Local Temperature Deviance And National Prices: The U.S. Natural Gas Market[1]

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ABSTRACT

In this study we investigate the price discovery process in the U.S. natural gas spot and futures markets. We explore the relationships between the spot and futures markets, the effect of U.S. temperature changes on these markets and, in addition, test whether New York City temperature changes have a special impact on the national market for natural gas. We find that most price discovery occurs in the futures market. We also find that colder days in winter and hotter days in summer result in higher gas prices, although daily changes in temperature have a stronger effect on prices during the winter. Furthermore, we find that the daily temperature changes in New York City, where the futures market for natural gas is physically located, have an additional effect on gas prices beyond what could be explained by the temperature changes aggregated across the U.S.

Keywords: Natural gas futures, Temperature effects, VAR

1. INTRODUCTION

Empirical studies have long connected various weather conditions with trading dynamics. One of the earlier examples is Roll (1985), who documents a strong relationship between orange juice futures prices and the weather in central Florida, the main supplier of fresh oranges. Correlation between orange juice futures prices and weather does not necessarily contradict market efficiency[2].

More recent studies of the stock market, however, find relationships between prices and weather that are hard to reconcile with the notion of rational behavior by economically motivated market participants. For example, Hirshleifer and Shumway (2003) examine daily market index returns in 26 countries from 1982 to 1997 and find a strong correlation between index returns and the amounts of morning sunshine in the city of the country's leading stock exchange; Kamstra, Kramer, and Levi (2003) document a strong relationship between the seasonal variation in the length of the day and the returns on major equity market indexes in eight countries; Cao and Wei (2005) examine financial markets in eight countries over varying time periods and discover a strong connection between temperature and stock returns. While at odds with purely rational market behavior, the results of these recent studies are in agreement with the results of research in the areas of psychology and human behavior. According to the psychology and behavior literature, weather conditions such as the temperature and the amount of sunshine or precipitation may affect the mood of market participants. Mood fluctuations in turn may result in changes in investors' degrees of risk aversion or trading aggressiveness. Hence, it is possible that weather conditions may have an effect on market prices or trading volumes through the behavior of market participants.

Carrying this line of thought further, if the behavior of local traders and market makers has an effect on the market, then trading in floor-based markets may be affected by local weather. Empirical evidence on such relationship is somewhat controversial. For example, Saunders (1993) examines the daily returns on indexes composed of stocks listed in New York and finds evidence supporting the hypothesis that local weather, measured by amount of cloud cover, systematically affects stock prices. Trombley (1997), however, questions the results and the methodology of the study and argues that "the relationship between the weather and the stock returns is neither as clean, nor as strong as Saunders suggests." Loughran and Schultz (2004) are also skeptical of the idea that local traders can influence stock returns. Instead the authors suggest that trading in the stock of a particular company can be affected by the local weather in the city where this company is headquartered. The authors do find evidence supporting a "localized" relationship between the trading volume in Nasdaq stocks and the weather in the city where the company is headquartered. However no such relationship is found with respect to returns. The results of our study contribute to the debate regarding whether trading in a floor-based market may be affected by temperature changes in the city where the market is located.

While studies of weather and temperature effects on financial markets are focused primarily on equity spot markets, futures markets seem to be at least as important for examining traders' behavior. On the one hand, the mood of traders may play a particularly important role in highly speculative futures markets. On the other hand, market participants in futures markets may be more sophisticated and experienced compared with the participants in spot markets. In this study we examine trading in the U.S. natural gas spot and futures markets and the effects of temperature changes on daily returns in these markets.

This is not the first study evaluating the effects of temperature changes on natural gas markets. Ates and Wang (2005) study the price relationships and volatility spillover effects between the daily spot and futures natural gas prices. In their model, authors also estimate the effects of temperature and inventory levels on natural gas prices. In our study we employ methodology similar to the one developed by Ates and Wang, however, our contribution is documenting the abnormal (or above the expected) impact of the local temperature changes in New York on prices and returns in national markets.

The U.S. market for natural gas is a particularly interesting object of research. The national benchmark for natural gas spot prices in the U.S is the price for gas delivered at Henry Hub in Louisiana. However, futures contracts for natural gas are traded on the floor-based New York Mercantile Exchange (NYMEX) located in the financial district of New York[3]. Thus, the natural gas market presents a great setting for testing the location bias phenomenon. Deviations in New York City temperature may affect NYMEX traders in two ways. On the one hand, according to previous literature, traders' mood and, therefore, trading activity may depend on the current temperature. On the other hand, NYMEX traders observing local temperature prior to the commencement of trading, or during lunch or cigarette breaks, may overweight local temperature conditions while estimating the overall temperature effect on natural gas future prices[4]. In this study we explore the relationship between the spot and futures markets, the effect of the U.S. temperature changes on these markets, and test whether New York City temperature changes have an above expected impact on the national natural gas market. Not surprisingly, we find that most price discovery occurs in the futures market. We also find that both the colder days in winter and hotter days in summer result in higher gas prices, although daily changes in temperature have a stronger effect on prices during the winter. Furthermore, interestingly, we find that daily temperature changes in New York City, where the futures market for natural gas is physically located, have an additional effect on gas prices beyond what could be explained by the temperature changes aggregated across the U.S.

The rest of the paper is organized as follows. The next section describes the data and provides the summary statistics. Section 3 provides the empirical results of the bivariate VAR-GARCH model followed by a discussion of the methodology in Section 4. We provide conclusions in Section 5.

2. DATA DESCRIPTION AND SUMMARY STATISTICS

We employ historical daily time series for the period from April 2001 to June 2006. The national benchmark for natural gas spot prices in the U.S is the price for gas delivered at Henry Hub in Louisiana. As a proxy for spot prices we use the next day volume-weighted average Henry Hub price for physical gas delivery contracts obtained from the Intercontinental Exchange (ICE). The futures prices are the daily settlement prices on nearby natural gas futures contracts obtained from NYMEX. Each contract is written on the delivery of 10,000 million British thermal units (mmBtu) of the natural gas at Henry Hub[5]. As a proxy for interest rates we use three-month Treasury bill rates obtained from the website of Federal Reserve Bank at St. Louis[6]. We use two types of temperature data. To measure the average temperature across the U.S. we employ the daily Heating Degrees Day (HDD) and Cooling Degrees Day (CDD) indexes supplied by the Energy Weather group and known as "Population /

Natural Gas Weighted HDD/CDD". The HDD index for individual weather station shows by how many degrees the average temperature on a current day falls below 65°F (the index equals zero on warmer days with the average temperature equaling or exceeding 65°F). Similarly, he CDD index for individual weather station shows by how many degrees the average temperature on a current day exceeds 65°F (the index is zero when it is colder than 65°F). The "Population / Natural Gas Weighted HDD/CDD" indexes are weighted averages based upon 200 U.S. cities. The data are first weighted by population to create values for each state and then, from a state level to a national level, the weighting is based upon natural gas consumption. To measure the local daily temperature in New York we take the average between the daily minimum and maximum temperatures reported by the weather station located closest to the Wall Street district. Both types of temperature data are obtained from MDA Federal (formerly Earth Satellite Corporation).

Consistent with previous studies of natural gas spot and futures markets, our analysis is conducted using the natural logarithms of spot prices and natural logarithms of futures prices adjusted for interest costs. More specifically, if lnF_t denotes the natural logarithm of the interest cost adjusted futures price then

$$lnF_t = lnF_{t,T} - rate_t \times (T-t)/360 \tag{1}$$

where $F_{t,T}$ is the price on day t of the nearby futures contract expiring on day T, $rate_t$ is the annual rate on three-month Treasury bills observed on day t, and the term $rate_t \times (T-t)/360$ reflects the premium for the deferred payment on the futures contract[7].

For some tests we need a measure of the average temperature across the U.S. We use the national "Population / Natural Gas Weighted HDD/CDD" indexes to construct such a measure, applying the following algorithm:

$$USAmidt_t = \begin{cases} 65 - usaHDD_t, \text{ if } usaHDD_t > usaCDD_t \\ 65 + usaCDD_t, \text{ otherwise} \end{cases} \tag{2}$$

where $USAmidt_t$ is a proxy for average temperature across the U.S. on day t, and $usaHDD_t$ and $usaCDD_t$ are HDD and CDD indexes for the U.S. on day t.

Table 1 reports summary statistics for variables used in our analysis. S_t is the spot price for natural gas, F_t is the price of the nearby futures contract for natural gas, ΔlnS_t is the change in the natural logarithm of the spot price, ΔlnF_t is the change in the natural logarithm of the natural gas futures price adjusted for interest costs , $basis_t$ is the difference between the natural logarithm of the interest adjusted futures price and the natural logarithm of the spot price, $\Delta usaHDD_t$ is the change in the HDD index, , $\Delta usaCDD_t$ is the change in the CDD index, $\Delta NYCmidt_t$ - is the change in the mid-temperature in New York City, and $\Delta USAmidt_t$ is the change in the average temperature index $USAmidt_t$ constructed from combining HDD and CDD indexes.

Table 1 Summary Statistics

Here S_t is the spot price, F_t is the price of the nearby futures contract, ΔlnS_t - changes in natural logarithm of natural gas spot price, ΔlnF_t - changes in natural logarithm of natural gas futures price adjusted for interest costs (ln$F_{t,T}$ - rate*(T-t)/360**)** , $basis_t$ – difference between natural logarithm of natural gas interest adjusted futures price and natural logarithm of natural gas spot price, $\Delta usaHDD_t$ – change in Heating Degrees Day (HDD) index weighted by population and gas consumption across the U.S., $\Delta usaCDD_t$ - change in Cooling Degrees Day (CDD) index weighted by population and gas consumption across the U.S., $\Delta NYCmidt_t$ - change in mid-temperature in New York city measured at the station located closest to the Wall Street district), $\Delta USAmidt_t$ - change in average temperature index $USAmidt_t$ constructed from combining HDD and CDD indexes ($USAmidt_t = 65 - usaHDD_t$, *if* $usaHDD_t > usaCDD_t$, and $USAmidt_t = 65 + usaCDD_t$, otherwise).

	S_t	F_t	ΔlnS_t	ΔlnF_t	$basis_t$	$\Delta usaHDD_t$	$\Delta usaCDD_t$	$\Delta USAmidt_t$	$\Delta NYCmidt_t$
N	1220	1220	1220	1220	1220	1220	1220	1220	1220
Mean	5.57757	5.68397	0.00014	-0.00100	-0.00115	-0.00549	0.01122	0.02541	-0.00410
Median	5.45985	5.56150	-0.00014	-0.00132	-0.00165	0.00000	0.00000	0.08500	0.50000
Std Dev	2.40879	2.42027	0.05191	0.03645	0.05236	2.60913	0.88861	3.00760	6.75394
Maximum	18.41370	15.37800	0.57154	0.32445	0.51752	11.32000	5.26000	11.08000	29.00000
Minimum	1.71960	1.83000	-0.56495	-0.13040	-0.38477	-9.82000	-4.36000	-12.07000	-36.50000
Skewness	1.33396	1.18475	0.42247	0.62124	0.45134	0.09102	-0.05466	-0.14228	-0.28542
Kurtosis	3.04156	2.13518	29.56385	5.95434	13.73500	2.63270	7.08993	1.95311	1.73111

3. EMPIRICAL TESTS

If there is an abnormal influence created by changes in NY temperature, it should be most apparent in days when temperature changes in NY are drastically different than the average temperature change in the overall USA. Therefore, in the first step of our analysis we inspect the volatility of spot and futures returns during the days when the change in New York City temperature was substantially different from the changes in temperature across the U.S. on average. As a measure of volatility we use the absolute values of spot and futures returns. We classify trading days into "regular" days and "extreme" days based on the relative temperature changes in NY compared to the overall country. Then, we test the equivalence of the medians of absolute returns during regular days with those during the days of "extreme" New York temperature movements. In addition, we compare the medians of absolute values of *basis* during the "regular" days with values during "extreme" days.

In our tests we use two alternative procedures for classifying days into "regular" and "extreme". Under the first procedure, the measure $diff_t$ is constructed as the absolute difference between the temperature change in New York and the average temperature change across the USA. More specifically,

$$diff_t = \begin{cases} abs(\Delta NYCmidt_t) - abs(\Delta USAmidt_t), if & sign(\Delta NYCmidt_t) = sign(\Delta USAmidt_t) \\ abs(\Delta NYCmidt_t) + abs(\Delta USAmidt_t), if & sign(\Delta NYCmidt_t) \neq sign(\Delta USAmidt_t) \end{cases} \tag{3}$$

Here $\Delta NYCmidt_t$ is the temperature change in New York City on day t compared to day $t-1$, and $\Delta USAmidt_t$ is the average temperature change across the USA on day t compared to day $t-1$ (see equation (2) above for an explanation of how we construct $USAmidt_t$). The observations are then classified into "extreme" or "regular" based on the value of *diff*. Values of *diff* lying more than one standard deviation from the mean are classified as "extreme."[8]

Under the second procedure, we first run the OLS regressions of daily changes in New York mid temperature on daily changes in national HDD and CDD indexes. The observations are then classified into "extreme" or "regular" based on the absolute value of the residuals from the regression. If the absolute value of the residual falls more than one standard deviation from the mean of the absolute values of the residuals from the regression, then the corresponding observation is marked as "extreme".

Table 2 reports the median volatility and absolute basis during regular and "extreme" days classified according to both procedures. In both cases the spot and futures price volatility and the absolute value of the basis are significantly higher during days when the temperature changes in New York City substantially deviate from the average temperature changes across the U.S., indicating that temperature changes in NY might have abnormal effects on natural gas prices above the expected.

In order to evaluate the effect of New York City temperature changes on spot and futures prices more precisely, as well as to account for other factors affecting futures and spot prices, we further conduct a multivariate regression analysis. The trading in natural gas futures takes place on NYMEX's physical floor in lower Manhattan. The delivery of natural gas occurs at Henry Hub located in Louisiana near the town of Erath. The transactions for next day delivery contracts that we use as a proxy for spot prices are conducted through ICE's electronic platform. However, if the prices on spot and futures markets are related, and if the local temperature has a disproportional impact on trading in one market, the local temperature in that market may also have an impact on the other markets through the price relationships between the markets. For example, if the futures market drives prices in the spot market, the temperature changes in New York City may have an impact in both markets. This would explain the results reported in Table 2. To account for the interrelation between the spot and futures markets we estimate the bivariate vector autoregression (VAR) model similar to the one developed by Ates and Wang (2005) in their study. The basic model is described by the following two equations below:

$$\Delta \mathrm{lnS_t} = \alpha_0 + \sum_i \alpha_i \Delta \mathrm{lnS_{t-i}} + \sum_j \beta_j \Delta \mathrm{lnF_{t-j}} + \theta_1 basis_{t-1} + \sum_k \varphi_k X_{t,k} + \varepsilon_t$$
$$\Delta \mathrm{lnF_t} = \gamma_0 + \sum \gamma_i \Delta \mathrm{lnS_{t-i}} + \sum \delta_j \Delta \mathrm{lnF_{t-j}} + \theta_2 basis_{t-1} + \sum_k \phi_k X_{t,k} + \eta_t \quad (4)$$

Here the variables ΔlnS_{t-i} and ΔlnF_{t-i} are lagged terms of the dependent variables; $basis_{t-1}$ serves as a cointegrating term; and $X_{t,k}$ denotes the following independent variables: $\Delta usaHDD_t$ is the, change in Heating Degrees Days (HDD), $\Delta usaCDD_t$ is the change in Cooling Degrees Days (CDD), $biaswinter_t$ is equal to the residual from regressing the change in mid-temperature in New York City, $\Delta NYCmidt_t$, on $\Delta usaHDD_t$ and $\Delta usaCDD_t$ during winter months (Oct-Mar) and zero otherwise, and $biassummer_t$, which is equal to the residual from regressing the change in mid-temperature in New York City, $\Delta NYCmidt_t$, on $\Delta usaHDD_t$ and $\Delta usaCDD_t$ during summer months (May-Aug) and zero otherwise.

Table 2 Univariate Tests

The numbers provided in the table are medians and differences in medians for "extreme" and "regular" observations. To obtain the results reported under "Procedure 1", a measure *diff* is constructed as the absolute difference in change of temperature in New York from the change in the average temperature across the USA, $USAmidt_t$. More specifically,

$$diff_t = \begin{cases} abs(\Delta NYCmidt_t) - abs(\Delta USAmidt_t), if \quad sign(\Delta NYCmidt_t) = sign(\Delta USAmidt_t) \\ abs(\Delta NYCmidt_t) + abs(\Delta USAmidt_t), if \quad sign(\Delta NYCmidt_t) \neq sign(\Delta USAmidt_t) \end{cases} \quad (3)$$

Here $\Delta NYCmidt_t$ is the temperature change in New York City on day *t* from day *t-1*, and $\Delta USAmidt_t$ is the average temperature change across the USA on day *t* from day *t-1*. To construct a proxy for $USAmidt_t$, we use the national "Population / Natural Gas Weighted HDD/CDD" indexes, applying the following algorithm:

$$USAmidt_t = \begin{cases} 65 - usaHDD_t, \text{ if } usaHDD_t > usaCDD_t \\ 65 + usaCDD_t, \text{ otherwise} \end{cases} \quad (2)$$

The observations are then classified into "extreme" or "regular" based on value of *diff.* If corresponding value of measure *diff* exceeds one standard deviation then the corresponding observation is marked as "extreme".

To obtain the results reported under "Procedure 2" the residuals are computed from the OLS regressions of daily changes in New York mid temperature on daily changes in national HDD and CDD indexes. The observations are then classified into "extreme" or "regular" based on absolute value of residuals from the regression. If the absolute value of the residual exceeds one standard deviation then the corresponding observation is marked as "extreme".

	Abs(ΔlnS_t)			**Abs(ΔlnF_t)**			**Abs(basis)**		
	extreme	**regular**	**Diff (1-2)**	**extreme**	**regular**	**Diff (1-2)**	**extreme**	**regular**	**Diff (1-2)**
Procedure 1	0.0250	0.0226	0.0024*	0.0217	0.0192	0.0025*	0.0267	0.0201	0.0067***
Procedure 2	0.0252	0.0221	0.0030**	0.0222	0.0190	0.0032**	0.0255	0.0204	0.0051***

***, **, * - significant at 1%, 5%, and 10% level using Wilcoxon non-parametric test for two samples.

Table 3 VAR models for the futures and spot returns

Models (1) and (2) (VARX(5,0) and VARX(5,0)-ARCH(1) respectively) are described by the following system of equations:

$$\begin{aligned}\Delta\ln S_t &= \alpha_0 + \sum_i \alpha_i \Delta\ln S_{t-i} + \sum_j \beta_j \Delta\ln F_{t-j} + \theta_1 basis_{t-1} + \sum_k \varphi_k X_{t,k} + \varepsilon_t \\ \Delta\ln F_t &= \gamma_0 + \sum \gamma_i \Delta\ln S_{t-i} + \sum \delta_j \Delta\ln F_{t-j} + \theta_2 basis_{t-1} + \sum_k \phi_k X_{t,k} + \eta_t\end{aligned} \tag{4}$$

Where variables ΔlnS_{t-i} and ΔlnF_{t-i} are lagged terms of dependent variables, $basis_{t-1}$ serves as a cointegrating term, and $X_{t,k}$ denotes independent variables: $\Delta usaHDD_t$, change in Heating Degrees Days (HDD), $\Delta usaCDD_t$, change in Cooling Degrees Days (CDD) index, $biaswinter_t$, which is equal to the residual from regressing change in mid-temperature in New York City, $\Delta NYCmidt_t$, on $\Delta usaHDD_t$ and $\Delta usaCDD_t$ during winter months (Oct-Mar) and zero otherwise, and variable $biassummer_t$, which is equal to the residual from regressing change in mid-temperature in New York City on $\Delta usaHDD_t$ and $\Delta usaCDD_t$ during summer months (May-Aug) and zero otherwise. In both models the errors are assumed to be normally distributed, but in model (1) they are independently and identically distributed, whereas model (2) accounts for heteroskedasticity.

	Model (1)				**Model (2)**			
	ΔlnF_t		ΔlnS_t		ΔlnF_t		ΔlnS_t	
Equation	**Estimate**	**t Value**	**Estimate**	**t Value**	**Estimate**	**t Value**	**Estimate**	**t Value**
Constant	-0.00053	-0.48	-0.00081	-0.65	-0.00071	-0.67	-0.00071	-1.07
ΔlnS_{t-1}	-0.00112	-0.04	-0.2789***	-8.32	0.01522	0.52	-0.14126***	-5.81
ΔlnS_{t-2}	0.00812	0.27	-0.13947***	-4.15	0.00576	0.2	-0.16092***	-6.44
ΔlnS_{t-3}	0.03613	1.22	-0.01429	-0.43	0.04201	1.49	0.04088*	1.9
ΔlnS_{t-4}	-0.02621	-0.91	0.02864	0.88	-0.0131	-0.48	0.09261***	4.95
ΔlnS_{t-5}	-0.00343	-0.15	0.04424*	1.69	0.00552	0.25	0.09046***	6.54
ΔlnF_{t-1}	-0.00796	-0.23	0.77081***	19.67	-0.03478	-1.01	0.57704***	24.97
ΔlnF_{t-2}	0.03807	0.95	0.12217***	2.7	0.02609	0.68	0.1046***	3.56
ΔlnF_{t-3}	0.03434	0.86	0.10766**	2.38	0.01696	0.44	0.06725**	2.5
ΔlnF_{t-4}	-0.05192	-1.31	-0.03942	-0.88	-0.04281	-1.12	-0.03457	-1.29
ΔlnF_{t-5}	-0.00016	0.00	-0.01088	-0.25	-0.02872	-0.78	-0.14357***	-5.63
$basis_{t-1}$	-0.02813	-1.54	0.09599***	4.68	-0.01944	-1.12	0.17262***	16.68
$\Delta usaHDD_t$	0.0014***	3.37	0.00415***	8.89	0.0009**	2.24	0.00244***	9.19
$\Delta usaCDD_t$	0.00149	1.25	0.00392***	2.93	0.00127	1.12	0.00345***	4.7
$biaswinter_t$	0.00061**	2.39	0.00092***	3.16	0.00056**	2.24	0.00059***	3.42
$biassummer_t$	0.00033	0.87	-0.00005	-0.11	0.00035	0.96	0.00005	0.19

***, **, * - significant at 1%, 5%, and 10% level.

If spot and futures prices follow a non-stationary process, the simple regression model where the spot and futures prices serve as dependent variables will be misspecified. Therefore, to avoid this problem, we use the spot and futures daily returns. In addition, to account for possible cointegration between spot and futures returns, we include the basis as the proxy for the cointegrative term in both equations of our model.

Table 3 reports the results for two alternative specifications of the VAR model. Both Model (1) and Model (2) are based on equations (4), but they differ in the assumptions we impose on the ε_t and η_t error generation processes. In both models the errors are assumed to be normally distributed, but in Model (1) they are independently and identically distributed, whereas Model (2) accounts for heteroskedasticity. The estimation results are qualitatively similar in both cases. The results demonstrate a significant feedback from lagged futures prices to the spot prices and from the lagged spot prices to the spot prices. However, the lagged spot prices do not appear to significantly impact futures market prices. These results are consistent with other studies that document the leading role of futures in price discovery on both futures and spot markets[9].

Consistent with Ates and Wang (2005), the results for both models indicate a significant impact of the temperature variables on both the futures and spot markets. The signs of the coefficients for $\Delta usaHDD_t$ and $\Delta usaCDD_t$ are positive indicating an increase in prices in response to a drop in temperature during cold days (captured by $\Delta usaHDD_t$ variable) and an increase in prices in response to a rise in temperature during hot days (captured by $\Delta usaCDD_t$ variable). The $\Delta usaHDD_t$ variable has a significant effect on both futures and spot markets, whereas $\Delta usaCDD_t$ significantly affects only the spot prices. Both results are consistent with the demand for natural gas as a heating fuel during the winter months and demand for natural gas as fuel for electricity generators to power air conditioning systems during the summer months[10].

The interesting result, however, is the significant and positive coefficient for the $biaswinter_t$ variable. This indicates that, in winter, a larger relative increase in New York temperatures compared to the average temperature change across the U.S. results in higher returns in futures and spot markets. For example, a temperature drop across the U.S. during the winter months accompanied by a smaller drop in the New York temperature will result in a higher price jump compared with the price jump triggered by the same temperature drop across the U.S., but accompanied by a larger drop in the New York temperature. This result is not consistent with the hypothesis that New York traders overreact to local temperature fluctuations. Rather, it may imply a mood-based trading during winter months. The results also appear to somewhat contradict the Cao (2005) study which documents a negative correlation between temperature and stock returns.

The results for the $biassummer_t$ variable are insignificant. This is not unexpected, since the role of natural gas is less important for cooling than it is for heating.

4. DISCUSSION

Most of our analysis is focused on price changes (returns) in response to the temperature changes. Indeed, to the degree that current temperature changes contain new information about future temperature changes, this relationship would be consistent with a market reaction to the new information regarding future demand and supply for natural gas. However, some studies have shown that market dynamics can be affected by the temperature level itself. For example, Cao and Wei (2005) find a negative relation between the temperature level and stock returns in stock markets across the world. Furthermore, an unexpected long period of extreme temperature (e.g. heat waves or cold waves) may itself carry new information regarding the future natural gas supply and demand[11].

Suppose a heat wave occurs over most of the U.S., but not in the northeast (or, specifically, New York City). While the day-to-day temperature changes both across the U.S. and in New York may be similarly low (except for the first day of the heat wave), the extreme temperature differences may persist over an extended period of time[12]. To see whether the analysis based on differences in temperatures rather than differences in temperature changes will affect our results we repeated our analysis this time based on differences in temperatures. Thus, to compare the futures and spot absolute returns, the observations were classified into extreme and regular based on difference in temperatures rather than difference in changes in temperature between the U.S. and New York City.

Classifying the observations by differences in temperatures rendered similar although weaker results than the ones reported in Table 2. We also estimated VAR models (equations 4) where we replaced variables $biaswinter_t$ and $biassummer_t$, by the variables $temp\_biaswinter_t$ and $temp\_biassummer_t$, obtained by regressing the mid-temperature in New York City, $NYCmidt_t$, on $usaHDD_t$ and $usaCDD_t$. The results were very similar to the ones reported in Table 3. This is not very surprising given high (above 50%) correlations between $biaswinter_t$ and $temp\_biaswinter_t$, and $biassummer_t$, and $temp\_biassummer_t$.

It is possible that the relationships between the levels of temperature, temperature changes and natural gas spot and futures prices may be better explained by non-linear models[13]. We leave this to the future research.

5. CONCLUSION

In this study we investigate the U.S. natural gas spot and futures markets. In particular, we estimate the lead-lag relationship between the spot and futures prices as well as the impact of temperature changes on both markets. Futures trading is mostly floor based and located in New York City, whereas the delivery of natural gas occurs at Henry Hub in Louisiana. This structure of the natural gas market allows us to investigate if the local temperature deviations (New York City) have an abnormally strong effect on market prices and trading activity.

We find that daily futures prices lead spot prices, and that both spot and futures markets are significantly influenced by the contemporaneous average temperature. It also appears that local temperature changes in New York have an abnormally strong effect on national spot and futures prices for natural gas. It is possible that this effect is related to the fact that most trading in natural gas futures is physically located in New York, with local traders on the floor-based NYMEX playing a significant role in the daily trading activity. Our results seem to indicate that this bias created by New York traders is not due to an overweighting of local temperature conditions, but rather to mood-based trading on relatively warmer days.

A suggestion for future research is to include inventory levels of stored natural gas, as well as trading volumes from the spot and futures markets into the analysis to gain further information on the effects of local weather on trading activity.

ENDNOTES

1. The authors would like to thank CNBC correspondent Melissa Francis, conference participants at Chapman University, as well as the discussants and other session participants at the 2007 Southern Finance Association Meetings and 2008 Eastern Finance Association Meetings for their valuable comments and suggestions. All errors are of course our own.
2. In fact, Roll (1985) notes that while orange juice futures prices do seem to be informationally inefficient, this effect is driven by exchange-imposed trading restrictions on price movements. In the absence of such restrictions, the market would be informationally efficient.
3. NYMEX has offered trading in small-sized energy contracts through CME's all-electronic Globex platform since 2002. However, the Globex-traded e-miNYs, have been rather unsuccessful, possibly because they were not fungible with the regular NYMEX contracts. In an attempt to change the situation, in late summer 2005 NYMEX moved trading in e-miNYs from CME's Globex platform to its own ClearPort platform.
4. The impetus for this study was a news report on CNBC that associated price movements in the energy futures complex with current temperature conditions at the New York Mercantile Exchange. Specifically, increases in natural gas futures prices were linked to unusually cold conditions in Manhattan. Thus, the reporting seemed to implicitly suggest that trader behavior may be impacted by differences between New York and national temperatures.
5. For detailed contract specification see the Appendix.
6. http://research.stlouisfed.org/fred2/categories/116
7. See, for example, Garbade and Silber (1983).

8. We tried two-standard deviations as the cut-off point for extreme measurements for robustness. The results are qualitatively the same. We reported one-standard deviation results in order to have more extreme observations and thus less effect of potential outliers.
9. See for example, Chan (1992) on leading role of futures in equity-index market.
10. The demand for natural gas may increase during hot days in the summer due to the increase in demand for the air conditioning, and therefore, electricity, part of which can be generated by burning the gas. Nevertheless, the role of natural gas is probably less important during the summer months.
11. During the extended periods of extremely high or low temperatures the consumption of the natural gas necessary to generate electricity for air conditioning or for heating may increase, decreasing the amounts of stored gas.
12. We thank anonymous referee for pointing this out.
13. See, for example, Boudoukh, Richardson, Shen, and Whitelaw (2007) study of the frozen concentrated orange juice futures market.
14. Source: NYMEX webpage http://www.nymex.com/NG_spec.aspx

APPENDIX

Specifications for the Natural Gas Futures Contract[14]

Trading Unit	10,000 million British thermal units (mmBtu).
Price Quotation	U.S. dollars and cents per mmBtu.
Trading Hours *(All times are New York time)*	Open outcry trading: 10:00 AM to 2:30 PM. Electronic trading (CME Globex®): 6:00 PM (current trade date) to 5:15 PM (next trade date).
Trading Months	72 consecutive months commencing with the next calendar month.
Minimum Price Fluctuation	\$0.001 (0.1¢) per mmBtu (\$10.00 per contract).
Maximum Daily Price Fluctuation	\$3.00 per mmBtu (\$30,000 per contract) for all months. If any contract is traded, bid, or offered at the limit for five minutes, trading is halted for five minutes. When trading resumes, the limit is expanded by \$3.00 per mmBtu in either direction. If another halt were triggered, the market would continue to be expanded by \$3.00 per mmBtu in either direction after each successive five-minute trading halt. There will be no maximum price fluctuation limits during any one trading session.
Last Trading Day	Trading terminates three business days prior to the first calendar day of the delivery month.
Settlement Type	Physical
Delivery	The Sabine Pipe Line Co. Henry Hub in Louisiana. Seller is responsible for the movement of the gas through the Hub; the buyer, from the Hub. The Hub fee will be paid by seller.
Delivery Period	Delivery shall take place no earlier than the first calendar day of the delivery month and shall be completed no later than the last calendar day of the delivery month. All deliveries shall be made at as uniform as possible an hourly and daily rate of flow over the course of the delivery month.
Grade and Quality Specifications	Pipeline specifications in effect at time of delivery.

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