How Much Did Speculation Contribute to Recent Food Price Inflation?

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Abstract

Recent increases in commodity prices have led to calls for the regulation of speculators. These calls have come from many reputable quarters including leading agricultural and food policy institutions such as International Food Policy Research Institute as well as different members of the U.S. Congress. They are based on an assumption that speculative activities are a primary or major source of the volatility in the markets and that controlling these activities through regulations would bring more stability to the market. The paper tests this hypothesis and assesses the contribution of speculative activities in the commodity markets over the past decade to price inflation. The paper argues that government regulatory policies to control speculation in commodity markets is a second best solution that would probably yield neutral or negative benefits to the very people the policy aims to protect.

Keywords: speculators, inflation, prices, ARIMA

Introduction

Recent increases in food prices engendered panic in many policy circles around the world as many government officials and interested academics and policy wonks searched for culprits and perpetrators of these increases. The World Bank, for example, notes on its website that "High fuel costs have resulted in higher agriculture costs, falling food stocks, and land shifted out of food production to produce biofuels." Similarly, the Indian Finance Minister, Mr. P. Chidambaram, while addressing the Development Committee of World Bank and IMF in Washington on April 13, 2008, argued that high crude oil and galloping food prices were imposing a crushing burden on developing countries. The Minister blamed rising food prices on diversion of food crops for biofuels. The Food and Agriculture Organization (FAO) notes in its Food Outlook that total global food imports will surge above $1,000 billion for the first time in

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2008, up about 20 per cent from 2007 level. “Food,” the FAO Food Outlook concludes, “is no longer the cheap commodity that it once was.” The estimates are that wheat and rice prices are up 120 percent and 75% respectively. The effect of these increases on the world’s poor is significant because they spend the majority of their incomes on food and even slight increases in prices can have devastating impacts on their welfare. Thus, these projections of shifts in the trajectories of global food prices and demand and supply conditions have important strategic implications for all stakeholders in the agri-food supply chain as well as governments and public policy makers. Finally, there were some who believed that speculators were responsible for the rising food prices and, therefore, new policies must be developed and implemented to control speculative behavior in the market. For example, a May 2008 paper by the International Food Policy Research Institute (IFPRI) identified eight initiatives to address the rising commodity prices, and while acknowledging that speculation is not the cause of the problem but its consequence, proceeded to recommend a need for policies that “calm markets with the use of market-oriented regulation of speculation . . .”

This short research paper seeks to determine the extent to which speculation may explain the rising commodity prices that occurred between late 2006 and mid 2008. In doing this, the paper defines speculation as the proportion of open interest in the commodity futures market that is accounted for by non-commercial traders. This will provide the level of speculation activity in the commodity futures and options markets at any period by looking at the proportion of open contracts that the buyers or the sellers had no intention of delivering or taking delivery of. For these non-registered traders, their whole purpose of participating in the market is to make money on the spread and not in acquiring physical assets for trade.

The paper argues that speculator actions can increase volatility in markets by removing and introducing products from and into the market in ways that enhance their probability of increasing their spreads and, hence, their potential profits. But the futures price, which is what the speculator seeks to move, is different, even if it is correlated with the spot market price for commodities. On the other hand, the food price increases that occurred involved prices that consumers were paying on the spot market, and not the futures market.

The Model

The data used in the study is a time series data and hence the first thing we wanted to do was to determine if the characteristics of a time series – the mean and variance – are constant over time? If the mean and variance are constant over time, then the series is stationary. If the mean and variance change, then the series is nonstationary. We used the Dickey Fuller test and Phillips-Perron test to test for the hypothesis of unit root tests in the price and proportion of speculators in the markets.

We use a simple OLS model as well as an ARIMA (Auto Regressive Integrated Moving Average), model for the study. The application of the ARIMA methodology for the study of time series analysis is attributed to Box and Jenkins and Reinsel (1994). ARIMA models have been already applied to forecast commodity prices (Weiss, 2000; Chinn, LeBlanc, and Coibion, 2001). A major difference between regression and ARIMA in terms of application is that regression deals with autocorrelation either in the error term by eliminating or factoring out such autocorrelation before estimates of relationships are made, whereas ARIMA models attempt to build in such autocorrelation -- where it exists - in the modeling process itself (Veney,J. and Luckey,1983). The ARIMA model uses a combination of autoregressive and moving average specification. A series with a moving average component is one where each observation is a function of the current random shock plus some portion of the previous random shock(s). A series with an autoregressive component is one in which each observation is a function of the random shock, plus some fraction of the previous observation(s). We have included two lags in both the AR and MA and used the first differenced prices regressed against the explanatory variable of the first differenced proportion of speculators.

Results

Unit root tests

The Dickey Fuller test and Phillips-Perron test for unit root tests indicated that all the three price variables do have unit root at 1% significance level, implying that they are not stationary. So we first differenced the price variables to make these variables stationary. The same tests for the proportion of the speculators in corn, wheat and soybean markets also indicated that the hypothesis of unit root test is not rejected at the 5 % significance level. For this reason we also first differenced these speculation variables to make them stationary.

We regressed the first differenced value of the corn, wheat and soybean prices against their respective first differenced proportion of speculators. Results are shown in Table 1. One of the problems in a time series data is autocorrelation. To detect the presence of autocorrelation, we run the Ljung Box Q-test described as a white noise process and Durbin Watson test. For corn, wheat, and soybean markets, only the DW test indicated that there is autocorrelation present. We also run the Q-test to detect if there is autocorrelation present. For corn and soybean markets the Q test indicated that there is no autocorrelation detected, while for wheat both tests revealed that there are no autocorrelation problems. These results suggest that only for wheat, using ARIMA might be a good estimation. For corn and soybean, using ARIMA did not get rid of the presence of the autocorrelation and hence the choice might not seem justified.

The estimated coefficients for the explanatory variable of speculators in wheat and soybean markets are not significant when both OLS and ARIMA models are used. Where as for corn market, both models showed that the speculators coefficient are significant at 5 % significance level. Regardless of which market and significance, all the signs of the coefficients for the speculators were negatively related with the each of the prices.

The R square results for the OLS models are less than 0.05. Including the lagged prices in each model slightly increases the R-squares for wheat and substantially for the corn and soybean market. For this reason, we run all the above regressions by including the respective lagged prices. For corn and wheat, only the D-W test indicated the presence of autocorrelation, for soybean both The Q-test and D-W test revealed the presence of autocorrelation. We have also run the ARIMA models for each of the previous OLS counterparts with two lags for both the AR and MA. Results are shown in Table 2. Only in the soybean market that the Q-test and D-W tests indicated that there is no autocorrelation.

When the price lags were included in the explanatory variables, in both the OLS and ARIMA specifications, the coefficients of the speculators are not statistically significant in all the corn, wheat and soybean markets. However, the prices lags were found out to be statistically significant at 1 % significance level in explaining the price movement in the corn market, and only significant at 1 % significance level in the wheat market in the ARIMA model only , and at 5 % significance level in the soybean market when OLS was used.

Conclusion

In this paper we attempted to assess the contribution of speculative activities in the commodity markets over the past decade to price inflation. Specifically, the paper sought to determine the extent to which speculative activities in principal commodity markets contributed to the price inflation observed in past decade. Arguing that government regulatory policies to control speculation in commodity markets is a second best solution that would probably yield neutral or negative benefits to the very people the policy aims to protect, it suggests that speculators should be left to the regulatory controls of the market by enforcing trading rules, prosecuting rule breakers with existing laws and improving transparency of trading activities. The non-significance of the estimated coefficients in both the OLS and ARIMA models seems to support this notion. The paper calls for careful appreciation of market conditions that require interventions and counsels that such interventions be undertaken with caution if unintended consequences are to be avoided.

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Table 1.Results of OLS and ARIMA models when the explanatory variable is only the proportion of speculators

	OLS model	ARIMA model
D.cornprice	Coefficient (standard error)	Coefficient (standard error)
cornspeculators	-37.9102 ** (14.89863)	-42.95175 ** (17.0786)
cons	19.04864 *** (6.776871)	21.25497 *** (7.536272)
D.wheatprice		
wheatspeculators	-18.91639 (26.70591)	-24.12501 (46.56985)
cons	13.1244 (15.21291)	15.89889 (26.49951)
D.soyprice		
soyspeculators	-14.11375 (26.90899)	-18.62907 (41.63969)
cons	10.73764 (13.5594)	13.34416 (19.64131)

Note: **, and *** represents significance at the 5% and 1% significance level, respectively.

Table2.Results of OLS and ARIMA models when the explanatory variable is only the proportion of speculators and price lag for each commodity

	OLS model	ARIMA model
	Coefficient (standard error)	Coefficient (standard error)
PriceLag1.	0.07673 *** (0.025803)	0.102007*** (0.022966)
cornspeculators	-8.12347 (17.49327)	17.2205 (23.7911)
cons	-3.28039 (9.94684)	-17.8528 (13.11216)
D.wheatprice	Coef.	Coef.
PriceLag1.	-0.00094 (0.023076)	0.040471 * (0.0228)
wheatspeculators	-19.1684 (27.5396)	-19.6872 (44.77507)
cons	13.43007 (17.01882)	6.585394 (25.99768)
D.soyprice	Coef.	Coef.
PriceLag1.	0.051025 ** (0.022479)	0.039292 (0.02522)
soyspeculators	5.6342 (27.76033)	-4.93152 (41.18387)
cons	-11.327 (16.46045)	-3.00677 (23.28688)

Note: *, **, and *** represents significance at the 10%, 5% and 1% significance level, respectively.