academicJournals

Vol. 7(5), pp. 156-169, May, 2015
DOI: 10.5897/JAERD2014.0633
Articles Number: 2A3619A53094
ISSN 2141-2154

http://www.academicjournals.org/JAERD

Journal of Agricultural Extension and Rural Development

Full Length Research Paper

Revisiting uncertainty and price forecast indicators in corn and wheat markets

Hélyette Geman[1,2]* and Pedro Vergel Eleuterio[1]

[1]Birkbeck, University of London, London, England.
[2]Johns Hopkins University, United States.

Received 19 August, 2014; Accepted 24 March, 2015

The purpose of this paper is twofold: First, we look at the fundamentals of spot prices of corn and wheat and analyse several measures of dispersion, arguing that the use of the standard deviation of prices is more instructive for regulators and world food organisations than volatility, that is, standard deviation of returns. Second, we look at alternative predictors of corn and wheat spot prices and exhibit that the average value of the forward curve introduced by Borovkova and Geman (2006) performs better than individual forward prices to forecast spot prices at future dates.

Key words: Grain markets, volatility of returns, standard deviation of prices, geometric average of forward prices, commodity spot price predictors.

INTRODUCTION

It is usually recognized that Futures markets incorporate information quicker than spot markets due to low transaction costs, liquidity and the feasibility of long and short positions. Price discovery allows the transfer of price information, from commercial merchants that have more accurate information about planting decisions and future harvests to other players that do not have access to this information. If the number of players on the buy and sell sides with full information was large enough, the expectation of futures prices should in principle be an unbiased prediction of spot prices.

In contrast to crude oil prices which started rising in 2002, followed by copper, gold and other metals, agricultural commodity prices were essentially flat (declining in fact if adjusted for inflation) until 2006. In the agricultural year 2006-2007, different weather events around the world sent corn and wheat prices to unprecedented levels. As of that moment, food price risk became a large concern, for government and regulators alike.

Our goal in the first part of this article is to argue that the famous volatility (that is, standard deviation of returns) that is widely discussed, analysed and estimated in the financial markets is not the most informative quantity in the case of commodities, particularly agricultural commodities. We propose instead to focus on the signals provided by the coefficient of variation of prices on one hand, and the standard deviation of price levels on the other hand.

In the second part of the paper, we compare the quality of future price prediction provided by individual forward contracts versus the geometric average of the forward curve introduced in Borovkova and Geman (2006). We show that the latter performs better for corn and wheat spot prices. The measures presented in the first and second parts of the paper are highly related because they all provide important information for participants in the

*Corresponding author. E-mail: hgeman@hotmail.com.

market, including farmers, consumers, and government regulators and policymakers.

Since the measures of dispersion and the predictive power of Futures prices, the two focal points of our study, are directly linked to the realities of the physical markets themselves, we also provide the reader with the essential background needed to understand the corn and wheat markets. Explanations of the physical commodities are vital in order to be able to see how Futures prices are capturing the market.

FUNDAMENTALS OF CORN AND WHEAT MARKETS

Corn

As a feed, corn is the highest valued among the cereal grains for its energy content, consisting of 65% starch, 4% oil and 10% fibre. In temperate climates, corn must be planted in the spring. Corn is a more water efficient crop than soybeans or alfalfa but requires a larger amount of fertilizers. A corn crop producing six to nine tonnes of grains per hectare requires 31 to 50 kg of phosphate fertilizer while a soybean crop requires 20 to 25 kg per hectare (Geman and Vergel Eleuterio, 2013).

The United States is the biggest producer of corn in the world, followed by China, Brazil, and the EU-27. Main world exporters are the United States, Argentina, Brazil, and Ukraine. The biggest importers are Japan, South Korea, the European Union and Mexico. Depending on the government policy and climate conditions, China alternates between years of high exports and high imports, thus making it a source of uncertainty for the world corn market.

In the US, corn production accounts for over 95% of total feed grains production. Of the other feed grains, sorghum accounts for 2.9, barley for 1.5 and oats for 0.5%. The Chicago Mercantile Exchange (CME) offers a wide variety of financial derivatives written on corn including corn Futures, a mini-corn Futures contract, calendar swaps, and a wide variety of options contracts, including new crop options.

Wheat

A fundamental staple of the human diet, wheat comprises approximately 20% of calories and proteins consumed on a global scale. Worldwide, approximately 10% of wheat grain production is used annually for feed. A high starch content of roughly 70% dry matter makes this cereal grain rich in carbohydrates. In addition to having a greater amount of protein (hard and durum wheat have more proteins than soft wheat) than corn or barley, wheat protein is also of a higher calibre, making the grain a valued substitute for corn. It is important to note, however, that the content and quality of crude protein and starch can vary with growing conditions, wheat species, fertilizers, and other factors.

Common (or bread) wheat grain is primarily processed into flour for bread, pastry, and the confectionary industry. The production of bread and similar products is aided by gluten, a protein unique to wheat, which helps dough to rise. Gluten is commonly used to thicken foodstuffs including soup, gravy, and sauces. Durum wheat, which is lower in gluten content, is used in the production of pastas, semolina, couscous, pizza bases, and other flat breads.

The main producers of wheat are EU-27, China, India, and the US. Major exporters are the US, EU-27, and Australia and the largest importers include Egypt, Brazil, Indonesia, Japan, Algeria EU-27 and South Korea. Wheat futures, including a mini-wheat Futures contract, calendar swaps and options contracts as well as Black Sea Wheat Futures, Kansas City Wheat Futures (KC Wheat), options and swaps from the Kansas City Board of trade (KCBT) can be purchased through the CME. Other products include Minneapolis Grain Exchange - Chicago Board of Trade Wheat Spread options (commonly known as MGEX-CBOT Wheat Spread Options) as well as Futures and short-dated new crop options.

Links between corn and wheat

In Crops and Man (1975), renowned botanist Jack Harlan stated the following: “Fully domesticated plants are artefacts produced by man as much as an arrowhead, a clay pot, or a stone axe.” This is certainly true of most, if not all, agricultural commodities currently traded and consumed on a global scale. Centuries of research and careful breeding (for example, to create hybrids) together with the development of fertilizers, pesticides, and herbicides have resulted in better quality crops, higher yields, and greater resistance to pests and adverse weather conditions.

Corn and wheat are two central agricultural commodities which have benefited from such developments. With incomes rising in developing countries such as China and India, there has been a shift from basics such as rice and wheat to more expensive foodstuffs including meat, dairy, and vegetable oils. The increase in demand for meat and dairy requires the expansion of the meat production industry which, in turn, requires more feed grains. Although the rate of population growth has slowed significantly with the decline in birth rates, demographers still forecast a rise to ten billion just after 2050. Providing nourishment for everyone will require at least 35% more calories than what is currently produced today. Taking into account the continual increase in meat consumption, the percentage of grains needed is much greater. Animal nutrition, which is ultimately dependent on agricultural commodities, will be crucial in meeting objectives for meat production.

Both corn and wheat are used for animal feed. Corn and its by-products are valued for their high energy content but have low protein content and need to be supplemented in order to provide the appropriate amount of proteins and amino acids. For this reason, corn is traditionally mixed with soybean meal when used as an animal feed. Wheat that is not fit for human consumption or food processing is used for animal feed. With a higher amount of protein, minerals, oil and fibre than wheat grain, wheat bran - a by-product of the dry milling process used to make flour and produce pasta from durum wheat - is also a major animal feed. The link of corn, wheat and soybeans is apparent in the offering of financial products. The CME offers a wide variety of cross commodity financial products such as wheat-corn spread options and soybean-corn price ratio options.

Wheat and corn also share important connections through crop rotation, double cropping, and intercropping. It has long been shown that crop rotation – a planting method involving the growth of various crops in a strategic, sequential order – of corn, soybean, and wheat in a three year rotation results in improved soil quality, reduced risk of pests and pathogens, better weed control and most importantly, sustained yields. A study by Michigan State University (Lipps et al., 2001) reports that including wheat in the rotation is vital for increasing yields of other crops like corn and soybeans by at least 10%. In addition, crop rotation can be beneficial in reducing risks associated with poor weather conditions; for example, during the drought of 2012, wheat yields were above average while corn was adversely affected. Double-cropping, when a second crop is planted after harvesting the first, is also common in the cases of corn, wheat and soybeans. In the US, it is usual to find double-cropping, for example, with corn and alfalfa rotating in colder areas or corn and soybeans in areas with longer summers. A third crop, such as winter wheat, can also be added to the rotation. In “relay intercropping”, two crops are planted in the same field; for example, soybeans can be planted on a field where wheat is currently growing.

Since the start of 2004, a dramatic increase has prevailed in the open interest of CBOT Corn and CBOT Wheat Futures contracts. The biggest rise in open interest was for CBOT wheat, which increased from around 100,000 contracts in 2005 to a high of 550,000 in 2006. Corn followed and by spring 2006, banks accounted for 20% of the total open interest for wheat and 12% for corn. Additionally, from mid-2007 to mid-2008, we observe a widening of the spread between wheat and corn prices. This coincided with a period of in-creased prices due to tight wheat supplies, record wheat prices, human consumption demand being inelastic to prices, and a large amount of trading carried out by index funds. Historically, CBOT Wheat and CBOT Corn have moved together, with the price of wheat typically one to two dollars higher than corn. Only on very rare occasions does this spread invert. However, corn prices reached a record high in April 2011 and surpassed the price of wheat of wheat due to a growing demand for corn-based ethanol and tight level of supplies not seen since the 1930s (Figure 1).

VOLATILITY, COEFFICIENT OF VARIATION AND STANDARD DEVIATION OF PRICES OF CORN AND WHEAT

Traditionally, finance literature has concentrated on the use of returns rather than prices, and volatility rather than standard deviation of prices as a measure of variation. It started with the Portfolio Theory of Markowitz (1958) where the naturally important quantities to analyse are returns on stocks, whatever the initial wealth owned by the investor. It continued with the Black-Scholes-Merton (1973) model, in which the mathematical assumption on the underlying stock price was expressed through the stochastic dynamics of its returns.

Turning to commodities, the monthly volatility of returns - with returns classically approximated by log differences - is computed from monthly data as follows:

$$Volatility = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(\Delta \ln p_i - \frac{1}{n}\sum_{i=1}^{n}\Delta \ln p_i\right)^2}$$

where p_i is the dollar value of the CBOT closing price of the commodity nearby future contract on month *i* and *n* is the number of monthly observations. It is annualized by multiplying the monthly volatility, as calculated above, by $\sqrt{12}$. We calculate the annualized volatility in a similar way when using daily or weekly data, by multiplying volatility by $\sqrt{250}$ or $\sqrt{52}$, respectively .

From an econometric point of view, the use of returns makes sense since the return series is more likely to be stationary, which leads to the use of a wide range of econometric tools. This reasoning is not optimal, however, for agricultural commodities. The repeated crises since 2006 have brought the focus on the right entity of concern, namely the price prevailing in the world market. Price levels are reflected in the cost of food and food security for poorer individuals who have no interest in returns, and in turn for policymakers.

Hence, an investigation of the different measures of dispersion of prices (and not just returns) is, in our view, hard to avoid when dealing with food commodities. Different types of participants may benefit from distinct measures of dispersion. For instance, since farmers are directly affected by price volatility, which can have a long term influence on producers and their production schedule, they should be most concerned with the standard deviation of prices. This measure best captures intra-year volatility of the price level driven by low stock to use ratio, or tight supply. In contrast, investors care about the return of the asset and the risk attached, which is

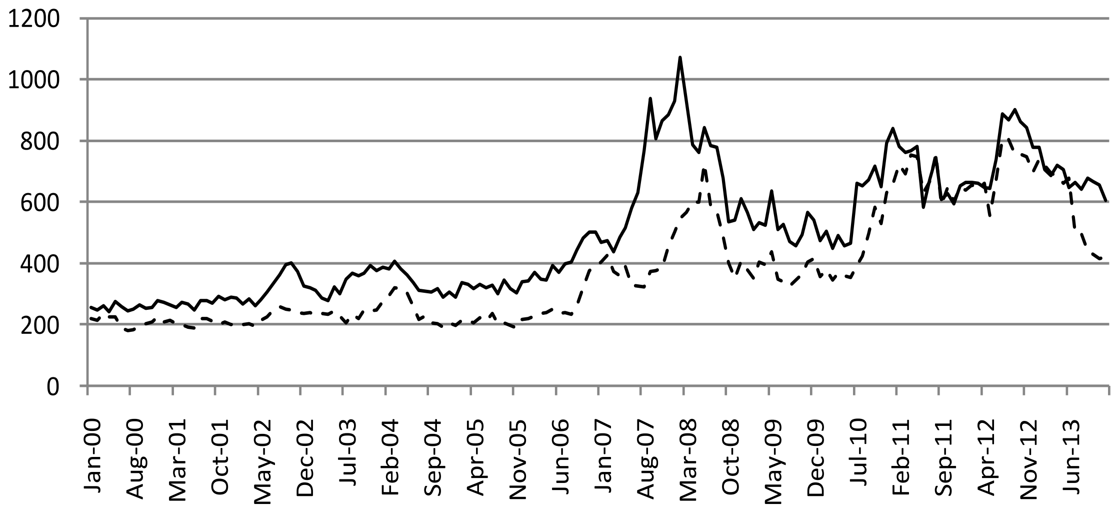

Figure 1. First nearby prices of CBOT Wheat (solid line) and CBOT Corn (dash line) in US cents per Bushel.

best measured by the volatility of returns. Government regulators and policymakers would benefit from using the coefficient of variation since it gives better intra-year information (for example, in 2004 when there was a dramatic increase in the open interest of corn and wheat Futures contracts); this measure could allow them to confront changing conditions more quickly.

The coefficient of variation lies somewhat in the middle of volatility and standard deviation of prices. Like volatility, it is independent of units of measurement; however, its computation bears directly on prices. The annualised coefficient of variation, CV, is usually defined as the ratio of standard deviation σ and the mean μ of the price series:

$$CV = \frac{\sigma}{\mu}$$

It is customary to use the sample standard deviation and the sample mean when calculating the coefficient of variation. In the continuity of our analysis above, we use monthly prices and annualize in the same way. We recall that the standard deviation of the sample of size *n* is computed as:

$$Standard\ deviation = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(p_i - \frac{1}{n}\sum_{i=1}^{n} p_i\right)^2}$$

We use in the formulas above monthly data from January 2000 to December 2013. The first nearby, F1, is used as a proxy for the spot price, S_t, throughout the paper. The contracts chosen for each commodity are their respective world benchmarks. In the case of wheat, we use Future contracts on No. 2 Soft Red Winter wheat and for corn, the No. 2 Yellow Corn Future contract, both traded on the CME Futures U.S. Exchange. In all cases, we respect the 'last trading day' rule for consistency.

Corn

From Figures 2 and 3 depicting the results in Table 1, we obtain a clearer picture of the pros and cons of each measure. Starting with volatility, we observe values around 20% until 2003, increasing to around 30% from 2004 to 2007, with a peak of 47% in 2008 and values well over 30% afterwards. The coefficient of variation also shows low values up to 2003, and then starts exhibiting a spiky behavior. Turning to the standard deviation of prices, we observe in the years 2000 to 2003 values lower than 100, then much higher, which should have been a striking signal for regulators and policy makers.

The year 2004 was an exceptional year for corn: Remarkably low levels of carried stock from 2003 and the 2004 harvest the largest one on record. The effects of both scarcity and abundance of grains that year are easily observable in the price movements. Corn prices reached a maximum in April at 316.5 cents per bushel and went down to 192.5 by November to partially recover by the end of year. This intra-year variation is particularly well reflected in the coefficient of variation and the standard deviation of prices, making the case for these two values we propose to bring a large attention to. Regulators should have read in these numbers warnings for the bigger crises to come.

Wheat

In the case of CBOT wheat, we also observe how the alternative measures of dispersion give different views on

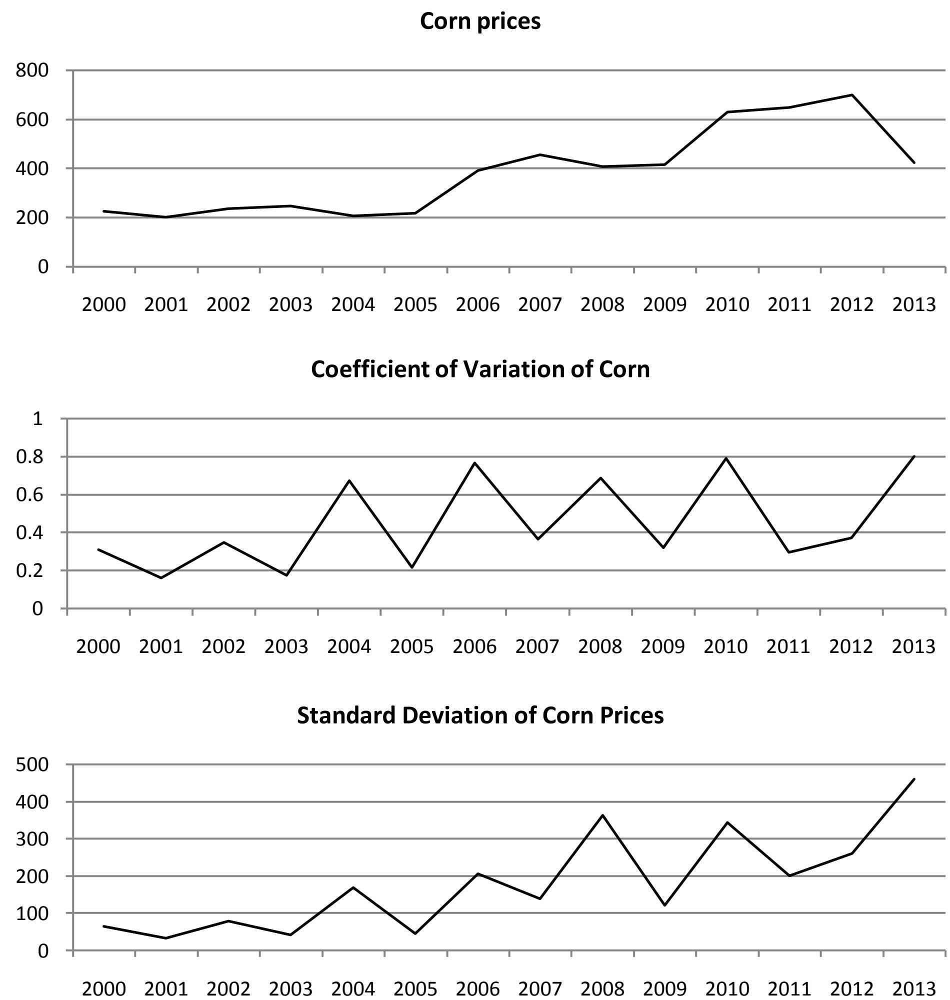

Figure 2. CBOT corn: Closing price, coefficient of variation, and standard deviation of prices per year from 2000 to 2013.

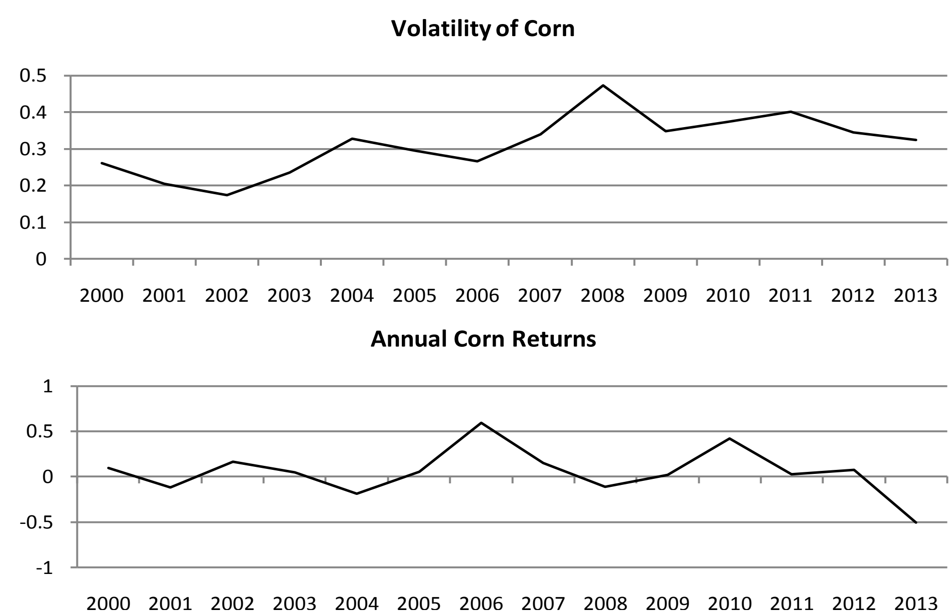

Figure 3. CBOT corn annualized monthly volatility and annual returns from 2000 to 2013.

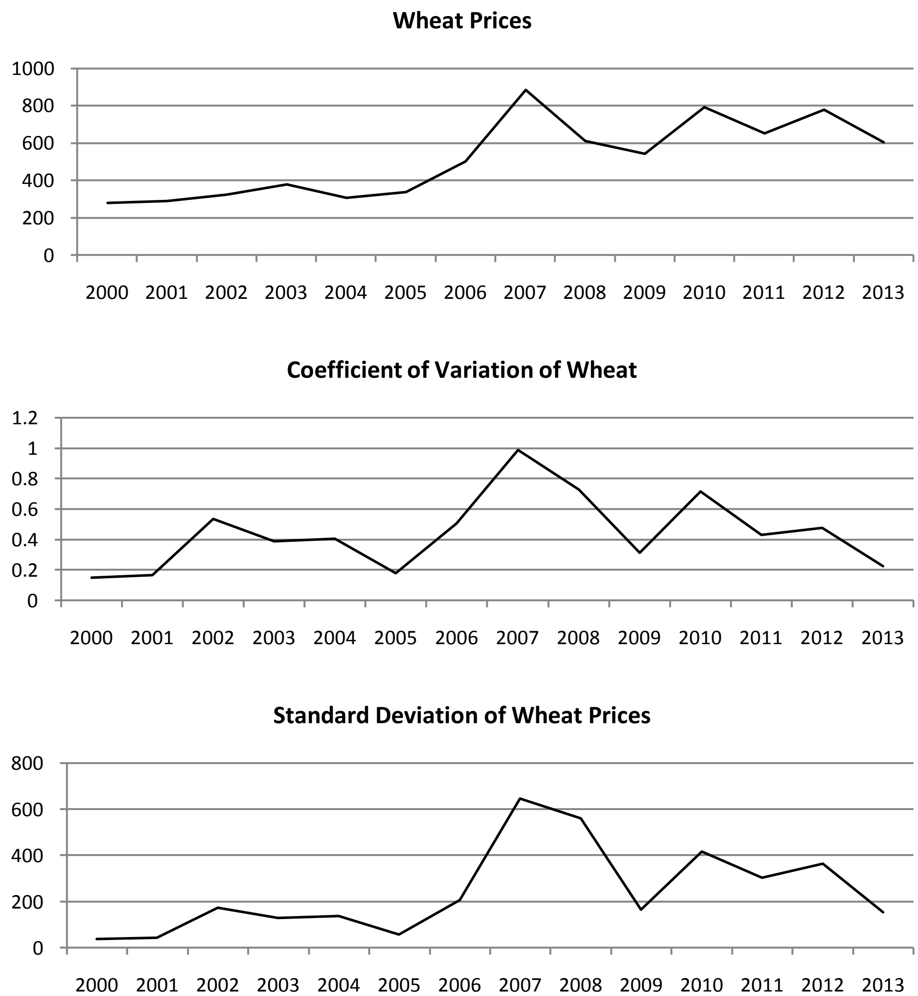

Figure 4. CBOT wheat: Closing price, coefficient of variation, and standard deviation of prices per year from 2000 to 2013.

what happened in recent years. While volatility presents a clear upward trend from 2006 until it started declining in 2011, this decline happens much earlier in both the annualised coefficient of variation and standard deviation (Table 2 and Figures 4 and 5).

In conclusion, for both corn and wheat, the increase of the coefficient of variation and standard deviation of prices was much more dramatic than volatility as of the middle of the year 2005 and could have been a warning signal for governments and regulators.

EXAMINATION OF ALTERNATIVE PREDICTORS OF SPOT PRICES

There is a long history of price expectations models, beginning with Hicks' publications "Value and Capital" (1939, 1946) and "Capital and Growth" (1965). It was Muth (1961) who developed the econometric version of the Rational Expectations Hypothesis. Following his work, numerous studies have been conducted to test the unbiasedness of the forward exchange rate as a predictor of the spot exchange rate in the future; for example, Cornell (1977), Geweke and Feige (1979), Hansen and Hodrick (1980), Longworth (1981), and Frenkel (1981). There also exist empirical studies for commodities, including those of Goss (1983), and Pieroni and Riociarelli (2005).

Lucas (1972) extended the Rational Expectations Hypothesis (REH) to macroeconomics and was awarded a Nobel Prize for his work (Lucas, 1995). According to his perspective, the REH is a conjecture that can be the core of an empirically testable price expectations model. The REH implies that the forward price at date *t* for maturity date *t*+ *h*, F_t, should be an unbiased predictor of the commodity spot price at *t*+*h*:

$$f(t, t+h) = E_p(S(t+h)/I_t) + u_{t+h}$$

Where I_t is the filtration incorporating all information until date *t*, and *u* is an error term with conditional expected value of 0 and uncorrelated to the information at time *t*.

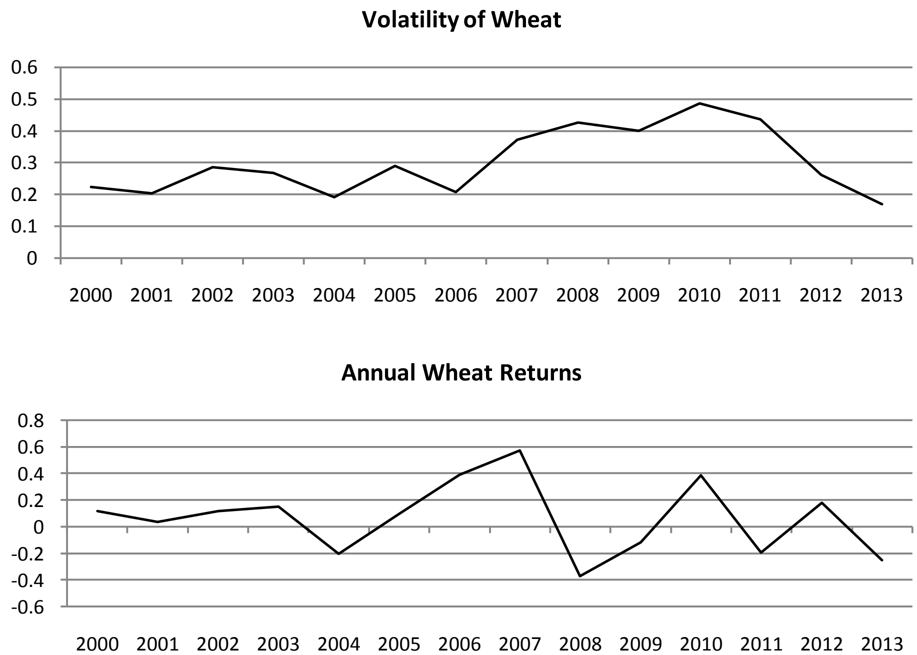

Figure 5. CBOT wheat: Annualised monthly volatility and annual returns from 2000 to 2013.

By adding the no- arbitrage assumption and changing the probability measure, the above relationship can be written as an exact equality.

In this paper, we adapt the tests of the REH in the style of Muth (1961) to find the optimal lag *h*, if any, for an estimate of the future spot price.

Individual forward contracts as predictors of future spot prices

In order to test the relationship between spot and forward prices, we use log prices of Futures daily data for corn and wheat. Under constant interest rates or absence of correlation of these to the underlying asset, arguably the case for agricultural commodities, forward and Future prices are equal. Both commodities have Future contracts with delivery months in March, May, July, September and December (examples of forward curves in Figure 6) and their last trade date is the last business day prior to the 15th calendar day of the contract month. The first test involves running the regression:

$$\ln S_t = \alpha + \beta \ln f_{t-h} + \varepsilon \quad (1)$$

With *h* expressed in number of months. In this analysis, we are interested in the results of the F-tests on the intercept of the regression and the slope of the lagged forward price. If α=0 and β=1, even if the series are not stationary, they are cointegrated and hence the forward price is an unbiased predictor of the future spot price. The main drawback of this test is that it could be allocating a predictive power to the forward price that could also be attributed to the lagged spot price. Hence, a second F-test is used based on the regression:

$$\ln S_t - \ln S_{t-h} = \alpha + \rho \quad (\ln f_{t-h} - \ln S_{t-h}) + \varepsilon \quad (2)$$

In this test, the change in the spot price, $\ln S_t - \ln S_{t-h}$,is explained by $\ln f_{t-h} - \ln S_{t-h}$, a quantity that defines the magnitude of backwardation or contango at date *t-h*. This test deals with log differences, which are generally stationary, and subtracts the effect of the lagged spot price from both sides of the equation. When ρ =1, the regression represented by Equation (2) reduces to that of Equation (1) when β = 1.

We pose two questions. First, do forward prices before the planting period of corn predict spot prices after the harvest in the US? Second, will these estimates be affected by the proximity of the observed forward prices to the contract expiry date? In order to answer these questions, we test the predictive power of each maturity with its corresponding spot price, that is, we compare how the July Future price observed at time *t-h* predict July spot prices, the September Future prices predict September spot prices, etc.

First, we place ourselves at two particular points in time: the beginning of February and the beginning of April. These are the dates when observations of the forward curve are taken; *date t-h* in Table 3, for a length of 10 business days. The corn heading (stage of development of grains where the head pushes its way

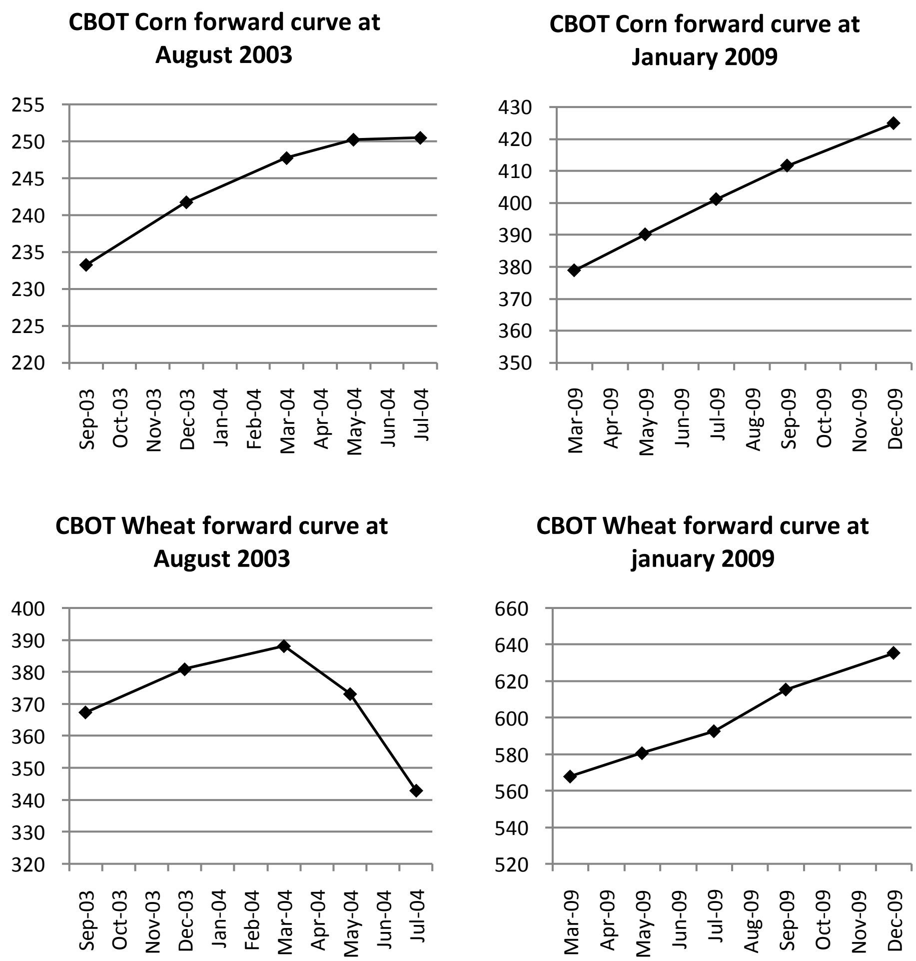

Figure 6. Forward curves of CBOT corn and wheat, August 2003 and January 2009.

through the flag leaf sheath) and harvesting happen during the summer months. The farmer will be interested in inferring information about prices after the harvest, that is, after September, from the forward curve. Accordingly, the October corn option contract is the most traded.

From Table 3, we clearly see that forward prices observed at the beginning of February produce better estimates of corn spot prices than the ones observed in the beginning of April, when planting is already underway (most planting is done in the US from April to May). Although the March Futures contract maturing the following year offers unbiased predictions of future March spot prices in both cases, the earliest contract that provides some post-harvest information is the December Futures contract (Table 3).

We note an important effect on the predictive power of the forward prices as the contracts get closer to expiry. When we compare results from Table 3 with the results from Table 4, where we observe the forward curve during the last 10 trading days before maturity of the contract, in general, the predictive power of the forward prices is greatly reduced.

Similar questions can be asked for wheat, although the case of wheat is markedly different. First, as we did in the case of corn, we compare the results derived from forward curves observed at the beginning of February to those observed at the beginning of April (Table 5). At the beginning of February we only obtain unbiased estimates of spot prices from the September Futures contract (it is important to note that March is a weather/moisture critical period in the heading of wheat in the southern hemisphere), whereas at the beginning of April, we obtain unbiased estimates from all maturities. When we turn our attention to the issue of closeness-to-expiry effects in wheat, we note that the predictive power of many of the maturities is greatly reduced (Table 6). Furthermore, as with corn, short term maturities have little predictive power for future spot prices.

In conclusion, the predictive power of individual forward contracts seems to be most negatively impacted at times of planting, heading and harvesting, and in the days

Table 1. CBOT Corn: Annual returns, annualized monthly volatility, coefficient of variation, standard deviation of prices, and year closing prices from 2000 to 2013.

Years	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Annual returns	0.09	-0.12	0.16	0.04	-0.18	0.05	0.59	0.15	-0.11	0.02	0.42	0.03	0.08	-0.50
Volatility	0.26	0.20	0.17	0.24	0.33	0.30	0.27	0.34	0.47	0.35	0.37	0.40	0.35	0.32
CV	0.31	0.16	0.35	0.18	0.67	0.22	0.77	0.37	0.69	0.32	0.79	0.30	0.37	0.80
SD	64.58	33.37	79.32	41.52	169.21	45.32	206.35	138.28	363.16	121.08	343.86	201.34	261.15	459.23
Price	224.75	199.75	235.25	246	204.75	215.75	390.25	455.5	407	414.5	629	646.5	698.25	422

Table 2. CBOT Wheat: Annual returns, annualized monthly volatility, coefficient of variation, standard deviation of prices, and year closing prices from 2000 to 2013.

Years	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Annual returns	0.12	0.03	0.12	0.15	-0.20	0.10	0.39	0.57	-0.37	-0.12	0.38	-0.20	0.18	-0.25
Volatility	0.22	0.20	0.28	0.27	0.19	0.29	0.21	0.37	0.43	0.40	0.49	0.44	0.26	0.17
CV	0.15	0.17	0.53	0.39	0.41	0.18	0.51	0.99	0.73	0.31	0.72	0.43	0.48	0.23
SD	38.93	45.64	173	130.64	139.27	57.90	206.43	646.39	560.92	165.98	417.44	303.96	364.05	155.21
Price	279.5	289	325	377	307.5	339.25	501	885	610.75	541.5	794.25	652.75	778	605.25

Table 3. F-test results for equations (1) and (2) for CBOT corn, with forward curves observed at approximately February 1 to 14 and April 1 to 14 respectively.

Observation period of the forward curve:		From: Last trade date of F1 March - 30 days; To: Last trade date of F1 March - 20 days				Observation period of the forward curve		From: Last trade date of F1 May - 30 days; To: Last trade date of F1 May - 20 days			
Approx. Date:		1-14 February				Approx. date		1-14 April			
Maturities	h	Equation (1)		Equation (2)		Maturities	h	Equation (1)		Equation (2)	
		F-test	p-value	F-test	p-value			F-test	p-value	F-test	p-value
May	2	0.38	0.69	0.10	0.91	Jul	2	9.12	<0.01	4.56	0.01
Jul	4	4.18	0.02	0.97	0.38	Sep	4	11.91	<0.01	17.72	<0.01
Sep	6	15.54	<0.01	11.03	<0.01	Dec	7	3.72	0.03	3.42	0.04
Dec	9	1.84	0.16	3.99	0.02	Mar	10	0.45	0.64	0.33	0.72
Mar	12	0.76	0.47	0.24	0.79	May	12	0.43	0.65	0.40	0.67

days when Future contracts are close to expiry.

Optimal lags of prediction of future contracts

A study of forward prices, not by maturity but by their position inside the current forward curve, may better represent traders' daily activities. In order to build consistent monthly data series, we use the individual maturities to create continuous series of deliveries, based on how close they are to the spot price. We refer to them as second nearby Future contracts, that is, F2, third nearby F3, etc. (Table 7). We adapt Equations (1) and (2) to find the optimal lag among the first 24 lags for each nearby, F2 to F7:

$$\ln S_t = \alpha + \beta \ln F_{t-i} + \varepsilon \quad (1)$$

Table 4. F-test results for equations (1) and (2) for CBOT Corn, with forward curves observed between March 1st to 14th and May 1st to 14th, respectively.

Observation period of the forward curve		From: Last trade date of F1 March– 10 days To: Last trade date of F1 March				Observation period of the forward curve		From: Last trade date of F1 May– 10 days; to: Last trade date of F1 May			
Approx. Date:		1-14 March				Approx. date:		1-14 May			
		Equation (1)		Equation (2)				Equation (1)		Equation (2)	
Maturities	h	F-test	p-value	F-test	p-value	Maturities	h	F-test	p-value	F-test	p-value
May	2	3.71	0.03	3.52	0.03	Jul	2	5.37	<0.01	10.44	<0.01
Jul	4	16.26	<0.01	12.14	<0.01	Sep	4	4.13	0.02	10.51	<0.01
Sep	6	13.90	<0.01	10.07	<0.01	Dec	7	6.34	<0.01	3.22	0.04
Dec	9	4.31	0.02	4.75	0.01	Mar	10	1.00	0.37	0.69	0.50
Mar	12	0.65	0.52	0.66	0.52	May	12	0.21	0.81	0.10	0.90

Table 5. F-test results for equations (1) and (2) for CBOT wheat, with forward curves observed at approximately February 1st to 14th and April 1st to 14th, respectively.

Observation period of the forward curve		From: Last trade date of F1 March - 30 days; To: Last trade date of F1 March - 20 days				Observation period of the forward curve:		From: Last trade date of F1 May - 30 days; To: Last trade date of F1 May- 20 days			
Approx. Date:		1-14 February				Approx. Date:		1-14 April			
		Equation (1)		Equation (2)				Equation (1)		Equation (2)	
Maturities	h	F-test	p-value	F-test	p-value	Maturities	h	F-test	p-value	F-test	p-value
May	2	93.74	<0.01	67.17	<0.01	Jul	2	9.26	<0.01	1.18	0.31
Jul	4	38.70	<0.01	19.80	<0.01	Sep	4	2.72	0.07	1.76	0.18
Sep	6	4.00	0.02	0.67	0.52	Dec	7	15.13	<0.01	1.58	0.21
Dec	9	17.64	<0.01	11.67	<0.01	Mar	10	7.34	<0.01	1.96	0.14
Mar	12	7.65	<0.01	7.96	<0.01	May	12	11.91	<0.01	1.29	0.28

Table 6. F-test results for equations (1) and (2) for CBOT wheat, with forward curves observed at approximately March 1st to 14th and May 1st to 14th, respectively.

Observation period of the forward curve		From: Last trade date of F1 March– 10 days; To: Last trade date of F1 March				Observation period of the forward curve		From: Last trade date of F1 May– 10 days; To: Last trade date of F1 May			
Approx. Date:		1-14 March				Approx. date:		1-14 May			
		Equation (1)		Equation (2)				Equation (1)		Equation (2)	
Maturities	h	F-test	p-value	F-test	p-value	Maturities	h	F-test	p-value	F-test	p-value
May	2	38.52	<0.01	15.22	<0.01	Jul	2	0.51	0.60	13.84	<0.01
Jul	4	13.26	<0.01	5.03	<0.01	Sep	4	3.13	0.05	6.07	<0.01
Sep	6	6.21	<0.01	0.40	0.67	Dec	7	7.72	<0.01	1.37	0.26
Dec	9	16.78	<0.01	6.44	<0.01	Mar	10	5.46	<0.01	3.23	0.04
Mar	12	12.37	<0.01	4.05	0.02	May	12	10.38	<0.01	4.28	0.02

Table 7. Individual Future contracts and their position in the forward curve through time.

Nearby	F1	F2	F3	F4	F5	F6	F7
Year 1	Mar	May	Jul	Sep	Dec	Mar	May
	May	Jul	Sep	Dec	Mar	May	Jul
	Jul	Sep	Dec	Mar	May	Jul	Sep
	Sep	Dec	Mar	May	Jul	Sep	Dec
	Dec	Mar	May	Jul	Sep	Dec	Mar
Year 2	Mar	May	Jul	Sep	Dec	Mar	May
…	…	…	…	…	…	…	

Table 8. Relationship between individual contracts, nearby Future contracts and optimal lags.

Location in the curve	Observed prices at t-h and corresponding h for each maturity									
Spot: Nearby	**Mar**	**h**	**May**	**h**	**Jul**	**h**	**Sep**	**h**	**Dec**	**h**
F2	May	2	Jul	2	Sep	2	Dec	3	Mar	3
F3	Jul	4	Sep	4	Dec	5	Mar	6	May	5
F4	Sep	6	Dec	7	Mar	8	May	8	Jul	7
F5	Dec	9	Mar	10	May	10	Jul	10	Sep	9
F6	Mar	12	May	12	Jul	12	Sep	12	Dec	12
F7	May	14	Jul	14	Sep	14	Dec	15	Mar	15

$$\ln S_t - \ln S_{t-i} = \alpha + \rho \quad (\ln F_{t-i} - \ln S_{t-i}) + \varepsilon \quad (2)$$

With i = 1,2,3,…, 24 months. Additionally, we extend the methodology proposed by Muth (1961) with a non-parametric test, the Wilcoxon signed-rank test, which allows for the absence of the strict assumptions needed to apply the F-test, such as the absence of serial correlation, which is present in both commodities. This test also takes into account the magnitude of the changes in the comparison of both distributions (Campbell and Dufour, 1991).

By studying each nearby we can infer how the position of the individual maturities on the forward curve affect their predictive power. For example, in Table 7, at the beginning of Year 1, March of year 2 occupies the penultimate point of our forward curve, F6, and as time passes the same March maturity will become the fifth, fourth, third, second and finally at the beginning of year 2, that March contract will be the first nearby and reach expiry.

We depict the distance h for each Future contract from the examples in previous subsections in the first two columns of Table 8, which we extend to all contracts up to the seventh nearby.

When we study each contract, since we have unequally spaced maturities, we can only obtain an interval of lags where the prediction is unbiased and an average lag when each nearby will have the highest predictive power. The 'theoretical' optimal lag will depend on the point in time when we observe the forward curve. For example, in the case of the fourth nearby, if we observe F4 in March, it corresponds to the September Future contract, and the theoretical optimal lag should be six months, that is, the September Future price predicts the September spot price. If we observe F4 in May, it corresponds to the December Future contract and the optimal lag is seven. If we are in July, F4 corresponds to the March Future contract and lag eight, and so on. Hence, a result between six and eight would mean all individual maturities on average give an unbiased prediction at F4. We derive all the theoretical optimal lag intervals with the help of Table 8 for each nearby in the first column of Table 9.

With our tests, we obtain a choice of lags in Equation (2) that includes the theoretical lag interval for each nearby, with the only partial exception of F3 in corn, meaning that, in general, individual maturities keep predictive power as time passes (Table 9). However, Durbin-Watson tests reveal autocorrelation in the residuals across all lags in both commodities. The presence of autocorrelation could be explained by the behaviour of the many market players who use technical analysis, which is based on signals such as moving averages for momentum trading.

When we study the optimal lags in Table 9 (lags with the highest p-values from Equation (2)), in some cases they fall outside their respective theoretical lag interval. In the case of CBOT corn, only the optimal lags for F2 and F3 are inside the theoretical lag interval, while for the rest of the nearby Future contracts the optimal lags are lower. Lower optimal lags indicate that when individual Future contracts are in nearby positions F4 to F7, the best

Table 9. Intervals of theoretical optimal lags, choice of monthly lags in which F-tests and Wilcoxon signed-rank tests present p-values greater than 0.05, and optimal lag, from second to seventh nearby for CBOT corn (top) and CBOT wheat (bottom).

Parameter	Theoretical optimal lag Interval	Equation(1a)	Equation(2a)	Wilcoxon Test	Optimal Lag	
		Choice of lags	Choice of lags	Choice of lags	Highest p-value lag	p-value
CBOT corn						
F2	2 - 3	2 - 5	2 - 3	2 - 11	2	0.34
F3	4 - 6	3 - 7	3 - 5	4 - 13	4	0.30
F4	6 - 8	4 - 11	4 - 14	5 - 15	5	0.29
F5	9 - 10	5 - 16	5 - 16	6 - 17	7	0.45
F6	12	6 - 18	6 - 17	6 - 19	9	0.5
F7	14 - 15	7 - 20	7 - 17	8 - 21	11	0.56
CBOT wheat						
F2	2 - 3	-	2 - 11	3 - 12	7	0.84
F3	4 - 6	-	4 - 12	6 - 15	7	0.78
F4	6 - 8	-	6 - 14	7 - 16	10	0.96
F5	9 - 10	-	8 - 15	8 - 18	12	0.95
F6	12	-	9 - 16	10 - 20	12	0.76
F7	14 - 15	-	10 - 17	11 - 22	13	0.67

Table 10. Choice of monthly lags in which F-test and Wilcoxon signed-rank test present p-values greater than 0.05 and respective individual lags with the highest p-value

Summary results	Eq (1b) F-test		Eq (2b) F-test		Wilcoxon	Optimal Lag	p-values
	Choice of lags	Highest p-value lag	Choice of lags	Highest p-value lag	Choice of lags	Highest p-value lag	Eq (2b) F-test
$\bar{F}$(F2 to F6)							
CBOT corn	4-12	6	4-6	5	4-7	5	0.27
CBOT wheat	-	-	6-12	9	7-16	9	0.9
$\bar{F}$ (F3 to F7)							
CBOT corn	5-16	8	5-12	6	6-17	6	0.21
CBOT wheat	-	-	8-14	11	8-18	11	0.91

predictions do not correspond to the months suggested by the theoretical interval but to future spot prices that happen earlier. In contrast, in the case of CBOT Wheat, only the optimal lags for F6 are inside the theoretical lag interval, while optimal lags obtained for F2 to F5 are higher, that individual Future contracts offer a better prediction of later future spot prices. Consequently, while for CBOT wheat, maturities expiring one year ahead a twelve month prediction(F6 is exactly at lag 12), they only offer a nine month prediction for CBOT Corn.

These features could be explained by a fundamental difference in the global trade of corn and wheat. In the case of corn, world prices are usually set by the US domestic supply-demand forces and farmers in the Southern hemisphere, namely Argentina (generally the second largest exporter of corn), adjust their crop output in reaction to US corn harvests and prices (with US news during the summer curtailing the predictive power of the forward curves). Wheat, on the other hand, is grown in more places and climatic conditions than any other cereal grain, from cold environments near the Arctic Circle to tropical regions close to the Equator; there are up to 20 species and more than 25,000 varieties in existence. Hence, CBOT wheat (it is worth noting that although the CBOT Wheat futures contract is linked to the price of No. 2 Soft Red winter wheat, it is generally used in hedging activities for all kinds of wheat), is less dependent on a single country of production and the arrival of news from all over the world has an influence in the predictive power of the forward curves in the short term, although long term predictions are more reliable than in the case of CBOT corn.

Testing the geometric average $\bar{F}$as a predictor of future spot prices

The seasonal cost-of-carry model for commodity forward curves developed by Borovkova and Geman (2006) introduces the geometric average of the forward prices as an alternative to the spot price for the first state variable when managing a portfolio of seasonal or non-seasonal commodity Futures:

$$\bar{F} = \left(\prod_{T=1}^{N} F(t,T) \right)^{\frac{1}{N}}$$

This quantity has the merit of being less volatile than the noisy spot price and always observable. Two other points are worth noting: first, if the N months encompass an integer number of calendar years, $\bar{F}$ is a measure that is, by construction, devoid of seasonality, as proposed by Borovkova and Geman (2006), who study seasonal energy commodities such as natural gas and heating oil. Second, in our setting, it seems reasonable to expect that the whole forward curve contains more information to build estimators of future spot prices than an individual Futures contract.

In order to study the relationship between $\bar{F}$ and the spot price for each of the commodities, we compute $\bar{F}$ as the average of maturities across twelve months (Figure 7). Equations (1) and (2) have been adjusted to study the relationship between the spot price and $\bar{F}$ through the following regressions:

$$\ln S_t = \alpha + \beta \ln \bar{F}_{t-j} + \varepsilon \quad (3)$$

$$\ln S_t - \ln S_{t-j} = \alpha + \rho \left(\ln \bar{F}_{t-j} - \ln S_{t-j} \right) + \varepsilon \quad (4)$$

with *j* = 1,2,3,…,24 months.

In Equation (4), spot price changes,$\ln S_t - \ln S_{t-j}$, are explained by $\ln \bar{F}_{t-j} - \ln S_{t-j}$ at the optimal lag. In Table 10, we provide two different constructions of $\bar{F}$. In the first one, $\bar{F}$ is built using the second nearby to the sixth, while in the second construction, the second nearby is avoided and $\bar{F}$ includes the third to the seventh nearby future contracts. In practice, it is usual to avoid the second nearby in the construction of$\bar{F}$.

For each commodity, $\bar{F}$ shows intervals of lags where econometric tests have p-values above 0.5. Additionally, each $\bar{F}$ captures the difference in range of prediction found in the nearby futures at their optimal lags, for instance, the $\bar{F}$ of wheat captures the fact that Future contracts relatively further from the spot price offer a better prediction. Hence, in the case of wheat, the optimal lags of $\bar{F}$ are 9 and 11 respectively for each construction of $\bar{F}$, which are much higher than those of corn, 5 and 6 res-pectively. These facts show the reliability of $\bar{F}$throughout time and as a better predictor than individual maturities for both wheat and corn markets.

When we explore the best construction of$\bar{F}$, results are also consistent with previous findings for each nearby. The best $\bar{F}$ for wheat includes the maturities further along the forward curve, from F3 to F7, while $\bar{F}$ for corn clearly benefits from including F2 to F6, which increases its p-value to 0.27.

Conclusion

We argue in this paper in favour of alternative estimators of price dispersion in corn and wheat markets, namely the consideration of the coefficient of variation and standard deviation of prices since their levels are the quantities defining the cost of food supply for population around the world.

We also analyse the performance of several forward measures as predictors of future spot prices. We find that the average value of all liquid forward contracts provides several advantages over the use of forward prices of individual maturities; in particular, during the periods of planting, heading, and harvesting, these have a much lower predictive power.

Individually, these measures provide a limited amount of information; however, together they provide a wealth of information based not only on returns but directly on prices. In effect, these indicators combined provide participants with an important toolbox that can be used to analyse the performance of the corn and wheat markets.

Conflict of Interest

The authors have not declared any conflict of interest.

REFERENCES

Bai J, Perron P (2003). Computation and analysis of multiple structural change models. J. Appl. Econometrics 18: 1-22.

Borovkova S, Geman H (2006). Seasonal and Stochastic Effects in Commodity Forward Curves. Rev. Derivatives Res. 9:167-186.

Campbell B, Dufour JM (1991). Over-rejections in rational expectations models. Econ. Lett.35:285-290.

Cornell B (1977). Spot Rates, Forward Rates, and Exchange Market Efficiency. J. Finan. Econ. 5:55-65.

Frenkel JA (1981). Flexible exchange rates, prices and the role of 'news': lessons from the 1970s. J. Polit. Econ. 89: 665-705.

Geman H, Vergel Eleuterio P (2013). "Investing in fertilizer–mining companies in times of food scarcity. Resour. Policy 38(4):470-480.

Geweke JF, Feige EL (1979). Some Joint Tests of the Efficiency of Markets for Forward Foreign Exchange. Rev. Econ. Stat. 61:334-41.

Goss BA (1983). The semi-strong efficiency of the London Metal Exchange. Appl. Econ. 15:681-698.

Hansen LP, Hodrick RJ (1980). Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis. J. Polit. Econ. 88:829-853.

Harlan JR (1975). Crops & Man. American Society of Agronomy & the Crop Science Society of America, Madison, Wisconsin.

Hicks JR (1946). Value and Capital, 2nd edition. Oxford: Clarendon Press.

Hicks JR (1965). Capital and Growth. Oxford: Clarendon Press.

Lipps P, Beuerlein J, Loux M, Wilson H, Eisley B, Lentz E (2001). Improving Wheat Fields in Ohio. The Ohio State University. Available at http://ohioline.osu.edu/iwy/index.html

Longworth D (1981). Testing the Efficiency of the Canadian Dollar - U.S. Exchange Market under the Assumption of No Risk Premium. J. Finan. 36(1): 43-49.

Lucas RE (1972). Expectations and the Neutrality of Money. J. Econ. Theory 4:103-124.

Lucas RE (1995). Monetary Neutrality. Prize Lecture.

Muth JF (1961). Rational Expectations and the Theory of Price Movements. Econometrica 29:315-335.

Pieroni L, Riociarelli M (2005). Testing rational expectations in primary commodities markets. Appl. Econ. 37:1705-1718.