THE COMPONENTS OF NATURAL GAS PRICE VOLATILITY

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Overview

Estimating a static coefficient for a deseasoned gas storage or weather variable implicitly assumes that market participants react identically throughout the year (and over each year) to that variable. In this analysis we model natural gas returns as a linear function of gas storage and weather variables, and we allow the coefficients of this function to vary continuously over time. This formulation takes into account that market participants continuously try to improve their forecasts of market prices, and this likely means they continuously change the scale of their reaction to changes in underlying variables. We use this model to also calculate conditional natural gas volatility and the proportion of volatility attributable to each factor. We find that return volatility is higher in the winter, and this increase is attributable to increases in the proportion of volatility due to weather and natural gas storage. We provide time series estimates of the changing proportion of volatility attributable to each factor, which is useful for hedging and derivatives trading in natural gas markets.

Methods

We first test for parameter stability using the Brown, Durban, and Evans (1975) 'homogeneity test'. Doing so we reject the null of stable regression coefficients. We then run various tests regarding the structural form of the parameters.

The above results motivate a model where the coefficients are allowed to be updated in a Bayesian fashion when new information arrives, much like the views of market participants. An appropriate specification in this case is a time-varying-parameter model where the parameters are updated using the Kalman filter.

Estimation of the model is done using the Kalman Filter and Prediction Error Decomposition. The likelihood function was maximized using the optim function in the R (2014) programming language. This time-varying-parameter model will estimate varying regression coefficients, but also affords an estimate of conditional volatility through the conditional variance of forecast errors from the Kalman filter (see Kim and Nelson (1989)). The present analysis further decomposes this conditional volatility into the contribution from each factor. We do so by calculating the conditional variance without each variable. The difference between the full conditional variance and the conditional variance without the variable, affords the conditional variance attributable to that variable.

Results

The model was estimated using varying initial parameters and the maximum log-likelihood over the many estimations was 1650. The standard deviation of the error terms in the measurement equation (σe) is 5.49%. The standard deviations of the error terms in the intercept, Storage, and HDD transition equations ($\sigma \xi$) are 0.0015, 0.4811, and 0.0001 respectively (these reflect the units of independent variables).

While each coefficient shows substantial variation, the storage coefficient exhibits marked seasonal variation. The storage coefficient appears to be a stationary series, and has a mean of 0.08. The range of variation through the seasons is from -2.40 to 1.99. The weather coefficient shows some seasonal variation, however the mean of this coefficient seems to vary with time. For the period 1999 to 2007, the mean was 0.0010. For the period 2008 to 2014 the mean dropped to 0.0002. This 80% drop is evidence that market participants vary their reaction to underlying variables over multiyear periods, as well as throughout the year. Further research may be able to determine why market participants became less sensitive to weather after 2007, perhaps it was a shift in overall winter weather severity.

To confirm the above we tested for a unit root in each of the coefficient series. Both the intercept and the weather coefficient contained a unit root. However, the storage coefficient rejected a unit root at the 1% level of significance. The augmented Dickey-Fuller test for a unit root was employed.

The mean forecast uncertainty from the TVP model is 10.60%, whereas the mean absolute value of natural gas returns is 5.31%. The unconditional standard deviation of returns from the GARCH(1,1) model is 8.45%. This shows, on average, there is more forecast uncertainty in natural gas returns than would be implied by the error term alone.

In the summer, storage accounts for 50% of volatility with approximately 25% of the volatility coming from weather and the intercept term. However in the winter, the proportion of forecast volatility due to weather often becomes the prime component of volatility (often accounting for 40% of the total) and the portion attributable to storage drops to around 30%.

This shows the marked effect of winter on the drivers of natural gas volatility. Moreover, it is consistent with common accounts of traders focusing on storage amounts during the summer injection season, as this is an indicator of whether there will be enough working gas in storage to meet winter demand.

Conclusions

In this analysis we have modeled natural gas returns explicitly allowing for market participants to learn over time, and to react differently to present changes in economic variables. This learning and adaptation, and the attendant parameter uncertainty, constitutes another source of time varying conditional volatility.

In so doing we have found evidence of significant variation in the coefficients linking natural gas returns and its underlying fundamental factors. Further, we found the time series of the Kalman filtered estimates of the Stor coefficient did not contain a unit root. This implies that we can make inferences about future coefficient values. The modeling and out-of-sample prediction of future Storage coefficient values would be useful to include within future research. We also found evidence that the weather (HDD) coefficient did contain a unit root, and weather became a less important determinant of natural gas returns in 2007.

In an original application of the TVP model, we decomposed conditional volatility into a time series of each contributing factor to that volatility. This showed that storage is the dominant component of natural gas volatility throughout the year, with weather being the largest contributing factor only during periods in the winter. Lastly, we showed that results of this analysis have particular applications to hedging and trading in natural gas markets.