Do Speculators in Futures Markets Make Cash Markets More Volatile?

Yingzi Li
yingzi.li@email.wsu.edu
and
T. Randall Fortenbery
r.fortenbery@wsu.edu
509-335-7637

School of Economic Sciences
Washington State University
PO Box 646210
Pullman, WA 99164-6210

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Yingzi Li and T. Randall Fortenbery*

* Graduate Student and Tom Mick Chair, School of Economic Sciences,
Washington State University

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Abstract

This paper investigates the extent to which speculative trade in futures markets contributes to volatility in cash markets. By analyzing coffee, crude oil and wheat we find that futures and cash prices are cointegrated in levels and exhibit bi-directional causality in variance. Thus, factors causing higher futures price volatility will also cause higher cash price volatility. Results suggest increases in speculative activity are associated with decreases in futures price volatility, thus cash price volatility. On balance it appears that policies which limit speculative trade contribute to de-stabilizing cash prices, rather than reducing volatility as intended.

Key words: speculation, cash price volatility, cointegration, causality in variance, crude oil, wheat, coffee

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Introduction

Beginning in late 2007, most commodity markets experienced an increase in average price levels, accompanied by higher volatility (Figure 1). Several studies have attempted to explain this price behavior. Many have focused on the futures markets of the underlying commodities. Some of them blame speculators for the recent price action based on the observation that speculative positions increased significantly before price increases were observed (Masters, 2008; Masters, 2010; Singleton, 2012). Influenced by these accusations, the U.S. Commodity Futures Trading Commission (CFTC) approved limits on the size of speculative positions for 28 core physical commodities in October 2011, intending to mitigate speculative influence in futures markets. These limits immediately stirred debate regarding their necessity or effectiveness in managing speculators and the potential adverse effect on commercial entities that use derivatives to hedge price risk.

Several other studies failed to find causality between speculation and price movements and concluded that speculators do not destabilize futures markets (Brunetti and Büyükşahin, 2009; Büyükşahin and Harris, 2011; Sanders and Irwin, 2011; Hamilton and Wu, 2012; Irwin and Sanders, 2012). These appear to have had less influence in driving recent policy initiatives.

Despite the number of previous studies, the body of the research is not complete. Most of the earlier studies focused on speculative influences on price levels rather than price volatility. Further, they were directed at speculative influences on commodity futures prices and did not explicitly examine the influence on cash prices. In this paper we examine whether speculation in futures markets contributes to increased volatility in cash prices. This is an important consideration because cash price volatility reflects the price risk faced by both producers and consumers of the physical commodity and much of the debate about speculative influence is really a debate about the way other market participants are impacted by futures price activity. The focus of this work is on crude oil[1], wheat, and coffee. These products differ in terms of commodity category (they cover energy, and both imported and exported food stuffs, as well as both thin and deep futures markets), and the characteristics of their futures markets. Crude oil is the largest natural resource commodity in futures trading, wheat futures contracts are one of the oldest and most actively traded agricultural futures in the U.S., and the coffee futures market represents both a thin market and one with no domestic production. Further, the potential of the coffee futures market to impact the price risk faced by cash market participants has already been alluded to Fortenbery and Zapata (2004).

Literature Review

Masters(2008; 2010) and Singleton (2012) argued speculators were a major driver in the 2008 run-up in commodity futures, particularly energy futures prices. Their conclusions were based on observing increases in speculative futures positions prior to observing futures price increases. They essentially observed correlation with position changes leading price changes, but did not rigorously test for causality.

[1] For crude oil, spot market and spot price are often used instead of cash market and cash price. But in this paper we do not interchange the words and use cash market and cash price for all the three commodities.

Several other studies introduced more rigor to test for the existence of excessive speculation. Alquist and Gervais (2011) used Working's T-index (Working, 1960) to test for excessive speculation and found that the index did increase in 2008 when the price of oil increased dramatically. However, this index also reached similar levels in 2003 and 2005 when oil prices were low. Moreover, the index was low at the end of 2010 when the net long non-commercial positions in futures markets was high, suggesting that speculative pressures were subdued by hedging demand from commercial firms. Their findings suggested that it may be misleading to claim excessive speculation merely by noticing a high level of speculative positions. Similar results were presented by Ripple (2008) and Büyükşahin and Harris (2011).

Irwin and Sanders (2012) pointed out that Singleton's measure of index fund positions in oil futures was in fact inferred from CFTC data on agricultural futures which had little relation to index funds' actual positions in oil. Hamilton and Wu (2012) demonstrated that the agricultural index fund positions used by Singleton predicted the futures price of oil more accurately than the futures price of agricultural commodities. Moreover, their model also predicted the U.S. stock market. They argued, therefore, that the positive predictive correlation found by Singleton (2012) on the basis of a very short sample period was probably driven by the 2008 recession. Hamilton and Wu (2012) extended the sample period by two years and found the predictive correlation breaks down.

Some studies have analyzed speculative price influences using more detailed non-public data. Brunetti and Büyükşahin (2009) employed the CFTC Large Trader

Reporting System (LTRS) which offers unique, highly disaggregated position-level data to analyze five futures markets: crude oil, natural gas, corn, three-month Eurodollars and the mini-Dow. They considered both returns and volatility and concluded that speculative trading activity reduced futures price volatility. Brunetti, Büyükşahin et al. (2011) studied specific categories of traders and tested whether positions taken by speculators, such as hedge funds and swap dealers, caused changes in oil futures prices or price volatility. Their results were consistent with speculators providing liquidity to the market and reacting to market conditions rather than vice versa.

Büyükşahin and Harris (2011) also employed CFTC LTRS to test the relation between crude oil prices and trading positions of various types of traders in the crude oil futures market. Using Granger causality tests between price and position data at daily and multiple day intervals, they found little evidence that the non-commercial (speculative) position changes Granger-cause price changes; instead, they suggested that price changes preceded changes in speculative positions. Similarly, Sanders and Irwin (2011) found no statistically significant relationship between growth in the volume of oil futures contracts and oil futures returns, realized volatility or implied volatility.

The above studies focused on the relationship between speculation and futures prices. As far as we know no studies have directly tested the speculative influence on commodity cash price volatility in the current market environment even though the role of futures speculation on cash market volatility has been studied and described in earlier work. Further, it is not reasonable to informally extend recent futures market work to cash markets directly since short term fluctuations in commodity futures prices may not lead to cash price instability. For example, Alquist, Kilian et al. (2011) examined the out-of-sample accuracy of daily and monthly oil futures prices and found no compelling evidence that oil futures prices help forecast the oil spot price.

Figlewski (1981), Chen, Cuny et al. (1995) and Bessembinder and Seguin (1992) found a positive contemporaneous association between different cash prices and their corresponding futures market trading activities. Nevertheless, the findings could not be used as evidence of futures speculation causing higher cash price volatility because correlation is not causation (Figlewski, 1981). Kamara (1982) found that the introduction of commodity futures trading generally reduced or at least did not increase cash price volatility. Antoniou and Foster (1992) and Gulen and Mayhew (2000) considered time-varying patterns of price volatility and came to a similar conclusion. These studies all considered the impact of a new futures market on cash price stability.

There are other studies focused on the effects of different levels of futures trading activity on cash market volatility. Darrat and Rahman (1995) reported no evidence of causality running from S&P 500 futures trading (both volume and open interest) to cash price volatility. By contrast, Chatrath, Ramchander et al. (1996) argued that currency futures trading (trading volume) had a significant positive (and hence destabilizing) causal impact on the cash price volatility. Adrangi and Chatrath (1998) reported that surges in the participation of large speculators and small traders destabilize exchange rate volatility.

Earlier work focusing on the impact of futures trading activity on cash price volatility directly used a variable (trading volume or open interest) in one market and a variable (cash price volatility) in another market without first determining the actual pricing relationship between the two markets. We argue that this kind of testing suffers from information loss. Instead of testing the relationship of speculation in futures markets on cash price volatility directly, we first test whether there is a causal relationship in both mean and variance between the futures and cash prices for one commodity. In cases where volatility spillover exists, we then test whether speculators' activities in the futures market affect futures price volatility. If the increase of speculative positions in the futures market increases (decreases) the futures price volatility, then it will also increase (decrease) the corresponding cash price volatility when volatility spillover effects are found.

Data and Methodology

Data

The analysis presented here focuses on three markets: coffee, crude oil, and wheat. Futures and cash prices for all three markets are daily prices provided by the Commodity Research Bureau (CRB). The coffee futures price is for the nearby Coffee C contract traded on the Intercontinental Exchange (ICE). It is the world benchmark for Arabica coffee. The coffee futures price series is continuous and the rollover from contract to contract takes place on the first business day of each delivery month.

The crude oil futures price is for the second nearby Brent Crude contract also traded on ICE. It is generally accepted as the world's crude oil benchmark. The second nearby is chosen because there is a futures contract for oil delivery every month. Thus, the nearby is always for delivery in the current month.

The wheat futures price is for the #2 Soft Red Winter Wheat contract traded at the Chicago Mercantile Exchange (CME). Similar to coffee, we use the nearby contract to develop a continuous futures price series that rolls over on the first business day of each delivery month.

To detect long-run relationships, the initial sample period runs from January 1, 1990 through January 23, 2012. Since the different markets vary slightly in trading days, the numbers of observations for the three commodities are not equal. There are 5,514, 5,590 and 5,553 observations coffee, oil, and wheat, respectively.

The futures market position data are from the CFTC Commitments of Traders reports (COT). These reports provide each Tuesday's open interest for markets in which 20 or more traders hold positions equal to or above the reporting levels established by the CFTC.

Causality in Variance

Following Granger, Robins et al. (1986) who discuss causality in variance, we test whether futures price Granger-causes cash price in variance in the following way. First, two information sets are considered: $I_n : CP_{n-j}, j \geq 0$, and $J_n : CP_{n-j}, FP_{n-j}, j \geq 0$, where CP stands for cash price and FP for futures price.

Second, the futures price Granger-causes cash price in variance if:

$$E\left[\left(CP_{n+1}-E\left(CP_{n+1}\mid J_n\right)\right)^2 \mid I_n\right] \neq E\left[\left(CP_{n+1}-E\left(CP_{n+1}\mid J_n\right)\right)^2 \mid J_n\right]$$

The reverse relationship from the cash price to the futures price is defined similarly.

We use the multivariate generalized autoregressive conditional heteroscedasticity model (M-GARCH model) to test for the causality in variance between futures and cash prices:

$$X_t = E\left(X_t \mid J_{t-1}\right)+\varepsilon_t$$

where X_t is a 2×1 vector of the futures and cash prices and $E\left(X_t \mid J_{t-1}\right)$ is a 2×1 vector of conditional means of the two prices given the information set. ε_t is the error term, which will be modeled as a GARCH (1,1) – BEKK representation (Engle and Kroner, 1995). This leads to:

$$\varepsilon_t \sim N\left(0, H_t\right)$$

$$H_t = C_0^{'}C_0 + A^{'}\varepsilon_{t-1}\varepsilon_{t-1}^{'}A + G^{'}H_{t-1}G$$

$$H_t = \begin{pmatrix} h_{FP,t} & h_{FP-CP,t} \\ h_{CP-FP,t} & h_{CP,t} \end{pmatrix} \quad A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \quad G = \begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{pmatrix} \quad \varepsilon_t = \begin{pmatrix} \varepsilon_{FP,t} \\ \varepsilon_{CP,t} \end{pmatrix}$$

where h_{FP} and h_{CP} are conditional variances of the futures and cash prices, respectively.

Expanding this expression gives the conditional variance for the futures price:

$$h_{FP,t} = c_1 + a_{11}^2\varepsilon_{FP,t-1}^2 + 2a_{11}a_{21}\varepsilon_{FP,t-1}\varepsilon_{CP,t-1} + a_{21}^2\varepsilon_{CP,t-1}^2 + g_{11}^2 h_{FP,t-1} + 2g_{11}g_{21}h_{FP-CP,t-1} + g_{21}^2 h_{CP,t-1}$$

Therefore, the cash price does not cause the futures price in variance if and only if

$a_{21} = 0$ and $g_{21} = 0$.

Similarly, the conditional variance for the cash price is:

$$h_{CP,t} = c_2 + a_{12}^2 \varepsilon_{FP,t-1}^2 + 2a_{12}a_{22}\varepsilon_{FP,t-1}\varepsilon_{CP,t-1} + a_{22}^2\varepsilon_{CP,t-1}^2 + g_{12}^2 h_{FP,t-1} + 2g_{12}g_{22}h_{FP-CP,t-1} + g_{22}^2 h_{CP,t-1}$$

The futures price does not cause the cash price in variance if and only if $a_{12} = 0$ and $g_{12} = 0$.

In order to estimate the parameters in the GARCH (1,1) model and test for the causality in variance, we need to first model the price means, $E\left(X_t \mid J_{t-1}\right)$. If the two price series (cash and futures) are stationary, we could use a vector autoregression model (VAR) for the means. If they are non-stationary, we could take differences and then estimate a VAR on the differences. However, if the commodity price pairs are not stationary but are integrated of the same order, then we could estimate a cointegration model (in the error correction model – ECM form). It is desirable to model the price means using a cointegration model because it will allow us to identify the long-run relationship between the means of the two price series. If two variables are cointegrated, they have a long-run equilibrium relationship and are moving together. Further, the direction of causality and the speed of adjustment to price shocks in either market can be estimated.

In this case, parameter estimation consists of two steps. First, we use maximum likelihood estimation to obtain consistent estimates of the parameters in the mean equation in the presence of GARCH effects; and second the GARCH model is estimated with the parameters in the mean equation as given. If the futures price

Granger-causes the cash price in variance, we conduct the two samples t-tests to see whether the increase in speculators' positions in the futures market leads to an increase or a decrease in the futures price volatility (and hence cash price volatility).

Cointegration Analysis

Consider a futures market and a cash market for the same underlying commodity. It is reasonable to expect the two markets react similarly to new market information. Cointegration models (in the ECM form) have been widely used to test whether this is in fact true. Based on price stationarity tests (reported below), we estimate bi-variate cointegration models for each of the commodity markets to identify whether the futures and cash markets are moving together in the long-run

The model used to examine the cointegration relations is based on Johansen and Juselius (1990). The ECM specification is:

$$\Delta X_t = \Gamma_1 \Delta X_{t-1} + \ldots + \Gamma_{k-1} \Delta X_{t-k+1} + \Pi X^*_{t-k} + \Phi D_t + \varepsilon_t \quad (t = 1, \ldots, T) \tag{1}$$

Under this specification, ε_t is $\mathrm{IN}_p(0, \Lambda)$[2]; X_t is a $p \times 1$ vector of endogenous variables, $\Gamma_1, \ldots, \Gamma_{k-1}, \Pi, \Phi$ are matrices of parameters to be estimated, $X_{-k+1}, \ldots, X_0$ are fixed with k corresponding to the lag length in the VAR(k) model, D_t contains deterministic variables (i.e. dummies, etc.), and ΠX^*_{t-k} is the error correction term where X^*_{t-k} contains X_t and constant, trend or dummy variables that belong to the long-run equilibrium.

[2] The error terms are modeled as GARCH (1,1) rather than independent normal distribution, so the cointegration model assumption is violated. However, Mantalos (2001) and Cavaliere, Rahbek et al. (2010) showed that the cointegration test with GARCH errors is consistent with a large data set.

The test for cointegration depends on the rank of the Π matrix. If Π has full rank (r=p), then the vector process X_t is stationary. If the rank of Π is 0, then the ECM corresponds to a traditional differenced vector time series model. If the rank of Π lies between the two extreme cases, then there are r cointegrating vectors among X_t .

To formally test the rank of Π, we use both the likelihood ratio test, often called the trace test or the Johansen test, and the maximum eigenvalue test. The test statistics are:

$$\tau_{p-r} = -T \sum_{i=r+1}^{p} \ln\left(1-\hat{\lambda}_i\right), \text{ and } \delta_r = -T \ln\left(1-\hat{\lambda}_{r+1}\right)$$

In the trace test statistic formula, $\hat{\lambda}_i$ is the i^{th} largest eigenvalue of matrix Π. The null hypothesis of the test is that there are r cointegrating relations (therefore p-r common stochastic trends). The alternative hypothesis is that there are at least r+1 cointegrating relations (therefore at most p-r-1 common stochastic trends). We select the number of cointegrating vectors based on the following criterion:

$$r = \tilde{r} \text{ when } \left\{\tau_{p-\tilde{r}+1} > C_{p-\tilde{r}+1} \text{ and } \tau_{p-\tilde{r}} \le C_{p-\tilde{r}}\right\}$$

where C_{p-r} is the critical value under the null hypothesis that there are r cointegrating vectors.

In the maximum eigenvalue test statistic formula, $\hat{\lambda}_{r+1}$ is the $(r+1)^{th}$ largest eigenvalue of matrix Π. The null and alternative hypotheses are the same as that for the trace test. The decision rule is given as:

$$r = \tilde{r} \text{ when } \left\{\delta_{\tilde{r}-1} > C_{\tilde{r}-1} \text{ and } \delta_{\tilde{r}} \le C_{\tilde{r}}\right\}$$

where C_r is the critical value under the null hypothesis that there are r cointegrating vectors.

Two Samples t-test

To focus on the period when commodity prices began to exhibit increased volatility, the sample period for the two samples t-test is from the first week of 2007 to the last week of 2011. We use both futures and options position information. Three different position variables are used as measures of speculators' activities. First, we use the total non-commercial open interest (NonComm) as the measure of the absolute number of speculative positions. Using this measure allows us to test Master's assertion concerning speculators' price influence because his argument appears to be based on observing increases in this measure before observing increases in prices.

Second, we use the percentage of non-commercial total open interest relative to total market open interest (PCofNonComm) as a measure of the market share of speculative positions. Witherspoon (1993) argued that when the positions of agents trading exclusively in the futures market (speculators) exceeded those trading in the cash market (hedgers) beyond some boundary level cash prices will become more volatile. PCofNonComm is an appropriate variable to measure the relative speculation suggested by Witherspoon's theory. If this theory is correct, then it should be the percentage of speculative positions rather than the absolute number of speculative positions that influence cash price volatility.

Third, we use Non-commercial net-long open interest (NonCommNetL) to measure how many more long positions compared to short positions speculators hold. Some scholars argue that the recent increase in speculative positions is mainly reflected by increases in long positions. The argument is that this brings significant buying pressure to the market and leads to an increase in both price levels and price volatility. Using NonCommNetL allows us to test whether the increase of the speculative trade on the long side makes futures prices more volatile.

We use four statistics to measure futures price volatility to check the sensitivity of the results: weekly variance, weekly realized volatility, absolute weekly return and weekly trading range. Since the COTs report each Tuesday's positions, we count each week from Wednesday to the next Tuesday. Most of the weeks have five trading days, but some weeks have days without trading and hence contain only four, three or even two trading days.

The weekly variance is the sample variance of the futures price for each week:

$$Variance_t = \frac{\sum_{i=1}^{N_t} \left(P_t^i - \overline{P}_t \right)}{N_t},$$

where $Variance_t$ is the sample weekly variance of the t^{th} week, N_t is the number of trading days of this week, P_t^i is the futures price of the i^{th} trading day of this week, and $\overline{P}_t$ is the average price of this week.

The realized price volatility is calculated following Merton (1980):

$$realized\ volatility_t = \sum_{i=1}^{N_t} \left(r_t^i \right)^2 ,$$

where $r_t^i = \ln P_t^i - \ln P_t^{i-1}$ is the i^{th} rate of return in week t.

Absolute return is also often used a measurement of price volatility (Halova 2012). It is calculated as:

$$absolute\ return_t = | \ln P_t^{N_t} - \ln P_t^1 | ,$$

where $P_t^{N_t}$ is the futures price of the last day of week t and P_t^1 is the futures price of the first day of that week.

Using range as another measure of volatility is discussed in Corrado and Truong (2007). It is defined as:

$$range_t = | P_t^{\max} - P_t^{\min} | ,$$

where $P_t^{\max}$ and $P_t^{\min}$ are the highest and lowest prices in week t, respectively.

Our interest is in testing whether an increase in speculative positions is associated with an increase in the futures price volatility. Therefore, for each of the three position variables, we take the difference between the adjacent Tuesday's positions to construct the series of position changes. Thus, we get four groups of volatility measures which correspond to a decrease in the positions and also four groups of volatility measures which correspond to an increase in the positions for each of the position variables.

If the increase in the speculators' position causes the futures market to become more volatile, we will expect the average futures price volatility in the weeks which experience an increase in the speculators' position to be greater than the average futures price volatility in the weeks which experience a decrease in speculators' positions. Then we can formulate a two samples t-test with the hypothesis that the mean in the increased speculator position sample is greater than the mean in the decreased speculator position sample. The test statistic is:

$$t = \frac{\overline{vol}_{increase\ in\ positions} - \overline{vol}_{decrease\ in\ positions}}{sd\left(\overline{vol}_{increase\ in\ positions} - \overline{vol}_{decrease\ in\ positions}\right)}$$

The null hypothesis is the negation of the research hypothesis, i.e., the mean weekly volatility when speculator positions increase is less than the mean weekly volatility when speculator positions decrease.

Results

Unit Root Tests

As discussed above, we need to first test whether the price series are stationary to determine which model to use for understanding the relationship between mean prices. If they are non-stationary we need to determine whether each pair of prices are integrated of the same order to decide whether cointegration is appropriate for identifying the relationships between futures and cash price means.

Three types of unit root tests are implemented: Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), and the Phillips-Perron (PP) tests. Moreover, we use three models for the DF and ADF tests: models without intercepts or trends, models with intercepts, and models with intercepts and trends. We use two models for the PP test: models with intercepts and models with intercepts and trends. The null hypotheses of the unit root tests are that unit roots exist. Table 1 gives the results of the unit root tests. We cannot reject the null hypothesis for any of the six price series; however, the first-order differences of the price series are stationary. This means the series are I(1) and thus cointegration is an appropriate test for evaluating price relationships between cash and futures for all three commodities.

Lag-length determination of the ECM for the mean

The determination of the optimal lag length of the ECMs is identified based on the Schwartz Bayesian (SB) and Hannan-Quinn (H-Q) information criteria. Because the information criteria are based on different penalties, they do not need to suggest the same lag length. The SB criterion tends to penalize more for adding variables into the model. However, the decision rules for both criteria are the same: the smaller value, the better model. We chose the model with the smallest H-Q or/and the smallest SB. As Table 2 shows, we chose lag lengths of 6, 7, and 4 for coffee, oil and wheat, respectively.

Cointegration Tests

Using the above lag lengths, estimation of the ECMs and tests for cointegration were conducted. In all three bi-variate models, the error-correction term X^{*}_{t-k} includes a constant. For coffee and wheat, a dummy variable is used with 1 indicating the rollover date and 0 for others to account for the rollover effect.

The cointegration test results from the trace as well as the maximum eigenvalue tests are shown in Table 3. The results confirm our intuition that cash and futures prices move together in the long run. The trace test statistic for coffee is significant at 10% level. All other statistics are significant at 5% level.

<u>Causality in variance</u>

Table 4 gives the results of the parameter estimates in the GARCH model. The parameters used to test for causality in variance from futures price to cash price, a_{12} and g_{12}, and the ones used to test for causality in variance from cash price to futures price, a_{21} and g_{21}, are all significantly different from 0. The means there is a bi-directional causal relationship in variance between the futures and cash prices of coffee, oil, and wheat. Thus, if speculative activity is found to result in increased volatility in futures prices, then there will also be volatility spillover to the cash market. This, in turn, suggests that cash market participants will face increased price risk as a result of futures traders speculative activity.

<u>Two Samples t-test</u>

Tables 5.1, 5.2 and 5.3 give the results for the two samples t-tests. Panels a, b and c of each table show the results with the position variables NonCommercial, PCofNonAll and NonCommercialNetLong, respectively. The first half of each panel shows the results for the null hypothesis “Volatility is greater when speculators’ position decreases than when it increases”; while the lower half of each panel shows the results for testing the opposite statement “Volatility is greater when speculators’

position increases than when it decreases".

The results demonstrate that when we use NonCommercial and PCofNonAll as the position variables, for all three commodities and for all four volatility measures, we cannot reject the first hypothesis that "Volatility is greater when speculators' positions decrease than when they increase", and almost all the tests[3] for the second hypothesis that "Volatility is greater when speculators' positions increase than when they decrease" reject the null hypothesis. This suggests that the statement "Volatility is greater when speculators' positions decrease than when they increase" is true. Since there is volatility spillover from the futures market to the cash market, then we can further conclude that increased levels of speculative activity in futures markets helps to reduce cash price volatility, or at the very least does not contribute to increased cash price volatility.

However, when we use NonCommercialNetLong to measure speculator activity, the results are inconsistent. For coffee, we cannot reject any of the two opposite hypotheses using any of the four volatility measures. This means we cannot conclude that the change in the non-commercial net long positions will influence coffee futures price volatility. Oil and wheat are similar except that when absolute weekly return is used as the volatility measure, the hypothesis that "Volatility is greater when speculators' positions decrease than when they increase" is rejected. However, given that it is rejected for the other measures it is likely that increases in non-commercial net long positions has no effect on oil and wheat futures price volatilities either.

[3] Only in the test for oil using realized volatility fails to reject the hypothesis that "Volatility is greater when speculators' position increases than when it decreases".

Because high futures price volatility will cause high cash price volatility, this also means that the cash markets are likely unaffected when non-commercial net long positions increase.

Speculators in the futures market play an important role in providing liquidity to the market. However, the extent to which their positive market contributions are diminished, or even turn negative, as their market exposure increases has been actively debated in recent years. Based on the results here, we find that from 2007 to 2011, when commodity prices were experiencing increased volatility, relative to earlier time periods, increases in the total number of speculative positions or the percentage of speculative positions relative to the overall market size was associated with a decrease in weekly price volatility. Changes in net long positions of speculators appear to have no effect on price volatility. This indicates, at least for the markets considered here, that speculative participation in futures markets has provided liquidity while not exceeding the boundary identified by Witherspoon. Thus, speculative behavior has not played a destructive role in commodity price formation. On balance, the results suggest that policies focused on limiting speculative activity will likely be more harmful to the market, as opposed to contributing to an increase in market stability.

Conclusions

This paper examines whether speculators' activities in crude oil, wheat and coffee futures markets make cash prices of these commodities more volatile. The conclusions are similar across the three different commodities. First, the futures and cash prices of each of the three commodities are cointegrated. Second, there exists bi-directional volatility spillover between the futures and cash prices for all the three commodities but no evidence is been found to support the hypothesis that increases in speculative positions increases futures price volatility, thus they do not impact cash price volatility. In fact, there is strong evidence suggesting that increases in speculative positions actually contribute to decreased futures price volatility. As a result, the CFTC limits on the size of speculative positions for 28 core physical commodities approved in October 2011 is not expected to contribute to the stabilization of commodity prices, either in futures or cash markets. In order for public policy initiates to impact market volatility in a positive way a more complete understanding of the drivers of recent price volatility is necessary.

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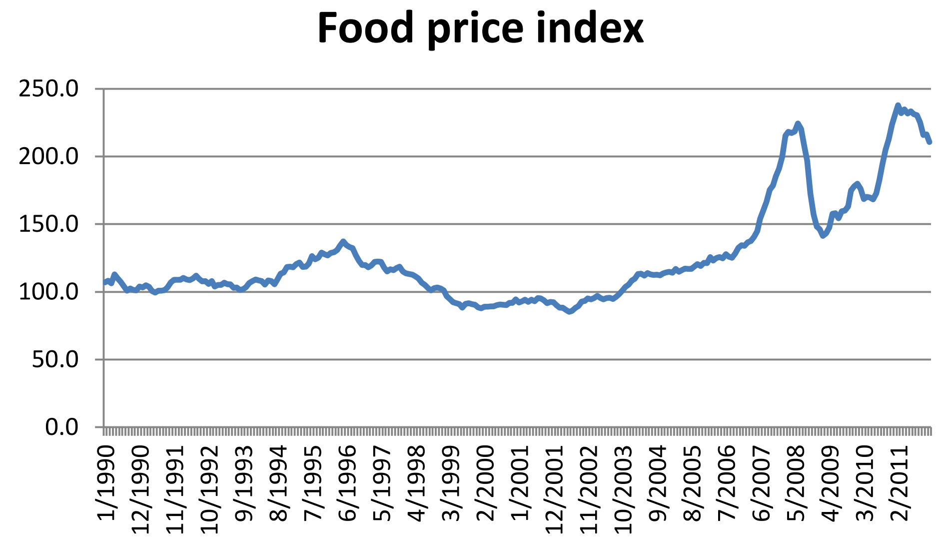
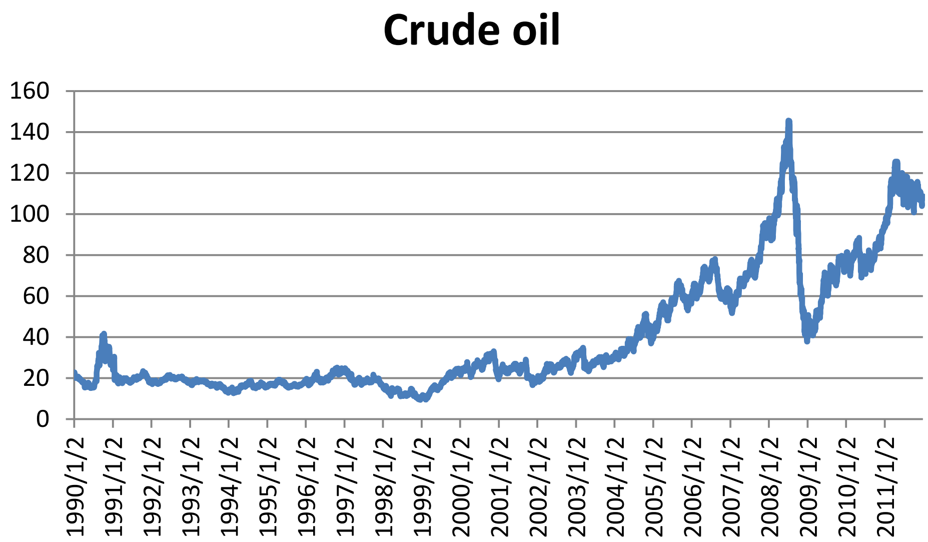
Figure 1 Annual food price index and crude oil price from 1990 Jan to 2011 Dec.



Data source: Food and Agriculture Organization of the United Nations (2002-2004=100).



Data source: Commodity Research Bureau

Table 1 Unit Root Test

		Coffee				Oil				Wheat			
		Cash Price	Δ Cash price	Futures price	Δ Futures price	Cash Price	Δ Cash price	Futures price	Δ Futures price	Cash Price	Δ Cash price	Futures price	Δ Futures price
DF Test	Without intercept or trend	0.05	−73.111	−0.271	−73.428	0.976	−68.237	0.694	−68.562	−0.623	−74.231	−0.541	−71.494
	With intercept	−1.432	−73.111	−1.974	−73.426	−0.071	−68.258	−0.369	−68.586	−2.51	−74.225	−2.158	−71.488
	With intercept and trend	−1.888	−73.11	−2.315	−73.423	−1.928	−68.306	−0.221	−68.633	−3.256	−74.224	−2.946	−71.485
ADF Test	Without intercept or trend	0.017	−54.426	−0.292	−55.278	0.718	−46.373	0.762	−48.2	−0.629	−54.626	−0.591	−53.907
	With intercept	−1.464	−54.429	−2.003	−55.278	−0.307	−46.396	−0.287	−48.228	−2.522	−54.622	−2.263	−53.903
	With intercept and trend	−1.928	−54.431	−2.346	−55.278	−2.187	−46.448	−2.163	−48.281	−3.271	−54.622	−3.065	−53.901
PP Test	With intercept	−1.481	−73.132	−1.991	−73.44	−0.254	−68.275	−0.291	−68.642	−2.386	−74.31	−2.143	−71.441
	With intercept and trend	−1.937	−73.138	−2.332	−73.44	−2.107	−68.332	−2.143	−68.701	−3.131	−74.32	−2.932	−71.443

Note: The Dickey-Fuller test, Augmented Dickey-Fuller test and Phillips-Perron test share the same 5% critical value for the model without intercept or trend, model with intercept and model with intercept and trend. These are -1.939, -2.863, and -3.413 respectively. The three tests consistently show that the cash and futures prices of the three commodities are not stationary. However, the first-order differences of all the price series show strong stationarity. Therefore, all the price series are I(1) series.

Table 2 Lag length determination

	Model	k	T	SB	H-Q
	VAR(10)	10	5504	3.892	3.857
	VAR(9)	9	5504	3.887	3.856
	VAR(8)	8	5504	3.886	3.858
Coffee	VAR(7)	7	5504	3.881	3.856
	VAR(6)	***6***	***5504***	***3.878***	***3.856***
	VAR(5)	5	5504	3.880	3.861
	VAR(4)	4	5504	3.877	3.862
	VAR(3)	3	5504	3.891	3.878
	VAR(2)	2	5504	3.926	3.917
	VAR(1)	1	5504	4.116	4.110
	VAR(10)	10	5580	-0.875	-0.907
	VAR(9)	9	5580	-0.878	-0.908
	VAR(8)	8	5580	-0.882	-0.908
Oil	***VAR(7)***	***7***	***5580***	***-0.885***	***-0.908***
	VAR(6)	6	5580	-0.884	-0.904
	VAR(5)	5	5580	-0.873	-0.890
	VAR(4)	4	5580	-0.863	-0.876
	VAR(3)	3	5580	-0.823	-0.843
	VAR(2)	2	5580	-0.618	-0.626
	VAR(1)	1	5580	-0.538	-0.543
	VAR(10)	10	5543	8.008	7.974
	VAR(9)	9	5543	8.003	7.972
	VAR(8)	8	5543	7.998	7.970
Wheat	VAR(7)	7	5543	7.995	7.970
	VAR(6)	6	5543	7.989	7.967
	VAR(5)	5	5543	7.986	7.967
	VAR(4)	***4***	***5543***	***7.981***	***7.965***
	VAR(3)	3	5543	7.980	7.968
	VAR(2)	2	5543	7.979	7.970
	VAR(1)	1	5543	7.991	7.985

Table 3 Trace and Eigen Value Tests of Cointegration

	p-r	r	Eig. Value	Trace	λ_{max}
Coffee	2	0	0.003	18.25*	16.549**
	1	1	0.000	2.157	0
Oil	2	0	0.023	131.679**	129.886**
	1	1	0.000	1.513	0
Wheat	2	0	0.005	30.967**	27.815**
	1	1	0.001	4.817	5.552

Note: Given by Johansen and Juselius (1990), the 5% critical value for testing the null hypothesis of r=0 and r=1 are 20.164 and 9.142 in the trace test; and 15.752 and 9.094 in the maximum eigenvalue test.

**: significant at 5% level.

* : significant at 10% level.

Table 4 Causality in Variance

	Coffee		Oil		Wheat	
Parameter	Estimate	P-value	Estimate	P-value	Estimate	P-value
c_{11}	0.1014	0	0.0377	0	0.2038	0.1322
c_{12}	0.0949	0	0.0401	0	-0.5496	0.3153
c_{22}	0.0981	0	-0.01	0.0002	1.1328	0.0001
a_{11}	0.2225	0	0.205	0	0.2658	0
a_{12}	0.0672	0	-0.0494	0	-0.183	0
a_{21}	0.081	0	0.0682	0	-0.1023	0
a_{22}	0.2545	0	0.2918	0	0.4599	0
b_{11}	0.9766	0	0.9791	0	0.938	0
b_{12}	-0.0116	0	0.0102	0	0.0925	0
b_{21}	-0.0208	0	-0.0232	0	0.0514	0
b_{22}	0.9622	0	0.9554	0	0.8659	0

Table 5 Results for the two samples t tests (Data: 2007-2011)

5.1 Coffee

a. Position data use NonCommercial all	T.S.	Pvalue	Conclusion
$H_0 : \mathrm{Var}_{Decrease\ in\ position} \geq \mathrm{Var}_{Increase\ in\ position}$	2.13	0.983	Fail to reject
$H_0 : \mathrm{Range}_{Decrease\ in\ position} \geq \mathrm{Range}_{Increase\ in\ position}$	2.44	0.992	Fail to reject
$H_0 : \mathrm{AbsReturn}_{Decrease\ in\ position} \geq \mathrm{AbsReturn}_{Increase\ in\ position}$	2.99	0.998	Fail to reject
$H_0 : \mathrm{RealizedVol}_{Decrease\ in\ position} \geq \mathrm{RealizedVol}_{Increase\ in\ position}$	2.76	0.997	Fail to reject
$H_0 : \mathrm{Var}_{Decrease\ in\ position} \leq \mathrm{Var}_{Increase\ in\ position}$	2.13	0.017	Reject
$H_0 : \mathrm{Range}_{Decrease\ in\ position} \leq \mathrm{Range}_{Increase\ in\ position}$	2.44	0.008	Reject
$H_0 : \mathrm{AbsReturn}_{Decrease\ in\ position} \leq \mathrm{AbsReturn}_{Increase\ in\ position}$	2.99	0.002	Reject
$H_0 : \mathrm{RealizedVol}_{Decrease\ in\ position} \leq \mathrm{RealizedVol}_{Increase\ in\ position}$	2.76	0.003	Reject

b. Position data use PCofNonAll	T.S.	Pvalue	Conclusion
$H_0 : \mathrm{Var}_{Decrease\ in\ position} \geq \mathrm{Var}_{Increase\ in\ position}$	2.3	0.989	Fail to reject
$H_0 : \mathrm{Range}_{Decrease\ in\ position} \geq \mathrm{Range}_{Increase\ in\ position}$	2.8	0.997	Fail to reject
$H_0 : \mathrm{AbsReturn}_{Decrease\ in\ position} \geq \mathrm{AbsReturn}_{Increase\ in\ position}$	2.99	0.998	Fail to reject
$H_0 : \mathrm{RealizedVol}_{Decrease\ in\ position} \geq \mathrm{RealizedVol}_{Increase\ in\ position}$	3.33	0.999	Fail to reject
$H_0 : \mathrm{Var}_{Decrease\ in\ position} \leq \mathrm{Var}_{Increase\ in\ position}$	2.3	0.011	Reject
$H_0 : \mathrm{Range}_{Decrease\ in\ position} \leq \mathrm{Range}_{Increase\ in\ position}$	2.8	0.003	Reject
$H_0 : \mathrm{AbsReturn}_{Decrease\ in\ position} \leq \mathrm{AbsReturn}_{Increase\ in\ position}$	2.99	0.002	Reject
$H_0 : \mathrm{RealizedVol}_{Decrease\ in\ position} \leq \mathrm{RealizedVol}_{Increase\ in\ position}$	3.33	0.001	Reject

c. Position data use NonCommercialNetLong	T.S.	Pvalue	Conclusion
$H_0 : \text{Var}_{\text{Decrease in position}} \geq \text{Var}_{\text{Increase in position}}$	0.49	0.688	Fail to reject
$H_0 : \text{Range}_{\text{Decrease in position}} \geq \text{Range}_{\text{Increase in position}}$	-0.16	0.436	Fail to reject
$H_0 : \text{AbsReturn}_{\text{Decrease in position}} \geq \text{AbsReturn}_{\text{Increase in position}}$	-1.24	0.108	Fail to reject
$H_0 : \text{RealizedVol}_{\text{Decrease in position}} \geq \text{RealizedVol}_{\text{Increase in position}}$	0	0.501	Fail to reject
$H_0 : \text{Var}_{\text{Decrease in position}} \leq \text{Var}_{\text{Increase in position}}$	0.49	0.312	Fail to reject
$H_0 : \text{Range}_{\text{Decrease in position}} \leq \text{Range}_{\text{Increase in position}}$	-0.16	0.564	Fail to reject
$H_0 : \text{AbsReturn}_{\text{Decrease in position}} \leq \text{AbsReturn}_{\text{Increase in position}}$	-1.24	0.892	Fail to reject
$H_0 : \text{RealizedVol}_{\text{Decrease in position}} \leq \text{RealizedVol}_{\text{Increase in position}}$	0	0.499	Fail to reject

5.2 Crude Oil

a. Position data use NonCommercial all	T.S.	Pvalue	Conclusion
$H_0 : \mathrm{Var}_{Decrease\ in\ position} \geq \mathrm{Var}_{Increase\ in\ position}$	1.47	0.928	Fail to reject
$H_0 : \mathrm{Range}_{Decrease\ in\ position} \geq \mathrm{Range}_{Increase\ in\ position}$	1.48	0.929	Fail to reject
$H_0 : \mathrm{AbsReturn}_{Decrease\ in\ position} \geq \mathrm{AbsReturn}_{Increase\ in\ position}$	0.16	0.564	Fail to reject
$H_0 : \mathrm{RealizedVol}_{Decrease\ in\ position} \geq \mathrm{RealizedVol}_{Increase\ in\ position}$	2.39	0.991	Fail to reject
$H_0 : \mathrm{Var}_{Decrease\ in\ position} \leq \mathrm{Var}_{Increase\ in\ position}$	1.47	0.072	Reject
$H_0 : \mathrm{Range}_{Decrease\ in\ position} \leq \mathrm{Range}_{Increase\ in\ position}$	1.48	0.071	Reject
$H_0 : \mathrm{AbsReturn}_{Decrease\ in\ position} \leq \mathrm{AbsReturn}_{Increase\ in\ position}$	0.16	0.436	Fail to reject
$H_0 : \mathrm{RealizedVol}_{Decrease\ in\ position} \leq \mathrm{RealizedVol}_{Increase\ in\ position}$	2.39	0.009	Reject

b. Position data use PCofNonAll	T.S.	Pvalue	Conclusion
$H_0 : \mathrm{Var}_{Decrease\ in\ position} \geq \mathrm{Var}_{Increase\ in\ position}$	2.75	0.997	Fail to reject
$H_0 : \mathrm{Range}_{Decrease\ in\ position} \geq \mathrm{Range}_{Increase\ in\ position}$	2.89	0.998	Fail to reject
$H_0 : \mathrm{AbsReturn}_{Decrease\ in\ position} \geq \mathrm{AbsReturn}_{Increase\ in\ position}$	0.75	0.772	Fail to reject
$H_0 : \mathrm{RealizedVol}_{Decrease\ in\ position} \geq \mathrm{RealizedVol}_{Increase\ in\ position}$	2.27	0.988	Fail to reject
$H_0 : \mathrm{Var}_{Decrease\ in\ position} \leq \mathrm{Var}_{Increase\ in\ position}$	2.75	0.003	Reject
$H_0 : \mathrm{Range}_{Decrease\ in\ position} \leq \mathrm{Range}_{Increase\ in\ position}$	2.89	0.002	Reject
$H_0 : \mathrm{AbsReturn}_{Decrease\ in\ position} \leq \mathrm{AbsReturn}_{Increase\ in\ position}$	0.75	0.228	Fail to reject
$H_0 : \mathrm{RealizedVol}_{Decrease\ in\ position} \leq \mathrm{RealizedVol}_{Increase\ in\ position}$	2.27	0.012	Reject

c. Position data use NonCommercialNetLong	T.S.	Pvalue	Conclusion
$H_0 : \text{Var}_{\textit{Decrease in position}} \geq \text{Var}_{\textit{Increase in position}}$	-0.42	0.336	Fail to reject
$H_0 : \text{Range}_{\textit{Decrease in position}} \geq \text{Range}_{\textit{Increase in position}}$	-2	0.423	Fail to reject
$H_0 : \text{AbsReturn}_{\textit{Decrease in position}} \geq \text{AbsReturn}_{\textit{Increase in position}}$	-1.55	0.062	Reject
$H_0 : \text{RealizedVol}_{\textit{Decrease in position}} \geq \text{RealizedVol}_{\textit{Increase in position}}$	-1.1	0.135	Fail to reject
$H_0 : \text{Var}_{\textit{Decrease in position}} \leq \text{Var}_{\textit{Increase in position}}$	-0.42	0.664	Fail to reject
$H_0 : \text{Range}_{\textit{Decrease in position}} \leq \text{Range}_{\textit{Increase in position}}$	-2	0.577	Fail to reject
$H_0 : \text{AbsReturn}_{\textit{Decrease in position}} \leq \text{AbsReturn}_{\textit{Increase in position}}$	-1.55	0.938	Fail to reject
$H_0 : \text{RealizedVol}_{\textit{Decrease in position}} \leq \text{RealizedVol}_{\textit{Increase in position}}$	-1.1	0.865	Fail to reject

5.3 Wheat

a. Position data use NonCommercial all	T.S.	Pvalue	Conclusion
$H_0 : \mathrm{Var}_{Decrease\ in\ position} \geq \mathrm{Var}_{Increase\ in\ position}$	2.68	0.996	Fail to reject
$H_0 : \mathrm{Range}_{Decrease\ in\ position} \geq \mathrm{Range}_{Increase\ in\ position}$	3.07	0.999	Fail to reject
$H_0 : \mathrm{AbsReturn}_{Decrease\ in\ position} \geq \mathrm{AbsReturn}_{Increase\ in\ position}$	1.33	0.908	Fail to reject
$H_0 : \mathrm{RealizedVol}_{Decrease\ in\ position} \geq \mathrm{RealizedVol}_{Increase\ in\ position}$	2.36	0.99	Fail to reject
$H_0 : \mathrm{Var}_{Decrease\ in\ position} \leq \mathrm{Var}_{Increase\ in\ position}$	2.68	0.004	Reject
$H_0 : \mathrm{Range}_{Decrease\ in\ position} \leq \mathrm{Range}_{Increase\ in\ position}$	3.07	0.001	Reject
$H_0 : \mathrm{AbsReturn}_{Decrease\ in\ position} \leq \mathrm{AbsReturn}_{Increase\ in\ position}$	1.33	0.092	Reject
$H_0 : \mathrm{RealizedVol}_{Decrease\ in\ position} \leq \mathrm{RealizedVol}_{Increase\ in\ position}$	2.36	0.01	Reject

b. Position data use PCofNonAll	T.S.	Pvalue	Conclusion
$H_0 : \mathrm{Var}_{Decrease\ in\ position} \geq \mathrm{Var}_{Increase\ in\ position}$	1.58	0.942	Fail to reject
$H_0 : \mathrm{Range}_{Decrease\ in\ position} \geq \mathrm{Range}_{Increase\ in\ position}$	2.46	0.993	Fail to reject
$H_0 : \mathrm{AbsReturn}_{Decrease\ in\ position} \geq \mathrm{AbsReturn}_{Increase\ in\ position}$	3.03	0.999	Fail to reject
$H_0 : \mathrm{RealizedVol}_{Decrease\ in\ position} \geq \mathrm{RealizedVol}_{Increase\ in\ position}$	2.84	0.998	Fail to reject
$H_0 : \mathrm{Var}_{Decrease\ in\ position} \leq \mathrm{Var}_{Increase\ in\ position}$	1.58	0.058	Reject
$H_0 : \mathrm{Range}_{Decrease\ in\ position} \leq \mathrm{Range}_{Increase\ in\ position}$	2.46	0.007	Reject
$H_0 : \mathrm{AbsReturn}_{Decrease\ in\ position} \leq \mathrm{AbsReturn}_{Increase\ in\ position}$	3.03	0.001	Reject
$H_0 : \mathrm{RealizedVol}_{Decrease\ in\ position} \leq \mathrm{RealizedVol}_{Increase\ in\ position}$	2.84	0.002	Reject

c. Position data use NonCommercialNetLong	T.S.	Pvalue	Conclusion
$H_0: \text{Var}_{\textit{Decrease in position}} \geq \text{Var}_{\textit{Increase in position}}$	-0.26	0.397	Fail to reject
$H_0: \text{Range}_{\textit{Decrease in position}} \geq \text{Range}_{\textit{Increase in position}}$	-0.64	0.262	Fail to reject
$H_0: \text{AbsReturn}_{\textit{Decrease in position}} \geq \text{AbsReturn}_{\textit{Increase in position}}$	-1.71	0.044	Reject
$H_0: \text{RealizedVol}_{\textit{Decrease in position}} \geq \text{RealizedVol}_{\textit{Increase in position}}$	-1	0.159	Fail to reject
$H_0: \text{Var}_{\textit{Decrease in position}} \leq \text{Var}_{\textit{Increase in position}}$	-0.26	0.603	Fail to reject
$H_0: \text{Range}_{\textit{Decrease in position}} \leq \text{Range}_{\textit{Increase in position}}$	-0.64	0.738	Fail to reject
$H_0: \text{AbsReturn}_{\textit{Decrease in position}} \leq \text{AbsReturn}_{\textit{Increase in position}}$	-1.71	0.956	Fail to reject
$H_0: \text{RealizedVol}_{\textit{Decrease in position}} \leq \text{RealizedVol}_{\textit{Increase in position}}$	-1	0.841	Fail to reject

Note: 10% significance level is used for tests in tables 5.1, 5.2 and 5.3.