. However, diagnostic tests such as Ljung-Box Q-statistics and Engle’s and White’s ARCH tests tell the presence of conditional heteroscedasticity in all the index return series. We then start fitting ARMA-GARCH specifications. Our fitted specifications include basic GARCH models to Leveraged-GARCH (Glosten, Jagannathan, & Runkle, 1993) and Exponential-GARCH models (Nelson, 1991). We also test Arch-in-mean terms (Engle, Lilien, & Robins, 1987) in our specifications. The assumption of normal distribution of errors is also relaxed for all the specifications against the alternative assumptions that include Student’s t-distribution and generalized error distribution (GED).

LGARCH or EGARCH specifications appear to be the most appropriate for the sample indices based on the results (unreported) of LLRT and Q-statistics, and principle of parsimony. Note that ARMA and GARCH terms and assumptions of error distributions are specific to the individual behavior of the index return series. Unlike many other studies that use one specification for all the indices, we use most appropriate specification for each index return series. This way we attempt to avoid any misspecification issues in index return series.

After having appropriate specification for return series, we introduce the mood proxy variables in the mean and variance equations simultaneously. To control for the known Monday effect[2] (e.g., French, 1980; Harris, 1986; Wong, Hui, & Chan, 1992), we include Monday dummy. For known tax related anomaly[3] (e.g., Chan, 1986; Grinblatta & Moskowitzb, 2004; Lakonishok & Smidt, 1986), we introduce two dummy variables; one for month of January and the other for month of July. This is due to difference in fiscal year of the sample countries.

In order to avoid the possible problems of multicollinearity between SAD and weather variables (Jacobsen & Marquering, 2008), following Dowling and Lucey (2008), we

[2] Monday effect refers to lower returns on Monday than other trading day in a week

[3] Tax effect refers to stock returns pattern at turn of the tax year, typically higher returns in the first month (January or July) of a new tax year

group SAD variables with weather indicator variables which appear not to have correlation with SAD variables. The remaining weather variables are tested in separate groups. The groups are as follow:

1. SAD Winter, SAD Fall, Fog, Thunder Storm, Rain or Drizzle and Lunar.
2. Raw Temperature, Raw Humidity, Raw Cloud Cover Ratio, Air Pressure, Visibility, Wind Speed and Lunar
3. Deseasonalized values of group 2 variables
4. Top 10% values of group 2 variable, below 10% values of group 2 variables and Lunar
5. Top 10% values of group 3 variable, below 10% values of group 3 variables and Lunar

After introducing the groups into the pre-specified GARCH models, we again run the diagnostic tests (Q-statistics and Log Likelihood) and choose between LGARCH and EGARCH specifications with an optimal error distribution assumption but without changing the ARMA and GARCH terms. It is important to note here that our results are sensitive to the choice of GARCH model and assumption of the error distribution. Therefore, we carefully and closely analyze the diagnostic tests' results and attempt to choose the best parsimonious model. We believe that our testing approach is robust and better than which is used by other studies using only one model specification for all the indices. One-size-fit-all approach may lead to biased results due to possibility of misspecification.

4. Empirical Results

4.1. Index Returns

Table 1 presents the results of SAD variables, indicator variables (Fog, Thunder, Rain or Drizzle) and Lunar. Generally, there is no significant relation between index returns and these variables. However, in both Indian markets, Bombay and NSE, SAD effect is significant which is consistent with Kamstra et al. (2003). Also note that Indian markets also have significantly positive relationship with Rain or Drizzle, meaning that rainy days provide greater returns as compared to the normal days.

TABLE 1 HERE

Table 2 shows the results of raw and deseasonalized weather variables, while Table 3 presents the results of extreme weather variables. In Table 2, for 5 out of 6 markets, raw temperature has negative relation with returns. However, only two relations are significant i.e., for Karachi and Bombay markets. If these results are combined with the results of respective extreme temperatures in Table 3 we see that, in Karachi market, the negative coefficient of raw temperature seems to be due to strong positive relationship between extreme low raw temperature and returns. The extreme low raw temperature leads to high returns in KSE which is consistent with Cao and Wei (2005) who find such relation for various markets. In Bombay market, extreme low or high raw temperature does not significantly affect the market returns. The extreme raw high temperature in Chittagong and Colombo leads to lower market returns, although general relationship between temperature and returns in Table 2 is insignificant for these markets. The deseasonalized temperature appears to be significantly negatively related to returns in Indian markets only (see Table 2). This is possibly because of significantly low returns in extremely high deseasonalized temperature in these markets, see Table 3.

The raw cloud cover ratio that is found to be negatively related to returns in various studies on developed markets (e.g., S.-C. Chang et al., 2008; Hirshleifer & Shumway, 2003 ; Saunders, 1993) appears to have no relation with returns in south Asian markets. Deseasonalized cloud cover ratio is significantly related to returns in Karachi market only but the direction of the relationship is opposite to the direction that is found in developed markets. In extreme weather setting (Table 3), extreme high raw cloud cover ratio leads to lower returns in Bombay market. The Karachi market is positively influenced by extreme raw and deseasonalized cloud cover ratio.

The raw visibility appears to have negative impact on returns in Lahore market only, while deseasonalized visibility is negatively affecting returns in Lahore and Bombay markets. Extreme values of visibility are affecting returns only in Pakistani markets. Air pressure and wind speed do not appear to have any impact on returns in South Asian markets.

In Table 2, the relation between Lunar and returns is mostly negative showing that returns are lower on the dates that are close to full moon but this relation is significant only for Colombo and Chittagong markets. Our Lunar results for Indian and Pakistani markets are consistent with Yuan et al. (2006) who find similar results for these markets.

TABLE 2 & 3 HERE

4.2. Volatility

In Table 1, SAD variables appear to be strongly influencing the volatility in almost all the markets. SAD winter is reducing volatility in Indian markets while in other market, it increases the volatility of returns. SAD fall has negative relation with volatility in markets of Karachi and Lahore. The Indian and Bangladesh markets does not respond significantly to SAD fall. However, volatility in Colombo market respond positively to SAD fall. Indicator variable Fog has significant negative relation with volatility in Karachi and Colombo markets only.

Rain or drizzle appears to be decreasing volatility of returns in both Indian markets. Interestingly, rainy days in Indian markets seem to give positive returns with decreased volatility. The relationship between lunar phase and returns volatility is strong in Bombay, NSE and Colombo markets. Colombo market seems to have negative returns on days near to full moon with higher returns volatility.

In Table 2, raw and deseasonalized temperature and humidity seem to have negative influence on volatility in Pakistani and Siri Lankan markets. Cloud cover ratio increases the volatility in Pakistani markets only. Visibility and wind speed appear to have strong influence on volatility in Colombo market only.

In Table 3, the general direction of the relationship between extreme temperatures (raw and deseasonalized) volatility is inverse with a few significant coefficients for Lahore, Karachi and Colombo markets. Extreme levels of visibility also have negative relation with volatility in general but the coefficients are significant for Lahore (raw high and raw low) and Bombay and NSE (deseasonalized high only). Extreme values of humidity and wind speed also have some significant coefficients for different markets but the direction of the relationship is mixed.

5. Conclusions

We study the impact of weather and biorhythmic variables on the index returns and volatility in six stock markets of the south Asia. The stock markets of this region are considered to be emerging with promising performance over the last decade. These markets are also considered to be highly volatile.

We adopt a robust testing approach and select the best parsimonious model with ARCH effects representing the unique data generating process of returns for each market. We control for known Monday and tax related anomalies by introducing relevant dummy variables. Both raw and deseasonalized weather variables along with respective 20% extreme values are examined.

We find significant positive effects of SAD and rain on returns in Indian markets (Bombay and NSE). General temperature has negative influence on returns. Other variables also seem to be influencing the returns in some direction in different settings. SAD and rain appear to be reducing the volatility in these markets while size of the moon appears to increase the volatility in Indian markets.

The relationship of SAD and returns is insignificant for the countries other than India. However, little evidence is found for the effects of other weather variables on returns in different settings. The weather variables seem to be more related to volatility in the countries other than India. Many variables have significant relationship with volatility in these countries.

Overall, our findings suggest that mood proxy variables have some convincing influences in South Asian markets. They may influence returns, volatility of returns or both.

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Table 1
Results of Group 1

Variable\Market	Lahore	Karachi	Chittagong	Bombay	NSE, India	Colombo
Model Specification and Error Distribution	ARMA(1,1)-TARCH(1,1) Gaussian	ARMA(1,1)-TARCH(1,1) Gaussian	ARMA(5,3)-TARCH(2,2) Student's t	ARMA(3,2)-EGARCH(1,1) Gaussian	ARMA(3,2)-EGARCH(1,1) Gaussian	ARMA(3,2)-EGARCH(1,1) Gaussian
			Mean Equation			
SAD Winter	-0.0307	0.0151	-0.0929	0.1670*	0.1841*	0.2508
SAD Fall	0.0416	-0.0089	0.0473	-0.0069	-0.0173	-0.0635
FOG	0.1185	-0.0800	-0.0498	0.1337	0.1568	-0.0016
THUNDER	-0.0804	0.0031	0.0464	-0.0230	0.0137	-0.0131
RAIN or DRIZZLE	0.1226	0.0961	0.0721	0.1277**	0.1306**	-0.0086
LUNAR	0.0126	-0.0121	-0.0612*	-0.0431	-0.0432	-0.0427*
			Variance Equation			
SAD Winter	0.0964***	0.0238**	0.0768***	-0.0337*	-0.0369**	0.1950***
SAD Fall	-0.2703***	-0.0850***	0.0042	-0.0054	0.0018	0.0423***
FOG	-0.0027	-0.1504**	-0.0619	0.3588	0.3289	-0.8935**
THUNDER	-0.2880***	0.0697	0.1717*	-0.0373	-0.0362	-0.0134
RAIN or DRIZZLE	0.1808**	0.0685	-0.0028	-0.0391***	-0.0382***	0.0344
LUNAR	-0.0273	-0.0104	-0.0102	0.0307***	0.0339***	0.0591***
Log likelihood	-5423.7220	-4851.5940	-3129.8590	-5222.0386	-5213.5050	-4009.7830
Q-Stat Prob. (Residuals)						
Lag 6	0.2560	0.1370	0.1710	0.1390	0.3780	0.1230
Lag 10	0.2270	0.1350	0.2490	0.1710	0.1790	0.1736
Lag 15	0.5430	0.3910	0.2450	0.3790	0.3020	0.1615
Q-Stat Prob. (Sq. Residuals)						
Lag 6	0.3610	0.5980	0.2620	0.2900	0.4090	0.1083
Lag 10	0.2840	0.7750	0.7890	0.3750	0.5690	0.1226
Lag 15	0.1780	0.6830	0.3410	0.0600	0.1440	0.4182

* significant at 10%, ** significant at 5%, *** significant at 1%

Group 1: SAD Winter, SAD Fall, Fog, Thunder Storm, Rain or Drizzle and Lunar

Table 2
Results of Group 2 & 3

	Raw Weather						Deseasonalized Weather					
Variable\Market	Lahore	Karachi	Chittagong	Bombay	NSE, India	Colombo	Lahore	Karachi	Chittagong	Bombay	NSE, India	Colombo
Model Specification and Error Distribution	ARMA(1,1)-TARCH(1,1) Gaussian	ARMA(1,1)-TARCH(1,1) Gaussian	ARMA(5,3)-TARCH(2,2) Student's t	ARMA(3,2)-EGARCH(1,1) Gaussian	ARMA(3,2)-EGARCH(1,1) Gaussian	ARMA(3,2)-EGARCH(1,1) Gaussian	ARMA(1,1)-EGARCH(1,1) Student's t	ARMA(1,1)-EGARCH(1,1) Student's t	ARMA(5,3)-EGARCH(2,1) Generalized	ARMA(3,2)-TARCH(1,1) Generalized	ARMA(3,2)-TARCH(1,1) Generalized	ARMA(3,2)-EGARCH(1,1) Gaussian
			Mean Equation						**Mean Equation**			
Temperature	-0.0005	-0.0168*	-0.0024	-0.0316**	-0.0232	0.0112	-0.0107	0.0037	-0.0165	-0.0433**	-0.0457**	0.0102
Humidity	-0.0013	-0.0025	0.0009	0.0019	0.0008	0.0055*	-0.0026	-0.0005	0.0002	-0.0008	-0.0023	0.0056
Cloud Cover Ratio	0.0079	0.0062	0.0161	-0.0044	0.0027	-0.0120	0.0042	0.0168*	0.0141	-0.0048	-0.0071	-0.0074
Air Pressure	------	-0.0071	-0.0009	0.0011	0.0008	0.0168	------	-0.0029	0.0036	0.0098	0.0027	0.0087
Visibility	-0.0435***	-0.0081	0.0173	-0.0048	-0.0141	-0.0104	-0.0308**	-0.0136	0.0171	-0.0303*	-0.0285	-0.0077
Wind Speed	0.0017	0.0008	-0.0189	0.0091	0.0080	0.0153	-0.0003	-0.0003	-0.0157	0.0264	0.0255	0.0141
Lunar	0.0171	0.0072	-0.0747**	-0.0430	-0.0484	-0.0332	0.0080	-0.0108	-0.0611*	-0.0347	-0.0404	-0.0325
			Variance Equation						**Variance Equation**			
Temperature	-0.0075***	-0.0034	-0.0246**	0.0018	0.0028	-0.0425***	-0.0013	0.0054	-0.0045	-0.0011	0.0002	-0.0685***
Humidity	-0.0011	-0.0014**	-0.0003	0.0005	0.0006	-0.0053**	-0.0017*	-0.0017	0.0013	-0.0010	-0.0007	-0.0110***
Cloud Cover Ratio	0.0239***	0.0137***	0.0026	-0.0053	-0.0052	-0.0076	0.0214**	0.0221**	0.0022	-0.0059	-0.0062	-0.0153**
Air Pressure	------	0.0004	-0.0009	-0.0009	-0.0009	0.0023	------	0.0006	-0.0063	-0.0074	-0.0072	0.0016
Visibility	-0.0057	0.0234***	0.0209	-0.0035	-0.0029	0.0058**	-0.0035	0.0083	0.0027	-0.0044	-0.0048	0.0082***
Wind Speed	0.0163	0.0075*	-0.0061	0.0068	0.0052	0.0224***	-0.0263*	-0.0054	-0.0036	0.0141	0.0172	0.0326***
Lunar	-0.0120	0.0079	-0.0145	0.0294***	0.0346***	0.0563***	-0.0005	-0.0004	-0.0212	0.0275	0.0280	0.0605***
Log likelihood	-5407.1540	-4858.2940	-3146.3600	-5226.4530	-5218.2770	-4004.0706	-5264.1091	-4735.4060	-3150.1381	-5174.9668	-5173.4785	-3996.6388
Q-Stat Prob. (Residuals)												
Lag 6	0.3490	0.1660	0.0900	0.1080	0.1950	0.1198	0.1699	0.1498	0.5179	0.2694	0.4171	0.1632
Lag 10	0.1660	0.1660	0.1760	0.1230	0.1160	0.1526	0.1982	0.2949	0.5757	0.2724	0.2923	0.3141
Lag 15	0.4860	0.4860	0.1890	0.1710	0.2540	0.1395	0.4098	0.6171	0.4706	0.3973	0.4268	0.1692
Q-Stat Prob. (Sq. Residuals)												
Lag 6	0.6200	0.5400	0.1470	0.1390	0.2410	0.1116	0.7514	0.6013	0.1801	0.4877	0.4639	0.1177
Lag 10	0.8280	0.7740	0.6370	0.1930	0.3550	0.1299	0.9915	0.9617	0.7231	0.4991	0.6705	0.1196
Lag 15	0.8580	0.5920	0.7410	0.1350	0.1860	0.3483	0.9999	0.9990	0.6840	0.3865	0.4951	0.2875

* significant at 10%, ** significant at 5%, *** significant at 1%

'------' shows unavailable results

Group 2: Raw Temperature, Raw Humidity, Raw Cloud Cover Ratio, Air Pressure, Visibility, Wind Speed and Lunar

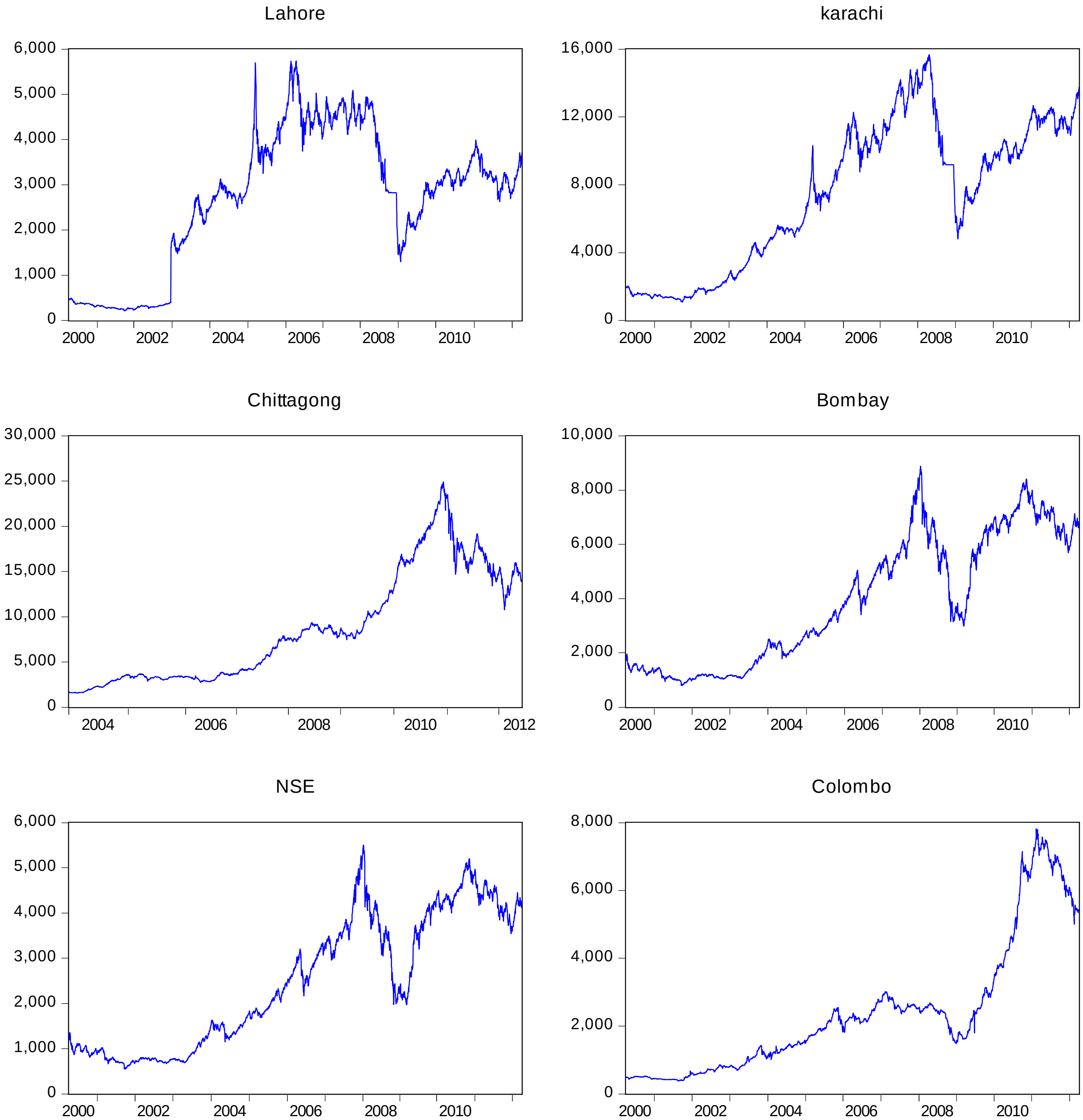
Group 3: Deseasonalized values of group 2 variables

Table 3
Results of Group 4 & 5

	Extreme Raw Weather						Extreme Deseasonalized Weather					
Variable\Market	Lahore	Karachi	Chittagong	Bombay	NSE, India	Colombo	Lahore	Karachi	Chittagong	Bombay	NSE, India	Colombo
Model Specification and Error Distribution	ARMA(1,1)-EGARCH(1,1) Student's t	ARMA(1,1)-EGARCH(1,1) Student's t	ARMA(5,3)-TARCH(2,2) Gaussian	ARMA(3,2)-TARCH(1,1) Generalized	ARMA(3,2)-EGARCH(1,1) Student's t	ARMA(3,2)-EGARCH(1,1) Gaussian	ARMA(1,1)-EGARCH(1,1) Gaussian	ARMA(1,1)-EGARCH(1,1) Student's t	ARMA(5,3)-TARCH(2,1) Students' t	ARMA(3,2)-EGARCH(1,1) Student's t	ARMA(3,2)-EGARCH(1,1) Student's t	ARMA(3,2)-EGARCH(1,1) Gaussian
			Mean Equation						**Mean Equation**			
Temperature Low	0.1069	0.1358**	-0.0765	0.0703	0.0942	0.1041	-0.0672	-0.0007	0.0739	0.0993	0.0938	-0.0113
Temperature High	-0.1140	-0.0122	-0.1811**	0.0290	0.0067	-0.0907*	-0.0846	0.0364	-0.0459	-0.1314*	-0.1301*	-0.0197
Humidity Low	-0.0358	0.0101	-0.2699***	-0.1520*	-0.1371*	-0.1132*	0.0332	0.0030	-0.0487	-0.0997	-0.0892	-0.1894***
Humidity High	0.0518	0.0870	0.0447	0.1625*	0.1181	-0.1424**	-0.0078	0.0062	0.0803	-0.1352*	-0.1515*	0.0049
Cloud Cover Low	------	------	------	------	------	------	0.2639***	0.0369	-0.1024	-0.0946	-0.1006	0.0715
Cloud Cover High	0.0473	0.0958*	0.0191	-0.2071**	-0.1761*	------	-0.0266	0.0861*	-0.0093	-0.0885	-0.0729	-0.0177
Air Pressure Low	------	0.0459	-0.0509	0.1037	0.1118	-0.1012**	------	0.0770	0.0112	-0.0653	-0.0473	-0.0658
Air Pressure High	------	0.0282	0.0267	0.1243	0.1233	0.0106	------	0.0336	-0.0088	0.0828	0.0807	0.0005
Visibility Low	-0.0642	0.0003	-0.0237	-0.0025	0.0334	-0.0141	0.0249	0.0693	-0.0484	0.0491	0.0621	-0.0313
Visibility High	-0.1039	0.1559**	0.0661	-0.1118	-0.0911	-0.0814	-0.3216***	0.1276*	-0.0094	-0.0709	-0.0751	-0.0331
Wind Speed Low	-0.0874	-0.0184	0.0203	0.0424	0.0277	0.0081	-0.0378	-0.0166	0.0900	0.0402	0.0150	-0.0475
Wind Speed High	-0.0156	-0.0213	-0.0509	-0.0398	-0.0613	0.0395	0.0063	0.0820*	-0.0199	0.0282	0.0414	-0.0262
Lunar	0.0212	0.0014	-0.0769*	-0.0349	-0.0296	-0.0299	0.0139	-0.0005	-0.0749**	-0.0376	-0.0422	-0.0339
			Variance Equation						**Variance Equation**			
Temperature Low	-0.0053	-0.1084**	0.2420**	0.0140	-0.0095	0.0178	-0.0805*	-0.0151	0.0061	-0.0190	-0.0154	0.2004***
Temperature High	-0.0076	-0.1174***	-0.0210	0.0353	0.0282	-0.0080	-0.1275***	0.0209	-0.0579	-0.0016	-0.0021	-0.1040**
Humidity Low	0.0434	0.0705	-0.1960**	0.0198	0.0075	0.1059**	-0.0041	0.0063	-0.0243	-0.0048	-0.0154	0.0958**
Humidity High	0.0060	0.1174**	0.0046	-0.0240	-0.0462	0.0606	0.0344	-0.1546***	0.0084	0.0065	-0.0006	-0.1911**
Cloud Cover Low	------	------	------	------	------	------	-0.0678	-0.0898**	-0.0022	0.0506	0.0530	0.0992**
Cloud Cover High	0.1014*	-0.1282**	-0.0990	0.0683	0.0730	------	-0.0208	0.1281**	0.0919**	0.0221	0.0234	-0.0482
Air Pressure Low	------	0.0304	-0.0982	-0.1293***	-0.0524	-0.0403	------	0.0086	0.0814**	0.0193	0.0189	-0.0306
Air Pressure High	------	0.0617	-0.2206***	-0.0321	-0.0421	0.0552	------	0.0274	0.0000	-0.0402	-0.0409	0.0392
Visibility Low	-0.0951*	-0.0243	0.3147**	-0.0171	-0.0326	-0.0939**	0.0293	-0.0091	-0.0347	-0.0053	-0.0134	-0.0507
Visibility High	-0.0571*	0.0252	0.0347	-0.0378	-0.0447*	-0.3574	-0.0659**	0.0479	0.0483	-0.0473*	-0.0479*	0.0147
Wind Speed Low	0.0603	-0.0267	-0.2595**	-0.0123	0.0082	0.0512	0.1130**	0.0995**	-0.0203	-0.0268	-0.0263	0.0108
Wind Speed High	0.0128	-0.0113	-0.1288	0.0629	0.0409	0.0614*	0.0507	0.0662	-0.1256***	0.0126	0.0074	0.1622***
Lunar	-0.0009	0.0012	0.0801**	0.0355*	0.0125	0.0531***	0.0074	-0.0030	-0.0200	0.0128	0.0140	0.0588***
Log likelihood	-5261.7234	-4723.9803	-3236.2997	-5168.3342	-5151.4918	-4000.0120	-5370.1279	-4719.9903	-3135.2245	-5156.3119	-5150.3253	-3986.6428
Q-Stat Prob. (Residuals)												
Lag 6	0.1507	0.2263	0.2007	0.2081	0.3069	0.1351	0.1242	0.1722	0.2099	0.2197	0.1644	0.1313
Lag 10	0.2922	0.2872	0.4280	0.1743	0.1923	0.2317	0.2749	0.2098	0.2548	0.2871	0.1611	0.2594
Lag 15	0.6954	0.6602	0.2808	0.3236	0.3313	0.1568	0.6072	0.4735	0.2386	0.4140	0.3299	0.1801
Q-Stat Prob. (Sq. Residuals)												
Lag 6	0.7979	0.7538	0.1652	0.3829	0.2503	0.1728	0.4089	0.6252	0.2023	0.2726	0.3407	0.1621
Lag 10	0.9954	0.9909	0.4942	0.5011	0.5620	0.1078	0.7470	0.9757	0.7702	0.4338	0.5748	0.1124
Lag 15	1.0000	0.9999	0.3526	0.3372	0.1039	0.3182	0.9050	0.9996	0.7111	0.4936	0.1897	0.3730

* significant at 10%, ** significant at 5%, *** significant at 1%
'------' shows unavailable results
Group 4: Top 10% values of Raw weather variables, below 10% values of Raw weather variables and Lunar
Group 5: Top 10% values of Deseasonalized weather variables, below 10% values of Deseasonalized weather variables and Lunar

Figure 1 -- Market Performance (Index Values)



Appendix

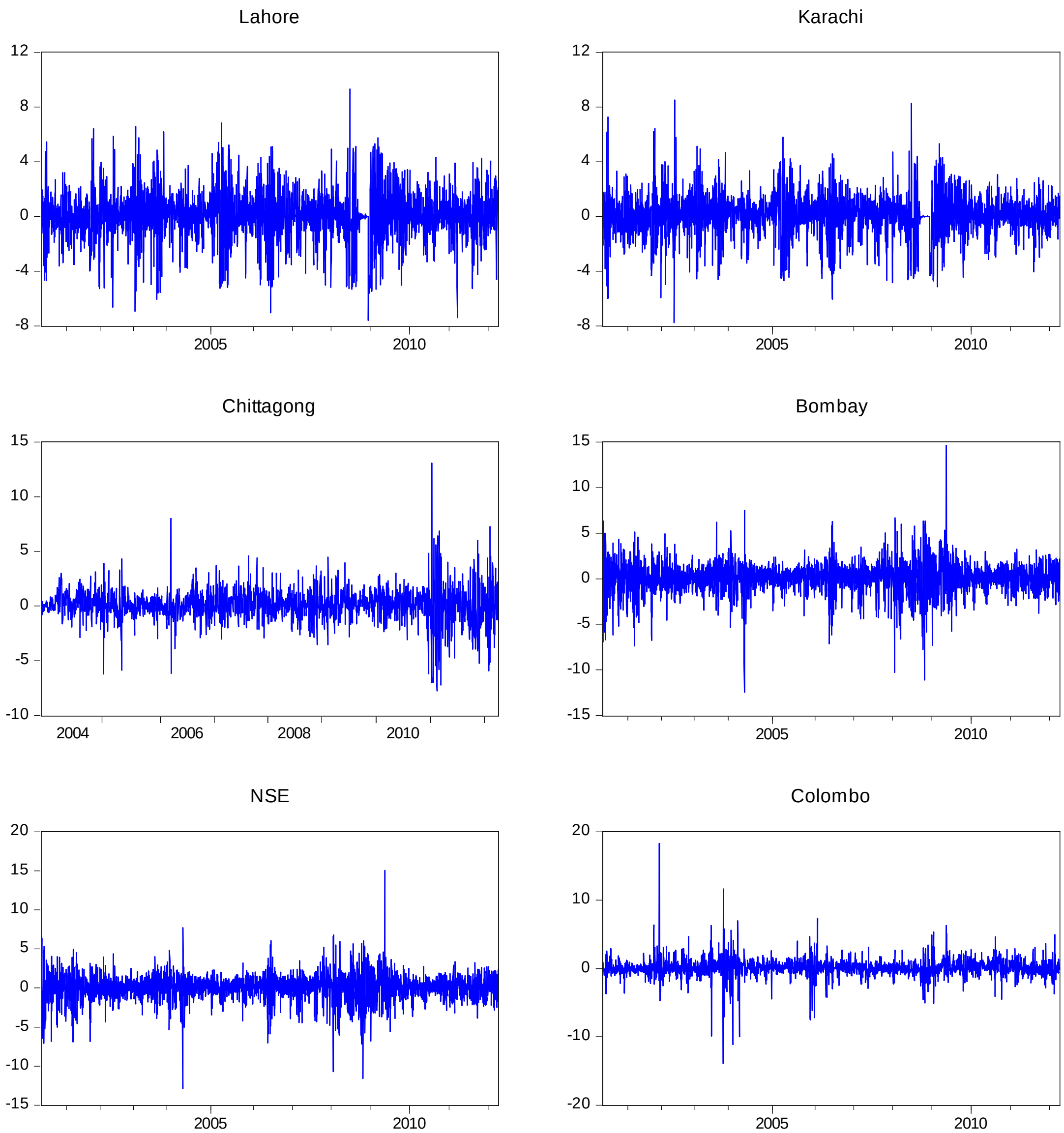


Figure 2 -- Returns

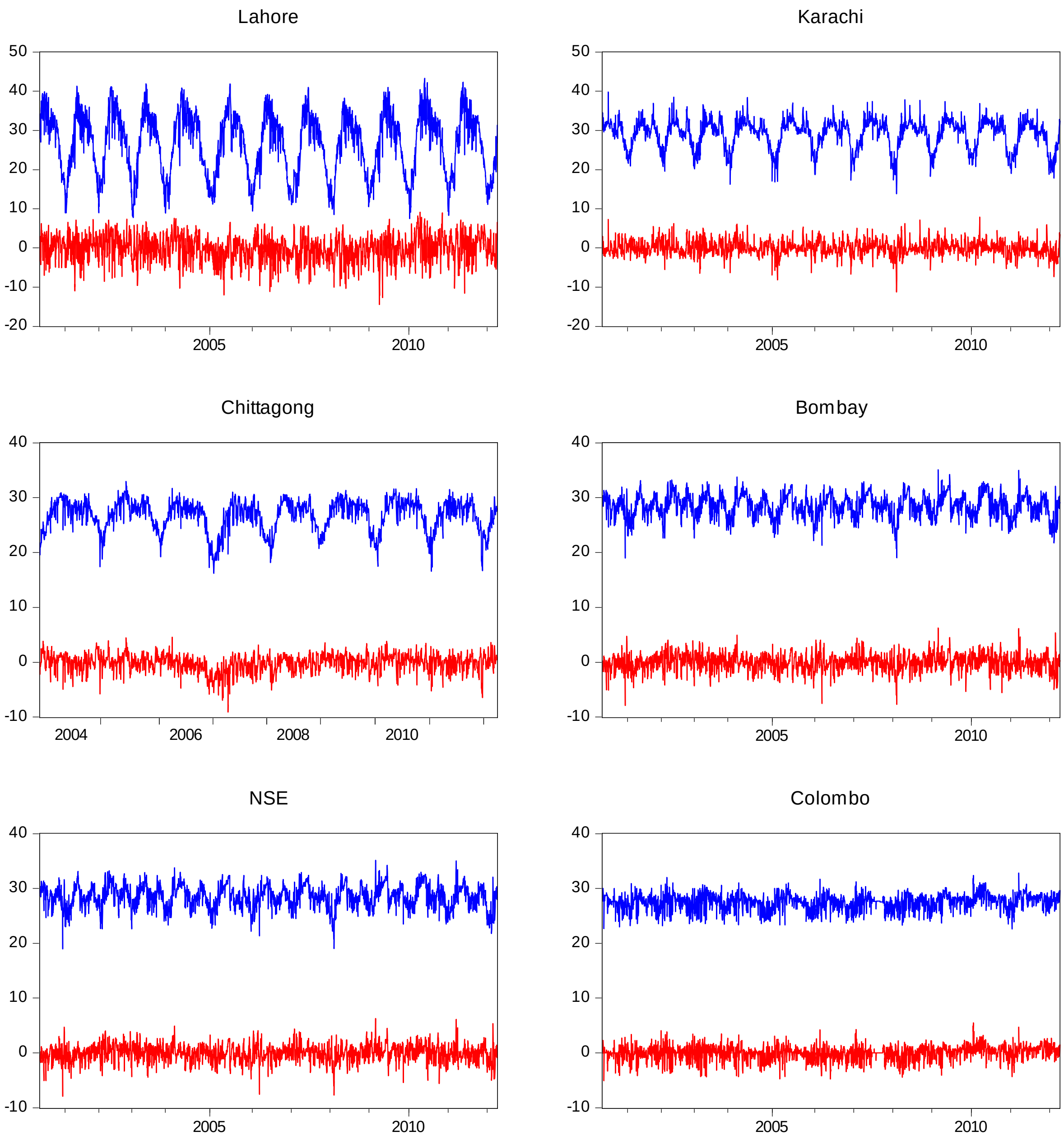


Figure3 -- Temprature

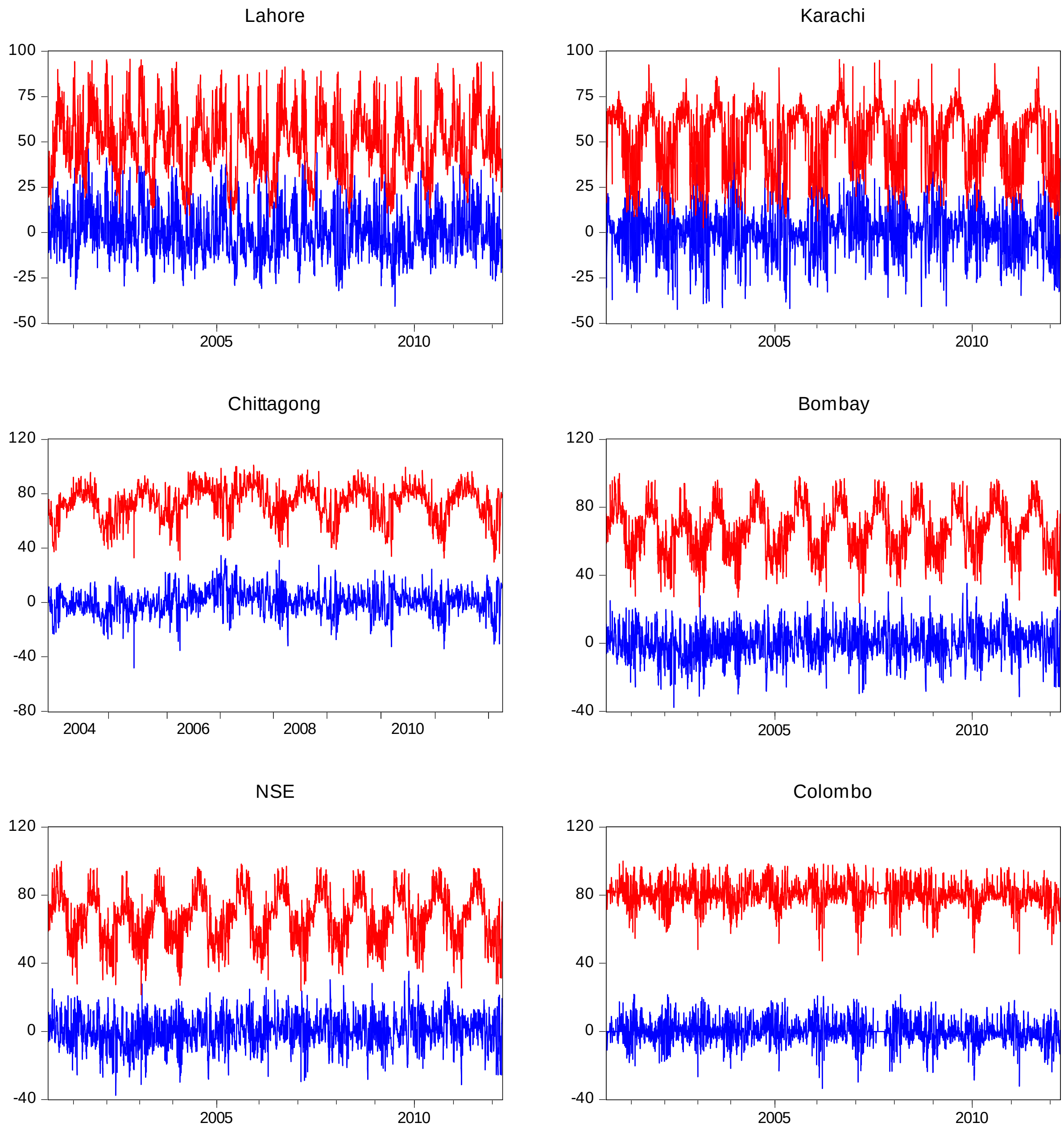


Figure 4 -- Humidity

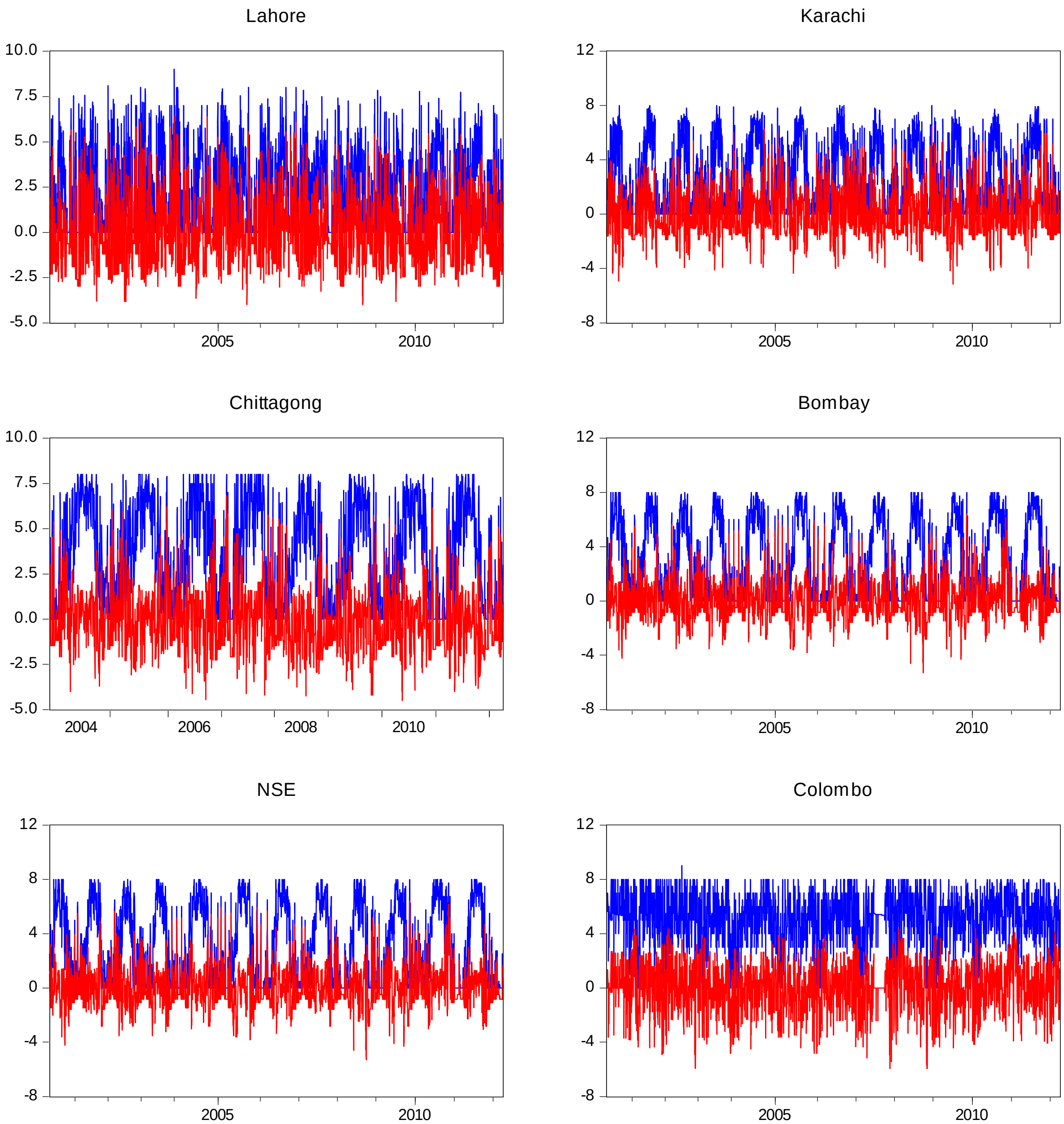
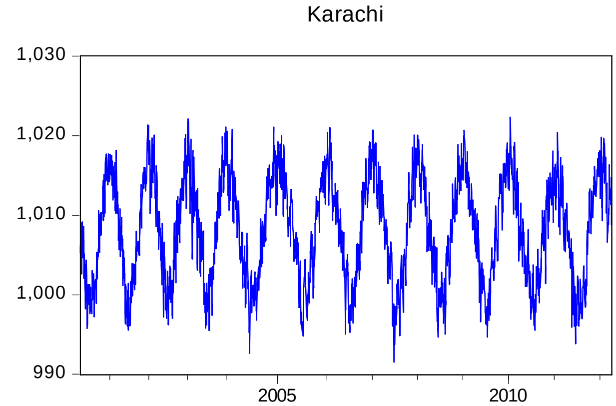
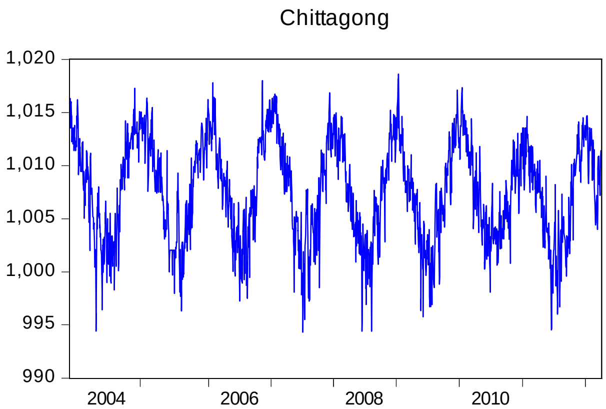
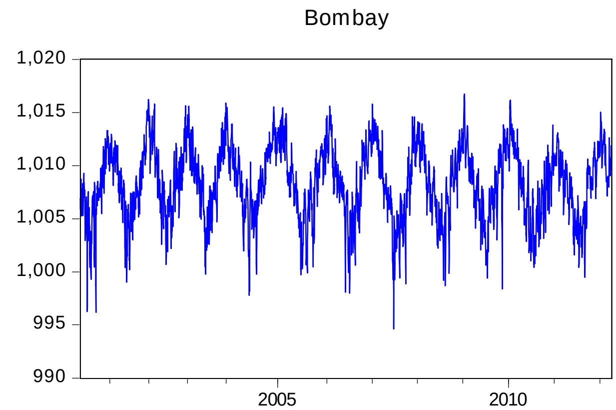


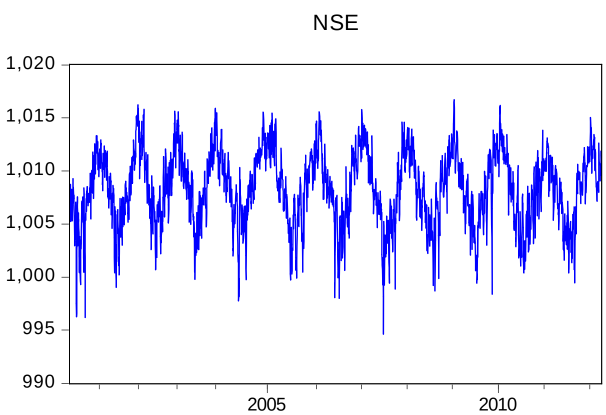
Figure 5 -- Cloud Cover

Figure 6 -- Air Pressure









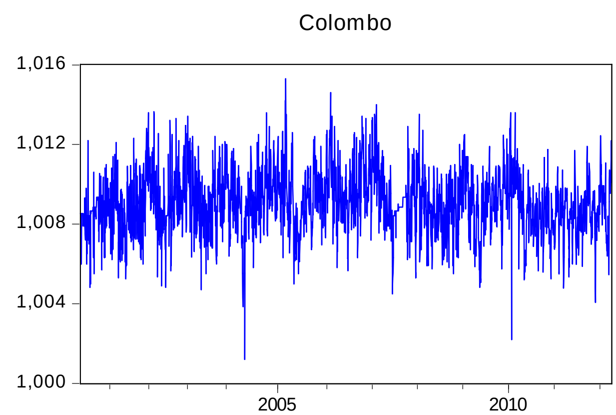
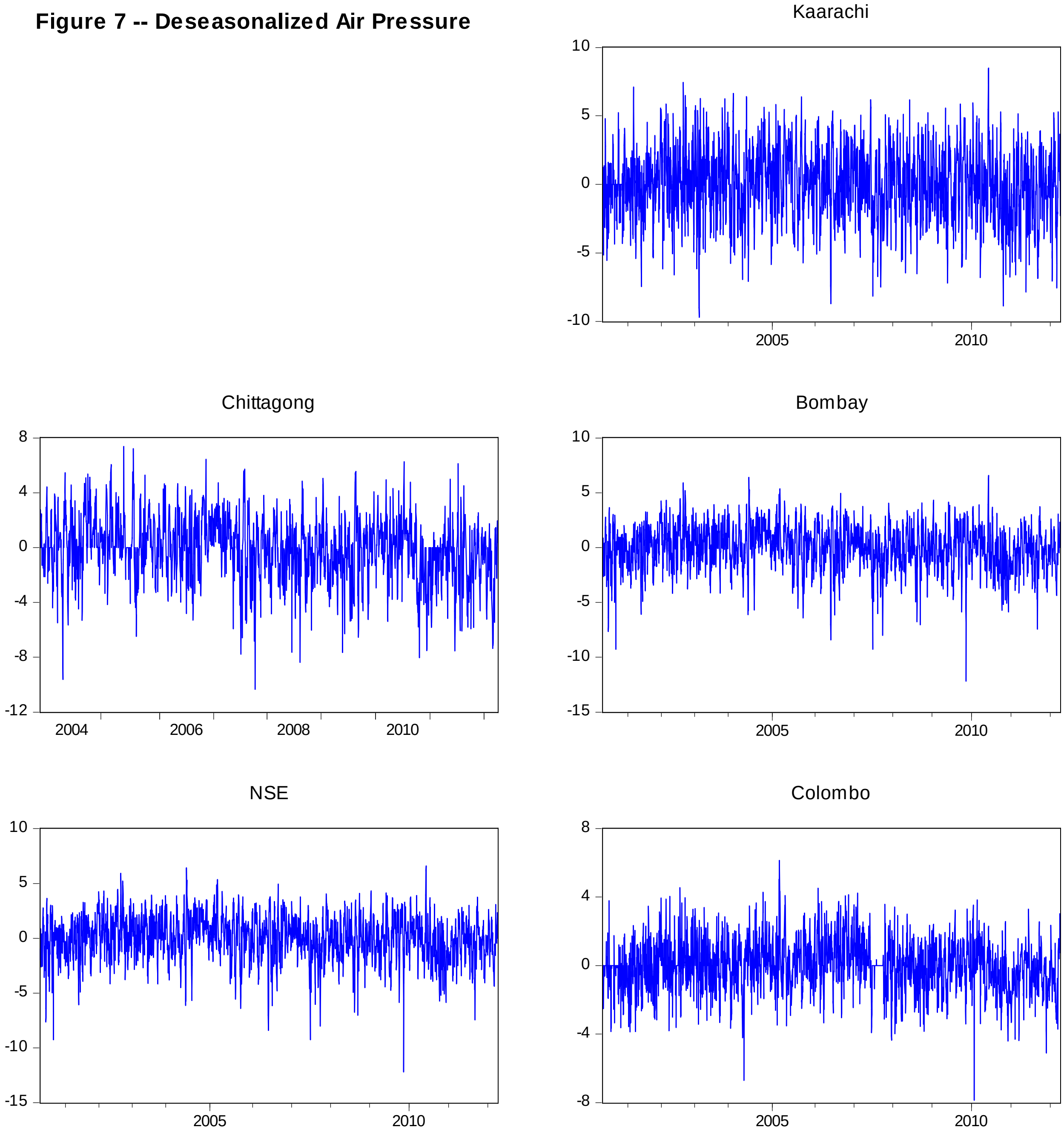


Figure 7 -- Deseasonalized Air Pressure



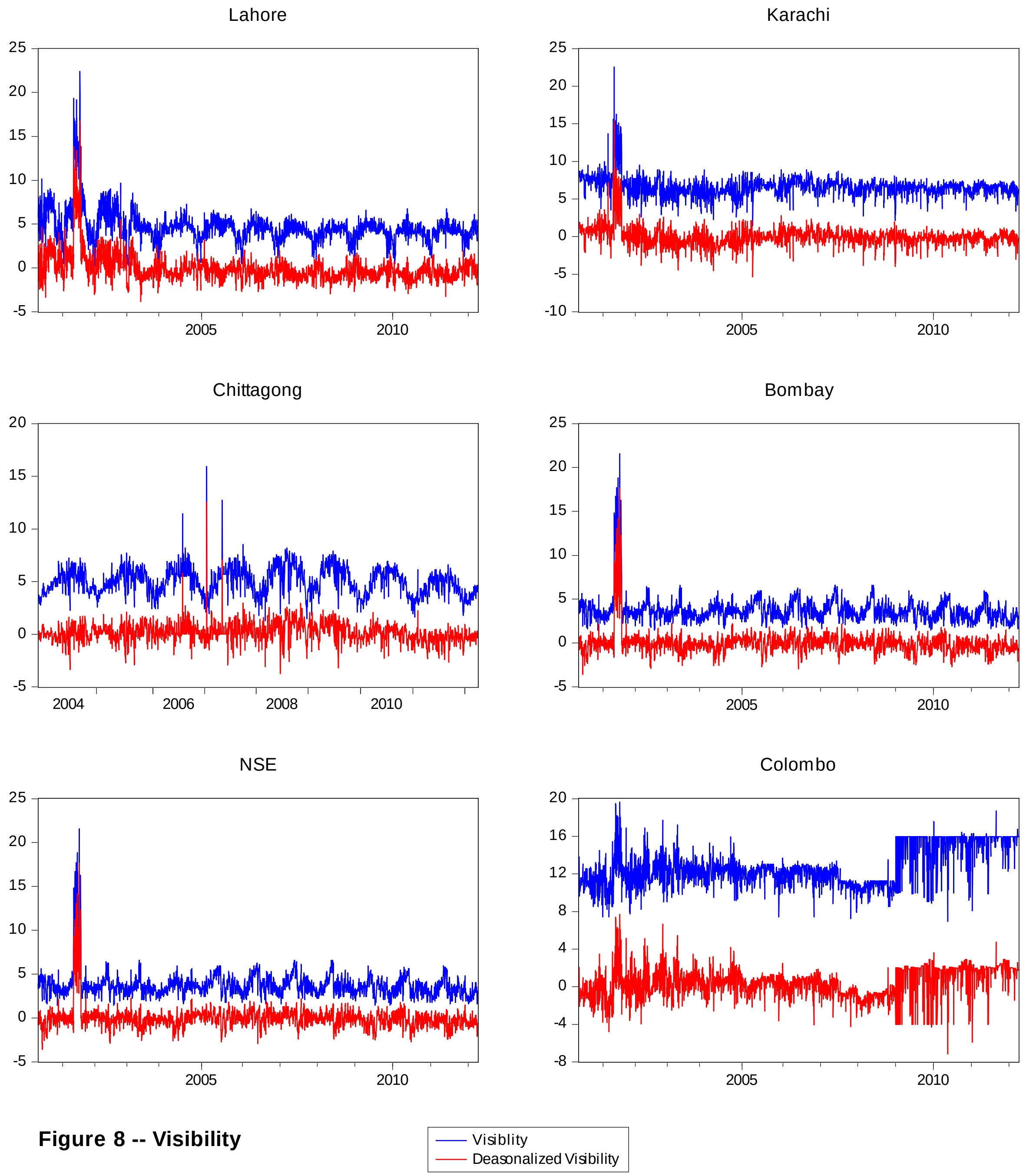


Figure 8 -- Visibility

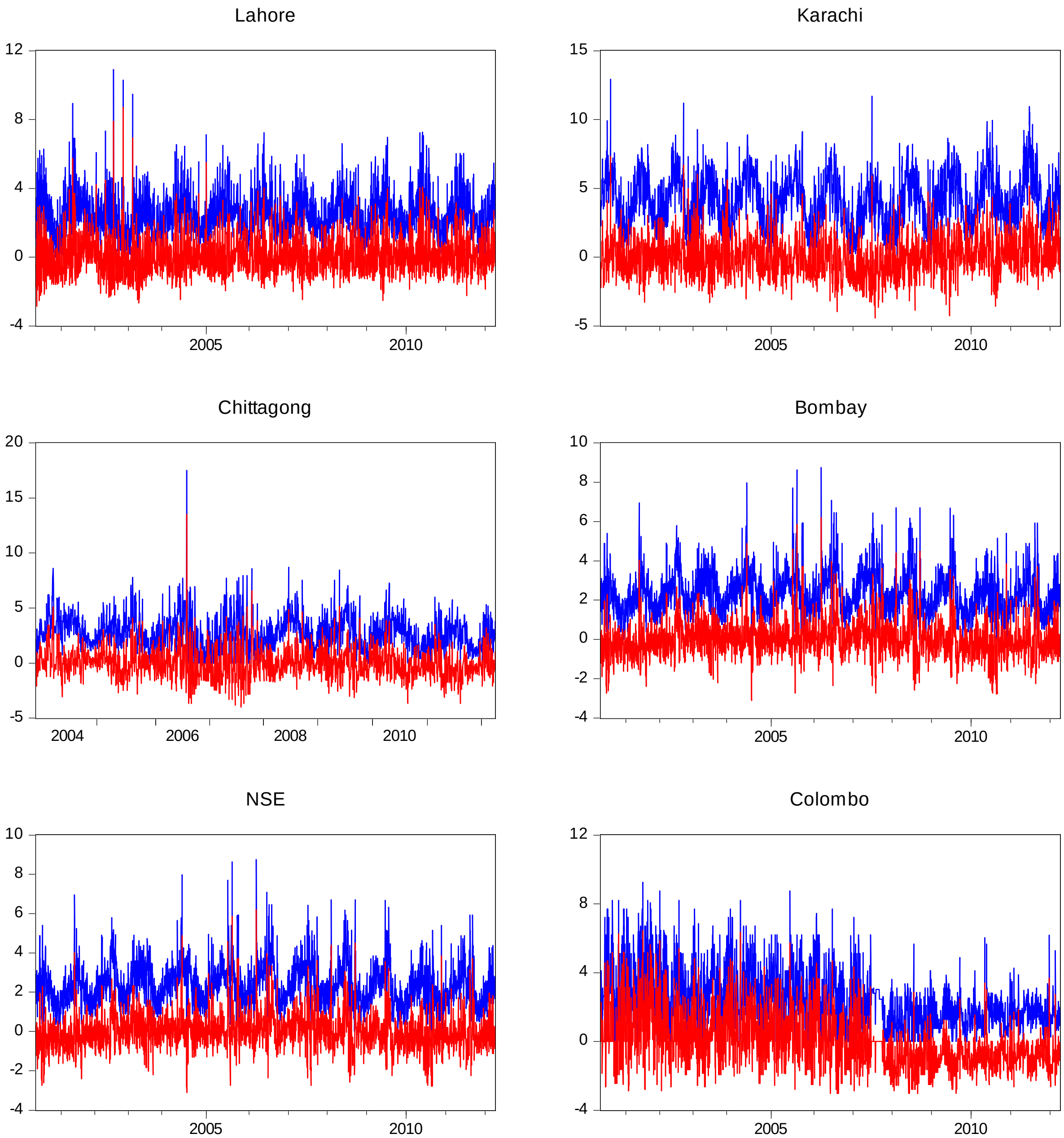


Figure 9 -- Wind Speed

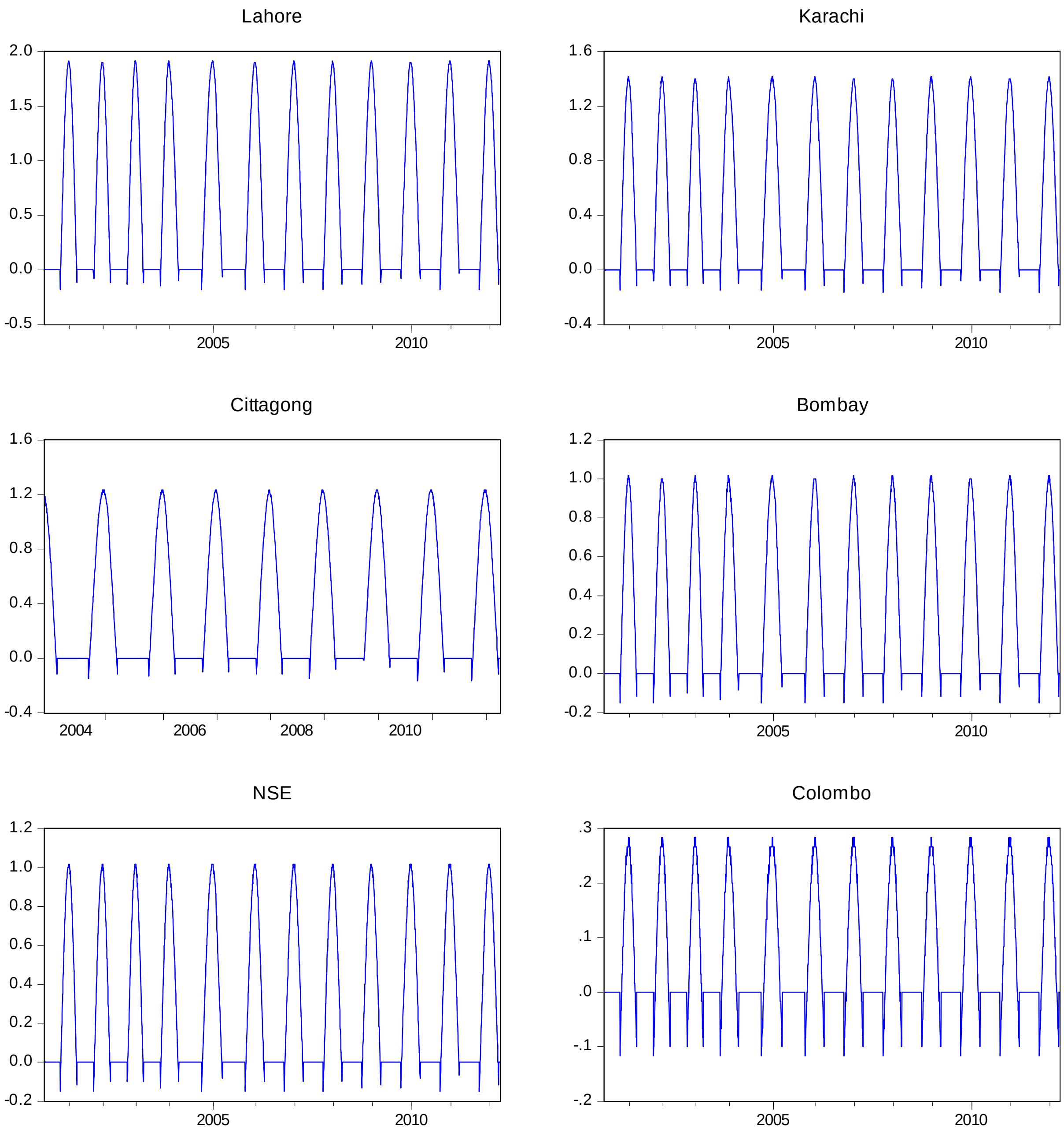


Figure 10 -- SAD