Energy and Agricultural Commodities Revealed through Hedging Characteristics: Evidence from Developing and Mature Markets

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Overview

Among the range of ethanol related policy targets, the Renewable Fuel Standard (RFS) introduced in the US via the Energy Policy Act (2005) has created a statutory demand for ethanol. Schnepf (2011) provides a detailed account of the policy and its implications. The effect of these measures on corn prices are examined by Carter *et al.* (2012). Using a structural VAR, Carter *et al.* (2015) find that corn prices were 30% higher between 2006 and 2010 as a result of the RFS. The linkage between ethanol and corn is, however, considerably more complex than this result alone portrays. The role of policy regimes in the interplay between ethanol processing margins, input costs (food and energy products) and output values (ethanol and distillers' dried grains (DDGs)) is studied by Abbott (2013). Abbott (2013) finds that the processing margin (crush spread) absorbs fluctuations in input and output values under some policy regimes, while under others the margin is less flexible and simply transmits price volatility between food and energy commodities.

These studies demonstrate the magnitude and the complexity of the impact of policy shifts on the prices (and, in the latter case, volatilities) of corn and ethanol. Increasing volatility increases the importance of hedging for industry participants. Our paper uses the hedging characteristics of ethanol and corn to shed light on aspects of these commodities. We reveal important differences between available spot data sets for ethanol (an emerging commodity); we find that sophisticated modelling does not result in improved hedge performance. Using a rolling window methodology reveals a substantial discontinuity in the hedgability (especially of corn), which is related to inventory shortage around the 2013 harvest with reference to early work by Working (1933).

Methods

We first examine eight different spot data series for ethanol by calculating optimal hedge ratios using the simple regression model. The ratios are tested in and out of sample in a minimum variance framework. This allows us to choose a preferred spot data series for ethanol to use in subsequent work. Our second approach involves a rolling windows framework. We calculate optimal hedge ratios for corn and ethanol using a vector autoregression model (Sims, 1980), both with and without an error correction component to take account of (identified) cointegration, as well as by the simple regression model. The average out of sample effectiveness of each model is calculated across the period of study. Our third approach makes a graphical presentation over time of the results from the second approach. By revealing the change in hedge effectiveness over time we are able to relate hedging characteristics to inventory effects around the harvest season.

Our choice of models is supported by summary statistics and information criteria analysis. Our results are supported by a series of robustness tests which vary the lags used in the models, and which vary the in and out of sample window lengths.

Results

Substantial differences between ethanol spot data sets emerge at the summary statistics level, and translate into differences in hedge effectiveness results. The choice of spot data sets is considered in detail, with significant implications for the literature. By investigating simple and system-based models for estimating futures hedge ratios, the empirical analysis lends support to the *simple is better* finding in relation to hedging commodities. By adopting a rolling window methodology for calculating hedge effectiveness we are able to see the evolution of effectiveness over time, and thus identify an anomaly in 2013 which sheds light on the implications of new and old season harvests for risk management.

Differences in the characteristics of ethanol data sets are seen to be a consequence primarily of data collection methodology. A detailed explanation for this variation is provided, together with empirically robust guidance as to the most suitable proxy for spot ethanol prices. For both corn and ethanol, our rolling windows analysis of hedge effectiveness based on simple and sophisticated estimation models indicates no benefit from using the more sophisticated system-based models, though the simple regression model generates some improvement over the naive ratio. This is compatible with recent literature on commodity hedging (see for example Alexander et al, 2015). The rolling window analysis also reveals a substantial drop in hedge effectiveness towards the end of the sample period. Further analysis shows that this drop is a consequence of a brief period of extreme backwardation around the 2013 harvest, which we explain in terms of the inventory shock caused by the poor 2012 harvest, and the consequent interaction between new and old season inventories around the 2013 harvest.

Conclusions

This study has important implications for researchers, traders, hedgers and policy makers. An understanding of the spot data variation for ethanol is important for researchers. The issue may not be confined to ethanol but may also affect the literature on other emerging commodity markets. The *simple is better* finding in relation to futures hedge ratio estimation models is of particular relevance to hedgers and traders. Of concern to the literature is the implication of new and old season harvests to rolling window hedges. While the basis effect at harvest time is relatively short-lived, the rolling window methodology extends the effect on hedge performance to a calendar year or more. Policy makers should note the implications of increasing ethanol demand for corn inventories, with the consequent weakening of risk management mechanisms in 2013. We show that the irregularity is caused by a small number of outlying data points. This serves as a reminder to hedgers that extreme events, the occasions which hedging is often intended to protect against, may be the very occasions when futures hedging is least effective.

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