Maturity effect and storage announcements: the case of natural gas

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Abstract: This paper considers the maturity effect in the nearby natural gas futures contract while controlling for the impact of the weekly change in gas inventories as released by the USA Energy Information Administration (EIA). Using data from January 2005 until July 2007, we investigate whether the surprise created by the EIA announcement, i.e. the difference between the numbers released and what was expected by a group of analysts surveyed by Bloomberg, also has an influence on the volatility of natural gas futures prices. We also investigate whether the variance of the survey estimates has a significant influence on the futures price volatility. We find that volatility is higher on announcement days, especially when gas inventories are lower than expected. The magnitude of the surprise also has a significant impact on volatility on announcement days. The variance of the survey estimates, on the other hand, is rarely significant.

Keywords: derivatives; futures; volatility; estimates; surprises.

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1 Introduction

Samuelson (1965) was first to suggest that the variability of a futures price increases as the maturity date of the contract approaches, and this observation was coined the maturity effect. Serletis (1992) provides support for the maturity effect in energy futures but also finds that there could be other factors responsible for futures price volatility as including trading volume in the regression reduces the explanatory power of time to maturity. Walls (1999) finds that the maturity effect is stronger for electricity futures than other energy futures such as crude oil, unleaded gas and heating oil, and that including trading

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volume in the regression does not alter the significance the time left until maturity. Daal et al. (2006) use a much larger set of futures contracts and find that the maturity effect is absent in most of them. They find, however, that energy futures has a strong maturity effect (as well as seasonality effects), especially natural gas. Arago and Fernandez (2002) use a bivariate GARCH error-correction model to study the maturity effect in the BEX-35 futures contract. Regarding natural gas storage announcements, Linn and Zhu (2004) find that volatility in futures prices is higher on storage announcement dates. To our knowledge, there does not exist any study combining maturity effect and storage announcements and this is the gap filled by this paper.

If the price of a commodity is driven by supply and demand, the release of information on the inventory of the commodity should have an impact on its price, especially when the inventory level disclosed is different from what was expected. Being less prone to geopolitical risk than, say, crude oil, the market for natural gas is likely to be particularly sensitive to the storage announcements made every Thursday by the USA Energy Information Administration (EIA). Moreover, there are agencies, such as Bloomberg, that survey analysts before each announcement and this allows us to tell whether the inventory level disclosed is higher or lower than expected given the average survey estimates. It is also interesting to look at the variance of the survey estimates, as a greater dispersion in the opinion of natural gas analysts should trigger a more intense reaction once inventory levels are announced.

In this paper, we consider the maturity effect on the volatility of the nearby natural gas futures price while controlling for storage announcement dates, the surprise created by the announcements given its expected value and the variance of the estimates gathered in Bloomberg surveys. We find that volatility is higher on announcement dates although controlling for these does not reduce the explanatory power of the time left until maturity. We find that negative surprises have a greater impact on volatility than positive surprises, and that the magnitude of the surprise is a significant factor explaining volatility. The variance in the analysts' estimates has very little explanatory power for the volatility of the futures price.

The paper is structured as follows: The coming section describes the data used and the methodology employed, Section 2.1 provides regression results testing for the maturity effect in the presence related to natural gas storage announcements, Section 2.2 provides regression results when trading volume is included as an explanatory variable and Section 3 concludes.

2 Data and methodology

We consider the daily futures price of the nearby natural gas futures contract trading on the NYMEX from January 1, 2005 to July 13, 2007, which gives us 627 daily observations. We have chosen to follow the contract with the nearest maturity date instead of all natural gas contracts as our goal is not to discredit the maturity effect but to check whether storage announcements can provide further explanations to the volatility of natural gas prices, and studying this contract only allows us to run many different regression models. Moreover, the nearby contract is the one with the most volume and the largest open interest and thus its price should be most reflective of the natural gas market, and Daal et al. (2006) have shown that natural gas is one of the commodities with the strongest maturity effect.

We calculate intraday volatility on day t using the extreme value method, i.e.

$$\text{Volatility}_t = \frac{(\ln(\text{High}_t) - \ln(\text{Low}_t))^2}{4\ln(2)},$$

where High_t and Low_t denote the highest and the lowest prices of the nearby futures contract on day t, respectively. As Parkinson (1980) shows, this measure can be used as an estimator of the variance of the price if the latter follows a random walk with zero drift.

As opposed to crude oil, natural gas is less prone to geopolitical risk thus its price is more likely to be driven by supply and demand. Therefore, the weekly release of natural inventories by the USA EIA is likely to have an impact of the behaviour of natural gas traders. The EIA releases the level of natural gas in storage every Thursday at 10:30 Eastern Time, i.e. while natural gas futures contracts are traded (natural gas futures on the NYMEX trade from 10:00 am until 2:30 pm). If there is a holiday on Tuesday or Wednesday of a week, the report is made available on Friday. It may also happen that Thursday is a holiday, in which case the report if made available on Wednesday as long as Monday and Tuesday are working days. The weekly report consists of the working gas stocks, stated in billions of cubic feet (bcf), in three regions of the USA and for the country as a whole, estimated for the two Fridays preceding the report, the implied net change in stocks between these two weeks, the stocks that prevailed at the same date a year earlier, the five-year average and the difference in percentage between the actual stocks and the five-year average. Note that the first estimate for a Friday can be revised the following week. In this study, we restrict our attention on the weekly change in natural gas stocks.

Before the release of the weekly natural gas report, Bloomberg surveys between 18 and 25 analysts with respect to the change in natural gas inventories. Using these surveys it is possible to calculate an expected value for the change in inventories as well as a variance of these estimates. Bloomberg computes the average, the median, the high and low estimates, but we had to calculate the variance of these estimates. These survey figures are likely to have an impact on natural gas futures prices as many traders rely on these estimates to conduct their trading and thus differences between the inventories released and their estimates are likely to induce traders to adjust their positions. A wider dispersion of these estimates could also have an impact on announcement days as this implies that some traders have to make more significant position adjustments. We have collected the Bloomberg weekly survey numbers for the changes in natural gas inventories from January 1, 2005 to July 13, 2007, and some summary statistics of these estimates are shown in Table 1.

Table 1 Descriptive statistics of the Bloomberg survey estimates on changes in natural gas inventories reported by US Energy Information Administration from January 1, 2005 to July 13, 2007.

Number of surveys	131
Number of surprises (actual change $\neq$ expected change)	126
Number of negative surprises	58
Number of positive surprises	68
Average difference between actual and expected	8.37
Average surprise (positive or negative)	8.70
Average negative surprise	7.95
Average positive surprise	9.34
Average variance of survey estimates	108.48
Average variance of survey estimates given a surprise	108.80
Average variance of survey estimates given a negative surprise	97.68
Average variance of survey estimates given a positive surprise	118.28
Number of surveys with negative expected change in inventories	53
Number of surveys with positive expected change in inventories	77
Number of surveys with null expected change in inventories	1
Average variance of survey estimates when expected change in inventories is negative	178.30
Average variance of survey estimates when expected change in inventories is positive	61.18

Using these data, we construct the following variables:

ind_a: Dummy equal to 1 on days natural gas inventories are released, 0 otherwise.

m×ind_a: Given by ind_a × abs (Actual release − Bloomberg survey average), where abs stands for absolute value. This variable gives the magnitude of the surprise on inventories announcement days, whether the surprise is positive or negative.

v×ind_a: Given by ind_a × [variance of Bloomberg survey estimates]. This variable gives the variance of the survey estimates on inventories announcement days.

ind_neg: Dummy equal to 1 on announcement days where the figure released is lower than expected given the Bloomberg survey estimates, 0 otherwise.

ind_pos: Dummy equal to 1 on announcement days where the figure released is greater than expected given the Bloomberg survey estimates, 0 otherwise.

m×ind neg: Given by ind_neg × abs(Actual release − Bloomberg survey average). This variable gives the magnitude of the surprise when the latter is negative.

m×ind pos: Given by ind_pos × abs(Actual release − Bloomberg survey average). This variable gives the magnitude of the surprise when the latter is positive.

v×ind neg: Given by ind_neg × [variance of the Bloomberg estimates]. This variable gives the variance of the survey estimates on negative-surprise announcement days.

v×ind pos: Given by ind_pos × [variance of the Bloomberg estimates]. This variable gives the variance of the survey estimates on positive-surprise announcement days.

Unit root tests (Dickey-Fuller) have been performed for all variables and non-stationarity is not a problem in our sample. The analysis will be separated in two parts. We will first analyse the relationship between volatility, time to maturity and the variables related to inventories announcements. The second part adds trading volume in each of the regressions in the first part. Trading volume is used as a proxy for other variables that could also influence volatility.

2.1 Volatility, time to maturity and inventories announcements

To evaluate the impact of the number of days remaining until maturity and of the different variables related to inventories announcements, we run the regressions

$$\text{Volatility}_t = \alpha + \beta \ln(\tau_t) + \gamma_1 x_{1,t} + \gamma_2 x_{2,t} + \ldots + \epsilon_t,$$

where α is a constant, τ_t denotes the number of working days left before the contract maturity and the $x_{i,t}$s represent variables related to inventories announcements.

As can be seen in Table 2, the number of days left until maturity always has a significant explanatory power on daily volatility. In regression (2), we can see that the dummy variable identifying announcement dates (ind_a) is significant in the presence of time to maturity without taking any explanatory power from the latter. Hence volatility is higher on announcement dates regardless of the time to maturity. There were very few days without surprise (actual inventories ≠ expected inventories) and thus the dummy for announcement days with surprise does not give much more information than the dummy for announcement days alone. If, however, we separate negative surprises (ind_neg) from positive ones (ind_pos), as is done in regression (6), we find that the negative-surprise dummy has more explanatory power than positive-surprise dummy. That is, announcement days where the inventories released are lower than expected are more likely to experience higher volatility than when the inventories released are higher than expected.

Regression (3) shows that the magnitude of the surprise (absolute value of inventories released minus expected inventories) on an announcement day has a greater impact on volatility than the mere fact that there be an announcement on that day. If we separate negative-surprise from positive-surprise days and control for the magnitude of the surprise, as is done in regression (7), we find that the magnitude of the surprise is a significant factor on positive-surprise days only. That is, negative-surprise days generate higher volatility regardless of the magnitude of the surprise while positive-surprise days may experience higher volatility if the surprise is significant. In Table 1, we can see that positive surprises are greater on average than negative surprises.

Table 2 Regression results for the model $\text{Volatility}_t = \alpha + \beta \ln(\tau_t) + \gamma_1 x_{1,t} + \gamma_2 x_{2,t} + ... + \epsilon_t$

$\text{Volatility}_t = \alpha + \beta \ln(\tau_t) + \gamma_1 x_{1,t} + \gamma_2 x_{2,t} + ... + \epsilon_t,$

	$ln(\tau)$	*ind_a*	$m \times ind\_a$	$v \times ind\_a$	*ind_neg*	*ind_pos*	$m \times ind\_neg$	$m \times ind\_pos$	$v \times ind\_neg$	$v \times ind\_pos$	*F*	*R2*
1	–.000128***										12.31	.0193
	(–3.51)											
2	–.000130***	.000228***									11.50	.0355
	(–3.58)	(3.24)										
3	–.000131***	5.65E–05	2.05e–05***								10.19	.0468
	(–3.64)	(0.60)	(2.71)									
4	–.000131**	.000158		6.39E–07							8.33	.0386
	(–3.62)	(1.84)		(1.40)								
5	–.000131***	5.18E–05	1.97E–05**	1.04E–07							7.64	.0468
	(–3.64)	(0.53)	(2.32)	(0.20)								
6	–.000130***				.000323***	.000184**					8.63	.0399
	(–3.59)				(3.26)	(2.00)						
7	–.000132***				.000195	–1.78E–05	1.61E–05	2.17E–05**			6.55	.0501
	(–3.66)				(1.34)	(–0.14)	(1.19)	(2.28)				
8	–.000133***				.000369**	7.57E–05			–4.73E–07	9.20E–07	5.89	.0453
	(–3.69)				(2.54)	(0.69)			(–0.43)	(1.82)		
9	–.000133***				.000266*	–3.46E–05	2.32E–05	1.74E–05	–1.30E–06	4.81E–07	4.94	.0529
	(–3.68)				(1.66)	(–0.27)	(1.54)	(1.61)	(–1.07)	(0.84)		

Notes: where α is a constant, τ_t is the number of working days left until maturity of the contract and each $x_{i,t}$ is a variable related to natural gas inventories announcements:

ind_a is a dummy identifying natural gas inventories announcement days

ind_neg is a dummy identifying negative surprises, i.e. the level of inventories released by the EIA is lower than the average Bloomberg survey estimate

ind_pos is a dummy identifying positive surprises

m represents the magnitude of the surprise (the difference between expected and actual inventories in absolute value)

v represents the variance of the Bloomberg survey estimates

t-statistics are in parentheses

*** means significant at the 1% level, ** means significant at the 5% level and * means significant at the 10% level (two-tailed tests).

The coefficients on the constant are not shown and the period covered is from January 1, 2005 to July 13, 2007.

When considering the variance of the survey estimates, we find in Regression (4) that it takes much explanatory power from ind_a but not enough to be significant. If we combine the variance of the survey estimates with the magnitude of the surprise, as is done in Regression (5), then the variance of the survey estimates has almost no explanatory power. In Regression (8), we find that the variance of the survey estimates has some explanatory power on positive-surprise days only. Note, however, that it has the wrong sign for negative-surprise days but without significance. In Regression (9), we find that announcement days with negative surprises generate volatility regardless of the magnitude of the surprise or the variance of the survey estimates. For positive surprise days, however, volatility is more dependent on the magnitude of the surprise and on the variance of the survey estimates. In Table 1, we can see that the variance of estimates on positive surprise days is higher on average than on negative-surprise days.

2.2 Including volume in the regression

Many authors (Serletis, 1992 and Walls, 1999, for instance) have shown that there may be other factors influencing volatility which effects transpire through the trading volume. In this subsection, we run the regressions

$$\text{Volatility}_t = \alpha + \beta_1 \ln(\tau_t) + \beta_2 \text{Volume}_t + \gamma_1 x_{1,t} + \gamma_2 x_{2,t} + \ldots + \epsilon_t,$$

where α is a constant, τ_t is the number of working days until maturity of the futures contract, Volume_t is the trading volume on day t and the xi,ts are variables related to inventories announcements.

As can be seen in Regression (1) of Table 3, including volume in the regression take away a good portion of the significance of the time to maturity. Note, however, that including a dummy for announcement days, as in done in Regression (2), reduces the significance of volume and EIA announcements seem to be one variable affecting volume. If we include the magnitude of the surprise, as is done in Regression (3), then trading volume has less explanatory power.

As before in this entire table, we can see that the variance of the survey estimates does not have good explanatory power on volatility, while the magnitude of the surprise appears to be more important on positive-surprise days than on negative-surprise days. For negative surprises, the announcement itself creates more volatility than the magnitude of the surprise.

Table 3 Regression results for the model $\text{Volatility}_t = \alpha + \beta_1 \ln(\tau_t) + \beta_2 \text{Volume}_t + \gamma_1 x_{1,t} + \gamma_2 x_{2,t} + \ldots + \epsilon_t$

$$\text{Volatility}_t = \alpha + \beta_1 \ln(\tau_t) + \beta_2 \text{Volume}_t + \gamma_1 x_{1,t} + \gamma_2 x_{2,t} + \ldots + \epsilon_t,$$

	ln(τ)	*Volume*	*ind_a*	*m×ind_a*	*v×ind_a*	*ind_neg*	*ind_pos*	*m×ind_neg*	*m×ind_pos*	*v×ind_neg*	*v×ind_pos*	*R2*
1	–.000103***	1.97E-06***										.1068
	(–2.95)	(7.82)										
2	–.000105***	1.92E-08***	.000189***									.1180
	(–3.08)	(7.63)	(2.81)									
3	–.000107***	1.89E-08***	4.63E–05	1.72E–05**								.1259
	(–3.08)	(7.50)	(0.51)	(2.37)								
4	–.000106**	1.91E-08***	.000139*		4.64E–07							.1196
	(–3.05)	(7.57)	(1.69)		(1.06)							
5	–.000107***	1.89E-08***	4.63E–05	1.72E–05**	1.55E–09							.1259
	(–3.07)	(7.49)	(0.50)	(2.11)	(-0.003)							
6	–.000105***	1.91E-08***				.000285***	.000135					.1216
	(–3.59)	(7.60)				(3.00)	(1.52)					
7	–.000108***	1.89E-08***				.000181	–4.24E–05	1.32E–05	1.90E–05**			.1292
	(–3.66)	(7.50)				(1.29)	(–0.14)	(1.02)	(2.09)			
8	–.000108***	1.89E-08***				.000324**	5.42E–05			–3.95E–07	6.86E–07	.1246
	(–3.11)	(7.49)				(2.32)	(0.51)			(–0.38)	(1.41)	
9	–.000109***	1.87E-08***				.000239	–5.16E–05	1.91E–05	1.67E–05	–1.08E–06	2.67E–07	.1307
	(–3.12)	(7.44)				(1.56)	(–0.42)	(1.32)	(1.61)	(–0.92)	(0.49)	

Notes: where α is a constant, τ_t is the number of working days left until maturity of the contract and each $x_{i,t}$ is a variable related to natural gas inventories announcements:

Volume$_t$ is the trading volume on day t

ind_a is a dummy identifying natural gas inventories announcement days

ind_neg is a dummy identifying negative surprises, i.e. announcement days where inventories released are lower than the average Bloomberg survey estimate

ind pos is a dummy identifying positive surprises

m gives the magnitude of a surprise (absolute value of actual inventories minus expected inventories)

v gives the variance of the Bloomberg survey estimates on announcement days

t-statistics are in parentheses, *** means significant at the 1% level, ** means significant at the 5% level and * means significant at the 10% level (two-tailed tests).

The coefficients on the constant are not shown and the period covered is from January 1, 2005, to July 13, 2007

3 Conclusions

In this paper, the maturity effect in the nearby natural futures contract while controlling for the effect of storage announcements. We find that the maturity effect is always significant and not affected by the inclusion of variables related to natural gas storage announcements. We find, however, that the occurrence of an announcement has a significant impact on daily volatility, especially when lower-than-expected inventories are released. For days with greater-than-expected inventories announcements, the magnitude of the surprise and the variance in the survey estimates about inventories change significantly affect volatility.

When we include trading volume in the regression, we find that the time to maturity loses a good portion of its significance. In this case, storage announcement variables take some explanatory power from trading volume when included in the regression. Hence dummy for announcement dates and the surprise created by an announcement are some variables affecting volume and daily volatility.

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