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ORIGINAL RESEARCH

Further evidence on the explanatory power of spot food and energy commodities market prices for futures prices

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Abstract This research is focused on analyzing spillover effects from crude oil to agricultural commodities futures markets. Moreover, emphasis is placed on the "reverse" relationships between spot and futures markets with particular attention given to the interrelationships. The study is interesting for reasons of economics and finance as well as for taking into account geo-political considerations. This study lends insight into the empirical validity of reverse regressions hypothesizing that spot prices today contain information useful for predicting forward rates in the future. This paper considers the importance of the effects of temporal aggregation as well as alternative time series model specifications and assumptions on the distributions of residuals. In addition to the assumption of normality, the paper considers use of a fat-tailed distribution (multivariate t-distribution) to examine the robustness of results that are based on the normality assumption. Finally, models are compared in terms of *ex post* predictive validity.

Keywords Commodities prices · Oil · Temporal aggregation · Causality · Non-normality

JEL Classification Q14 · Q4 · G1 · D4 · C1

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1 Introduction

This primary purpose of this research is to analyse spillover effects from crude oil to agricultural commodities futures markets. Emphasis is placed on the “reverse” relationships between spot and futures markets with particular attention given to the interrelationships. The primary purpose of this paper is to lend insight into the empirical validity of reverse regressions hypothesizing that spot prices today help to predict forward rates in the future and the importance of temporal aggregation and alternative distributional assumption on the error terms in estimating such relationships. The study is interesting for reasons of economics and finance as well as for econometrics and statistics. Primary commodities prices are known to be extremely volatile. As indicated by Brown (2008), a majority of developing countries and a significant percentage of developed countries are heavily dependent on primary commodities for export earnings. Particularly for less developed countries, dependence on primary commodities leaves them vulnerable to commodities price shocks.

The importance of energy markets in explaining volatility in agricultural commodities prices has been a topic of considerable interest. The oil price transmission to agricultural commodity prices states that a rise in oil prices results in higher agricultural commodity prices by increasing costs of production through its impacts on fertilizer, chemicals, transportation costs, and other inputs. Scholarly work focused on the relationship between the energy sector and agricultural commodities has been published by, Yu et al. (2006), Baffes (2007), Zhang and Reed (2008), Balcombe (2010) and Gilbert (2010a, b), Saghaian (2010), Nazlioglu (2011), Trujillo-Barrera et al. (2012), and Cartwright and Riabko (2015). Baffes (2007) reports that among non-energy commodities, oil prices have the highest pass-through to food commodities and fertilizers. Saghaian (2010) using time-series and directed graph theory approaches, finds a correlation between oil and commodity prices, but the evidence of a (Granger) causal link is mixed. Cartwright and Riabko (2015) find mixed results depending on temporal aggregation and model specification. Campiche et al. (2007) examined the covariability between crude oil prices and corn, sorghum, sugar, soybeans, soybean oil and palm oil prices over the period 2003–2007. Beak and Seo (2015) consider the spillover effects from volatility in oil markets onto financial markets. The literature indicates that the relationship between oil prices and those of agricultural commodities is far from clear-cut justifying ongoing study.

While beyond the scope of this research studies such as Fung et al. (2003) and Frino et al. (2010) have considered relationships as between commodity futures prices between markets and taking into account size of market. Also, more recently, there have been investigations such as those by Muhammed and Kebede (2009), Chen et al. (2010) and Roberts and Schlenker (2013) focused on a second transmission mechanism. i.e., that the increases in oil prices results in the growth of corn- and soybean-based biofuels production that drives up demand for these agricultural commodities increasing the agricultural commodity prices. Finally, an added consideration in analyzing the oil to food commodity price transmission is the geo-political price-distorting considerations. It is generally understood that fluctuations in oil prices can endanger economic and political stability. Nowhere was this phenomenon more noticeable than during the Arab Spring protests. The immediate cause of protests in Algeria was raising food prices. In Kuwait, the Emir announced 14 months of free staple foods for nationals as part of a general subsidy package. In Egypt, food subsidies have been a bone of contention in domestic politics since the bread riots of 1977 (Woertz 2011). In Saudi Arabia, recognizing that by 2016 all wheat and a high percentage of other agricultural commodities will be imported, government policy incents the execution of bilateral agreements with host countries having rich agricultural sectors providing guaranteed rights to export commodities from the host to Saudi Arabia. Such agreements are intended to lock-in long-term investments and guarantees of food commodities while circumventing the uncertainties of the open market (Harrigan 2014).

This research analyzes empirically the possible effects of oil prices on wheat, soy, and corn futures contract prices at a future point in time. Consideration is given to the effects of temporal aggregation on any such relationships and the implications for alternative assumptions on the error terms. This paper does not seek to directly address the issues concerning efficiency of markets nor does it take on the task of determining price response to "fundamentals" such as weather as in the work by Pindyck (2001). While commodity prices such as wheat and oil exhibited considerable volatility over the period of study (for example, the price of oil rising from 70 USD in 2006 to over 140 USD in 2008, declining to just under 40 USD in 2009 and rising to near 110 USD in 2011), this work does not address the possible roles of basic supply and demand shifts versus the role of speculation (Knittel and Pindyck 2013).

It is well-known that intertemporal effects in financial models are prevalent. Intertemporal effects have been recognized at least since the work of Merton (1976) and Black (1976) and the phenomena of fat tails associated with financial series has been studied since the seminal work of Mandelbrot (1963). Temporal aggregation has been a frequent topic of past and recent research in economics and finance. Problems of temporal aggregation arise frequently in economics and econometric analysis as a consequence of using macro or aggregated data to estimate underlying micro, or disaggregate relationships. Results from research indicate that effects of temporal aggregation can adversely impact statistical estimation, inference and dynamic lag structures. Evidence relevant to this analysis (Engle and Liu 1972; Rowe 1976; Cartwright and Lee 1987; Marcellino 1999; Silvestrini and Veredas 2005) indicates that time series aggregation will most certainly influence standard errors on parameter estimates as standard errors are likely to increase with aggregation. Therefore, t-ratios are likely to change as well. While goodness-of-fit measures might increase with aggregation, forecast accuracy with macro-level aggregations might deteriorate owing to information loss due to the averaging of observations associated with an underlying micro-level structure. Generally, the results show adverse effects of temporal aggregation on statistical estimation, inference and on dynamic lag structures.

Following Silvestrini and Veredas (2005), aggregation of time series raises many issues relevant for the practitioner. For example, if a time series can be characterized by a particular specification at one level of aggregation, what is the correct specification at an alternative aggregation? If data are available at both micro and macro levels of aggregation, which series should be modeled? If information loss owing to aggregation is of concern, how best measure the information loss?

In addition to considering alternative conditional volatility models and temporal aggregation, this research considers that the error distributions may not be normally distributed and that the error terms are best modelled under assumptions of non-normality and asymmetric volatility. Liu and Brorsen (1995), Doong et al. (2005) and Chang et al. (2012), have considered related issues. In particular, Liu and Brorsen (1995) test a GARCH-stable process as a model of the distribution of daily futures prices and find that the GARCH-stable process cannot be rejected as a model of 12 of the 37 price series considered. More specifically, this research considers residual behavior under both the assumptions of the normal and t-distributions.

Following this Introduction, Sect. 2 sets forth the models and methodology of interest. The focus of this section is on the justification and specification of reverse regressions and the introduction of the time series models applied in this research. Section 3 provides a description of the data. Taking Cartwright and Riabko (2015) as a point of departure, in order to develop understanding of the consequences of aggregation when modeling commodities futures contract price data, models are estimated and evaluated at increasingly higher levels of temporal aggregation; daily, weekly and monthly. This research extends the work by analyzing increasingly complex models under alternative assumptions on the distribution of the errors. The results are reported in Sect. 4. Section 5 considers the issue of forecasting performance of selected models evaluating forecast efficiency and possible gains from application of models with higher orders of complexity. The summary and conclusions from the empirical work appear in the final section.

2 Models and methodology

2.1 Model

Since the 1970s, empirical research on financial markets behavior and performance has emphasized the efficient market hypothesis, which states that given a particular financial contract with developed forward and spot markets, the forward price reflects all information possessed by persons active in that market. Therefore, in an open market, the forward price should be an unbiased predictor of the future spot price (Fama 1965). Empirical tests of this relationship take the form of a regression

$$s(t+k) = \Psi + \beta f^k(t) + \varepsilon(t+k) \tag{1}$$

where $s(t)$ = the spot price on contracts of wheat at period t; $f(t)$ = the average of the 30-day forward contract price recorded at period $t-1$; $\varepsilon(t)$ = error disturbance assumed distributed normal and independently with zero mean variance σ^2; k = number of periods into the future from the time period t.

The efficient market hypothesis implies that the estimate of the constant term is not significantly different from zero and the estimate of β is not significant different from 1.0. Research as considered relationships between spot and futures commodity markets considering arbitrage and hedging opportunities. The research by Lin et al. (2003) is an example of these directions for research.

Note that $f^k(t)$ is 30-day forward price. Weekly and monthly data series were constructed from daily data averaging time intervals taking into account multiple contracts, week-ends and trading holidays.

In this paper, interest is in the reverse regression, i.e.

$$f^k(t+k) = \Psi + \beta s(t) + \varepsilon(t+k) \tag{2}$$

or more generally, interest is in the model

$$f^k(t+k) = \Psi' + \beta' s(t) + \delta' o(t) + \varepsilon'(t+k) \tag{2'}$$

where $f^k(t)$ = the average of the k-day forward contract price recorded at period t; $s(t)$ = the spot price on contracts of wheat at period t; $o(t)$ = the spot price for oil (Brent) at period t; $\varepsilon(t)$ = error disturbance assumed distributed normal and independently with zero mean variance σ^2; k = number of periods into the future from the time period t.

A precedent for such reverse regressions has been established in exchange rate models by Campbell and Shiller (1987), Engel and West (2005), and Chen et al. (2008). Fundamentally, (2) points to the notion that today's market state (and past realizations in the dynamic case considered below) effects the forward-looking variable. Simply put, (1) asks the question "Are futures prices (1) an unbiased and/or (2) accurate predictor of subsequent spot prices?" Equation (2) and its extended formulation (2)' reverse the question by asking "Is there information content in today's spot price(s) useful (unbiased and accurate) for predicting subsequent futures prices"?

The argument underlying (2) and ($2'$) is as follows. Futures prices reflect the price that both the buyer and the seller agree will be the price of the given commodity upon delivery. Therefore, these prices provide direct information about investor's expectations about the future price of the agricultural commodity of interest. Like the prices of every other risky asset, however, commodity futures prices include risk premiums, to reflect the possibility that spot prices at the time of delivery may be higher or lower than the contracted price. The difference is expressed as a percentage of the current spot price. As risk premiums may be large and volatile over time, agricultural commodity futures prices might not be the best predictor of futures prices.

The current, or spot price, of the commodity of interest as well as other commodity prices, e.g., oil, transmitting information about the future state might be useful for predicting future price movements. Given certain simplifying assumptions, the opportunity cost of storing a commodity is the foregone interest rate (Hotelling 1931). Therefore, in theory, the expected rate of return to holding a commodity should be identical to the interest rate. Practically, holding commodity stocks often provides some advantages or flexibilities for manufacturers in managing operational risks. Such benefits (net of storage costs) are called "convenience yields" and should be reflected as a premium, mostly positive, in the current commodity price. The expected rate of return of oil stocks may not be identical to the interest rate, and a forecast based on the current spot price may tend to over predict future oil prices. This research intends to lend insight into the presence and extent of any spot market to futures market transmission or spillover effects.

Technically, the idea is that the price of the commodity in question today reflects expectations of future changes in market conditions, so it should be a useful predictor. Further, this research intends to test the empirical validity of the hypothesis that there is pass-through from the current (spot) price of oil to the futures contract price. In the context of this research, if contemporaneous or strict causality from the spot to the futures market is owing to supply chain transmission of effects from energy markets to food commodity prices, the monthly unit of aggregation can be entertained as appropriate. Following Chen et al. (2008), it is recognized that endogeneity problems in such models make sorting out of the dynamic causality difficult, if not impossible, and parameter instability exacerbates the statistical problems. In this paper, alternative methods and specifications are applied in an effort to gain insight into the issues of aggregation, acknowledging that the issues of causal interpretation are not resolved.

2.2 Time series methodology

As research has shown inadequacy of static models, this research extends the results above to estimate a dynamic formulation of ($2'$) shown in Eq. (3).

$$f^k(t+k) = \Psi'' + \varphi'' f^k(t+k-1) + \beta'' s(t) + \delta'' o(t) + \varepsilon''(t+k) \qquad (3)$$

where $f(t+k-1)$ indicates the lagged dependent variable at time $t+k-1$. The coefficient $0 \geq \phi < 1$ and the error term is assumed to have zero expectation and constant variance. The model is well-known in economics and finance as a lagged dependent variable (LDV) model, or more specifically, Eq. (3) is a restricted form of the autoregressive distributed lag (ADL) in which the specification above implies an infinite geometric lag on the variables s(t) and o(t). A more detailed discussion of the infinite geometric lag is provided by Judge et al. (1985).

With respect to model estimation and forecasting, this research considers the GARCH and EGARCH time series models with daily, weekly and monthly data under alternative assumptions on the error terms, i.e., normal and t distributions. The analysis and prediction of temporal dependence in the second-order moments of financial returns is recognized as important in financial modelling (Bauwens et al. 2006).

Following Engle (1982), Bollerslev (1986), Bollerslev et al. (1994) and Engle (2002) consider the time series, $y_t = E_{t-1}(y_t) + \varepsilon_t$, where $E_{t-1}(y_t)$ is the conditional expectation of y_t at time $t - 1$ and ε_t is the error at time period t. The generalized autoregressive conditional heteroscedastic (GARCH) model of Bollerslev (1986) is given as

$$\varepsilon_t = h_t^{1/2}\eta_t,\ \eta_t \sim N(0,1) \tag{4}$$

$$h_t = \omega + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2 \tag{5}$$

where $\omega > 0$, $\alpha_j \geq 0$ and $\beta_j \geq 0$ are sufficient to ensure that the conditional variance $h_t > 0$. L is the backshift operator. In Eq. 5 α_j represents the ARCH effect, β_j captures the GARCH effects and $(\alpha_j + \beta_j)$ measures the persistence of the shocks to the variable of interest I to long-run persistence. Provided that the roots of $(1 - \alpha(L) - \beta(L))$ and $(1 - \beta(L))$ lie outside the unit circle, then ε_t^2 exhibits stability and covariance stationarity.

An alternative model proposed by Nelson (1991) accommodates asymmetry between positive and negative shocks as well as leverage. The proposed Exponential GARCH (EGARCH) interprets ARMA models for the logarithm of the condition variances such that

$$ln\, h_t = \omega + \sum_{i=1}^{p} \alpha_i |\eta_{t-i}| + \sum_{i=1}^{p} \gamma_i \eta_{t-i} + \sum_{j=1}^{q} \beta_j ln\, h_{t-j}. \tag{6}$$

In Eq. (6) $| \eta_{t-i} |$ and η_{t-I} capture the size and sign effects, respectively, of the standardized shocks, i.e., $\eta_{t-I} = (\varepsilon_{t-i}/\sigma_{t-i})$. More specifically, (6) implies that the leverage effect allowing the variance to respond differently following negative or positive shocks of equal magnitude is exponential and that the forecasts of the conditional variance are necessarily non-negative. The presence of leverage effects can be tested by $\gamma_i < 0$. The impact is asymmetric if $\gamma_i \neq 0$. So, the model estimates both the sign and magnitude effects. McAleer (2005) and McAleer et al. (2007) provide a discussion of differences between GARCH and EGARCH models. Other methods and specifications such as GJR-GARCH (Glosten et al. 1992) are interesting, however, EGARCH has been applied to capture size and assign effects as the methods uses standardized residuals to capture conditional shocks and there are no restrictions on the parameters for the conditional variance.

As concerns the assumed distribution of the residual or error terms, since the paper by Fama (1965), there has been considerable evidence of the importance of non-normality of the error in financial models. Significant contributions in this area include Affleck-Graves and McDonald (1989), Richardson and Smith (1993) and Dufour et al. (2003). In this paper, both the normal and t distributions are considered.

Table 1 Descriptive statistics for agricultural commodities, daily time series (n = 1861 in local currency)

Series	No. of observations	No. of missing observations	Mean	SD
Soy, Spot (US)	1797	64	1185.816	254.793
Soy, 30-Future (US)	1797	64	1179.647	245.714
Wheat, Spot (US)	1797	64	666.557	147.480
Wheat, 30-Future (US)	1797	64	684.250	148.070
Wheat, Spot (France)	1819	42	194.763	46.565
Wheat, 30-Future (France)	1819	42	192.223	43.806
Maize, Spot (US)	1797	64	519.375	148.467
Maize, 30-Future (US)	1797	64	520.902	141.656
Corn, Spot (Brazil)	1771	90	25.289	4.552
Corn, 30-Future (Brazil)	1730	131	25.085	4.151
Brent Oil, Spot	1797	43	91.651	23.168
Brent Oil, 30-Future	1797	41	91.754	22.756

3 Data

The empirical analysis is based on daily, weekly, and monthly prices. Spot and 30-day futures prices data were collected for U.S. soy, wheat and maize contracts. Wheat futures data have been collected for France and corn 30-day futures and spot prices were collected for Brazil. Spot and futures price data for Brent oil have been collected on a consistent basis with the data for agricultural commodities. The daily spot rates and daily futures rates were taken from the International Grain Council (International Grain Council 2013) data base which corresponds to International Exchange (ICE) data. The ICE Brent Crude Futures contract is a deliverable contract based on EFP delivery with an option to cash settlement. On the daily basis, the data cover 14 November 2006 through 31 December 2013; 1861 daily observations. Aggregate data, i.e., weekly and monthly series, have been computed directly from the daily data series in order to guarantee correspondence between the series over time.

It is well-known that the situation of missing observations in financial time series is common. While it is not the primary focus of this study, the methodology used to replace or impute missing observations is important. Overall, the series were virtually complete having less than 5 % of the observations missing. Descriptive statistics for the time series analyzed are shown in Table 1. Missing observations were imputed using simple linear interpolation for missing observations was applied.

4 Model results

4.1 Daily data

Following Engle (1982), Bollerslev (1986), Bollerslev et al. (1994) and Engle (2002), the GARCH procedure is applied to estimate the parameters the multivariate generalized autoregressive heteroscedastic model for daily weekly and monthly observations. In this procedure the conditional variances are modeled as univariate generalized autoregressive conditionally heteroscedastic models and the covariances are modeled as nonlinear functions of the conditional variances (Engle 2002). While only the final selected specifications are reported, for the GARCH (p,q) models alternative values for p and q were tested. The popularity of the GARCH(1,1) model is indicated by a significant body of literature, e.g. Nelson (1990). The GARCH(1,1) model has often been found sufficient to capture the main features of the volatility process.

While the models are estimated over alternative levels of aggregation, Drost and Nijman (1993) have shown that classical GARCH assumptions are not robust to the specification of the sampling interval. Models are also estimated using the EGARCH specification (Nelson 1991) and the results are reported for models under the assumption that the errors are distributed as normal as well as t. Issues concerning time series modelling of commodity prices, and oil prices in particular, can be found in the papers by Chen and Lin (2014) and Bopp and Lady (1991).

This study uses the algorithms available in STATA, *Time Series, Release 12* (1985–2011). With respect to the coefficient estimates shown in the tables below, labels accompanied by−n and−t, refer to models estimated under the assumptions of normality and t, respectively. With respect to the EGARCH models, following the STATA conventions, the estimated coefficient earch measures the sign effect such that values not significantly different from zero, less than zero or greater than zero imply symmetric responses to shocks, positive shocks generate less volatility than negative shocks or positive shocks are more destabilizing than negative shocks. The coefficient egarcha captures the magnitude effect, and egarch measures the estimated persistence effect.

France and the U.S. are the largest of the global wheat markets for which data are available for this research. The U.S. wheat series is first analyzed with respect to the autocorrelation structure. The autocorrelation function (ACF) and partial autocorrelation function (PACF) indicate that first differences of the series are appropriate for achieving stationarity. As described above, the estimated model is of the form (3) after differencing, i.e.,

$$\Delta f^k(t+k) = \Psi''' + \varphi'' \Delta f^k(t+k-1) + \beta''' \Delta s(t) + \delta''' \Delta o(t) + \varepsilon'''(t+k) \qquad (7)$$

The plot of the first-differenced futures series, shown in Fig. 1, indicates that the series is approximately zero-mean and the evidence of heteroscedasticity is apparent. The first-differenced series for Brent oil is shown in Fig. 2. The series exhibits considerable volatility, but it is approximately zero-mean. On the basis of the Phillips-Perron test, the null hypothesis that the dependent variable contains a unit root can be rejected at any reasonable significance level. Testing for Granger causality, there is only evidence of causality as between the dependent variable and itself lagged one period.

Results from estimation of the daily models are shown in Table 2. It is well-known that owing to the nonconvexity and nonlinearity of the models in this research that estimates can be difficult to compute. Such difficulties arise in this research and only results for the estimable models are shown. It is possible to compute estimates using nonlinear programming techniques, although this approach has not been taken in this current study (Altay-Salih et al. 2003).

The procedures applied to the U.S. daily wheat data are followed precisely using the data for French wheat. The series is shown in Fig. 3. As above, based on the ACF and PACF for the data series on the prices for futures contracts, the data are first differenced. The results for the Phillips-Perron test for a unit root suggest estimation with first differences of the series for France.

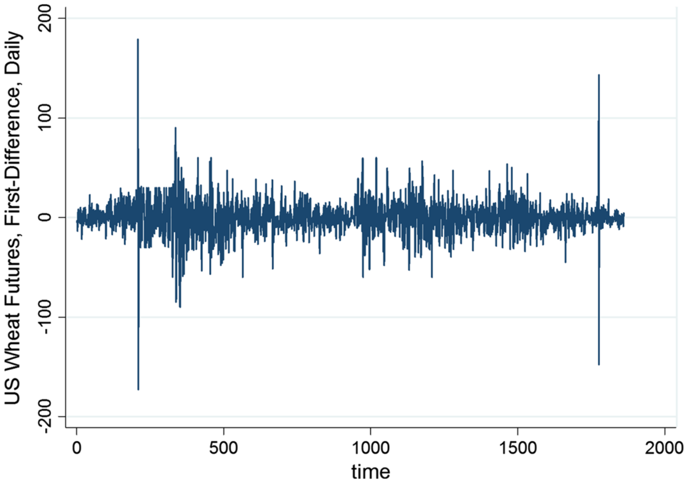

Fig. 1 Daily wheat, futures-30 day (US), first differences

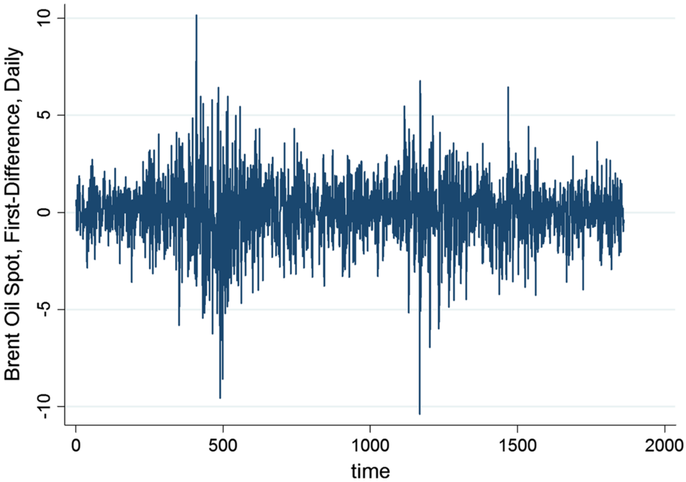

Fig. 2 Daily brent oil, spot first differences

Based on the Granger causality tests (Granger 1969), it appears that the differenced futures series is caused by the lagged values of itself the differenced spot price series, but not the differenced oil price series. There is causality as between the differenced spot price and the differenced oil price. Both the GARCH and EGARCH specifications yield significant coefficients on the error structures, but perhaps, more interesting is that the model for France yields significant coefficients on the lagged dependent variable or on the differenced spot price series, with significance being sensitive to the distributional assumption of the error term.

As above, the soy series is first analyzed beginning with the autocorrelation function (ACF) and partial autocorrelation function (PACF) and it appears that first differences of the series are appropriate for achieving stationarity. Applying the Phillips-Perron test, the

Table 2 Model results, daily data, n = 1861

	φ″	β″	δ″	arch(1)-n	garch(1)-n	arch(1)-t	garch(1)-t	earch-n	egarcha-n	egarch-n	earch-t	egarcha-t	egarch-t
Wheat (US)	.014 (.030)	−.016 (.024)	−.226 (.213)	.173** (.012)	.759** (.021)								
	−.007 (.024)	−.004 (.020)	.280 (.177)			.128** (.019)	.868** (.017)						
	.007 (.027)	−.007 (.022)	.215 (.190)					.124** (.009)	.210** (.023)	.932** (.009)			
	−.002 (.023)	−.006 (.021)	.245 (.178)								.060** (.015)	.145** (.021)	.984** (.005)
Wheat (FR)	.029 (.029)	.047** (.018)	.035 (.045)	.106** (.005)	.900** (.004)								
	.064** (.021)	.004 (.015)	.035 (.029)			.083** (.005)	.923** (.005)						
	.031 (.025)	.032* (.019)	.017 (.046)					.038** (.005)	.111** (.006)	.993** (.001)			
	.057** (.020)	.006 (.016)	.034 (.028)								.062** (.013)	.133** (.020)	.993** (.003)
Soy (US)	.036 (.024)	−.023 (.019)	.203 (.233)	.071** (008)	.921** (.009)								
	.024 (.023)	−.022 (.020)	.159 (.202)			.060** (.012)	.936** (.012)						
	.036 (.023)	−.034* (.019)	.293 (.256)					.007 (.010)	.148** (.017)	.987** (.004)			
	.017 (.021)	−.024 (.001)	.189 (.199)								.011 (.014)	.132** (.022)	.993** (.004)

Table 2 continued

	φ″	β″	δ″	arch(1)-n	garch(1)-n	arch(1)-t	garch(1)-t	earch-n	egarcha-n	egarch-n	earch-t	egarcha-t	egarch-t
Maize (US)	.040* (.023)	−.038* (.020)	−.118 (.137)	.058** (.006)	.934** (.007)								
	.046** (.022)	−.027 (.020)	−.095 (.127)			.061** (.012)	.935** (.012)						
	.037* (.020)	−.033* (.017)	−.097 (.131)					.005** (.001)	.027** (.006)	−.987** (.003)			
	.045** (.022)	−.020 (.020)	−.099 (.126)								.007 (.013)	.135** (.022)	.993** (.005)
Corn (BR)	.168** (.022)	−.010 (.007)	.002 (.002)	.684** (.021)	.644** (.009)								
	.075** (.024)	−.003 (.008)	−.005** (.002)			.174** (.024)	.831** (.019)						
	−.172** (.027)	.001 (.009)	.001 (.002)					.025** (.008)	.698** (.019)	−.929** (.008)			

Standard errors shown in parentheses

* Significance at the 95 % confidence level

** Significance at the 99 % confidence level or better

– Not estimable or excluded from the model

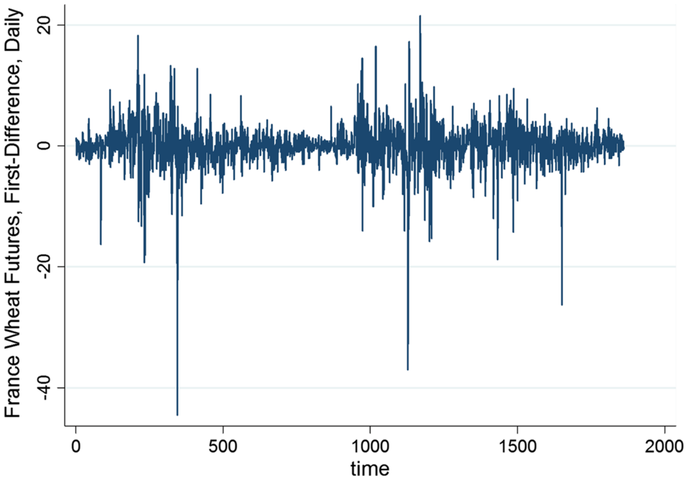

Fig. 3 Daily wheat, futures-30 day (France), first differences

null hypothesis that the dependent variable contains a unit root can be rejected at any reasonable significance level. Granger causality tests fail to indicate the presence of causality associated with the variables in either direction. The differenced series for U.S. soy futures is shown in Fig. 4. As described above, the model given in Eq. (7) is estimated.

Analysis of the maize series yields a ACF and PACF indicating first differences are required to achieve stationarity. The differenced series is shown in Fig. 5. On the basis of the Phillips-Perron test, the null hypothesis that the dependent variable contains a unit root can be rejected at any reasonable significance level. Testing for Granger causality, the null hypothesis of no evidence of causality can only be rejected in the case of the dependent variables and itself lagged one period.

First differences of the Brazilian corn futures prices are shown in Fig. 6. First-differencing of the Brazilian corn futures series data yield a PACF and ACF suggesting that the series is stationary. There is no indication that the series has a unit root. There is evidence of causality from the lagged dependent variable to the dependent variable. Additionally, there is evidence of causality from the corn spot price to the futures price and all of the variables indicate some causality in the direction of the corn spot price. Interestingly, there is causality from the corn futures price to the differenced spot oil price series. In this case, only the GARCH(1,1), the GARCH(1,1) under the assumption of t-distributed errors and the EGARCH(1,1) models under the assumption of normality errors models are estimable. It is not unusual with GARCH and EGARCH specifications that convergence is difficult.

Estimation of the GARCH(1,1) is executed under the assumption of the t-distribution requires relaxing the tolerance and applying the Davidson-Fletcher-Powell method (DFP) in place of the Newton–Raphson (NR) default. These methods are discussed in Judge, et al. 1985, pp. 955–960). The EGARCH under the assumption of t-distributed errors requires is not estimable owing to the flat surface of the log likelihood function.

For the daily data, the GARCH and EGARCH specifications capture the error processes quite well. The lagged dependent variable is significant in 5 of 11 cases indicating some, although a very small, pass-through effect for those cases. The model for U.S. wheat performs poorly. There is some evidence of a relationship between the differenced futures price and the differenced spot price of the commodity in question for French wheat. The

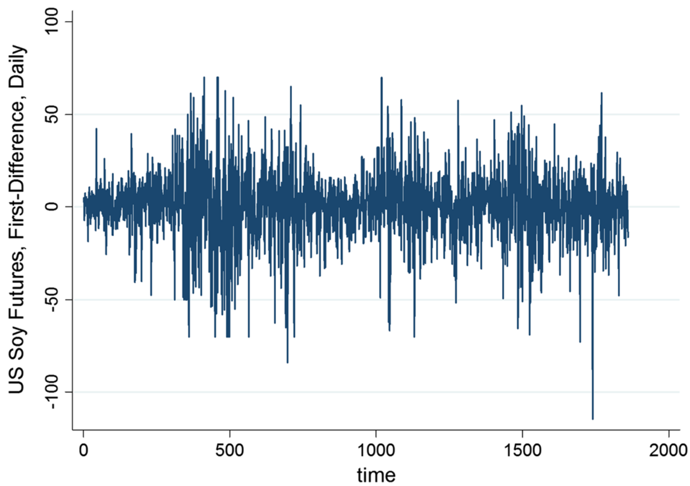

Fig. 4 Daily soy futures-30 day (US), first differences

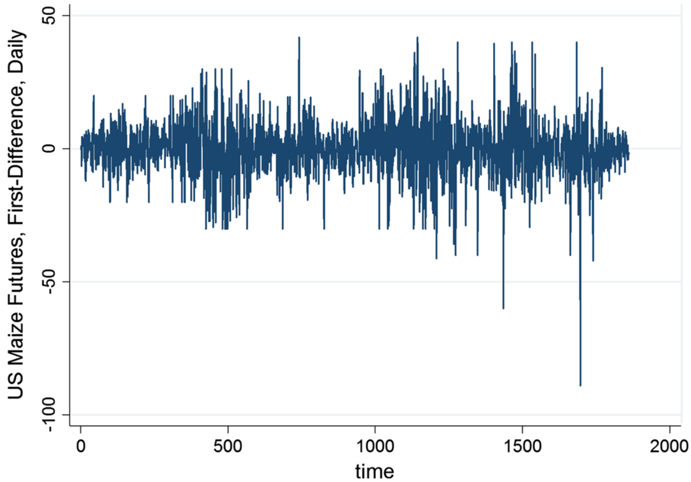

Fig. 5 Daily maize futures-30 day (US), first differences

daily GARCH (1,1) and EGARCH (1,1) models under the assumption of normally distributed errors show significant coefficient estimates for the differenced spot wheat price variable. Models for Brazilian corn show significant coefficient estimates on the differenced lagged dependent variable at the 99 % confidence level. The coefficient estimate for the differenced oil price series for the GARCH(1,1)-t model is also significant at the 99 % confidence level. The EGARCH(1,1) is not estimable owing to nonconvexity of the likelihood function as discussed above. Overall, the sign effects (earch) indicate that positive shocks tend to be more destabilizing than negative shocks. The size effects (egarcha) are positive indicating that lagged large market movements result in large movements in following period. For all models and specifications the errors show large persistence effects (egarch) indicating that the series have quite long memories.

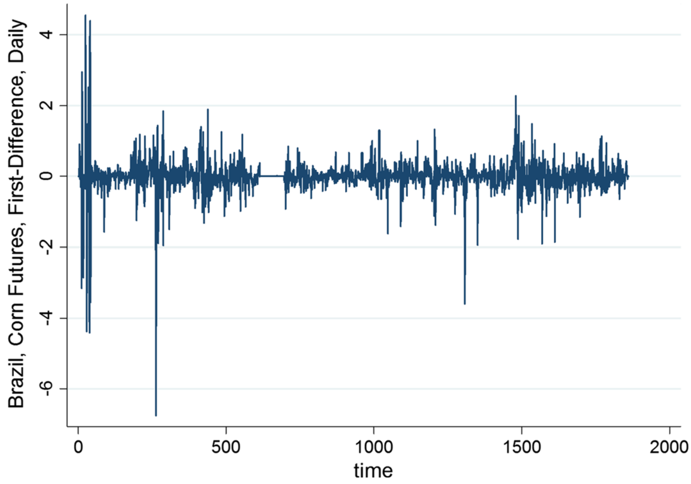

Fig. 6 Daily corn futures-30 day (Brazil), first differences

4.2 Weekly data

The data are aggregated to the weekly level on a calendar day basis. That is, the weekly data are aggregated and averaged so as to correspond to the trading days in the daily data set. Models are estimated consistent with Sect. 4.1 and the results are summarized n Table 2. The ACF and PAC for the weekly wheat series indicate nonstationarity with a sinusoidal decay of the ACF and a PACF that has significant positive and negative values at lags 1 and 2. The series appears stationarity after first differencing, so no further transformations are applied. On the basis of the Phillips-Perron test, the null hypothesis that the dependent variable contains a unit root can be rejected at any reasonable significance level. Testing for Granger causality, there is evidence of causality as between the dependent variable and itself lagged one period and well as the dependent variable and the differenced oil price series.

The weekly aggregated time series data for France have an ACF which decays and becomes insignificant at long lags. The PACF shows two significant values at lags 1 and 2. On the basis of this result and the Phillips-Perron test, first differences of the series are used for estimation purposes.

The results from the Granger causality tests are consistent with findings reported for the U.S. weekly data. The most interesting result with respect to the French data is that the EGARCH(1,1) with the t-distribution results in coefficient estimates significant at the 5 % significance level or better for all the variables including those relevant to the error structure. While the difference spot price series for oil is quite significant across the models for the U.S. wheat series, the differenced oil price series is only significant for the EGARCH model with t-distributed errors for France.

The soy futures and spot series are analysed as above. Again, the ACF and PACF indicate first-differences are required to achieve stationarity. The Phillips-Perron test indicates rejection of the null hypothesis. There appears to be Granger causality between the dependent variable and itself lagged one period as well as causality from the lagged dependent variable to the differenced spot rate. The result indicates the well-known problem of endogeneity associated with models such as those analysed in this paper. Estimation of the EGARCH model with the assumption of t-distributed errors required using the DFP method of optimization rather than the default NR method (Judge et al., pp. 955–960). The results are presented in Table 3.

The time series behaviour of the maize series is very similar to the soy series as concerns the PACF and ACF. First-differences of the series are taken which seems to achieve stationarity and the Phillip-Perron test indicates that the series does not contain a unit root. Granger causality tests indicate the presence of causality from the lagged and first-differenced futures price to the differenced spot price series. The GARCH and the EGARCH specifications under the assumption of t-distributed errors performs best with both the estimated coefficients on the lagged first-difference of the futures price and the sport price variable appearing as significant at the 95 % confidence level or better.

The Brazilian corn series are analysed and first-differenced. There is no indication of a unit root. Granger causality tests indicate only causality from the differenced oil price to the differenced spot price series. The results for the corn series models are quite interesting in that in three of the four models (GARCH under assumption of t-distributed errors, EGARCH under both normality and t-distributed errors) both the lagged dependent variable and the differenced spot oil price are significant at the 99 % confidence level. However, notice that for reasons of estimability, the GARCH (1) parameter is unestimable under normality and the t-distribution and the differenced spot corn price coefficient seems unestimable in the EGARCH-normal model irrespective of the optimization technique. In the latter case, the differenced corn spot price variable was dropped from the equation with little effect on the estimation of the other coefficients.

The weekly models perform well. The differenced lagged dependent variable is significant in all cases, and most interesting, there are significant coefficient estimates for the differenced oil price series for U.S. Wheat, French Wheat (EGARCH-t) and for all cases excepting GARCH(1,1)-n with respect to Brazilian corn. With respect to interpretation of the coefficient estimates on the error process, the overall conclusions remain consistent with those for the daily models. Aggregation effects clearly impact the magnitude of the coefficient estimates and the SEs tend to increase for the weekly estimates as indicated by theory. So, while aggregation results in better model performance as indicated by the significance of coefficient estimates, the increase in SEs suggests increased uncertainty as concerns reliability.

4.3 Monthly data

Consideration of models using the monthly data indicates that an alternative approach to that taken for daily and weekly data is required. Results for the monthly models are problematic. The fact there are considerably fewer observations is a problem in and of itself especially for estimating complex models. In some cases the log likelihood functions are generally quite flat, and therefore, coefficient estimates tend to be unstable. The optimization problem is far more prevalent than that for the weekly data. As discussed above (Sect. 4.2), the DFP method was used rather than the default NR method (Judge et al., pp. 955–960). However, consistent with the analysis thus far, the results are presented in Table 4.

Analyzing, first the data for U.S. wheat futures contracts, the PACF and ACF indicate that the series is somewhat more complex than the disaggregate data with the ACF dying out according to a sinusoid and the PACF exhibiting significant values at lags 1,2, 5,6 and 7. First-differences appear sufficient to achieve stationarity, however. The differenced

Table 3 Model results, weekly data, n = 372

	φ″	β″	δ″	arch(1)-n	garch(1)-n	arch(1)-t	garch(1)-t	earch-n	egarcha-n	egarch-n	earch-t	egarcha-t	egarch-t
Wheat (US)	.330**	.005	.234**	.319**	.686**								
	(.061)	(.011)	(.108)	(.057)	(.043)								
	.258**	.0004	.186**			.270**	.756**						
	(.055)	(.054)	(.483)			(.058)	(.062)						
	.305**	−.007	.256**					.165**	.436**	.943**			
	(.054)	(.010)	(.090)					(.042)	(.057)	(.017)			
	.224**	−.001	.164**								.176**	.157**	.992**
	(.045)	(.009)	(.081)								(.038)	(.049)	(.009)
Wheat (FR)	.354**	.035	.094	.167**	.813**								
	(.061)	(.045)	(.119)	(.032)	(.034)								
	.295**	.019	.121			.177**	.826						
	(.052)	(.039)	(.088)			(.046)	(.660)						
	.258**	−.034	.103					.169**	.023	.991**			
	(.033)	(.034)	(.081)					(.017)	(.015)	(.005)			
	.322**	−.059*	.227**								−.079**	.240**	−.970**
	(.038)	(.033)	(.087)								(.016)	(.101)	(.023)
Soy (US)	.192**	.058	−.430	.094**	.843**								
	(.063)	(.071)	(.816)	(.030)	(.051)								
	.296**	.012	−.358			.161**	.792**						
	(.055)	(.059)	(.652)			(.073)	(.078)						
	.188**	.046	−.686					.092	.150**	.977**			
	(.059)	(.077)	(.770)					(.040)	(.044)	(.019)			
	.192**	.011	−.627								.101**	.301**.	974**
	(.051)	(.060)	(.590)								(.049)	(.088)	(.029)

Table 3 continued

	φ″	β″	δ″	arch(1)-n	garch(1)-n	arch(1)-t	garch(1)-t	earch-n	egarcha-n	egarch-n	earch-t	egarcha-t	egarch-t
Maize (US)	.238**	−.088	.068	.111**	.797**								
	(.055)	(.054)	(.407)	(.039)	(.072)								
	.217**	−.088*	−.016			.135**	.799**						
	(.051)	(.052)	(.336)			(.062)	(.088)						
	.230**	−.076	−.112					.048	.222**	.928**			
	(.053)	(.053)	(.388)					(.035)	(.045)	(.047)			
	.209**	−.084*	.124								.053	.273**	.946**
	(.050)	(.050)	(.339)								(.050)	(.100)	(.047)
Corn (BR)	.288**	−.072	−.016	.220**	–								
	(.068)	(.048)	(.019)	(.067)									
	.325**	−.013	−.027**			.674**	–						
	(.051)	(.031)	.010			(.298)							
	−.266**	–	−.105**					.583**	.787**	.243**			
	(.059)		(.011)					(.109)	(.189)	(.075)			
	.300**	−.029	−.027**								.103	.322**	.732**
	(.054)	(.035)	(.008)								(.098)	(.126)	(.115)

Standard errors shown in parentheses

* Significance at the 95 % confidence level

** Significance at the 99 % confidence level or better

– Not estimable or excluded from the model

Table 4 Model results, monthly data, n = 86

	φ″	β″	δ″	arch(1)-n	garch(1)-n	arch(1)-t	garch(1)-t	earch-n	egarcha-n	egarch-n	earch-t	egarcha-t	egarch-t
Wheat (US)	−.338	.606	−.358			1.415	.709						
	(.922)	(.920)	(.816)			(3.350)	(.146)						
Wheat (FR)	.252	.031	−.265	.223	.673**								
	(.275)	(.292)	(.234)	(.164)	(.182)								
	.061	.237	.094			.500	.700**						
	(.200)	(.219)	(.200)			(.638)	(.162)						
	−.214	.413**	.490**								.010	.605**	−.946**
	(.197)	(.197)	(.178)								(.141)	(.205)	(.028)
Soy (US)	.703	−.278	−1.630**	.205	.693**								
	(.458)	(.439)	(.858)	(.151)	(.238)								
	.795	−.481	−.274			−.051	.238						
	(.484)	(.441)	(1.249)			(.074)	(.217)						
	.466**	−.219	.447					.023	−.546**	−.477**			
	(.469)	(.432)	(1.285)					(.172)	(.285)	(.239)			
	.861*	−.517	−.400								.141	−.187	−.414
	(.498)	(.438)	(1.425)								(.229)	(.317)	(.429)
Maize	.870**	−.634**	.771					.849**	.403	.363			
	(.291)	(.229)	(.596)					(.215)	(.379)	(.232)			
Corn (BR)	.384**	−.066	−.031	−.028	−.993								
	(.146)	(.130)	(.027)	(.034)	(.142)								
	.276**	−.009	−.005			.097	.677						
	(.152)	(.130)	(.023)			(.181)	(.594)						
	.466**	−.231**	−.033					.103	−.531**	.946**			
	(.105)	(.106)	(.025)					(.176)	(.155)	(.026)			

Standard errors shown in parentheses

* Significance at the 95 % confidence level

** Significance at the 99 % confidence level or better

– Not estimable or excluded from the model

series for U.S. wheat futures prices is shown in Fig. 7. The time series plot is representative of the series analyzed in this research in the sense that the differences at the monthly level are considerable less volatile than either the daily or weekly series. The fact that the coefficient estimates are very different as between models is a concern and this is believed to be attributable to a small size and the estimation demands of relatively complex models.

Applying the time series procedures to the monthly data for France yields an ACF which exhibits a sinusoidal pattern with the estimated values decreasing at increasing lags. The PACF exhibits a significant value at lag 1. Diagnostic checks indicate first-differencing of the data series. Testing the series for the presence of a unit root suggests the series is stationary.

Granger causality tests estimated on the pairwise basis show evidence of causality from the differenced futures price to the differenced spot price. The result points to the issue endogeneity as discussed by Chen et al. (2008). As indicated above, the problem of optimization and convergence is not surprising and precludes estimation of the GARCH specification under the normality assumption. What is surprising is that the EGARCH model under the assumption of the t-distribution yields significant results for both the difference wheat and oil spot price series, respectively. Further, the results concerning the error structure indicate that there is not a statistically significant sign effect, however, both the magnitude and persistence effect are significant. The magnitude effect is positive indicating that volatility increases with large price movements and the persistence effect indicates a long and significant memory.

The monthly soy and maize models were estimated using the same approach as above. First-differences were used for the analysis. The results from the monthly soy series are not promising as for the most part, the estimated coefficients are not significant and any reasonable of confidence. The results for the maize series are even less interesting as the likelihood surfaces for the respective models are quit flat and estimation is only possible for the EGARCH model under the assumption of normality.

The Brazilian corn futures prices are analyzed. Consistent with the methodology thus far, the first-differences of the variable are taken to achieve stationarity. On the basis of the Phillips-Perron test, there is no indication of a unit root in the differenced series. Overall,

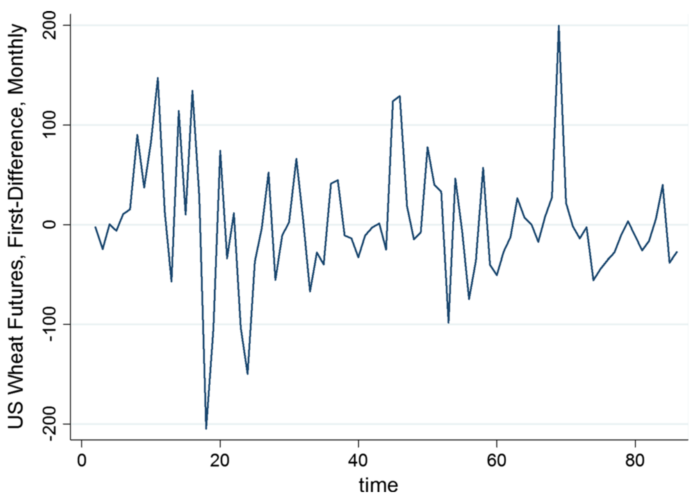

Fig. 7 Monthly wheat futures-30 day (US), first differences

consistent with previous results using monthly data series, the estimated coefficients are generally not statistically significant and the EGARCH model under the t-distribution is not estimable.

4.4 General observations

As concerns model estimation, it is possible to make a few generalizations concerning this research thus far. The first, and most obvious, concerns the relative performance of the models with respect to time aggregation. On the basis of significance of coefficients, summarized in Table 5, it is of particular interest that the daily and weekly models indicate significance of the first-order autoregressive coefficient estimates as well as those estimates for the first-differenced spot market and oil market prices, respectively. The monthly model performs quite poorly on this basis. It is also of interest to observe the relative frequency of significance of the first-order autocorrelation coefficient with respect to the weekly models. Overall, it seems reasonable to assert that on the basis of significance of the parameter estimates, there is reason to favor the weekly model.

Consistent with expectations based on theory, temporal aggregation tends to result in increased standard errors of the coefficient estimates. The results in this research are consistent with the results reported by Cartwright and Riabko (2015). With respect to the terms related to the error structures, the daily and monthly models are the most interesting. The GARCH and EGARCH coefficient estimates are generally significant under the assumptions normality and t-distributed errors. More specifically, the significance of the earch-n and t- indicates that the signs are positive indicating that the respective markets take positive news as more destabilizing than negative news. Technically, this asymmetry could possibility be the due to the periodicity and temporal aggregation of the data. Temporal aggregation has impacts on the serial correlation of prices associated with changes in volatility (Shiller 1984) and volatility movements and asymmetric effects differ depending on the sampling frequency (Diaw and Olivero 2011). Of course, the interpretation is dependent on what constitutes good or bad news. For example, Zheng et al. (2008) find that for a set of agricultural commodities high price news is more destabilizing that low price news.

Again, with respect to the daily and weekly models, the results for the egarcha coefficients indicates that the processes modelled are asymmetric in the sense that the conditional variance responds positively to the magnitude of market movements. Finally, the earch term measuring persistence is generally significant and the estimates are on the order of .9 suggesting that the processes have considerable memory and volatility takes a long time to die out.

With these general observations noted, the research turns to evaluate forecasting performance in the following section of the paper.

5 Forecast results

In this section, results are reported on the forecast performance of models estimated above for *ex post* forecasting. Focus is on the weekly models based on the observation that the weekly aggregation models aggregation weekly models yield the strongest results over the estimation period. The interest is in gaining understanding concerning the usefulness of the models for generating forecasts over and above modelling the historical time period. Issues of forecast performance with respect to volatility models has been studied by numerous

Table 5 Summary of results, signficance of coefficient estimates daily, weekly, monthly (based on counts for coefficients significant at the 5 % level or better)

	φ″	β″	δ″	arch(1)-n	garch(1)-n	arch(1)-t	garch(1)-t	earch-n	egarcha-n	egarch-n	earch-t	egarcha-t	egarch-t
Daily	9	5	1	5	5	5	5	4	5	5	2	4	4
Weekly	20	3	8	5	4	5	3	3	4	5	3	5	5
Monthly	6	3	3	0	3	0	1	1	2	3	0	1	1

researchers Cumby et al. (1993), Figlewski (1997) and Jorion (1995). Essentially, the issue has been that in spite of highly significant in-sample parameter estimates, standard volatility models explain little of the variability in *ex-post* squared returns. Andersen and Bollerslev (1998) have addressed many of the issues. In the interest of practicality of application, this research analyzes the in-sample mean squared error (MSE) to out-of-sample MSE on the *ex-post* basis.

It is well-known that there are many issues and solutions to the selection of hold-out samples and metrics designed for testing predictive accuracy of time series models. For purposes of this research, it seems reasonable that 80 % of the observations are used for estimation and the remaining 20 % for out-of-sample forecasting. To test the *ex-post* forecasting accuracy of the weekly models, the sample is divided into two periods, estimating the model over the first 298 observations and holding out the remaining 74 observations for forecasting. A recent discussion of related issues and solutions can be found in Fildes and Petropoulos (2013).

Table 6 reports the means and standard deviations of the sample and hold-out periods. It is important to recognize that the standard deviation of the U.S. wheat series over the estimation period is 7.395 as opposed to 5.600 over the hold-out period. This suggests that *ex-post* forecast performance will likely exceed the in-sample MSE owing to the relative stability of the series used for the hold-out period. Excepting for U.S. soy prices, the data for the other series analyzed exhibit standard deviation in the estimation period exceeding that for the hold-out sample.

Table 7 reports the forecast bias measured by the mean forecast error (MFE) and the MSE of the one-step ahead forecast errors. If using the MFE and MSE of the squared one-step ahead forecast errors is accepted as a reasonable criteria for forecast bias and variability, then the GARCH models are preferred to the EGARCH models overall. An interesting exception being the case of Brazilian corn where the EGARCH model under the t-distribution performs quite well. If one selects a model based on relative in-sample to out-of-sample performance, there appears to be little or no advantage to be achieved by using the more complex models EGARCH and EGARCH-t. It is of interest to recognize that the *ex post* forecasts indicate a negative bias (MFE) across commodities and models. As indicated in the final section, future research will be concerned specifically with forecasting including issues of variance and bias.

6 Summary and conclusions

This paper analyzes empirically the possible relationship between selected agricultural commodities futures prices and spot oil prices as well as the effects of temporal aggregation on the specification of alternative models of futures contract prices, and

Table 6 Descriptive statistics for the estimation sample and hold-out periods

Variable	$\text{Mean}_{\text{(in-sample)}}$	$\text{SD}_{\text{(in-sample)}}$	$\text{Mean}_{\text{(hold-out)}}$	$\text{SD}_{\text{(hold-out)}}$
Wheat (US)	.346	7.395	−.699	5.600
Wheat (FR)	.344	7.561	−.709	3.894
Soy (US)	3.197	38.858	−2.262	40.002
Maize (US)	1.394	21.906	−4.667	18.715
Corn (BR)	.042	.879	−.106	.708

Table 7 Forecast performance, weekly data

Variable	Model	$MSE_{(in\text{-}sample)}$	$MFE_{(in\text{-}sample)}$	$MSE_{(hold\text{-}out)}$	$MFE_{(hold\text{-}out)}$	$MSE_{(in\text{-}sample)}/MSE_{(hold\text{-}out)}$
Wheat (US)	GARCH(1,1)	53.832	.078	31.293	−.432	1.720
	GARCH(1,1)-t	51.450	.116	30.767	−.618	1.672
	EGARCH(1,1)	56.170	.066	32.450	−.819	1.731
	EGARCH(1,1)-t	52.998	−.073	31.451	−.873	1.675
Wheat (FR)	GARCH(1,1)	60.896	.308	17.644	−.343	3.451
	GARCH(1,1)-t	61.097	.160	17.041	−.564	3.585
	EGARCH(1,1)	NA	NA	NA	NA	NA
	EGARCH(1,1)-t	70.200	.045	20.824	−.808	3.354
Soy (US)	GARCH(1,1)	1550.362	−1.968	1527.343	−7.821	1.015
	GARCH(1,1)-t	1614.769	−2.536	1563.352	−8.516	1.033
	EGARCH(1,1)	1551.631	−3.280	1540.948	−9.152	1.007
	EGARCH(1,1)-t	1635.795	−3.148	1566.918	−9.220	1.033
Maize (US)	GARCH(1,1)	586.576	−.448	488.910	−5.776	1.200
	GARCH(1,1)-t	591.051	−.441	487.990	−5.835	1.211
	EGARCH(1,1)	NA	NA	NA	NA	NA
	EGARCH(1,1)-t	559.090	−1.088	496.347	−6.329	1.126
Corn (BR)	GARCH(1,1)	.970	.019	.587	−.103	1.652
	GARCH(1,1)-t	.983	.081	.559	−.102	1.758
	EGARCH(1,1)	1.003	.028	.604	−.092	1.661
	EGARCH(1,1)-t	.888	.001	.551	−.120	1.612

consequently, on the understanding of the empirical relationship between the markets. Alternative models have been specified and tested under alternative assumptions on the error structures.

As concerns the first sections of the paper and estimation results, a key conclusion from this research is that reverse regressions can lend insight into the behavior of futures markets. In addition, in some markets and units of temporal aggregation the oil price does impact the futures prices. However, the relationship is by no means consistent or prevalent. This result tends to support Saghaian (2010) suggesting while there might be correlation, detecting strict causality or modelling the relationship is difficult.

Consistent with past theoretical and empirical work in the area of temporal aggregation it is quite clear that temporal aggregation does impact the relationships between the variables as well as the model coefficient estimates and standard errors or inference. In this research, considering relative significance of the coefficients at alternative levels of aggregation, the results favor the use of the weekly unit of aggregation, the intuitive explanation being that the signal-to-noise ratio is very low in the case of daily data and the information content useful for modeling and forecasting is removed or filtered by the aggregation of the data. To suggest a definitive "optimal" aggregation level based upon research thus far is overly ambitious, but this work provides useful insight.

The application of the alternative error structure specifications does yield some useful generalizations. Overall, the results are sensitive to the alternative distributional assumptions, but not markedly so. With respect to the EGARCH models it is the case that for most commodities considered under alternative units aggregation, the sign effects indicate that positive shocks tend to be more destabilizing than negative shocks and the magnitude effects (egarcha) are small, but positive. The persistence effects (egarch) are quite large indicating that the series have quite long memories. These results are interesting, but the relative sophistication of the models does not come without cost as indicated by the difficulties in estimation for some models. Finally, with respect to forecasting, based on out-of-sample MSE, arguably the results favor the GARCH models over the EGARCH models, but this is certainly dependent on the model selection metric.

Going forward, it is intended that research will focus on two interrelated issues. First, the matter of the transmission mechanism by which agricultural commodity future prices are impacted by energy prices needs further study. Accepting that there is correlation between the series in some cases does not suggest there is strict causality. A case for causality is based on the premise that as energy is an input to agricultural commodity output at multiple points in the supply chain, a causal relationship seems entirely reasonable. In short, alternative variables of for the energy input must be considered and alternative specifications should be entertained. Second, with respect to methodology, it is possible that in some cases the processes under consideration might well be modelled applying stochastic volatility regime switching models (Goutte 2013). Finally, there are certainly issues of forecasting. The evidence in this research indicates that there are not gains from application of increasingly complex models. Thus far, the issues of forecasting have been placed second to considering model specification and estimation over units of aggregation and distributional assumptions. Future research will assign increased priority to forecasting.

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