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Are natural gas spot and futures prices predictable?☆

Vinod Mishra [*,1], Russell Smyth [2]

Department of Economics, Monash University, VIC 3800, Australia

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ABSTRACT

We answer two questions concerning natural gas spot and futures prices. The first is: Can natural gas futures prices predict natural gas spot prices? The second is: Are natural gas spot and futures prices weak form efficient or can they be predicted based on examination of historical data? To answer these questions, we use daily data for Henry Hub natural gas spot and futures prices. Our answer to the first question is that natural gas futures prices do not predict the magnitude of future natural gas spot prices any better than what would be predicted by a random walk model. This result has important implications for many financial analysts and policy institutions that have used commodity futures prices to predict movements in spot prices. The answer to the second question is that when we apply a unit root test that allows for heteroskedasticity and two structural breaks, natural gas spot and futures prices are predictable. We then simulate a contrarian trading strategy for spot and futures prices to show under what circumstances trading in spot and futures prices are also profitable. The results point to the need to accommodate heteroskedasticity when applying unit root tests to model energy spot and futures prices with high-frequency data, such as daily data.

1. Introduction

In this paper, we seek to answer two related research questions. The first is: Can natural gas futures prices predict natural gas spot prices in the future? To do so, we examine the out-of-sample forecast performance of natural gas futures prices in predicting natural gas spot prices at future dates. Our main finding is that almost all of our models, based on natural gas futures prices or spot-future spread, do not perform any better than our benchmark random walk model. Having answered our first question largely in the negative, we proceed to answering a second research question: Are spot and futures prices predictable? To do so, we test the weak form of the efficient market hypothesis (EMH) using a series of unit root tests. Our answer is that once one accounts for heteroskedasticity and structural breaks, natural gas spot and futures prices are mean reverting and, hence, predictable. We then simulate a contrarian trading strategy for spot and futures prices to show under what circumstances trading in spot and futures prices are also profitable. We show that knowledge that spot and futures prices are predictable can be used to devise a profitable trading strategy, although the level of profitability will vary depending on the market and the holding period of the investment.

The issue of whether natural gas futures prices can predict natural gas spot prices in the future is important for several reasons. The first is that it has become accepted among traders and policy institutions that futures prices do, in fact, predict spot prices in the future. Alquist and Kilian (2010) report evidence that in various policy institutions, including several central banks and the International Monetary Fund, it is widely considered that futures prices are not only a good predictor of future spot prices, but are better predictors of spot prices than econometric forecasts. Futures-based forecasts inform policy-making discussions, which, in turn, influence financial markets' perceptions of macroeconomic stability and future economic growth. In these circumstances, it is important to test whether these commonly held assumptions are accurate. Second, whether futures prices do predict spot prices is an issue that has not been settled (see e.g. contrasting findings in Alquist and Kilian, 2010 and Reichsfeld and Roache, 2011). Third, it is generally accepted that despite the approach to forecasting in policy-making institutions, that futures prices have not been a good predictor of future spot prices in the commodity price boom (Reichsfeld and Roache, 2011). This suggests that there is a need for further empirical evidence with more recent data.

We seek to do this using daily data on spot and futures prices for natural gas over the period January 1997 to March 2014. Our dataset has the advantage that it spans the entire period of the commodity boom. We conduct a systematic evaluation of the out-of-sample predictive accuracy of natural gas futures-based forecasts. Our forecasting approaches closely follow those used by Alquist and Kilian (2010), who tested whether the futures price of oil predicts the spot price of oil over the period January 1991 to February 2007. We extend their analysis to natural gas markets and use data over a more recent period.

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* Corresponding author.
E-mail addresses: vinod.mishra@monash.edu (V. Mishra), russell.smyth@monash.edu (R. Smyth).
[1] Tel.: +61 3 99047179.
[2] Tel.: +61 3 99051560.

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Alquist and Kilian (2010) found that oil futures prices fail to improve on the accuracy of simple no-change forecasts. Our findings for natural gas prices are largely consistent with Alquist and Kilian's (2010) findings for oil prices. Both findings contradict the received wisdom among financial analysts and policy-makers when it comes to forecasting spot prices for commodities.

Having established that natural gas futures prices largely do not predict natural gas spot prices; in the second part of the paper, we examine whether natural gas spot and futures prices are predictable using unit root tests. Unit root tests have become a common method to test for a random walk in financial data and there are many such studies (see Lim and Brooks, 2011). For the purposes of benchmarking, we begin with conventional unit root and stationarity tests—Augmented Dickey Fuller (ADF) (Dickey and Fuller, 1979), Phillips and Perron (1988) and KPSS (Kwiatkowski et al., 1992)—in addition to two well-known unit root tests with two structural breaks; namely, Lee and Strazicich (2003) and Narayan and Popp (2010).[3] To illustrate the importance of accommodating heteroskedasticity in addition to structural breaks, with high-frequency data, we employ the Narayan et al. (2015) unit root test.[4]

The issue of whether natural spot and futures prices contain a unit root is important for financial analysts. If natural prices contain a unit root, the market is weak form efficient, meaning that prices fully reflect all the information present in the market and, hence, there is no scope for making profits using either technical analysis or fundamental analysis of financial markets. As Malkiel (2003) puts it, in an efficient market, an investor cannot earn returns greater than those that could be obtained by holding a randomly selected portfolio of individual stocks (with a comparable level of risk). However, if natural gas spot and futures prices are found to be mean reverting, this suggests that it is possible for investors to make a profit through predicting natural gas price movements based on historical data.

There has been a large literature that has examined the predictability of spot and futures energy prices using a range of unit root tests (Barros et al., 2014; Elder and Serletis, 2008; Ghoshray and Johnson, 2010; Lee et al., 2006; Lee and Lee, 2009; Presno et al., 2014; Maslyuk and Smyth, 2008; Ozdemir et al., 2013; Sadorsky, 1999; Serletis, 1992). The results from existing studies have been mixed. Some studies have concluded that spot and/or futures energy prices are mean reverting and, hence, predictable (Elder and Serletis, 2008; Lee et al., 2006; Lee and Lee, 2009; Sadorsky, 1999; Serletis, 1992). Other studies have concluded that spot and/or futures energy prices are non-stationary or persistent or find mixed evidence that spot and futures prices are stationarity (Barros et al., 2014; Ghoshray and Johnson, 2010; Maslyuk and Smyth, 2008; Ozdemir et al., 2013; Pindyck, 1999; Presno et al., 2014).

When testing for a unit root in spot and futures prices, researchers typically employ high-frequency data (such as daily or weekly data). High-frequency financial data is subject to heteroskedasticity. Failure to account for heteroskedasticity in the data lowers the power to reject the unit root null hypothesis (Narayan et al., 2015). We make a methodological contribution to the unit root literature that tests the EMH in energy spot and futures prices in that we pay particular attention to heteroskedasticity and structural breaks when testing for a unit root in high-frequency spot and futures energy price data. The focus on accommodating heteroskedasticity is particularly important given that there is much evidence in the existing literature that has employed unit root tests that natural gas prices follow a random walk or exhibit high persistence, even after allowing for structural breaks (see e.g. Barros et al., 2014; Ferreira et al., 2005; Lee and Lee, 2009; Pindyck, 1999; Presno et al., 2014).

Our paper contributes to several recent 'conversations' in this journal. The first concerns the modelling of natural gas spot and futures prices (Kani et al., 2014; Shahbaz et al., 2014). The second are studies focusing on whether futures prices can predict spot prices (Yang and Zhang, 2013). The third is the modelling of a random walk through the application of unit root tests across a range of topics (Emirmahmutoglu and Omay, 2014; Tiwari and Kyophilavong, 2014). The fourth is the modelling of high-frequency data (Haugom et al., 2014).

2. Data

The data consisted of daily observations for spot and futures prices for natural gas for all trading days between 01 January 1997 and 03 March 2014 (the latest data available at the time of this study) collected from the U.S. Energy Information Administration (EIA) website.[5] This is a total of 4294 observations. The spot prices are the Henry Hub natural gas spot prices and the futures prices are for the 1-, 2-, 3- and 4-month futures contracts.

We use Henry Hub natural gas spot and futures prices because it is the benchmark price for North American natural gas (American Petroleum Institute, 2014). As the American Petroleum Institute (2014, p. 17) notes: "The Henry Hub is interconnected with 13 different intra- and interstate pipelines. Because of its central location and its high degree of interconnectedness, the Henry Hub is used as the delivery point for the New York Mercantile Exchange's (NYMEX) natural gas futures contract". There are many other markets that are now as big as Henry Hub, with some markets even having a larger number of spot transactions than Henry Hub. Examples are Alberta, Canada, Chicago Citygate, and Dawn, Ontario (American Petroleum Institute, 2014). However, the natural gas futures contract traded on NYMEX are written for delivery at the Henry Hub only. Therefore, it is expected that the natural gas futures prices reflect the market expectations for the future value of Henry Hub spot prices. Hence, given the objectives of the study, we use Henry Hub spot and futures prices.

All prices are expressed in dollars per million Btu. All the analyses were performed on the natural log of the series. The time series for the natural gas spot and futures price series are graphed in Figs. 1 and 2. Table 1 presents descriptive statistics for daily spot and futures prices for natural gas for 1–4 month contracts over the sample period. The difference between the futures and spot price narrows as the futures price approaches maturity, but is consistently positive. The natural gas market is in contango, which is defined as the situation in which near month futures are cheaper than those expiring further into the future, which generates an upward sloping curve for future prices over time. A contangoed market typically results when investors prefer to pay a premium to have the commodity in the future rather than paying the storage and carry costs of acquiring the commodity in the present. Natural gas typically exhibits contango, as storing fossil fuel can be quite costly. Some, however, have noted that it is somewhat surprising is that natural has continued to maintain an upward sloping futures curve despite increasing supply (Cummans, 2013).[6]

[3] The Lee and Strazicich (2003) and Narayan and Popp (2010) tests have been shown to have better size and power properties, and to estimate the break dates more accurately, than alternative two break unit root tests, such as Lumsdaine and Papell (1997) (see Lee and Strazicich, 2003; Narayan and Popp, 2013).

[4] Other applications of the Narayan et al. (2015) test (or earlier working paper versions) in the commodities/energy area are Mishra and Smyth (2014); Narayan and Liu (2011); Salisu and Fasanya (2013) and Salisu and Mobolaji (2013). Of these, Salisu and Fasanya, 2013 is the only previous study to apply Narayan et al. (2015) to energy prices (oil prices). But, they do not consider energy futures prices. There are no previous applications of Narayan et al. (2015) to natural gas spot or futures prices.

[5] http://www.eia.gov/dnav/ng/ng_pri_fut_s1_a.htm (last accessed March 15, 2014).

[6] More information available at: http://www.nasdaq.com/article/contango-report-natural-gas-silver-and-wheat-face-rising-prices-cm254450#ixzz3tbJPTXH7

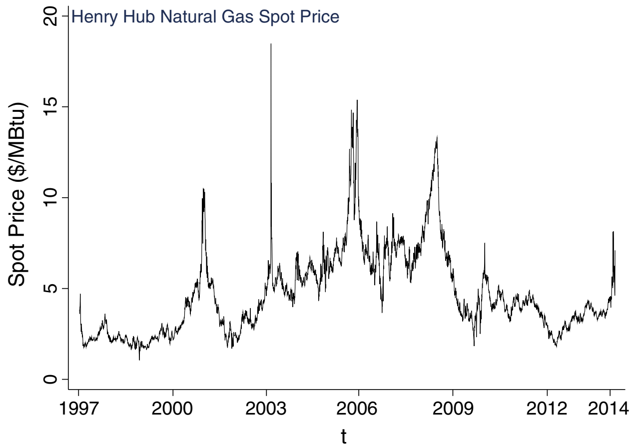

Fig. 1. Time series plot of daily natural gas spot prices.

3. Can natural gas futures prices predict natural gas spot prices in the future?

3.1. Alternative forecasting models

As discussed in the introduction, it is commonly assumed that natural gas futures prices reflect the market expectations of future spot prices and that they can be used as early predictors for demand and supply conditions in the natural gas market in the future. It is for this reason that futures prices are used by central banks in developing their inflation and output forecasts, used by natural gas producers in planning production and inventory decisions and used by policy makers to ensure energy security.

In this section we put the above-mentioned assumption to the test by looking at the out-of-sample forecast performance of futures prices in predicting spot prices at future dates. A futures contract states the price that will be paid and the date of delivery in some future period. Let the nominal price of a natural gas futures contract in period t that matures in h periods be:

$$\mathrm{F}_{\mathrm{t}}^{(\mathrm{h})}, \mathrm{h} = 1, 2, 3, 4$$

and the spot price in the same period be S_t. The assumption that the expected future price at date $t+h$, conditional on information available at t, will be futures price $F_t^{(h)}$ implies:

$$E_t\left[S_{t+h|t}\right] = F_t^{(h)}, h = 1, 2, 3, 4$$

In terms of a forecasting model, this would mean:

$$\hat{S}_{t+h|t} = F_t^{(h)}, h = 1, 2, 3, 4$$

Another approach towards forecasting the spot price of natural gas is to use the spread between spot price and the futures price as an indicator of whether the price of natural gas is likely to go up or down. This approach can be formulated in the form of several competing forecasting models (Alquist and Kilian, 2010). The simplest model can be written as

$$\hat{S}_{t+h|t} = S_t\left(1 + \ln\left(\frac{F_t^{(h)}}{S_t}\right)\right), h = 1, 2, 3, 4$$

Another approach could be to allow for the possibility that the spread is a biased predictor and relax the assumption of zero intercept in the above equation, giving:

$$\hat{S}_{t+h|t} = S_t\left(1 + \hat{\alpha} + \ln\left(\frac{F_t^{(h)}}{S_t}\right)\right), h = 1, 2, 3, 4$$

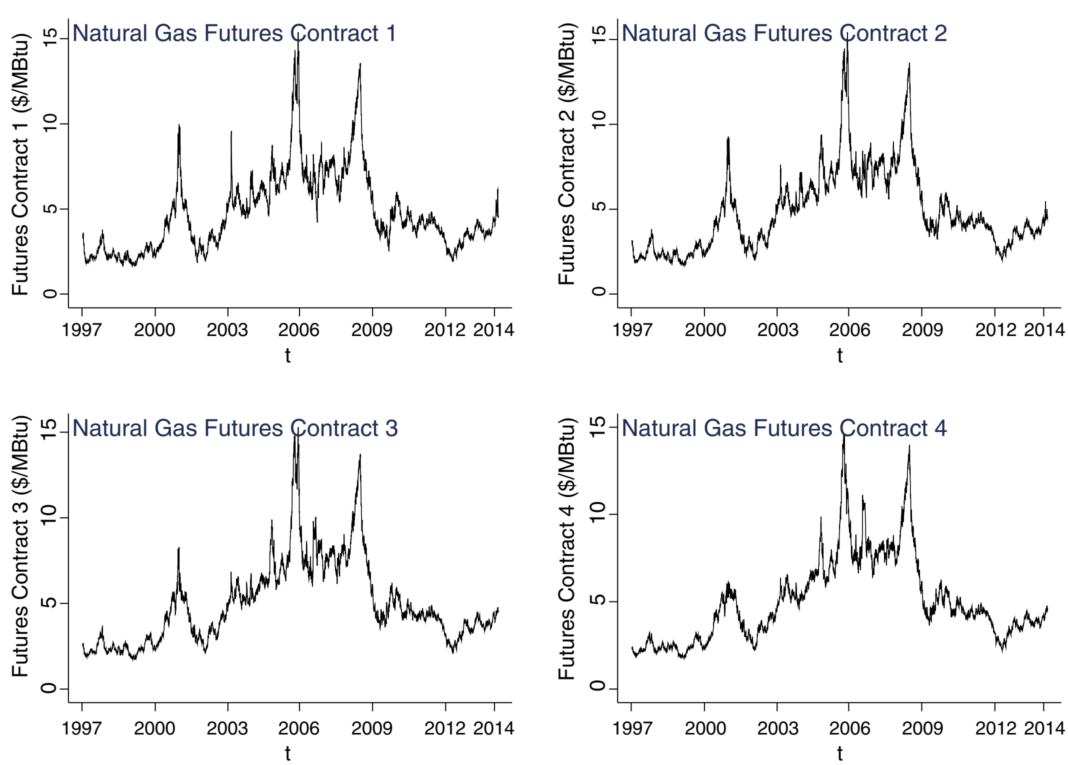

Fig. 2. Time series plot of daily natural gas futures prices for 1- to 4-month contracts.

Table 1
Descriptive statistics of natural gas spot and futures prices during the sample period.

Series	Observations	Mean	Std. Dev.	Min.	Max.	Skewness	ARCH(1) LM test
Spot Price	4294	4.70	2.34	1.05	18.48	1.28	1644.47***
Futures—1 M	4294	4.77	2.36	1.63	15.38	1.23	69.04***
Futures—2 M	4294	4.89	2.40	1.66	15.43	1.21	142.20***
Futures—3 M	4294	4.97	2.44	1.70	15.29	1.19	68.05***
Futures—4 M	4294	5.03	2.44	1.74	14.61	1.10	63.90***

Notes: Sample consisted of daily data on natural gas spot and futures prices for all the trading days for the period 07 January 1997–03 March 2014. All the prices are expressed in US dollars per million Btu. All further analyses were conducted using the natural log of the series. Results for the ARCH LM test were filtered using a AR(1) model, given the data is daily, and the residuals were tested for ARCH effects.

Moreover, one can also relax the proportionality assumption, in an alternative specification to get the following equation:

$$\hat{S}_{t+h|t} = S_t\left(1+\hat{\beta}\ln\left(\frac{F_t^{(h)}}{S_t}\right)\right), h = 1,2,3,4$$

In the most general form, both the proportionality and biasedness assumption can be relaxed to obtain a specification, which reduces to the previous three specifications under special cases:

$$\hat{S}_{t+h|t} = S_t\left(1+\hat{\alpha}+\hat{\beta}\ln\left(\frac{F_t^{(h)}}{S_t}\right)\right), h = 1,2,3,4$$

Here, $\hat{\alpha}$ and $\hat{\beta}$ can be estimated using ordinary least squares in a recursive regression framework.

A natural benchmark to which the forecasting performance of the above models (i.e. the models in which futures prices predict spot prices in the future) can be compared is the random walk model without drift. Based on this model, changes in spot prices are unpredictable; hence, the best estimate of the future spot price is the current spot price. This can be mathematically written as

$$\hat{S}_{t+h|t} = S_t, h = 1,2,3,4$$

If the forecast performance of futures prices-based models is better than the random walk model, that would imply that futures prices contain more information than what is already embedded in the spot prices and are better than predicting the future spot prices than the model that assumes futures prices to be unpredictable (the random walk model).

3.2. Forecast evaluation criteria

Whether or not a particular forecasting model performs better than a benchmark model may also depend upon the loss function used by the forecaster. In order to ensure that our assessment of the predictive performance of the above models is not purely driven by the choice of the loss function, we use the following forecast evaluation measures:

(1) *Mean Squared Prediction Error* (*MSPE*): This is one of the most common forecast evaluation tools used in the literature: Let us say the predicted value of h period ahead forecast at time t is given as $\hat{S}_{t+h}$, and the actual value that realises at time $t+h$ is S_{t+h}, then the prediction error will be defined as

$$\hat{e}_{t+h} = \left(\hat{S}_{t+h} - S_{t+h}\right)$$

The sum of squared prediction errors (SPE) will be given as

$$SPE = \left(\hat{S}_{t+h} - S_{t+h}\right)^{2.}$$

Dividing the number of periods over which the prediction is generated into the sum of squared prediction errors, we obtain the mean squared prediction error:

$$MSPE = \frac{\sum_T^{T+H}\left(\hat{S}_{t+h} - S_{t+h}\right)^2}{H}$$

where H is the total number of time periods over which forecasting is performed.

(2) *Forecast Bias*: This is given as the average of prediction error

$$Bias = \frac{\left(\hat{S}_{t+h} - S_{t+h}\right)}{H}$$

(3) *Mean Absolute Prediction Error* (*MAPE*): This is a measure of the absolute error between the predicted value and the actual out-of-sample value. Using the notation developed above, the sum of absolute errors is given as

$$APE = \sum_{t=T}^{T+h}|\hat{S}_{t+h} - S_{t+h}|$$

We can obtain the mean of the above sum of absolute errors by diving it by the number of periods for which the forecasting is performed:

$$MAPE = \frac{\sum_{t=T}^{T+h}|\hat{S}_{t+h} - S_{t+h}|}{H}$$

(4) *Success Ratio* (*SR*): This is a test statistic proposed by Pesaran and Timmermann (1992), which is based on the number of times a forecasting model correctly predicts the sign of the change in the spot price. This statistic measures whether the value of SR is significantly different from the success ratio that would be obtained when the realized values S_{t+h} and the forecasts $\hat{S}_{t+h}$ are independent.

Apart from calculating the forecast evaluation loss functions, we also follow an approach similar to Alquist and Kilian (2010) and formally test the null hypothesis that a given forecasting model is as accurate as the random walk model against the alternative that the forecasting model is more accurate than the random walk model.[7]

[7] We use the Matlab programs written by Ron Alquist, freely downloadable from the *Journal of Applied Econometrics* data archive [http://qed.econ.queensu.ca/jae/]

Table 2
Forecast performance of 1-month futures prices in predicting the spot price.

$\hat{S}_{t+1\|t}$	MSPE	Bias	MAPE	Success ratio
S_t	1.324	0.009	0.710	–
$F_t^{(1)}$	0.972 (0.213)	−0.119	0.984 (0.182)	0.571 (0.001)
$S_t(1+\hat{\alpha}+\hat{\beta}\ ,\ \ln(\frac{F_t^{(1)}}{S_t}))$	3.937 (1.000)	−0.057	1.927 (1.000)	0.482 (0.981)
$S_t(1+\hat{\beta}\ ,\ \ln(\frac{F_t^{(1)}}{S_t}))$	3.716 (1.000)	−0.136	1.821 (1.000)	0.492 (0.616)
$S_t(1+\hat{\alpha}+\ ,\ \ln(\frac{F_t^{(1)}}{S_t}))$	3.453 (0.501)	−0.043	1.788 (0.350)	0.481 (0.987)
$S_t(1+\ ,\ \ln(\frac{F_t^{(1)}}{S_t}))$	0.968 (0.157)	−0.107	0.981 (0.113)	0.571 (0.001)

Notes: First row is the benchmark random walk model, second row is futures prices predicting future spot prices model and third–sixth rows present different variations of spot-future spread predicting spot prices. The MSPE and MAPE results are presented as ratios to the benchmark random walk model (for which the actual values are reported). Bias is defined as the average amount by which S_{t+h} exceeds the prediction. The success ratio is defined as the fraction of forecasts that correctly predict the sign of the change in the price of natural gas. The p-values for the success ratio are based on Pesaran and Timmermann (1992). The initial estimation window was for the period January 1997–December 2002. For the forecasting models based on 1, 2, 3 and 4 months, the initial estimation window begins in February 1997, March 1997, April 1997 and May 1997, respectively. The sample period of January 2003–March 2014 was used for forecast evaluation, using a recursive framework.

Table 4
Forecast performance of 3-month futures prices in predicting the spot price.

$\hat{S}_{t+3\|t}$	MSPE	Bias	MAPE	Success ratio
S_t	2.834	0.153	1.148	–
$F_t^{(3)}$	1.043 (0.866)	−0.472	0.989 (0.353)	0.565 (0.001)
$S_t(1+\hat{\alpha}+\hat{\beta}\ ,\ \ln(\frac{F_t^{(3)}}{S_t}))$	2.238 (1.000)	−0.228	1.474 (1.000)	0.482 (0.939)
$S_t(1+\hat{\beta}\ ,\ \ln(\frac{F_t^{(3)}}{S_t}))$	1.787 (1.000)	−0.234	1.334 (1.000)	0.482 (0.883)
$S_t(1+\hat{\alpha}+\ ,\ \ln(\frac{F_t^{(3)}}{S_t}))$	2.851 (0.742)	−0.275	1.674 (0.617)	0.485 (0.911)
$S_t(1+\ ,\ \ln(\frac{F_t^{(3)}}{S_t}))$	1.028 (0.792)	−0.419	0.984 (0.246)	0.565 (0.000)

Notes: See notes to Table 2.

3.3. Estimation and results

We used roughly one-third of the sample (for the period 1 January 1997–31 December 2002) for conducting the initial estimates, while the remaining two-thirds of the sample (for the period 1 January 2003–03 March 2014) was used for out of sample forecast evaluation. We used a recursive framework to generate one-step-ahead static forecasts.

The results of forecast evaluation are presented in Tables 2-5. In Table 2 we present the forecast evaluation of predictions based on 1-month futures prices. In Tables 3-5 we present the forecast evaluation of predictions based on 2-month, 3-month and 4-month futures prices, respectively. The first row of each table presents the actual values of MSPE, Bias and MAPE for the random walk model. As the random walk model predicts no change from the previous period, the SR is not defined for this model. Rows 2–6 in each table present the MSPE, Bias, MAPE and SR expressed as the ratio of the benchmark random walk model. This provides an easy way to compare the performance of each model with the benchmark model.

One general conclusion that can be derived by looking at these tables is that almost all of the models based on futures prices or spot-future spread do not perform any better than the benchmark random walk model. Looking at the loss function based on MSPE (first column in each table), we notice that the futures price-based model and spot-futures spread-based model, without intercept and trend, performs marginally better than the benchmark at the 1-month horizon; however, the improved accuracy remains statistically insignificant at traditional levels of significance. Looking at the MAPE metric, the same result is confirmed for all forecast horizons. In all cases, the size of bias associated with the benchmark random walk model is smaller than the size of bias associated with all the other models. These results are consistent with the findings in Alquist and Kilian (2010) for the crude oil market.

The only advantage futures-based models seem to have over the benchmark random walk model is in predicting the sign of the change in natural gas prices. In all the tables, we see that the futures price-based model and spot-futures spread-based model, without intercept and trend, performs significantly better than the benchmark random walk model when we use the success ratio as a criteria for forecast evaluation. This result is contrary to what Alquist and Kilian (2010) found for the crude oil market.

An overall conclusion that we can draw from the above discussion is that futures prices do contain some information relevant for predicting the direction of change in the spot prices in the United States natural gas market; however, it is not enough to predict the magnitude of prices, any better than what would be predicted by a random walk model.

4. Are natural gas spot and futures prices predictable?

Having concluded that natural gas futures prices do not predict the magnitude of future natural gas spot prices any better than what would be predicted by a random walk model, we next ask whether natural gas spot and futures prices are predictable, based on unit root tests.

4.1. Unit root tests

We do not reproduce the method for the ADF, Phillips-Perron and KPSS tests, nor the unit root tests with structural breaks proposed by Lee and Strazicich (2003) or Narayan and Popp (2010), given that these tests are well known in the literature.

We outline the method in Narayan et al. (2015) because it is relatively new and still in working paper form. High-frequency data is often characterised by time-varying volatility, also known as ARCH/GARCH effects. Narayan et al. (2015) argued that structural break unit root tests based on standard linear models (independently and identically distributed (iid) innovations) are inappropriate if the data has significant ARCH effects. Narayan et al. (2015) propose a unit root test with two endogenous structural breaks that specifically include a GARCH(1,1) model in the data generating process. This test allows for

Table 3
Forecast performance of 2-month futures prices in predicting the spot price.

$\hat{S}_{t+2\|t}$	MSPE	Bias	MAPE	Success ratio
S_t	2.001	0.014	0.958	–
$F_t^{(2)}$	1.029 (0.785)	−0.301	0.979 (0.188)	0.583 (0.001)
$S_t(1+\hat{\alpha}+\hat{\beta}\ ,\ \ln(\frac{F_t^{(2)}}{S_t}))$	2.697 (1.000)	−0.169	1.638 (1.000)	0.478 (0.983)
$S_t(1+\hat{\beta}\ ,\ \ln(\frac{F_t^{(2)}}{S_t}))$	2.383 (1.000)	−0.236	1.499 (1.000)	0.491 (0.376)
$S_t(1+\hat{\alpha}+\ ,\ \ln(\frac{F_t^{(2)}}{S_t}))$	2.979 (0.607)	−0.156	1.688 (0.428)	0.483 (0.956)
$S_t(1+\ ,\ \ln(\frac{F_t^{(2)}}{S_t}))$	1.014 (0.664)	−0.271	0.9975 (0.109)	0.583 (0.000)

Notes: See notes to Table 2.

Table 5
Forecast performance of 4-month futures prices in predicting the spot price.

$\hat{S}_{t+4\|t}$	MSPE	Bias	MAPE	Success ratio
S_t	3.724	0.015	1.317	–
$F_t^{(4)}$	1.003 (0.526)	−0.591	0.984 (0.272)	0.559 (0.000)
$S_t(1+\hat{\alpha}+\hat{\beta}\ ,\ \ln(\frac{F_t^{(4)}}{S_t}))$	2.475 (0.998)	−0.401	1.553 (1.000)	0.476 (0.991)
$S_t(1+\hat{\beta}\ ,\ \ln(\frac{F_t^{(4)}}{S_t}))$	1.675 (1.000)	−0.293	1.365 (1.000)	0.483 (0.960)
$S_t(1+\hat{\alpha}+\ ,\ \ln(\frac{F_t^{(4)}}{S_t}))$	2.895 (0.764)	−0.457	1.758 (0.946)	0.473 (0.996)
$S_t(1+\ ,\ \ln(\frac{F_t^{(4)}}{S_t}))$	0.977 (0.317)	−0.516	0.967 (0.092)	0.559 (0.001)

Notes: See notes to Table 2.

two structural breaks in the intercept of the time series and jointly estimates the autoregressive parameter (for an ADF based unit root test) and the GARCH parameter using maximum likelihood estimation. The data generating process is specified as

$$y_t = \alpha_0 + \pi y_{t-1} + D_1 B_{1t} + D_2 B_{2t} + \varepsilon_t$$

Here, $B_{it} = 1$ for $t > T_{Bi}$ otherwise $B_{it} = 0, T_{Bi}$ are structural break points, where $i = 1, 2$. D_1 and D_2 are break dummy coefficients. ε_t follows the first-order GARCH (1,1) model of the form:

$$\varepsilon_t = \eta_t \sqrt{h_t}, h_t = \kappa + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}$$

Here, $\kappa > 0, \alpha \geq 0, \beta \geq 0$ and η_t is a sequence of iid random variables with zero mean and unit variance.

The unknown break dates (T_{B1} and T_{B2}) are estimated using a sequential procedure. Initially, the location of the first break date is determined using the maximum absolute t-value of the break dummy coefficient D_1, as follows:

$$\hat{T}_{B1} = arg \max_{\hat{T}_{B1}} \left| t_{\widehat{D1}}(T_{B1}) \right|$$

Next, imposing the first break estimate as given, a second break date can be searched:

$$\hat{T}_{B2} = arg \max_{\hat{T}_{B2}} \left| t_{\widehat{D2}}(T_{B2}) \right|$$

The 5% critical values based on 50,000 replications for $N = 500$ are given in Narayan et al. (2015).[8] It is to be noted that the critical values depend on the relative location of the two breaks and the value of the two GARCH parameters.

4.2. Results

Table 6 presents the results for the ADF, Phillips-Perron and KPSS tests with an intercept. There is strong evidence that natural gas spot and futures prices contain a unit root. Table 7 presents the results for the Lee and Strazicich (2003) Lagrange multiplier (LM) unit root test with two breaks in the intercept (Model AA in Lee and Strazicich, 2003). In each case, the Lee and Strazicich (2003) unit root test concludes that the spot and futures prices contain a unit root. Table 8 presents the results for the Narayan and Popp (2010) unit root test with two breaks in the intercept (Model M1 in Narayan and Popp, 2010). The unit root null hypothesis cannot be rejected for any series at the 5% level or better.

Each of these tests ignore the possible existence of heteroskedasticity in the data. The last column of Table 1 reports the result of the ARCH LM test to examine whether there is heteroskedasticity in the spot and futures prices series. In order to conduct this test, we first filtered the each series using an AR(1) model, then used the residuals to run an ARCH LM test. The null hypothesis of no arch effect was rejected at the 5% level; indicating the presence of significant time varying volatility in the natural gas spot and futures price series. As the data was of daily frequency, the choice of filtering it with an AR(1) seems the obvious choice; however, as a robustness check we also repeated the ARCH LM test after filtering the data using an AR(5) model (to capture weekly seasonality) and an AR(24) model (to capture monthly seasonality). The results were found to be robust to choice of different lags for filtering the series. We also computed the Durbin–Watson statistics after each filtering and it ranged between 1.92 and 1.98, suggesting that the filtered data is independent of autocorrelations in each case. As the models with different AR lags produced the same results, we only report the most parsimonious AR(1) model in the paper.

[8] These are also reproduced at the bottom of Table 9 below.

Table 6
Results of traditional unit root and stationarity tests.

Series	Intercept only ADF test	PP test	KPSS test
Spot price	−2.28	−2.70	2.60***
Futures—1 M	−2.47	−2.36	2.68***
Futures—2 M	−2.48	−2.21	2.81***
Futures—3 M	−2.42	−2.15	2.99***
Futures—4 M	−2.31	−2.01	3.18***

Notes: ADF = Augmented Dickey Fuller; PP = Phillips Perron; KPSS is the Kwiatkowski et al., 1992) stationarity test. *** denotes significance at 1% level.

Table 9 reports the results of the Narayan et al. (2015) test with two structural breaks in the intercept. The Narayan et al. (2015) test suggests that natural gas spot and futures prices are mean reverting, and hence predictable, in each case at the 5% level.

Overall, when we use conventional unit root tests with up to two structural breaks, we find that natural gas spot and futures prices contain a unit root. When we employ a unit root test that simultaneously accommodates structural breaks and heteroskedasticity, we find that natural gas spot and futures prices are mean reverting. Our results highlight the importance of accommodating heteroskedasticity and suggest that just allowing for structural breaks is not sufficient to reject the unit root null in natural gas spot and futures prices. Our results are consistent with previous studies that have found natural gas prices contain a unit root when applying tests that do not allow for heteroskedasticity (Ferreira et al., 2005; Lee and Lee, 2009; Pindyck, 1999; Presno et al., 2014). It is accommodating heteroskedasticity that is driving the results. More generally, the results point to the need to accommodate heteroskedasticity when testing for a unit root in high-frequency energy spot and futures price data.

Most of the first breaks across the three tests occur in 1998, 1999, 2000, 2001 or 2003. Several of the second breaks occur in 2003, 2008 or 2009. The breaks differ somewhat across the tests and there is no clear relationship between the first and second break. Fig. 3 plots the time series for natural has spot prices with breaks in the intercept showing the breaks identified by the three unit root tests with structural breaks that we employ. For the Narayan et al. (2015) test, for futures prices the first intercept break is always (1 to 4 months ahead) found to be March 1999, while the second intercept break always coincides with early July 2008: July 3 for spot and July 7 for futures (when oil prices peaked). This did not happen for the other tests with breaks in Tables 7 and 8. That the first intercept break changes so much in Table 9 may seem surprising, if one thinks that forward prices depend on spot prices, but our analysis in Section 3 suggests that there is hardly any association between the two.

While the breaks differ across different tests, in general the break dates can be linked to global economic events that have affected global energy and financial markets and are similar to those identified in

Table 7
Results for Lee and Strazicich (2003) LM unit root test with two structural breaks.

Series	Break in intercept Test statistic	TB1	TB2
Spot price	−3.22	21 Feb. 2003	12 Nov. 2009
Futures—1 M	−3.11	26 Sep. 2001	21 Feb. 2003
Futures—2 M	−3.01	31 Jan. 2001	21 Feb. 2003
Futures—3 M	−2.55	21 Feb. 2003	20 May 2009
Futures—4 M	−2.25	21 Feb. 2003	02 Jun. 2009

Critical values for unit root test

Break in intercept only (Model AA)

1%	5%	10%
−4.54	−3.84	−3.50

Notes: TB_1 and TB_2 are the dates of the structural breaks. λ_j denotes the location of the breaks.

Table 8
Results for Narayan and Popp (2010) unit root test with two structural breaks.

Series	Break in intercept		
	Test statistic	TB1	TB2
Spot price	−3.44	02 Dec. 1998	21 Feb. 2003
Futures—1 M	−3.78	30 Sep. 1998	26 Sep. 2001
Futures—2 M	−3.19	26 Sep. 2001	27 Aug. 2009
Futures—3 M	−2.57	27 Dec. 2000	29 Jul. 2009
Futures—4 M	−2.11	29 Jul. 2009	13 Jun. 2012

Critical values for unit root test

1%	5%	10%
Model M1 (break in intercept only)		
−4.672	−4.081	−3.772

Notes: The critical values are taken from Narayan and Popp (2010).

previous studies (see e.g. Maslyuk and Smyth, 2008; Salisu and Fasanya, 2013). The break dates in 1998 and 1999 coincide with the Asian financial crisis. The break dates in 2001 coincide with the 9/11 terrorist attacks on the World Trade Center in New York. The breaks in 2003 could be linked to the outbreak of the Gulf War in Iraq, which commenced in March 2003. The breaks in mid-2008 coincide with the peak in oil prices and those in 2008 and 2009 coincide with the global financial crisis.

5. Trading strategies based on mean reversion

In order to analyse how one can profitably exploit the findings of mean reversion, we look at the performance of a contrarian trading strategy at various holding periods for spot and futures prices. A mean reverting series does not drift too far from its long-term average; hence, one can devise a trading strategy of leaning against the wind (contrarian strategy). Pursuing a contrarian strategy, an investor buys stock when prices are falling (i.e. when most of the market is selling) knowing that they will rise to the mean level in the near future and sells stocks when prices are rising (i.e. when market is buying) knowing that the prices will fall in the future, when she can then buy back for less money. If the finding of mean reversion holds, the investor can make above normal profit by following this strategy. However, the profitability of such a trading strategy will also depend on how frequently prices revert to the mean value, i.e. the trading frequency or the holding period between two trades.

In the current section, we look at the economic significance of our results by simulating a contrarian trading strategy for spot and futures prices. We start with a hypothetical sum of $100 used for trading in spot and future markets. As the profitability of trading strategy might depend upon the holding period, we implement this trading strategy for various holding periods in the range of 1 day–4 months. The trading strategy works as follows:

- In period 1, the trader observes the market and starts trading in period 2 onwards.
- In period 2 onwards, she buys at the market price if the price has gone down compared to the last period and sells if the price has gone up compared to the last period. If the price remains unchanged compared to the last period, she continues holding the previous period's position.
- In the last period she liquidates her portfolio at the market price.

Comparing the value of the portfolio in the last period with the initial value of $100, we can evaluate the profitability of this trading strategy. For simplicity, we have assumed that the transaction costs and commissions associated with trading are zero. Table 10 presents the return for spot and futures prices for various holding periods. The lower panel of this table also presents the overall return for the sample, assuming that the trader believes prices to be unpredictable and hence invests her initial $100 in buying at the current market price, holds it for all future periods and liquidates her investment in the last period at the market price. This overall return serves as a benchmark return, based on the assumption of a random walk.

Comparing the returns for a contrarian strategy with the benchmark return, we notice that the contrarian strategy mostly outperforms the random walk model; however, results are sensitive to the choice of market and the choice of holding period. More specifically, a contrarian strategy performs very well for holding periods of 1–3 months in the spot market. On the other hand, the contrarian strategy seems to be most profitable in the futures market for the relatively short holding periods of 1 day–1 week. The contrarian strategy is also profitable for the holding periods of 2 months–4 months in the futures markets; however, in some instances, its profitability is not higher than the random walk model. We note that the contrarian trading strategy seems to be very profitable in almost all the markets at the 2 months holding period, compared to the 1 and 3 months holding period. This result can be attributed to our particular choice of sample period, trading strategy or some other un-observed feature specific to our sample.

Overall, we can say that the conclusion derived from analysing the unit root properties of natural gas spot and futures market can be used for devising a profitable trading strategy; however, the level of profitability of such a trading strategy will vary from one market to another and will depend on the holding period of the investment and the nature of trading strategy.

Table 9
Results for Narayan et al. (2015) test with two structural breaks in the intercept.

Series	Test statistic	TB1	TB2
Spot price	−8.51**	24 Feb. 2003	03 Jul. 2008
Futures—1 M	−4.44**	19 Mar. 1999	07 July 2008
Futures—2 M	−3.97**	19 Mar. 1999	07 July 2008
Futures—3 M	−3.75**	19 Mar. 1999	07 July 2008
Futures—4 M	−3.81**	01 Mar. 1999	07 July 2008

The 5% critical values for $N=500$ and GARCH parameters $[\alpha,\beta]$

$[\alpha,\beta]$		[0.05,0.90]			[0.45,0.50]			[0.90,0.05]	
$t1/t2$	0.4	0.6	0.8	0.4	0.6	0.8	0.4	0.6	0.8
0.2	−3.65	−3.69	−3.66	−3.60	−3.59	−3.58	−3.56	−3.54	−3.55
0.4		−3.66	−3.65		−3.58	−3.58		−3.51	−3.58
0.6			−3.67			−3.60			−3.52

Notes: The 5% critical values for Narayan et al. (2015) test are provided in the table below. ** indicates rejection of the null hypothesis of a unit root at the 5% level of significance.

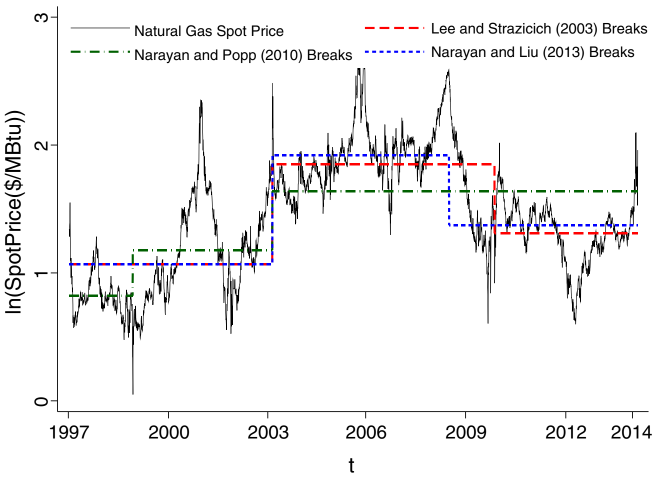

Fig. 3. Time series plot of daily natural gas spot price with breaks in the intercept according to the Lee and Strazicich (2003); Narayan and Popp (2010) and Narayan et al. (2015) tests.

6. Conclusion

We have answered two questions concerning the predictability of natural gas spot and futures prices. Do natural gas futures prices predict natural gas spot prices? Are natural gas spot and futures prices weak form efficient or can they be predicted based on examination of historical data? We find that natural gas futures prices do not predict the magnitude of future natural gas spot prices any better than what would be predicted by a random walk model. This finding is consistent with the result obtained in Alquist and Kilian (2010) for crude oil markets using the same methodology. This result is important because it questions the validity of a common assumption that futures prices reflect the market expectations of future spot prices. It has important implications for many policy institutions, including central banks, that have used commodity futures prices to predict movements in spot prices.

Table 10
Contrarian strategy returns for natural gas spot and futures prices.

Holding period/trading frequency ➔	1 day	1 week	1 month	2 months	3 months	4 months
Contrarian strategy						
Series						
Spot price	−73.91	−76.91	315.57	1879.00	174.57	18.24
Futures—1 M	5519.58	60.59	28.93	900.43	58.35	76.51
Futures—2 M	3438.11	114.43	−26.25	1786.24	171.92	46.53
Futures—3 M	963.11	155.75	1.33	461.55	260.96	72.88
Futures—4 M	768.44	498.96	−68.38	44.41	216.83	89.62
Return over the sample period (expected return under the assumption of random walk)						
Spot price	85.60					
Futures—1 M	34.73					
Futures—2 M	47.22					
Futures—3 M	74.51					
Futures—4 M	94.86					

Notes: (1) The contrarian trading strategy was implemented under the assumption that an investor starts with a $100 sum at the beginning of the sample period, which is fully invested in the selected market in the beginning and the buy/sell decisions in subsequent periods are made at the frequency of the holding period by looking at the market movement in the previous period. (2) The hypothetical investor buys at the market price if the price has gone down compared to the last period and sells if the price has gone up compared to the last period. If the price remains unchanged compared to the last period, she continues holding the previous period's position. (3) The portfolio is liquidated in the last period at market prices and the returns on investment are reported above. (4) The lower panel returns are calculated under the assumption that an investor fully invests $100 in the selected market in the beginning of the sample period and liquidates the investment at the end of sample period.

To answer the second question, we use a series of alternative unit root tests. When we employ a unit root test that simultaneously allows for heteroskedasticity and multiple structural breaks, natural gas spot and futures prices are predictable. Findings in the existing literature that have examined the EMH using unit root tests have been mixed. In the case of natural gas prices, existing studies have failed to find mean reversion. We show that this reflects failure to accommodate heteroscedasticity with high-frequency data. That the weak form of the EMH is rejected implies that there is potential for investors to make profits through trading in natural gas futures using technical analysis. We show that a contrarian trading strategy applied to natural gas spot and futures prices can outperform a random walk model, although the level of profitability depends on the specific model and holding period.

The major policy implication here is that in circumstances in which investors can analyse price movements to make profits, there is greater justification (and need) to regulate natural gas markets, relative to the situation if natural gas markets were weak form efficient. In addition to having important implications for market traders and regulators, in terms of future modelling exercises of this sort, the results point to the need to accommodate heteroskedasticity when applying unit root tests model energy spot and futures prices with high-frequency data, such as daily data.

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