Futures Commodities Prices and Media Coverage

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Abstract

In this paper, we examine the effects of media coverage of commodity price increases and decreases on the price of the commodity and how media coverage in other commodities affects prices. We provide evidence of the relationship between media coverage (and its intensity) and the price level of agricultural commodities and oil futures.

We find that price movements are correlated with media coverage of up, or an increase, in prices. The direction of the correlation is robust and positive for media coverage of ups and negative for downs. Finally, we find that even though volatility is higher for the set of days in which there is media coverage, this hides important dynamics between media coverage and volatility. The volatility of market-adjusted returns is negatively correlated with media coverage, both ups and downs. Markets days with intense media coverage of commodity prices tend to have lower volatility.

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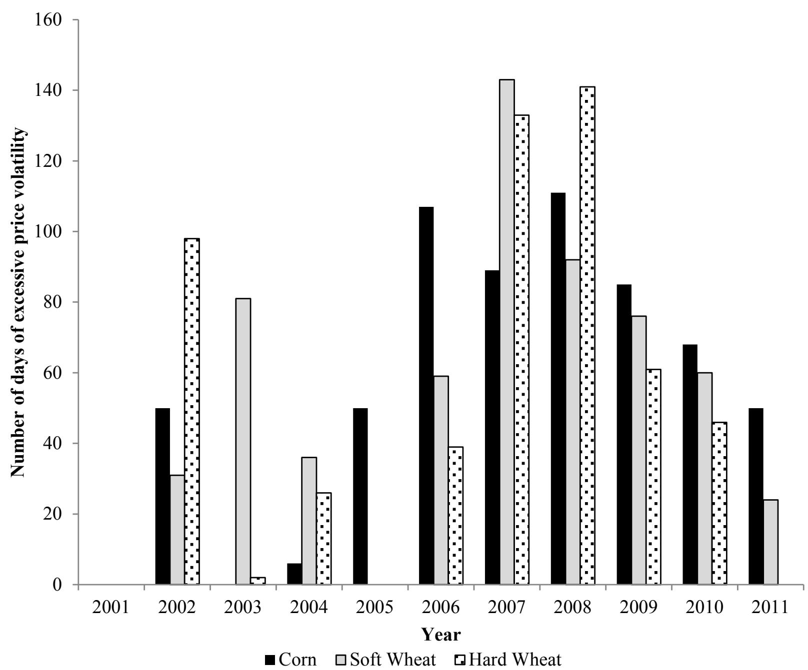
1. Introduction

The world faces a new food economy that likely involves both higher and more volatile food prices, and evidence of both phenomena was on view in 2011. After the food price crisis of 2007–08, food prices started rising again in June 2010, with international prices of maize and wheat roughly doubling by May 2011. The peak came in February 2011, in a spike that was even more pronounced than that of 2008, according to the food price index of the Food and Agriculture Organization of the United Nations. Although the food price spikes of 2008 and 2011 did not reach the heights of the 1970s, price volatility—the amplitude of price movements over a particular period of time—has been at its highest level in the past 50 years. This volatility has affected wheat and maize prices in particular. For soft wheat, for example, there were an average of 41 days of excessive price volatility per year between December 2001 and December 2006 (according to a measure of price volatility recently developed at IFPRI[i]). From January 2007 to June 2011, the average number of days of excessive volatility more than doubled to 88 a year.

High and volatile food prices are two different phenomena with distinct implications for consumers and producers. High food prices may harm poorer consumers because they need to spend more money on their food purchases and therefore may have to cut back on the quantity or the quality of the food they buy or economize on other needed goods and services. For food producers, higher food prices could raise their incomes—but only if they are net sellers of food, if increased global prices feed through to their local markets, and if the price developments on global markets do not also increase their production costs. For many producers, particularly smallholders, some of these conditions were not met in the food price crisis of 2011.

Apart from these effects, price volatility also has significant effects on food producers and consumers. Greater price volatility can lead to greater potential losses for producers because it implies price changes that are larger and faster than what producers can adjust to. Uncertainty about prices makes it more difficult for farmers to make sound decisions about how and what to produce. For example, which crops should they produce? Should they invest in expensive fertilizers and pesticides? Should they pay for high-quality seeds? Without a good idea of how much they will earn from their products, farmers may become more pessimistic in their long-term planning and dampen their investments in areas that could improve their productivity. (The positive relationship between price volatility and producers' expected losses can be modeled in a simple profit maximization model assuming producers are price takers. Still, it is important to mention that there is no uniform empirical evidence of the behavioral response of producers to volatility.) By reducing supply, such a response could lead to higher prices, which in turn would hurt consumers.

Figure 1: Evolution of the Number of Days of Excessive Price Volatility



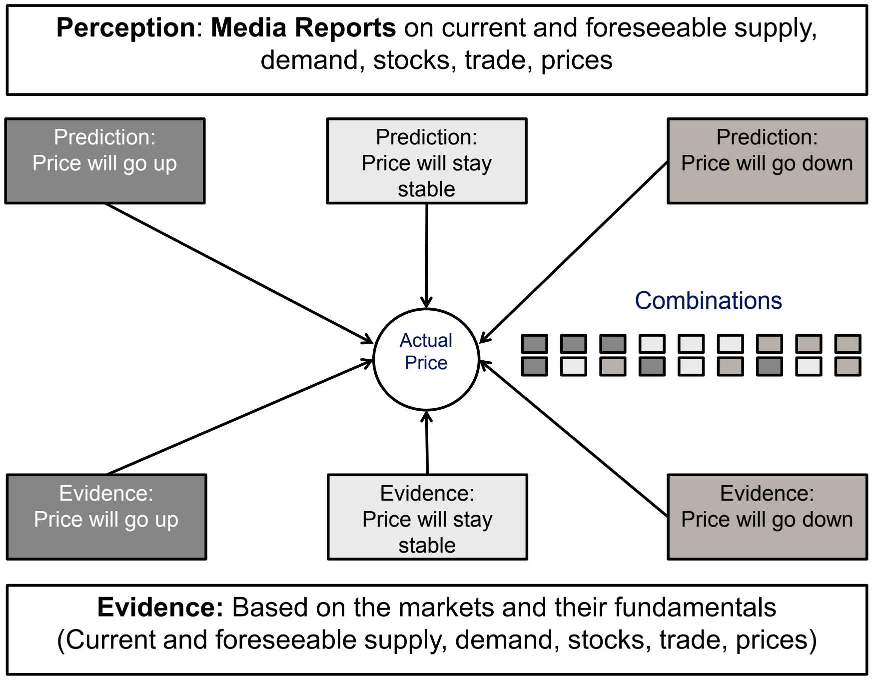
Note: This figure shows the results of a model of the dynamic evolution of daily returns based on historical data going back to 1954 (known as the Nonparametric Extreme Quantile (NEXQ) Model). This model is then combined with extreme value theory to estimate higher-order quantiles of the return series, allowing for classification of any particular realized return (that is, effective return in the futures market) as extremely high or not. A period of time characterized by extreme price variation (volatility) is a period of time in which we observe a large number of extreme positive returns. An extreme positive return is defined to be a return that exceeds a certain preestablished threshold. This threshold is taken to be a high order (95%) conditional quantile, (i.e. a value of return that is exceeded with low probability: 5 %). One or two such returns do not necessarily indicate a period of excessive volatility. Periods of excessive volatility are identified based a statistical test applied to the number of times the extreme value occurs in a window of consecutive 60 days.

It is important to remember that in rural areas, the line between food consumers and producers is blurry. Many households both produce and consume agricultural commodities. Therefore, if prices become more volatile and these households reduce their spending on seeds, fertilizer, and other inputs, this may affect the amount of food available for their own consumption. And even if households are net sellers of food, producing less and having less to sell will reduce their household income and thus still affect their consumption decisions.

Finally, increased price volatility over time can also generate larger profits for investors, drawing new players into the market for agricultural commodities. Increased price volatility may thus lead to increased—and potentially speculative—trading that in turn can exacerbate price swings further.

The question that this paper tries to answer is: what is the role of the media in influencing price levels and price volatility of agricultural commodities? Specifically, we examine the effects of media coverage of commodity price increases (ups) and decreases (downs) on the price of the commodity and how media coverage in other commodities affects prices. As shown in Figure 2 for each commodity, there are evidence-based market fundamentals such as current and foreseeable supply, demand, stocks, trade, and current prices which allow for the prediction of the price development for the specific commodity. There are three clear "possible futures" based – with margins of error – on this evidence: prices will either (1) go up, (2) stay stable, or (3) go down. Then there is the perception presented in media reports, which - in an ideal world - would only amplify the experts' opinion on "possible futures." The actual price can then reflect nine combinations. There are three combinations where price development based on market fundamentals and reporting on these developments in the media is identical and the marginal effect of media should be minimal. On the other hand, the six combinations in which evidence and perception differ (where, for example, all market fundamentals show that prices will stay stable or even fall but the media report that prices will go up) could be a case in which the media can have a significant effect in influencing agricultural prices.

Figure 2: Effects of Media on Prices



For example, in 2010, the media overreacted to the news of Russia's wheat export ban and failed to explain that global wheat production and stocks were sufficient to compensate for the loss of Russia's wheat. Moreover, every piece of news during August to October 2010—even the US Department of Agriculture's better-than-expected projection that the world would harvest only 5 percent less wheat than the previous year—seemed to elicit a spike. The number of media articles on the price of wheat rose significantly between August and October 2010, and 57 percent of the total number of media articles with any reference to wheat prices reported that wheat prices were going to increase. This number was 93 percentage points higher than the same measure in an average quarter for 2010 (see table 1).[4]

Among the major reasons for the price increases reported in the media were the fires in Russia (62 percent) and low inventories because of low production and stocks (25 percent), even though the inventories and stocks were sufficient and significantly higher than in the 2008 crisis. Only 7 percent of

[4] To analyze all media articles, we use Sophic Intelligence Software, which is built on the Biomax BioXMä Knowledge Management Suite. Each day, global food- and commodity-related news articles are loaded into Sophic Intel for linguistic analysis and semantic object network mapping. Sophic Intel generates wiki reports and heatmaps based on terms and phrases found in press articles that influence commodity price volatility and food security. The average quarter for 2010 has 122 articles where it is mentioned that wheat prices are increasing while the quarter from August to October 2010 has 210 articles, i.e. 72% higher.

articles referred to policies, such as export bans, which had in fact been the major reason for the increase in prices. This lack of information on global production led governments around the world to engage in panic buying that exacerbated the situation and pushed up prices.

Another clear example is what has been happening since June 2012. Global maize and soybean prices have skyrocketed in June-July 2012, and experts fear that price increases will be unabated as dry weather in the US Midwest continues for at least another week.

US corn crops have been hard hit by the drought conditions, which began in May and stunted crops in the crucial pollination phase. While US government officials argue that this year's increased corn acreage will offset the drop in yields, agricultural and trade analysts fear that the length and severity of the drought could continue to have a substantial impact on prices (see Figure 3). Since June 1, the Chicago Board of Trade (CBOT) corn contract for December delivery has risen 30%, closing at $6.56 on July 2.

Table 1: Analysis of Media articles referring to food prices

Reason referred in media article	Reference to prices going up		
	All	All of 2010	Aug - Oct 2010
Financial	78	42	10
Inventories	222	99	40
Policies	84	37	12
Disasters and Civil Effects	377	159	101
Total of references to prices going up	761	337	163
Total articles	1238	585	288

Source: Authors' own calculations

Note: The periods correspond to the following dates: All- refers to articles between August 1 2998 to July 22 2011,; All 2010 - refers to January 1 2010 to December 31st 2010; and Aug-Oct 2010 - refers to 1st of August 2010 to October 31st 2010. The qualifiers used in each of the categories are: (a) Financial: domestic food price, expectations, expected prices, futures markets, hedge, hedging, interest rate, international food price, monetary policy, rates, speculation, trade, trade barrier, trading volume; (b) inventories: corn production, domestic production, domestic supply, emergency reserves, maize production, reserves, rice production, storage, supply, surplus, and wheat production; (c) policies: export ban, export quota, food security, import quota, import restrictions, price controls, and taxes; and (d) disasters and civil effects: drought, earthquake, famine, fire, flood, frost, hurricane, nutrition, plague, poverty, riots.

Figure 3: Weekly Global Maize and Soybean Prices, June 2012

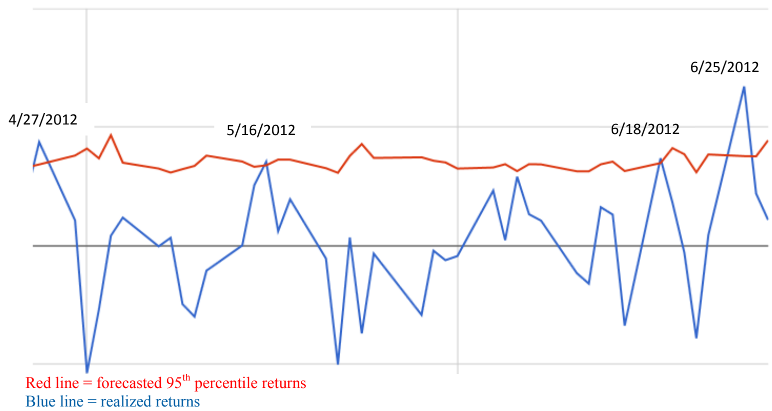
Soybean prices have experienced similarly sharp spikes, seeing their highest levels in nearly four years (see Figure 3). The jump in prices has been caused by a combination of dry weather throughout the US and South America, decreased acreage in favor of more profitable corn, record levels of Chinese imports, and a subsequent rapid rate of stock disappearance. A June USDA report cites soybean disappearance of 707 million bushels in May, the second largest on record. Increased Chinese imports are being driven by strong demand from the Chinese crushing industry, reduced domestic soybean production, and stockpiling of soybeans to guard against any potential shortage resulting from US and Argentine droughts. Since June 1, CBOT soybean contracts for September have risen 14%, closing at $14.52 on July 2.

Both the Maize and the Soybean Excessive Food Price Variability Early Warning Systems (according to a measure of price volatility recently developed at IFPRI[5]) have shown levels above normal (moderate and excessive volatility[6]) since June. In both cases, realized returns have been above the forecasted 95th percentile returns in several instances, particularly in the case of maize (see Figure 4).

[5] C. Martins-Filho, M. Torero, and F. Yao, "Estimation of Quantiles Based on Nonlinear Models of Commodity Price Dynamics and Extreme Value Theory" (Washington, DC: International Food Policy Research Institute, 2010), mimeo. Specifically A time period of excessive price volatility: A period of time characterized by extreme price variation (volatility) is a period of time in which we observe a large number of extreme positive returns. An extreme positive return is defined to be a return that exceeds a certain preestablished threshold. This threshold is normally taken to be a high order (95 or 99%) conditional quantile, (i.e. a value of return that is exceeded with low probability: 5 or 1%). In this model we are using the 95% quantile.

[6] For further details see http://www.foodsecurityportal.org/soybean-price-volatility-alert-mechanism.

Figure 4: Maize Price Volatility, April – June 2012



Note: An abnormality occurs when an observed return exceeds a certain preestablished threshold. This threshold is normally taken to be a high order (95 percent) quantile—that is, a value of return that is exceeded with low probability (5 percent).

Media attention to corn and soybean prices has been consistently high in June (see Figure 5), highlighting the level of global concern about food prices. As seen during the Russian droughts of 2010, however, it is important that policymakers not react with knee-jerk policies such as stockpiling and export restrictions. While such policies may appease the population of a particular country or region, they can have devastating consequences for global food prices and food security.

This paper contributes to the literature by providing evidence of the relationship between media coverage (and its intensity) and the price level of agricultural commodities and oil futures. It uses a robust estimation method to account for the particularities of the data and uses a unique data set to measure the extent of media coverage.

We find that price movements are correlated with the media coverage of ups, or increases, in prices. The direction of the correlation is robust and positive for media coverage of ups and negative for downs. The same results hold when we analyze the daily returns for these commodities. Furthermore, attention is given to the distribution of the effects in time to allow for delays in the response of the prices or returns. Finally, we find that even though volatility is higher for the set of days on which there is media coverage, this hides important dynamics between media coverage and volatility. The volatility of market-adjusted returns is negatively correlated with media coverage, both ups and downs. Market days with intense media coverage of commodity prices tends to have lower volatility. This points to the potential of using media coverage to bring attention to price surges and at the same time decrease volatility during food crises times or in times when there is above normal volatility.

Figure 5: Media Articles Mentioning High Maize and Soybean Prices, June 2012

Date	Articles Mentioning High Maize Prices	Articles Mentioning High Soybean Prices
6-1-2012	0	0
6-4-2012	2	3
6-5-2012	1	0
6-6-2012	4	0
6-7-2012	0	0
6-8-2012	9	5
6-11-2012	1	0
6-12-2012	1	2
6-13-2012	5	1
6-14-2012	3	1
6-15-2012	2	1
6-18-2012	1	1
6-19-2012	0	0
6-20-2012	1	1
6-21-2012	4	0
6-22-2012	0	0
6-25-2012	0	0
6-26-2012	1	0
6-27-2012	2	0
6-28-2012	0	1
6-29-2012	1	0

This paper is divided in six sections, including the introduction. Section 2 summarizes previous literature on the effect of media and information on future prices; Section 3 describes the data we have developed for this paper. Section 4 presents the econometric model we estimate and Section 5 presents the key results. Finally, Section 6 presents the key conclusions.

2. Previous Literature

The effect of information shocks on markets has a long history in economics. The efficient market hypothesis in its simplest form purports that markets prices should 'fully' reflect available information. Generally, the tests of this hypothesis are for the semi-strong form, where the question is if prices efficiently adjust to information that is available (Fama 1970). These tests exploit the variation induced by informational events, such as stock splits, policy announcements, dividend information, etc., essentially comparing abnormal around the news events. As a whole, the efficient market hypothesis fairs well with the data (Fama 1970).

The effect of news events on futures prices has been studied by various authors, and the differences in methodology and in what is meant by news abound. Rucker et al. (2005) estimate the effect of different types (periodic, aperiodic, and irregular events) on lumber futures prices to help shed light on the volatility of lumber prices. They find that periodic and aperiodic event types are absorbed quickly in comparison to irregular events. Their study is not a test of market efficiency since they do not exploit variation in timing of the news but are interested in the structural aspects of the response in markets to the types of events in the study.

Pruit (1987) studies the effects of the Chernobyl nuclear accident on the prices of agricultural futures commodity prices produced in the Chernobyl area. He exploits the evolution of the news in the days surrounding the accident and finds that the commodities experienced an increase in volatility that was short-lived and that prices were affected, as the efficient market hypothesis would predict.

Carter and Smith (2007) estimate the effect of news concerning the contamination of a corn supply on the price of corn; they find that prices were affected and that the negative effect persisted for at least a year.

Another vein of studies explores the effects of news on recalls and food safety on the prices of the products. McKenzie and Thomsen (2001) find that red meat recalls due to contamination (food safety information) negatively affects beef prices but that the transmission is not across all margins, meaning that farm-level prices do not respond to this information. In a similar study, Schlenker and Villas-Boas (2009) explore the effects of information on mad cow disease on purchases and futures prices. They find that future prices were negatively affected by the discovery of the first mad cow and that information that is not “news” (such as a talk show host providing the information already available on mad cow disease, thus bringing attention to the issue rather than providing new information) had half of the effect of the announcement that mad cow disease was a problem in the meat supply. Smith, van Ravenswaay, and Thompson (1988) study the impact of milk contamination on consumer demand and find that media coverage had an impact on demand for milk and that negative media coverage had larger impacts. These studies show that media coverage can have a large impact on food prices, regardless of if the information is “news” or is just bringing attention to the issues.

In the case of prices, media coverage of a price movement might be a signal of volatility in the market. Given the extreme prices in food commodities that we observed during 2011, the effect of media coverage on the price of these commodities is increasingly important. News reports of food price increases and decreases do not provide “new” information to markets, as they are reporting the tendencies of the price series as they occur. However, as we mentioned before, focusing attention on the dynamics of prices can serve as a signal of other underlying issues or could reinforce the tendency by updating the beliefs not just of investors but also of consumers. By exaggerating or downplaying the importance of price increases, the media can cause welfare losses because agents will make decisions based on information that may not necessarily reflect the true nature of the pricing process.

3. Data

We use various data sources to estimate the impact of media coverage on futures markets. The first is daily futures price data from the Chicago Board of Trade for futures of Maize, Soft, Soybean, Rice, and Oil and from the Kansas City Board of Trade for Hard Wheat. The future prices selected are the closest to maturity each day. We augment these price data with market variables such as the SP index, the daily exchange rates between the US dollar and the currencies of major participant countries in the agricultural commodity markets (for example, Canada, Thailand, China, Australia, and The European Union).

The variables of interest for this paper are the measures of media coverage. Every day, we monitor a comprehensive set of RSS feeds[7] drawn from global media outlets via Google news. A total of 31 feeds related to global food prices and food security are monitored; these feeds include search strings such as “food prices,” “food crisis,” “agricultural development,” “commodity prices,” “price of maize,” “price of wheat,” “price of oil,” “price of rice,” “price of soybean,” etc. Stories are tagged with a star if they are about: 1. global food security or food prices, 2. ongoing national, regional, or global food crises, 3. prices (international, regional, and national) or crop conditions of major agricultural commodities (wheat, corn, soybeans, and rice), 4. oil prices, 5. agricultural trade (export bans, import or export forecasts, etc.), or 6. agricultural/food policy research.

[7] RSS stands for Really Simple Syndication. Also called web feeds, RSS is a content delivery vehicle. It is the format used when you want to syndicate news and other web content. When it distributes the content, it is called a feed.

At the end of each day, all starred articles are converted into .txt files and saved using the format "title_month_day_year.txt." The day's .txt files are then uploaded into the IFPRI Food Security Media Analysis System (FOMA), a tool built by Sophic Systems Alliance called Sophic Intelligence Software. This software, which is built on the Biomax BioXM Knowledge Management Suite, uses linguistic and semantic object network-mapping algorithms to analyze the relationships between key terms found in each article. When articles are uploaded each day, the tool mines the complete database of articles for a select set of key words. Sophic Intelligence Software generates a detailed analysis of the text within the articles and look at phrases in the articles that may influence commodity price volatility and food security. Table 2 lists the key words used to determine an "up" or "down" movement within our database of articles. For example, an article containing the words "soybean" and "surge" would denote an "up" movement in soybean prices; if the soybean "up" report on a given day is listed as 5, this means that on that day, 5 articles contained words suggesting a rise in soybean prices. On a daily basis, the system provides reports analyzing movement (increases - ups or decreases - downs) in commodities prices. These reports provide a count of the number of articles each day with "up" or "down" movements for each commodity by analyzing the text within the articles

Table 2 : Keywords suggesting changes in prices

Up	Down
High	Low
Increase	Decrease
Rise	Reduce
Higher prices	Collapse
Grow	Lower
Gain	Shrink
Enlarge	Decline
Surge	Negative
High prices	Weakened
High food prices	Depressed
Raise	Lose
Positive	Plunge
Rising food prices	

We use these "up" and "down" variables to measure the intensity of coverage of a price trend. Articles that show up on weekends and holidays when the market is closed are moved to the next day the market is open. With these data, we construct a panel of 6 commodities (Soft Wheat, Hard Wheat, Maize, Rice, Soybeans and Oil) that spans from August 3, 2009 to the present day. In “market time”, we obtain 707 periods (days) for a total of 4,242 observations.

Using these series, we construct daily returns for futures, defined as $r_{it} = 100 * \ln(\frac{P_{i,t}}{P_{i,t-1}})$, where P_{it} is the closing price for commodity *i* on day *t*. The price series and the corresponding daily returns are displayed in Figures 6 and 7.

As is customary when analyzing futures price time series, we will use the rate of return series in our analysis in addition to the price levels. This accounts for serial correlation in the price series, i.e. it accounts for the unit root in the data. We present results for the Dickey Fuller unit root tests for the panel in Table 3. The panel version of the test assumes a common autocorrelation parameter and relies on large T asymptotics. The tests provide evidence that the log-price levels have a unit root and that the returns (first difference) are stationary.

Table 3: Augmented Dickey Fuller Panel Unit Root Tests

	Obs	Commodities	Periods	Chi-2	Df	P-value	Evidence
Price Levels							
No-Trend	4242	6	707	10.1235	12	0.605	Cannot Reject Unit Root
Trend	4242	6	707	5.384711	12	0.944	Cannot Reject Unit Root
Trend-Demean	4242	6	707	8.788379	12	0.721	Cannot Reject Unit Root
Returns							
No-Trend	4236	6	706	231.4766	12	0.000	Reject Unit Root
Return-Trend	4236	6	706	200.5179	12	0.000	Reject Unit Root

Table 4 shows the summary statistics for the variables used in the analysis. The price returns are on average similar to other market variable returns. Across all commodities, the average *daily* return is 0.028% compared to a 0.038% return for the S&P index. We bring attention to the higher volatility in commodities returns, as evidenced by the larger standard error of the mean and the wider ranges in comparison to the exchange rate returns and the S&P index. The largest negative return in the sample is for soybean at -14.08% and the biggest gains in returns are for rice with 13.23% in a day.

Figure 6: Futures Prices for commodities

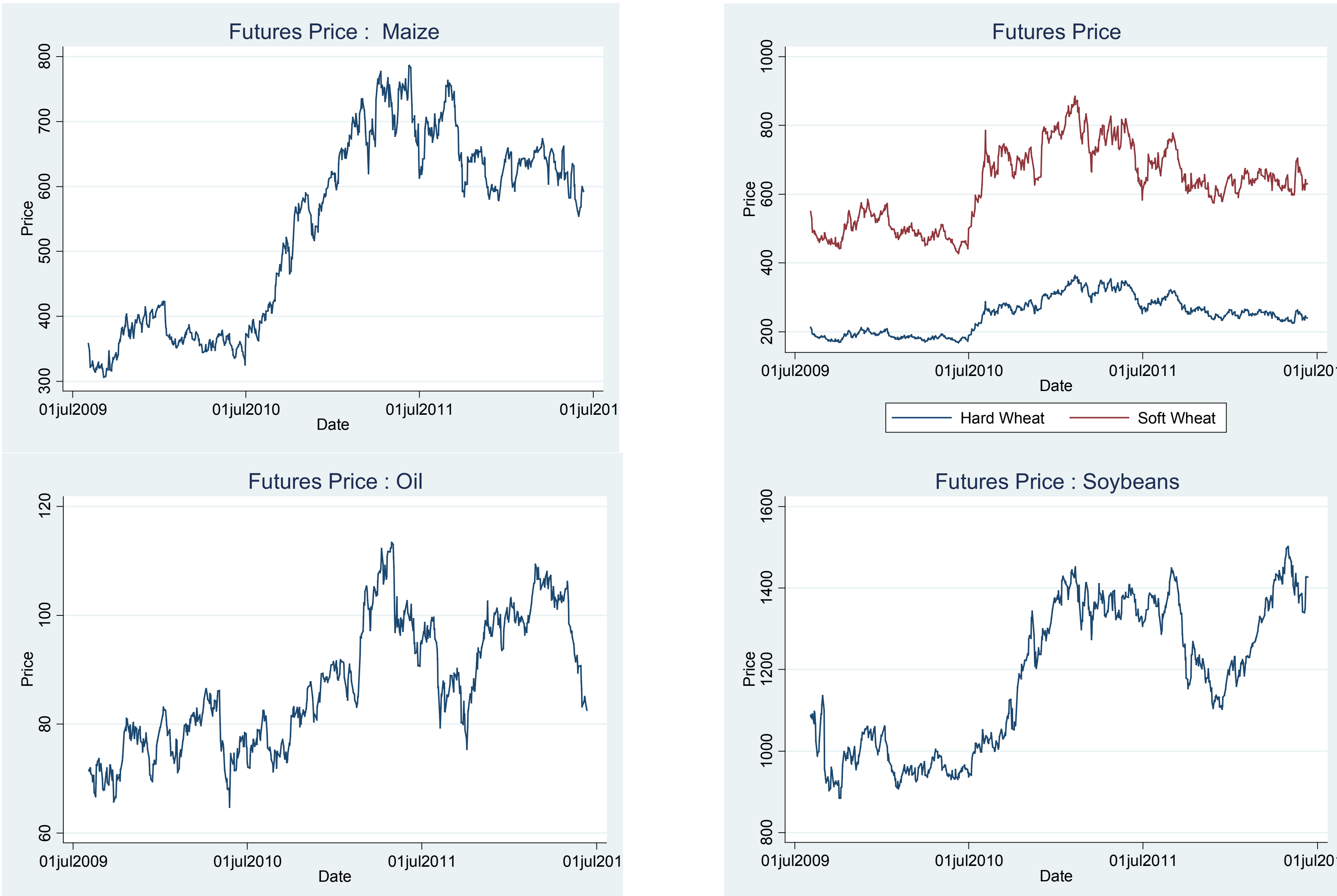


Figure 7: Futures Returns for commodities

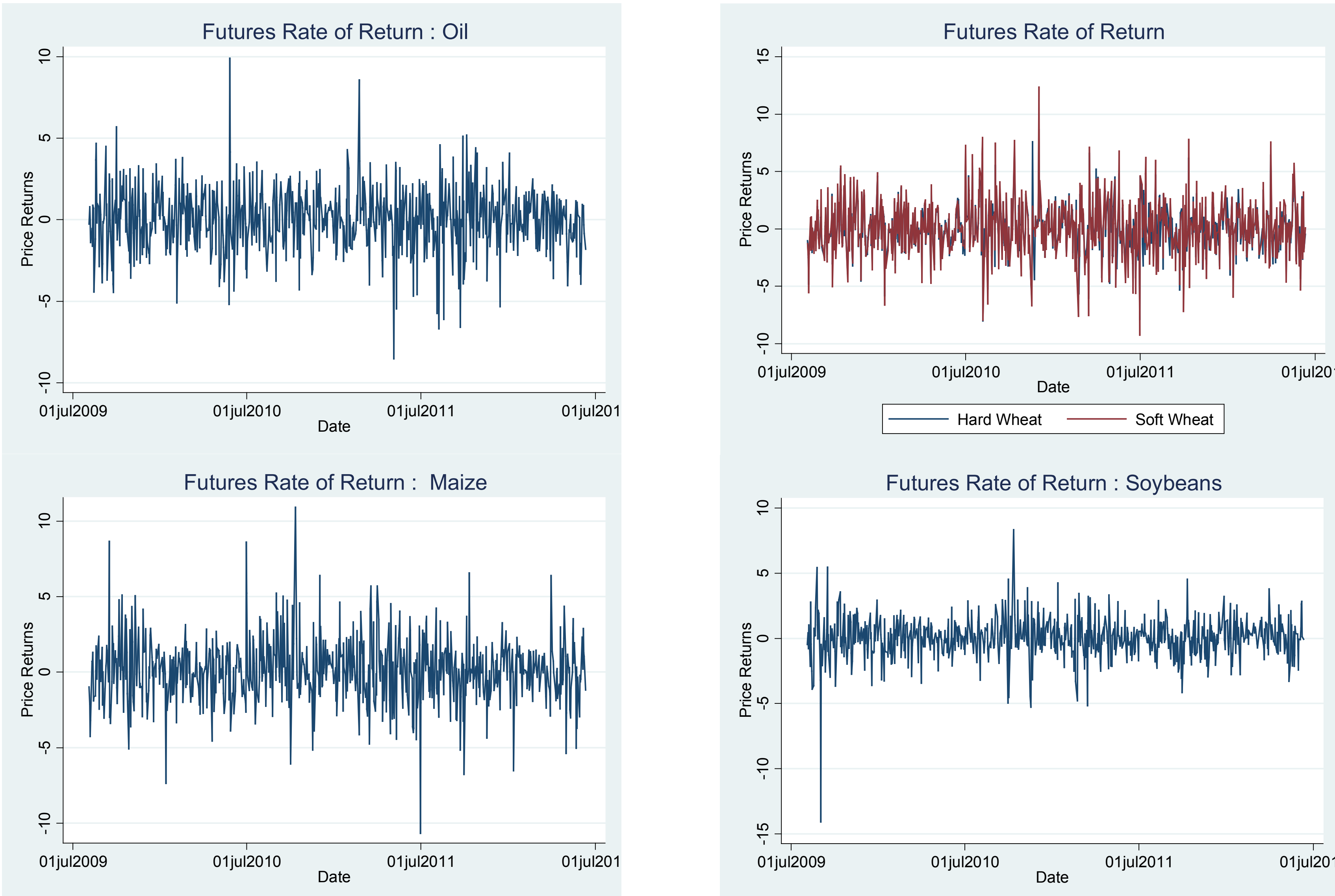


Figure 8: Media Coverage of Price Changes, Ups and Downs

We present the up and down variables used in the analysis for each commodity. The most activity in news coverage is for Maize, Wheat, and Rice. In Table 4, we can corroborate the impressions from Figure 8. Wheat and Rice have an average of just over 1 increase in price news per day, followed by Maize at 0.78 per day. For the decrease in price news, the activity is lower across the commodities, averaging about 1 news article per 2 days related to a price decrease in Maize, Rice, and Wheat and around 1 per 5 day period for Soybeans and Oil.

Table 4 : Summary Statistics

	Mean	SE	Median	Min	Max	Obs.
Hard Wheat						
Price	248.23	1.99	252.43	168.38	363.03	707
Log-Price	5.491	0.008	5.53	5.13	5.89	707
Price Returns	0.017	0.081	-0.01	-8.00	8.66	706
Increase in price news	1.017	0.080	0	0	25	707
Decrease in price news	0.564	0.047	0	0	12	707
Maize						
Price	536.70	5.44	586.75	306.25	786.00	707
Log-Price	6.246	0.011	6.37	5.72	6.67	707
Price Returns	0.071	0.080	0.00	-10.68	10.93	706
Increase in price news	0.785	0.057	0	0	14	707
Decrease in price news	0.576	0.051	0	0	12	707
Oil						
Price	87.13	0.44	85.19	64.78	113.39	707
Log-Price	4.459	0.005	4.44	4.17	4.73	707
Price Returns	0.020	0.074	0.06	-8.53	9.90	706
Increase in price news	0.236	0.023	0	0	5	707
Decrease in price news	0.133	0.017	0	0	5	707
Rice						
Price	14.00	0.06	14.07	9.43	18.39	707
Log-Price	2.632	0.005	2.64	2.24	2.91	707
Price Returns	0.004	0.067	-0.04	-5.41	13.23	706
Increase in price news	1.099	0.078	0	0	16	707
Decrease in price news	0.484	0.040	0	0	11	707
Soft Wheat						
Price	625.59	4.21	635.50	428.00	884.50	707
Log-Price	6.422	0.007	6.45	6.06	6.79	707
Price Returns	0.019	0.092	-0.07	-9.25	12.35	706
Increase in price news	1.003	0.079	0	0	25	707
Decrease in price news	0.560	0.047	0	0	12	707

Table 4: Summary Statistics (continuation)

Soybeans						
Price	1179.21	6.73	1201.50	885.00	1502.00	707
Log-Price	7.061	0.006	7.09	6.79	7.31	707
Price Returns	0.038	0.059	0.07	-14.08	8.34	706
Increase in price news	0.168	0.022	0	0	8	707
Decrease in price news	0.228	0.028	0	0	6	707
Total						
Price	448.48	6.27	337.19	9.43	1502.00	4242
Log-Price	5.385	0.023	5.82	2.24	7.31	4242
Price Returns	0.028	0.031	0.00	-14.08	13.23	4236
Increase in price news	0.718	0.026	0	0	25	4242
Decrease in price news	0.424	0.017	0	0	12	4242
Market Variables						
Return SP Index	0.038	0.019	0.091	-6.896	4.632	4236
Return Exchange rate- AU	0.023	0.013	0.032	-4.457	3.214	4236
Return Exchange rate-EU	-0.020	0.010	0.000	-2.046	2.385	4236
Return Exchange rate-CND	-0.005	0.010	-0.010	-2.131	3.368	4236
Return Exchange rate- CHINA	-0.010	0.002	-0.001	-0.573	0.621	4236
Return Exchange rate- JP	-0.026	0.009	-0.033	-2.230	3.002	4236
Return Exchange rate- MX	0.009	0.011	-0.033	-2.528	3.708	4236
Return Exchange rate- THAI	-0.010	0.004	0.000	-1.127	1.043	4236
Return T-bill 30 year rate	-0.069	0.027	0.000	-8.611	7.612	4236

4. Econometric Model

To quantify the effect of media coverage on returns, we use a market model in that we control for market level variables to focus on returns that are not explained by current market conditions.

In our estimation, we use 2 major frameworks. First, the regression of price levels accounting for the serial correlation in the prices. It is well known that fixed effects methods are not consistent with for small N; Nickell (1981), and IV-GMM methods can be used to estimate these models (Anderson and Hsiao 1981;, Arellano and Bond 1991; Arellano and Bover 1995). These methods suffer from weak instrument problems which have been addressed by Blundell and Bond (1998) by proposing the further moment restriction in the form of lag differences. We use insights from these methods to estimate the impact of our media variables in an inherently dynamic structure of the price data.

The equation we estimate is:

$$p_{i,t} = \alpha_i + \theta p_{i,t-1} + \gamma^u UP_{it} + \gamma^d DOWN_{it} + \beta X_t + \varepsilon_{it} \qquad \text{Eq. 1}$$

Where *i*=Hard Wheat, Maize, Oil, Rice, Soft Wheat, Soybeans

t= 1…T (1 is 08/03/2009 and T is 06/12/2012 in 'market time')

p_{it} is the log price level

α_i is a commodity specific intercept (fixed effect)

UP_{it} is the number of 'increase in price of *i* news for day *t*

$DOWN_{it}$ is the number of 'decrease in price' of *i* news for day *t*

X_t is a matrix of market variables at date t

ε_{it} is a random error term which, depending of the specification, will have a different structure

We assume that the news variables are predetermined or sequentially exogenous, that is that $E[\varepsilon_{it}|\alpha_i, X_t, Up_{i,t-k}, Down_{i,t-k}] = 0 \; for \; k = 1 \ldots t$ which allows us to use moment restriction to obtain a GMM-IV estimator. This equation might also contain lags of the regressors and/or additional lags of y, but it captures the essential feature of the model that we want to estimate. Namely, a dynamic effect of media coverage on the price level for which the speed of adjustment is governed by the coefficient of lagged price level[8].

The sequential exogeneity assumption implies that the regressors are uncorrelated to past and present values of the error term. It does not rule out correlation between the regressors and the individual effect. Lagged price levels will be correlated by construction with the fixed effect and with lagged error term, but they may also be correlated with contemporaneous ε if ε is serially correlated, which is not ruled out by the sequential exogeneity assumption. Thus, lagged price level is effectively an endogenous explanatory variable in the equation with respect to both α and ε.

The moment conditions we exploit are

$$\mathrm{E}[\Delta UP_{it-k}\, \varepsilon_{it}] = 0 \; and \; \mathrm{E}[\Delta Down_{t-k} \varepsilon_{it}] = 0 \text{ for k=1…K}$$ [9]

[8] To avoid issues of cointegration of commodity prices and exchange rates, we use the return to the market (exchange) variables, which are stationary.

[9] We use K=5 based on Akaike's Criterion and the 5 day market 'week`

The estimator $\nu = [\theta, \gamma^u, \gamma^d, \beta]$ is consistent as T → ∞ as long as $E[Z_{it}\varepsilon_{it}] = 0$, since it retains its time-series with the regressors being predetermined, where Z is the matrix of instruments, i.e the market controls, lagged differences, and individual effects.

The moment conditions assume that for a set of k values, the lag differences in the news appearance are uncorrelated with the errors at time t. In theory, we could use all past differences, but this would worsen the weak instrument problem that is inherent in this assumption as the number of available instruments increases with T. This kind of procedure was devised for small T and large N panels (Arellano and Bond 1991), which is not our case. In our case, we have a large T and OLS and fixed effects maintain their consistency. In addition, under the market efficiency hypothesis, sequential exogeneity is a plausible assumption, as all the information in the news variables in the time periods before t should be already reflected in the price of the commodity. The parameter we identify is the effect of changes in the appearance of news in the previous days of the prices of commodities, i.e media coverage variation arising from differences in news coverage intensity across commodities and time is an essential source of exogenous variation.

As mentioned before, regressors can contain lag variables of media coverage. In this case, the model we estimate is :

$$p_{i,t} = \alpha_i + \theta p_{i,t-1} + \Sigma_{k=0}^{K} \{\gamma_k^u UP_{it} + \gamma_k^d DOWN_{it}\} + \beta X_t + \varepsilon_{it} \qquad \text{Eq. 2}$$

where K is the number of lags we include.

We also estimate a similar procedure using the price returns to account for the unit root in the price process. Estimates for these two procedures are comparable if we account for the serial correlation parameter θ, but inevitably some information is lost when the data is first difference.

The equation in return form is:

$$r_{i,t} = \theta \Delta r_{i,t-1} + \gamma^u \Delta UP_{it} + \gamma^d \Delta DOWN_{it} + \beta \Delta X_t + \Delta\varepsilon_{it} \qquad \text{Eq. 3}$$

Alternatively, we use the following specification of the returns which accounts for the possible persistent correlation for each commodity and better exploits the variation in the media coverage variables.

$$r_{it} = \alpha_i + \breve{\gamma}^u UP_{it} + \breve{\gamma}^d DOWN_{it} + \breve{\beta}\Delta X_t + \breve{\varepsilon}_{it} \qquad \text{Eq. 4}$$

We note that the $\breve{\gamma}$ are different parameters than the γ parameters. These can be related by $\breve{\gamma} \sim \frac{\gamma}{1-\theta}$. We cluster the standard errors by date and allow for auto-correlated (AR1) common disturbances and arbitrary heteroskedasticity, using a truncated kernel as recommended in Thompson (2009). Thus, we allow standard errors to adjust for the possibility that the true specification is:

$$r_{it} = \alpha_i + \breve{\gamma}^u UP_{it} + \breve{\gamma}^d DOWN_{it} + \breve{\beta}\Delta X_t + \breve{\varepsilon}_{it}$$
$$\breve{\varepsilon}_{it} = \psi_t + \pi_{it}$$
$$\psi_t = \rho\psi_{t-1} + d_t \qquad \text{Eq. 5}$$

We also explore the effects of news in the past five market days to see the short-lived but persistent effects that the news data might reflect. Once news about a price increase appears, the likelihood that reports of this price increase appear the next days is higher. Thus, the news data might have "runs," meaning that we will see consecutive news reports followed by no news reports for a long period. We estimate a distributed lag model parallel to the specification above to see if the "runs" in news are also reflected in the price (returns). In this case, the equation for return becomes:

$$r_{it} = \alpha_i + \Sigma_{k=0}^{5}\left\{\breve{\gamma}_k^u UP_{it-k} + \breve{\gamma}_k^d DOWN_{it-k}\right\} + \breve{\beta}\Delta X_t + \rho\psi_{t-1} + d_t + \pi_{it} \qquad \text{Eq. 6}$$

Since we have a long panel time series dimension and a short panel variable, we use procedures that require large T and include commodity fixed effects to account for persistent commodity shocks and allow a flexible specification of the error terms to allow for persistent common shocks. Our procedures exploit the long time series aspect of the data and allow for a flexible data generating process for the error term; thus the correlations we uncover are , if not causal, very well uncovering how the dynamics of media coverage affects or are related to the price setting mechanism in commodities markets.

Finally, to explore the effects of media coverage on price volatility, we estimate the following model (in addition to simple difference in variance tests); this is informed by the estimations in Ohlson and Penman (1985) and Dubofsky (1991):

$$e_{it}^2 = \rho e_{it-1}^2 + \Sigma_{k=0}^{K}\{\breve{v}^u UP_{i,t-k} + \breve{v}^d DOWN_{i,t-k}\} + \pi_{it}$$

where

$$e_{it} = p_{it} - \hat{\theta}p_{it-1} - \hat{\alpha}_i - \hat{\beta}\Delta X_t \qquad \text{Eq. 7}$$

5. Results

Price Levels

Changes in future commodity prices due to media coverage of price dynamics are shown in Table 5. In columns (1)–(6), the dependent variable is the log of the price for each commodity.

Table 5 : Log Price Levels of Commodities

OLS and Fixed Effects Estimates	(1)	(2)	(3)	(4)	(5)	(6)
UPS in price news	-0.086	0.018	0.015	0.00046	0.0006	0.00045
	[0.019]***	[0.0032]***	[0.0022]***	[0.00027]*	[0.00027]**	[0.00025]*
DOWSN in price news	0.098	-0.0037	-0.0087	-0.00075	-0.00079	-0.0008
	[0.025]***	[0.0049]	[0.0028]***	[0.00045]*	[0.00045]*	[0.00040]**
L.price_ln				1	0.99	0.99
				[0.00018]***	[0.0028]***	[0.0032]***
Constant	5.41	7.06	6.73	0.00012	0.046	0.081
	[0.015]***	[0.010]***	[0.017]***	[0.00098]	[0.020]**	[0.022]***
Commodity Effects	No	Yes	Yes	No	Yes	Yes
Market Controls	No	No	Yes	No	No	Yes
Observations	4242	4242	4236	4236	4236	4236

*HAC-SE (in brackets) and Statistics robust to both arbitrary heteroskedasticity and arbitrary common autocorrelation. Clustered on date. *<.10 **<.05 ***<.01*

The baseline model is given in columns (1) to (3), where we include only the media coverage (increase and decrease in price news) and we estimate via OLS, adding regressors from one column to the other. By estimating the price level equation, omitting the individual effects and the autocorrelation in the price level, we obtain significant results; the signs of the coefficients are not intuitive. This specification implies that the appearance of one news article reporting an increase in price is correlated with a 8.6%[10] decrease in the price level, while for a decrease in price media coverage the effect is an increase of 9.8%. Adding commodity-specific fixed effects flips the sign (2) and implies a 1.8% *increase* in the price level per news article reporting price increases and a 0.37% price decrease per article reporting a

[10] The short run effects are obtained by multiplying the estimates by 100, since the specification is in a log-linear form.

decrease in price. Adding the market controls (3) slightly changes the estimates, but the direction of the effects remains.

In columns (4) to (6), we run similar regressions but account for the autocorrelation as in equation 1. The short run effects are very low, as expected. The estimates imply between 0.046% and 0.06% increase in price of the commodity futures response per increased price news and between 0.075% and 0.08% decrease in price per decreased price news. The effect is only significant at the 10% level for the decrease in price media coverage. The significant estimate for media coverage of price decreases in column (6) implies a 0.08% decrease in the price level per decrease in price news article in the short run and a 0.8% decrease in the 'long' run[11]. For the increase in price coverage, the estimates are around 0.045% and 0.45% in the short run and the long run, respectively, and are only significant at the 10% level.

In Table 6, we present results for the distributed lag version of the model, as in Eq. 2. As before, we add regressors sequentially from one column to the other. The estimates are in accord with the previous ones and reveal that there is a split in the effect of the media coverage variable, with 0.056% decrease in the price due to media coverage of price increases 5 days before (per article) and symmetric increase of 0.054% on the day of the appearance of the news (per article). A parallel dynamic can be seen in the decrease in price media coverage. From these estimates, we can gather some of the dynamics between prices and media coverage; news or media coverage of price increases tend to be followed with price increases, as expected, but there is a dampening effect of price increases due to media coverage in the previous days. The converse happens with media coverage of price decreases. We reiterate that "long run" effects can be obtained by multiplying the short run effects discussed by 10, and that these effects on prices are economically meaningful[12].

[11] Note that since we are using daily data, the 'long run' is no necessarily a long time period. The long run estimates are obtained by scaling the coefficient by the autocorrelation parameter, i.e $\frac{\gamma}{1-\theta}$ as defined in Eq. 1. Since the estimates is very close to one, we can approximate the effect by $1000 * \gamma$.

[12] In addition, we note that more flexible specifications that allow for commodity specific trends and commodity specific autocorrelation parameters were estimated and the results are qualitatively the same.

Table 6 : Log Price Levels of Commodities ADL Estimates

	(1)	(2)	(3)
L.price_ln	1	0.99	0.99
	[0.00020]***	[0.0027]***	[0.0033]***
UPS in price news	0.00066	0.00073	0.00054
	[0.00022]***	[0.00028]***	[0.00026]**
L.IUPS in price news	0.00024	0.00031	0.00025
	[0.00024]	[0.00031]	[0.00029]
L2.UPS in price news	-0.00084	-0.00077	-0.00059
	[0.00024]***	[0.00032]**	[0.00031]*
L3.UPS in price news	-0.000023	0.000042	0.0001
	[0.00022]	[0.00030]	[0.00028]
L4.UPS in price news	-0.00038	-0.00032	-0.00041
	[0.00021]*	[0.00026]	[0.00027]
L5.UPS in price news	-0.00056	-0.0005	-0.00056
	[0.00021]***	[0.00028]*	[0.00027]**
DOWNS in price news	-0.00091	-0.00094	-0.0009
	[0.00034]***	[0.00045]**	[0.00041]**
L.DOWNS in price news	-0.00012	-0.00015	-0.0001
	[0.00033]	[0.00045]	[0.00041]
L2.DOWNS in price news	0.00086	0.00083	0.00075
	[0.00031]***	[0.00040]**	[0.00037]**
L3.DOWNS in price news	0.000084	0.000059	0.00012
	[0.00032]	[0.00043]	[0.00038]
L4.DOWNS in price news	0.00072	0.00069	0.00066
	[0.00033]**	[0.00042]	[0.00039]*
L5.DOWNS in price news	0.00052	0.0005	0.00067
	[0.00030]*	[0.00039]	[0.00036]*
Constant	0.00086	0.045	0.073
	[0.0012]	[0.019]**	[0.022]***
Commodity Effects	No	Yes	Yes
Market Controls	No	No	Yes
Observations	4212	4212	4212

*HAC-SE (in brackets) and Statistics robust to both arbitrary heteroskedasticity and arbitrary common autocorrelation. Clustered on date. *<.10 **<.05 ***<.01*

Price Returns

We now turn to the discussion of the return equations, in Eq. 3 and 4. Table 7 present the results of these estimations without using the moment conditions. Column (1) is Equation 3 without the lag difference in return term nor controls, in (2) we add controls, and columns (3) and (4) are the complete specification as shown in Eq.3. The first thing to note is that with the differenced data, it is much more difficult to detect changes due to media coverage. To use methods that rely on the data being stationary, the price to pay is losing some information when the difference is done.

In columns (5) and (6), we estimate Eq. 3 with commodity fixed effects and omitting the lagged difference, and the results are unchanged. The principal difficulty with this specification is that the media coverage variable is differenced and that throws out most of the useful variation. In columns (7) and (8), we estimate Eq.4 with the media coverage variable that is not differenced. In this case, the effects are only significant at the 10% level; however, it is reassuring that the effects are comparable to those we found in the levels equation. Here the effect of media coverage of price increases (ups) is estimated at 0.048 percentage points per news article and a decrease of 0.07 percentage points in the returns with media coverage of price decreases.

Table 7: Dependent Variable: Daily Price Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D.UPS in price news	0.019	0.013	0.019	0.02	0.019	0.013		
	[0.021]	[0.019]	[0.021]	[0.021]	[0.021]	[0.019]		
UPS in price news							0.048	0.027
							[0.027]*	[0.025]
D.DOWNS in price news	-0.035	-0.037	-0.034	-0.035	-0.035	-0.037		
	[0.030]	[0.028]	[0.031]	[0.030]	[0.030]	[0.028]		
DOWNS in price news							-0.077	-0.07
							[0.045]*	[0.041]*
LD.price_ln			3.016	1.795				
			[2.109]	[2.131]				
Constant	0.028	-0.133	0.028	-25.445	0.038	-0.123	0.048	-0.108
	[0.057]	[0.151]	[0.056]	[35.330]	[0.061]	[0.162]	[0.063]	[0.162]
Commodity Effects	No	No	No	No	Yes	Yes	Yes	Yes
Market Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	4236	4236	4230	4230	4236	4236	4236	4236

HAC-SE (in brackets) and Statistics robust to both arbitrary heteroskedasticity
*and arbitrary common autocorrelation. Clustered on date. *<.10 **<.05 ***<.01*

The results for the estimation of Eq. 5 and 6 are presented in Table 8. Columns (1) through (3) are the estimates of Eq. 5 using a two-step GMM procedure that exploits the comment conditions we mentioned in the previous section. The direction of the effects remains unchanged and the magnitudes are much larger. In column (3) where commodity fixed effects and markets controls are included, the estimates imply a strong relationship between media coverage and price returns. For every media article indicating ups, the returns increase by 0.135 percentage points and for articles indicating downs, 0.20 percentage points. In column (4), we estimate the distributed lag version of the equation and we can see that the effects for media coverage of down is potentially bigger, with up to 0.38 percentage point decrease for a 2 day period.

Table 8: Dependent Variable: Price Returns with Difference instruments(DIV)

	(1)	(2)	(3)	(4)
UPS in price news	0.151	0.151	0.135	0.146
	[0.059]**	[0.059]**	[0.054]**	[0.071]**
DOWNS in price news	-0.091	-0.091	-0.173	-0.204
	[0.089]	[0.089]	[0.083]**	[0.100]**
L.I UPS in price news				0.121
				[0.074]
L2.UPS in price news				-0.121
				[0.077]
L3.UPS in price news				-0.016
				[0.062]
L.DOWNS in price news				-0.184
				[0.088]**
L2.DOWNS in price news				0.107
				[0.090]
L3.DOWNS in price news				-0.035
				[0.086]
Commodity Effects	No	Yes	Yes	Yes
Market Controls	No	No	Yes	Yes
Observations	4212	4212	4212	4212

SE (in brackets) and Statistics robust to both arbitrary heteroskedasticity

*and arbitrary common autocorrelation. Clustered on date. *<.10 **<.05 ***<.01*

The instruments are 5 lagged differences of media coverage for each commodity. In total there are 20

excluded instruments in the regressions.

Volatility

We explore changes in price volatility due to media coverage in two ways. First, we use a simple F-test for differences in the variance of prices on days on which there is news and those on which there is no news. The question of whether the volatility of futures prices is different on days onw hich there is media coverage is of fundamental interest; namely, we want to know whether the volatility of the rate of return on futures prices increases on days on which there is media coverage indicating ups (positively correlated) or downs (negative correlated). The second approach is a regression version of the first and consists of estimating Eq. 7 that uses the squared residuals of the price level regressions discussed before[13].

We note that the ratio of the estimated variance of the rate of return (and the price level) on days with news relative to no-news days, $\frac{\sigma^2_{no-news}}{\sigma^2_{news}}$ is distributed as an F-statistic under the null hypothesis of equal variances. Table 9 shows the results of these tests for each type of coverage, namely days on which there are up news, down news, and any type of news. The null hypothesis is that the ratio is equal to one; the alternatives are given in the column headers.

Table 9: Fisher Tests for difference in variances in price levels.

	Obs	Ha:Ratio<1	Ha:Ratio>1	Ha:Ratio!=1	F-Stat	SD-No news	SD- News
UPS-in price news	4242	0.003	0.997	0.005	0.879	1.454	1.551
Downs- in price news	4242	0.196	0.804	0.393	0.957	1.482	1.514
Any-News	4242	0.033	0.967	0.066	0.922	1.464	1.525

The tests in Table 9 show that the volatility of price levels is not the same for the days on which there is news and the days on which there is no news of changes in prices. For the days on which there are up news in comparison to those on which there is no news or down news, there seems to be higher volatility (p-value 0.003). The comparison between decreases in price news days and increases or no news days yields no significant differences in volatility (p-value 0.393). Comparing the results for any type of news, we can conclude that NO NEWS is better than NEWS in terms of price level volatility.

[13] These residuals are essentially market adjusted returns.

We conduct a similar test for the futures price returns and present the results in Table 10. The test unequivocally points to higher variances/volatility on the days on which there is media coverage.

Table 10: Fisher Tests for difference in variances in price returns

	Obs	Ha:Ratio<1	Ha:Ratio>1	Ha:Ratio!=1	F-Stat	SD-No news	SD- News
UPS- in price News	4236	0.000	1.000	0.000	0.805	1.947	2.170
DOWNS-in price News	4236	0.001	0.999	0.003	0.858	1.983	2.141
Any-News	4236	0.000	1.000	0.000	0.800	1.930	2.158

To further analyze volatility, we present a graphical analysis of the residuals, given that this simple test might not reflect the heterogeneity in volatility due to the intensity of media coverage. What we mean by this is that creating dichotomous groups that agglomerate a day with one up news with a day with 10 up news might give the impression that media coverage is positively correlated with volatility when it could also be the opposite. Figure 9 makes a good case for this point.

The figures show that for days with fewer than 5 articles of up or down news, the residuals are very spread out in comparison to ones on a day with more than 5 articles. This evidence points to lower volatility when media coverage is more intense.

Table 11 shows the estimations that put the graphs in a regression framework (Eq.4). The message to take away from these regression results is that volatility seems to be negatively correlated with the down media coverage and that these effects are lagged, i.e. the manifest themselves 1 and 2 days after the news appears. For the up media coverage, the regressions are not as conclusive. There is a significant increase in volatility after the news has appeared, but this effect is overwhelmed by the negative effect of days farther in the past. In summary, the evidence points to volatility being negatively correlated with media coverage.

Figure 9: Squared Residual vs. Intensity of Media Coverage

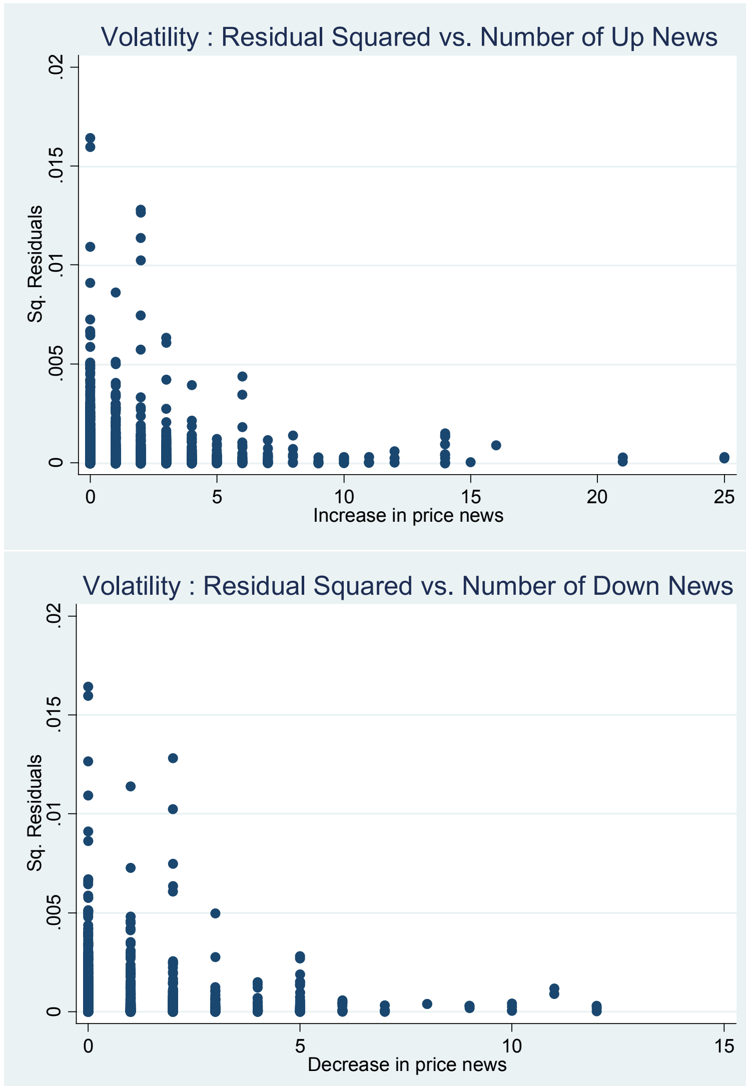


Table 11: Squared residuals (WITH controls) of Commodities Prices

OLS, Fixed Effects and ADL Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
L.Sq. Residuals	0.084	0.069	0.064	0.084	0.069	0.063
	[0.028]***	[0.027]***	[0.026]**	[0.027]***	[0.026]***	[0.026]**
UPS in price news	0.089	0.02	-0.0048	0.052	0.018	0.0038
	[0.073]	[0.073]	[0.072]	[0.077]	[0.075]	[0.074]
DOWNS in price news	0.085	0.033	0.043	0.099	0.045	0.052
	[0.13]	[0.12]	[0.12]	[0.13]	[0.13]	[0.13]
L.I UPS in price news				0.29	0.26	0.24
				[0.10]***	[0.10]**	[0.098]**
L2.UPS in price news				-0.0047	-0.037	-0.045
				[0.078]	[0.079]	[0.081]
L3. UPS in price news				0.12	0.08	0.034
				[0.084]	[0.084]	[0.082]
L4. UPS in price news				-0.09	-0.12	-0.16
				[0.084]	[0.085]	[0.085]*
L5.UPS in price news				0.031	-0.0029	-0.031
				[0.077]	[0.079]	[0.083]
L. DOWNS in price news				-0.29	-0.34	-0.36
				[0.14]**	[0.14]**	[0.13]***
L2.DOWNS in price news				-0.21	-0.27	-0.24
				[0.094]**	[0.094]***	[0.093]***
L3.DOWNS in price news				-0.094	-0.16	-0.099
				[0.10]	[0.10]	[0.10]
L4.DOWNS in price news				0.18	0.12	0.17
				[0.11]	[0.11]	[0.11]
L5.DOWNS in price news				-0.062	-0.12	-0.081
				[0.098]	[0.098]	[0.098]
Commodity Effects	No	Yes	Yes	No	Yes	Yes
Market Controls	No	No	Yes	No	No	Yes
Observations	4230	4230	4230	4212	4212	4212

*HAC-SE (in brackets) and Statistics robust to both arbitrary heteroskedasticity and arbitrary common autocorrelation. Clustered on date. *<.10 **<.05 ***<.01*

6. Conclusions

We have looked at three important aspects of commodity markets (the price level, the returns these levels imply, and the volatility of these markets) and relate them to coverage of those markets in the media. We uncover interesting correlations between price dynamics and media coverage intensity.

The findings that more news report of up or downs reinforce the price movement in the direction of the report strengthen our case that increased media attention in some periods of food crises can exacerbate price increases. We analyze the price level first because this is what poor consumers of these commodities will feel. We proceeded to analyze the returns because the behavior of investors and speculators are conditional on them. We find similar conclusions for the returns equations. Returns also increase with media coverage of ups in the price levels.

The results for volatility show the importance of accounting for the intensity of media coverage and the delayed response that can be expected, as by construction changes in volatility are only observed after various changes in the price levels. In addition, we find that the media has good potential for reducing volatility. The variability of commodities return and prices tends to decrease as more attention is paid by the media to the situation in those commodities markets.

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