Do Commodity Index Traders Destabilize Agricultural Futures Prices?*

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FOR PHD SESSION

Abstract

Motivated by repeated price spikes and crashes over the last decade, we investigate whether the intensive investment activities of commodity index traders (CITs) has destabilized agricultural futures markets. Using a stochastic volatility model, we treat conditional volatility as an unobserved component, and analyze whether it has been affected by the expected and unexpected open interest of CITs. However, with respect to twelve increasingly financialized grain, livestock, and soft commodities, we do not find robust evidence that this is the case. We thus conclude that justifying a tighter regulation of CITs by blaming them for more volatile agricultural futures markets appears to be unwarranted.

JEL Classification: G10, G18, Q14

Keywords: Commodity Index Traders, Futures Prices, Agricultural Markets, Stochastic Volatility Model, Kalman Filter

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*We are indebted to participants of the research seminars of the Johann Heinrich von Thünen-Institute in Braunschweig, Germany, as well as the Chair of Empirical Economics, the Chair of Monetary Economics, and the Institute of Econometrics and Economic Statistics of the Westphalian Wilhelminian University of Münster, especially to Martin Banse, Robert Hahn, Philipp Kaufmann, Philip Michaelis, Stephan Rudolph, Rainer Schüssler, Mark Trede, Ernst-Oliver von Ledebur, and Bernd Wilfling, for helpful comments and suggestions. We thank Katarina Cohrs and Timo Quartier for excellent research assistance.

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1. Introduction and Literature Review

Up to mid-2008 futures prices of many important agricultural commodities experienced a sharp increase, then crashed down during the world financial crisis, and finally rose again until most recently. Simultaneously, these markets have gone through an intensive financialization process, as shown by the growing investment activities of commodity index traders (CITs). Commodity index products have a variety of forms, but many are benchmarked to well-diversified and transparent indicators like the Standard & Poor's–Goldman Sachs Commodity Index (S&P-GSCI) and the Dow Jones–UBS Commodity Index (DJ-UBSCI). Nearly all of the commodity index products are based on passive, long-only, fully collateralized commodity futures positions taken by CITs.[1] Taken together, skyrocketing and then plummeting agricultural prices coupled with growing futures trading by CITs have led many politicians, regulators, and part of the media to blame CITs for increasingly volatile commodity markets. If correct, the destabilizing role of CITs would imply welfare losses for both hedgers and investors through higher uncertainty (Gilbert, 1985; Stein, 1987), and ultimately affect consumers and producers once translated into spot markets (Agricultural Economics, 2008; Gilbert and Morgan, 2010).

As summarized by Karpoff (1987), we have sound knowledge that futures price volatility is positively influenced by the volume traded. Various models have been proposed to explain this relationship, drawing on traders with asymmetric information (Copeland, 1976; Epps and Epps, 1976) or divergent beliefs (Harris and Raviv, 1993; Shalen, 1993). Focusing on commodity markets, most studies confirm that increased trading volume comes along with increased futures price volatility, which is measured by absolute or squared returns (Clark, 1973; Cornell, 1981; Kocagil

[1] Stoll and Whaley (2010) estimate that the total commodity index investment in the United States was about $174 billion in 2009. According to the Commodity Futures Trading Commission (CFTC, 2008), about 24% of all commodity index investors are index funds, 42% institutional investors, 9% sovereign wealth funds, and 25% retail investors. For further details on commodity index investment see, for example, Irwin and Sanders (2011).

and Shachmurove, 1998; Moosa and Silvapulle, 2000; Wang and Yau, 2000; Ciner, 2002; Chen et al., 2004), the squared logarithmic ratio of intra-day high and low prices (Serletis, 1992; Herbert, 1995; Ripple and Moosa, 2009), and generalized auto-regressive conditional heteroscedasticity (GARCH)-type models (Bessembinder and Seguin, 1993; Foster, 1995; Fujihara and Mougoué, 1997; Girma and Mougoué, 2002). Only a minority of older studies does not detect a significantly positive influence of trading volume on futures price volatility (Rutledge, 1984; Garcia et al., 1986).

However, since futures trading in commodity markets is done by both hedgers and speculators, we cannot simply conclude which type of trader affects futures price volatility. With respect to the broad category of speculators, which nowadays includes (probably the biggest) part of CITs, no enhancing influence is found by Brorsen and Irwin (1987) for six agricultural commodities and copper (1978-1984) and Irwin and Yoshimaru (1999) for 23 agricultural, energy, and metal commodities (1988-1989), both covering periods prior to the intensive financialization process of raw material markets. Focusing on the latter, the same result is obtained by Bryant et al. (2006) for three agricultural commodities, crude oil, and gold (1995-2003), Haigh et al. (2007) for crude oil and natural gas (2003-2004), and Brunetti et al. (2011) for corn, crude oil, and natural gas (2005-2009). By contrast, analyzing corn, gold, and soybeans (1983-1990), Chang et al. (1997) detect that the positive effect of speculators' trading volume on volatility is much stronger than that of other traders. However, they cannot detect whether speculators possess superior information or are merely noise traders. Similarly, with respect to silver prices (1986-1988), Daigler and Wiley (1999) show that the positive volume-volatility relationship is mainly driven by the general public which they assume to be dominated by uninformed and thus destabilizing speculators. Finally, drawing on nine agricultural, energy, and metal commodities (1994), Irwin and Holt (2004) also conclude that speculative trading increases futures price volatility, but explain this relationship by valuable private information instead of noise trading.

With focus on CIT data, different strands of literature have emerged in most recent times. Sanders et al. (2010) classify CITs as non-commercial, and calculate Working's T-index for 2006-2008, measuring the degree of excessive speculation. However, since values are within historical ranges, they doubt whether CITs are responsible for the commodity price boom up to mid-2008.[2] Apart from that, Tang and Xiong (2010) document that futures prices included in the S&P-GSCI and the DJ-UBSCI have become increasingly correlated over the last decade, reflecting the financialization process of raw material markets. By contrast, Stoll and Whaley (2010) find the levels of correlation to be quite low, so that either CITs have little effect on futures returns or return variability is driven by factors other than commodity index investing. In addition, Stoll and Whaley (2010) and Irwin et al. (2011) highlight that the opening and rolling of large index positions are not to blame for increased spreads which may disturbe the maturing futures price to converge to the spot price.

More important, the vast majority of studies detect little or no effect of CITs on returns of agricultural futures (Brunetti and Büyüksahin, 2009; Aulerich et al., 2010; Gilbert, 2010a,b,c; Irwin and Sanders, 2010, 2012; Sanders and Irwin, 2010, 2011a,b; Stoll and Whaley, 2010, 2011). Only Gilbert (2010a) and Singleton (2011) find evidence that CITs contributed to the rise in oil and metals prices from 2006 to 2008. However, their methodology of extrapolating CIT positions reported for tiny agricultural commodities to large energy and metal markets appears to be critical, so that the findings should be interpreted with caution (Sanders and Irwin, 2011c). Apart from that, Capelle-Blancard and Coulibaly (2012) document that CITs do not Granger-cause agricultural futures prices.

With respect to the influence of CITs on futures price volatility, prior results are

[2] Note that since not all CITs necessarily trade for speculative purposes only, the results of Sanders et al. (2010) can be interpreted as an upper range of Working's T-index.

ambiguous, ranging from little positive or no effects (Aulerich et al., 2010 for 2006-2008; Tang and Xiong, 2010; Irwin and Sanders, 2012) to more or less pronounced negative effects (Brunetti and Büyüksahin, 2009; Aulerich et al., 2010 for 2004-2005; Irwin and Sanders, 2010; Sanders and Irwin, 2011a). In addition, even though most studies focus on agricultural markets, only Irwin and Sanders (2012) cover the most recent commodity price boom, but use time series with just 15 quarterly observations. Thus, the question whether CITs indeed destabilize agricultural futures prices does not appear to be answered yet, which is regrettable given the on-going debate on tighter regulation of commodity investors.[3]

In order to provide new empirical evidence on this issue, we draw on the two most widely used datasets on CITs provided by the CFTC: the CIT supplement to the weekly commitments of traders (COT) report, which explicitly includes a CIT category, and the disaggregated COT (DCOT) report, which includes the category of swap dealers who are largely identical to CITs in case of agricultural commodities (CFTC, 2008). Based on these datasets, we make use of a stochastic volatility (SV) model which has been favored in most recent research in order to avoid possible endogeneity problems of GARCH-type approaches, and analyze twelve agricultural commodities traded on different futures exchanges in the United States. We refer to the period from 2006 to 2011 which covers the most recent spikes and crashes of agricultural futures prices. In sum, our paper thus aims at sheding new light on the open question whether CITs destabilize agricultural futures prices, using the best publicly available dataset on CITs in the United States, the longest possible observation period, and a more powerful econometric technique compared to previous studies.[4]

[3]For instance, in the United States the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 includes substantial innovations of US financial market law, and is currently implemented, amongst others, by the CFTC with respect to commodity markets. Similarly, the European Commission prepares a broad-based reform of its "Markets in Financial Instruments Directive" (MiFID) which is also aimed at limiting speculation on commodity futures markets.

[4]Note that even though the data from the COT-CIT and the DCOT reports are widely used in order to analyze the influence of CITs, we are aware of their serious shortcomings, most notably with respect to the frequency, the high degree of aggregation, and the trader classification.

The paper proceeds as follows: Section 2 describes the data and the structure of the agricultural futures markets which we analyze. Section 3 introduces the methodology. Section 4 provides the empirical results. Section 5 briefly concludes.

2. Data and Market Structures

We use futures prices of the first-nearby contract written on the following twelve agricultural commodities: Cocoa, coffee 'C', yellow corn no. 2, cotton no. 2, feeder cattle, lean hogs, live cattle, soybean oil, yellow soybeans no. 2, sugar no. 11, soft red wheat no. 2 and hard red wheat.[5] Cocoa, coffee, cotton, and sugar are traded at the New York Board of Trade (NYBT), corn, soybean oil, soybeans, and soft wheat at the Chicago Board of Trade (CBT), feeder cattle, lean hogs, and live cattle at the Chicago Mercantile Exchange (CME), and hard wheat at the Kansas City Board of Trade (KCBT). All futures prices are taken from Thomson Reuters Datastream, and are quoted in US-cents per ton (cocoa), bushel (corn, soybeans, and wheat), and pound (all others), respectively. Since information on the market structures are available for Tuesdays only, we calculate continuous weekly (Wednesday–Tuesday) returns in percent ($R_t = \ln(P_t/P_{t-1}) \cdot 100\%$).

Aggregate trading volume and open interest of all futures contracts written on the respective commodity are also taken from Thomson Reuters Datastream, and then summed for each Tuesday. Since January 2006, the CFTC provides the CIT supplement to its weekly COT report, in which the number of outstanding long and short contracts of the twelve agricultural markets examined is split up among commercial and non-commercial large traders (i.e., hedgers and speculators), non-reporting (i.e., small) traders, and CITs. Accordingly, our analysis covers the period from January 2006 to December 2011 (313 weeks). Alternatively, we use data on the market structures from

[5] In order to construct continuous futures price time series, we always draw on the first-nearby contract, and roll over to the second-nearby on the first day of the first-nearby's delivery month. However, based on the analysis of Carchano and Pardo (2009), alternative roll criteria are expected to lead to similar results.

the weekly DCOT report, in which the CFTC distinguishes between processors and merchants, swap dealers, managed money, other reporting, and non-reporting traders, starting in mid-June 2006 (290 weeks).[6] The COT-CIT and the DCOT report both refer to combined futures and delta-adjusted options positions.

The links between the original COT, the COT-CIT, and the DCOT report are straightforward. In the COT-CIT report, commodity-index-related entities among the commercial and non-commercial traders from the COT report are grouped into the CIT category. In the DCOT report, commercial traders from the COT report are subdivided into processors and merchants and swap dealers, while non-commercial traders are disaggregated into managed money and other reporting traders. However, even though CITs and swap dealers are largely identical in case of agricultural commodities, they do not match perfectly. On the one hand, the CIT category also includes pension and other investment funds which directly trade on the futures markets rather than using swap dealers. These traders are classified as managed money or other reporting traders in the DCOT report. On the other hand, the swap dealer category also includes traders who do not have commodity-index-related positions, so that they are not grouped as CITs.

In Figures 1 and 2, we show aggregate open interest for the twelve agricultural commodities examined in comparison to the time series of the first-nearby futures price from 2006 to 2011. The figures visualize several interesting characteristics. First, the twelve futures markets are very different in size, ranging from corn with a high of more than 2.5 million open contracts to feeder cattle with a low of about 20,000 open contracts. Second, for most agricultural commodities, we observe a substantial increase in aggregate open interest from 2006 to early 2008, followed by a sharp decline

[6] Processors and merchants include traditional users and producers of the commodity who are actively engaged in the physical markets, and need the futures to hedge their risks. Swap dealers are traders who deal primarily in swaps, and hedge their transactions in the futures market. Managed money refers to positions held by commodity trading advisors (CTA), commodity pool operators (CPO), and hedge fund managers who conduct futures trading on behalf of clients. Other reporting traders are large enough to report but do not fit into one of the above categories.

during the world financial crisis. However, over the last two years, nearly all markets recovered, and nine of them even reached new record highs with respect to the number of outstanding contracts. Third, most futures prices also skyrocketed up to early 2008, then crashed down during the world financial crisis, and finally rebounded, leading to new record highs for eight agricultural commodities.

[Figures 1 and 2 about here]

In Figures 3 and 4, we display the shares of open interest by type of trader based on the COT-CIT data. We use long positions in order to calculate these shares since CITs are always deeply net long in the twelve agricultural markets examined. By contrast, commercial traders are predominantely net short, while for non-commercial traders no clear conclusion can be drawn. The figures visualize that in general non-commercial traders hold the largest part of the outstanding long positions, and non-reporting traders constitute the smallest group. More important, CITs also have a substantial share on the long side of each market, ranging from a minimal mean value of 15% in case of cocoa to a maximal mean value of about 40% in case of soft wheat. In sum, Figures 1 to 4 thus justify our interest in whether the strong investment activities of CITs are responsible for the severe ups and downs of agricultural futures prices over the last decade, leading to more volatile markets.

[Figures 3 and 4 about here]

3. Methodology

In order to analyze whether commodity index investing has destabilized agricultural futures prices, we draw on Adrangi and Chatruth (1998), and measure how conditional volatility has been affected by the expected and unexpected open interest of CITs. Alternatively, we follow Wang (2002), and examine the influence of their expected and unexpected net positions on conditional volatility. In both cases, as in Bessembinder and Seguin (1992), we control for volatility persistence by including lagged volatility, and for the impact of aggregate trading activity by drawing on expected and unexpected overall trading volume and open interest, respectively.

As shown by Board et al. (2001), conventional approaches for modelling conditional volatility, such as GARCH-type models, suffer from a simultaneity bias once variables representing information-based trading activity are included. This simultaneity bias arises since trading activity cannot be assumed to be even weakly exogenous. Instead, conditional volatility and trading activity are jointly determined by information arrival. Recent research has thus focused upon SV models in which conditional volatility is treated as an unobserved component. While in GARCH-type models conditional volatility is specified to be a particular function of lagged squared unexpected returns and its own past, SV models assume that it is driven by an unobserved, latent factor, i.e., new information.

In the SV model, returns are described by:

$$r_t = \sigma_t \epsilon_t, \tag{1}$$

where $r_t = R_t - \mu_t$ is the mean-adjusted return, σ_t is the standard deviation of the error term ϵ_t, and $\epsilon_t \overset{i.i.d.}{\sim} N(0,1)$. Squaring and taking natural logarithms, $\ln(\cdot)$, of eq. (1) leads to the linear model:

$$\ln(r_t^2) = \ln(\sigma_t^2) + \ln(\epsilon_t^2), \tag{2}$$

where the mean and the variance of $\ln(\epsilon_t^2)$ are known to be $\psi(1/2) - \ln(1/2) \approx -1.27$ and $\pi^2/2$, respectively, with $\psi(\cdot)$ denoting the Digamma function (Abramovitz and Stegun, 1970, p. 943). The measurement equation then reads:

$$y_t = h_t + \xi_t, \tag{3}$$

where $y_t = \ln(r_t^2) + 1.27$, $h_t = \ln(\sigma_t^2)$, and $\xi_t \overset{i.i.d.}{\sim} (0, \pi^2/2)$.[7] Conditional volatility is specified in the transition equation:

$$h_t = \alpha + \phi h_{t-1} + \sum_{j=1}^{2} (\delta_j EA_{j,t} + \pi_j UA_{j,t}) + \gamma ET_t + \lambda UT_t + \theta D_t \times UT_t + \eta_t, \qquad (4)$$

where $EA_{j,t}$ and $UA_{j,t}$, with $j = 1, 2$, are expected and unexpected overall trading volume and open interest, respectively; ET_t and UT_t are expected and unexpected open interest of CITs, respectively; D_t is a indicator variable that is equal to 1 for a positive shock in the open interest of CITs, and 0 otherwise; and $\eta_t \overset{i.i.d.}{\sim} N(0, \delta^2)$, which is uncorrelated with ξ_t in eq. (3) (Harvey et al., 1994, Appendix A).[8]

In order to allow for possibly asymmetric responses of conditional volatility to shocks in the open interest of CITs, we include an interaction variable in eq. (4), defined as the product of the indicator variable, D_t, and the unexpected open interest of CITs, UT_t. The coefficient estimate for unexpected open interest of CITs, λ, thus represents the marginal impact of a negative shock in the open interest of CITs on conditional volatility. Summing this and the coefficient estimate for the interaction variable, θ, measures how conditional volatility is influenced by a positive shock in the open interest of CITs. The statistical significance of the latter effect is judged based on a likelihood ratio test.

With focus on the last three exogenous variables in eq. (4), we establish the following three hypotheses: First, if γ is statistically significant and positive, expected open interest of CITs increases conditional volatility. However, since the expected component of the open interest of CITs is informationless, we do not assume this hypothesis to hold. Second, if λ is statistically significant and *negative*, unexpected negative open interest of CITs increases conditional volatility. In this case, CITs destabilize the mar-

[7] If the assumption of normality for ϵ_t in eq. (1) needs to be relaxed, the variance of ξ_t has to be estimated unrestrictedly (Harvey et al., 1994, Section 6).

[8] Note that the Kalman filter approach is still valid when ϕ equals unity. The only difference then is that the first observation is needed to initialize the Kalman filter, whereas in case of $|\phi| < 1$ the unconditional distribution of h_t is available at $t = 0$ (Harvey et al., 1994).

ket by holding less futures contracts than expected. Third, if $(\lambda + \theta)$ is statistically significant and positive, unexpected positive open interest of CITs increases conditional volatility. In this case, CITs destabilize the market by holding more futures contracts than expected. In sum, we thus interpret an enhancing effect of one or several of the last three exogenous variables in eq. (4) on conditional volatility as evidence for the destabilizing role of CITs in agricultural futures markets.

As in Bessembinder and Seguin (1992), aggregate trading activity and the open interest of CITs are decomposed into expected and unexpected components by using an auto-regressive integrated moving average (ARIMA) model. The expected component is the fitted value from the ARIMA model, while the unexpected component is the difference between the actual time series and the fitted component.[9] Alternatively, as proposed by Adrangi and Chatruth (1998) and Wang (2002), we decompose the time series by using the technique of Hodrick and Prescott (1997; HP filter).

As proposed by Harvey et al. (1994) and Ruiz (1994), we estimate the SV model in eqs. (3) and (4) by using quasi maximum likelihood (QML) and the Kalman filter. Based on simulation exercises, it can be shown that the QML method works well for sample sizes typically encountered in financial economics, and is usually to be preferred to the corresponding method of moments estimator. Even though the SV model is not conditionally Gaussian, estimates can be obtained by treating ξ_t in eq. (3) as though it were i.i.d. N(0, $\pi^2/2$), and maximizing the resulting quasi-likelihood function via the Kalman filter.[10] Asymptotic standard errors are derived by using the results of Dunsmuir (1979, p. 502).

[9] The order of integration is determined by an Augmented Dickey-Fuller (ADF) test which examines the null hypothesis of a unit-root against the alternative hypothesis of (trend-)stationarity. The optimal lag length of the AR(p) and the MA(q) term is chosen by computing all ARIMA models for p, q = (0, …, 3) and then selecting that specification with the lowest value of Akaike's information criterion (AIC). All ARIMA models are estimated via maximum likelihood (ML).

[10] "It is often asserted in books and papers that the Kalman filter is not optimal unless the noise is Gaussian. However, as our derivation (...) has shown, that is simply untrue. Such statements arise from erroneous interpretations of Kalman filter derivations. Even if the noise is not Gaussian, the Kalman filter is still the optimal linear filter" (Simon, 2006, p. 130).

4. Empirical Results

4.1. Summary Statistics and Model Selection

The SV model in eqs. (3) and (4) is based on weekly futures price returns and trading activity variables. Panel A of Table 1 provides summary statistics of the return distributions of the twelve agricultural commodities examined. It shows that the mean return is never statistically significantly different from zero. In addition, returns on feeder and live cattle appear to be least volatile as indicated by the lowest maximum and minimum values (in absolute terms), and the lowest (unconditional) standard deviations. Interestingly, these two livestock commodities are characterized by relatively small futures markets and less severe price spikes and crashes over the last decade (see Figures 1 and 2). By contrast, the return distributions of all other agricultural commodities examined have double-digit maximum and minimum values, and standard deviations almost or more than twice as high as in case of feeder and live cattle. Finally, except for wheat, all return distributions appear to be non-Gaussian, which, however, does not affect the derivation of the SV model in Section 3.

Next, we determine the order of integration of aggregate trading volume and the various open interest variables for the twelve agricultural commodities examined. As shown by various ADF tests, all time series contain a unit-root except for trading volume which appears to be stationary in each case.[11] Based on the order of integration, we then disentangle the trading activity variables into expected and unexpected components, using the most appropriate ARIMA model and the HP filter, respectively. Panel B of Table 1 shows the ARIMA specifications chosen.

[Table 1 about here]

[11]Results are not shown, but can be obtained from the authors upon request.

4.2. Regression Results

Based on the decomposition of the trading activity variables, we are now ready to estimate the SV model in eqs. (3) and (4). In our main model, we use the open interest of CITs for approximating index-based trading activities, and the ARIMA decomposition for disentangling expected and unexpected components. Given our interest in whether CITs have destabilized agricultural futures markets, we focus on the parameter estimates of the volatility equation (4).

Results are shown in TABLE 2. Interestingly, some findings are the same among almost all agricultural commodities examined. First, the constant term, representing the time-invariant level of conditional volatility, is never statistically significant except for soybean oil. Second, lagged volatility always has a highly statistically significant and positive influence except for hard wheat, confirming our expectation of time-varying but persistent conditional volatility. In addition, since the auto-regressive parameter estimate is always smaller than unity, we have stationary conditional volatility processes, implying that shocks die out in finite time. Third, variables representing aggregate trading activity are either not statistically significant or do not show any consistent influence. The sole exception is unexpected overall trading volume which has a statistically significant and positive influence except for soybean oil and hard wheat, confirming earlier results in the literature as discussed in SECTION 1.

More important, expected open interest of CITs does not affect agricultural futures price movements in a consistent way. Only for feeder cattle and hard wheat, it leads to a statistically significant increase in conditional volatility. Similarly, unexpected negative open interest of CITs does not show any consistent influence either. Only for cotton, live cattle, and (again) hard wheat, it results in a statistically significant increase in conditional volatility. Summing the coefficient on a negative shock and the coefficient on the interaction variable from eq. (4) gives the effect of unexpected positive open interest of CITs. Since the parameter estimate is not statistically significant in almost each case, we conclude that positive shocks in open interest of CITs do not affect agricultural futures price fluctuations either. Only for soft wheat, unexpected positive open interest of CITs leads to a statistically significant increase in conditional volatility. In sum, we are thus unable to provide empirical evidence that the intensive investment activities of CITs, represented by their open interest and decomposed in its expected and unexpected component by an ARIMA model, has destabilized agricultural futures prices over the last six years on a large scale.

[TABLE 2 about here]

4.3. Robustness Checks

As a first robustness check of our results, we replace open interest by net positions of CITs in order to account for index-based trading activities. Results are shown in TABLE 3. As in case of the main model presented in SECTION 4.2, some characteristics appear to be quite similar among most of the twelve agricultural commodities examined. Lagged volatility always has a positive effect which is often statistically significant (except for cocoa, feeder cattle, and hard wheat) but never equals unity, indicating stationary processes. Variables representing aggregate trading activity do not show any consistent effect except for unexpected overall trading volume which has a statistically significant and positive influence in half of all cases. More important, for none of the twelve agricultural commodities examined, expected net positions of CITs lead to a statistically significant increase in conditional volatility, while negative shocks do so only for live cattle and soybeans. Finally, only in case of soybean oil, unexpected positive net positions of CITs have a statistically significant and positive effect. All in all, we thus again deny that CITs, represented by their net positions which are disentangled into expected and unexpected components by an ARIMA model, has destabilized agricultural futures prices over the last six years in a meaningful way.

[Table 3 about here]

In order to show that our results are robust to the choice of the method of decomposition as well, we next disentangle the trading activity variables into expected and unexpected components by using the HP filter instead of an ARIMA model. Results are shown in Table 4. The most important insights are the following: Volatility persistence, characterized by the statistically significant auto-regressive parameter estimate, is given in each case. Unexpected overall trading volume leads to a statistically significant increase in conditional volatility except for corn and hard wheat. All other variables representing aggregate trading activity do not show any consistent effect. Similarly, expected and unexpected open interest of CITs do not lead to increased conditional volatility either. The only exceptions are feeder cattle in case of expected, cotton and live cattle in case of unexpected negative, and coffee and soybean oil in case of unexpected positive open interest of CITs. In sum, we thus repeat that the intensive investment activities of CITs, represented by their open interest and decomposed in its expected and unexpected component by the HP filter, has not made agricultural futures prices more volatile over the last six years on a large scale.

[Table 4 about here]

As a final robustness check, we approximate index-based trading activities by using the open interest of swap dealers, taken from the DCOT report, as a replacement for the open interest of CITs, taken from the COT-CIT report. Results are shown in Table 5. The principle findings can be summarized as follows: Volatility clusters, represented by the statistically significant influence of lagged volatility, are always present except for cocoa, cotton, and hard wheat. Among the variables representing aggregate trading activity, only unexpected trading volume has a statistically significant and positive effect in half of all cases. More important, neither expected nor unexpected open interest of swap dealers leads to a statistically significant increase in conditional volatility for any of the twelve agricultural commodities examined. All in all, we thus conclude that even representing index-based trading activities by the open interest of swap dealers does not allow us to conclude that agricultural futures markets have been destabilized over the last six years in any way.

[Table 5 about here]

5. Conclusion

Motivated by repeated price spikes and crashes over the last decade, we investigate whether the intensive investment activities of CITs has led to a destabilization of agricultural futures markets. Using a stochastic volatility model, we treat conditional volatility as an unobserved component, and analyze whether it has been affected by the expected and unexpected open interest of CITs. However, with respect to twelve increasingly financialized grain, livestock, and soft commodities, we do not find robust evidence that CITs can be held responsible for making their futures prices more volatile. Instead, we detect volatility persistence and a positive effect of unexpected overall trading volume, confirming prior results in the literature.

Our econometric findings have important policy implications. As generally accepted, futures trading is a valuable activity since it improves price discovery, enhances market efficiency, increases market depth and informativeness, and contributes to market completion. However, in order to justify their demand for curbing commodity speculation, for instance by implementing position limits, politicians, regulators, and part of the media regularly take increased price volatility as a major concern. Based on our empirical results, we argue that taking such measures in response to the allegedly destabilizing impact of CITs on agricultural futures prices is unwarranted.

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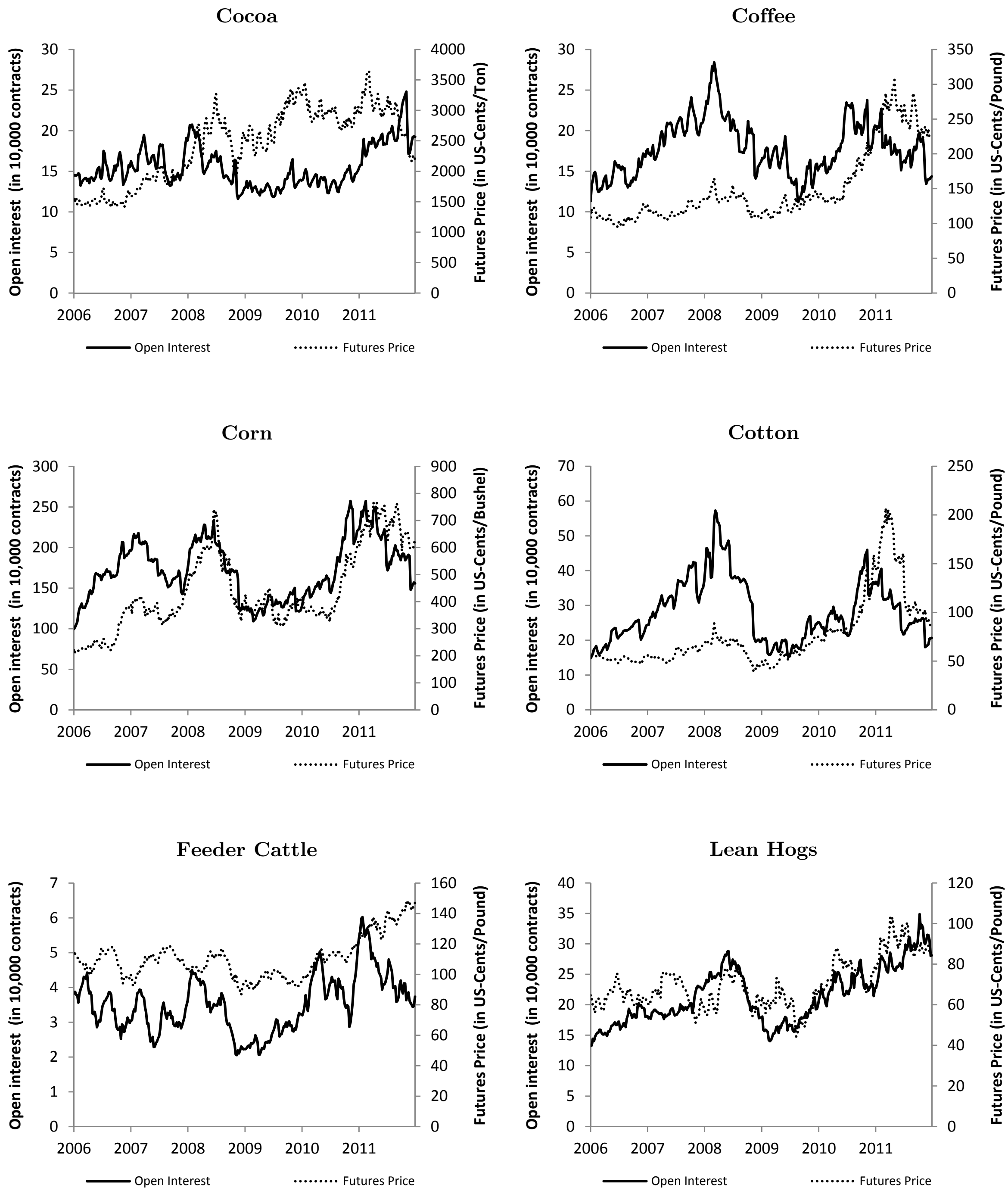
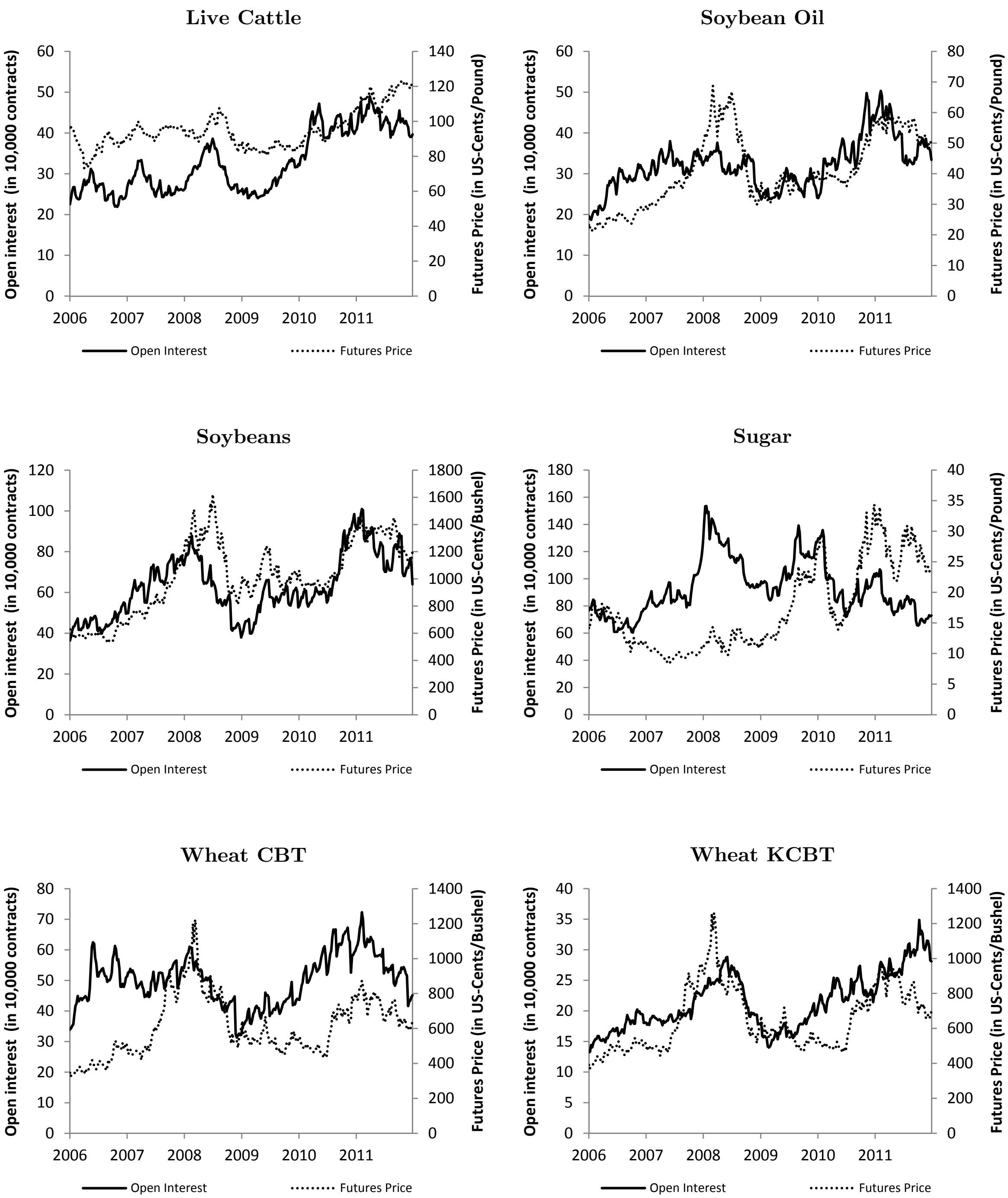
Figure 1: Open Interest and Futures Prices (1)



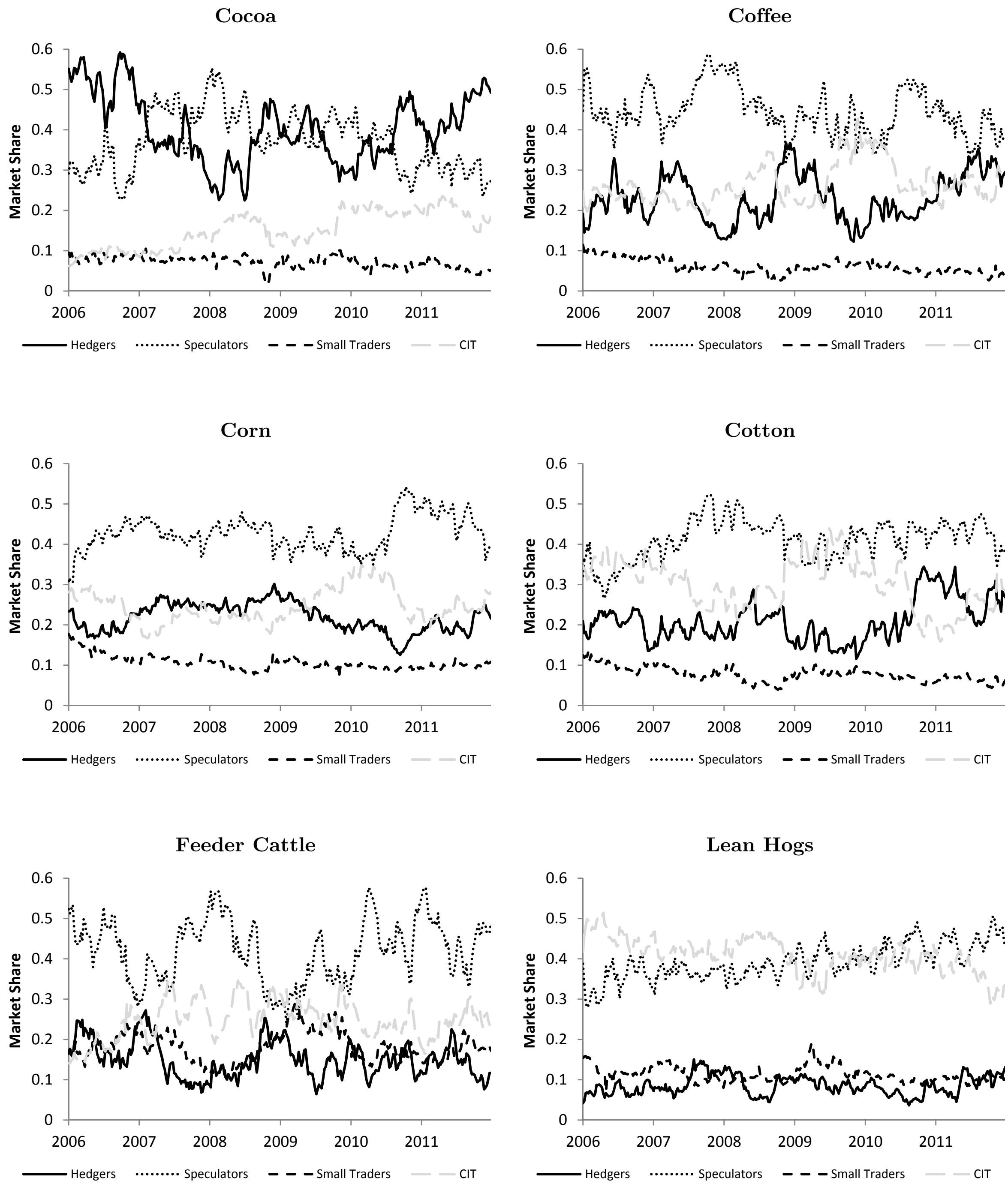
Notes: The figures display Tuesday's aggregate open interest and the price of the first-nearby futures contract.

Figure 2: Open Interest and Futures Prices (2)



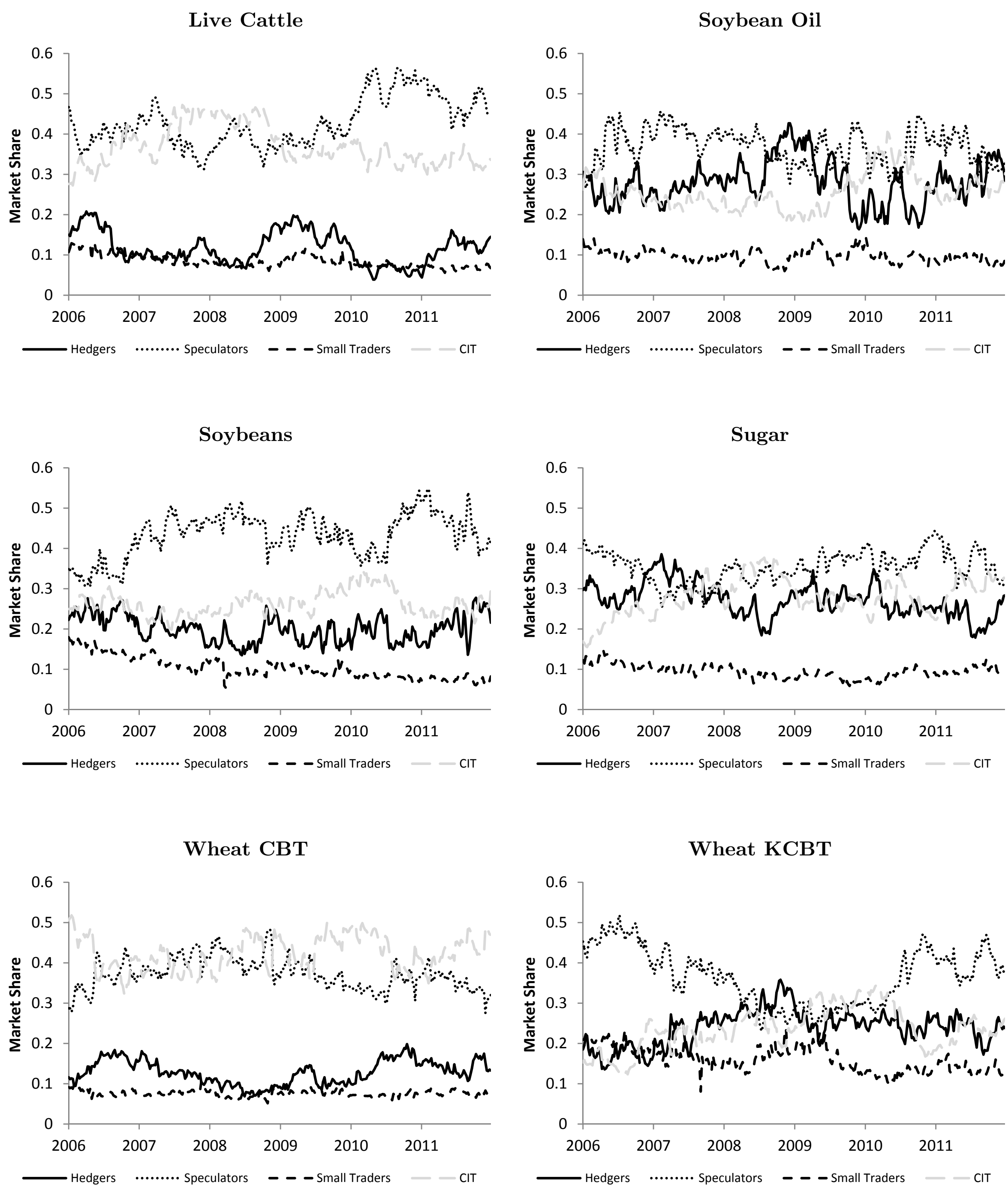
Notes: The figures display Tuesday's aggregate open interest and the price of the first-nearby futures contract.

Figure 3: Market Shares (1)



Notes: The figures display the shares of Tuesday's open interest by type of trader based on the long positions.

Figure 4: Market Shares (2)



Notes: The figures display the shares of Tuesday's open interest by type of trader based on the long positions.

Table 1: Summary Statistics and Model Selection

Panel A: Summary Statistics

	Mean	Max	Min	Stdev.	Skew	Kurt	JB
Cocoa	0.1153	14.3100	-16.7190	4.4107	-0.1087	4.0569	15.1391***
Coffee	0.2303	17.6627	-13.3038	4.4166	0.0202	3.6311	5.1999*
Corn	0.3388	18.4099	-16.4929	5.2276	-0.0230	3.9273	11.2067***
Cotton	0.1489	16.1534	-30.2142	5.1048	-0.8167	7.3245	99.8105***
Feeder Cattle	0.0818	7.9794	-9.0751	2.2029	-0.2071	4.0360	16.1858***
Lean Hogs	0.0905	19.3375	-12.5896	4.4292	0.7064	5.2559	92.1100***
Live Cattle	0.0787	9.1528	-10.8125	2.3062	0.1670	5.2846	69.3042***
Soybean Oil	0.2571	15.0093	-11.5969	3.9838	-0.0228	3.6610	5.7071*
Soybeans	0.2072	10.6774	-15.1842	4.0269	-0.4856	4.0450	26.4616***
Sugar	0.1634	17.1303	-22.9886	5.8684	-0.3377	4.0564	20.4409***
Wheat CBT	0.1994	18.8008	-17.6251	5.4168	0.0598	3.3970	2.2354
Wheat KCBT	0.1851	14.7807	-16.3728	4.8831	-0.0025	3.1935	0.4872

Notes: Summary statistics are shown for the return distributions of the twelve agricultural commodities examined. Continuous weekly returns (in percent) are calculated as the change in logarithmic settlement prices. JB denotes the value of the Jarque-Bera-statistic for the test of normality. ***, ** and * denote statistical significance at the 1%-, 5%- and 10%-level, respectively.

Panel B: Model Selection

	TV	OI	OICIT	NPCIT	OISD
Cocoa	(3, 0, 3)	(2, 1, 1)	(3, 1, 3)	(1, 1, 0)	(2, 1, 2)
Coffee	(2, 0, 3)	(2, 1, 2)	(1, 1, 0)	(3, 1, 3)	(2, 1, 2)
Corn	(3, 0, 3)	(2, 1, 2)	(3, 1, 2)	(3, 1, 3)	(2, 1, 2)
Cotton	(3, 0, 3)	(2, 1, 2)	(2, 1, 3)	(3, 1, 3)	(3, 1, 3)
Feeder Cattle	(3, 0, 3)	(3, 1, 0)	(3, 1, 1)	(1, 1, 2)	(1, 1, 1)
Lean Hogs	(3, 0, 2)	(1, 1, 1)	(2, 1, 3)	(1, 1, 1)	(2, 1, 0)
Live Cattle	(3, 0, 2)	(2, 1, 2)	(1, 1, 2)	(1, 1, 2)	(3, 1, 2)
Soybean Oil	(3, 0, 3)	(0, 1, 3)	(3, 1, 2)	(1, 1, 0)	(0, 1, 1)
Soybeans	(2, 0, 1)	(3, 1, 2)	(1, 1, 0)	(1, 1, 0)	(1, 1, 0)
Sugar	(1, 0, 0)	(3, 1, 2)	(1, 1, 1)	(3, 1, 3)	(3, 1, 3)
Wheat CBT	(3, 0, 2)	(3, 1, 2)	(1, 1, 0)	(3, 1, 3)	(3, 1, 3)
Wheat KCBT	(3, 0, 2)	(0, 1, 3)	(2, 1, 3)	(2, 1, 2)	(3, 1, 2)

Notes: ARIMA(p, d, q) specifications are shown for the time series of aggregate trading volume (TV), aggregate open interest (OI), open interest (OICIT) and net positions of CITs (NPCIT), and open interest of swap dealers (OISD) for the twelve agricultural commodities examined. The order of integration is determined by an ADF test which examines the null hypothesis of a unit-root against the alternative hypothesis of (trend-)stationarity. The optimal lag length of the AR(p) and the MA(q) term is chosen by computing all ARIMA models for p, q = (0, ..., 3) and then selecting that specification with the lowest value of the AIC. All ARIMA models are estimated via ML.

Table 2: Regression Results – CITs, Open Interest, ARIMA Decomposition

	Cocoa	**Coffee**	**Corn**	**Cotton**	**Feeder Cattle**	**Lean Hogs**
Constant	-2.7434	-8.5275	3.9877	-0.3183	3.6166	1.0037
Volatility	0.8332***	0.6562***	0.6100***	0.9550***	0.5700***	0.9494***
Exp. TV	-0.0116	-0.0111**	0.0048	-0.0807**	-0.0114	-0.0120***
Unexp. TV	0.0132*	0.0155***	0.0962*	0.1270***	0.0444**	0.0124***
Exp. OI	-0.0040	0.0342	0.0117**	-3.3306***	-0.2076	-0.1814
Unexp. OI	-0.0217	-0.0064	0.0535*	-0.6242*	-0.0524	0.0089
Exp. OICIT	-0.1061	-0.3222	-0.0935	1.8087	2.8069**	0.0940
Unexp. OICIT	-0.0294	-0.0106	-0.0198	-2.4702**	-0.0760	-0.0303
D×Un. OICIT	-0.0886	0.1272	0.0171	-1.5302	-1.0315	0.0215
Un. OICIT$^+$	-0.1180	0.1166	-0.0027	-4.0004***	-1.1075	-0.0088
Std. deviation	1.3161***	0.2286	0.2664	1.6200***	0.9200***	0.0384

	Live Cattle	**Soybean Oil**	**Soy-beans**	**Sugar**	**Wheat CBT**	**Wheat KCBT**
Constant	9.9999	1.1084***	-4.7555	-1.9981	-0.1705	-0.2537
Volatility	0.6251***	0.7507***	0.7621***	0.8677***	0.7334***	0.7683
Exp. TV	-0.0047**	-1.4345***	-0.0001	0.0001	-0.0003	0.0083
Unexp. TV	0.0062*	-1.5594***	0.0029**	0.0026***	0.0018*	-0.0090
Exp. OI	-0.0305	1.2155***	-0.0062	-0.0218**	0.0134	-0.1012
Unexp. OI	0.0081	-0.2122	-0.0048	0.0018	0.0011	0.0218
Exp. OICIT	-0.0659	-0.7061*	-0.0310	-0.0084	0.3239	1.3141*
Unexp. OICIT	-0.1017*	-1.6775	0.0312	0.0250	0.0217	-0.7184***
D×Un. OICIT	0.2301**	0.0815***	-0.0744*	-0.0419	0.0283*	0.7686**
Un. OICIT$^+$	0.1284	-1.5960	-0.0432	-0.0169	0.0500*	0.0502
Std. deviation	0.0678**	1.0866***	0.3320	0.1326	0.6350	0.3102*

Notes: Results are shown for the volatility equation (4). Volatility stands for lagged conditional volatility. TV, OI, and OICIT stand for aggregate trading volume, aggregate open interest, and open interest of CITs, respectively, in units of 1,000 contracts, which are decomposed into expected and unexpected components based on an ARIMA(p, d, q) model. D is an indicator variable which is equal to 1 if unexpected open interest of CITs is positive, and 0 otherwise. Un. OICIT$^+$ stands for unexpected positive open interest of CITs. Std. deviation is the standard deviation of the error term. ***, ** and * denote statistical significance at the 1%-, 5%- and 10%-level, respectively. The sample covers the period from January 2006 to December 2011 (313 weeks).

Table 3: Regression Results – CITs, Net Positions, ARIMA Decomposition

	Cocoa	**Coffee**	**Corn**	**Cotton**	**Feeder Cattle**	**Lean Hogs**
Constant	-0.9407	-0.9943	2.8511	-0.6129	9.0798	1.2893
Volatility	0.4865	0.4703**	0.5912***	0.8775***	0.3777	0.9051***
Exp. TV	0.0167	-0.0066	0.0001	-0.0062	-0.0100	-0.0198*
Unexp. TV	0.0099	0.0117**	0.0008	0.0118	0.0277	0.0207**
Exp. OI	0.0567	-0.0434	0.0103*	-0.0297	-0.3030	-0.2286
Unexp. OI	0.0380	-0.0275**	0.0033	-0.0107	-0.0454	-0.0079
Exp. NPCIT	0.1119	-0.5026**	-0.0391	0.0625	-0.3872	0.0440
Unexp. NPCIT	-0.3276	0.8367***	-0.0181	-0.5732	-0.4606	-0.0128
D×Un. NPCIT	0.2587	-1.4834***	0.0396	0.4801	0.8167	-0.0142
Un. NPCIT$^+$	-0.0689	-0.6467	0.0215	-0.0931	0.3561	-0.0270
Std. deviation	0.1336	0.4278	0.3121	1.0700***	0.4910	0.2953***

	Live Cattle	**Soybean Oil**	**Soy-beans**	**Sugar**	**Wheat CBT**	**Wheat KCBT**
Constant	9.9997	8.4483***	-9.9996	-2.6684	-0.2626	-0.6854
Volatility	0.6463***	0.5422***	0.2632***	0.7965***	0.7010***	0.6885
Exp. TV	-0.0045**	-0.0109***	-0.0001	0.0001	0.0082	-0.0031
Unexp. TV	0.0067**	0.0042***	0.0024**	0.0027***	0.0359	0.0093
Exp. OI	-0.0291	0.2456***	-0.0114	-0.0233**	0.0186	-0.0360
Unexp. OI	0.0064	-0.0717***	-0.0020	0.0038	-0.2666	0.0122
Exp. NPCIT	-0.0167	-1.4557***	-0.3974***	0.0132	-0.3165	0.0250
Unexp. NPCIT	-0.2063**	0.5282***	-0.1861**	0.0361	0.0015	-0.2774
D×Un. NPCIT	0.3846***	0.0544*	0.4196***	-0.1119**	0.2250	0.3359
Un. NPCIT$^+$	0.1783	0.5826***	0.2335	-0.0758	0.2265	0.0585
Std. deviation	0.0620	0.2216***	0.7356*	0.1347	0.9260	0.0010*

Notes: Results are shown for the volatility equation (4). Volatility stands for lagged conditional volatility. TV, OI, and NPCIT stand for aggregate trading volume, aggregate open interest, and net positions of CITs, respectively, in units of 1,000 contracts, which are decomposed into expected and unexpected components based on an ARIMA(p, d, q) model. D is an indicator variable which is equal to 1 if unexpected net positions of CITs are positive, and 0 otherwise. Un. NPCIT$^+$ stands for unexpected positive net positions of CITs. Std. deviation is the standard deviation of the error term. ***, ** and * denote statistical significance at the 1%-, 5%- and 10%-level, respectively. The sample covers the period from January 2006 to December 2011 (313 weeks).

Table 4: Regression Results – CITs, Open Interest, HP Filter

	Cocoa	**Coffee**	**Corn**	**Cotton**	**Feeder Cattle**	**Lean Hogs**
Constant	-0.2778	-0.1637	3.0968	0.3045**	3.6688	1.0138
Volatility	0.9315***	0.9546***	0.7785***	0.9248***	0.5694***	0.9501***
Exp. TV	0.0652***	-0.0080	0.0001	-0.0027**	-0.0115	-0.0120***
Unexp. TV	0.0217**	0.0190***	0.0009	0.0083***	0.0443**	0.0124***
Exp. OI	0.0709	0.0682	0.0118**	0.0087	-0.2080	-0.1844
Unexp. OI	0.0902***	0.0005	0.0053*	0.0026	-0.0526	0.0090
Exp. OICIT	-2.0899***	-0.8513**	-0.0935	0.1403	2.8110**	0.0956
Unexp. OICIT	0.6230	0.0883	-0.0199	-0.0397*	-0.0781	-0.0300
D×Un. OICIT	-1.1645***	0.2399*	0.0168	-0.0261	-1.0238	0.0209
Un. OICIT$^+$	-0.5415***	0.3282*	-0.0031	-0.0658*	-1.1019	-0.0091
Std. deviation	0.0344***	0.1637***	0.2630	0.0279***	0.0001	0.0380

	Live Cattle	**Soybean Oil**	**Soy-beans**	**Sugar**	**Wheat CBT**	**Wheat KCBT**
Constant	1.9999	0.0255	0.0001	0.0001	0.0001	3.5050
Volatility	0.5208***	0.9917***	0.7246***	0.7950***	0.7309***	0.9552***
Exp. TV	-0.0045*	-0.0002***	-0.0001	0.0001*	-0.0003	0.0046
Unexp. TV	0.0065**	0.0020***	0.0029***	0.0028***	0.0019*	0.0079
Exp. OI	-0.0349	0.0157	-0.0065	-0.0232	0.0133	0.0495
Unexp. OI	0.0106	0.0054	-0.0048	0.0014	0.0010	0.0342
Exp. OICIT	-0.0636	-0.3180**	-0.0032**	-0.0133	0.3253	-0.1017
Unexp. OICIT	-0.1199*	-0.0059	0.0296	0.0293	0.0224	-0.1630
D×Un. OICIT	0.2510**	0.0387*	-0.0611	-0.0465*	0.0282	0.1445
Un. OICIT$^+$	0.1311	0.0328*	-0.0315	-0.0172	0.0506	-0.0185
Std. deviation	0.0578	0.0001	0.4032**	0.2478***	0.0002	0.0001

Notes: Results are shown for the volatility equation (4). Volatility stands for lagged conditional volatility. TV, OI, and OICIT stand for aggregate trading volume, aggregate open interest, and open interest of CITs, respectively, in units of 1,000 contracts, which are decomposed into expected and unexpected components based on the HP filter. D is an indicator variable which is equal to 1 if unexpected open interest of CITs is positive, and 0 otherwise. Un. OICIT$^+$ stands for unexpected positive open interest of CITs. Std. deviation is the standard deviation of the error term. ***, ** and * denote statistical significance at the 1%-, 5%- and 10%-level, respectively. The sample covers the period from January 2006 to December 2011 (313 weeks).

Table 5: Regression Results – Swap Dealers, Open Interest, ARIMA Decomposition

	Cocoa	**Coffee**	**Corn**	**Cotton**	**Feeder Cattle**	**Lean Hogs**
Constant	-0.7051	1.9999	0.0001	-0.3596	0.0001	1.4582
Volatility	0.5434	0.4571***	0.4544***	0.7685	0.8252***	0.9588***
Exp. TV	-0.0039	-0.0126**	-0.0004**	0.0059	-0.0130	-0.0135***
Unexp. TV	0.0232***	0.0168***	0.0021***	-0.0076	0.0101	0.0132***
Exp. OI	0.1586	-0.2165**	-0.0309***	0.1576***	-0.0605	0.0939
Unexp. OI	-0.0116	-0.0182	0.0003	-0.0889*	-0.0424	-0.0090
Exp. OISD	0.5831	-0.2512	-0.0668	0.1938	3.9851	0.1949
Unexp. OISD	-0.0163	0.0877	0.0002	-0.1346	-0.8751	-0.0298
D×Un. OISD	-0.0639	-0.0438	0.0204	0.1229	0.4922	0.0210
Un. OISD^{+}	-0.0802	0.0439	0.0206	-0.0117	-0.3829	-0.0088
Std. deviation	0.4011	0.2253	0.0002	0.4410***	0.0320	0.0384

	Live Cattle	**Soybean Oil**	**Soy-beans**	**Sugar**	**Wheat CBT**	**Wheat KCBT**
Constant	-0.7627	4.8306	0.5552	0.7927*	3.2937	1.9998
Volatility	0.8310***	0.5422***	0.8791***	0.8251***	0.7321***	0.4141
Exp. TV	-0.0140	-0.0109	-0.0001	0.0003**	-0.0002	0.0019
Unexp. TV	-0.0012	0.0042	0.0023***	0.0039	0.0027	0.0096*
Exp. OI	0.0520	0.2456	-0.0217	-0.0347	-0.0261	-0.1266
Unexp. OI	0.0027	-0.0717	-0.0108	-0.0043	0.0001	0.0298
Exp. OISD	0.2680	-1.4557	0.4032	-0.0829	-0.0338	0.1173
Unexp. OISD	-0.1606	0.5282	0.0451	0.0304	0.0533	-0.1447
D×Un. OISD	0.1437	0.0544	-0.0920**	-0.0518	-0.0901	0.1644
Un. OISD^{+}	-0.0169	0.5826	-0.0469	-0.0214	-0.0368	0.0197
Std. deviation	0.5260	0.0163	0.0642	0.0711	0.0666*	0.1220

Notes: Results are shown for the volatility equation (4). Volatility stands for lagged conditional volatility. TV, OI, and OISD stand for aggregate trading volume, aggregate open interest, and open interest of swap dealers, respectively, in units of 1,000 contracts, which are decomposed into expected and unexpected components based on an ARIMA(p, d, q) model. D is an indicator variable which is equal to 1 if unexpected open interest of swap dealers is positive, and 0 otherwise. Un. OICIT^{+} stands for unexpected positive open interest of swap dealers. Std. deviation is the standard deviation of the error term. ***, ** and * denote statistical significance at the 1%-, 5%- and 10%-level, respectively. The sample covers the period from mid-June 2006 to December 2011 (290 weeks).