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Does Futures Speculation Destabilize Spot Prices? New Evidence for Commodity Markets

Martin T. Bohl and Patrick M. Stephan

Motivated by repeated price spikes and crashes over the last decade, we investigate whether the growing market shares of futures speculators destabilize commodity spot prices. We approximate conditional volatility and analyze how it is affected by speculative open interest. In this context, we split our sample into two equally long subperiods and document whether the speculative impact on conditional volatility increases. With respect to six heavily traded agricultural and energy commodities, we do not find robust evidence that this is the case. We thus conclude that the financialization of raw material markets does not make them more volatile.

Key Words: agricultural and energy commodities, speculation, volatility

JEL Classifications: G10, G18, Q14, Q18, Q40

Between 2001 and mid-2008, commodity spot prices measured by the Commodity Research Bureau skyrocketed by 140%, then plunged by 40% until late 2008, and finally reached a new record high in mid-2011 before falling slightly. At the same time, the size of speculative positions in most commodity futures markets grew at a much higher speed than that of commercial participants, who are linked to business activities in the underlying spot markets, indicating that raw materials have become a new asset class. In sum, quickly rising and then crashing spot prices together with an increase in futures trading led many politicians, regulators, and part of the media to blame speculators for more and more volatile commodity markets.

At first glance, the destabilization hypothesis seems to be challenged by the lack of a proper theory. Because speculators almost exclusively operate on derivative markets, and futures trading constitutes a zero-sum game, it is unclear why an increase in noncommercial positions should affect commodity futures prices, not to mention spot prices. However, even if financial speculators do not influence the physical demand for a commodity at all, they may still distort spot prices indirectly given that the latter are related to futures prices through the arbitrage channel (Hamilton, 2009). In addition, futures prices generally lead or are at least interrelated to spot prices, which is evidenced by the literature on price discovery processes. Finally, financial market phenomena such as feedback

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trading and herding behavior, commonly attributed to badly informed speculative traders, are generally accepted as possible sources of more volatile futures prices, which are then transferred to spot markets (e.g. DeLong et al., 1990). Based on this theoretical background, we thus require the linkage between spot price volatility and speculative positions to be clearly detectable in the data to maintain the destabilization hypothesis of commodity markets (Irwin and Sanders, 2012a).

So far however, to the best of our knowledge, studies analyzing the effect of futures speculation on commodity price volatility are not scarce but have produced mixed results as a result of the use of different methods and data sets. In addition, most of them focus on futures rather than spot prices. The present article aims to extend the existing evidence by approximating conditional spot price volatility and analyzing how it is affected by speculative open interest. In this context, we split our sample into two equally long subperiods of 10 years each, ranging from 1992–2002 and from 2002–2012, and document whether the speculative impact on conditional volatility increases over time. This breakdown of the sample period is motivated by the intensive financialization of commodity markets over the last decade. We focus on six heavily traded agricultural and energy commodities, all of which are characterized by an unprecedented increase in speculative market shares over the last decade.

If the destabilization hypothesis holds true, we may argue that the increasing financialization of commodity markets induces instability. We are thus able to offer insights not only for academics and commodity investors, but also for decision-makers committed to fight market distortions by framing regulatory interventions. While Gilbert and Morgan (2010) provide an overview of the adverse consequences of increased agricultural price volatility, Kilian (2008) summarizes the severe economic effects of energy price shocks. In addition, our results are important for commodity hedgers who profit from welfare gains resulting from futures trading only if speculators do not increase spot market volatility and induce uncertainty (Stein, 1987).

Literature Review

The Relationship between Futures Trading and Commodity Price Volatility

In general, the process of arbitrage links futures markets closely to the underlying spot markets. The relationship between the two market segments can be described by the cost-of-carry model, which implies that the futures price equals the spot price adjusted by the time to maturity as well as the opportunity costs and the benefits of holding the asset.

Despite this well-known long-run relationship, it remains theoretically unclear how futures markets affect spot price volatility. On the one hand, it is argued that futures markets have a stabilizing effect because they improve price discovery, enhance market efficiency, increase market depth and informativeness, and contribute to market completion. As a result, futures trading may reduce spot price volatility (e.g., Stoll and Whaley, 1988). In addition, with focus on agricultural commodities, futures trading is expected to lower seasonal price ranges as a result of speculative support at harvest time (Powers, 1970).[1] On the other hand, increased futures trading may destabilize the underlying spot markets once badly informed speculative traders, attracted by relatively low transaction costs and high degrees of leverage, distort the price discovery process by inducing noise and thus lowering the information content of prices. In this case, spot market volatility is expected to increase (e.g., Stein, 1987).

With respect to the price discovery process, several studies show that futures markets have the potential to incorporate new information faster than spot markets and hence show price leadership. Empirical evidence suggests that

[1] According to Morgan (1999), futures traders will lower their expectations of future spot prices if they consider weather conditions to be surprisingly positive in the upcoming months so that yields will probably be higher than normal. Farmers will respond to this price signal by increasing storage holdings and thus not delivering crops to the market straight after harvest. In consequence, crop supply and spot price pressure might be lower during the harvest season compared with a situation without futures trading.

this result also holds true for important agricultural commodities (e.g., Yang, Bessler, and Leatham, 2001). Focusing on the wheat market, Crain and Lee (1996) find in particular that futures price volatility leads spot price volatility. In the case of crude oil, futures prices do not unambiguously lead spot prices but at least are interrelated to them (e.g., Kaufmann and Ullman, 2009). As shown by Silvério and Szklo (2012), the contribution of the oil futures market to price discovery has increased in recent years, evidencing the growing importance of factors particular to financial markets. Finally, there is empirical evidence of volatility spillovers from futures to spot markets for crude and heating oil and natural gas (Hammoudeh, Li, and Jeon, 2003).[2]

Following Karpoff (1987), we know that both in spot and in futures markets, volatility is positively correlated with trading volume. According to Bhar and Hamori (2005), the theoretical background of the volume–volatility relationship rests on the supply-and-demand model, whereas three competing explanations can be distinguished: the mixture-of-distribution hypothesis, the sequential-information-arrival hypothesis, and the noise-trading hypothesis. In addition, Daigler and Wiley (1999) identify so-called dispersion-of-beliefs theories associating extreme volume and volatility to heterogeneous trader behavior.

With focus on commodity markets, the vast majority of studies confirm that increased aggregate trading volume is accompanied by increased futures price volatility. In addition, Bessembinder and Seguin (1993) distinguish between expected and unexpected aggregate trading volume and find that futures price volatility is particularly driven by the shock component. Yang, Balyeat, and Leatham (2005) show that spot price volatility of agricultural commodities is positively affected by unexpected overall volume. With respect to the financialization process of raw materials, Irwin and Sanders (2012a, p. 377) sum up that "there is no doubt that uncertainty has increased dramatically in commodity markets over the last decade and this has been an important contributor to the groundswell in trading volumes" and price volatility.

The Effect of Traditional Speculators on Commodity Price Volatility

According to the glossary of the US Commodity Futures Trading Commission (CFTC), a hedger is "a trader who enters into positions in a futures market opposite to positions held in the cash market to minimize the risk of financial loss from an adverse price change or who purchases or sells futures as a temporary substitute for a cash transaction that will occur later." A speculator is characterized as "a trader who does not hedge, but who trades with the objective of achieving profits through the successful anticipation of price movements."

Given these two types of traders, we cannot simply conclude that increased spot or futures price volatility is undoubtedly caused by growing speculative positions, because futures trading in commodity markets is not limited to speculators but also (and often largely) done by hedgers. Kocagil (1997) exclusively focuses on the effect of futures speculation on spot prices of four metal markets and finds that at least it does not reduce volatility (sample period: 1980–1990). However, Kocagil (1997) sets speculators equal to inventory holders of the physical commodity who take speculative positions in the futures markets, which is not concordant to the CFTC's definition of noncommercial traders. In addition, Chatrath and Song (1999) use the same characterization of speculators as the CFTC and detect a negative relationship between spot price jumps and both the number of speculative futures contracts and the number of speculators for five agricultural commodities (1983–1995).

Regarding futures price volatility, Brorsen and Irwin (1987) do not find an enhancing influence of speculators for six agricultural commodities and copper (1978–1984), whereas Irwin and Yoshimaru (1999) confirm this result for 23 agricultural, energy, and metal commodities (1988–1989). Both studies cover periods

[2] Related to this, we also know that futures prices have predictive power for future spot prices both in the case of agricultural and energy commodities, especially during the ongoing financialization process (e.g., Reichsfeld and Roache, 2011).

before the financialization process of raw material markets. Brorsen and Irwin (1987) proxy speculation with the amount of money invested in technically traded futures funds divided by total open interest in the first nearby contract. In contrast, Irwin and Yoshimaru (1999) draw on the trading volume of large-commodity pool operators, a subset of all managed funds and pools, in the contract nearest to maturity.

With respect to the financialization process of commodity markets, the same conclusion is reached by Bryant, Bessler, and Haigh (2006) who analyze three agricultural commodities, crude oil, and gold (1995–2003), Haigh, Hranaiova, and Overdahl (2007) who consider crude oil and natural gas (2003–2004), and Brunetti, Büyüksahin, and Harris (2011) who focus on corn, crude oil, and natural gas (2005–2009). Bryant, Bessler, and Haigh (2006) use the CFTC's definition of speculators and work with the sum of the long and short contracts held by noncommercial traders as their speculative proxy. Haigh, Hranaiova, and Overdahl (2007) refer to the sum of commodity trading advisors, commodity pool operators, and associated persons as hedge funds and analyze the impact of their number and positions on futures price volatility. Brunetti, Büyüksahin, and Harris (2011) take the net positions of hedge funds and floor brokers to account for speculative trading.

By contrast, Chang, Pingear, and Schachter (1997) analyze corn, gold, and soybeans (1983–1990) and find the positive influence of speculative trading volume on futures price volatility to be substantially stronger compared with that of other traders. However, they are unable to differentiate whether speculators are noise traders or possess private information. Chang, Pingear, and Schachter (1997) use the CFTC's definition of speculators and approximate the trading volume for individual investors based on changes in their long and short positions. In a similar vein, Daigler and Wiley (1999) focus on silver prices (1986–1988) and show that the general public mainly drives the positive volume–volatility relationship. They assume the general public to be dominated by uninformed and thus destabilizing individual speculators and managed funds. Finally, Irwin and Holt (2004) draw on nine agricultural, energy, and metal commodities (1994) and also find that speculative trading leads to higher futures price volatility. However, they explain their finding with the help of valuable private information instead of noise trading. Irwin and Holt (2004) set speculators equal to managed money accounts, including large hedge funds and commodity trading advisors, and use their open interest and trading volume as speculative proxies.

With focus on the financialization process of commodity markets, a positive influence of speculative trading on futures price volatility is found by Du, Yu, and Hayes (2011) who analyze corn, crude oil, and wheat (1998–2009), Algieri (2012) who considers eight agricultural commodities (1995–2012) and McPhail, Du, and Muhammad (2012) who concentrate on corn. In particular, the studies of Algieri (2012) and Du, Yu, and Hayes (2011) benefit from focusing on subperiods with different levels of speculative trading. However, all three studies are based on Working's highly aggregated T-index, which only serves as a very rough measure of excessive speculation.

The Effect of Commodity Index Traders on Commodity Price Volatility

Apart from traditional speculators such as hedge funds and commodity pools, a new investment vehicle, called commodity index funds, has emerged over the last couple of years and is frequently blamed for increasing volatility in commodity markets as well. According to the glossary of the CFTC, a commodity index fund is defined as "an investment fund that enters into futures or commodity swap positions for the purpose of replicating the return of an index of commodity prices or commodity futures prices."[3]

In addition, a commodity index trader (CIT) can be described as "an entity that conducts futures trades on behalf of a commodity index fund or to hedge commodity index swap

[3] Two well-diversified and transparent benchmark indicators are the Standard and Poor's-Goldman Sachs (S&P-GSCI) and the Dow Jones-UBS Commodity Index (DJ-UBSCI).

positions." Commodity index products such as exchange-traded funds and exchange-traded notes build on passive, long-only, fully collateralized commodity futures positions taken by CITs. Following the "buy and hold" concept, CITs simply purchase commodities in futures markets and maintain their exposure through rollover strategies. According to the CFTC (2008), approximately 42% of all commodity index investors are institutional investors, 25% retail investors, 24% index funds, and 9% sovereign wealth funds. The CFTC estimates total commodity index investment in the United States to equal $200 billion at the end of 2011 (Irwin, 2012). Because commodity index products allow both institutional and retail investors to trade raw materials as if they were equities, the activities of CITs are sometimes also referred to as the equitization or securitization of commodity futures (Irwin and Sanders, 2012a).[4]

For important grain, livestock, and soft commodities, the CFTC provides information about the position holdings of CITs and also of swap dealers who largely match with CITs in the case of agricultural raw materials (CFTC, 2008). With focus on the impact of CITs on futures price volatility, prior studies, all using the CFTC's data sets, lead to ambiguous results, ranging from positive (Aulerich, Irwin, and Garcia, 2012, for the period from 2006–2008; Tang and Xiong, 2010) over neutral (Brunetti, Büyüksahin, and Harris, 2011, for corn; Bohl, Javed, and Stephan, 2013; Irwin and Sanders, 2012b) to negative effects (Brunetti, Büyüksahin, and Harris, 2011, for crude oil and natural gas; Irwin and Sanders, 2010; Aulerich, Irwin, and Garcia, 2012, for the period from 2004–2005; Sanders and Irwin, 2011). As proxies for speculative trading activity, these studies use the open interest (Aulerich, Irwin, and Garcia, 2012; Bohl, Javed, and Stephan, 2013), the percent of total open interest (Aulerich, Irwin, and Garcia, 2012) or long positions (Irwin and Sanders, 2010), net positions (Bohl, Javed, and Stephan, 2013; Brunetti, Büyüksahin, and Harris, 2011; Irwin and Sanders, 2010, 2012b; Sanders and Irwin, 2011), and the notional value, i.e., net positions times the nearby futures price (Irwin and Sanders, 2012b), respectively, held by CITs or swap dealers. In addition, Irwin and Sanders (2010) draw on Working's T-index, allocating all index trader positions to the speculator category. Alternatively, running a panel analysis, Tang and Xiong (2010) do not regress volatility estimates on speculative proxies, but on indicator variables, which show whether a given commodity is part of the S&P-GSCI and the DJ-UBSCI, respectively.[5]

Data and Market Structures

Nominal spot prices of yellow corn no. 2, West Texas Intermediate crude oil, Henry hub natural gas, yellow soybeans no. 1, raw sugar no. 11, and soft red wheat no. 2 are taken from Thomson Reuters Datastream. They are quoted in US cents per bushel (corn, soybeans, and wheat) and pound (sugar), respectively, and in US dollars per barrel (crude oil) and million British thermal units (natural gas), respectively. The prices belong to the spot markets in Springfield, Illinois (corn), Cushing, Oklahoma (crude oil), Erath, Louisiana (natural gas), and Chicago, Illinois (soybeans and wheat), respectively. Raw sugar is produced globally, and the spot price is calculated by the International Sugar Organization. Because data on the market structures are available for Tuesdays only, we use continuously compounded weekly (Wednesday through Tuesday) returns in percent.

We use futures contracts for corn, soybeans, and wheat from the Chicago Board of Trade, for crude oil and natural gas from the New York Mercantile Exchange, and for sugar from the Intercontinental Exchange.[6] Data on trading volume and open interest for each Tuesday are

[4] For more details about CITs and swap dealers, see, for instance, CFTC (2008), Irwin and Sanders (2011), and Stoll and Whaley (2010).

[5] For a literature review about the effects of CITs on agricultural futures returns (not volatility) in general and during the consecutive roll periods in particular, see Irwin (2012).

[6] Up to December 2004, futures contracts on sugar were traded at the Coffee Sugar Cocoa Exchange and up to July 2008 at the New York Board of Trade.

also taken from Thomson Reuters Datastream. Since October 1992, information on Tuesday's closing open interest can be found in the weekly Commitments of Traders (COT) report issued by the CFTC, in which the number of outstanding long and short contracts of major futures markets is split into commercial and noncommercial large traders (i.e., hedgers and speculators) as well as nonreportables (i.e., small traders). Our analysis thus covers the two decades from October 1992 to September 2012 (1043 weeks), which is split into two equally long subperiods called periods one and two. According to the explanatory notes of the COT report, a commercial position is held by an entity "engaged in business activities hedged by the use of the futures or option markets." The commercial category thus also includes swap dealers' hedging positions, which are not necessarily related to the physical commodity but reflect financial obligations in other market segments (e.g., as a result of forward trading).[7]

Although the publicly available COT data are widely used in academic research, we are aware of their shortcomings, most notably with respect to the frequency, the high degree of aggregation, and the trader classification (e.g., Büyüksahin and Harris, 2011). However, to make our results comparable to previous studies, we stick to the COT data set and draw careful conclusions. Afterward, we extend our analysis and conduct several robustness checks, including daily and more disaggregated data with respect to the types of traders.

Figure 1 shows spot prices and aggregate open interest for the six commodities examined. Apart from market-specific price movements over the first one and a half decades of our sample, the plots visualize that all spot prices skyrocketed up to early (wheat) or mid-2008 but then crashed down during the world financial crisis. The only exception is sugar whose spot price continued rising up to early 2010 before falling substantially. Over the last couple of years, however, spot prices of all commodities examined rebounded (except for natural gas), even leading to new record highs in the case of corn, soybeans, and sugar. Aggregate open interest also rose substantially over the first one and a half decades in all six cases, reflecting the increasing financialization of important agricultural and energy commodity markets. It declined quite sharply during the world financial crisis but then quickly recovered and reached new record highs in all cases except for sugar. Over the last 20 years, aggregate open interest increased by approximately four times in the case of corn and crude oil and almost 13 times in the case of natural gas, whereas the other raw materials rank in between.[8]

Figure 2 displays the corresponding shares of open interest by type of trader, which are expressed as the ratios of long plus short positions and two times the aggregate open interest. The share of speculators increased from approximately 10% in October 1992 up to 30% for corn, soybeans, and sugar; 40% for crude oil and wheat; and 60% for natural gas in September 2012. At the same time, the share of hedgers remained largely constant, and small traders lost more than half of theirs, except for natural gas where the share of hedgers also decreased substantially. The COT report shows that this development is qualitatively largely the same among many futures markets for raw materials. However, the selected agricultural and energy commodities constitute six of the most liquid and thus deserve closer attention.

Figures 1 and 2 mirror our concern that the benefits of increasingly financialized commodity markets serving the hedging needs of traders interested in the physical raw materials are offset by higher spot price volatility, possibly induced by speculative trading activity.

Methodology

Preliminary Model

To analyze the impact of noncommercial trading on commodity price movements, we draw

[7] For details on what is included in the commercial and noncommercial positions in the COT report see, for instance, Irwin and Sanders (2012b) and Stoll and Whaley (2010).

[8] For more empirical details on the financialization and structural change in commodity futures markets see, for instance, Irwin and Sanders (2012a).

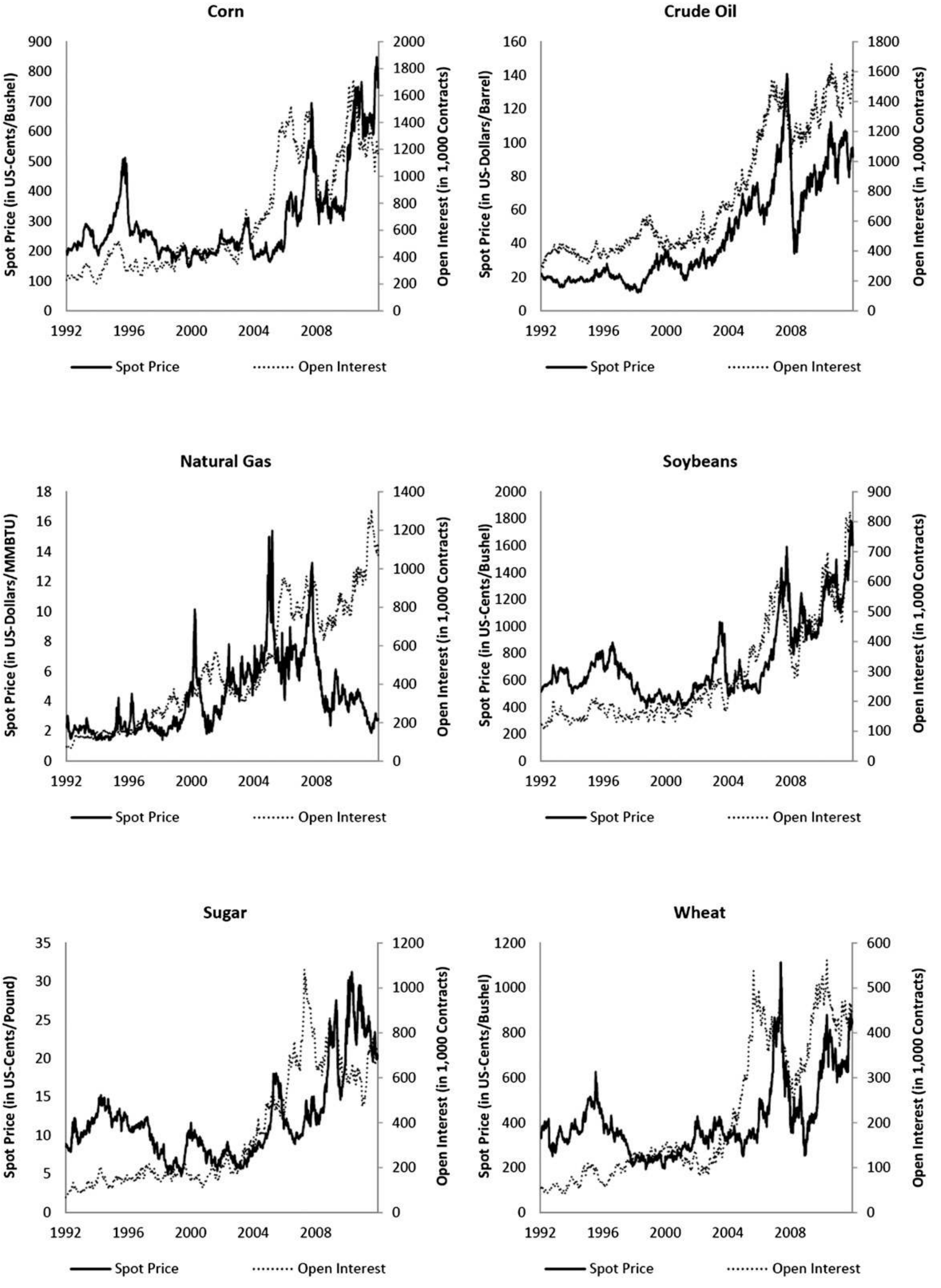

Figure 1. Spot Prices and Open Interest

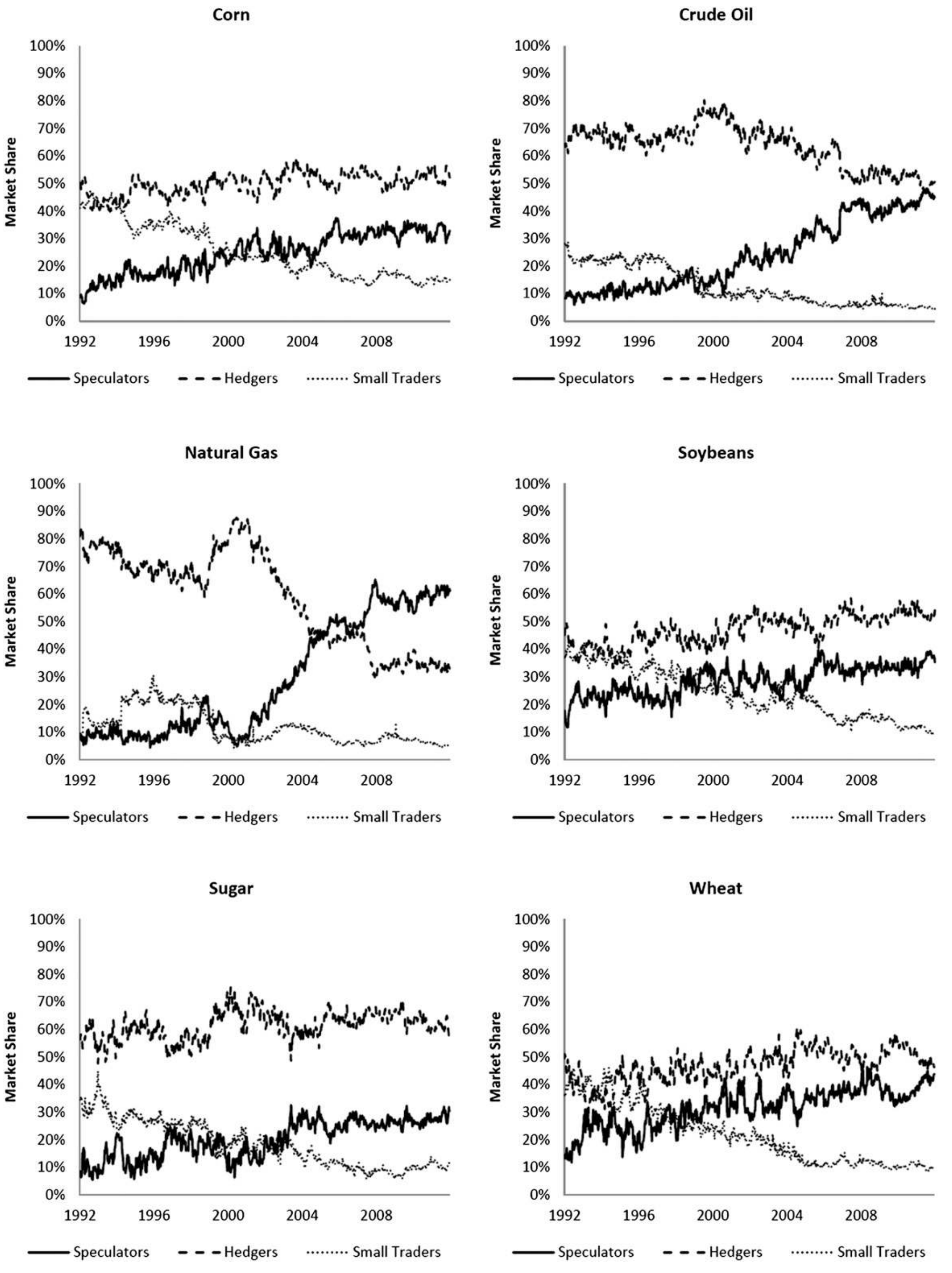

Figure 2. Shares of Open Interest by Type of Commodity Trader

on a generalized autoregressive conditional heteroscedasticity (GARCH) model and extend the volatility equation by speculative open interest. Like in Bessembinder and Seguin (1993), we control for the impact of aggregate trading activity by including both overall trading volume and open interest. Price changes are modeled as a first-order autoregressive (AR) process with a constant to account for possible return dependencies over time.

Our AR(1)-GARCH(1,1) model, extended by the aforementioned variables, thus reads:

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + u_t, \tag{1}$$

$$h_t = \beta_0 + \beta_1 u_{t-1}^2 + \beta_2 h_{t-1} + \delta TV_{t-1} + \pi OI_{t-1} + \gamma OISP_{t-1}. \tag{2}$$

r_t is the return in week t; u_t is the unexpected return; h_t is the conditional volatility of returns; and TV_{t-1}, OI_{t-1}, and $OISP_{t-1}$ are aggregate trading volume, aggregate open interest, and speculative open interest, respectively. These variables are used in first differences if the original time series are nonstationary. The order of integration (d) is determined using the Augmented Dickey-Fuller (ADF) test, which examines the null hypothesis of a unit root against the alternative hypothesis of (trend-) stationarity. Our speculative proxy is used in a couple of previous studies, as discussed above (Aulerich, Irwin, and Garcia, 2012; Bohl, Javed, and Stephan, 2013; Bryant, Bessler, and Haigh, 2006; Chatrath and Song, 1999; Haigh, Hranaiova, and Overdahl, 2007; Irwin and Holt, 2004).

We estimate the model in equations (1) and (2) for periods one and two through the maximum likelihood (ML) technique. For the return density, we draw on the Student's t-distribution (Model 1). A statistically significant and positive γ in one or both period(s) yields preliminary evidence that speculative open interest increases conditional volatility. Following Adrangi and Chatrath (1998), we use one-period lagged explanatory variables in the volatility equation (2) to mitigate possible endogeneity problems because lagged values of endogenous variables are classified as predetermined. As shown by Board, Sandmann, and Sutcliffe (2001), this simultaneity bias arises because information-based trading activity cannot be assumed to be even weakly exogenous. Instead, conditional volatility and trading activity are jointly determined by information arrival, as discussed in the literature review section.

According to Board, Sandmann, and Sutcliffe (2001), we do not estimate the effect of the three exogenous variables in equation (2) at one specific point in time but rather of exponentially weighted averages of their past values. In addition, Board, Sandmann, and Sutcliffe (2001) argue that the inclusion of both futures and spot volume in equation (2) may lead to multicollinearity problems because they usually are highly correlated (at least for equity markets). However, because we do not have data on spot volume for commodity markets, and thus do not consider this variable in equation (2) anyway, obviously their criticism does not affect our model. Finally, following Bhar and Hamori (2005), we also check the robustness of the preliminary model by including the lagged trading volume in equation (1) and thus accounting for possible feedback effects of the latter on the rate of return.

Main Model

As discussed in the literature review, the effect of aggregate trading activity and speculative open interest on conditional volatility may differ with respect to their expected and unexpected components (Bessembinder and Seguin, 1993). Positive shocks in speculative open interest may have a different impact on price fluctuations than negative ones (Wang, 2002). In consequence, we modify equation (2) to obtain:

$$\begin{aligned} h_t = {} & \beta_0 + \beta_1 u_{t-1}^2 + \beta_2 h_{t-1} + \delta_1 TVEX_{t-1} \\ & + \delta_2 TVUN_{t-1} + \pi_1 OIEX_{t-1} + \pi_2 OIUN_{t-1} \\ & + \gamma_1 OISPEX_{t-1} + \gamma_2 OISPUN_{t-1} \\ & + \gamma_3 D_{t-1} \cdot OISPUN_{t-1}. \end{aligned} \tag{3}$$

$TVEX_{t-1}$ and $TVUN_{t-1}$ are expected and unexpected aggregate trading volume, respectively; $OIEX_{t-1}$ and $OIUN_{t-1}$ are expected and unexpected aggregate open interest, respectively; $OISPEX_{t-1}$ and $OISPUN_{t-1}$ are expected and unexpected speculative open interest, respectively; and D_{t-1} is an indicator variable that is equal to one for a positive shock in speculative open interest and zero otherwise. Like in the case of the preliminary model, we estimate the model in equations (1) and (3) through ML using the Student's t-distribution as return density (Model 2).

To allow for possibly asymmetric responses of conditional volatility to shocks in speculative open interest, we include an interaction variable in equation (3), which we define as the product of the indicator variable D_{t-1} and the unexpected noncommercial open interest $OISPUN_{t-1}$. The coefficient estimate for unexpected noncommercial open interest, γ_2, thus represents the marginal impact of a negative shock in speculative open interest on conditional volatility. The sum of γ_2 and the coefficient estimate for the interaction variable, γ_3, measures how conditional volatility is influenced by a positive shock in speculative open interest. We judge the statistical significance of the latter effect based on the F-test.

Focusing on the last three variables in equation (3), we establish the following three econometric hypotheses. First, if γ_1 is statistically significant and positive, expected speculative open interest increases conditional volatility, which contradicts the efficient market hypothesis (EMH). Second, if γ_2 is statistically significant and negative, unexpected negative speculative open interest increases conditional volatility. In this case, speculators destabilize the respective commodity spot market by holding less futures contracts than expected. Third, if $(\gamma_2 + \gamma_3)$ is statistically significant and positive, unexpected positive speculative open interest increases conditional volatility. In this case, speculators destabilize the market by holding more futures contracts than expected. In sum, we interpret an enhancing effect of one or more of the last three variables in equation (3) on conditional volatility as evidence for the destabilizing effect of speculative trading activity on commodity spot prices. By contrast, based on the dispersion-of-beliefs models, a volatility-reducing impact of unexpected noncommercial trading activity suggests that speculators possess some private information.

Like in Bessembinder and Seguin (1993), aggregate trading activity and speculative open interest are decomposed into expected and unexpected components using an autoregressive moving average (ARMA[p, q]) model:

$$\begin{aligned} y_t = \theta_1 y_{t-1} + \ldots + \theta_p y_{t-p} + \varepsilon_t \\ + \varphi_1 \varepsilon_{t-1} + \ldots + \varphi_q \varepsilon_{t-q} \end{aligned} \tag{4}$$

$\{y_t\}$ is expressed in first differences if it is nonstationary in its original form. In this case, equation (4) constitutes an autoregressive integrated moving average (ARIMA[p, d, q]) model. The expected component is the fitted value from equation (4), whereas the unexpected component is the difference between the actual time series and the fitted component. From the analysis of the preliminary model, we already know whether the time series examined contain a unit root. The optimal lag length of the AR(p) and the MA(q) terms is chosen by computing all AR(I)MA models for p, q = (0, . . ., 3) and then selecting the specification that leads to the lowest value of Akaike's information criterion. All models are estimated using ML.[9]

Alternative Models

To check the robustness of our main model, we modify our analysis in different ways:

Apart from the Student's t-distribution, we experiment with the generalized error (GED; Model 3) and the normal distribution (Model 4) to check whether the choice of the return density matters for the ML optimization. In the case of the normal distribution, we draw on the Bollerslev and Wooldridge (1992) robust covariance matrix. Another technical modification is to use contemporaneous rather than one-period lagged exogenous variables in equation

[9] Board, Sandmann, and Sutcliffe (2001) criticize that given the usually high correlation of spot and futures volumes in equity markets, their decomposition into expected and unexpected components based on univariate ARIMA models will lead to the omitted variables problem. However, because we do not have data on spot volume for commodity markets, we are restricted to the use of futures volume only. In addition, we agree with Board, Sandmann, and Sutcliffe (2001) that detrending and differencing the original time series will lead to a loss of information but justify our approach by the fact that the GARCH model requires all exogenous variables to be stationary to be included in the specification.

(3) as in Wang (2002), being aware of the possible endogeneity problems (Model 5).

Following Adrangi and Chatrath (1998), we decompose the trading activity variables into expected and unexpected components using the Hodrick-Prescott-filter (HP-filter; Hodrick and Prescott, 1997) instead of the ARIMA model (Model 6). The HP-filter decomposes a time series $\{y_t\}$ into a permanent (stochastic), μ_t, and a temporary (stationary) component, $y_t - \mu_t$, based on the minimization of the following sum of squares:

$$(5) \quad \sum_{t=1}^{T}(y_t - \mu_t)^2 + \lambda \sum_{t=2}^{T-1}[(\mu_{t+1} - \mu_t) - (\mu_t - \mu_{t-1})]^2$$

where λ is an arbitrary constant reflecting the penalty of incorporating fluctuations into the trend. In line with Adrangi and Chatrath (1998), we find that there is a high degree of correlation between the expected (ARIMA) and permanent components (HP-filter) and between the unexpected (ARIMA) and temporary components (HP-filter), respectively.

Whereas equation (3) constitutes the fully edged specification of conditional volatility, three alternative versions are nested into it. First, excluding the indicator variable leads to a model that does not allow for possibly asymmetric responses of conditional volatility to shocks in speculative open interest (Model 7). Second, assuming that expected components are "informationless" (Board, Sandmann, and Sutcliffe, 2001, p. 801) motivates the exclusion of expected aggregate trading activity and expected speculative open interest (Model 8). Third, given that speculative open interest is part of aggregate open interest, excluding the latter might reduce possible multicollinearity problems (Model 9).

To account for possible seasonality effects, we include indicator variables for summer (July to September), fall (October to December), and winter (January to March) into the volatility equation (3) (Model 10).[10] As a consequence, the constant term in equation (3) measures the time-invariant volatility level in spring, whereas the parameter estimates of the seasonal indicators show whether price movements are higher or lower in the other three seasons. In the case of agricultural commodities, conditional volatility might be higher than normal in the harvest season when large price declines are caused by large supply (Crain and Lee, 1996).

To show that our results do not depend on the choice of the proxy for speculative trading activity, we follow Wang (2002) and measure how conditional volatility is influenced by expected and unexpected speculative net positions instead of noncommercial open interest (Model 11). While the open interest of speculators equals the sum of their long and short positions, speculative net positions are defined as the difference between noncommercial long and short positions. If speculators are net long (short), they expect prices to rise (fall) on average. The same speculative proxy is used by Bohl, Javed, and Stephan (2013), Brunetti, Büyüksahin, and Harris (2011), Irwin and Sanders (2010, 2012b), and Sanders and Irwin (2011), as discussed in the literature review. Alternatively, we account for noncommercial trading activity by directly using expected and unexpected speculative long and short positions, respectively (Model 12).

Instead of using weekly data, we also consider (holiday-adjusted) daily returns and aggregate trading activity, respectively, to check whether our results depend on the data frequency. To approximate daily speculative open interest, we assume the noncommercial market shares for Tuesday to be constant until the following Monday and multiply it with daily overall open interest (Model 13). Based on the daily data set, we also split both 10-year periods into two 5-year intervals each, resulting in period 1a (1b, 2a, 2b), which runs from October 1992 (1997, 2002, 2007) to September 1997 (2002, 2007, 2012) (Model 14). In particular, period 2b covers a timespan characterized by the fact that open outcry pit trading is mainly substituted by electronic platforms. In addition, we also calculate the weekly mean of returns and aggregate trading activity over the Wednesday to

[10] Models with indicator variables for spring, fall, and winter; spring, summer, and winter; and spring, summer, and fall, respectively, lead to results, which are qualitatively largely the same.

Tuesday interval, but stick to speculative open interest from Tuesday (Model 15).[11]

Finally, we draw on two additional data sets to analyze if different types of financial investors have similar effects on conditional volatility. Since January 2006, the CFTC provides the CIT supplement to its weekly COT report for important agricultural commodities. The COT-CIT report contains the number of outstanding long and short contracts for large traditional speculators and CITs (Model 16). Alternatively, we use data from the weekly Disaggregated COT (DCOT) report, in which the CFTC distinguishes between managed money (such as hedge funds and commodity pools) and so-called swap dealers who are engaged in financial hedging, starting in June 2006 (Model 17). According to the CFTC (2008), swap dealers are largely identical to CITs in the case of agricultural commodities.[12] The COT-CIT and the DCOT report both refer to combined futures and delta-adjusted options positions.

Empirical Results

Descriptive Statistics and Autoregressive Integrated Moving Average Specifications

The GARCH model is based on weekly returns and trading activity variables. Regarding the descriptive statistics of return distributions, Panel A of Table 1 shows that the mean is not statistically significantly different from zero in both subperiods for all six commodities examined. In addition, returns on natural gas appear to be most volatile as indicated by the largest maximum and minimum values (in absolute terms) and the highest (unconditional) standard deviation. Finally, all return distributions are skewed to the left (except for natural gas in period two) and show excess kurtosis (i.e., leptokurtosis). In consequence, the Jarque-Bera test of normality is clearly rejected in each case, thus motivating our choice of the Student's *t*-distribution as return density.[13]

Next, we determine the order of integration of the time series used in the GARCH analysis. We run the ADF test, which examines the null hypothesis of a unit root against the alternative hypothesis of (trend-)stationarity. We find a time series to be stationary if the ADF value is statistically significant at the 1% level based on MacKinnon's one-sided critical values. Results of the ADF tests are presented in Panel B of Table 1. It shows that spot prices of all six commodities examined contain a unit root in both periods, whereas the time series of returns do not. Aggregate trading volume appears to be stationary for all six commodities examined in period one and for crude oil and sugar also in period two. By contrast, aggregate and speculative open interest always contain a unit root except for soybeans in period one.

Based on the results of the ADF test, we disentangle the trading activity variables into expected and unexpected components, drawing on the most appropriate ARIMA models. The ARIMA specifications chosen are shown in Table 2. In sum, we find that parsimonious values for the AR and the MA terms are sufficient to describe the expected component of the time series examined reasonably well. For illustrative purposes, Figure 3 shows the unexpected speculative open interest based on ARIMA decompositions for the two 10-year periods combined, indicating a sharp increase in the magnitude of shocks in the second half of the sample in the case of all six commodities examined.

Preliminary Model and Main Model

We start our analysis by estimating the preliminary model in equations (1) and (2) without

[11] We do not use weekly averages of daily speculative open interest because the latter is only created artificially based on the assumption of constant noncommercial market shares over the Tuesday to Monday interval.

[12] Note that the CIT and swap dealer positions have a greater overlap with commercial positions used to approximate hedging activity than with noncommercial positions. For a good description of the relationships among the COT, the COT-CIT, and the DCOT data sets, see, for instance, Irwin and Sanders (2012b) and Stoll and Whaley (2010).

[13] Given the skewness of the return distributions, we also work with the skewed *t*-distribution but find that results are largely the same as in the case of the symmetric version.

Table 1. Descriptive Statistics and Augmented Dickey-Fuller Tests

Panel A: Descriptive Statistics

	Mean	Maximum	Minimum	Standard Deviation	Skew	Kurt	Jarque-Bera
Period one							
Corn	0.0389	12.7833	–12.9024	3.3798	–0.2152	4.6809	65.2319***
Crude oil	0.0663	17.9117	–23.9230	5.0640	–0.2174	4.4821	51.6947***
Natural gas	0.0906	34.3347	–34.8515	8.9076	–0.6248	8.2084	621.6020***
Soybeans	0.0135	10.4127	–12.9443	2.8148	–0.2424	4.4065	47.9510***
Sugar	–0.0374	14.3796	–19.4071	4.4123	–0.3269	4.5856	63.7337***
Wheat	0.0329	21.8725	–25.3423	4.1162	–0.1601	7.8071	502.8904***
Period two							
Corn	0.2173	22.1065	–18.2824	4.7914	–0.0568	4.7557	67.1964***
Crude oil	0.2085	21.8881	–25.1432	5.3202	–0.6341	5.4007	160.0334***
Natural gas	–0.0827	27.0501	–29.5989	7.9631	0.2438	4.0222	27.8446***
Soybeans	0.2152	11.6642	–16.5241	4.0476	–0.5339	4.2115	56.6156***
Sugar	0.2061	15.4243	–21.2440	4.6568	–0.2223	4.1025	30.6776***
Wheat	0.1511	21.4111	–19.7988	5.8098	–0.0686	4.0592	24.7643***

Notes: Descriptive statistics are shown for the return distributions of the six commodities examined. Continuously compounded weekly returns (in percent) are calculated as the change in logarithmic spot prices. *** Statistical significance at the 1% level.

Panel B: Augmented Dickey-Fuller (ADF) Tests

	Price	Return	TV	OI	OISP
Period one					
Corn	–1.9223	–21.6320***	–4.1952***	–3.1114	–3.6906**
Crude oil	–2.5591	–26.5923***	–4.0195***	–2.2224	–2.4925
Natural gas	–3.1896*	–23.1606***	–4.1485***	–3.3384*	–3.0397
Soybeans	–2.3220	–23.0624***	–6.2587***	–4.4074***	–4.4115***
Sugar	–2.6683	–22.1320***	–5.8355***	–3.5721*	–3.0942
Wheat	–1.8274	–23.1091***	–5.2376***	–2.5210	–3.5692**
Period two					
Corn	–2.3370	–23.8626***	–3.4431**	–1.9905	–2.1230
Crude oil	–2.4589	–23.8123***	–3.9929***	–1.9362	–2.5990
Natural gas	–2.7631	–21.7981***	–2.8944	–2.3450	–2.7657
Soybeans	–2.3123	–21.0625***	–3.4449**	–3.0517	–2.7743
Sugar	–2.6784	–23.4499***	–4.8561***	–1.9488	–2.4105
Wheat	–2.3275	–24.7461***	–3.8403**	–1.4526	–2.1622

Notes: ADF values are shown for the test of the null hypothesis of a unit-root against the alternative hypothesis of (trend-)stationarity. ***, **, and *Statistical significance at the 1%, 5%, and 10% level, respectively, based on MacKinnon's one-sided critical values. TV, trading volume; OI, open interest; OISP, speculative open interest.

distinguishing between expected and unexpected components of the trading activity variables. We use noncommercial open interest for approximating speculative trading activity (Model 1).

Figure 4 shows the conditional volatility processes for all six commodities examined based on the full sample. The GARCH processes clearly indicate that the degree of price fluctuations is not constant over time. Instead, we observe periods of high and low volatility, marking conditional heteroscedasticity. In addition, the GARCH processes for corn, natural gas, and soybeans are characterized by strong seasonal patterns. This motivates our idea to include indicator variables for different quarters in one of the robustness checks of the main model.

In the following, we restrict ourselves to the analysis of the parameter estimates for the two

Table 2. Autoregressive Integrated Moving Average (ARIMA) Specifications

	Period One			Period Two		
	TV	OI	OISP	TV	OI	OISP
Corn	(2, 0, 1)	(0, 1, 2)	(2, 1, 1)	(3, 1, 3)	(2, 1, 3)	(3, 1, 2)
Crude oil	(3, 0, 3)	(2, 1, 3)	(1, 1, 1)	(3, 0, 2)	(1, 1, 3)	(1, 1, 3)
Natural gas	(2, 0, 3)	(2, 1, 2)	(2, 1, 2)	(2, 1, 1)	(3, 1, 3)	(0, 1, 3)
Soybeans	(1, 0, 1)	(2, 0, 0)	(2, 0, 2)	(1, 1, 1)	(0, 1, 3)	(3, 1, 1)
Sugar	(2, 0, 1)	(2, 1, 1)	(1, 1, 2)	(2, 0, 1)	(2, 1, 3)	(1, 1, 2)
Wheat	(3, 0, 3)	(3, 1, 3)	(2, 1, 2)	(2, 1, 2)	(2, 1, 2)	(3, 1, 3)

Notes: ARIMA(p, d, q) specifications are shown for the time series of aggregate trading volume (TV), aggregate open interest (OI), and speculative open interest (OISP) for the six commodities examined. The optimal lag length of the AR(p) and the MA(q) term is chosen by computing all ARIMA models for p, $q = (0, \ldots, 3)$ and then selecting that specification with the lowest value of the Akaike's information criterion. All ARIMA models are estimated through maximum likelihood.

subperiods. Results for all six commodities examined are reported in Table 3. Given our research question, we focus on the volatility of equation (2).

Some findings are similar across all six commodities examined. First, the constant term, representing the time-invariant level of conditional volatility, is always smaller in period one than in period two and statistically significant only in the latter. Second, squared lagged residuals from the return equation (1) and lagged volatility have a highly statistically significant and positive influence in each case (except for crude oil and, partly, wheat in period one), confirming our expectation of time-varying but persistent conditional volatility. In addition, because their joint effect is always smaller than unity, we have stationary conditional volatility processes, implying that shocks die out in finite time. Third, aggregate trading volume always has a positive effect (except for the two energy commodities in period two), confirming prior results in the literature. However, this effect is statistically significant in two of three cases in period one only. Finally, aggregate open interest generally leads to a reduction in conditional volatility, which is sometimes statistically significant. Because this reduction is always bigger in period two than in period one (except for crude oil), we agree with Bessembinder and Seguin (1993) who argue that deeper markets have the potential to lower price fluctuations.

More important, speculative open interest does not show any consistent influence in either period for all six commodities examined. With focus on the statistically significant parameters, noncommercial trading activity increases conditional volatility for soybeans and lowers price movements for sugar, both in period one. Only in the case of natural gas, speculative open interest leads to a weakly statistically significant increase in conditional volatility in period two.

Based on the results of the preliminary model, we next turn to the main model in which we stick to noncommercial open interest for approximating speculative trading activity but now use the ARIMA decomposition for disentangling expected and unexpected components (Model 2). The results are shown in Table 4.

Again, all six commodities examined have some characteristics in common. GARCH effects, implying volatility clusters, are always present (except for crude oil in period one and sugar in period two) and indicate stationary conditional volatility processes. Variables representing aggregate trading activity are either not statistically significant or do not show any consistent influence. Expected (unexpected) aggregate trading volume increases conditional volatility for crude oil (corn, natural gas, and wheat) in period one and decreases price fluctuations for corn (crude oil and natural gas) in period two. Our findings are consistent with those of Bessembinder and Seguin (1993) for period one. With respect to period two, they imply that higher market liquidity, resulting from broader market participation and more active trade, has the potential to reduce

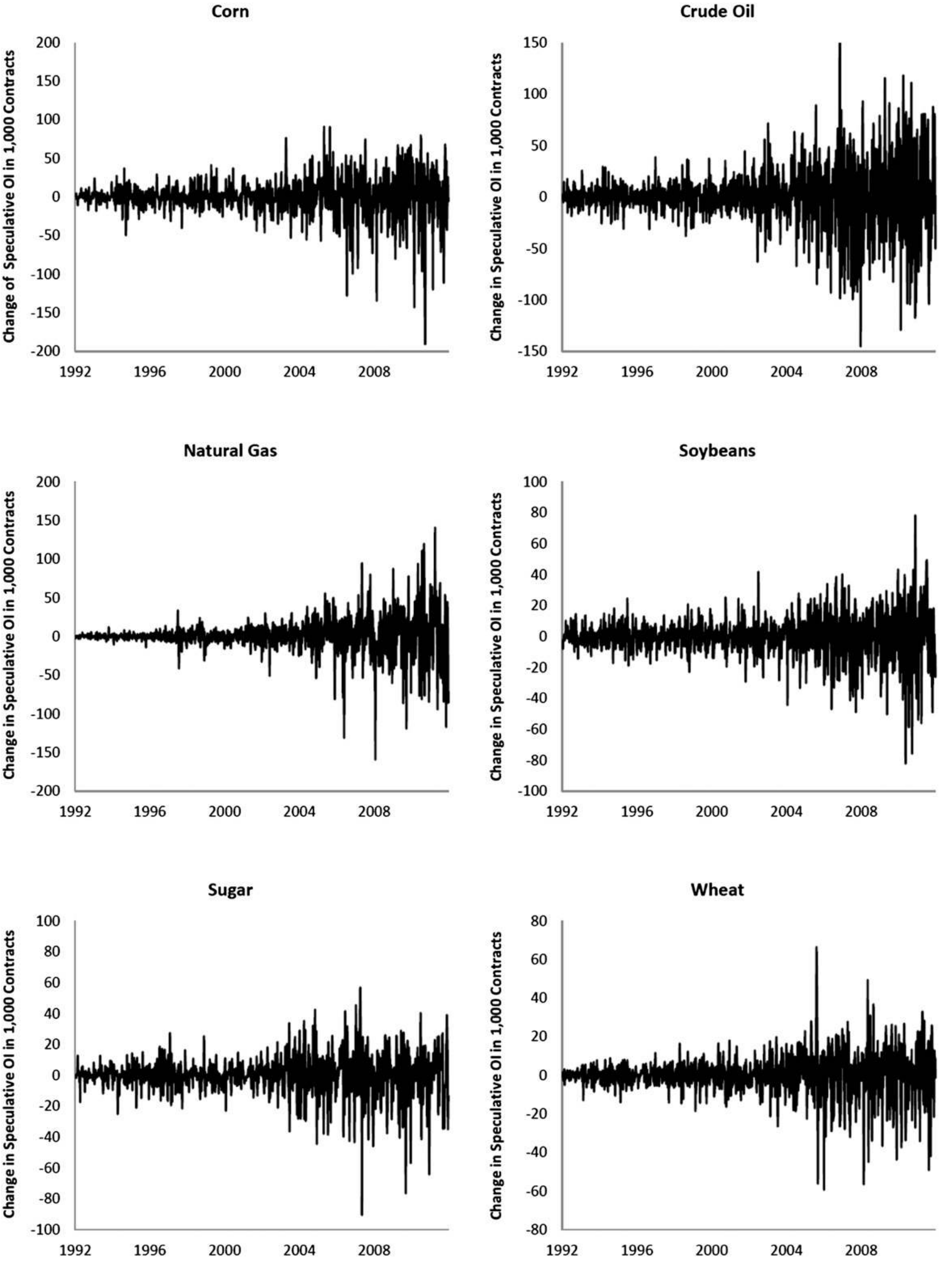

Figure 3. Unexpected Speculative Open Interest

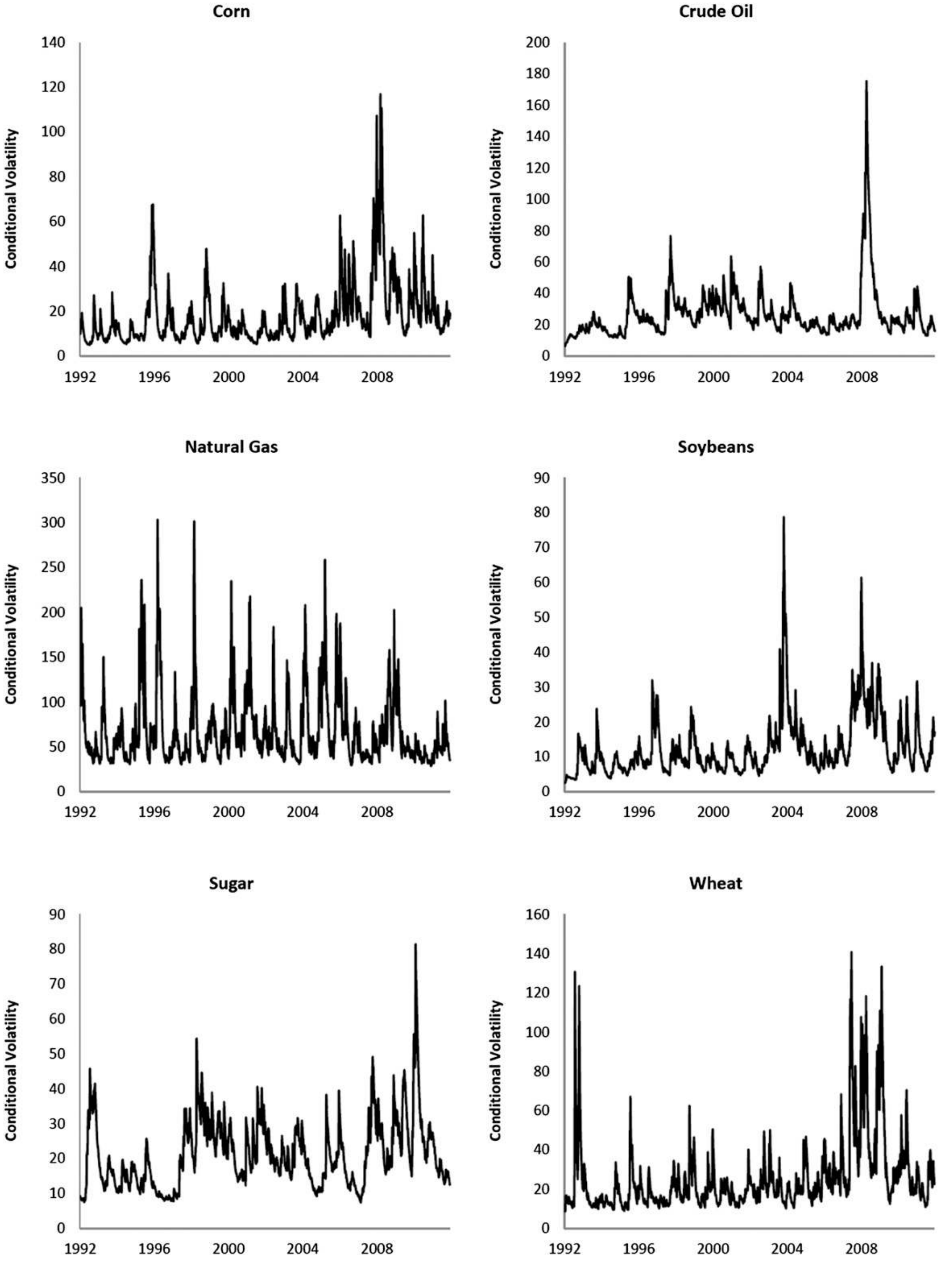

Figure 4. Conditional Volatility

Table 3. Preliminary Model

	Corn		Crude Oil		Natural Gas	
	Period One	Period Two	Period One	Period Two	Period One	Period Two
Constant	–0.6130	1.4077**	–0.3971	3.1442*	4.7266	6.8721**
Resid^2	0.1483***	0.0757**	0.0710	0.1326***	0.1606***	0.1674***
Volatility	0.7322***	0.8664***	0.0831	0.7549***	0.7096***	0.7265***
TV	0.0071***	0.0047	0.0423***	–0.0001	0.0220	–0.0130
OI	–0.0051	–0.0186	–0.0867	0.0263	0.0743	–0.4630*
OISP	–0.0538	–0.0363	0.1273	–0.0329	–0.7513	0.2926*
	Soybeans		**Sugar**		**Wheat**	
	Period One	Period Two	Period One	Period Two	Period One	Period Two
Constant	0.0487	1.2212**	0.5344	8.0253**	2.6804	2.9150**
Resid^2	0.0520*	0.1205***	0.0766**	0.1646**	0.1676***	0.1637***
Volatility	0.8749***	0.8102***	0.8899***	0.3545**	0.2198	0.7520***
TV	0.0054***	0.0087	0.0027	0.0068	0.0736**	0.0013
OI	–0.0147**	–0.0828	0.0520	–0.1833**	–0.0509	–0.0747
OISP	0.0199***	0.0433	–0.2652*	0.0224	–0.0060	–0.0176

Notes: Results are shown for the volatility equation (2) based on the Student's t-distribution and weekly data. Resid^2 and Volatility stand for the squared residual from the return equation (1) and conditional volatility, respectively. TV, OI, and OISP represent aggregate trading volume, aggregate open interest, and speculative open interest, respectively, in units of 1000 contracts. All explanatory variables are lagged by one period. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Period one (two) refers to the time span from October 1992 (2002) to September 2002 (2012).

conditional volatility (Irwin and Sanders, 2012a). Similarly, expected (unexpected) aggregate open interest leads to higher conditional volatility in period one in the case of the two energy commodities (corn) but lower price movements in period two in the case of crude oil (natural gas and soybeans). The positive effect of the expected component in period one is indicative of a possible violation of the EMH. The negative effect of expected and unexpected aggregate open interest in period two is in line with Bessembinder and Seguin (1993) who argue that price volatility can be mitigated by increased market depth.

More important, we find that expected speculative open interest increases conditional volatility in a statistically significant way in the case of corn, crude oil, and soybeans in period one and lowers it for corn in period two. Expected speculative open interest leads to a statistically significant increase in conditional volatility in period two for crude oil only. Unexpected negative speculative open interest does not show any consistent influence either. Only for natural gas, it results in a statistically significant increase in conditional volatility in period two.

Summing the coefficient on a negative shock and the coefficient on the interaction variable from equation (3) gives the effect of unexpected positive speculative open interest. This effect is statistically significant and negative in the case of corn, crude oil, and sugar in period one. Only for natural gas, unexpected positive speculative open interest leads to a statistically significant increase in conditional volatility in period two. All in all, we are unable to provide empirical evidence that growing futures speculation, represented by noncommercial open interest and decomposed in its expected and unexpected components by an ARIMA model, destabilized commodity spot prices over the last decade on a large scale.

Alternative Models

To check whether our results from the main model are robust, we run several alternative analyses. We summarize all findings in the following way. Table 5 shows the shares of

Table 4. Main Model

	Corn		Crude Oil		Natural Gas	
	Period One	Period Two	Period One	Period Two	Period One	Period Two
Constant	1.8486	0.2945	8.7095	2.7767	6.9956**	7.8866**
Resid^2	0.0944*	0.0210	0.0900	0.1479***	0.1574***	0.1539***
Volatility	0.6351***	0.9484***	0.1204	0.6883***	0.7254***	0.7577***
TVEX	0.0088	–0.0236***	0.0268***	0.0006	0.0209	–0.0242
TVUN	0.0209***	–0.0071	0.0005	–0.0071***	0.1518***	–0.0303**
OIEX	0.0513	0.1320	0.4802***	–0.2237*	1.4802**	–0.1973
OIUN	0.0572*	–0.0617	0.1779	–0.0234	–0.5922	–0.6234*
OISPEX	0.4973**	–0.3589*	1.3504**	0.4272***	–6.1254	–0.8627
OISPUN	–0.0608	0.0217	0.2214	0.0299	1.0791	0.4793**
D·OISPUN$^-$	–0.2284*	0.0329	–0.8491***	0.0349	–1.5436	–0.1425
OISPUN$^+$	–0.2892***	0.0547	–0.6277***	0.0648	–0.4646	0.3368*
	Soybeans		**Sugar**		**Wheat**	
	Period One	Period Two	Period One	Period Two	Period One	Period Two
Constant	0.7605	0.8990	–0.1687	1.8646	3.4326	2.0383
Resid^2	0.0489	0.1084***	0.0582	0.0758	0.1250**	0.1562***
Volatility	0.8837***	0.8373***	0.8236***	0.5364	0.3338	0.7235***
TVEX	0.0028	–0.0011	0.0364	–0.0062	0.0660	0.0007
TVUN	0.0104	0.0007	0.0210	–0.0024	0.0771*	0.0031
OIEX	–0.0141	0.1126	–0.6510*	–0.0981	0.8865	–0.5486
OIUN	–0.0133	–0.1440*	0.1182	–0.0686	–0.0374	–0.0590
OISPEX	0.0194*	–0.0085	0.5122	0.0361	–1.2169	0.5607
OISPUN	0.0529	0.0302	0.0410	–0.0691	0.3165	–0.4165
D·OISPUN$^-$	–0.0727	0.0075	–0.5076*	–0.2432	–0.8092	0.5046*
OISPUN$^+$	–0.0198	0.0377	–0.4666**	–0.3122	–0.4926	0.0881

Notes: Results are shown for the volatility equation (3) based on the Student's t-distribution and weekly data. Resid^2 and Volatility stand for the squared residual from the return equation (1) and conditional volatility, respectively. TV, OI, and OISP represent aggregate trading volume, aggregate open interest, and speculative open interest, respectively, in units of 1000 contracts, which are decomposed into expected (EX) and unexpected components (UN) based on an ARIMA(p, d, q) model. D is an indicator variable, which is equal to 1 if unexpected speculative open interest is positive and 0 otherwise. OISPUN$^+$ denotes unexpected positive speculative open interest. All explanatory variables are lagged by one period. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Period one (two) refers to the timespan from October 1992 (2002) to September 2002 (2012).

parameters in the volatility equations (2) and (3), which are statistically significant at least at the 10% level, based on the preliminary, the main, and all alternative models.

The results confirm that modeling conditional volatility by the GARCH technique appears to be appropriate for all six commodities examined and both subperiods. By contrast, most trading activity variables are rarely statistically significant in more than half of all cases. If they are, however, variables representing aggregate trading activity show a positive effect on conditional volatility in period one and a negative one in period two. In particular, in period one, the positive influence of unexpected aggregate trading volume for corn, natural gas, and wheat is consistent with the findings of Bessembinder and Seguin (1993), whereas the volatility-increasing effect of expected open interest for crude oil indicates a possible violation of the EMH. Furthermore, the negative effect of expected aggregate trading volume for corn in period two supports the argument of Irwin and Sanders (2012a) that higher market liquidity has the potential to reduce conditional volatility.

More important, expected speculative trading activity does not show any consistent

Table 5. Overview of Significant Parameters

	Corn				Crude Oil				Natural Gas			
	Period One		Period Two		Period One		Period Two		Period One		Period Two	
	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative
Const.	0.20		0.47		0.13		0.47		0.80		0.93	
Resid^2	0.94		0.60		0.44		1.00		1.00		1.00	
Vola	1.00		0.90		0.88		1.00		1.00		1.00	
TVEX		0.36	0.28	0.50	0.43	0.07	0.14	0.07	0.07	0.07	0.07	
TVUN	0.73	0.07	0.11	0.16	0.13	0.27	0.13	0.27	0.87	0.07	0.27	0.47
OIEX		0.38		0.12	0.54	0.08	0.08	0.23	0.38			0.15
OIUN	0.50		0.06	0.22	0.43		0.07	0.14		0.14		0.43
SPEX	0.31		0.12	0.35	0.15		0.31			0.23		0.23
SPUN$^-$				0.12	0.15	0.08	0.08		0.23		0.62	
SPUN$^+$		0.62	0.06	0.18		0.54		0.15	0.08	0.08	0.23	

	Soybeans				Sugar				Wheat			
	Period One		Period Two		Period One		Period Two		Period One		Period Two	
	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative
Const.	0.07	0.07	0.63		0.53		0.74		0.20		0.42	
Resid^2	0.56		0.95		0.75		0.80		0.94	0.06	1.00	
Vola	1.00		0.95		1.00		0.70		0.56		1.00	
TVEX	0.14	0.07	0.06	0.06	0.14	0.21	0.22	0.06	0.36			0.06
TVUN	0.47	0.07	0.32	0.05	0.47	0.07	0.05	0.11	0.67	0.13	0.05	0.05
OIEX		0.15		0.24	0.08	0.38	0.06	0.06		0.08		
OIUN				0.61	0.07	0.07		0.39	0.07	0.07		0.11
SPEX	0.46		0.18	0.06	0.08	0.08		0.24		0.08	0.06	0.06
SPUN$^-$			0.06	0.12	0.08		0.12	0.06	0.15			0.18
SPUN$^+$				0.35		0.85	0.06	0.24	0.08	0.15		

Notes: The table shows the shares of parameters in the volatility equations (2) and (3), which are statistically significant at least at the 10% level based on the preliminary, the main, and all alternative models. To improve the readability of the table, entries with shares of zero are left empty. Resid^2 and Vola stand for the squared residual from the return equation (1) and conditional volatility, respectively. TVEX (OIEX) and TVUN (OIUN) are expected and unexpected aggregate trading volume (open interest), respectively. SPEX, SPUN$^-$, and SPUN$^+$ represent the expected and the negative and positive unexpected component of the proxy variable for speculative trading activity. The following variables do not match with the variables in the first column of this table and thus are not considered for calculating the shares of significant parameters: the trading activity variables in Model 1 (which are not decomposed in expected and unexpected components), unexpected speculative open interest in Model 7 (which is not decomposed in negative and positive components), the constant term and the seasonal indicator variables in Model 10, and expected and unexpected speculative long and short positions in Model 12. Period one (two) refers to the timespan from October 1992 (2002) to September 2002 (2012).

influence at all. Unexpected negative (positive) noncommercial trading activity reduces price fluctuations for natural gas (corn, crude oil, and sugar) in period two. According to the dispersion-of-beliefs approach, this shows that speculators appear to possess private information, although not on a large scale. Based on our data sets and the GARCH methodology, we thus conclude that there is robust empirical evidence that speculators do not destabilize commodity spot prices on a large scale, either in the first 10-year period or over the last decade characterized by the increasing financialization process of raw material markets.

In particular, we find that our results do not depend on the return density (Models 3–4), the decomposition method for the trading activity variables (Model 6), alternative specifications of the volatility equation (Models 7–9), alternative speculative proxies (Models 11–12), and the data frequency (Models 13–15). Furthermore, once we use contemporaneous explanatory variables in equation (3), unexpected aggregate trading volume has a statistically significant and positive influence for all six commodities examined in both subperiods, indicating possible endogeneity problems (Model 5). Controlling for seasonality effects leads to the following insights (Model 10). For the four agricultural commodities, conditional volatility is generally (and in several cases statistically significantly) lower in the fall and the winter period, whereas in the harvest season, large supply leads to large price declines, causing higher market fluctuations. In the case of natural gas, conditional volatility is statistically significantly and substantially higher (smaller) in the third and fourth (first) quarters in period one. Finally, we are unable to document a destabilizing influence of electronic platforms compared with open outcry pit trading (Model 14). Similarly, CITs and swap dealers, engaged in financial hedging, do not lead to more volatile agricultural commodity markets either (Models 16–17).

Conclusion

Motivated by repeated price spikes and crashes over the last decade, we investigate whether the rapidly growing market shares of futures speculators destabilize spot prices of corn, crude oil, natural gas, soybeans, sugar, and wheat. We approximate conditional volatility using a GARCH model and analyze how it is affected by speculative open interest while controlling for volatility persistence and aggregate trading activity. We divide our sample into two subperiods where the market shares of speculators are larger in the second half than in the first and document whether the speculative impact on conditional volatility increases. However, with respect to the six heavily traded agricultural and energy commodities, we conclude that the financialization of raw material markets does not increase spot price volatility. Our findings are in line with the results of prior studies, which use the same speculative proxies and similar data sets but different methodological approaches and sample periods.

Our findings have important policy implications. To justify their demand for curbing commodity speculation, politicians, regulators, and part of the media regularly take increased spot price volatility as a major concern. However, based on our empirical results, we argue that taking these measures in response to the allegedly destabilizing impact of futures speculation on commodity spot prices is at least questionable. In addition, the US Commodity Futures Modernization Act, which became effective in late 2000 and implemented relaxed position limit regulations, apparently has not allowed speculators to make important agricultural and energy prices more volatile.

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