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Efficiency and Forecast Performance of Commodity Futures Markets

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Abstract: The present study empirically investigates market efficiency and the potential factors of inefficiency in the main non-energy commodity futures markets: maize, soybeans and wheat. With efficient markets, futures prices can be used as commodity price forecasts, with inefficient markets futures prices are not able to predict spot prices. Technically, exploring the drivers of inefficiency means to assess the determinants of forecast errors, i.e. the factors affecting the difference between realized spot prices and predicted future spot prices. The analysis is carried out using first a traditional test of efficiency for spot and futures prices and then implementing a more sophisticated GARCH analysis at a daily and weekly frequency. The results show that maize, soybeans and wheat markets are not informationally efficient. The realized price volatility of futures markets, the time to maturity, open interest, trading volumes and speculative measures are significant factors explaining forecast errors. In particular, short-term speculation (scalping activity) increases the noise in the information formation process. Similarly, price volatility, lack of liquidity and long contract maturity horizon raise forecast errors, while long-term speculation and speculative pressure reduce errors. The analysis suggests that knowing the causes of forecast errors, would allow to control for such factors and therefore to ameliorate the forecast accuracy of commodity prices.

Keywords: Futures Markets, Efficiency, Forecast Errors, GARCH, JEL: G14, C58, Q14

Introduction

A relevant feature of the new millennium has been the high volatility of commodity spot prices (Liu *et al*., 2018; Bampinas *et al*., 2019). Significant price fluctuations are dangerous since they generate uncertainty with adverse impacts on income and consumption. The price risks being faced by individuals or groups of agents can be however lessened using available market instruments. In particular, hedging via futures markets can play an important role and could have important stabilizing effects for the economy. The role of futures markets in providing the effective price discovery has been, thus, an area of extensive research in economics. Futures markets have been considered as a stabilization agent since price discovery would take place first in futures market and then transmitted to spot markets (Pizzi *et al*., 1998). Commodity market efficiency implies that prices should 'fully reflect' all information available[1], so that the current futures price of a commodity futures contract expiring at time t+1 is the 'best' forecast of the upcoming spot price which prevails at t+1. If futures markets provide an unbiased and precise forecast of future spot prices, they can effectively help agents and traders in both advanced and developing countries to manage risk by fixing price in advance of transactions, facilitate financing, promote efficient resource allocation and enable competitive price discovery (Laws and Thompson, 2004).

Efficient futures markets become therefore extremely useful to all the segments of an economy. Futures

[1] The term 'efficiency' will be used as short hand for informational efficiency in the remainder of the study.

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markets are helpful to producers because they can form a view of the price which is likely to prevail at a future point in time and, hence, can decide to select between various competing commodities. Similarly, futures markets make consumers aware of the price at which the commodity will be available at an upcoming point in time. In addition, futures trading is valuable to exporters since it gives an advance signal of the price which is expected to be present on the market and thereby would help exporters in quoting a realistic price, securing export contracts in a competitive market and hedging risks. Hence, informational efficiency is closely related to allocative efficiency through commodity storage that links current physical supply to arbitrage possibilities on current spot and expected spot prices, the latter being predicted by prices of futures contracts.

In brief, efficient futures markets could reduce the effects of price and output instability resulting from the production, marketing and storage of a commodity and could be a potential alternative to government interventions to stabilize price (Newbery and Stiglitz, 1981; Aulton *et al*., 1997; Algieri, 2014).

In this context, the present study first empirically investigates whether or not futures markets for the major grains-namely, wheat, maize and soybeans-are efficient. Then, it tries to evaluate the ability of futures prices to predict future spot prices by assessing the possible factors that could create a wedge between the current futures price and the underlying expected future spot price. The difference between the current futures price and the future spot price represents the forecast error and controlling for its drivers would improve forecasting accuracy and thus efficiency. The potential factors considered as drivers of the discrepancy between futures and spot prices, i.e., potential source of inefficiency, include the realized price volatility of futures markets, the time to maturity of commodity contracts, open interest, trading volumes and speculative measures. Methodologically, we implement a battery of traditional tests of efficiency complemented by a more complex GARCH analysis that evaluates the potential determinants of inefficiency. This analysis, carried out both at a daily and weekly frequency, becomes important from a policy perspective: A simple test of the efficiency of commodity markets does not imply any direct policy intervention, as variables related to policies do not enter the empirical analysis. Whether efficiency is rejected or not does not answer the question of how well futures markets perform relative to their price forecasting power, or whether a specific policy can improve or worsen this forecasting performance which is important for allocative efficiency. Evaluating magnitude and determinants of forecast errors secures, instead, a relative and continuous indicator of the performance of futures markets beyond the binary information efficiency tests.

The study provides several contributions to the extant literature. It explicitly examines the diversity across commodities and factors driving inefficiency, i.e., the determinants of forecast errors. This is, to our knowledge, an issue that has not yet been examined in the empirical literature. Indeed, while there is a large body of research that has examined market efficiency, a systematic analysis of the drivers of forecast errors has so far not been undertaken. This will thus shed light not only on how much information futures prices incorporate about future movement in spot prices, but will also identify which factors influence price predictions. A further novelty of the study relates to the evaluation of the role of speculation in commodity futures markets in determining efficiency by distinguishing between short-term and long-term speculation. This will allow us to have a finer analysis of the possible impact of financialisation in commodity markets. A final element of this study relates to the use of daily and weekly data in order to have a robustness check and a quantitative assessment of the results.

The study is organised in four sections. Section 2 gives a brief introduction and an overview of the literature on efficiency. Section 3 presents the research methodology, the selected data and the empirical results. The last Section concludes.

Market Efficiency

Forms of Market Efficiency

The concept of efficiency as applied to commodity futures markets is similar to the concept referred to in any other asset market (Kaminsky and Kumar, 1990). A market is efficient if it uses all of the available information in setting futures prices so that there is no opportunity for agents to profit from publicly known information. The idea behind the concept of efficiency is that investors process the information that is available to them and take positions in response to that information, as well as to their specific preferences. The market aggregates all the information and reflects it in the price so that it is impossible for agents to make economic profits by trading on the basis of the existing information set.

Samuelson (1965) was the first author to rigorously analyse the role of futures prices as predictors of future spot prices. He stated that under specific assumptions the sequence of futures prices for a given contract follows a martingale. Put differently, today's futures prices are the best unbiased predictor of tomorrow's futures prices. Furthermore, since by arbitrage futures prices and spot prices are equalized at maturity, futures prices are also unbiased predictors of future spot prices.

A few years later, Fama (1970) suggested distinguishing between a 'weak', 'semi-strong' and 'strong' form of market efficiency. The distinction is based on the different types of information that prices incorporate.

The 'weak' form of efficient market implies that current prices fully reflect the information contained in a historical sequence of prices; therefore, investors who rely on past price patterns cannot expect to receive any abnormal returns. In this way, prices follow a random-walk over time and are therefore not auto-correlated, which means that prices cannot be predictable. In finance literature, this is known as the Random Walk Hypothesis or, strictly speaking, the Efficient Market Hypothesis (EMH). EMH is based on the idea that asset prices in efficient markets incorporate all the accessible information; thus, price behaviour does not follow any pattern or trend. The more efficient the market, the more random the sequence of price changes generated by such a market and the most efficient market of all is one in which price changes are completely random and unpredictable.

The 'semi-strong' form implies that current asset prices mirror both historical price information and all other publically available market information (such as that concerning the macroeconomic environment). If markets are efficient in this sense, there is no possibility to realize abnormal returns on the basis of this information.

The 'strong' form of efficiency implies that prices include not only past prices and public information, but also insider information. In such a case, no investor could ever earn consistently superior returns (even an insider with his inside knowledge).

Since a failure of weak form efficiency implies a failure of semi-strong or strong form efficiency, we will confine our analysis to market efficiency in a weak sense. Let $F_{t,T}$ be the futures price at time t for delivery of a commodity at T. Let S_t be the spot price at date t and S_T the spot price expected to prevail at maturity T. Market efficiency in a weak sense implies that the current futures price, $F_{t,T}$, of a commodity futures contract expiring in T should equal on average the commodity spot price expected to prevail in T, i.e., $F_{t,T} = E_t\,[S_T]$ with E_t being the expectation in the futures market in period t. Thus, efficiency implies that $F_{t,T}$ is an unbiased forecast of S_T and that $F_{t,T}$ incorporates all relevant information including past spot and futures prices (Beck, 1994). Formally, tests of efficiency are carried out by regressing the upcoming spot price (S_T) on the current futures price ($F_{t,T}$):

$$S_T = \beta_0 + \beta_1 F_{t,T} + u_T \quad u_T \sim N(0,\sigma^2) \tag{1}$$

Equation 1 has been referred to as the 'level' specification. A variant of Equation 1 regresses spot price changes on 'the basis' (the difference between the current futures price and the contemporaneous spot price) (e.g., Fama and French, 1987, p. 63):

$$S_T - S_t = \beta_0 + \beta_1 \left(F_{t,T} - S_t\right) u_T \quad u_T \sim N(0,\sigma^2) \tag{2}$$

Equation 2 can be labelled the 'basis' specification. The difference between Equations 1 and 2 is that the variables in the level form-the future spot and current futures prices-are non-stationary $I(1)$ variables; i.e. they have unit roots and therefore the level regression could lead to a spurious regression problem as described in Granger and Newbold (1974) unless a cointegration analysis[2] is carried out. The basis form instead involves stationary $I(0)$ variables; therefore, the resulting regression coefficients would be consistent and no cointegration analysis would be required.

In both cases, efficiency and unbiasedness entail that the intercept is not significantly different from zero (i.e., $\beta_0 = 0$), that the slope is not significantly different from one (i.e., $\beta_1 = 1$) and that the residuals are white noise. However, efficient markets may reject the above joint hypothesis for a number of reasons, some of which include the presence of a risk premium[3] (Beck, 1993), the inability of the futures price to reflect all publicly available information (Beck, 1994) and the inefficiency of agents as information processors (Kaminsky and Kumar, 1990). Also, as noted for example by Fortenbery and Zapata (1993), lack of efficiency can occur for commodities in which returns to storage or transportation are non-stationary.

The ability of futures markets to predict subsequent spot prices has been subjected to a wide debate. Empirical evidence has often pointed to different results: For any given market, some studies find evidence of efficiency and others of inefficiency. In part, these apparently conflicting findings reflect differences in the time periods analysed and the adopted methodologies.

Kaminsky and Kumar (1990) examined excess returns in seven different commodity markets over the years 1976-1988 to investigate the issue of efficiency. The authors found that for long periods several markets are not fully efficient. The authors state that, even in the presence of a non-total efficiency, the empirical rejection

[2]See for instance Lai and Lai (1991), Fortenbery and Zapata (1993), Beck (1994), Zheng *et al.* (2012).

[3]According to the hedging theory originally proposed by Keynes (1930), commodity producers and inventory holders sell futures contracts at a price below the expected future spot price to avoid the price risk associated with their long positions in the underlying commodity. The risk premium compensates purchasers of futures contracts for bearing spot price risk. Put differently, risk premia in commodity futures prices could arise from the desire of producers of the physical commodity to hedge their price risk by selling futures contracts. In order to persuade a counterparty to take the other side, the equilibrium price of a futures contract might be pushed below the expected future spot price to produce a situation sometimes described as 'normal backwardation'. Market efficiency implies that futures market prices will equal expected future spot prices plus or minus a constant or, possibly, time-varying risk premia. Alternatively, futures prices will be unbiased predictors of future spot prices only if markets are efficient and if no risk premium is present (or if risk premium is time invariant).

of the efficiency hypothesis does not imply market failure. This is because, if investors are risk averse, a nonzero excess return may only reflect a time-varying risk premium. The results of this study however do not allow one to distinguish whether this is in fact the case.

Conversely, Kastens and Schroeder (1996) tested the Fama semi-strong form of efficiency for Kansas City July wheat futures from 1947 through 1995 and found that they were generally efficient. Furthermore, relative to the efficiency associated with forecasts constructed one to two months before harvest, the efficiency associated with the five- to six-month period before harvest increased since the early 1980s.

Aulton *et al*. (1997) presented the results of a study of market efficiency in relation to three distinct UK futures markets. The results provided evidence of efficiency and unbiasedness in relation to wheat, some concerns with respect to efficiency for potatoes and pig meat and some concerns about bias in relation to potatoes.

A group of studies found that long-run efficiency is common, but short-run efficiency is not. For instance, Kellard *et al*. (1999) presented tests for unbiasedness and efficiency across a range of commodity and financial futures markets and developed a measure of relative efficiency. They found that spot and futures prices are cointegrated with a slope coefficient that is close to unity, so that there is a long-run relationship between spot and futures prices. However, there is evidence that the long-run relationship does not hold in the short-run; specifically, changes in the spot price are explained by lagged differences in spot and futures prices as well as by the basis.

McKenzie and Holt (2002) observed that live cattle, hogs, maize and soybean meal futures markets are efficient and unbiased in the long-run, whilst some inefficiencies and pricing biases in the form of a dynamic lag structure exist in the short-run. As the authors pointed out, the long-run result can be due to the fact that the adopted cointegration approach did not allow for (long-run) time-varying risk premia.

Wang and Ke (2005) studied the efficiency of the Chinese wheat and soybean futures markets and found a long-term equilibrium relationship between the futures price and spot price for soybeans and weak short-term efficiency in the soybean futures market. In addition, they observed that the futures market for wheat is inefficient, likely because of over-speculation and government intervention in the market. Santos (2009) tested the efficiency properties of wheat, maize and oats futures prices from 1880 to 1890 and from 1997 to 2007. The author observed that, futures markets in both periods are efficient in the long-run: futures prices in each of these markets reflect the long-run fundamentals that determined their corresponding future spot prices. In the short-run while wheat markets are efficient, oat markets and maize markets are inefficient. Along those lines, Zheng *et al*. (2012) examined the efficiency of the Chinese non-GMO soybean futures market from the period 2003 to 2010 and argued that this futures market was efficient. Also, futures prices respond effectively to exogenous price shocks and spot prices move following futures prices.

Chinn and Coibion (2014) examined whether futures prices for energy, agriculture, precious and base metal commodities are unbiased and/or accurate predictors of subsequent prices. They documented significant differences both across and within commodity groups. Precious and base metals failed most tests of unbiasedness and were poor predictors of subsequent price changes, while energy and agricultural futures fared much better. They further noticed a broad decline in the predictive content of commodity futures prices since the early 2000s.

Jawadi *et al*. (2017) investigated the efficiency of oil, gas, electricity and coal markets and found that the considered commodity markets are informationally inefficient in the short-term, but informationally efficient in the long-term. The authors conclude that commodity markets might be used to hedge investor's portfolios, particularly for speculators and chartists in the short-term, while these investments might not be appealing in the long term.

Jebabli and Roubaud (2018) analysed weak-form efficiency in food and energy markets. Their findings indicated that all commodities exhibit long-term efficiency and short-term inefficiencies. The latter result can be explained by global economic conditions: the 2008 global financial crisis, financialisation of commodities markets and fluctuations in crude oil prices.

Papaioannou *et al*. (2019) examined the efficiency of four European electricity markets (Nord Pool, Italian, Spanish and Greek) testing the weak form of the Efficient Market Hypothesis. To quantify the level of efficiency deviation of each market from the 'benchmark market of random walk', they constructed a Composite Electricity Market Efficiency Index. The results indicate that all examined electricity markets are inefficient. In particular, the most inefficient is the Greek market, followed by the Italian, Spanish and Nord Pool markets.

In the same spirit as these studies, we present new evidence for maize, soybeans and wheat futures and spot prices. However, differently from the existing literature, we emphasize both the differences observable across commodities and the potential sources of market inefficiency including speculative activities.

Table 1 offers a selected summary of the literature on market efficiency in commodity futures.

Table 1: Overview of commodity market efficiency studies

Authors	Commodity futures markets	Period of Investigation	Methodology	Results
Kaminsky and Kumar (1990)	Maize, soybeans, wheat, cocoa, coffe, cotton, copper	1976-1988	Efficiency tests	Not fully efficient markets
Kastens and Schroeder (1996)	Kansas city wheat	1947-1995	Efficiency tests	Efficient market
Kellard *et al*. (1999)	Soybeans, live cattle, live hogs, gasoil, Brent crude oil, Deutsch mark/dollar exchange rate	different starting periods-1996	Cointegration analysis	Market inefficiencies exist
McKenzie and Holt (2002)	Live cattle, hogs, maize and soybean meal	1959-2000	GQARCHM-ECM framework	Market efficiency in the long-run, inefficiency in the short-run
Wang and Ke (2005)	Chinese soybeans, wheat	1998-2002	Cointegration analysis	Wheat market is inefficient, soybeans market is efficient
Zheng *et al*. (2012)	Chinese non-GMO soybeans	2003-2010	Cointegration analysis	Efficient market
Santos (2009)	Maize, oats, wheat	1880-1890 and 1997-2007	Cointegration analysis	Market efficiency in the long-run, inefficiency in the short-run for oats
Chinn and Coibion (2014)	Crude oil, natural gas, gasoline, gold, copper, lead, nickel, tin	1990-2012 heating oil, corn, soybeans, wheat,	Efficiency tests on GARCH analysis	Metal markets, energy markets (excluding heating oil), soybeans tend to be inefficient
Jawadi *et al*. (2017)	Crude oil, gas, electricity, coal	1997-2016	Multivariate cointegration tests	Market efficiency in the long-run, inefficiency in the short-run
Jebabli and Roubaud (2018)	Crude oil, maize, soybeans	2000-2015	Threshold cointegration and Hurst exponent	Market efficiency in the long-run, inefficiency in the short-run
Papaioannou *et al*. (2019)	Electricity	2005-2013	Composite Electricity Market Efficiency Index	Inefficient market

Source: Authors' elaborations

The Theoretical Model and the 'Basis'

In order to test the hypothesis of market efficiency, evaluate the predictive power of futures prices and determine the underlying causes of forecast errors, we start from the traditional equation in logarithm form given that futures prices tend to be more volatile at high prices than at low prices and a logarithmic transformation often succeeds in stabilizing the variance of the observed series (Aulton *et al*., 1997). The adoption of the log form is also a common practice in the statistical analysis of the prices of futures contracts (Garbade and Silber, 1983; Serletis and Scowcroft, 1991; Fortenbery and Zapata, 1993; Fujihara and Mougoué, 1997; Moosa and Silvapulle, 2000; Joyeux and Milunovich, 2010; Algieri and Leccadito, 2019). Using lower case letters for logs, the level equation can be written as:

$$s_T = \varphi_1 + \varphi_2 f_{t,T} + \xi_T \quad \xi_T \sim N\left(0, \sigma^2\right) \tag{3}$$

where, s_T is the spot price in log at the maturity T, $f_{t,T}$ is the futures in log at time t with delivery in period T, ϕ_1 mirrors the cost-of-carry- i.e., the cost associated with holding the commodity until the delivery date, given that maize, soybeans and wheat are storable commodities, the financial costs in the form of the opportunity cost of holding the commodities and a risk premium. The efficiency hypothesis requires that $\phi_1 = 0$ and $\phi_2 = 1$ and the forecast error term, ξ_T is white noise.

As previously explained, to establish which regression analysis is appropriate for testing market efficiency relations, we first evaluate the order of integration of the individual series entering Equation 3 using the Augmented Dickey Fuller (ADF) test. If the series s_T and, $f_{t,T}$ are found to be non-stationary, to have consistent estimates we make them stationary, subtracting the current log spot price s_t from both sides of equation 3 following the typical procedure adopted in the literature (Fama and French, 1987; Reichsfeld and Roache, 2011; Chinn and Coibion, 2014; Garcia *et al*., 2015; Jebabli and Roubaud, 2018) and estimate the model with Ordinary Least Squares (OLS):

$$s_T = s_t + \varphi_1 + \varphi_2\left(f_{t,T} - s_t\right) + \xi_T \tag{4}$$

Equation 4 indicates that the spread in the spot price for the period until delivery (s_T - s_t) is equal to the current spread between the futures price and the spot price ($f_{t,T}$ - s_t)-the 'basis'-plus the constant component of the risk premium ϕ_1 and a forecast error term ξ_T that can have an AR structure, for instance, the simplest AR(1):

$$\xi_T = K\ \xi_{T-1} + \eta_T \tag{5}$$

If the basis delivers an unbiased forecast of future spot price, i.e., if the basis is the optimal predictor of the change in the spot rate, then the market efficiency hypothesis implies that $\phi_1 = 0$, $\phi_2 = 1$ and $\xi_{T,t}$ has a conditional mean of zero. Put differently, evidence that ϕ_2 is positive means that the basis observed at t contains information about the change in the spot price from t to T. Equivalently, the current futures price has the power to forecast the future spot price.

The basis equation[4] is useful not only for gauging hypotheses such as unbiasedness ($\phi_2 = 1$) and market

[4] Note that one can equivalently express the basis relationship in terms of futures price at maturity $f_{T,T}$ rather than ex post spot price. For instance, we could replace the spot price s_T in Equation (4) with futures prices, as follows: $f_{T,T} - s_t = \phi_1 + \phi_2(f_{t,T} - s_t) + \xi_T$. The futures price on the day of contract expiration $f_{T,T}$ is hence used instead of the spot price series s_T. Theoretically, the two prices are the same at expiration since arbitrage will drive them together. In reality, the two

efficiency (ϕ_1 = 0 and ϕ_2=1), but also to provide quantitative measures of the predictive content of commodity futures.

The link between efficiency and forecast ability arises from realizing that the difference between the current futures price and the future spot price represents both the forecast error and the opportunity gains or losses realized from taking certain positions. The requirement that the forecast error is zero is consistent with both market efficiency (absence of profitable arbitrage opportunities) and unbiasedness property of forecaster (Chinn and Coibion, 2014).

We proceed with evaluating the residuals of Equation (4), if we find homoskedasticity we estimate in a second step via OLS the possible drivers of the squared values of the forecast errors[5] η_t in the case of an AR process or $\xi_t = \eta_t$ in case of insignificant *K*:

$$\hat{\eta}_t^2 = f\left(volatility,\ time\ to\ maturity,\ open\ interests,\ trading\ volume,\ speculative\ indices\right) \quad (6)$$

If we find heteroskedasticity in the residuals we proceed to embed Equation (4) in a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model with explanatory variables in the variance equation and hence evaluate which are the variables that may influence the forecast errors, namely if they depend on the realized price volatility of futures markets, the time to maturity, open interest, trading volumes and speculative measures.

In detail, the realized or historical volatility reflects the past price movements of the underlying asset. It is calculated as a standard deviation of a commodity's returns over a fixed number of days, where return is defined as the natural logarithm of the ratio of close-to-close prices. We consider the 20-day historical price volatility as computed by Bloomberg for each considered commodity.

Time to maturity refers to the days before the expiration of the futures contract, generally the greater the length of time to maturity, the greater the uncertainty of future spot price.

Open interest refers to the number of outstanding specific futures contracts at a given time; i.e., the total number of 'open' contracts that have not been settled at the end of each day; large open interest indicates more liquidity and increasing open interest means that new money is flowing into the marketplace. Trading volume refers to the volume of transactions that take place in the futures markets during a trading session; i.e., the number of futures contracts traded in a market during a day. It is a volume-based measure of market liquidity and thus of the 'breadth' of the market (Sarr and Lybek, 2002).

To measure the financialisation and speculation we consider three proxies: the *scalping index,* the *speculative pressure index and* the *Working-T Index*. Scalping is known as an intraday activity made up of instant transactions by traders which open and close contract positions within a very short period of time to make profits from the bid-ask spread. The scalping index, computed as the ratio of trading volume to open interest in future contracts, is a proxy for short-term speculation as it detects the attempt of earning profits within very short period of time (Peck, 1982; Robles *et al*., 2009; Du *et al*., 2011; Manera *et al*., 2013; Algieri *et al*., 2017). Formally, it is given by:

$$scalping\ index = \frac{TV}{OI} \quad (7)$$

where, *TV* indicates the trading volumes of futures contracts and *OI* refers to the open interest.

The speculative pressure and the Working Index can be thought of as proxies for long-term speculation (Manera *et al*., 2013). The speculative pressure index is calculated as the ratio between the sum of short and long positions of non-commercial traders (speculators) and the total open interest, namely:

$$speculative\ pressure = \frac{NCL + NCS}{OI} \quad (8)$$

where, *NCL* represents the non-commercial (speculative) position long, *NCS* non-commercial position short and *OI* the total open interest.

The *Working-T index* is an index based on the distinction between traders driven by profit-seeking behaviour (non-commercials) and those involved in the physical business of commodities for hedging reasons (commercials). It is expressed as follows:

$$Working-T\ index = \begin{cases} \left[1 + \frac{NCS}{CS + CL}\right] \cdot 100\ if\ CS \geq CL \\ \left[1 + \frac{NCL}{CS + CL}\right] \cdot 100\ if\ CS < CL \end{cases} \quad (9)$$

where, *NCS* indicates speculative short positions, *NCL* speculative long positions, *CS* represents commercial short positions and *CL* commercial long positions. Put

prices can differ and the futures price is often used because spot price data is not generally available for the same grade of commodity delivered at the same time and location as specified in the futures contract (e.g., Gray and Tomek, 1970; Fama and French, 1987; Beck, 1994). The use of futures price data avoids biases introduced by inaccurate spot price data.

[5] Technically, the transformation of error means takes place either considering absolute values or squared values of the forecast errors. Generally, an efficient futures market produces the smallest mean squared forecast error and vice-versa. Therefore, mean squared error is used extensively to evaluate the forecasting performance of futures markets.

differently, the nominator represents the speculation positions short and long. The denominator is the total amount of futures open interest resulting from hedging activity.

The Working-T index thereby measures the excess of speculation relative to hedging activity or the excess of non-commercial positions beyond what is technically needed to balance commercial needs.

Data

To examine the efficiency of futures markets for maize, soybeans and wheat and the predictive power of futures prices, time series are required of spot prices and futures prices. Daily closing price series for each selected commodity have been collected from Bloomberg database. They range from 3 January 1996 to 14 December 2012 for maize since spot prices are available starting from 1996 and from 3 January 1992 to 14 December 2012 for soybeans and wheat. A more detailed description of data is reported in Table 2.

Following Kellard *et al*. (1999), the future spot price is the cash price on the termination day of the futures contract, while the futures price series at time t is the futures price at contract purchase. All the considered commodities are traded at the Chicago Mercantile Exchange Group (CME). For maize and wheat, we have five contracts per year with delivery months in March, May, July, September and December. For soybeans, we consider six contracts spaced two months with delivery months in January, March, May, July, September and November.

We follow on a daily basis the nearest-to-maturity contract until its delivery month, at which time the position changes to the contract with the following delivery month, which is then the nearest-to-maturity contract. Put another way, we consider the futures contract closest to maturity until it expires, the so-called nearby contract[6]. Thus, we have 4209 daily observations for maize, 5263 for soybeans and 5284 for wheat. In detail, for each contract we have different daily data for futures and spot price; s_T is the spot price that is matched to the maturity date of the futures contract. Note that since s_T is the spot price at contract expiration or maturity, the value is the same for each contract duration.

The other data concerning the explanatory variables have also been collected from Bloomberg, with the exception of the data used to compute the Working-T index and the speculative pressure index that have been provided by the U.S Commodity Futures Trading Commission (CFTC) in its Historical Commitments of Traders reports on futures contracts traded at the CME.

[6] Multiple futures contracts are in fact issued simultaneously for a single underlying asset with various maturity dates. This might be the price of a futures contract on soybeans for delivery in 2 months, in 4 months, 6 months and so on. Considering nearby contracts avoids multiple overlapping time series of futures prices.

Estimation Results

The process of testing for efficiency initially requires tests for the order of integration of the individual series; if these series are found to be nonstationary, then it is necessary to make them stationary as a precondition for market efficiency. The initial idea of the typology of the series is given by the graphical inspection of the series as reported in Fig. 1. Each series seems to meander in a fashion characteristic of a random walk. To formally test for the presence of a unit root, the Augmented Dickey Fuller (ADF) in three settings (with constant, with a constant and trend and without constant and trend) has been implemented. The results (Table 3) indicate that the null of a unit root is not rejected for all the series in levels; therefore, we conclude that spot and futures prices are not stationary. Thus, we construct the basis to make the series stationary and test them again to see if after the procedure the series are I(0).

The results for the variables of the basis (Equation 4) show that they are stationary (Table 4), since we can reject the null hypothesis of unit root for all variables.

We proceed estimating Equation (4) with OLS using the Newey (1987) HAC standard errors to control for heteroskedasticity and autocorrelation of unknown form. The results reported in Table 5 reveal that the spread between the futures price and the spot price is always significant in explaining the spread in the spot price, while the constant component or risk premium is significant and negative only for maize. This would suggest that the market is in a 'contango' situation where the futures price is higher than the expected spot price. When the risk premium is negative/positive, it is the average reward for speculators going short/long in a future contract at t and reversing their position just prior to delivery (T).

The quantitative ability of maize, soybeans and wheat basis to account for ex-post price change is consistently low, with a max of R2 value of 0.09 for maize.

Then the robust HAC Wald test using the resulting estimates has been carried out to formally test for efficiency and unbiasedness (Table 5). Since the null is rejected, all the markets turn out to be inefficient and bised at 5% significance level. This implies that prices do not adjust quickly to new information and the qualitative ability of futures prices to predict ex-post price changes is low, especially for maize.

To evaluate if the residuals of the basis Equation 4 are homoskedastic or heteroskedastic, we perform the ARCH test (Table 5). The findings show that there is clear evidence of heteroskedasticity; therefore, the above estimations should be taken with caution. To have more robust results, increase the effectiveness of the estimates and to explain, at the same time, the possible drivers of forecast errors, we revert to a GARCH framework.

Table 2: Data

Commodity	Market exchange	Spot price	Futures contract	Contract months	Starting period	Total Obs.
Maize	Chicago Mercantile Exchange	Corn N. 2 Yellow CORNCH2Y Index	C 1 Comdty	March, May, July, September and December	19.1.1996 (January 1996-December 2012)	4209
Soybeans	Chicago Mercantile Exchange	Soybeans, N. 1 Yellow SOYBCH1Y Index	S 1 Comdty	January, March, May, July, August, September and November	23.1.9 (January 1992-December 2012)	5263
Wheat	Chicago Mercantile Exchange	Wheat N.2 Red Winter WEATCHEL Index	W 1 Comdty	March, May, July, September and December	20.1.92 (January 9 -December 2012)	5284

Table 3: Augmented dickey fuller test

	Log futures price				Log spot price			
Maize	Level	Prob.*	First Diff	Prob.*	Level	Prob.*	First Diff	Prob.*
Constant	-0.828	0.811	-62.143	0.000	-0.962	0.769	-67.358	0.000
With trend and intercept	-2.382	0.389	-62.164	0.000	-2.372	0.394	-67.382	0.000
With no constant and trend	0.468	0.816	-62.146	0.000	0.433	0.792	0.807	0.000
Soybeans								
Constant	-1.202	0.676	-72.099	0.000	-1.076	0.728	-60.399	0.000
With trend and intercept	-2.119	0.535	-72.098	0.000	-1.973	0.615	-60.401	0.000
With no constant and trend	0.746	0.875	-72.097	0.000	0.773	0.880	-60.395	0.000
Wheat								
Constant	-1.597	0.484	-75.204	0.000	-1.668	0.447	-73.756	0.000
With trend and intercept	-2.562	0.298	-75.206	0.000	-2.534	0.311	-73.759	0.000
With no constant and trend	0.374	0.792	-75.208	0.000	0.349	0.786	-73.760	0.000

Null Hypothesis: The variable has a unit root *MacKinnon (1996) one-sided p-values

Table 4: Augmented Dickey Fuller Test for stationarity, variables of the basis equation

	Log basis, $(f_{t,T}-s_t)$			$(s_T - s_t)$		
Maize	Level	Prob.*	Variable	Level	Prob.*	Variable
Constant	-6.107	0.0000	I(0)	-9.829	0.0000	I(0)
With trend and intercept	-6.156	0.0000	I(0)	-9.933	0.0000	I(0)
With no constant and trend	-4.576	0.0000	I(0)	-9.807	0.0000	I(0)
Soybeans						
Constant	-9.663	0.0000	I(0)	-11.658	0.0000	I(0)
With trend and intercept	-9.821	0.0000	I(0)	-11.677	0.0000	I(0)
With no constant and trend	-7.524	0.0000	I(0)	-11.475	0.0000	I(0)
Wheat						
Constant	-4.946	0.0000	I(0)	-10.936	0.0000	I(0)
With trend and intercept	-5.009	0.0002	I(0)	-10.955	0.0000	I(0)
With no constant and trend	-3.672	0.0002	I(0)	-10.936	0.0000	I(0)

Null Hypothesis: the variable has a unit root *MacKinnon (1996) one-sided p-values. Lag Length: Automatic-based on SIC, maxlag = 30

Table 5: Basis estimation, Newey-West HAC standard errors and covariance

	Maize	Soybeans	Wheat
ϕ_2 , basis $(f_{t,T}-s_t)$ coefficient	0.616***	0.592***	0.165**
	(0.107)	(0.143)	(0.078)
ϕ_1, constant	-0.019***	0.003	-0.009
	(0.006)	(0.003)	(0.007)
R-squared	0.090	0.036	0.014
S.E. of regression	0.095	0.066	0.103
Akaike info criterion	-1.871	-2.604	-1.709
Schwarz criterion	-1.868	-2.602	-1.706
Hannan-Quinn criter.	-1.870	-2.603	-1.708
Obs	4209.000	5263.000	5284.000
Wald Test[(a)] p-value	0.000	0.012	0.000
Arch Test[(b)] p-value	0.000	0.000	0.000

Note: The table presents estimated results by ordinary least squares of Equation 4. Dependent Variable: $(s_T - s_t)$. Standard errors are in brackets; statistical significance is denoted by ***p<0.01, **p<0.05, *p<0.10. [(a)] Test for Weak efficiency, H_0: market is efficent and unbiased =>:

$$H_0 : \varphi_1 = 0 \text{ and } \varphi_2 = 1 \quad vs \quad H_1 : \varphi_1 \neq 0 \text{ or } \varphi_2 \neq 1$$

[(b)] Residuals test for heteroskedasticity, H_o: Homoskedasticity vs. H_1: Heteroskedasticity

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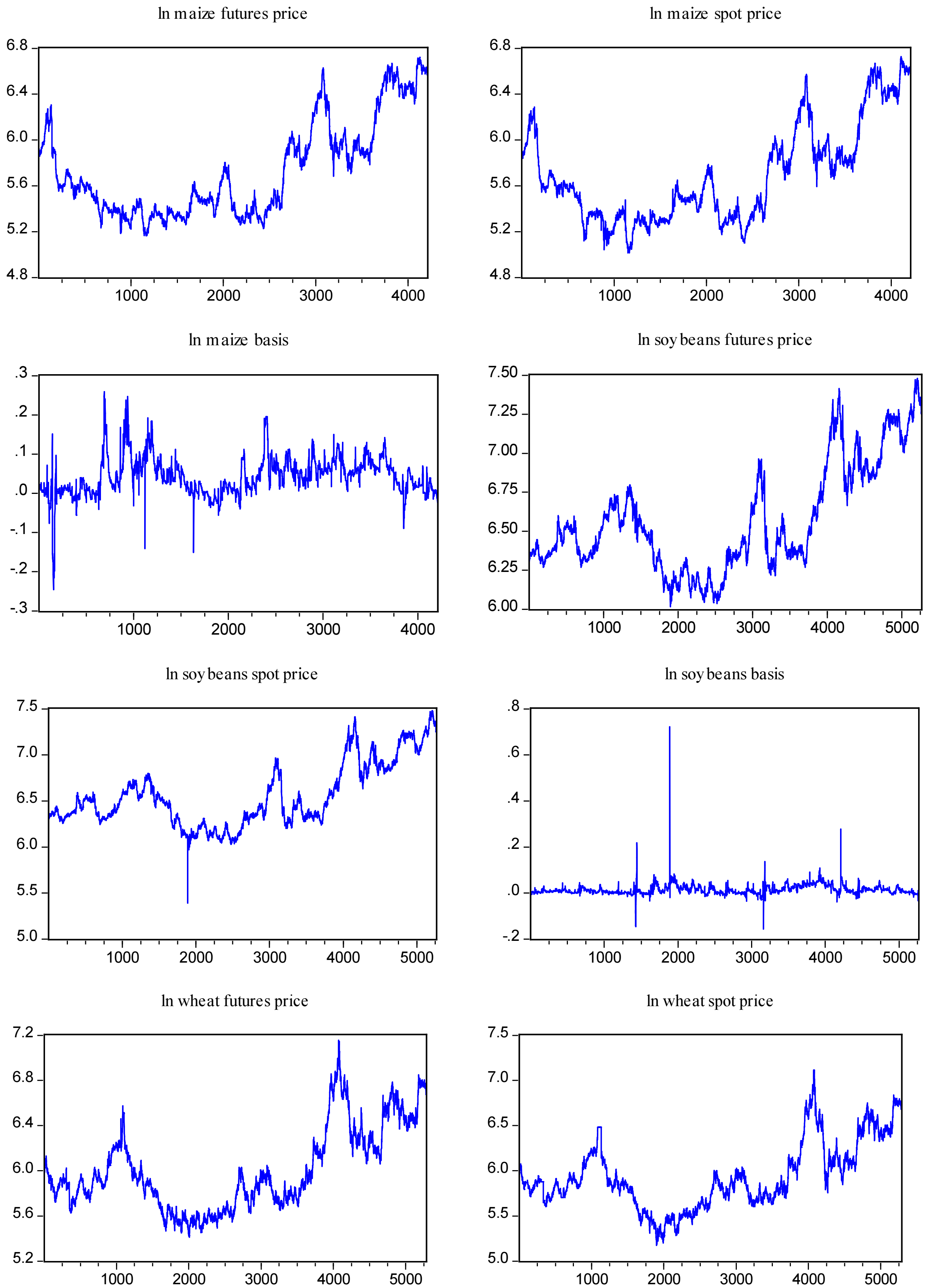

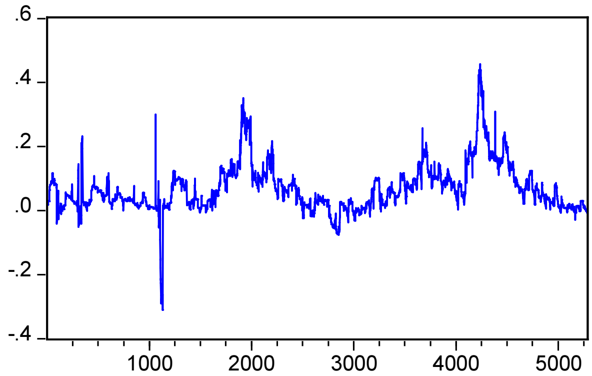

Fig. 1: Series developments

GARCH Modelling and Factors Influencing the Forecast Errors

Due to the presence of heteroskedasticity we estimate a GARCH (1, 1) model as follows[7]:

$$(s_T - s_t) \mid \Omega_T = \varphi_1 + \varphi_2 (f_{t,T} - s_t) + \xi_t \quad (9)$$

$$\xi_t \mid \Omega_t \sim iid \;\; N\left(0, \sigma_t^2\right) \quad (10)$$

$$\sigma_t^2 = \chi' X_t + \omega + \alpha \; \xi_{t-1}^2 + \beta \; \sigma_{t-1}^2 \quad (11)$$

where, the conditional mean Equation (9) indicates that, conditional on the information set available up to time t (Ω_t), the spread in the spot price for the period until delivery (s_T-s_t) is a function of the drift coefficient (ϕ_1), the current spread between the futures price and the spot price ($f_{t,T}$-s_t) and an error term (ξ_t). Equation (10) indicates that the forecast errors terms are, conditional on Ω_t, independently and identically normally distributed with zero mean and conditional variance σ_t^2. Equation (11) is the conditional variance equation and shows that the value of the conditional variance of forecast errors at time t, σ_t^2, depends on (a) a set of exogenous variables (X_t) with the associated coefficients χ to be estimated; (b) the long-term average value (ω); (c) the lagged squared residual term $(\alpha \; \xi_{t-1}^2)$, which denotes the size or magnitude of the past values of shocks or news; and (d) the past values of the variance itself $(\beta \; \sigma_{t-1}^2)$. In other words, the coefficient α represents the ARCH effect, or short-run persistence of shocks to returns and β represents the GARCH effect. The sum of the ARCH and GARCH coefficients (α+ β) indicates persistence in volatility clustering. The nearer it is to 1, the more persistent the volatility clustering.

[7] The AR(1) term in the mean equation (as in equation 5) has not been considered because it turned out to be not significant.

Given that data to construct the speculative pressure index and the Working index are available on weekly frequency, we estimate two GARCH models: one with daily data without the speculative pressure index and the Working index and the other with weekly data (the Friday series) which includes all explanatory variables.

The results for the daily estimations are reported in Table 5. The first part of each table sketches the outcomes for the mean equation and the second part highlights the variance equation. The variance effect of historical futures price volatility on forecast errors is uniformly positive and significant. This means that the higher the historical volatility, the higher the conditional variance of forecast error. This is because, when prices are more contaminated by noise and the market 'overreacts', forecast errors rise. This provides evidence that a behavioural explanation based on 'overreaction' whereby commodities with high volatility perform poorly, since the market does not correct itself, tends to hold. The effect of the days before maturity on the variance of forecast error is positive and significant with the exception of wheat. This means that the further the future contract is from maturity the less accurate are the predictions on spot prices. This is expected because as more and more information becomes available as maturity approaches, people are better able to make pricing decisions. The futures trading volume is negatively linked to forecast error, meaning that in liquid markets with many participants and transactions, prices tend to better reflect the underlying fundamentals. Put differently, the model reveals that increasing the volume of futures trading (i.e., more liquid markets) reduces the forecast error. Indeed, a lack of liquidity could drive persistent deviations from efficiency in a market. Conversely, short-term speculation proxied by the scalping index finishes creating noises and pushes the variance of forecast errors up.

In addition, the results indicate that the coefficients on both the residuals (ARCH term) and lagged conditional variance terms (GARCH term) in the conditional variance equation are highly statistically significant. The effect of 'news' (unexpected shocks) on commodity markets at time *t*-1 impacts current returns to a different extent, with a larger impact on wheat and soybeans (0.14) and a lesser effect on maize (0.085). The GARCH term (β) has a coefficient of 0.68 for maize and 0.61 for wheat and a smaller value of 0.56 for soybeans, which implies that 68%, 61% and 56% of a variance shock remains the next day, suggesting the presence of volatility clustering in the daily returns. The persistence parameters ($\beta+\alpha$) are large for all commodities, suggesting that shocks to the conditional variance are highly persistent and that the variance moves slowly through time, so that volatility takes a long time to die out following a shock.

Diagnostic tests are reported at the end of Table 5. They reveal that there is an absence of serial correlation among the squared standardized residuals, as highlighted by the Ljung-Box Q-Statistic. Furthermore, the ARCH-LM test shows that there are no ARCH remaining effects, confirming the strength of the adopted model. The Wald test (Table 5) to evaluate efficiency is in line with the previous results and it highlights that the three considered grain futures markets are not efficient, given that all the null hypotheses are rejected.

The results for weekly estimations are reported in Table 6. Price volatility in the specific futures market has an impact on the market conditions. In particular, when volatility increases the variance of the forecast errors rises. When expiration approaches, *ceteris paribus*, it becomes easier to predict future spot prices and thus the variance of forecast error decreases. The lack of liquidity in the futures market can be thought as a friction impeding the normal arbitrage process, therefore more liquidity implies a contraction in the variance of forecast errors.

We find that speculation significantly affects the forecast error. More precisely, the scalping index has a positive and significant coefficient in the variance equation, suggesting that short-term speculation increases the noises in the information formation process for maize and wheat markets. For soybeans, the variable is not significant. This different result from Table 5 can be due to the fact that soybean markets can be more sensitive to daily frequencies, meaning that the extension of the time period from daily to weekly allows the greater spreading of news with no significant impact in the open market.

The other long-run speculative indices have a negative and significant effect, thus suggesting that long-term speculation does not destabilize prices. This result points to the positive role of speculation based on market fundamentals[8] (which is more related to long-run speculation than to the scalping index) for the price formation process: If markets are competitive and speculative expectations rational, speculative activities bring prices closer to the 'true' price based on market fundamentals.

Additionally, our finding, according to which short-term speculation destabilizes while long-term speculation does not, is in line with Manera *et al*. (2013) and Bohl *et al*. (2018).

The Wald test for weekly data (Table 6) corroborates the previous results so that the considered futures markets are not efficient. This implies that futures prices are not an unbiased forecast of future realized spot prices and it is possible for an investor to gain sizeable profits. In this sense, the role of the futures markets in providing information on future demand and supply conditions and improving inter-temporal resource allocation is weakened, given futures prices do not 'fully reflect' the available information.

Multiplying the estimated GARCH parameters (Table 6) by the standard deviation of the considered explanatory variables, we obtain an indicator for the quantitative relevance of a certain factor to forecast error variance (Table 7). This procedure considers, for example, that a variable with a large estimated parameter can show very little variation and, therefore, does not contribute much to the forecast error. Table 7 illustrates that most of the variance comes from past shocks (ARCH-term) and the constant (ω) which measures for the inherent or characteristic volatility of the commodity. Compared to these two factors, the remaining explanatory variables, though in many cases statistically significant, add little to the overall forecast error. The beneficial impact of speculation as measured by the Working index (a) and the speculative pressure index (b) turns out to be only marginal. The impact of liquidity (trading volume) is larger than the impact of speculation, but is still rather small. Note, however, that this estimation does only prevail for the next period; i.e., it captures only short-term impacts. Due to the autoregressive GARCH term in the variance equation, short-term impacts are carried forward in the future and contribute also to forecast errors in the next period. The cumulative long-term effect can be calculated by dividing the short-term impact by (1-β) with β being the estimated GARCH coefficient. For β close to 0.5, the long-term impact is doubly as high as the short-term effect.

In order to gain a better understanding of the quantitative relevance of the factors related to market

[8]According to the Commission of the European Communities (2008), speculation based on market fundamentals involves trading regularly and making profits by anticipating price movements and taking appropriate positions. This type of speculation is positive and facilitates price discovery and risk management. Speculation based instead on market momentum is characterized by herding behaviour in times of skyrocketing prices, which can lead to the emergence of speculative bubbles, with market prices driven away from fundamental levels.

activity and contract maturity (which are rather small in Table 7 and cannot be compared among the commodities and specifications), we normalize the computed short-term impact by the standard deviation of the realized squared residuals (ξ_t^2) of the mean equation (9). This procedure shown in Fig. 2 (omitting the impact of the constant, ARCH and GARCH term) provides a proxy for the relative share of a factor's short-term impact on the forecast error in percentage. The figure emphasizes that liquidity reduces the forecast error by roughly 5 percent on average, with a higher impact on the wheat market where the value is of about 8 percent, while scalping activities can increase forecast errors by 4 percent on average. The number of calendar days before maturity is, as expected, an important factor of uncertainty, except in the case of maize: The closer the contract comes to its maturity date, the more precise the forecast gets. Again, long-term speculation measured by either one of the two indicators turns out to be negligible for improving the forecasting performance of the futures market given that it accounts only for 0.5 percent on average. The average impact of historical volatility is about two percent with a value higher than 3 percent for the wheat market. Nevertheless, times of excessive volatility can temporarily increase forecasting errors.

Table 5: Estimations for the Basis equation and forecast errors, daily frequency

Variables	**Maize**	**Soybeans**	**Wheat**
	Mean equation	*Mean equation*	*Mean equation*
Basis ($f_{t,T}$-s_t)	0.725***	0.714***	0.398***
	(0.009)	(0.021)	(0.010)
Constant	-0.017***	0.005***	-0.029***
	(0.001)	(0.0005)	(0.001)
	Variance Equation	*Variance Equation*	*Variance Equation*
Ln volatility 20d	0.00014***	0.00014***	0.0005***
	(1.25E-05)	(1.60E-05)	(4.57E-05)
Calendar days before maturity	3.69E-06***	6.60E-06***	2.43E-06***
	(6.17E-07)	(3.86E-07)	(6.92E-07)
Ln futures trading volume	-0.0002***	-0.00012***	-0.00017***
	(7.70E-06)	(4.29E-06)	(1.35E-05)
Ln scalping index	0.00012*	0.00029***	0.00029***
	(7.27E-05)	(8.03E-05)	(7.27E-05)
Constant, ω	0.0016***	0.0004***	-6.93E-05***
	(0.0001)	(5.59E-05)	(1.93E-05)
Arch, α	0.442***	0.588***	0.494***
	(0.026)	(0.037)	(0.038)
Garch, β	0.504***	0.321***	0.482***
	(0.012)	(0.017)	(0.023)
S.E. regression	0.095	0.067	0.106
Log likelihood	6002.40	8606.79	6562.84
Convergence	178 iterations	19 iterations	23 iterations
N. of obs	4209	5042	5064
AIC	-2.848	-3.410	-2.588
SC	-2.834	-3.399	-2.577
Ljung-Box p-value	0.71 (5);	0.53 (5);	0.20 (5);
	0.98 (10); 1.00 (20);	0.87 (10); 0.99 (20);	0.63 (10); 0.98 (20)
Arch(5) p-value	0.717	0.536	0.210
Jarque-Bera p-value	0.000	0.000	0.000
Wald Test p-value	0.000	0.000	0.000

Note: The table presents estimated results by GARCH of equations 9-11 using ML - ARCH (Marquardt) method. Standard errors are in brackets; statistical significance is denoted by ***p<0.01, **p<0.05, *p<0.10. AIC and SC are the Akaike and Schwartz information criteria. The numbers in brackets in the Ljung-Box statistics refers to the number of considered lags. Arch(5) is the Lagrange Multiplier test of ARCH effects up to the 5th order (H_0: no arch effect vs. H_1: arch effect up to the 5th order). Jarque-Bera is the χ^2 statistics for test of normality (H_0: normality vs. H_1: no normality). The Wald Test for Weak efficiency, H_0: market is efficent and unbiased =>:

$$H_0 : \varphi_1 = 0 \text{ and } \varphi_2 = 1 \quad vs \quad H_1 : \varphi_1 \neq 0 \text{ or } \varphi_2 \neq 1$$

Table 6: Estimations for the Basis equation and forecast errors, weekly frequency

Variables	Maize		Soybeans		Wheat	
	Mean Equation		*Mean Equation*		*Mean Equation*	
	(a)	(b)	(a)	(b)	(a)	(b)
Basis	0.533***	0.675***	0.444***	0.776***	0.299***	0.282***
	(0.0438)	(0.044)	(0.028)	(0.051)	(0.031)	(0.031)
Constant	-0.006*	-0.007**	0.001	-0.001	-0.016***	-0.016***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
	Variance Equation		*Variance Equation*		*Variance Equation*	
	(a)	(b)	(a)	(b)	(a)	(b)
Ln volatility 20d	0.001***	0.0004**	0.0004**	0.0003**	0.002****	0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0003)	(0.0003)
Calendar days	3.74E-06	-1.99E-06	4.09E-05***	4.01E-05***	5.57E-05***	8.70E-05***
before maturity	(7.32E-06)	(5.33E-06)	(5.23E-06)	(4.06E-06)	(9.74E-06)	(6.69E-06)
Ln futures	-0.001***	-0.0003***	-0.0002***	-0.0002***	-0.0006***	-0.001***
trading volume	(0.0001)	(0.0001)	(6.49E-05)	(5.15E-05)	(8.58E-05)	-0.0001
Ln scalping index	0.0006***	0.0006***	0.0001	8.37E-05	0.0009***	0.001***
	(0.0002)	(0.0002)	(8.69E-05)	(7.31E-05)	(0.0001)	(0.0001)
Ln Working index	-0.0006***	-0.0005	-0.0004***	-0.0004*	-0.0009***	-0.001***
(a) Ln speculative pressure index (b)	(0.0002)	(0.0004)	(9.66E-06)	(0.0002)	(0.0003)	(0.0002)
Constant, ω	0.008***	0.006***	0.003***	0.003***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Arch, α	0.340***	0.319***	0.459***	0.399***	0.471***	0.476***
	(0.060)	(0.053)	(0.083)	(0.065)	(0.080)	(0.084)
Garch, β	0.545***	0.562***	0.149**	0.319***	0.382***	0.265***
	(0.051)	(0.041)	(0.060)	(0.062)	(0.051)	(0.066)
S.E. of regression	0.098	0.098	0.068	0.068	0.105	0.105
Log likelihood	979.931	978.9575	1569.565	1554.787	1137.502	1147.813
Convergence	17 iterations	42 iterations	15 iterations	16 iterations	12 iterations	29 iterations
N. of obs	843	843	1038	1038	1044	1044
Akaike info criterion	-2.301	-2.299	-3.005	-2.976	-2.160	-2.180
Schwarz criterion	-2.245	-2.243	-2.957	-2.929	-2.113	-2.132
Ljung-Box p-value	0.36 (5);	0.20 (5);	0.61 (5);	0.18 (5);	0.57 (5);	0.81 (5);
	0.59 (10);	0.40 (10);	0.25 (10);	0.03 (10);	0.69 (10);	0.92 (10);
	0.76 (20);	0.66 (20);	0.31 (20);	0.03 (20);	0.04 (20);	0.02 (20);
Arch(5) p-value	0.404	0.242	0.636	0.211	0.611	0.829
Jarque-Bera p-value	0.000	0.000	0.000	0.000	0.000	0.000
Walf Test p-value	0.000	0.000	0.000	0.000	0.000	0.000

*The table presents estimated results by GARCH of equations 9-11 using ML-ARCH (Marquardt) method. Standard errors are in brackets; statistical significance is denoted by ***p<0.01, **p<0.05, *p<0.10. (a) refers to the model in which long-term speculation is proxied by the Working-T index; (b) refers to the model in which long-term speculation is proxied by the speculative pressure index. AIC and SC are the Akaike and Schwartz information criteria. The numbers in brackets in the Ljung-Box statistics refers to the number of considered lags. Arch(5) is the Lagrange Multiplier test of ARCH effects up to the 5^{th} order (H_0: no arch effect vs. H_1: arch effect up to the 5^{th} order). Jarque-Bera is the χ^2 statistics for test of normality (H_0: normality vs. H_1: no normality). The Wald Test for Weak efficiency, H_0: market is efficent and unbiased =>:*

$$H_o : \varphi_1 = 0 \text{ and } \varphi_2 = 1 \text{ vs } H_1 : \varphi_1 \neq 0 \text{ or } \varphi_2 \neq 1$$

Table 7: Short-term impact of one standard deviation shock on the forecast error variance (10^2)

	Maize	Soybeans	Wheat			
	(a)	(b)	(a)	(b)	(a)	(b)
Arch, α	0.674	0.645	0.431	0.355	1.019	1.026
Ln volatility 20d	0.040	0.016	0.016	0.012	0.070	0.035
Calendar days before maturity	0.010	-0.005	0.071	0.069	0.134	0.209
Ln futures trading volume	-0.120	-0.036	-0.034	-0.034	-0.104	-0.174
Ln scalping index	0.058	0.058	0.011	0.009	0.086	0.095
Ln Working index (a) Ln speculative pressure index (b)	-0.003	-0.011	-0.002	-0.009	-0.005	-0.023
Constant, ω	0.800	0.600	0.300	0.300	0.600	0.600

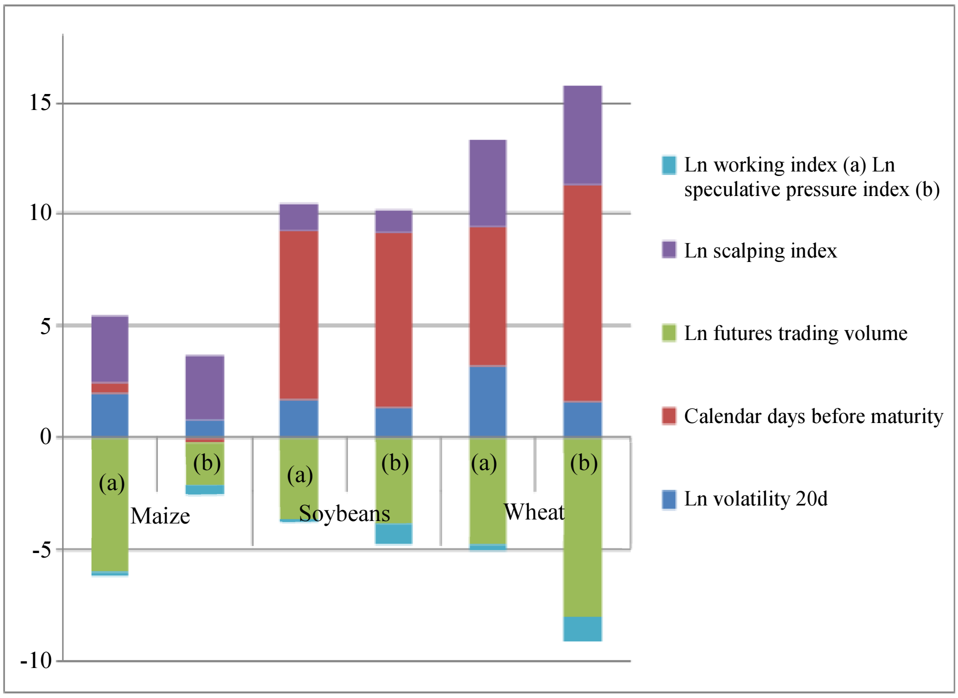

Fig. 2: Percentage share contribution of each factor to forecast errors in the short-run
The graph presents the percentage share contribution of each variable to forecast error. The values are obtained normalizing the short-term impact of each variable by the standard deviation of the realized squared residuals of the GARCH mean equation

Conclusion

The importance of futures markets stems from their ability to forecast spot prices at a specific future date so that agents are able to manage the risks associated with trading in a given commodity over time. Price discovery and risk transfer are the two main functions of futures markets. Additionally, efficient futures markets have an important role in providing a publicly available forecast of the spot price.

Using first an OLS model and then a more refined GARCH model with different frequency data, we investigated the efficiency of the major grains futures markets and the drivers of forecast errors. The analysis reveals that despite the data frequency used, futures prices are not consistent with the efficient market hypothesis, meaning that futures prices do not always capture all relevant information. While this flaw allows investors to gain excess profits, it distorts prices away from their fundamentals. We find that major factors that account for market inefficiency are historical price volatility and short-term speculation. Indeed, with high volatility or increasing scalping activities, prices become more contaminated by noises and forecast errors increase. This result is confirmed for both daily and weekly data frequency. Vice-versa, more liquidity in the market and the presence of long-term speculation would help futures markets to decrease noises and improve the allocation of resources over time. It should be noted, however, that the quantitative impact of long-term speculation is rather negligible. The average forecast error increases with time to maturity, because there is less information and more uncertainty for long-time horizons. Hence, futures prices closer to the expiration dates will provide better estimates of the future spot price than do those further away.

Our results indicate that the efficiency and the forecasting performance of commodity markets could be improved. We believe that the key to increasing efficiency is improved transparency in grains spot and futures markets: Greater transparency would enable the provision of more accurate information about grains. Comprehensive and timely information would include intraday transaction data and global grain shares holding. For instance, the U.S. Commodity Futures Trading Commission releases only weekly data on trading positions, although daily data exist, but are not publically available. Inadequate information makes it difficult for market participants to determine whether a specific grain price signal relates to changes in fundamentals or to commodity market events. This void similarly leads to detrimental practices such as intentionally imprecise information released to deceive market price movements. Some suggestions for improving information transparency in the commodity markets include the release of high frequency data in order to have an idea about short-term events upon which active commodity investment strategies are based. We reckon that more frequent information disclosure should be accomplished. Along this line, each commodity market could create a database that comprises a range of information. Gathering and disseminating commodity information in aggregate form would be a significant step towards superior transparency and could avoid severe short-term price fluctuations.

Additionally, policy measures could be addressed at monitoring financial markets in order to avoid scalping activities creating noise and destabilizing prices. Recent regulations on high-frequency trading could be seen as one step in this direction. Policies that reduce the liquidity (trading volume) of futures markets in general can, however, lead to higher forecast errors and could therefore have negative allocative effects on the physical market. This refers in particular to permanent transaction taxes or tight position limits. The impact of excessive speculation on forecast performance, though positive, is very small and almost negligible.

This current study has some limitations, which could be a source of further future extension. For instance, we have explored efficiency using daily and weekly data, but with the development of high frequency trading, the semi-strong efficiency hypothesis could also be tested for commodity markets. In addition, it would be interesting to better explain the sources of market inefficiency particularly whether and to what extent institutional structure, organization and regulation of futures markets shape market efficiency.

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Ethics

This study is an extended version of a background paper prepared for the ZEF Discussion Paper Series. The opinions expressed in this study are those of the authors and do not necessarily reflect the view of their Institutions.

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