Futures Commodities Prices and Media Coverage

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Outline

• Why?
• Previous studies
• What we do?
• How we do it
• Key results
• Conclusions
Real food prices have a high impact on consumers, especially the poor ones.

Can perceptions on food price development in mass media impact the real prices?

If this is the case
– how strong is the impact?
– what can be done to influence the perceptions?
A trend reversal, plus a new normal?

Food prices: 1990-2012

Jan ’90: 93.98
Jun ’08: 220.28
Feb ’11: 223.56
Mar ’12: 209.37

Source: World Bank
Historical Evolution of Corn Prices

Source: Datastream data.
Periods of Excessive 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.

Wheat Prices Soar After Russia Bans Exports

Steve Baragona | Washington06 August 2010

Importance of information

Why?
### Analysis of media articles referencing wheat prices

<table>
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<tr>
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<td>Financial</td>
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<td>Inventories</td>
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<td>Disasters and civil effects</td>
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<td>Total references to wheat price increases</td>
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<td>Total number of articles on wheat prices</td>
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<td>1,238</td>
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</tbody>
</table>

Why?
CBOT wheat prices

Nearest future price ($/bushel)

- Drought in Russia began
- Locust in Australia
- Wildfires in Russia
- USDA report
- Potential imports by Russia later denied
- Announcement Russia will ban exports

U.S. N° 2 Soft wheat

Why?
Global stocks of wheat

- June 2010: 187.1 million MT
- August 2010: 174.8 million MT
- 2007-2008: 124.9 million MT

Why?

CBOT wheat prices – IFPRI model to detect abnormal spikes

Source, Martins-Filho, Torero, Yao (2010)
Previous studies

• 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, Fama (1970).

• On the effects of news events of futures prices:
  – Rucker et al. (2005) estimate the effect on lumber futures prices to help shed light on the volatility of lumber prices
  – Pruitt (1987) studies the effects of the Chernobyl nuclear accident of the ag.
  – Carter and Smith (2007) estimate the effect of news concerning the contamination of the corn supply on the price of corn

• On 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
  – Schlenker and Villas-Boas (2009) explore the effects of information on mad cow disease had on purchases and futures prices
  – Smith, van Ravenswaay and Thompson (1988) study the impact of contamination of milk on consumer demand
• Why?
• Previous studies
• What we do?
• How we do it
• Key results
• Conclusions
**Perception:** Media Reports on current and foreseeable supply, demand, stocks, trade, prices

**Evidence:** Based on the markets and their fundamentals (Current and foreseeable supply, demand, stocks, trade, prices)

**Prediction:**
- Price will go up
- Price will stay stable
- Price will go down

**Combinations**

**What we do**
Our analytical approach

• Influence of media on price levels because this is what the poor consumers of these commodities will feel

• We proceeded to analyze the returns because the behavior of investors and speculators are conditional on them

• Finally look at effects on price volatility
Data

• **Prices:**
  – daily futures price data from the Chicago Board of Trade for futures of Maize, Soft, Soybean, Rice and Oil and from Kansas City Board of Trade for Hard Wheat.
  – 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.

• **Measures of media coverage:**
  – every day, we monitor a comprehensive set of RSS (Really Symple Syndication) feeds drawn from global media outlets via Google news. A total of 31 feeds related to global food prices and food security are monitored
  – Each media article is analyzed using linguistic and semantic object network-mapping algorithms to analyze the relationships between key terms found in each article.
  – 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.
  – The period spans from the 3rd of August of 2009 to the 11th of June of 2012. In “market time” we obtain 707 periods (days) for a total of 4,242 observations.

How we do it
Empirical implementation

1. For Price levels:

\[ p_{i,t} = \alpha_i + \theta p_{i,t-1} + \gamma^u U_{Pi,t} + \gamma^d D_{OWN_{it}} + \beta X_t + \varepsilon_{it} \]

\[ p_{i,t} = \alpha_i + \theta p_{i,t-1} + \sum_{k=0}^{K} \left( \gamma_k^u U_{Pi,t} + \gamma_k^d D_{OWN_{it}} \right) + \beta X_t + \varepsilon_{it} \]

Where:

- \( i \) = Hard Wheat, Maize, Oil, Rice, Soft Wheat, Soybeans
- \( t = 1 \ldots T \) (1 is 08/03/2009 and T is 06/12/2012 in ‘market time’)
- \( p_{it} \) is the log price level
- \( \alpha_i \) is a commodity specific intercept (fixed effect)
- \( U_{Pi,t} \) is the number of ‘increase in price of \( i \) news for day \( t \)
- \( D_{OWN_{it}} \) is the number of ‘decrease in price’ of \( i \) news for day \( t \)
- \( X_t \) is a matrix of market variables at date \( t \)
- \( \varepsilon_{it} \) is a random error term, which depending of the specification will have a different structure
- \( K \) is the number of lags

We assume that the news variables are predetermined or sequentially exogenous, that is that

\[ E[\varepsilon_{it} | \alpha_i, X_t, U_{P_{i,t-k}}, D_{OWN_{i,t-k}}] = 0 \text{ for } k = 1 \ldots t \]

which allow us to use moment restriction to obtain a GMM-IV estimator
Empirical implementation

2. For Price returns:

\[ r_{i,t} = \theta \Delta r_{i,t-1} + \gamma^u \Delta UP_{it} + \gamma^d \Delta DOWN_{it} + \beta \Delta X_t + \Delta \varepsilon_{it} \]

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

\[ r_{it} = \alpha_i + \tilde{\gamma}^u UP_{it} + \tilde{\gamma}^d DOWN_{it} + \tilde{\beta} \Delta X_t + \tilde{\varepsilon}_t \]

We note that the \( \tilde{\gamma} \) are different parameters than the \( \gamma \) parameters. These can be related by \( \tilde{\gamma} \sim \frac{\gamma}{1-\theta} \). 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).
Empirical implementation

3. For 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):

\[ e_{it}^2 = \rho e_{i,t-1}^2 + \sum_{k=0}^{K} \{ \tilde{\gamma}^u UP_{i,t-k} + \tilde{\gamma}^d DOWN_{i,t-k} \} + \pi_{it} \]

where

\[ e_{it} = p_{it} - \hat{\theta} p_{it-1} - \hat{\alpha}_i - \hat{\beta} \Delta X_t \]
## Results on Log Price levels

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*HAC-SE (in brackets) and Statistics robust to both arbitrary heteroskedasticity and arbitrary common autocorrelation. Clustered on date. *<.10 **<.05 ***<.01
## Results on Price Returns with Difference instruments(DIV)

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Lags 1-5 included for UPS and Downs

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.
Summarizing Effect Size of Media Influence

Key results

- Total effect: 4.5% (Down: 2.1%, Up: 2.4%)
- %Effect: 7.0% (Down: 3.8%, Up: 3.3%)
- Std. Effect: 8.9% (Down: 8.8%, Up: 1.8%)
Results on 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 (we don’t differentiate the intensity of media).

• We found that for days with fewer than 5 articles of up or down news, the residuals are very spread out in comparison to ones in day with more than 5 articles.

• This evidence points to lower volatility when media coverage is more intense.
Results on Volatility: Squared Residual vs. Intensity of Media Coverage

Key results

Volatility: Residual Squared vs. Number of Up News

Sq. Residuals vs. Increase in price news
Results on Volatility: Squared Residual vs. Intensity of Media Coverage

Volatility: Residual Squared vs. Number of Down News

Key results
Conclusions

• There are interesting correlations between the price dynamics and the media coverage intensity
• Increased media attention can exacerbate the increase in price (more than 8% of the change in prices)
• 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
The major policy implication is the crucial role of providing appropriate information as fast as possible so media reacts in the correct direction.
“In the real world, the right thing never happens in the right place and the right time. It is the job of journalists and historians to make it appear that it has”

Mark Twain