Price discovery in commodity derivatives: Speculation or hedging?

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Abstract

We investigate whether commodity futures or options markets play a more important role in the price discovery process in the six most actively traded markets: crude oil, natural gas, gold, silver, corn and soybeans. Using new information leadership techniques, we report new evidence and report that both markets make a meaningful contribution to price discovery in recent times, however, on average, options lead futures in reflecting new information for a majority of these commodities. In addition, we find that increased speculation, rather than hedging activity, in commodity derivatives is a key determinant of price discovery in the options markets.

JEL Classifications: G13, G14

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1. Introduction

There has been significant growth in commodity derivative trading activity due to the development of electronic markets (Tang and Xiong, 2012; Adams and Kartsakli, 2018). The Futures Industry Association report that global commodity futures volume increased six-fold from one to six billion contracts between 2007 and 2016. During this period, commodity futures options volume also increased by 100 million to 700 million contracts, while equity options volume decreased (Simon, 2014; Acworth, 2017). Futures option volume represents approximately 10-20% of the total commodity derivatives volume, a substantial fraction, however, relatively little is known about how information is incorporated into futures option prices. Boyd and Locke (2014) are an exception, concluding that during the period of their study (2005-2007), a majority of information is first reflected in natural gas futures, rather than options contracts.

A large literature has examined the role of speculators in commodity futures markets. For example, Haase, Zimmermann and Zimmermann (2016) review 100 commodity futures papers and conclude that we still do not have a clear understanding of the role of speculators in such markets. Furthermore, less is known about the role of speculators in commodity futures options. The recent growth in the popularity and liquidity of futures options can be attributed to the number of factors including: the development of electronic platforms allowing for real-time trading, increased transparency and ability to trade a wide range of hedging and speculative strategies across a large number of asset classes, lower margin costs, and weekly contracts which allow participants to trade around news (Wolf, 1982; Simon, 2014; Sammann, 2015).

As a result, in this paper we answer the following questions: how important are commodity options relative to futures in the price formation process, and who is responsible for such price discovery – speculators or hedgers? Using two years of recent intraday data and both conventional and new empirical techniques – Hasbrouck (1995) information share, Gonzalo and Granger (1995) component share and Yan-Zivot (2010)-Putniņš (2013) information leadership share, we provide a unique and comprehensive examination of price discovery in the agriculture (corn and soybeans), energy (crude oil and natural gas) and metal (gold and silver) commodity futures and option markets. These specific commodities are selected on the basis of having the largest futures and options trading volume on the Chicago Mercantile Exchange at the end of 2017. Following the significant growth in trading resulting from electronic trading and improved liquidity, we focus on a more recent sample period to report findings that are relevant and have implications for market participants and regulators today. Furthermore, we use two approaches developed by Working (1953) and Lucia and Pardo (2010) to identify speculation from hedging activity.

Our first key result is that although futures markets are more liquid in terms of quoted spreads and trading volume, in more recent times, US commodity options lead futures on average in reflecting new information in the crude oil, gold, silver, corn and soybean markets. This finding highlights the importance of instrument type, for example, recent developments in electronic platforms aiding the ability for traders to initiate a variety of real-time options trading strategies across a larger number of assets, no margin requirements for long strategies, or the right to trade (rather than obligation). It is likely such features make options attractive to commodity derivative traders (e.g., hedge funds, asset managers, high-frequency traders) and such trading activity results in options being an important venue for informed trading.

In support of our first key result, our second key result indicates that a significant determinant for why crude oil, gold, silver and soybean options lead their corresponding futures in price discovery is due to increased speculation in options and futures markets. This finding is robust using two different measures of speculation: the first incorporating hedging and speculative open interest defined by the US Commodity Futures Trading Commission (Working, 1953), and a second more general measure incorporating commodity derivative open interest and volume (Lucia and Pardo, 2010). In addition, we find that narrower spreads in crude oil and silver options are associated with increases in the options market's contribution to price discovery – indicating that informed traders trade strategically and choose a relatively more liquid market to hide their information.

Our paper contributes to two areas of the existing literature. First, our analysis contributes to the literature on how derivative instruments affect the nature of price discovery. Several studies examine price discovery in the commodity futures market with mixed findings. Garbade and Silber (1983) report that wheat, corn and orange juice futures lead spot markets. Hauptfleish, Putniņš and Lucey (2016) reach a similar conclusion in gold futures markets. In contrast, Dimpfl, Jung and Flag (2017) find that a majority of price discovery occurs in the underlying corn, wheat, soybeans and cattle markets.[1] To the best of our knowledge, Boyd and Locke (2014) provide the only other examination of price discovery in commodity futures and options markets using data in the 2005-2007 period. The authors sample options prices at 15-minute intervals and find that a majority of price discovery occurs in natural gas futures contracts. We contribute to the literature by reporting new evidence of price discovery in six different commodity futures options markets, and for a more recent time period. In addition, we estimate price discovery measures at low latencies and using new price discovery techniques that account for the noise differential between markets. Our approach results in a more accurate measurement of price discovery, allowing for more precise inferences to be made regarding its determinants and time-series patterns.

Second, our findings contribute to the literature examining the role of hedgers and speculators in commodity derivative markets. On one hand, the theory of backwardation suggests that futures hedging

[1] See Rosenberg and Traub (2009) and Chen and Gau (2010) for studies examining price discovery in currency futures markets. See Fleming, Ostdiek and Whaley (1996), Booth, So and Tse (1999), Bohl, Salm and Schuppli (2011) and Chen and Chung (2012) for studies examining price discovery in index/ETF derivative markets. See Chakravarty, Gulen and Mayhew (2004), Hsieh, Lee and Yuan (2008) and Patel, Putniņš, Michayluk and Foley (2018) for studies examining price discovery in options markets.

(speculation) leads to mispricing (corrects mispricing), thereby, harming (aiding) price discovery (Chen, Gau and Liao, 2016). In contrast, the dispersion theory suggests that futures speculation is undertaken by uninformed individuals, whereas, hedging activity is conducted by informed parties (e.g., bank, dealers, etc) (Wang, 2002). Our analysis adds to this literature by documenting the role of hedgers and speculators in the futures price formation process. We also uniquely report new evidence of the role of hedgers and speculators to price discovery in commodity options.

This paper proceeds as follows. Section 2 describes the data and details our methodology to estimate measures of price discovery and speculation/hedging. Section 3 reports our findings and Section 4 concludes.

2. Data and Methodology

2.1. Data

Intraday commodity futures and options quote data is obtained from the *Thomson Reuters Tick History* (*TRTH*) database provided by the *Securities Industry Research Centre of Asia-Pacific* (*SIRCA*) during a 24-month period between January 2016 and December 2017. We examine price discovery in the following markets: corn, soybeans, crude oil, natural gas, gold and silver, these commodities are selected on the basis that they have the highest daily trading volume at the end of 2017.[2]

< Table 1 here >

Table 1 presents contract specifications for each commodity (including futures/options trading symbol, futures unit/contract size, and futures/options minimum tick size). Corn and soybean derivatives are traded on the Chicago Board of Trade (CBOT), crude oil and natural gas derivatives are traded on the New York Mercantile Exchange (NYMEX), and gold and silver derivatives are traded on the Commodity Exchange (COMEX). All futures options are American style, the exercise of a call (put) option results in a long (short) position in the underlying futures contract. Upon the expiration of the futures contract, the short position is required to physically deliver the underlying commodity.

In Table 2 we report descriptive statistics of the futures and options daily trading activity. Futures volume and open interest are generally larger than the corresponding options figures. Corn and crude oil have the highest average daily futures trading volume (open interest) with over 500,000 (2,000,000) contracts traded in corn and almost 800,000 (1,100,000) contracts traded in crude oil. Silver and soybeans have the lowest futures volumes and open interest. A similar trading activity story is observed for

[2] See https://www.cmegroup.com/trading-hours.html for details of trading hours for each market.

commodity options. For example, we observe an average of approximately 180,000 crude oil and 4,000 silver options traded per day.

< Table 2 here >

In comparison, daily futures quoted spreads are much smaller than options quoted spreads.[3] Across all commodities average futures (options) quoted spreads range between 0.005 and 0.548 (0.258 and 10.691). For example, mean options spreads are approximately 20 times larger than futures spreads in the gold, silver and soybean markets.

The combination of lower trading activity and wider quoted spreads in options indicates that options are considerably less liquid than futures. Therefore, options prices are likely to be noisier, impacting the ability of conventional price discovery measures in accurately estimating price discovery (Yan and Zivot, 2010; Putniņš, 2013).[4]

2.2. Futures and options-implied price series

In order to compute price discovery measures, we need to construct futures and options-implied price series. For each commodity each day, we obtain one seamless futures price time series by rolling across futures contracts with the highest open interest. In the construction of the futures price series we omit contracts with bid-ask spreads greater than 50%. In contrast, the options data comprises several billion observations from contracts with different strike prices and expiration dates. As a result, following Hao (2016), we omit options with zero open interest, a bid-ask spread percent of greater than 50%, and time to maturity of less than five days and more than 90 days.

Using a similar approach to Muravyev, Pearson and Broussard (2013) we calculate the options-implied futures price series. Eq. (1) represents the European put-call parity relation to calculate the options-implied futures price for a given put-call pair,

$$F_t e^{-r(T-t)} = C_t(K,T) - P_t(K,T) + PV_t\big(D(t,T)\big) + Ke^{-r(T-t)}, \quad (1)$$

where F_t is the futures price at time t, $C_t(K,T)$ and $P_t(K,T)$ are the call and put option prices with strike price K and expiry date T, r is the continuously compounded London Interbank Offered Rate (LIBOR) rate per annum, and $T-t$ is the time to maturity.[5] Commodity options are American-style options, as a result,

[3] Daily quoted spreads (expressed in basis points) are defined as the average of the ratio of the difference between the ask and bid price, divided by the midpoint price.
[4] Boyd and Locke (2014) reach a similar conclusion and also report that commodity options prices are noisier than futures prices.
[5] The LIBOR rate is obtained from the Federal Reserve Bank of St. Louis.

Eq. (1) is adjusted to capture the ability to exercise early. Denoting the early exercise premium by $v_t(K,T)$, we have,

$$F_t e^{-r(T-t)} + v_t(K,T) = C_t(K,T) - P_t(K,T) + Ke^{-r(T-t)}, \tag{2}$$

where $v_t(K,T)$ is the early exercise premium at time t. The error from the put-call parity relation at every quote update is given by:

$$\varepsilon_t = C_t(K,T) - P_t(K,T) + Ke^{-r(T-t)} - F_t e^{-r(T-t)}. \tag{3}$$

The early exercise premium is then calculated as the average error term (i.e., Eq. (3)) for each day. Following on, the options-implied futures bid and ask price at time t are given by:

$$Implied\ Bid_t(K,T) = e^{r(T-t)}[C_t{}^{Bid}(K,T) - P_t{}^{Ask}(K,T) + Ke^{-r(T-t)} - v_t(K,T)], \tag{4}$$

$$Implied\ Ask_t(K,T) = e^{r(T-t)}[C_t{}^{Ask}(K,T) - P_t{}^{Bid}(K,T) + Ke^{-r(T-t)} - v_t(K,T)]. \tag{5}$$

2.3. Price discovery measures

Using the futures and options-implied prices we estimate conventional measures of price discovery. Following Hasbrouck (1995) and Gonzalo and Granger (1995) we compute the information share (*IS*) and component share (*CS*) measures of price discovery. Both *IS* and *CS* are reported to capture two different components: i) permanent component (innovations in the fundamental value) and a ii) temporary component (noise). Each day, for each put-call pair, and using prices sampled in event-time sampling frequency we estimate *IS* and *CS* from the parameter estimates and reduced form errors of a vector error correction model (VECM) with 200 lags:

$$\Delta p_{1,t} = \alpha_1(p_{1,t-1} - p_{2,t-1}) + \sum_{i=1}^{200}\gamma_i \Delta p_{1,t-i} + \sum_{j=1}^{200}\delta_i \Delta p_{2,t-j} + \varepsilon_{1,t}, \tag{6}$$

$$\Delta p_{2,t} = \alpha_2(p_{1,t-1} - p_{2,t-1}) + \sum_{k=1}^{200}\varphi_i \Delta p_{1,t-k} + \sum_{m=1}^{200}\phi_i \Delta p_{2,t-m} + \varepsilon_{2,t}, \tag{7}$$

where $\Delta p_{i,t}$ is the change in the log midquote price of asset i at time t. The normalized orthogonal to the VECM coefficients allows for the computation of *CS*:

$$CS_1 = \gamma_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1},\ \ CS_2 = \gamma_2 = \frac{\alpha_1}{\alpha_1 - \alpha_2}. \tag{8}$$

Using the covariance matrix of the VECM error terms (i.e., Eq. (9)) and its Cholesky factorization (Eq. (10)), allows for the computation of *IS* (Eq. (11)):

$$\Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}, \tag{9}$$

$$\Omega = MM', where\ M = \begin{pmatrix} m_{11} & 0 \\ m_{12} & m_{22} \end{pmatrix} = \begin{pmatrix} \sigma_1 & 0 \\ \rho\sigma_2 & \sigma_2(1-\rho^2)^{1/2} \end{pmatrix}. \tag{10}$$

$$IS_1 = \frac{(\gamma_1 m_{11} + \gamma_2 m_{12})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2},\ IS_2 = \frac{(\gamma_2 m_{22})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2}. \tag{11}$$

Following Baillie et al. (2002), we account for the ordering of prices in the VECM by estimating *IS* under both orderings and taking the simple average.

Prior studies use *IS* and *CS* to measure which market is the first to reflect new information (i.e., the permanent component of price changes). However, Yan and Zivot (2010), Putniņš (2013) and others show that *IS* and *CS* capture both permanent and temporary (i.e., noise) components of price discovery. Of particular concern, both *IS* and *CS* overstate the contribution of price discovery of the market with lower levels of noise. This is an issue for prior studies examining price discovery between underlying and derivative markets and will influence price discovery estimated between futures and options markets (Table 2 indicates that commodity futures are more liquid or less noisy than options markets). Consequently, the information leadership share (*ILS*) developed by Yan and Zivot (2010)-Putniņš (2013) provides a solution to this problem. *ILS* combines *IS* and *CS* to cancel out the dependence on noise, resulting in a measure which captures permanent price changes (information leadership) only:

$$ILS_1 = \frac{\left|\frac{IS_1 CS_2}{IS_2 CS_1}\right|}{\left|\frac{IS_1 CS_2}{IS_2 CS_1}\right| + \left|\frac{IS_2 CS_1}{IS_1 CS_2}\right|},\ ILS_2 = \frac{\left|\frac{IS_2 CS_1}{IS_1 CS_2}\right|}{\left|\frac{IS_1 CS_2}{IS_2 CS_1}\right| + \left|\frac{IS_2 CS_1}{IS_1 CS_2}\right|}. \tag{12}$$

We compute all three price discovery measures obtaining estimates which range between [0,1]. Values above 0.5 indicate that one market leads price discovery.

2.4. Identification of speculators and hedgers

Following Peck (1980), Sanders, Irwin and Merrin (2010) and Dimpfl, Flad and Jung (2017), we identify speculators and hedgers in commodity options and futures markets using the *WorkingT* index (Working, 1953). The intuition behind *WorkingT* is that it captures excess speculative trading activity required to balance the difference in unmatched long and short hedging activity. In order to estimate *WorkingT*, we use weekly data contained within the Commitment of Traders (COT) reports released by the Commodity Futures Trading Commission (CFTC) which identify the closing total outstanding contracts (i.e., open interest) of commercial and non-commercial options and futures traders, where the literature classes commercial traders as hedgers and non-commercial traders as speculators.[6]

Table 3 reports the average weekly net open interest (i.e., long minus short) combined across futures and options for hedgers, speculators and non-reportable parties. For all commodities, net hedgers have a net short position, in particular, when trading derivatives on crude oil and corn where traders are likely to protect the sale of such commodities. In contrast, with the exception of corn, net speculators have net long positions in futures and options, especially in crude oil derivatives. Such findings indicate a bullish sentiment among traders in most of the commodities examined in this study.

[6] COT data is obtained from: http://www.cftc.gov. The CFTC classifies traders as commercial or non-commercial on a yearly basis. We omit non-reportable open interest which identify small traders. The CFTC only reports the combined futures and options open interest data.

< Table 3 here >

Using Eq. (13) we calculate *WorkingT* for each commodity each week:

$$WorkingT = \begin{cases} 1 + \frac{S\_Short}{(H\_Long + H\_Short)} \ where\ H\_Short \geq H\_Long \\ 1 + \frac{S\_Long}{(H\_Long + H\_Short)} \ where\ H\_Short < H\_Long \end{cases}, \quad (13)$$

where *S_Long* (*S_Short*) is the long (short) options and futures open interest of non-commercial traders (speculators) and *H_Long* (*H_Short*) is the long (short) options and futures open interest of commercial traders (hedgers). *WorkingT* values above one indicate excess speculative trading activity which is required to cover hedging positions. If *WorkingT* is equal to one, this suggests there is no excess speculative trading activity.

< Table 4 here >

Table 4 reports descriptive statistics for the *WorkingT* measure of excess speculation. We observe evidence of excess speculation in all six commodity markets – *WorkingT* mean values ranging from 1.090 to 1.567. In all cases, we report similar mean and median values. The largest (smallest) mean levels of variation in excess speculation occur in natural gas (soybean) markets. For example, a mean *WorkingT* value of 1.567 indicates that 56.70% of speculative positions exceed the amount required to cover hedging activity in natural gas markets. In the subsequent analysis, we examine whether such excess speculation in commodities is associated with price discovery in options or futures markets.

3. Results

3.1. Price discovery estimates

For each commodity we estimate price discovery using conventional and new empirical techniques. Table 5 Panel A reports average daily values estimated using prices sampled in event-time and using 200 lags in the VECM. In all cases, both futures *IS* and *CS* (values slightly larger than 0.50, and approximately ranging from 0.50 to 0.60) indicate that commodity futures are on average the first to reflect new information relative to options markets. Figure 1 reports the time-series of options price discovery between 2016 and 2017. We observe downtrends in both the options *IS* and *CS* during the second half of the sample period for crude oil, natural gas, gold and silver (noting that futures *IS* is one minus options *IS*, similar for futures *CS*).

< Table 5 here >

< Figure 1 here >

In contrast, *ILS* suggests that on average commodity options lead futures in impounding new information with average values ranging from 0.576 to 0.623, the exception is natural gas, where options *ILS* is 0.477. Using futures *IS*, Boyd and Locke (2014) also find that natural gas futures lead options in price discovery between 2005 and 2007. Figure 1 shows uptrends in options *ILS* in the second half of the sample period for energy and metal commodities. Such trends are consistent with an increased preference for informed trading in options due to developments in electronic/real-time trading, the ability to implement various trading strategies, weekly contracts and so forth (Simon, 2014; Sammann, 2015). Options/futures *ILS* is relatively constant for agriculture commodities. Given that *ILS* is insensitive to noise differentials between the two markets, it provides the most accurate portrayal of price discovery between the two markets. Our findings indicate that both options and futures are important venues for informed trading, with options being the dominant venue more recently.

3.2. Does speculation or hedging drive price discovery in commodity derivative markets?

In this section we examine whether the trading activity of speculators or hedgers tends to be first impounded into futures or options prices. In a similar vein to Chakravarty, Gulen and Mayhew (2004) and Boyd and Locke (2014), for each commodity we estimate the determinants of options price discovery using the following time-series regression:

$$\frac{ILS_{i,t}}{(1-ILS_{i,t})} = \beta_0 + \beta_1 METRIC_{i,t} + \beta_2 OptVol_{i,t} + \beta_3 FutVol_{i,t} + \beta_4 OptOI_{i,t} + \beta_5 FutOI_{i,t} + \beta_6 OptQSpr_{i,t} + \beta_7 FutQSpr_{i,t} + \beta_8 Skew_{i,t} + \beta_9 Vola_{i,t} + \varepsilon_{i,t}, \tag{14}$$

where *ILS* is options price discovery in week *t* calculated using the Yan-Zivot (2010)-Putniņš (2013) information leadership share (*ILS*) with prices sampled in event time and 200 lags in the VECM. Due to the sensitivity of noise inherent in conventional measures of price discovery we use *ILS* to measure price discovery. To obtain a weekly *ILS* value, we take the daily value and average across the week (there are approximately 104 weeks during our two-year sample period). In Model 1 *METRIC* is *WorkingT* which captures speculative activity in options and futures markets. The independent variables include: total options and futures trading volume (*OptVol* and *FutVol*), options and futures open interest (*OptOI* and *FutOI*), options and futures quoted bid-ask spreads (*OptQSpr* and *FutQSpr*), skewness of futures returns (*Skew*) following Fernandez-Perez, Frijns, Fuertes and Miffre (2017), and 20-day intraday return volatility

(*Vola*).[7] A positive (negative) coefficient on the *METRIC* variable would indicate that increases (decreases) in excess speculation are associated with increases (decreases) in the options market's share of price discovery.

For each commodity, Table 6 Model 1 reports our regression model findings. For four of the six commodities (crude oil, gold, silver, and soybeans), we observe a positive and significant relationship between relative options *ILS* and *WorkingT*. Increases in excess speculation in the silver, soybeans and gold markets result in the largest increases in relative options *ILS* (*METRIC* coefficient estimates of 10.359, 7.081 and 6.225, respectively). These results suggest that increases in excess speculation in options and futures energy, metal and agriculture markets are associated with an increase in the share of price discovery occurring in options markets. Such findings are consistent with the growth in futures options trading activity resulting from the development of electronic platforms allowing for real-time trading, improvements in liquidity, and ability and flexibility to trade complex and various options strategies (Wolf, 1982; Simon, 2014; Sammann, 2015).

< Table 6 here >

Prior studies (e.g., Yan and Zivot, 2010; Putniņš, 2013; Hauptfleisch, Putniņš and Lucey, 2016) find that when the level of noise is different between the two markets of interest (which applies in our paper, where options are noisier or less liquid than the corresponding futures market), *IS* and *CS* are measures of the relative noise between two markets. In unreported findings, if we use the logit-transformed version of *CS* as the dependent variable in Eq. (14), we find that increased speculation in commodity derivative markets (as captured by the *WorkingT* variable) is associated with *lower* options *CS* in gold, silver and soybean markets. Similar results are found using *IS* as the dependent variable. Such findings indicate that there is a decrease in the relative noise in options market quotes when more speculative activity takes place in commodity derivative markets. In contrast using *ILS* as the dependent variable, we report that excess speculation is associated with an increase in the option market's contribution to price discovery. Consistent with prior studies, if the aim of the analysis is to determine which market is the first to reflect new information (i.e., permanent price changes), one must be careful in the measurement price discovery.

We report an adjusted R^2 ranging between 0.24 and 0.89 indicating a relatively strong fit for our regression models. We find that narrower spreads in crude oil and silver options are associated with

[7] Weekly *OptVol* (*FutVol*) is calculated as the sum of options (futures) volume across all contracts per week (weekly *OptOI* and *FutOI* is calculated in a similar vein). Weekly *OptQSpr* (*FutQSpr*) is calculated as the daily *OptQSpr* (*FutQSpr*) values averaged across the week (weekly *Skew* and *Vola* are calculated in a similar vein).

increases in the options market's contribution to price discovery, consistent with informed traders choosing a relatively more liquid market to trade strategically and maximize the value of their information (Chakravarty, Gulen and Mayhew, 2004). On the other hand, we observe a significant and negative relationship between relative options price discovery and futures bid-ask spreads (the exception is natural gas). This relationship is consistent with more informed trading/speculation in futures markets increasing adverse selection risks in futures markets, thereby, increasing futures spreads (Glosten and Milgrom, 1985). A similar adverse selection explanation is inherent in gold options markets (i.e., *OptQSpr* has a positive and significant coefficient estimate of 0.341, and *t*-statistic of 10.67).

In contrast, we find that neither speculation or hedging drives options price discovery in the natural gas and corn markets. Our natural gas findings are consistent with Boyd and Locke (2014) as: i) we also conclude that futures lead options in reflecting new information, and ii) we report a negative coefficient on the *WorkingT* variable (albeit statistically insignificant), which suggests that excess speculation in commodity derivatives markets is associated with increased (decreased) price discovery in futures (options) markets.

3.3. Robustness tests

In addition, we conduct several robustness tests in the estimation of price discovery measures and use an alternate measure for capturing speculation/hedging activity in commodity derivative markets. First, our price discovery estimates are robust to: i) sampling prices at a one-second frequency (see Table 5 Panel B), and ii) using 60 lags in the VECM (see Table 5 Panels C and D).

Second, we use an alternative approach to capturing speculation and hedging in commodity derivative markets. We follow Lucia and Pardo (2010) to infer daily hedging and speculative activity using options and futures open interest and volume. Each day we estimate the following:

$$R_t = \frac{\Delta OI_t}{V_t}\ x\ 1000, \tag{15}$$

where ΔOI_t is the daily change in options and futures open interest on day *t* and V_t is the total options and futures volume. The assumptions behind this measure is that new options and futures positions are a proxy for hedging activity, whereas, actual traded volume is a proxy for speculative activity. Higher (lower) values of *R* capture hedging (speculative) activity.

Table 4 reports descriptive statistics for the *R* measure. Mean and median values are similar for each commodity, with means ranging between 1.249 and 3.747. Based on the change in daily open interest, the largest levels of hedging are observed in metals, and the lowest in soybean markets.

We report qualitatively similar findings in Table 6 Panel A Model 2, if we re-estimate Eq. (14) using daily observations (instead of weekly observations) and where *METRIC* is the *R* measure of speculative/hedging activity (instead of *WorkingT* in Model 1). We observe that increases in speculation in options and futures markets (as captured by a negative coefficient estimate on the *R* variable) is associated with increased options price discovery (or decreased price discovery in commodity futures) in crude oil, gold, silver and soybean markets. Again, we observe that the magnitude of speculation in the silver, gold and soybeans markets results in the largest increases in options price discovery (*METRIC* coefficient estimates of -16.868, -9.880 and -9.544, respectively). We also report a similar adjusted R^2 between Models 1 and 2 (ranging between 0.21 and 0.89), indicating that our explanatory variables do a reasonable job in explaining the variation in options *ILS*.

Furthermore, in unreported findings we find that increased speculation captured by *R* in commodity derivative markets is associated with a decrease in the relative noise in options quotes (as measured by options *IS* or *CS*). In addition, our regression results in Table 6 Panel A Models 1 and 2 are qualitatively similar in Panel B if we estimate *ILS* using prices sampled at a one-second frequency.

4. Conclusion

The motivation for this paper arises from developments in the ability to trade commodity derivatives and resulting increases in trading activity, a lack of understanding regarding the role of futures options in price discovery, and due to a continued debate regarding the role of hedgers and speculators in the price formation of commodity derivatives. As a result, we provide a unique examination of price discovery in six different commodity futures options markets and we analyze the role of speculators and hedgers in the price discovery process.

Using intraday data, we estimate conventional and new empirical measures of price discovery, noting that they measure different components of price discovery. *IS* and *CS* are measures of the relative level of noise between the two markets, and *ILS* captures the relative speed with which each market reflects new information (this is the traditional focus of using such empirical measures of price discovery). Furthermore, using open interest and volume data, we use two measures – *WorkingT* and *R* to identify speculation and hedging activity in commodity derivatives markets.

Despite lower levels of liquidity, on average we find that options lead futures in reflecting new information in the crude oil, gold, silver, corn and soybean markets. Such findings are for example consistent with recent developments in trading platforms allowing various market participants the flexibility and ease to trade a variety of options strategies. Although a majority of price discovery occurs in options (approximately 0.55-0.60), a large fraction of price discovery occurs in futures markets (approximately 0.40-0.45).

In addition, we find that speculation is a significant determinant of price discovery in commodity derivatives. More specifically, we report that increased speculation in commodity derivatives is associated with increases in the options market’s contribution to price discovery. This result occurs in crude oil, gold, silver and soybean markets. In examining price discovery between markets of differing levels of liquidity, our findings highlight the importance of accounting for the noise differential using empirical measures such as *ILS*.

Future research can examine the level of price discovery in other commodity and other derivative markets. Furthermore, with the increasing popularity of futures options, increases in electronic trading, changing regulation and market structure, further research can examine the drivers of trading activity and price discovery, especially as other countries/exchanges introduce commodity derivative trading platforms.

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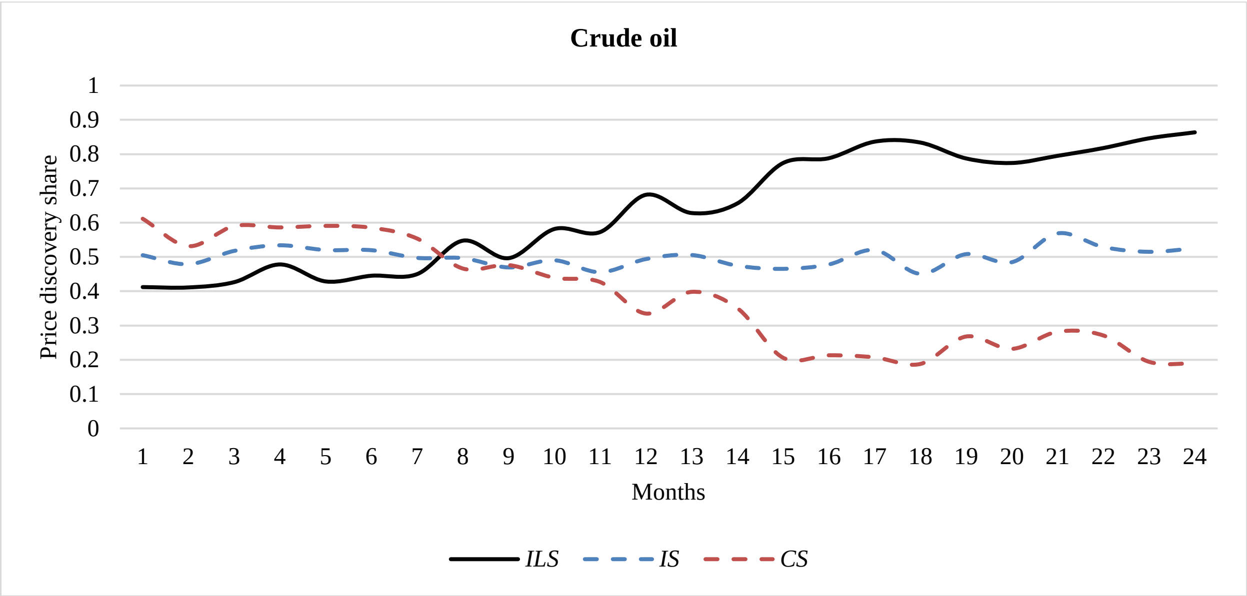
Figure 1: Price discovery over time

This figure reports the average options market price discovery shares for each commodity between January 1, 2016 and December 31, 2017. The price discovery shares are calculated using the: (i) Hasbrouck (1995) information share (*IS*), (ii) Gonzalo-Granger (1995) component share (*CS*), and (iii) Yan-Zivot (2010)-Putniņš (2013) information leadership share (*ILS*). Price discovery measures are estimated using prices sampled in event-time and using 200 lags in the VECM.

Energy



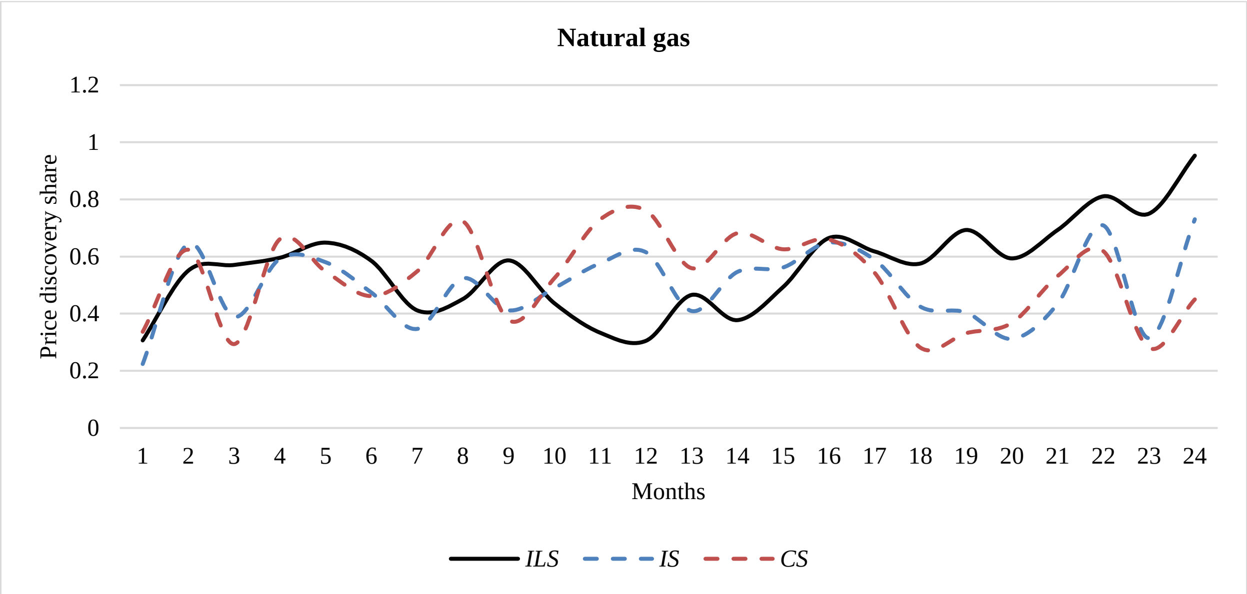
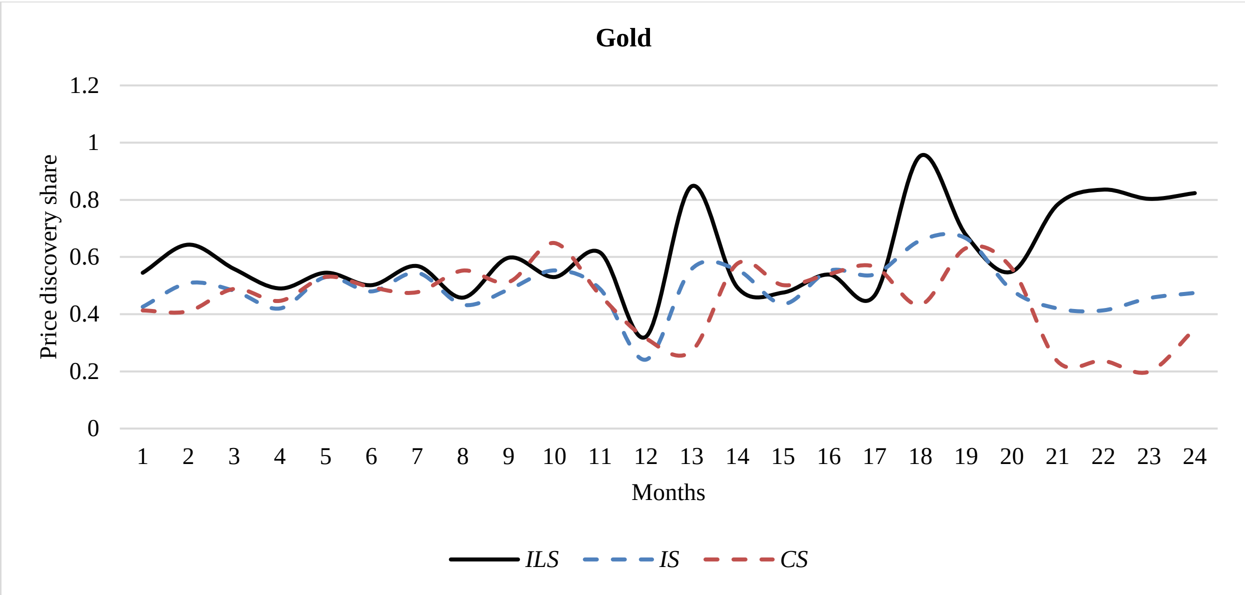


Figure 1: Price discovery over time – continued

Metals



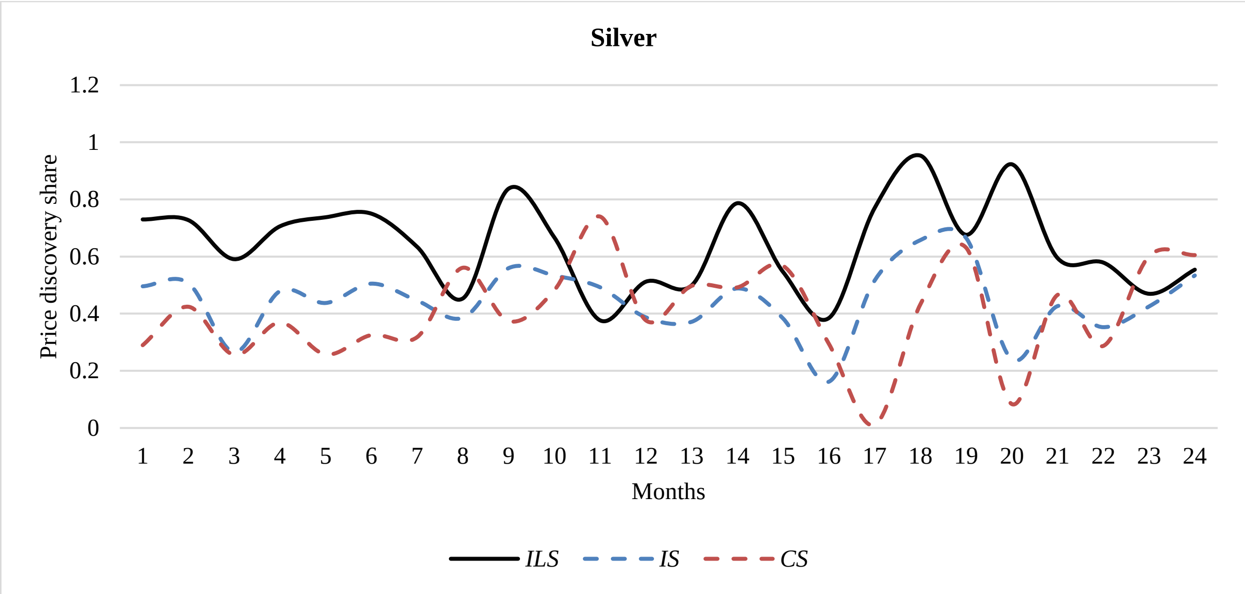
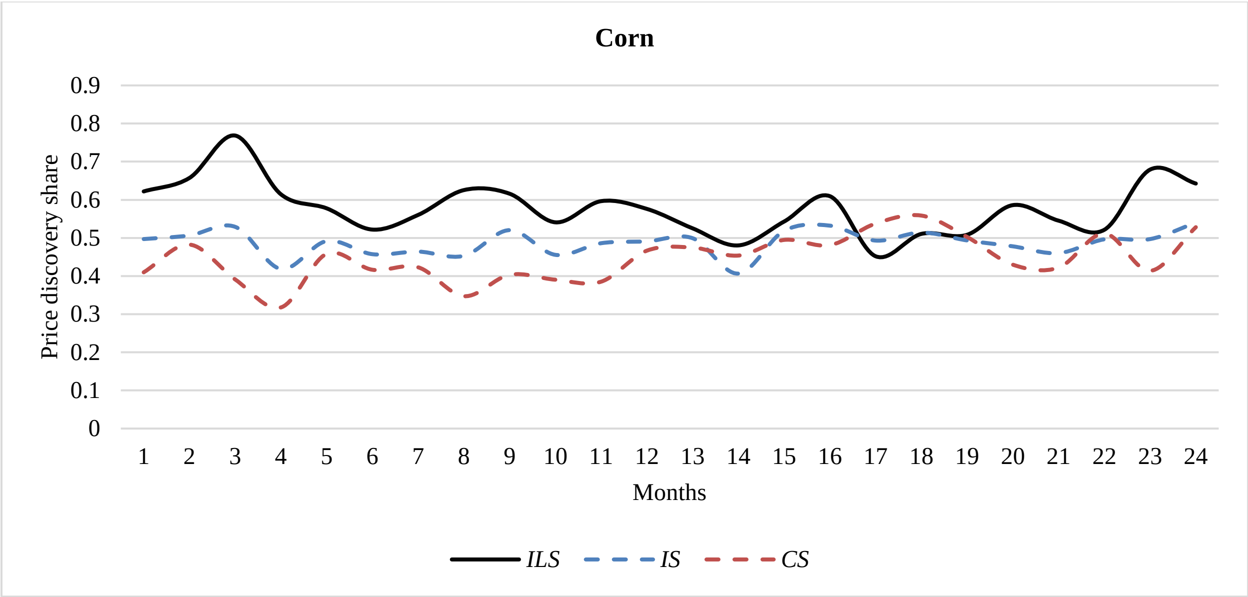


Figure 1: Price discovery over time – continued

Agriculture



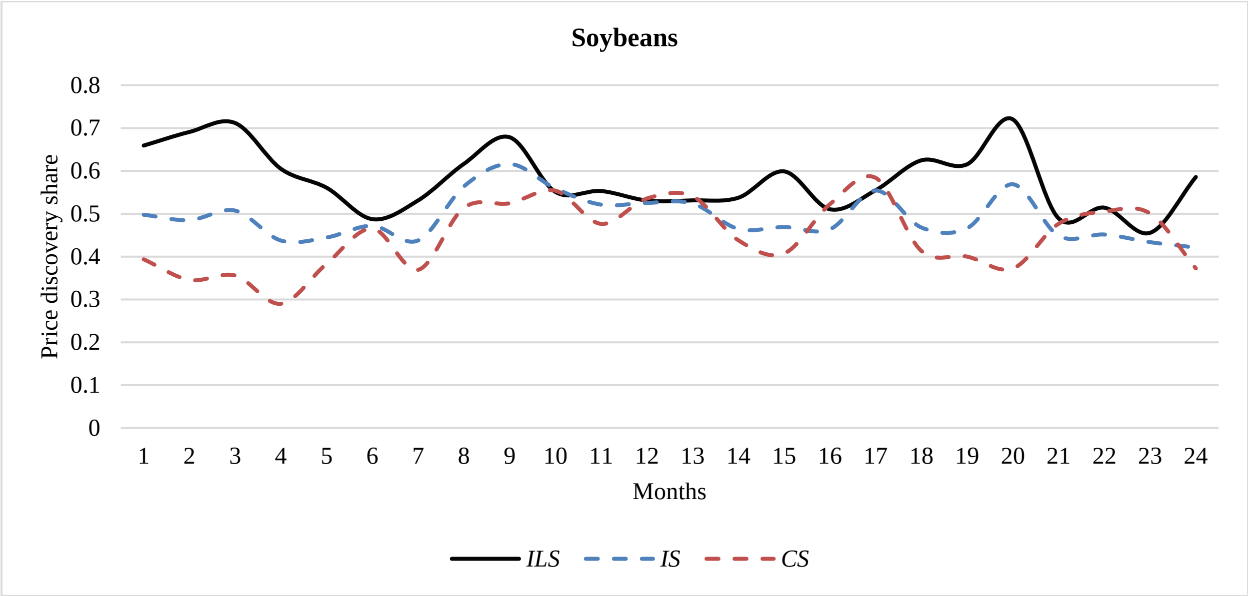


Table 1: Commodity derivative contract specifications

This table reports futures and options contract specifications obtained from the Chicago Mercantile Exchange for each commodity. The specifications include: exchange-listing, futures/options contract symbols, futures contract size/unit, futures/options minimum tick size, and options style. MMBtu is one million British thermal units.

Contract specifications	Exchange	Futures symbol	Futures unit	Futures minimum tick size	Options symbol	Options minimum tick size	Options style
Energy							
Crude oil (Light Sweet)	NYMEX	CL	1,000 barrels	1ct/barrel	LO	1ct/barrel	American
Natural gas (Henry Hub)	NYMEX	NG	10,000 mmBtu	0.1ct per MMBtu	LNE	0.1ct per MMBtu	American
Metals							
Gold	COMEX	GC	100 troy ounces	10ct per troy ounce	OG	10ct per troy ounce	American
Silver	COMEX	SI	5,000 troy ounces	0.5ct per troy ounce	SO	10ct per troy ounce	American
Agriculture							
Corn	CBOT	ZC	5,000 bushels	0.25ct/bushel	OZC	0.125ct/bushel	American
Soybean	CBOT	ZS	5,000 bushels	0.25ct/bushel	OZS	0.005ct/bushel	American

Table 2: Descriptive statistics

This table reports descriptive statistics of futures and options trading activity for each commodity between January 1, 2016 and December 31, 2017. Variables of interest include: daily futures returns (*Return*), daily futures return skewness (*Skew*), daily options and futures trading volume in thousands (*OptVol* and *FutVol*), daily options and futures open interest in thousands (*OptOI* and *FutOI*), and daily options and futures bid-ask spread (*OptQSpr* and *FutQSpr*).

	Mean	**Median**	**Std. dev.**	**Mean**	**Median**	**Std. dev.**
		Crude oil			**Natural gas**	
Return	0.149	0.000	0.697	0.905	3.004	0.846
Skew	-0.061	-0.124	0.523	-0.752	-0.465	0.888
FutVol	781.64	138.47	1,686.40	300.87	101.86	467.41
FutOI	1,154.05	590.76	1,374.50	750.09	476.65	771.61
FutQSpr	0.014	0.014	0.024	0.005	0.002	0.022
OptVol	178.66	160.36	83.77	12.12	10.42	7.04
OptOI	2,575.08	2,608.77	401.60	173.27	186.48	64.72
OptQSpr	0.443	0.371	0.331	0.315	0.076	2.171
		Gold			**Silver**	
Return	1.618	0.374	0.465	1.485	2.595	0.713
Skew	-0.785	-0.474	1.200	-0.715	-0.750	1.213
FutVol	340.88	10.16	825.54	141.91	5.87	279.32
FutOI	564.50	92.96	1,076.99	256.22	26.03	458.54
FutQSpr	0.096	0.085	0.982	0.013	0.006	0.036
OptVol	29.27	25.11	19.52	3.81	3.32	2.73
OptOI	862.60	935.60	220.33	99.54	104.29	26.44
OptQSpr	1.554	1.144	3.908	0.258	0.223	0.369
		Corn			**Soybean**	
Return	-0.761	2.737	0.529	0.475	1.057	0.537
Skew	-0.587	-0.482	1.102	-0.606	-0.337	0.974
FutVol	534.69	146.91	758.34	254.59	44.14	445.88
FutOI	2,034.04	1,074.87	2,321.25	746.55	231.84	1,087.95
FutQSpr	0.050	0.148	0.972	0.548	0.468	0.746
OptVol	74.46	60.04	47.64	72.45	60.25	42.16
OptOI	1,072.83	1,115.14	243.69	754.89	748.98	271.73
OptQSpr	3.350	3.463	2.551	10.691	10.606	6.069

Table 3: Net hedging and speculation in commodity derivative markets

This table reports the average weekly net open interest combined across futures and options contracts for each commodity divided into hedging, speculation and non-reportable activity expressed in thousands between January 1, 2016 and December 31, 2017. The CFTC defines: net hedging as the difference between producers and merchants long and short positions (i.e., commercial traders), net speculation as the difference between managed money long and short positions (i.e., non-commercial traders), and net non-reportable as the difference between non-reportable long and short positions.

Combined open interest	**Net hedging**	**Net speculation**	**Net non-reportable**
Crude oil	-217.362	233.057	7.122
Natural gas	-46.726	35.309	32.177
Gold	-131.365	147.821	18.446
Silver	-51.450	52.600	13.318
Corn	-235.178	-77.511	-23.178
Soybeans	-122.198	56.966	-49.658

Table 4: Speculation/hedging measures

This table reports descriptive statistics of the speculation/hedging measures for each commodity. These measures include: i) *WorkingT* captures excess speculation required to meet hedging activity (speculation and hedging activity is defined by the CFTC), and ii) *R* captures the percentage of hedging activity (change in open interest) as a fraction of speculative activity (volume) multiplied by 1000. We report weekly (daily) descriptive statistics for *WorkingT* (*R*). Our sample period is between January 1, 2016 and December 31, 2017.

	Mean	Median	Std. dev.	Mean	Median	Std. dev.
		Crude oil			**Natural gas**	
WorkingT	1.116	1.100	0.065	1.567	1.591	0.239
R	1.643	1.573	0.606	1.685	1.507	0.947
		Gold			**Silver**	
WorkingT	1.230	1.163	0.167	1.273	1.199	0.207
R	3.747	3.302	2.162	3.630	2.968	2.857
		Corn			**Soybean**	
WorkingT	1.259	1.271	0.090	1.090	1.083	0.057
R	1.905	1.645	1.001	1.249	1.172	0.589

Table 5: Price discovery in commodity derivative markets

This table reports the mean options and futures market price discovery shares for each commodity. The price discovery shares are calculated using the: (i) Hasbrouck (1995) information share (*IS*), (ii) Gonzalo-Granger (1995) component share (*CS*), and (iii) Yan-Zivot (2010)-Putniņš (2013) information leadership share (*ILS*). Panel A (B) reports price discovery measures in which we sample prices in event-time (one-second) sampling frequency and use 200 lags in the VECM. Panel C (D) reports price discovery measures in which we sample prices in event time (one-second) sampling frequency and use 60 lags in the VECM. Grey shading indicates price discovery estimates greater than 0.50. Our sample period is between January 1, 2016 and December 31, 2017.

	IS (Futures)	*IS* (Options)	*CS* (Futures)	*CS* (Options)	*ILS* (Futures)	*ILS* (Options)
Panel A: Event time sampling frequency						
Crude oil	0.502	0.498	0.606	0.394	0.377	0.623
Natural gas	0.518	0.482	0.725	0.275	0.523	0.477
Gold	0.522	0.478	0.570	0.430	0.401	0.599
Silver	0.554	0.446	0.578	0.422	0.387	0.613
Corn	0.521	0.479	0.571	0.429	0.424	0.576
Soybean	0.508	0.492	0.565	0.435	0.421	0.579
Panel B: One-second sampling frequency						
Crude oil	0.520	0.480	0.601	0.399	0.419	0.581
Natural gas	0.553	0.447	0.685	0.315	0.574	0.426
Gold	0.510	0.490	0.566	0.434	0.431	0.569
Silver	0.554	0.446	0.551	0.449	0.416	0.584
Corn	0.501	0.499	0.514	0.486	0.470	0.530
Soybean	0.568	0.432	0.606	0.394	0.468	0.532
Panel C: Event time sampling frequency						
Crude oil	0.520	0.480	0.595	0.405	0.376	0.624
Natural gas	0.508	0.492	0.593	0.407	0.519	0.481
Gold	0.512	0.488	0.557	0.443	0.410	0.590
Silver	0.548	0.452	0.596	0.404	0.382	0.618
Corn	0.512	0.488	0.568	0.432	0.422	0.578
Soybean	0.516	0.484	0.562	0.438	0.439	0.561
Panel D: One-second sampling frequency						
Crude oil	0.503	0.497	0.594	0.406	0.407	0.593
Natural gas	0.511	0.489	0.647	0.353	0.595	0.405
Gold	0.511	0.489	0.568	0.432	0.421	0.579
Silver	0.533	0.467	0.586	0.414	0.422	0.578
Corn	0.506	0.494	0.565	0.435	0.428	0.572
Soybean	0.516	0.484	0.578	0.422	0.438	0.562

Table 6: Speculation in commodity derivative markets

This table reports the coefficient estimates of the determinants of price discovery for each commodity from the following regression:

$$\frac{ILS_{i,t}}{(1-ILS_{i,t})} = \beta_0 + \beta_1 METRIC_{i,t} + \beta_2 OptVol_{i,t} + \beta_3 FutVol_{i,t} + \beta_4 OptOI_{i,t} + \beta_5 FutOI_{i,t} + \beta_6 OptQSpr_{i,t} + \beta_7 FutQSpr_{i,t} + \beta_8 Skew_{i,t} + \beta_9 Vola_{i,t} + \varepsilon_{i,t},$$

where *ILS* is options price discovery calculated using the Yan-Zivot (2010)-Putniņš (2013) information leadership share (*ILS*) at time *t*. *METRIC* represents each of the following speculation measures: i) *WorkingT* which is calculated on a weekly basis, or ii) *R* which is calculated on a daily basis. The independent variables include options and futures trading volume (*OptVol* and *FutVol*), options and futures open interest (*OptOI* and *FutOI*), options and futures bid-ask spread (*OptQSpr* and *FutQSpr*), skewness of futures returns (*Skew*), and 20-day intraday return volatility (*Vola*). *N* is the number of observations (weekly observations in Model 1,and daily observations in Model 2). Panel A (B) reports *ILS* in which we sample prices in event-time (one-second) sampling frequency and use 200 lags in the VECM. *t*-statistic values are shown in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A	Crude Oil		Natural Gas		Gold		Silver		Corn		Soybean	
	Model 1: *WorkingT*	Model 2: *R*	Model 1: *WorkingT*	Model 2: *R*	Model 1: *WorkingT*	Model 2: *R*	Model 1: *WorkingT*	Model 2: *R*	Model 1: *WorkingT*	Model 2: *R*	Model 1: *WorkingT*	Model 2: *R*
Intercept	0.090	3.022***	-17.654***	-24.745***	-11.419***	7.629***	-19.316	-77.385	-0.132	1.670**	-9.369***	8.077***
	(0.35)	(10.16)	(-3.59)	(-4.07)	(-17.77)	(3.02)	(-0.56)	(-1.28)	(-0.03)	(2.10)	(-5.15)	(5.22)
Metric	2.430***	-4.830	-1.428	12.859**	6.225***	-9.880***	10.359*	-16.868*	0.822	-0.420	7.081***	-9.544***
	(12.47)	(-1.56)	(-0.72)	(1.96)	(17.09)	(-6.00)	(1.72)	(-1.90)	(0.35)	(-0.78)	(5.99)	(-4.50)
OptVol	0.095***	0.118***	-19.540**	-18.600**	6.160***	1.080	-11.153**	8.067	-0.079	-0.083	0.707***	-0.711**
	(4.85)	(5.90)	(-2.50)	(-2.50)	(7.67)	(1.02)	(-2.60)	(1.20)	(-0.95)	(-0.99)	(3.27)	(-2.26)
FutVol	-0.004	-0.014**	1.320**	2.080***	0.037	-1.070***	1.640	-2.402**	0.173***	0.157***	-0.288**	-0.792***
	(-1.29)	(-2.23)	(2.42)	(3.13)	(0.45)	(-5.57)	(0.54)	(-2.16)	(7.74)	(5.25)	(-2.48)	(-3.91)
OptOI	-0.092***	-0.092***	2.840**	1.890**	-1.900***	-0.030	8.697***	1.310	-0.579***	-0.545***	-0.270***	0.069
	(-20.99)	(-20.49)	(2.59)	(2.55)	(-16.6)	(-0.40)	(4.24)	(0.05)	(-7.57)	(-7.90)	(-3.28)	(1.11)
FutOI	0.004	0.005	2.240***	2.250***	8.050***	-0.815***	-7.603***	3.869	0.320**	0.253**	0.387***	-0.378***
	(0.91)	(1.07)	(3.53)	(3.87)	(16.78)	(-3.74)	(-3.41)	(0.91)	(2.50)	(2.52)	(2.92)	(-3.93)
OptQSpr	-2.005***	-1.790***	2.125	8.919	0.341***	-0.002	-2.603***	3.563	0.003	0.008	0.002	0.041***
	(-36.7)	(-34.01)	(0.08)	(0.37)	(10.67)	(-0.07)	(-3.58)	(0.38)	(0.19)	(0.45)	(0.20)	(4.17)
FutQSpr	-4.723***	-4.322***	20.286	19.866	-0.536***	0.247***	-7.403***	1.745	-0.498***	-0.467***	-0.537***	-0.515***
	(-16.39)	(-14.71)	(1.07)	(1.07)	(-7.60)	(3.16)	(-3.48)	(0.58)	(-6.77)	(-10.96)	(-9.58)	(-8.93)
Skew	-0.134***	-0.192***	-3.897***	-3.468***	1.519***	0.073	5.884**	-7.069	0.075	0.052	0.167***	0.081
	(-8.00)	(-11.40)	(-3.54)	(-4.35)	(15.54)	(0.64)	(2.15)	(-1.57)	(1.32)	(1.02)	(3.13)	(1.53)
Vol	-0.211***	-0.047	-6.053***	-6.159***	3.797***	8.893**	-3.125	6.050*	1.729***	1.513***	3.468***	1.358***
	(-5.83)	(-1.38)	(-3.15)	(-3.27)	(13.48)	(2.43)	(-1.39)	(2.06)	(2.88)	(8.03)	(6.39)	(3.80)
N	97	439	97	439	97	467	97	467	97	447	97	447
Adj. R^2	0.55	0.56	0.24	0.21	0.54	0.75	0.89	0.89	0.48	0.48	0.37	0.39

Table 6: Speculation in commodity derivative markets – continued

Panel B	Crude Oil		Natural Gas		Gold		Silver		Corn		Soybean	
	Model 1: *WorkingT*	Model 2: *R*	Model 1: *WorkingT*	Model 2: *R*	Model 1: *WorkingT*	Model 2: *R*	Model 1: *WorkingT*	Model 2: *R*	Model 1: *WorkingT*	Model 2: *R*	Model 1: *WorkingT*	Model 2: *R*
Intercept	0.276	2.900***	-17.966***	-22.652***	-11.22***	-15.143***	-3.730	-16.084***	-14.078***	7.951***	-13.207***	4.427***
	(1.16)	(10.48)	(-4.12)	(-3.97)	(-16.29)	(-5.93)	(-0.11)	(-5.98)	(-3.25)	(9.10)	(-7.53)	(4.75)
Metric	1.817***	-8.859***	-0.960	7.993	5.242***	-4.187**	-8.307***	-18.612***	11.587***	-2.556***	9.314***	-5.113***
	(9.96)	(-3.07)	(-0.49)	(1.23)	(13.42)	(-2.52)	(-3.14)	(-4.49)	(4.55)	(-4.31)	(8.19)	(-4.14)
OptVol	0.106***	0.120***	-14.620*	-13.820*	4.210***	0.305	6.752**	1.460***	-0.049	-0.067	2.240***	1.060***
	(5.78)	(6.44)	(-1.91)	(-1.91)	(4.89)	(0.29)	(2.22)	(4.08)	(-0.54)	(-0.73)	(11.48)	(3.79)
FutVol	-0.013***	-0.029***	1.490***	1.940***	0.378***	-0.158	-4.240	-2.430***	0.161***	0.073**	-1.030***	-1.000***
	(-4.19)	(-5.05)	(2.81)	(2.98)	(4.35)	(-0.82)	(-1.43)	(-3.88)	(6.59)	(2.22)	(-10.40)	(-8.86)
OptOI	-0.084***	-0.083***	1.630	1.070	-1.780***	-0.259***	-13.330	-40.13***	-0.581***	-0.261***	-0.742***	-0.264***
	(-20.39)	(-19.79)	(1.53)	(1.51)	(-14.48)	(-3.38)	(-1.26)	(-3.32)	(-6.93)	(-3.44)	(-10.13)	(-4.21)
FutOI	0.015***	0.015***	2.380***	2.400***	6.600***	-0.482**	35.830***	8.941***	0.288**	-0.375***	1.140***	0.214**
	(3.83)	(3.66)	(4.410)	(4.70)	(12.84)	(-2.19)	(2.83)	(5.09)	(2.05)	(-3.38)	(9.35)	(2.22)
OptQSpr	-1.621***	-1.461***	9.026	12.196	-0.095***	-0.372***	5.233	14.171***	0.065***	0.082***	-0.040***	0.004
	(-31.69)	(-29.83)	(0.36)	(0.50)	(-2.78)	(-10.23)	(1.40)	(3.20)	(3.79)	(4.39)	(-4.23)	(0.42)
FutQSpr	-3.719***	-3.356***	13.957	14.264	-0.932***	-0.299***	1.792*	4.873***	-1.123***	-0.758***	-0.741***	-0.616***
	(-13.78)	(-12.28)	(0.77)	(0.80)	(-12.32)	(-3.79)	(1.75)	(3.75)	(-13.90)	(-16.16)	(-13.71)	(-11.52)
Skew	-0.092***	-0.142***	-3.419***	-3.124***	2.340***	1.264***	-4.556***	-9.868***	-0.180***	-0.400***	0.011	-0.114**
	(-5.88)	(-9.04)	(-3.09)	(-3.90)	(22.33)	(10.92)	(-3.38)	(-5.05)	(-2.88)	(-7.05)	(0.22)	(-2.13)
Vola	-0.288***	-0.165***	-7.561***	-7.629***	7.828***	5.688***	6.781***	9.528***	3.415***	0.482**	3.445***	0.239
	(-8.52)	(-5.19)	(-4.09)	(-4.18)	(25.91)	(15.42)	(5.94)	(7.14)	(5.19)	(2.32)	(6.68)	(0.69)
N	97	439	97	439	97	467	97	467	97	447	97	447
Adj. R^2	0.50	0.51	0.23	0.22	0.76	0.85	0.84	0.79	0.59	0.59	0.31	0.37