Futures Markets Efficiency: evidence from unevenly spaced contracts

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Abstract

The hypothesis that futures price is an unbiased predictor of the future spot price has been one of the most controversial topics in the empirical literature on market efficiency. The conflicting results provided so far are not robust to the time period considered or to the econometric method chosen for testing. The aim of this paper is to analyse futures markets for five widely traded commodities and test their efficiency within a new estimation framework which takes into account the unevenly spaced data features of the contracts resulting from the seasonal nature of production and from the institutional aspects of the market. Such an important characteristic of the time series data, although overlooked in all previous studies, can be considered one important source in an attempt to explain the highly variable and contrasting conclusions reached in the empirical literature on commodity market efficiency.

The estimation procedure is carried out within a quasi-ECM framework *by regime* which allows us to test the market efficient hypothesis for two different set of contracts according to their sampling pattern. Therefore, more accurate and rigorous results are provided in this paper, which, to a certain extent, reconcile the conflicting evidence produced so far. We also calculate measures of the degree of inefficiency based on forecast error variances to compare the performance of each regime within the same market. Combined regimes measures are used for a comparison across the different markets.

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1. Introduction

Most economic agents make present decisions based on assumptions about future events, whose uncertainty can be reduced by futures trading; futures markets, operating across a wide range of financial assets and soft and hard commodities, provide a mechanism whereby a trader can "lock-in" to a price at a specified future date and thus manage (hedge) the risks of trading in a given commodity or financial product. Such a mechanism is effective only if the market is efficient; in this case the futures price is an optimal predictor of the spot price at contract termination, the only admissible difference between the two being a random unpredictable zero-mean error. The Efficient Market Hypothesis (EMH) relies on the joint assumption that economic agents form their expectations in a rational manner and that they are risk neutral. This implies that in an efficient futures market the current futures price, F_t, of a contract for delivery at time $t+1$ embodies all the information available for predicting the spot price, S^e_{t+1}, which is expected to be determined by the market forces at that time, so that there is no opportunity for the traders to earn profits from publicly available information (Fama, 1970 and Malkiel, 1992). Therefore, the futures price can be considered an unbiased predictor of the future spot price. Empirically, the unbiasedness hypothesis has been assessed by carrying out regressions of the observed spot price on the previous period futures price and, conditionally on the estimated residuals being a white noise process, by testing that the intercept is not significantly different from zero and the slope coefficient is not significantly different from one. However, in order to avoid the spurious regression problem (Granger and Newbold, 1974) which arises potentially from the typical non-stationarity feature of spot and futures prices time series data, the testing procedure has to be conducted within a cointegration and error correction framework. The existence of cointegration between the two price series ensures that they exhibit a compatible behaviour in the long run and consequently cointegration is a necessary, although not sufficient, condition for efficiency. Cointegration *just* implies that the residuals from the long run relationship are stationary. For the futures market to be deemed efficient it is also required that they are white noise; if they are autocorrelated past price information can also be used to predict future spot prices and this contradicts the requirement that the futures price instantaneously and fully reflects all available information. A common alternative to testing for cointegration between spot and lagged forward rate is to test the EMH by regressing the percentage change in the spot price (s_t-s_{t-1}) on a constant and on the percentage basis (f_{t-1}-s_{t-1}). Such a specification allows for classical inference because both the dependent and independent variable are stationary. Again, the market is efficient if the data are consistent with the hypothesis that the intercept is not significantly different from zero and the slope coefficient from unity.

The voluminous empirical literature on market efficiency has provided highly variable and conflicting results. These can differ because of the statistical issues associated with the testing procedure or because of different methods of data analysis. Various interpretations have been advanced for the cases in which data led to a rejection of the unbiasedness hypothesis; some of them refer to the presence of a time varying risk premium, others to the violation of the assumption of rational expectations evidenced by the presence of systematic forecast errors. Another line of explanation is based on the argument that measurement errors and misspecification can bias the coefficient estimates. Although it is generally recognised that it is often difficult to obtain high quality data, Cornell (1989), referring to the foreign exchange markets, criticises studies that fail to use data sampling procedures that observe the market rules governing delivery on foreign exchange contracts and that fail to incorporate transactions costs in terms of bid-asks spreads. Bekaert and Hodrick (1993) argue that another source of bias is represented by the poor small sample properties of the regression equation; given the regime shifts in fiscal and monetary policies during the last two decades the results are not stable over time; running regressions across various regimes provides an incorrect estimate of the unconditional covariance between the analysed series since the OLS estimator ignores regime switches.

The aim of this paper is to investigate thoroughly another source which may account for the diversity of existing evidence; such a diversity may reflect a lack of attention to the specific properties of the data series and the institutional features of the market. We develop appropriate econometric methodologies for testing market efficiency focusing on the unevenly spaced data issue. An issue which has not been explicitly addressed so far in the empirical literature. The application of appropriate techniques to accommodate these issues across a range of soft commodities markets should enhance the understanding of the operation of such markets.

Unlike financial futures, commodity futures contracts are strongly characterised by seasonal effects which, in turn, lead to a greater likelihood of unevenly spaced data. Standard time series techniques should only be applied in the context of evenly spaced observations. In this paper an attempt is made to devise tools for analysing unevenly spaced data; the task is rendered more complex by the fact that the price time series are likely to be the non-stationary. Therefore, it is necessary to design modelling and testing procedures for unit root uneven spaced processes and cointegration analysis for the long run relationship between spot and futures prices.

In this paper the efficiency hypothesis is not only assessed and compared across five commodity futures markets, namely corn, wheat, cocoa, coffee and cotton, but particular attention will be also paid to the evaluation of the degree of inefficiency. Following Kellard *et al.* (1999), R^2-like measures are provided to allow a quantitative comparison of the functioning of different futures markets analysed.

The paper is organised as follows: section 2 deals with the sampling issues, section 3 provides efficiency tests obtained following the usual procedures adopted in the empirical literature which will serve as a sort of benchmark for the analysis presented in section 4, where the unevenly spaced data feature is extensively examined; section 5 deals with the same issue in the context of unit root testing; finally section 6 summarises the results offering some concluding remarks.

2. Data and sampling issues

To test the efficiency of futures market in the context of unequally spaced data, five different commodities are selected; specifically, corn, wheat, cocoa, coffee and cotton. The futures prices for corn and wheat were quoted in the Chicago Board of Trade Exchange (CBOT), those for cocoa and coffee in the New York Cocoa-Sugar-Coffee Exchange (CSCE), while futures prices for cotton are available from the New York Cotton Exchange (NYCE). The sample period extends approximately from 1980 to 1998, all contract details are reported in the Appendix. For all commodities, except cotton, the contracts months are March, May, July, September and December. Cotton contract months are March, May, July, October and December. Thus, one of the most important features of the data analysed is that the series are characterised by an irregular settlement pattern due, in turn, to the seasonal nature of production; the data are unevenly spaced since May, July and September contracts are two months apart from the previous one, while December and March are three months apart as far as corn, wheat, cocoa and coffee commodities are concerned. Cotton contracts follows an analogous pattern with the May, July and December contracts being two months apart from the previous contract, while three months separate October and March contracts from the antecedent one.

To analyse the efficiency of futures markets time series of the future spot price, S_t, and futures prices, $F_{t-\tau}$, that correspond to those spot prices are required. The future spot price is the cash price on the termination day of the futures contract (Crowder and Hamed, 1993), thus the frequency of each series depends on how many contract months there are for each commodity. For all commodities analysed in this study there are five contracts per year and thus a time series of five termination spot prices per year. A contract is open for many months and the sequence of daily futures prices reflects the changing market expectations about the level of the spot price which will prevail on the last day of trading. Therefore, in order to construct the series $F_{t-\tau}$ it is necessary to select one of the futures prices observed while the contract is open to be matched with the termination spot price. The futures price is selected by working backwards 56 days from the contract termination date (τ=56). The matching futures prices should be sampled from a specific day, less than two months from the last day of trading, otherwise we incur in the problems associated with overlapping data, namely the residuals from the regression of S_t on $F_{t-\tau}$ will suffer from autocorrelation. This effect induces the appearance of inefficiency even in efficient markets.

The usual process of testing for efficiency involves two stages; in the first the necessary condition of cointegration (given the non-stationary behaviour of the time series) is tested; in the second, if the cointegration condition is satisfied, one can proceed to test whether the futures price at contract purchase is an unbiased predictor of the spot price at contract termination. The cointegrating regression is usually specified in logarithms of the data series as

$$s_t = \beta_0 + \beta_1 f_{t-\tau} + u_t \tag{1}$$

where $f_{t-\tau}$ is the logarithm of the lagged futures price and s_t is the logarithm of the spot price that is matched at the settlement date of the futures contract.

The unbiasedness hypothesis requires that β_0=0 and β_1=1 and u_t is white noise process. If the series are cointegrated and at least the second restriction is not rejected, then in the long-run the data offer some empirical support to the hypothesis that the difference between the spot price and the futures price is due just to a constant mean. The analysis can, thus, move further and consider a short-run error correction regression relating the change in spot price to the percentage basis ($f_{t-\tau}$-$s_{t-\tau}$) and lagged changes in spot and futures prices, as in (2). The statistical significance of lags in (2) is generally considered evidence of inefficiency since they provide additional information with respect to the basis.

$$s_t - s_{t-\tau} = \theta_0 + \theta_1\left(f_{t-\tau} - s_{t-\tau}\right) + \sum_{i=1}^{k}\lambda_i\left(s_{t-i} - s_{(t-\tau)-i}\right) + \sum_{i=1}^{k}\gamma_i\left(f_{t-i} - f_{(t-\tau)-i}\right) + \varepsilon_t \qquad (2)$$

In (2) $s_{t-\tau}$ is the logarithm of the spot price sampled on the same day as $f_{t-\tau}$ and f_t is the logarithm of the futures price sampled the same day as s_t.

3. Testing for market efficiency

The first step of the analysis involves a replication of the usual procedure for testing the futures markets efficiency hypothesis. Therefore at this stage data are treated ignoring the unequally spaced date issue. As discussed in the introduction section, if the series are non stationary it is required to test for cointegration, as a precondition for market efficiency, and subsequently for unbiasedness. Although we deal with the problem of testing for the presence of an autoregressive unit root in unequally spaced time series in greater detail in section 5, the application of the traditional Augmented Dickey-Fuller test suggests that the futures and spot prices series can be considered non-stationary processes.

Table 1 reports the results of the cointegration tests obtained by applying the Johansen method of reduced rank regression[1]. The procedure outlined in Johansen (1988) requires the specification of a vector error correction model (VECM) of the *m*-variable VAR system of the time series vector X_t:

[1] PcFiml, Doornik and Hendry, 1997.

$$\Delta X_t = \delta_0 + \delta_1 \Delta X_{t-1} + \ldots + \delta_{k-1} \Delta X_{t-k+1} + \Pi X_{t-k} + \upsilon_t$$

In this analysis *m*=2 and $X_t=(s_t, f_{t-\tau})$ for all commodities and Π has a maximum rank of 2. Since X_t is a vector of I(1) variables, ΠX_{t-k} has to be stationary for ν_t to be stationary. In such a case the matrix Π has reduced rank of 1 and the series are cointegrated.

For all commodities, the null of no-cointegration is rejected at 5% significance level. The selection of just one lag for cotton leads to the rejection of the null of reduced rank, implying that the series are stationary; this conflicts with the earlier conclusions based on the Dickey-Fuller test. However, the result may be sensitive to the lag length selected, and imposing a lag length of 4, we cannot reject that there exist at least one cointegration vector.

The joint restriction β_0=0 and β_1=1, imposed on the cointegrating vector, is rejected for all commodities, as evidenced by the likelihood ratio test results reported in Table 2. However, the unit slope restriction on the cointegrating vector is rejected just for cocoa and for coffee (at 3.5%). Consequently, there is evidence to support the hypothesis of efficiency and unbiasedness in the long run. However, long run efficiency is not sufficient for short run forecast efficiency, the evaluation of which is based on the estimation of equation (2).

The results of the short-run OLS regression (2) are reported in Table 3 for all the five commodities analysed. The lag lengths were selected through general-to-specific testing starting from *k*=10 and then eliminating the lags that were insignificant at 5% level but, at the same time, preserving the symmetry on lag length for the lagged changes in spot and futures prices. This procedure removes all residual autocorrelation. However we are left with normality problems for coffee and cotton, which are likely to be due to some extreme observations.

The test statistics presented in Table 4, for the null hypothesis that the coefficients of all the lagged variables are zero, suggest that information embodied in the lagged differenced terms is useful to predict short run movements in the spot price of corn, wheat and cocoa but not for coffee and cotton. Table 5 reports the short-run regressions omitting all lagged changes in spot and futures prices; it is worth noting that the estimated coefficients for the constant and the basis do not seem to be particularly sensitive to the inclusion of the lags in the case of corn and wheat, while they are not robust to the dynamic specification selected for cocoa, coffee and cotton short-run models.

Table 6 shows the results obtained in testing for unbiasedness in the short run regression (2). For corn, wheat and cotton the hypothesis that the basis coefficient is not significantly different from unity cannot be rejected. The constant term is not significantly different from zero only for cocoa, coffee and cotton. Consequently, the joint hypothesis that θ_0=0 and θ_1=1 is marginally accepted only for wheat at 0.06 significance level.

The estimates reported in Table 3 and the unbiasedness tests shown in Table 6 indicate the existence of short-run inefficiency in at least two out of five markets analysed. Given the social costs associated with inefficiency (Stein, 1986) and that the costs of hedging rises as a market becomes less efficient (Krehbiel and Adkins, 1993), it is of particular value to provide a measure of the degree of inefficiency, as pointed by Kellard *et al*. (1999).

Following Kellard *et al*. (1999) we provide three different measures of the degree of inefficiency for the five markets. The first one, ϕ_c, is calculated as the ratio of the estimated error variance of the short run OLS regression to the sample variance of the forecast error based on futures price (s_t-$f_{t-\tau}$), corrected for degrees of freedom:

$$\phi_c = \frac{(n-2k-2)^{-1}\sum_{t=1}^{n}\hat{\varepsilon}_t^2}{(n-1)^{-1}\sum_{t=1}^{n}\left[(s_t - f_{t-\tau}) - \left(\overline{s_t - f_{t-\tau}}\right)\right]^2}$$

where *n* is the number of observation used in estimating equation (2) and *(2k+2)* is the total number of estimated parameters. If the ratio assumes the value 1, then the market is efficient because the futures price is *relatively* able to forecast the subsequent spot price, a value of zero implies complete inefficiency and values between 0 and 1 varying degrees of inefficiency. The degree of inefficiency is given by (1-ϕ_c).

The inefficiency criterion reported in Table 7 suggest that cotton, corn and wheat markets are characterised by a high degree of efficiency; the coffee market appears less efficient and the cocoa one very inefficient.

Both conventional testing and efficiency measure are useful for assessing the *relative* merits of two predictors, the futures price and a forecast based on regression (2), but not to evaluate the absolute quality of forecasts. The difficulty that can arise by using such measures is that a market could be considered efficient even in the case in which the futures price is giving a negligible contribution in predicting the spot price. The absolute predictor quality issues have been tackled in Kellard *et al.* (1999) by computing two adjusted coefficient of determination-like measures; the first compares the forecasts based on regression (2) with prediction from the last available spot price, $\overline{R}_1^2$:

$$\overline{R}_1^2 = 1 - \frac{(n-2k-2)^{-1}\sum_{t=1}^{n}\hat{e}_t^2}{(n-1)^{-1}\sum_{t=1}^{n}\left[\left(s_t - s_{t-\tau}\right) - \left(\overline{s_t - s_{t-\tau}}\right)\right]^2}$$

while the second allows us to compare futures prices as a predictor of the spot rate with prediction based on the most recent spot price, $\overline{R}_2^2$:

$$\overline{R}_2^2 = 1 - \frac{(n-1)^{-1}\sum_{t=1}^{n}\left[\left(s_t - f_{t-\tau}\right) - \left(\overline{s_t - f_{t-\tau}}\right)\right]^2}{(n-1)^{-1}\sum_{t=1}^{n}\left[\left(s_t - s_{t-\tau}\right) - \left(\overline{s_t - s_{t-\tau}}\right)\right]^2}$$

Both measures[2] are reported in Table 7 and it is worth stressing that they are specific to the particular 56 days horizon chosen. According to the last row of the table corn futures price alone explains 28 per cent of the variability in spot price changes, wheat futures price accounts for 26 per cent and cotton futures prices for 23 per cent of the variability of the respective spot price changes. In the case of cocoa and coffee, a large negative value for $\overline{R}_2^2$ implies that

[2] The two adjusted coefficient of determination-like measures are related to ϕ_c through, $\phi_c = \frac{1-\overline{R}_1^2}{1-\overline{R}_2^2}$

the futures price is a very poor predictor of the spot price compared to the last available observation for this latter series. For the coffee market the negative $\overline{R}_2^2$ is accompanied by a very low $\overline{R}_1^2$; by contrast the cocoa market $\overline{R}_1^2$ measure is quite high. The large discrepancy between the two coefficient of determination-like measures accounts for the very low efficiency value ϕ_c for cocoa futures.

Table A below summarises the most relevant results obtained so far, while details of the estimated models are contained in the appendix.

It is worth emphasising that the results discussed so far, although they may provide an indication on how the five futures markets function, cannot by any means be considered definitive since they crucially depend on the simplifying assumption that ignores the unevenly spaced pattern of the contracts. The next section deals with this important institutional issue in detail.

Table A Results ignoring spacing issue - Model 1

	CORN	WHEAT	COCOA	COFFEE	COTTON
Contracts	Mar, May, Jul, Sep, Dec	Mar, May, Jul, Sep, Dec	Mar, May, Jul, Sep, Dec	Mar, May, Jul, Sep, Dec	Mar, May, Jul, Oct, Dec
CI: slope=1	not rejected	not rejected	rejected	rejected at 3.5%	not rejected
Short-run regression					
Lag order	5	7	7	7	7
Lags coeffs=0	rejected	rejected	rejected	not rejected	not rejected
Basis coeff. = 1	not rejected	not rejected	rejected	rejected	not rejected
Constant = 0	rejected	rejected	not rejected	not rejected	not rejected
Efficiency ϕ_c	0.89	0.84	0.49	0.69	0.98
$\overline{R}_1^2$	0.36	0.38	0.29	0.04	0.24
$\overline{R}_2^2$	0.28	0.26	-0.45	-0.40	0.23

4. The unequally spaced data issue

All the results in the previous section were obtained ignoring the fact that the time series for spot and futures prices in the case of all the five commodities analysed are unevenly spaced due to the institutional pattern of the contracts. As already mentioned, May, July and September contracts are two months apart from the previous contract, while December and March are 3 months apart for corn, wheat, cocoa and coffee. Cotton contracts follow a similar pattern with the May, July and December contracts being two months apart from the previous contract, while three months separate October and March contracts from the preceding one. We can thus single out two regimes, the first consists of all the observations for contracts which are two months apart, while the second regime is represented by the three months apart contracts. This can also be seen as an example of ordered regressions, while in the context of non-linear autoregressions the ordering criterion is endogenous to the time series analysed (often the value assumed by the lagged variable with respect to a threshold), futures contracts observations are ordered according to the institutional pattern of the settlements.

In order to take into account the fact that the contracts occur at uneven time intervals across the year, we adopt two estimation procedures: in the first one we amend the OLS regression (2) by including additive and multiplicative dummy variables (regime dummies), which assume value 1 for observations related to May, July and September contracts and zero otherwise when corn, wheat, cocoa and coffee markets are analysed, while for cotton the dummy takes value 1 for May, July and December and zero for March and October. Regression (2) from now on is referred to as Model 1 while Model 2 is obtained by including the regime dummies. The two models are reported in the box below:

Model 1

$$s_t - s_{t-\tau} = \theta_0 + \theta_1\left(f_{t-\tau} - s_{t-\tau}\right) + \sum_{i=1}^{k} \lambda_i \left(s_{t-i} - s_{(t-\tau)-i}\right) + \sum_{i=1}^{k} \gamma_i \left(f_{t-i} - f_{(t-\tau)-i}\right) + \varepsilon_t$$

Model 2

$$s_t - s_{t-\tau} = \theta_0 + \theta_1\left(f_{t-\tau} - s_{t-\tau}\right) + \sum_{i=1}^{k} \lambda_i \left(s_{t-i} - s_{(t-\tau)-i}\right) + \sum_{i=1}^{k} \gamma_i \left(f_{t-i} - f_{(t-\tau)-i}\right) +$$
$$\delta_0 * D_t + \delta_1\left(f_{t-\tau} - s_{t-\tau}\right) * D_t + \sum_{i=1}^{k} \alpha_i \left(s_{t-i} - s_{(t-\tau)-i}\right) * D_t + \sum_{i=1}^{k} \beta_i \left(f_{t-i} - f_{(t-\tau)-i}\right) * D_t + \upsilon_t$$

D_t = 0 for March, and December (or March and October for cotton) contracts

D_t = 1 for May, July and September (or May, July and December for cotton) contracts

The second procedure we adopt is based on the specification of two different autoregressions run separately on the observations belonging to each regime. The use of an indicator variable such as the dummies included in Model 2 in a single regression context constrains the residual error variance to be constant across regimes; note also that the lag order can vary over regimes. In the box below the two regimes are described formally:

Regime 1

$$\left(s_t - s_{t-\tau}\right) = \theta_0^{(1)} + \theta_1^{(1)}\left(f_{t-\tau} - s_{t-\tau}\right) + \sum_{i=1}^{k_{11}} \lambda_i^{(1)} \left(s_{t-i} - s_{(t-\tau)-i}\right) + \sum_{i=1}^{k_1} \gamma_i^{(1)} \left(f_{t-i} - f_{(t-\tau)-i}\right) + \varepsilon_t^{(1)}$$

Regime 2

$$\left(s_t - s_{t-\tau}\right) = \theta_0^{(2)} + \theta_1^{(2)}\left(f_{t-\tau} - s_{t-\tau}\right) + \sum_{i=1}^{k_2} \lambda_i^{(2)} \left(s_{t-i} - s_{(t-\tau)-i}\right) + \sum_{i=1}^{k_2} \gamma_i^{(2)} \left(f_{t-i} - f_{(t-\tau)-i}\right) + \varepsilon_t^{(2)}$$

In the next paragraph the analysis of each market is reported, while in paragraph 4.2 we offer a summarising discussion of the results obtained across the five markets.

4.1 Analysis of the unequally spaced contracts

Corn

Table 1A reports the estimated Model 1 and Model 2. The first one is the same as Table 3 and has been discussed in the previous section. The bottom panel of the table reports the F-test for the joint exclusion of all the binary variables. For the corn market the dummies coefficients appear to be not significantly different from zero; the hypothesis of the equality of the estimated error variances from Model 1 and Model 2 cannot be ruled out on the basis of the other F-test reported in bottom panel of Table 1A. Table 2A reports the unbiasedness tests for Model 2. Although we cannot reject the hypothesis that the coefficient of the basis is equal to unity, the constant term is significantly different from zero.

Table 3A presents the results for the short-run regressions *by regime*; regime 1 contains observations only for May, July and September contracts, while observations for March and December contracts constitute regime 2. The short run dynamics seems to vary a great deal across regimes (the residual sum of squares is 0.53 in the first regime and drops dramatically to 0.07 in the second one). In the first one three lags are needed to get white noise residuals[3], while in the second five lagged terms are included to describe adequately the behaviour of the change in the spot prices. Table 4A is analogous to Table 5 for the two regimes, results for regressions omitting all the lagged changes in spot and futures prices are reported; with the exception of the regime 2 intercept, the constant and the basis coefficient appear robust with respect to the inclusion of lags. The hypothesis that the coefficient of the basis is not significantly different from unity is always accepted. *Regime 1a* (Table 3A) is obtained by imposing the same lag structure in both regimes (k_1=k_2=5), while *Regime 1b* represents the most parsimonious model specification achieved when we select the lag order by adopting a 5% level of significance criterion. The variance of the residuals remains high across the three specifications. It is worth noting that although the dummies are not jointly significant in Model 2, the uneven spaced data feature of the contracts is picked up by the estimation of the two different regimes.

[3] Note that the third lag for the difference in the futures prices is retained at 11% level of significance.

These results, however, may be driven by three extreme observations for the 1996 March, May and July contracts. The change in the spot price, *(s_t-s_{t-t})*, is thus modelled including some impulse dummies; one for the 34th and the 43rd observation and the first difference of a dummy variable for the 82nd observation. From the results reported in Table 1A it appears that the change in the spot price for corn can be adequately described by the basis and the three dummy variables, no lagged differenced terms are required to capture the short-run dynamics. The regime dummy variables are not jointly significant, although the one allowing for changes in the intercept can be retained at a significance level of 6%. The estimated regressions by regime are reported in Table 3A; for both regimes, once it has been allowed for the inclusion of impulse dummy variables (or their differences) to neutralise extreme observations, lagged differenced terms are no longer necessary.

Table 5A presents the efficiency measures for 56 days forecast horizon for Model 2 and for the two regimes; those for Model 1 are also reported for comparison. The short run efficiency measure based on the ratio of the estimated error variance and the sample variance of the forecast error is very similar for the two models, the degree of inefficiency associated with Model 2 is slightly higher (0.122) than the one obtained for Model 1 (0.108); on the other hand, the first R-squared-like measure is higher for Model 2 than for Model 1. This compares the forecasts based on the short run regression with prediction from the last available spot price. The lower part of Table 5A shows the efficiency measures calculated for each regime along with a weighted average of the two. Focusing on the results for Regime 1 with 3 lags and Regime 2 with 5 lags, it is interesting to note that the short run efficiency measure is higher for the first regime; the R_1-squared coefficient is higher in regime 2, while the R_2-squared coefficient is higher in regime 1. Both measures are well below the value obtained for Model 1 and Model 2. The weighted average of the short run regime efficiency measures, is obtained from:

$$\mathrm{f}_c^* = \frac{\left[n_1 (n_1 - 2k_1 - 2)^{-1} \sum_{t=1}^{n1} \hat{e}_{1t}^2 + n_2 (n_2 - 2k_2 - 2)^{-1} \sum_{t=1}^{n2} \hat{e}_{2t}^2 + \right] / (n_1 + n_2)}{\left[n_1 (n_1 - 1)^{-1} \sum_{t=1}^{n1} \left[(s_{1t} - f_{1t-\mathrm{t}}) - \left(\overline{s_{1t} - f_{1t-\mathrm{t}}} \right) \right]^2 + n_2 (n_2 - 1)^{-1} \sum_{t=1}^{n2} \left[(s_{2t} - f_{2t-\mathrm{t}}) - \left(\overline{s_{2t} - f_{2t-\mathrm{t}}} \right) \right]^2 \right] / (n_1 + n_2)}$$

where n_1 and n_2 are the numbers of the observations for regime 1 and regime 2, respectively[4]. Although the R^2-like measures are both lower than those obtained for Model 1 and Model 2, it is particularly interesting to note that the combined ϕ_c measure implies a perfectly efficient market. Thus, it is possible to conclude that in order to assess the efficiency of a market it is necessary to take into proper account the unevenly spaced data feature since by ignoring it on the basis of the results obtained from Model 1 we would have concluded that the corn market shows a certain degree of inefficiency, as claimed by other authors so far (e.g. Beck, 1994). Of course, although very encouraging, this result depends necessarily on the specific forecast horizon we have analysed.

Wheat

Table 1B reports the estimated Model 1 and Model 2 for the wheat market; the hypothesis that all the regime dummy variables are not jointly significant is rejected and, according to the test for the equality of the estimated error variances, we argue that there is no difference in the variances of the residuals obtained from the two models only at a significance level of 9%. Table 2B reports the unbiasedness test for model 2. Again the data support the hypothesis that the basis coefficient is unity but not that the constant term is zero; this can be due to the presence of a constant risk premium. Regressions by regime are reported in Table 3B. The first two columns show the estimates obtained selecting the lag order by eliminating all lagged terms which were not significant at the 5% nominal level, while in the third and fourth column of the table we report the estimates obtained imposing the 7 lag structure in both regimes, i.e. the same dynamic behaviour detected in model 1. Focusing on the first two columns of Table 3B, it is worth stressing that the dynamic specification is quite different in the two regimes. Five lags of both the changes in spot price and in futures price are needed for the first one, while just one lag is enough to ensure white noise residuals in the second regime.

The fact that the lag structure in both regimes is more parsimonious than the one of model 1 is very common with non-linear time series models. When a linear specification is imposed, more lags are often necessary to capture the nonlinearity features of the data in order to minimise the residual sum of squares. Once we allow for different dynamic behaviour in the two regimes we

[4] The combined coefficients of determination-like measures are calculated analogously.

are able to accept the hypothesis that the estimated error variances are not different. Turning attention to the unbiasedness hypothesis, in both regimes the constant term is significantly different from zero, while only in the first regime we cannot reject the hypothesis that the basis coefficient is equal to unity. Table 4B shows the short run models for the two regimes estimated without the inclusion of any lagged term. As expected the value of constant term and the coefficient of the basis of regime 1 are affected by the presence of the lagged variables, while the same parameters appear more robust in regime 2. Table 5B reports the efficiency measures for 8 week forecasting horizon. The lower degree of inefficiency is obtained from model 1 (0.161), while model 2 allowing for the presence of the regime dummy variables reduces the error variance of the short run regression compared to the sample variance of the forecast error based on futures price, therefore the degrees of inefficiency is higher (0.436). Considering the absolute predictor quality issue, it is worth stressing that the R_1-squared measure is much higher for model 2 than for model 1 (0.581 *vs* 0.377), The R_2-squared coefficient is 0.258 meaning that the futures price is superior to the most recent spot price as a predictor. Comparing the efficiency measures across the two regimes, the results point out that for the second regime (whatever the lag structure) the degree of inefficiency is lower than for the first one, while the R-squared-like coefficients are higher for regime 1.

Combined measures are also calculated. The ϕ_c coefficient turned out to be lower than the one based on the estimated model 1 but higher with respect to model 2; the R_1-squared coefficient, on the contrary, increases in comparison to model 1 but not to model 2. On the other hand, the R_2-squared measure is higher when averaging across regimes than for the two models.

Cocoa

In Table 1C we report the estimated Model 1 and Model 2 for the cocoa market; the first specification allows for the inclusion of 7 lagged terms in both models. There is not a significant difference between the estimated error variances from the two models and the joint exclusion of all dummy variables in Model 2 can be accepted only at a significance level as low as 8%. Noticing that, once we include the regime dummies the fifth, sixth and seventh lags are no longer significant, we propose a different specification which allows for just four lags; it now turns out that the dummies are jointly significant. This result is robust to the inclusion of some impulse binary variables, necessary to pick up some extreme observations. It is worth emphasising that the unbiasedness hypothesis confined to the hypothesis that the basis coefficient is equal to unity is not rejected for Model 2 with four lags but it is when the lags are seven or when we ignore the unevenly spaced data issue and estimate the simplified Model 1. As stressed before when discussing the wheat results, it is plausible to argue that more lags are indeed necessary in model 1 in order to capture the unevenly spaced feature of the data.

Table 4C reports the estimated short-run dynamics for the two regimes, which again appear to vary a great deal moving from one regime to the other; once we allow for a different lag structure (10 lags are included in the first regime and just 2 in the second) we cannot rule out that the estimated error variances are equal. In the same table we also report a specification which includes some impulse dummies for regime 2. For both regimes it is apparent that the hypothesis that the futures price is an unbiased predictor of the spot price at termination can be rejected. In Table 6C we compute the usual measures to assess the inefficiency of the cocoa market. Focusing on the ϕ_c measure we obtain a high degree of inefficiency equal to 0.507 in the case of model 1, 0.598 for model 2 with 7 lags and 0.471 when just four lags are included. The same measure increases when we consider the two regimes separately (0.689 and 0.647) or combined (0.669). The R_1-squared coefficient is generally high, while the R_2-squared is always negative pointing out that the futures price is substantially inferior as a predictor when compared to the most recent spot price. Nevertheless, prediction gains can be achieved from futures price information in this market through the short run regression implied by Model 2.

The cocoa market represents an instructive example of the fact that a market may appear less inefficient when one tries to model the data spaced at uneven intervals by means of a pooled estimation with regime dummies, while by carrying out the analysis by regimes the efficiency (or lack of it) may be assessed more rigorously.

Coffee

The first step of the analysis for the coffee market is presented in Table 1D, where the estimates for Model 1 and Model 2 are reported; a common dynamic structure is selected by including seven lags in both models. Although some of the regime dummies are highly significant, according to the F-test shown in the bottom panel of the table they can be jointly rejected. An alternative specification, leaving unaltered the lag structure, allows for the inclusion of some impulse dummies to pick up the exceptionally high values assumed by some observations. The presence of the binary terms appear to warrant higher power to the test in discriminating between the null hypothesis that the regime terms are not relevant and the alternative hypothesis, so that we are now allowed to include them in modelling the short run behaviour of the change in the coffee spot price. The efficiency tests reported in Table 3D offer further support to the claim that the coffee market is inefficient as we have already pointed out in section 3. In this case the inefficiency is not caused by the presence of a constant risk premium (the constant terms are not significantly different from zero), but by the fact that the coefficient of the basis is not equal to unity. This is also confirmed by the result shown in the subsequent Table 4D obtained when we disaggregate the contract data according to the two regimes. As for the previous markets, we calculate the 56 days forecast horizon efficiency measures, the degree of inefficiency is very high for this market, the highest value is the one based on the estimation of model 2 with the impulse dummies. The value of the R_1-squared coefficient of determination is very low, with the exception of the models in which binary variables were included; as it was the case for cocoa, the R_2-squared coefficient is always negative. It seems that the coffee market is *genuinely* inefficient and it is possible to argue that previous considerations about its functioning are supported even when the unevenly spaced data issue is not overlooked.

Cotton

The estimates for Model 1 and Model 2 for the cotton market are reported in Table 1E; two different dynamic specifications are allowed. In the first seven lagged terms of both the change in the spot and futures prices are included, while in the second we allow just for six lags because when we estimate model 2 with the regime dummies the seventh lag is no longer significant for the change in both prices. Model 1b and Model 2b differ from the previous ones because of the presence of two impulse dummies. Whatever the preferred specification we can reject the hypothesis that there are significant regime effects captured by the dummy variables. This can be due to the fact that for the cotton market, although as for the other commodities we have three contracts in the first regime and two in the second, there is a higher degree of alternation between the regimes. In order to clarify this point, it is worth noticing that for corn, wheat, cocoa and coffee in a year period the contracts are such that three consecutive observations belong to the first regime and the other two to the second regime; in the case of cotton two consecutive observations belong to the first regime, the third to the second regime, the fourth to the first again and the last to the second regime. Thus, the lower regime persistence in the cotton market is hardly captured by the regime dummies.

Turning to the unbiasedness hypothesis, it is not rejected when tested within model 1 but it is when we adopt model 2 specification. When we disaggregate the data according to the two regimes (Table 4E), the estimates are quite different and for both regimes we can not rule out that the cotton market is efficient. For regime 2 two different specifications are proposed, one in which we impose the same lag structure as in the first regimes (9 lags) and a more parsimonious one which includes only three lagged terms for both spot and futures price changes and an impulse dummy to avoid non-normality problems with the estimated residuals. Table 6E reports the efficiency measures; the degree of inefficiency appears to be very low for this market, and the coefficient of determination-like measures are also reasonably high and comparable in magnitude to those obtained for the corn and wheat markets. A comparison between the regimes, selecting 9 lags in the first one and 3 in the second one, seems to favour regime 1 in terms of the efficiency measure and the regime two with respect to the coefficient of determination-like measures. The analysis of the cotton market highlights the fact that when dealing with data with low regime persistence it is preferable to conduct the testing task by regime since when we pool all the contracts the unevenly spaced feature of the data is less likely to become evident and this may lead to inaccurate conclusions about the functioning of the market.

4.2 Summary of the results

Table B offers a summarising picture of the results obtained by modelling the unequally spaced data feature of the contracts by means of binary variables which assume unit value for all the observations of contracts two months apart from the previous one and zero otherwise (Model 2). The joint significance of the dummy terms is not rejected for wheat, cocoa and coffee, thus highlighting that the pattern of the data cannot be overlooked and needs to be adequately modelled in order to provide more robust conclusions on the functioning of the markets examined.

The unbiasedness hypothesis tests corroborate the results obtained ignoring the spacing issue for corn, wheat and coffee; the corn efficiency measures remains almost constant across the two specifications, while for wheat the ϕ_c coefficient decreases from 0.84 to 0.56 but the $\overline{R}_1^2$ coefficient improves from 0.38 to 0.58. For coffee the ϕ_c becomes very low (0.16) if impulse dummies are included in model 2 in order to get rid of non-normality problems. Impulse dummies account for the high value of the $\overline{R}_1^2$ coefficient, which otherwise would be as low as 0.05; overall, model 2 provides additional evidence to the claim that the coffee market is inefficient.

Table B Results using regime dummies - Model 2

	CORN	WHEAT	COCOA	COFFEE	COTTON
Contracts	D=1 for May, Jul, Sep D=0 for Mar, Dec	D=1 for May, Jul, Sep D=0 for Mar, Dec	D=1 for May, Jul, Sep D=0 for Mar, Dec	D=1 for May, Jul, Sep D=0 for Mar, Dec	D=1 for May, Jul, Dec D=0 for Mar, Oct
Lag order	5	7	4	7	7
Dummy coeffs=0	not rejected	rejected	rejected	rejected	not rejected
Equal variance	not rejected	not rejected	not rejected	rejected	not rejected
Basis coeff. = 1	not rejected (not rejected)	not rejected (not rejected)	not rejected (rejected)	rejected (rejected)	rejected (not rejected)
Efficiency ϕ_c	0.88 (0.89)	0.56 (0.84)	0.30* (0.49)	0.16** (0.69)	0.78*** (0.98)
$\overline{R}_1^2$	0.37 (0.36)	0.58 (0.38)	0.54* (0.29)	0.78** (0.04)	0.40*** (0.24)
$\overline{R}_2^2$	0.28 (0.28)	0.26 (0.26)	-0.53 (-0.45)	-0.40 (-0.40)	0.23 (0.23)
*Estimating Model 2 without impulse dummies: ϕ_c=0.53 and $\overline{R}_1^2$=0.19 **Estimating Model 2 without impulse dummies: ϕ_c=0.68 and $\overline{R}_1^2$=0.05 ***Estimating Model 2 without impulse dummies and with 6 lags ϕ_c=0.95 and $\overline{R}_1^2$=0.27					

Results ignoring the spacing issue are reported in parenthesis

The hypothesis that the basis coefficient is equal to unity cannot be rejected for cocoa if the short-run dynamics is specified according to Model 2; at this stage, a possible interpretation for this finding is that failing to take into account the institutional data features may induce the appearance of inefficiency. However, the ϕ_c efficiency measure for cocoa is only slightly higher than before (0.53 *vs* 0.49) and the $\overline{R}_1^2$ coefficient is worsened (0.19 *vs* 0.29). Opposite results are found for cotton, although all the efficiency measures remain quite high, we have to reject the hypothesis that the basis coefficient is equal to unity. This result may be due to the fact that Model 2 specification may not be the appropriate one to tackle the unequally spaced data issue; in the case of cotton, as pointed out before, given the contract settlements, the two regimes alternate more often than for the other markets analysed. With lower regime persistence the spacing feature of the data is less likely to show up within the simple framework of model 2; a more complex, but at the same time more flexible, specification, such the one *by regime*, may indeed be necessary to unveil the unequally spaced pattern of cotton data.

As reported in Table C, by allowing for the estimation of two distinct regimes with different dynamics, the unbiasedness hypothesis is not definitely rejected for cotton market regime 2 but for the first regime it is not rejected at a significance level of 9.75%. This finding may account for the conflicting results obtained when testing the EMH for model 1 and model 2. The ϕ_c coefficient is very high in both regimes (0.96 and 0.84) giving a combined measure of 0.91; the $\overline{R}_2^2$ coefficient is very low in the first regime (0.05) and high in the second (0.40), the combined value of 0.25 is, therefore, mainly due to the contribution of regime 2. In the first regime the futures price is as good as the most recent spot price as a predictor, while in the second regime the futures price is definitely superior. Prediction gains can be achieved from futures price information through regime regressions which also include some impulse dummies for regime 2; the combined $\overline{R}_1^2$ coefficient has a value of 0.32 obtained as weighted average of 0.09 for regime 1 and 0.50 for regime 2.

For the corn market the analysis by regime supports the previous evidence that the futures price is an unbiased predictor of the future spot price; the most relevant result that emerges for this market is that on calculating separate efficiency measures for each regime and then averaging them the market appears to be perfectly efficient. In the first regime the ϕ_c is equal to 1.03 and in the second one it is slightly lower, 0.88, giving a combined ϕ_c measure of unity. The $\overline{R}_1^2$ coefficient is higher in regime 2 (0.28) than in regime 1 (0.21) providing a combining measure of 0.22, which is lower compared to the ones obtained estimating model 1 (0.36) and model 2 (0.37). The same applies to the $\overline{R}_2^2$ coefficient which, combining the value 0.23 from regime 1 and 0.18 from regime 2, is equal to 0.22. Both R-squared measures point out that corn futures price is better than the last spot price as a predictor.

For the wheat market too the two sets of contracts seem to be characterised by different dynamic structures; while five lags are required in the first regime a more parsimonious specification with only one lag can be achieved for the second regime. For this latter we have to reject the hypothesis that the basis coefficient is equal to unity; on the other hand the first regime appears consistent with the EMH. It can be considered the dominant regime (with 50 observations out of 82), which has likely driven the results obtained from model 1 and model 2.

Turning to the efficiency measure ϕ_c, it is higher in regime two (0.73) than in regime 1 (0.65) giving a combined value of 0.67 which is greater with respect to that based on model 2 (0.56) but smaller if compared to the one calculated from model 1 (0.84).

Table C Results specifying two regimes

	CORN	WHEAT	COCOA	COFFEE	COTTON
Contracts	R1: May, Jul, Sep, R2: Mar, Dec	R1: May, Jul, Sep, R2: Mar, Dec	R1: May, Jul, Sep, R2: Mar, Dec	R1: May, Jul, Sep, R2: Mar, Dec	R1: May, Jul, Dec, R2: Mar, Oct
Obs	94 R1: 57 R2: 37	82 R1: 50 R2: 32	75 R1: 45 R2: 30	95 R1: 57 R2: 38	95 R1: 57 R2: 38
Dynamics vary between regimes	Yes R1: 3 lags R2: 5 lags	Yes R1: 5 lags R2: 1 lag	Yes R1: 10 lags R2: 2 lags	Yes R1: 5 lags R2: 3 lags	Yes R1: 9 lags R2: 3 lags
Equal variance between regimes	rejected	not rejected	not rejected	not rejected	not rejected
Basis coeff. = 1	R1: not rejected R2: not rejected (not rejected) [not rejected]	R1: not rejected R2: rejected (not rejected) [not rejected]	R1: rejected R2: rejected (rejected) [not rejected]	R1: rejected R2: rejected (rejected) [rejected]	R1: not rejected R2: not rejected (not rejected) [rejected]
Efficiency ϕ_c	R1: 1.03 R2: 0.88 Combined: 1.00 (0.89) [0.88]	R1: 0.65 R2: 0.73 Combined: 0.67 (0.84) [0.56]	R1: 0.31 R2: 0.18* Combined: 0.25* (0.49) [0.53]	R1: 0.59 R2: 0.62 Combined: 0.60 (0.69) [0.16]	R1: 0.96 R2: 0.84 Combined: 0.91 (0.98) [0.78]
$\overline{R}_1^2$	R1: 0.21 R2: 0.28 Combined: 0.22 (0.36) [0.37]	R1: 0.58 R2: 0.28 Combined: 0.52 (0.38) [0.58]	R1: 0.68 R2: 0.49* Combined: 0.63* (0.29) [0.19]	R1: 0.18 R2: 0.10 Combined: 0.15 (0.04) [0.78]	R1: 0.09 R2: 0.50** Combined: 0.32** (0.24) [0.40]

$\overline{R}_2^2$	R1: 0.23 R2: 0.18 Combined: 0.22 (0.28) [0.28]	R1: 0.36 R2: 0.01 Combined: 0.28 (0.26) [0.26]	R1: -0.04 R2: -1.87 Combined: -0.50 (-0.53) [-0.53]	R1: -0.39 R2: -0.46 Combined: -0.41 (-0.40) [-0.40]	R1: 0.05 R2: 0.41 Combined: 0.25 (0.23) [0.23]
*Estimating regime 2 without impulse dummies: ϕ_c=0.35 and combined ϕ_c=0.33; $\overline{R}_1^2$ =-0.01 and combined $\overline{R}_1^2$ =0.50 **Estimating regime 2 without impulse dummies and with 9 lags: ϕ_c=1.86 and combined ϕ_c=1.34; $\overline{R}_1^2$ =-0.40 and combined $\overline{R}_1^2$ =0.02					

Results ignoring the spacing issue are reported in round parenthesis;
Results using regime dummies are reported in square parenthesis;

Both R-squared coefficients are higher in the first regime, the combined $\overline{R}_1^2$ coefficient is 0.52, which is only slightly lower than the value obtained from model 2 (0.58) but much higher then the model 1 value of 0.32. The $\overline{R}_2^2$ combined value of 0.28 is almost entirely due to the contribution of the first regime (0.36) since the second one is as low as 0.01. As expected it indicates that the futures prices is as good as the most recent spot price as a predictor.

The evidence provided by the estimated regime models strengthens the claim that the markets for cocoa and coffee are very inefficient. The hypothesis that the basis coefficient is equal to unity is rejected in each regime for both markets. The cocoa ϕ_c combined measure is 0.25, much lower than the values obtained from the previous specifications (0.49 in model 1 and 0.53 in model 2). The $\overline{R}_1^2$ coefficient is equal to 0.68 in regime 1 and the value of 0.49 for regime 2 is due to the inclusion of some impulse dummies variables. Otherwise it would be as low as -0.01; the combined $\overline{R}_1^2$ is however much higher (0.63) than the one provided by model 1 (0.29) and model 2 (0.19). It is thus possible for the cocoa market to achieve prediction gains through the regime short-run regressions. The negative $\overline{R}_2^2$ measure for both regimes and their weighted average (-0.50) confirms that the most recent spot price is a better predictor than the futures price.

The performance of the coffee market is quite poor when assessed on the basis of its efficiency measure ϕ_c, which is equal to 0.60 when averaging the two regime values of 0.59 and 0.62. Such values are closer to the one obtained from model 1 (0.69) but much higher than the corresponding value of 0.16 from model 2. The $\overline{R}_1^2$ coefficient is low in each regime (0.18 in the first and 0.10 in the second) and the combined one of 0.15 is much lower than the 0.74 one obtained from model 2. The $\overline{R}_2^2$ coefficient is about -0.40 in both regimes and is in line with the values obtained previously, thus confirming that also for the coffee market the spot price is a superior predictor with respect to the futures price.

5. Unit root testing

In this section the potential non-stationarity feature of the data is discussed conducting the traditional Dickey-Fuller tests (DF). The series analysed are the spot price at termination date (s_t), the futures prices sampled on the same date (f_t), the spot ($s_{t-\tau}$) and futures ($f_{t-\tau}$) price sampled 56 days before the termination date, the change in the spot price (s_t-$s_{t-\tau}$) and in the futures price(f_t-$f_{t-\tau}$) and the basis ($f_{t-\tau}$-$s_{t-\tau}$); all variables are in logarithmic form.

The unit root tests are carried out for each commodity over the entire sample and over the two subsamples represented by the two regimes in order to take into account the unequally spaced pattern of the observations.

Corn

The test results reported in Table 6A for the corn market series make it difficult to classify the variables as unequivocally stationary or non-stationary; the test is very sensitive to the choice of the sample period, to the number of lags selected and to the presence of dummy variables, included to capture the potential regime change due to the unequal spacing pattern of the observed data or to neutralise some possible outliers.

According to the test reported in the first row of Table 6A, the spot price series should be considered stationary; however, the last part of the sample period contains three observations (for March, May and July contracts) whose value is exceptionally high with respect to all the other observations. As pointed out by Franses and Haldrup (1994) the neglected presence of outliers or “aberrant” observations can lead to a spurious finding of stationarity. This problem is tackled in three alternative ways. In the first one the test is conducted on a sub-sample, thus excluding the “extreme” observations. In this case the series turns out to be non-stationary, as expected; the same conclusion is reached when the three observations are replaced by the average value of the observation immediately before and after the three ones (s_t-adj.). The third method is the one suggested by Franses, i.e. the inclusion of dummy variables in the DF auxiliary regression; it can be shown that the DF test based on this enlarged regression asymptotically follows the distribution tabulated by Dickey and Fuller.

The series appears to be non-stationary when the regime dummy, *D*, is included, but not when other impulse dummies are inserted in the Dickey-Fuller regression in order to get rid of the non-normality problems caused by outliers.

The series of the futures price at termination date, f_t, appears to be non-stationary only when the regime variable and seven impulse dummies are included; analogously, the series $s_{t-\tau}$ should be considered stationary in all cases, apart from the one in which *D* is included. However the regime variable turns out to be not significantly different from zero in this case.
The series $f_{t-\tau}$ is non-stationary when the Dickey-Fuller test is conducted for the sub-sample which excludes the extreme observations and when these are replaced by the average value of the closest observations. Both the changes in the spot and futures prices appear to be stationary, as expected, although it is necessary to include some impulse dummies in order to obtain a good specification for the basic Dickey-Fuller equation. As far as the *basis* is concerned, it can be considered a stationary series only if the DF test is conducted including the regime indicator variable and three impulse dummies.

The results obtained testing for unit roots in the two separate regimes (Table 7A) are in line with those discussed above; although the basis and the change in the spot and in the futures prices can unequivocally be considered the realisation of stationary processes, the results for the series in levels are conflicting and not robust to the lag selection and to the inclusion of impulse dummy variables.

Wheat
Table 6B presents the results for the wheat market series. The logarithm of the spot price at termination date appears to be stationary when the presence of extreme observations is accounted for by restricting the sample (third row) or by adjusting the series (fourth row) by substituting the extreme observations with the average of the neighbouring ones. The series

should also be considered stationary when the regime dummy variable is included. The only case in which it turns out to be non-stationary is when the DF test is performed on the series without any kind of adjustment for possible outliers and just one lag is included (second row). The evidence for the series of the futures price sampled at termination date makes it a borderline case, the DF test values are very close to the critical ones. Only when the regime dummy is introduced we do find a significant rejection of the null of non-stationarity; however note that the dummy is significant only at 9% significance level.

The results for the series of the spot prices considered 56 days before the last business day of the contract month are very sensitive to the specification adopted and to the selection of the lag order. The series appears to be non-stationary when one allows for different regime patterns by including the *D* variable and when the series is adjusted and four lags are included in the DF regression. The series of futures prices $f_{t-\tau}$ should be considered non-stationary, although the conclusion is not particularly robust with respect to the number of lags selected, the inclusion of more lags (5) leads to reject the null of non-stationarity.

The change in the spot and in the futures prices are stationary, although to avoid misspesification problems it is necessary to include the regime dummy variable for the first series. The basis variable turns out to be stationary, but due to non-normality problems in the DF regression five impulse dummies needed to be included.

Unit root tests by regime are reported in Table 7B. Level series appear to be stationary, although for most of the series the empirical values are very close to the critical ones. In interpreting the non-stationarity tests, it is worth noting that the size of both subsamples is very small, 50 observations in the first regime and 32 in the second one. The Dickey-Fuller test might be affected by a small sample-type distortion.

Cocoa

Results for the cocoa series are reported in Table 7C. Carrying out the DF test over the entire sample we are not able to reject the null of non-stationarity for the spot and futures prices series considered at termination date or lagged 56 days. The series of the basis and the change of spot and futures prices appear to be stationary. Unlike the corn and wheat series, cocoa price series are not heavily affected by extreme observations, allowing us to draw more clear-cut conclusions about the nature of the trend in the variables. Further support to these conclusions is provided by the tests carried out for the two separate regimes; the only unexpected result concerns the basis series in regime one, where it is not possible to reject the null of non-stationarity. However, in the context of foreign exchange markets (Baillie and Bollerslev, 1994), it has been shown that the series corresponding to the basis (forward premium), although being stationary, is strongly characterised by such a high persistence or long memory that the DF test is not powerful enough to distinguish it from pure non-stationarity.

Coffee

According to the results reported in the first panel of Table 7D, the coffee prices series can be considered integrated variables, although this conclusion is reached after estimating the DF regression with additional dummy terms to take into account some extreme values assumed by the series. The $f_{t-\tau}$ series represents the only exception, as it turns out to be stationary. The null hypothesis of non-stationarity is definitely rejected for the change in spot and futures prices. Similarly to the cocoa case, the coffee basis series is likely to be characterised by long memory features which yield a non-significant ADF test for the whole sample and in the first regime. With the exception of the basis series, the fact that the coffee series data are unequally spaced do not seem to affect the unit root testing since the series appear to behave similarly within the two different regimes.

Cotton

As Table 7E shows, the price series for cotton appear to be stationary over the full sample. However, these results depend greatly on the lag structure selected and on the presence of dummy variables, which have been included to obtain a correct specification of the DF regressions. The analysis of the individual series within the two regimes provides some valuable (additional) information to explain the unexpected stationarity in the level series; with just few exception, the spot and futures prices series appear to be non-stationary in both regimes. Although this finding may well be due to the power loss of the DF test in the small size subsamples, it is also plausible to argue that it is the alternation of regimes that induces a sort of spurious stationarity in the series. Therefore, the unevenly spaced data feature should be carefully accounted for when carrying out unit root tests. The change of the spot and the futures price are clearly stationary, while the basis series turns out to contain a unit root over the complete sample and in the first regime.

6. Concluding remarks

The aim of this paper was to analyse futures markets for five widely traded commodities and test their efficiency within a new estimation framework which takes into account the unevenly spaced data features of the contracts resulting from the seasonal nature of production and from the institutional aspects of the market. Such an important characteristic of the time series data, although overlooked in all previous studies, can be considered one important source in an attempt to explain the highly variable and conflicting conclusions reached in the empirical literature on commodity market efficiency.

The examination of corn, wheat, cocoa, coffee and cotton markets has shed interesting light on the adequate estimation techniques that have to be followed in testing for market efficiency. All contracts are characterised by an irregular settlement pattern since some contracts are two months apart while others are three months distant. We can thus single out two regimes; the first consists of all the observations for the two months apart contracts while the second includes the other contracts. We propose two alternative estimation procedures. In the first one we modify the quasi-ECM model proposed by Kellard *et al.* (1999) by including additive and multiplicative dummy variables (regime dummies), whose values change according to the time interval between two subsequent contracts; they assume value 1 for observations related to two months apart contracts and zero otherwise. The second procedure adopted is based on the specification of two different autoregressions run separately on the observations belonging to each regime.

One of the most relevant insights is that when a market is efficient by failing to accommodate for the institutional features of the historical data inaccurate conclusions may be reached: the most instructive example was given by the corn market, which turns out to be completely efficient when the unequally spaced issue is adequately tackled, but may be considered, to a certain extent, inefficient when it is ignored. Although the futures and spot prices are cointegrated with a long run slope coefficient of unity, in the short-run there is evidence of inefficiency. By estimating the short run models separately for each regime the market appear to be perfectly efficient.

On the other hand, if the market is really inefficient, such a conclusion is reinforced when the analysis is conducted by regime as was the case for the cocoa and coffee markets. Another issue of interest is how unevenly spaced the data are, as we noted for the cotton market. If the contracts belonging to the different regimes alternate very often this can hide the very uneven spaced feature of the observations, so that it turned out to be appropriate to carry out the efficiency analysis by examining the two regimes separately.

In this paper we also provide measures for the degree of inefficiency rather than simply testing whether the basis coefficient is equal to unity. The degree of inefficiency is calculated in terms of the performance of futures prices to forecast spot price with respect to prediction obtained by the best fitting quasi-ECM model. For a forecast horizon of 56 days, the results suggest that corn, as already mentioned, is perfectly efficient when the estimation of the short-run model is carried out by regime. The wheat market would be 16% inefficient if the unevenly spaced data issue were ignored, but the degree of inefficiency rises to 33% when this is given by the weighted average of the two regime measures of 35% and 27%. The degree of inefficiency associated with cotton market regime 1 is very low, just 4%, while the second regime is 16% inefficient. By combining the regimes the market is 9% inefficient; without any adjustment to model the irregular pattern of the contracts the cotton market would have appeared to be much less inefficient, just 2%. Cocoa and coffee market are very inefficient. The first is 75% inefficient when the two disagreggated measures by regimes are combined and would be 47% if the unequally spaced data series were modelled within the framework of the ECM augmented by the regime dummies. The coffee market is about 40% inefficient in both regimes. For cocoa and coffee markets large negative values of a coefficient of determination-like measure which compares forecasts based on futures prices with prediction from the last available spot price suggest that the latter outperforms the futures prices as a predictor.

The unevenly sampled data issue turned out to be also relevant in the context of testing for unit roots. The traditional Dickey-Fuller test in some cases may lead to incorrect considerations about the non-stationarity features of the data if one fails to take into proper account the time series properties of the variables examined.

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APPENDIX

Contract Details

Commodity	Spot Exchange	Future Exchange	Contract Period	Contract Months	S_t	F_t	$S_{t-\tau}$	$F_{t-\tau}$
					mean (st.dev.)	mean (st.dev.)	mean (st.dev.)	mean (st.dev.)
CORN	Chicago Board of Trade	Chicago Board of Trade (CBOT)	03/80 to 09/98	Mar, May, Jul, Sep, Dec	258.45 c/bu (59.85)	267.30 c/bu (61.12)	259.02 c/bu (58.32)	267.29 c/bu (54.30)
WHEAT	Chicago Board of Trade	Chicago Board of Trade (CBOT)	05/82 to 09/98	Mar, May, Jul, Sep, Dec	344.32 c/bu (63.78)	353.47 c/bu (69.48)	347.81 c/bu (58.85)	350.76 c/bu (59.60)
COCOA	Ivory Coast	Coffee, Sugar and Cocoa Exchange Inc. (CSCE)	03/84 to 12/98	Mar, May, Jul, Sep, Dec	1749.97 $/metric t. (439.31)	1480.83 $/TE (432.29)	1754.47 $/metric t. (459.51)	1511.85 $/TE (447.63)
COFFEE	Brazil	Coffee, Sugar and Cocoa Exchange Inc. (CSCE)	03/80 to 12/98	Mar, May, Jul, Sep, Dec	126.71 c/lb (46.88)	129.12 c/lb (42.09)	127.44 c/lb (47.17)	128.12 c/lb (40.19)
COTTON	Memphis	New York Cotton Exchange (NYCE)	03/80 to 12/98	Mar, May, Jul, Oct, Dec	67.91 c/lb (12.13)	71.17 c/lb (11.75)	67.21 c/lb (12.31)	70.57 c/lb (11.47)

Table 1 Tests of Cointegration rank

Commodity	H_0:r	λ-max	Trace	Lag length	Comment
CORN	0 1	20.88** 7.05	27.93** 7.05	5	reject non-cointegration
WHEAT	0 1	18.69* 4.55	23.24* 4.55	4	reject non-cointegration
COCOA	0 1	24.62** 5.01	29.63** 5.01	2	reject non-cointegration
COFFEE	0 1	18.63* 4.96	23.59** 4.96	3	reject non-cointegration
COTTON	0 1	59.59** 13.49**	73.09** 13.49	1	Spot and Futures prices are I(0)
COTTON	0 1	18.72* 7.18	25.90** 7.18	4	reject non-cointegration

The reported l *-max* and *Trace* values are obtained using small sample degrees of freedom correction (Reimers, 1992).
** Rejection of the null hypothesis at 1% significance level
* Rejection of the null hypothesis at 5% significance level

Table 2 Testing restrictions on the cointegrating vector

Test: β_0=0 and β_1=1 in cointegrating regression		
Commodity	$\chi^2(2)$	*p*-value
CORN	21.723	0.0000
WHEAT	6.3279	0.0423
COCOA	22.558	0.0000
COFFEE	12.092	0.0024
COTTON	12.343	0.0021
Test: β_1=1 in cointegrating regression		
Commodity	$\chi^2(1)$	*p*-value
CORN	1.0031	0.3166
WHEAT	0.4364	0.5089
COCOA	27.629	0.0000
COFFEE	4.549	0.0356
COTTON	1.4425	0.2328

Table 3 OLS Regression (2)

	CORN	WHEAT	COCOA	COFFEE	COTTON
θ_0	-0.048 *(-4.022)*	-0.024 *(-2.132)*	0.008 *(0.246)*	0.003 *(0.175)*	-0.023 *(-1.698)*
θ_1	1.192 *(5.523)*	0.873 *(4.452)*	0.036 *(0.133)*	0.054 *(0.343)*	0.681 *(3.530)*
λ_1	0.282 *(1.998)*	0.032 *(0.260)*	0.659 *(2.266)*	0.332 *(1.153)*	0.330 *(1.761)*
λ_2	0.090 *(0.618)*	0.361 *(2.877)*	-0.297 *(-1.082)*	-0.266 *(-0.906)*	-0.019 *(-0.098)*
λ_3	-0.338 *(-2.356)*	-0.079 *(-0.635)*	-0.173 *(-0.634)*	0.045 *(0.156)*	-0.018 *(-0.093)*
λ_4	0.062 *(0.459)*	-0.044 *(-0.338)*	0.156 *(0.601)*	0.209 *(0.735)*	-0.089 *(-0.480)*
λ_5	0.158 *(1.148)*	0.043 *(0.334)*	-0.461 *(-1.805)*	0.204 *(0.739)*	-0.072 *(-0.375)*
λ_6		0.009 *(0.067)*	-0.664 (-2.538)	-0.205 *(-0.745)*	0.201 *(1.081)*
λ_7		-0.387 *(-3.042)*	0.715 *(2.628)*	0.282 *(1.073)*	-0.395 *(-2.228)*
γ_1	-0.104 *(-0.575)*	0.086 *(0.589)*	-0.525 *(-2.098)*	-0.169 *(-0.579)*	-0.072 *(-0.411)*
γ_2	-0.001 *(-0.008)*	-0.501 *(-3.417)*	0.305 *(1.238)*	0.138 *(0.477)*	-0.188 *(-1.084)*
γ_3	0.442 *(2.467)*	0.109 *(0.723)*	-0.027 *(-0.111)*	0.003 *(0.012)*	0.110 *(0.646)*
γ_4	0.157 *(0.898)*	0.339 *(2.232)*	0.120 *(0.532)*	-0.118 *(-0.428)*	0.202 *(1.192)*
γ_5	-0.476 *(-2.662)*	0.191 *(1.263)*	0.330 *(1.501)*	-0.167 *(-0.635)*	-0.095 *(-0.546)*
γ_6		0.048 *(0.337)*	0.406 *(1.837)*	0.035 *(0.133)*	-0.136 *(-0.792)*
γ_7		0.148 *(1.033)*	-0.634 *(-2.790)*	-0.481 *(-1.914)*	0.224 *(1.321)*
				ARCH [0.0196]	
				Norm. [0.0000]	Norm. [0.0043]
Obs.	89	75	68	88	88
Variables	12	16	16	16	16
RSS	0.6012653	0.4308150	0.3000796	1.5841092	0.4581157

t-statistics are reported in parenthesis

Table 4 Joint test of zero restrictions on the coefficients of lagged variables in short-run regressions

Commodity	F test	*p*-value
CORN	F(10,77) = 2.1016	0.0342
WHEAT	F(14,59) = 2.0560	0.0283
COCOA	F(14,52) = 2.9893	0.0021
COFFEE	F(14,72) = 1.2981	0.2301
COTTON	F(14,72) = 1.1617	0.3230

Table 5 OLS Regression for $s_t - s_{t-\tau} = \theta_0 + \theta_1 \left(f_{t-\tau} - s_{t-\tau} \right) + \varepsilon_t$

Commodity	θ_0	θ_1	*p*-value for θ_1=1	*p*-norm.	*p*-autoc.	*p*-ARCH	*p*-heter.	*p*-RESET
CORN	-0.044 *(-3.750)*	1.1391 *(5.847)*	0.47					
WHEAT	-0.020 *(-1.986)*	0.867 *(5.162)*	0.43	0.0010				
COCOA	-0.003 *(-0.113)*	-0.021 *(-0.131)*	0.00	0.0023				
COFFEE	-0.009 *(-0.574)*	0.126 *(0.896)*	0.00	0.0000		0.0000		
COTTON	-0.033 *(-2.806)*	0.869 *(5.268)*	0.43		0.0176		0.0038	0.0062

t-statistics are reported in parenthesis;

Table 6 Testing for market efficiency in short run regression (2)

COMMODITY	$\theta_0=0$	$\theta_1=1$	$\theta_0=0;\ \theta_1=1$
CORN	16.176 [0.0001]	0.794 [0.3729]	20.518 [0.0000]
WHEAT	4.546 [0.0330]	0.422 [0.5158]	5.447 [0.0656]
COCOA	0.0604 [0.8058]	12.587 [0.0004]	59.049 [0.0000]
COFFEE	0.031 [0.8607]	36.477 [0.0000]	41.785 [0.0000]
COTTON	2.8817 [0.0896]	2.7348 [0.0982]	24.296 [0.0000]

Table 7 Efficiency Measures for 56 days forecast horizon

	CORN	WHEAT	COCOA	COFFEE	COTTON
ϕ_c	0.892	0.839	0.493	0.685	0.979
Degree of Ineff.	0.108	0.161	0.507	0.315	0.021
$\overline{R}_1^2$	0.357	0.377	0.287	0.042	0.244
$\overline{R}_2^2$	0.279	0.258	-0.445	-0.400	0.227

CORN_CBOT

Table 1A OLS Regressions for Model 1 and Model 2

CORN	Model 1	Model 2	Model 1a	Model 2a
θ_0	-0.048 *(-4.022)*	-0.028 *(-0.730)*	-0.036 *(-3.423)*	0.001 *(0.043)*
θ_1	1.192 *(5.523)*	0.739 *(1.455)*	0.891 *(5.002)*	0.632 *(2.049)*
λ_1	0.282 *(1.998)*	0.169 *(0.771)*		
λ_2	0.090 *(0.618)*	0.150 *(0.481)*		
λ_3	-0.338 *(-2.356)*	-0.376 *(-0.791)*		
λ_4	0.062 *(0.459)*	0.611 *(0.631)*		
λ_5	0.158 *(1.148)*	0.404 *(0.905)*		
γ_1	-0.104 *(-0.575)*	-0.116 *(-0.423)*		
γ_2	-0.001 *(-0.008)*	-0.219 *(-0.607)*		
γ_3	0.442 *(2.467)*	0.309 *(0.653)*		
γ_4	0.157 *(0.898)*	-0.433 *(-0.481)*		
γ_5	-0.476 *(-2.662)*	-0.290 *(-0.635)*		
δ_0		-0.027 *(-0.620)*		-0.048 *(-1.888)*
δ_1		-0.099 *(-0.151)*		0.118 *(0.299)*
α_1		0.833 *(1.706)*		
α_2		0.103 *(0.195)*		
α_3		-0.053 *(-0.104)*		
α_4		-0.645 *(-0.659)*		
α_5		-0.368 *(-0.772)*		
β_1		-0.610 *(-1.200)*		
β_2		0.137 *(0.246)*		
β_3		0.290 *(0.548)*		
β_4		0.755 *(0.820)*		
β_5		-0.206 *(-0.403)*		
d34			-0.267 *(-3.128)*	-0.275 *(-3.152)*
d43			0.322 *(4.015)*	0.343 *(4.311)*
dd82			0.208 *(3.708)*	0.208 *(3.783)*
Obs.	89	89	93	93
Variables	12	24	5	7
RSS	0.6012653	0.4996127	0.556436	0.522478
H_0: $\delta_0=\delta_1=\alpha_1=\alpha_2=\alpha_3=\alpha_4=\alpha_5=\beta_1=\beta_2=\beta_3=\beta_4=\beta_5=0$ $F(12,65) = 1.1021$ [0.3738]				
F test for testing the equality of the estimated error variances for Model 1 and Model 2: $F(77,65) = 1.01591$ [0.47636]			F test for testing the equality of the estimated error variances for Model 1a and Model 2a: $F(88,86) = 1.04079$ [0.42659]	

t-statistics are reported in parenthesis

Table 2A Testing for Market Efficiency

CORN	$q_0=0$	$q_1=1$	$q_0=0;\ q_1=1$	$q_0+d_0=0$	$q_1+d_1=1$	$q_0+d_0=0;$ $q_1+d_1=1$
Model 1 (lags=5)	16.176 [0.0001]	0.794 [0.3729]	20.518 [0.0000]			
Model 2 (lags=5)				7.779 [0.0053]	0.772 [0.3797]	12.893 [0.0016]
Model 1a (lags=0)	11.714 [0.0006]	0.376 [0.5399]	23.764 [0.0000]			
Model 2a (lags=0)				16.397 [0.0001]	1.0432 [0.3071]	26.195 [0.0000]

Table 3A CORN OLS regression *by regime*

CORN	Regime 1	Regime 2	Regime 1a	Regime 1b	Regime 1d	Regime 2d
	(May, July, September)	(March, December)	(May, July, September)	(May, July, September)	(May, July, September)	(March, December)
θ_0	-0.065 *(-3.541)*	-0.045 *(-1.044)*	-0.070 *(-3.415)*	-0.055 *(-3.598)*	-0.048 *(-3.733)*	-0.015 *(-0.816)*
θ_1	1.346 *(3.791)*	0.629 *(1.968)*	1.391 *(3.432)*	1.224 *(4.063)*	0.743 *(2.744)*	0.956 *(3.440)*
λ_1	-0.281 *(-1.222)*	0.097 *(0.300)*	-0.376 *(-1.343)*			
λ_2	0.178 *(0.828)*	0.656 *(2.199)*	0.356 *(1.188)*			
λ_3	0.055 *(0.281)*	-0.008 *(-0.025)*	-0.044 *(-0.151)*			
λ_4		-0.260 *(-0.784)*	0.110 *(0.428)*			
λ_5		0.775 *(2.289)*	-0.275 *(-1.247)*			
γ_1	0.378 *(1.364)*	-0.152 *(-0.487)*	0.514 *(1.474)*			
γ_2	-0.016 *(-0.061)*	-0.670 *(-2.337)*	-0.199 *(-0.565)*			
γ_3	-0.405 *(-1.637)*	-0.075 *(-0.228)*	-0.362 *(-1.141)*			
γ_4		0.012 *(0.038)*	0.003 *(0.011)*			
γ_5		-0.494*(-1.571)*	0.266 *(0.984)*			
d21					-0.274 *(-2.845)*	
d26					0.345 *(3.916)*	
dd49					0.208 *(3.420)*	
d14						-0.146 *(-2.095)*
dd28						0.090 *(2.381)*
dd35						0.106 *(2.841)*
Obs.	54	32	52	57	56	36
Variables	8	12	12	2	5	5
RSS	0.5325995	0.0728981	0.5058993	0.6364721	0.379134	0.084927
F test for testing the equality of the estimated error variances for Regime 1 and Regime 2: F(46,20) = 3.17656 [0.00333]						
F test for testing the equality of the estimated error variances for Regime 1a and Regime 2: F(40,20) =3.46991 [0.00205]						
F test for testing the equality of the estimated error variances for Regime 1b and Regime 2: F(55,20) =3.17482 [0.00301]						
F test for testing the equality of the estimated error variances for Regime 1d and Regime 2d: F(51,31) = 2.418528 [0.00509]						

t-statistics are reported in parenthesis

Table 4A OLS Regression for $s_t - s_{t-\tau} = \theta_0 + \theta_1 \left(f_{t-\tau} - s_{t-\tau} \right) + \varepsilon_t$

CORN	θ_0	θ_1	*p*-value	*p*-heteros.
Regime 1	-0.055 *(-3.598)*	1.224 *(4.063)*	0.4577	--
Regime 2	0.001 *(0.031)*	0.630 *(2.532)*	0.1366	[0.0377]

t-statistics are reported in parenthesis; *p*-value refers to the hypothesis θ_1=1

Table 5A Efficiency Measures for 56 days forecast horizon

CORN	Model 1 *(lags=5)*	Model 2 *(lags=5)*
ϕ_c	0.892	0.878
Degree of Ineff.	0.108	0.122
$\bar{R}_1^2$	0.357	0.367
$\bar{R}_2^2$	0.279	0.279

CORN	Regime 1 *(lags=5)*	Regime 2 *(lags=5)*	Combined Regimes	Regime 1 *(lags=3)*	Regime 2 *(lags=5)*	Combined Regimes	Regime 1 *(lags=0)*	Regime 2 *(lags=5)*	Combined Regimes
ϕ_c	1.082	0.882	1.046	1.026	0.882	1.000	1.008	0.882	0.987
Degree of Ineff.	-0.082	0.118	-0.046	-0.026	0.118	0.000	-0.008	0.118	0.013
$\bar{R}_1^2$	0.167	0.278	0.186	0.210	0.278	0.222	0.217	0.278	0.238
$\bar{R}_2^2$	0.230	0.182	0.222	0.230	0.182	0.222	0.223	0.182	0.228

Table 6A Unit root tests for CORN series

Entire sample (94 obs.)							
	lags	sample		t-adf	c.v.	dummies	diagnostics
s_t	1	3-94	const.	-3.00	-2.893		ARCH [0.0157]
s_t	1	3-80	const.	-2.64	-2.899		norm. [0.0093]
s_t-adj.	1	3-94	const.	-2.74	-2.893		
s_t	3	5-94	const.	-2.69		D	
s_t	1	3-94	const.	-2.98		D, d33, d34, d43, d70, dd82	
f_t	4	6-94	const.	-3.44	-2.893		
f_t	4	6-80	const.	-3.00	-2.899		
f_t-adj.	4	6-94	const.	-3.25	-2.893		
f_t	4	6-94	const.	-3.10		D	
f_t	1	3-94	const.	-2.00		D, d33, d34, d43, d70, dd82, d84, dd85	
$s_{t-\tau}$	1	3-94	const.	-3.42	-2.893		
$s_{t-\tau}$	1	3-80	const.	-2.95	-2.899		
$s_{t-\tau}$-adj.	5	3-94	const.	-3.34	-2.893		
$s_{t-\tau}$	2	4-94	const.	-2.81		D (not signif.)	
$s_{t-\tau}$	1	3-94	const.	-3.95		dd15, d34, d35, dd83	heter. [0.0194]
$f_{t-\tau}$	1	3-94	const.	-3.07	-2.893		heter. [0.0304]
$f_{t-\tau}$	1	3-80	const.	-2.56	-2.899		norm. [0.0329]
$f_{t-\tau}$-adj.	0	3-94	const.	-2.49	-2.893		
$f_{t-\tau}$	4	6-94	const.	-3.08		D (not signif.)	
$f_{t-\tau}$	1	3-94	const.	-3.30		dd15, d34, d44, d74, dd83	
s_t-$s_{t-\tau}$	0	2-94	const.	-7.43	-2.893		ARCH [0.0294], norm. [0.0008]
s_t-$s_{t-\tau}$	0	2-94	const.	-9.58		D, d34, d43	
f_t-$f_{t-\tau}$	0	2-94	const.	-8.08	-2.893		norm. [0.0016]
f_t-$f_{t-\tau}$	0	2-94	const.	-9.89		d43, d82	
$f_{t-\tau}$-$s_{t-\tau}$	4	2-94	const.	-2.748	-2.893		norm. [0.0000], RESET [0.0035]
$f_{t-\tau}$-$s_{t-\tau}$	4	2-94	const	-4.002		D, d34, d35, d84	

Table 7A Unit root tests for CORN_CBOT series *by regime*

Regime1 (57 obs.)						
	lags		t-adf	c.v.	dummies	diagnostics
s_t	0	const.	-2.524	-2.914		norm [0.0006]
s_t	0	const.	-3.223		d21	
f_t	1	const.	-2.865	-2.915		norm [0.0001]
f_t	1	const.	-3.916		d49	
$s_{t-\tau}$	1	const.	-3.196	-2.915		RESET [0.0389]
$f_{t-\tau}$	0	const.	-2.477	-2.914		
s_t-$s_{t-\tau}$	0	const.	-6.050	-2.914		norm [0.0074]
s_t-$s_{t-\tau}$	0	const.	-8.270		d21, d26	
f_t-$f_{t-\tau}$	0	const.	-6.515	-2.914		norm. [0.0182]
f_t-$f_{t-\tau}$	0	const.	-8.334		d26, d49	
$f_{t-\tau}$-$s_{t-\tau}$	0	const.	-6.039	-2.914		norm. [0.0000],RESET [0.0024]
$f_{t-\tau}$-$s_{t-\tau}$	0	const.	-9.535		d21, d51	norm. [0.0343],RESET [0.0057]
Regime 2 (37 obs.)						
	lags		t-adf	c.v.	dummies	
s_t	0	const.	-2.979	-2.945		
f_t	0	const.	-3.021	-2.945		
$s_{t-\tau}$	0	const.	-3.191	-2.945		
$f_{t-\tau}$	0	const.	-2.897	-2.945		
s_t-$s_{t-\tau}$	0	const.	-6.670	-2.945		
f_t-$f_{t-\tau}$	0	const.	-6.231	-2.945		
$f_{t-\tau}$-$s_{t-\tau}$	0	const.	-5.963	-2.945		norm. [0.0000]
$f_{t-\tau}$-$s_{t-\tau}$	0	const.	-8.738		d6, d14, d30	norm. [0.0120], autoc. [0.0324]

WHEAT_CBOT

Table 1B OLS Regression for Model 1 and Model 2

WHEAT	Model 1	Model 2
θ_0	-0.024 *(-2.132)*	0.059 *(1.606)*
θ_1	0.873 *(4.452)*	-0.004 *(-0.008)*
λ_1	0.032 *(0.260)*	-2.068 *(-2.735)*
λ_2	0.361 *(2.877)*	0.163 *(0.270)*
λ_3	-0.079 *(-0.635)*	0.035 *(0.198)*
λ_4	-0.044 *(-0.338)*	-0.161 *(-0.637)*
λ_5	0.043 *(0.334)*	-0.036 *(-0.096)*
λ_6	0.009 *(0.067)*	0.274 *(0.369)*
λ_7	-0.387 *(-3.042)*	-0.173 *(-0.422)*
γ_1	0.086 *(0.589)*	2.143 *(2.437)*
γ_2	-0.501 *(-3.417)*	-0.338 *(-0.563)*
γ_3	0.109 *(0.723)*	-0.259 *(-1.146)*
γ_4	0.339 *(2.232)*	0.028 *(0.111)*
γ_5	0.191 *(1.263)*	-0.052 *(-0.169)*
γ_6	0.048 *(0.337)*	0.303 *(0.495)*
γ_7	0.148 *(1.033)*	-0.077 *(-0.220)*
δ_0		-0.125 *(-3.059)*
δ_1		1.405 *(2.632)*
α_1		2.253 *(2.941)*
α_2		0.271 *(0.439)*
α_3		-0.152 *(-0.436)*
α_4		0.789 *(1.738)*
α_5		-0.407 *(-0.980)*
α_6		-0.437 *(-0.574)*
α_7		-0.049 *(-0.109)*
β_1		-2.050 *(-2.293)*
β_2		0.008 *(0.013)*
β_3		0.698 *(1.881)*
β_4		-0.174 *(-0.396)*
β_5		0.501 *(1.399)*
β_6		-0.287 *(-0.457)*
β_7		0.144 *(0.371)*
Obs.	75	75
Variables	16	32
RSS	0.4308150	0.2110500
H_0: $\delta_0=\delta_1=\alpha_1=\alpha_2=\alpha_3=\alpha_4=\alpha_5=\alpha_5=\alpha_6=\alpha_7=$ $\beta_1=\beta_2=\beta_3=\beta_4=\beta_5=\beta_6=\beta_7=0$ F(16,43) = 2.7985 [0.0037]		
F test for testing the equality of the estimated error variances for Model 1 and Model 2: F(59,43) = 1.48772 [0.0868]		

t-statistics are reported in parenthesis

Table 2B Testing for Market Efficiency

WHEAT	$q_0=0$	$q_1=1$	$q_0=0$; $q_1=1$	$q_0+d_0=0$	$q_1+d_1=1$	$q_0+d_0=0$; $q_1+d_1=1$
Model 1 (lags=7)	4.546 [0.0330]	0.422 [0.5158]	5.447 [0.0656]			
Model 2 (lags=7)				13.17 [0.0003]	2.591 [0.1075]	13.512 [0.0012]

Table 3B OLS regression *by regime*

WHEAT	Regime 1	Regime 2	Regime 1a	Regime 2a
	(May, July, September)	(March, December)	(May, July, September)	(March, December)
θ_0	-0.060 *(-3.901)*	0.034 *(2.724)*	-0.076 *(-3.728)*	0.051 *(1.268)*
θ_1	1.333 *(5.832)*	0.471 *(2.360)*	1.256 *(4.800)*	0.321 *(1.040)*
λ_1	0.169 *(1.327)*	-0.499 *(-2.724)*	0.126 *(0.934)*	-0.368 *(-0.974)*
λ_2	0.191 *(1.552)*		0.175 *(1.253)*	0.158 *(0.407)*
λ_3	-0.486 *(-3.514)*		-0.475 *(-2.918)*	-0.063 *(-0.173)*
λ_4	0.065 *(0.503)*		0.042 *(0.262)*	0.431 *(1.289)*
λ_5	-0.244 *(-1.905)*		-0.255 *(-1.595)*	-0.080 *(-0.178)*
λ_6			-0.065 *(-0.416)*	-0.292 *(-0.693)*
λ_7			-0.231 *(-1.384)*	0.109 *(0.270)*
γ_1	0.118 *(0.685)*	0.187 *(1.205)*	-0.012 *(-0.056)*	0.032 *(0.121)*
γ_2	0.212 *(1.247)*		0.163 *(0.792)*	-0.301 *(-1.110)*
γ_3	0.383 *(2.401)*		0.463 *(2.256)*	-0.194 *(-0.690)*
γ_4	-0.156 *(-1.008)*		-0.202 *(-1.012)*	-0.361 *(-1.418)*
γ_5	0.398 *(2.460)*		0.445 *(2.477)*	-0.239 *(-0.634)*
γ_6			0.136 *(0.660)*	-0.124 *(-0.319)*
γ_7			0.098 *(0.461)*	-0.059 *(-0.161)*
Obs.	45	31	43	25
Variables	12	4	16	16
RSS	0.1973118	0.1074777	0.1765280	0.0587480
F test for testing the equality of the estimated error variances for Regime 1 and Regime 2: F(33,27) = 1.50204 [0.14095]			F test for testing the equality of the estimated error variances for Regime 1a and Regime 2a: F(27,9) = 1.001611 [0.53531]	

t-statistics are reported in parenthesis

Table 4B OLS Regression for $s_t - s_{t-t} = q_0 + q_1\left(f_{t-t} - s_{t-t}\right) + e_t$

WHEAT	θ_0	θ_1	*p*-value	*p*-Autoc.
Regime 1	-0.048 *(-3.604)*	1.068 *(4.922)*	0.7531	0.0415
Regime 2	0.023 *(1.914)*	0.536 *(2.606)*	0.0242	--

t-statistics are reported in parenthesis; *p*-value refers to the hypothesis $\theta_1=1$

Table 5B Efficiency Measures for 56 days forecast horizon

WHEAT	Model 1 *(lags=7)*	Model 2 *(lags=7)*	Regime 1 *(lags=7)*	Regime 2 *(lags=7)*	Combined Regimes	Regime 1 *(lags=5)*	Regime 2 *(lags=1)*	Combined Regimes
ϕ_c	0.839	0.564	0.682	1.037	0.780	0.651	0.728	0.673
Degree of Ineff.	0.161	0.436	0.318	-0.037	0.220	0.349	0.272	0.327
$\overline{R}_1^2$	0.377	0.581	0.562	-0.027	0.445	0.581	0.277	0.517
$\overline{R}_2^2$	0.258	0.258	0.358	0.010	0.289	0.356	0.008	0.283

Table 6B Unit root tests for WHEAT_CBOT series

Entire sample (82 obs.)							
	lags	sample		t-adf	c.v.	dummies	diagnostics
s_t	5	7-82	const.	-3.09	-2.900		
s_t	1	2-82	const.	-2.52	-2.898		
s_t-adj.	6	8-66	const.	-3.78	-2.900		
s_t	5	7-82	const.	-3.13	-2.900		
s_t	5	7-82	const.	-3.46		D	
f_t	4	6-82	const.	-2.90	-2.899		
f_t	4	6-66	const.	-2.82	-2.899		
f_t-adj.	4	6-82	const.	-2.94	-2.899		
f_t	4	6-82	const.	-3.05		D [0.09]	
$s_{t-\tau}$	5	7-82	const.	-3.04	-2.900		Norm. [0.0495]
$s_{t-\tau}$	6	8-66	const.	-4.60	-2.900		
$s_{t-\tau}$-adj.	6	8-82	const.	-3.65	-2.900		
$s_{t-\tau}$	4	6-82	const.	-2.24	-2.899		
$s_{t-\tau}$	0	7-82	const.	-2.46	-2.897	D	
$f_{t-\tau}$	0	2-82	const.	-2.45	-2.897		
$f_{t-\tau}$	0	2-66	const.	-2.85	-2.897		
$f_{t-\tau}$-adj.	5	7-82	const.	-3.30	-2.900		
$f_{t-\tau}$-adj.	0	2-82	const.	-2.41	-2.897		
$f_{t-\tau}$	0	2-82	const.	-2.44		D	
s_t-$s_{t-\tau}$	3	5-82	const.	-3.80	-2.899		Norm. [0.0197]
s_t-$s_{t-\tau}$	3	5-82	const.	-3.56		D	
f_t-$f_{t-\tau}$	0	2-82	const.	-7.83	-2.897		
$f_{t-\tau}$-$s_{t-\tau}$	3	5-82	const.	-2.94	-2.899		Norm. {0.0032]
$f_{t-\tau}$-$s_{t-\tau}$	3	5-82	const.	-5.83		d20, d24, d48, d55, d82	Norm. [0.0218]

Table 7B Unit root tests for WHEAT_CBOT series *by regime*

Regime1 (50 obs.)						
	lags		t-adf	c.v.	dummies	diagnostics
s_t	2	const.	-2.982	-2.924		
f_t	3	const.	-3.514	-2.926		
$s_{t-\tau}$	3	const.	-3.308	-2.926		
$f_{t-\tau}$	2	const.	-2.894	-2.924		
$s_t-s_{t-\tau}$	0	const.	-6.218	-2.921		
$f_t-f_{t-\tau}$	0	const.	-6.492	-2.921		
$f_{t-\tau}-s_{t-\tau}$	2	const.	-2.523	-2.924		Norm. [0.0033]
$f_{t-\tau}-s_{t-\tau}$	0	const.	-12.713		d12, d15, d24, d33, d50	
Regime 2 (32 obs.)						
	lags		t-adf	c.v.	dummies	
s_t	0	const.	-3.216	-2.959		Norm. [0.0291]
f_t	0	const.	-3.381	-2.959		Norm. [0.0488]
$s_{t-\tau}$	0	const.	-3.552	-2.959		
$f_{t-\tau}$	0	const.	-2.978	-2.959		
$s_t-s_{t-\tau}$	0	const.	-7.803	-2.959		
$f_t-f_{t-\tau}$	3	const.	-4.709	-2.971		
$f_{t-\tau}-s_{t-\tau}$	0	const.	-4.724	-2.959		Norm. [0.0000]
$f_{t-\tau}-s_{t-\tau}$	0	const.	-7.730		d10, d19	RESET [0.0416]

COCOA _CSCE

Table 1C OLS Regressions for Model1 and Model 2

COCOA	Model 1 (lags=7)	Model 2 (lags=7)	Model 1a (lags=4)	Model 2a (lags=4)	Model 1b (lags=4)	Model 2b (lags=4)
θ_0	0.008 *(0.246)*	-0.115 *(-1.525)*	0.023 *(0.730)*	-0.105 *(-1.650)*	0.001 *(0.052)*	-0.105 *(-2.194)*
θ_1	0.036 *(0.133)*	-0.839 *(-1.032)*	0.240 *(1.023)*	-0.715 *(-1.426)*	0.161 *(0.866)*	-0.715 *(-1.895)*
λ_1	0.659 *(2.266)*	0.360 *(0.348)*	0.685 *(2.524)*	0.130 *(0.199)*	0.734 *(3.455)*	0.130 *(0.265)*
λ_2	-0.297 *(-1.082)*	-1.245 *(-1.499)*	-0.170 *(-0.601)*	-1.068 *(-1.841)*	-0.168 *(-0.762)*	-1.068 *(-2.448)*
λ_3	-0.173 *(-0.634)*	0.010 *(0.013)*	0.086 *(0.322)*	0.306 *(0.502)*	0.210 *(1.003)*	*0.306 (0.667)*
λ_4	0.156 *(0.601)*	-0.147 *(-0.228)*	0.248 *(0.958)*	-0.233 *(-0.642)*	0.191 *(0.943)*	-0.233 *(-0.853)*
λ_5	-0.461 *(-1.805)*	-1.226 *(-1.227)*				
λ_6	-0.664 (-2.538)	0.701 *(0.628)*				
λ_7	0.715 *(2.628)*	-0.556 *(-0.705)*				
γ_1	-0.525 *(-2.098)*	0.393 *(0.411)*	-0.595 *(-2.450)*	0.393 *(0.641)*	-0.692 *(-3.640)*	0.393 *(0.852)*
γ_2	0.305 *(1.238)*	1.237 *(1.710)*	0.008 *(0.030)*	1.002 *(1.873)*	0.073 *(0.366)*	1.002 *(2.490)*
γ_3	-0.027 *(-0.111)*	0.312 *(0.425)*	-0.189 *(-0.805)*	-0.168 *(-0.300)*	-0.179 *(-0.974)*	-0.168 *(-0.399)*
γ_4	0.120 *(0.532)*	0.287 *(0.532)*	-0.054 *(-0.236)*	0.252 *(0.789)*	0.0145 *(0.082)*	0.252 *(1.048)*
γ_5	0.330 *(1.501)*	0.657 *(1.036)*				
γ_6	0.406 *(1.837)*	-0.361 *(-0.445)*				
γ_7	-0.634 *(-2.790)*	0.280 *(0.394)*				
δ_0		0.150 *(1.671)*		0.209 *(2.658)*		0.149 *(2.424)*
δ_1		0.778 *(0.844)*		1.654 *(2.723)*		1.333 *(2.836)*
α_1		-0.093 *(-0.083)*		0.434 *(0.587)*		0.639 *(1.145)*
α_2		0.904 *(0.915)*		1.992 *(2.646)*		1.703 *(2.982)*
α_3		-0.667 *(-0.761)*		-0.612 *(-0.878)*		-0.260 *(-0.491)*
α_4		0.289 *(0.322)*		1.721 *(2.651)*		1.380 *(2.775)*
α_5		-0.074 *(-0.069)*				
α_6		-1.475 *(-1.274)*				
α_7		1.509 *(1.719)*				
β_1		-0.598 *(-0.588)*		-0.971 *(-1.429)*		-1.211*(-2.362)*
β_2		-0.937 *(-1.102)*		-1.804 *(-2.699)*		-1.545 *(-3.055)*
β_3		0.048 *(0.059)*		-0.066 *(-0.107)*		-0.071 *(-0.153)*
β_4		-0.087 *(-0.115)*		-1.146 *(-2.084)*		-0.875 *(-2.091)*
β_5		0.433 *(0.594)*				
β_6		0.817 *(0.957)*				
β_7		-1.219 *(-1.566)*				
			Autoc. [0.0020]			
			Norm. [0.0040]			
d32					0.366 *(5.146)*	0.325 *(4.632)*
d3839					-0.145 *(-3.002)*	-0.145 *(-3.338)*
d49					0.165 *(2.367)*	0.171 *(2.620)*
d62					0.146 *(2.130)*	0.158 *(2.562)*
Obs.	68	68	71	71	71	71
Var.	16	32	10	20	14	24
RSS	0.3000796	0.1691769	0.4577099	0.3218674	0.2596999	0.1678264

H_0: $\delta_0=\delta_1=\alpha_1=\alpha_2=\alpha_3=\alpha_4=\alpha_5=\alpha_6=\alpha_7=\beta_1=\beta_2=\beta_3=\beta_4=\beta_5=\beta_6=\beta_7=0$ F(16,36) = 1.741[0.0829]	H_0: $\delta_0=\delta_1=\alpha_1=\alpha_2=\alpha_3=\alpha_4=\beta_1=\beta_2=\beta_3=\beta_4=0$ F(10,51) = 2.1524 [0.0366]	H_0:$\delta_0=\delta_1=\alpha_1=\alpha_2=\alpha_3=\alpha_4=\beta_1=\beta_2=\beta_3=\beta_4=0$ F(10,47) = 2.5729[0.0143]
F test for testing the equality of the estimated error variances for Model 1 and Model 2: F(52,36) = 1.2280 [0.2602]	F test for testing the equality of the estimated error variances for Model 1a and Model 2a: F(61,51) = 1.1889 [0.2637]	F test for testing the equality of the estimated error variances for Model 1b and Model 2b: F(57,47) = 1.2759 [0.1957]

t-statistics are reported in parenthesis;
F test for testing the equality of the estimated error variances for Model 1 and Model 1a: F(61,52) = 1.3002 [0.1667]

Table 2C Joint test of zero restrictions on the coefficients of lagged variables in short-run regressions

COCOA	F test	*p*-value
Model 1 (lags=7)	$F(14,52) = 2.9893$	0.0021
Model 1a (lags=4)	$F(8,61) = 1.4748$	0.1852
Model 1b (lags=4)	$F(8,57) = 2.5366$	0.0195

Table 3C Testing for Market Efficiency

COCOA	$q_0=0$	$q_1=1$	$q_0=0;\ q_1=1$	$q_0+d_0=0$	$q_1+d_1=1$	$q_0+d_0=0;$ $q_1+d_1=1$
Model 1 (lags=7)	0.0604 [0.8058]	12.587 [0.0004]	59.049 [0.0000]			
Model 2 (lags=7)				0.5128 [0.4739]	5.9791 [0.0145]	39.611 [0.0000]
Model 1a (lags=4)	0.5323 [0.4656]	10.474 [0.0012]	82.541 [0.0000]			
Model 2a (lags=4)				5.0476 [0.0247]	0.0313 [0.8596]	31.696 [0.0000]
Model 1b (lags=4)	0.0027 [0.9586]	20.397 [0.0000]	112.57 [0.0000]			
Model 2b (lags=4)				1.3125 [0.2519]	1.8504 [0.1737]	37.716 [0.0000]

Table 4C OLS regression (2) *by regime*

COCOA	Regime 1	Regime 2*a*	Regime 2*b*
	(May, July, September)	(March, December)	(March, December)
θ_0	0.009 *(0.179)*	-0.039 *(-1.249)*	-0.024 *(-1.067)*
θ_1	-0.950 *(-2.710)*	-0.177 *(-1.008)*	-0.100 *(-0.794)*
λ_1	-1.521 *(-4.431)*	0.267 *(0.849)*	0.291 *(1.292)*
λ_2	-0.561 *(-1.220)*	-0.449 *(-1.410)*	-0.528 *(-2.321)*
λ_3	-1.005 *(-2.409)*		
λ_4	0.112 *(0.310)*		
λ_5	-0.322 *(-0.914)*		
λ_6	-0.287 *(-0.807)*		
λ_7	-0.828 *(-2.243)*		
λ_8	-0.838 *(-2.182)*		
λ_9	-0.239 *(-0.584)*		
λ_{10}	-0.992 *(-2.683)*		
γ_1	1.064 *(4.273)*	-0.160 *(-0.636)*	-0.081 *(-0.449)*
γ_2	0.372 *(1.115)*	0.480 *(1.875)*	0.487 *(2.678)*
γ_3	0.662 *(2.101)*		
γ_4	-0.539 *(-1.833)*		
γ_5	0.106 *(0.316)*		
γ_6	0.196 *(0.583)*		
γ_7	0.504 *(1.551)*		
γ_8	0.583 *(1.745)*		
γ_9	0.022 *(0.060)*		
γ_{10}	0.885 *(2.630)*		
d9			-0.153 *(-3.059)*
d20			0.126 *(2.448)*
d1617			0.107 *(3.035)*
Obs.	35	28	28
Variables	22	6	9
RSS	0.0472094	0.1027164	0.0443748

F test for testing the equality of the estimated error variances for Regime 1 and Regime 2*a*: $F(22,13) = 1.28568$ [0.32568]

F test for testing the equality of the estimated error variances for Regime 1 and Regime 2*b*: $F(13,19) = 1.5549$ [0.18565]

t-statistics are reported in parenthesis

Table 5C OLS Regression for $s_t - s_{t-\tau} = \theta_0 + \theta_1\left(f_{t-\tau} - s_{t-\tau}\right) + \varepsilon_t$

COCOA	θ_0	θ_1	*p*-value	*p*-autoc.	*p*-norm.
Regime 1	0.025 *(0.502)*	0.104 *(0.331)*	0.0045	0.0153	0.0498
Regime 2	-0.034 *(-1.241)*	-0.0121 *(-0.831)*	0.0000	--	--

t-statistics are reported in parenthesis; *p*-value refers to the hypothesis θ_1=1

Table 6C Efficiency Measures for 56 days forecast horizon

COCOA_CSCE	Model 1 *(lags=7)*	Model 2 *(lags=7)*	Model 1a *(lags=4)*	Model 2a *(lags=4)*	Model 1b *(lags=4)*	Model 2b *(lags=4)*
ϕ_c	0.493	0.402	0.629	0.529	0.382	0.299
Degree of Ineff.	0.507	0.598	0.371	0.471	0.618	0.701
$\overline{R}_1^2$	0.287	0.419	0.039	0.191	0.416	0.542
$\overline{R}_2^2$	-0.445	-0.445	-0.529	-0.529	-0.529	-0.529
COCOA_CSCE	Regime 1 *(lags=10)*	Regime 2a *(lags=2)*	Combined Regimes	Regime 1 *(lags=10)*	Regime 2b *(lags=2)*	Combined Regimes
ϕ_c	0.311	0.353	0.331	0.311	0.177	0.247
Degree of Ineff.	0.689	0.647	0.669	0.689	0.823	0.753
$\overline{R}_1^2$	0.675	-0.013	0.504	0.675	0.493	0.630
$\overline{R}_2^2$	-0.043	-1.869	-0.496	-0.043	-1.869	-0.496

Table 7C Unit root tests for COCOA_CSCE series

Entire sample (75 obs.)						
	lags		t-adf	c.v.	dummies	diagnostics
s_t	2	const.	-1.760	-2.902		
f_t	2	const.	-1.885	-2.902		
$s_{t-\tau}$	4	const.	-1.768	-2.903		
$f_{t-\tau}$	3	const.	-1.830	-2.902		
s_t-$s_{t-\tau}$	4	const.	-4.403	-2.903		Norm [0.0036]
s_t-$s_{t-\tau}$	3	const.	-4.024		d32	
f_t-$f_{t-\tau}$	0	const.	-9.410	-2.901		
$f_{t-\tau}$-$s_{t-\tau}$	2	const.	-2.785	-2.902		Norm [0.0000], RESET [0.0211]
$f_{t-\tau}$-$s_{t-\tau}$	1	const.	-3.376	-2.901	d25, d27, d32	
Regime 1 (45 obs.)						
	lags		t-adf	c.v.	dummies	diagnostics
s_t	1	const.	-1.613	-2.930		
f_t	4	const.	-1.805	-2.936		norm. [0.0255]
f_t	4	const.	-2.318		d22	
$s_{t-\tau}$	1	const.	-2.158	-2.930		
$f_{t-\tau}$	1	const.	-2.244	-2.930		
s_t-$s_{t-\tau}$	3	const.	-4.692	-2.934		
f_t-$f_{t-\tau}$	3	const.	-4.434	-2.934		RESET [0.0301]
f_t-$f_{t-\tau}$	5	const.	-3.183		d15, d16	
$f_{t-\tau}$-$s_{t-\tau}$	0	const.	-2.498	-2.929		
Regime 2 (30 obs.)						
	lags		t-adf	c.v.	dummies	
s_t	0	const.	-2.446	-2.996		Norm [0.0043]
s_t	6	const.	-1.875	-2.997		
f_t	1	const.	-1.865	-2.971		Norm [0.0449]
f_t	4	const.	-2.015	-2.985		
$s_{t-\tau}$	6	const.	-1.877	-2.997		Norm [0.0049]
$s_{t-\tau}$	6	const.	-1.239		d12	
$f_{t-\tau}$	6	const.	-1.960	-2.997		
s_t-$s_{t-\tau}$	0	const.	-5.117	-2.996		
f_t-$f_{t-\tau}$	0	const.	-5.358	-2.996		
$f_{t-\tau}$-$s_{t-\tau}$	0	const.	-2.996	-2.996		Norm [0.0000]
$f_{t-\tau}$-$s_{t-\tau}$	1	const.	-4.425		d10	RESET [0.0409]

COFFEE _CSCE

Table 1D OLS Regression for Model 1 and Model 2

COFFEE	Model 1 (lags=7)	Model 2 (lags=7)	Model 1a (lags=7)	Model 2a (lags=7)
θ_0	0.003 *(0.175)*	-0.020 *(-0.558)*	0.012 *(-1.045)*	-0.06 *(-3.247)*
θ_1	0.054 *(0.343)*	0.297 *(0.936)*	0.078 *(0.780)*	0.533 *(3.342)*
λ_1	0.332 *(1.153)*	-0.635 *(-1.280)*	-0.044 *(-0.236)*	-0.683 *(-2.836)*
λ_2	-0.266 *(-0.906)*	-0.107 *(-0.242)*	-0.205 *(-1.108)*	-0.408 *(-1.857)*
λ_3	0.045 *(0.156)*	-0.101 *(-0.155)*	0.087 *(0.478)*	0.282 *(0.875)*
λ_4	0.209 *(0.735)*	0.098 *(0.144)*	0.034 *(0.193)*	0.036 *(0.109)*
λ_5	0.204 *(0.739)*	0.655 *(1.092)*	0.344 *(1.983)*	1.012 *(3.418)*
λ_6	-0.205 *(-0.745)*	-0.249 *(-0.528)*	-0.129 *(-0.749)*	-0.357 *(-1.565)*
λ_7	0.282 *(1.073)*	-0.622 *(-1.478)*	0.006 *(0.034)*	-0.538 *(-2.648)*
γ_1	-0.169 *(-0.579)*	0.390 *(0.779)*	0.077 *(0.418)*	0.558 *(2.296)*
γ_2	0.138 *(0.477)*	0.046 *(0.099)*	0.091 *(0.490)*	0.279 *(1.205)*
γ_3	0.003 *(0.012)*	0.115 *(0.170)*	-0.013 *(-0.074)*	-0.286 *(-0.850)*
γ_4	-0.118 *(-0.428)*	-0.035 *(-0.064)*	-0.029 *(-0.170)*	0.078 *(0.296)*
γ_5	-0.167 *(-0.635)*	-0.847 *(-1.627)*	-0.323 *(-1.946)*	-1.170 *(-4.550)*
γ_6	0.035 *(0.133)*	-0.157 *(-0.347)*	0.009 *(0.054)*	0.170 *(0.750)*
γ_7	-0.481 *(-1.914)*	0.306 *(0.731)*	-0.195 *(-1.207)*	0.340 *(1.685)*
δ_0		0.029 *(0.658)*		0.057 *(2.488)*
δ_1		-0.380 *(-0.990)*		-0.650 *(-3.382)*
α_1		1.571 *(2.448)*		1.082 *(3.413)*
α_2		-0.167 *(-0.253)*		0.347 *(1.075)*
α_3		0.143 *(0.187)*		-0.069 *(-0.183)*
α_4		0.207 *(0.271)*		0.108 *(0.292)*
α_5		-0.534 *(-0.778)*		-0.853 *(-2.526)*
α_6		-0.213 *(-0.350)*		0.053 *(0.180)*
α_7		1.342 *(2.252)*		0.723 *(2.380)*
β_1		-1.099 *(-1.688)*		-0.876 *(-2.760)*
β_2		0.110 *(0.175)*		-0.284 *(-0.902)*
β_3		0.014 *(0.018)*		0.268 *(0.704)*
β_4		-0.099 *(-0.153)*		-0.157 *(-0.498)*
β_5		0.905 *(1.472)*		1.178 *(3.905)*
β_6		0.313 *(0.538)*		-0.110 *(-0.377)*
β_7		-1.180 *(-2.103)*		-0.701 *(-2.486)*
d30				0.328 *(4.283)*
d48			-0.462 *(-4.766)*	-0.485 *(-6.109)*
d73			0.535 *(7.141)*	0.456 *(7.064)*
d86			0.303 *(3.088)*	0.416 *(4.891)*
d8788			0.352 *(5.089)*	0.351*(6.058)*
	ARCH [0.0196]			
	Norm. [0.0000]	Norm. [0.0000]		
Obs.	88	88	88	88
Var.	16	32	20	37
RSS	1.5841092	1.2173887	0.5835920	0.2575798

H_0: $\delta_0=\delta_1=\alpha_1=\alpha_2=\alpha_3=\alpha_4=\alpha_5=\alpha_6=\alpha_7=\beta_1=\beta_2=\beta_3=\beta_4=\beta_5=\beta_6=\beta_7=0$ F(16,56) = 1.0543 [0.4183]	H_0: $\delta_0=\delta_1=\alpha_1=\alpha_2=\alpha_3=\alpha_4=\alpha_5=\alpha_6=\alpha_7=\beta_1=\beta_2=\beta_3=\beta_4=\beta_5=\beta_6=\beta_7=0$ F(16,51) = 3.2039 [0.0008]
F test for testing the equality of the estimated error variances for Model 1 and Model 2: F(72,56) = 1.0121 [0.4853]	F test for testing the equality of the estimated error variances for Model 1a and Model 2a: F(68,51) = 1.6993 [0.0246]

t-statistics are reported in parenthesis

F test for testing the equality of the estimated error variances for Model 1 and Model 1a: $F(72,68) = 2.5636$ [0.0001]

Table 2D Joint test of zero restrictions on the coefficients of lagged variables in short-run regressions

COFFEE	F test	*p*-value
Model 1 (lags=7)	$F(14,72) = 1.2981$	0.2301
Model 1a (lags=7)	$F(14,68) = 1.738$	0.0679

Table 3D Testing for Market Efficiency

COFFEE	$q_0=0$	$q_1=1$	$q_0=0$; $q_1=1$	$q_0+d_0=0$	$q_1+d_1=1$	$q_0+d_0=0$; $q_1+d_1=1$
Model 1 (lags=7)	0.031 [0.8607]	36.477 [0.0000]	41.785 [0.0000]			
Model 2 (lags=7)				0.1219 [0.7270]	25.15 [0.0000]	28.019 [0.0000]
Model 1a (lags=7)	1.0912 [0.2962]	84.563 [0.0000]	109.63 [0.0000]			
Model 2b (lags=7)				0.2009 [0.6540]	108.26 [0.0000]	131.86 [0.0000]

Table 4D OLS regression *by regime*

COFFEE	Regime 1	Regime 2*a*	Regime 2*b*
	(May, July, September)	(March, December)	(March, December)
θ_0	-0.003 *(-0.132)*	0.017 *(0.679)*	0.015 *(0.623)*
θ_1	0.122 *(0.610)*	0.117 *(0.509)*	0.078 *(0.357)*
λ_1	0.685 *(1.800)*	-0.403 *(-0.724)*	-0.325 *(-0.621)*
λ_2	0.155 *(0.424)*	0.628 *(1.123)*	0.726 *(1.498)*
λ_3	-0.057 *(-0.163)*	-1.278 *(-2.249)*	-0.817 *(-1.966)*
λ_4	-0.634 *(-1.917)*	0.745 *(1.232)*	
λ_5	1.015 *(2.818)*	-0.416 *(-0.763)*	
γ_1	-0.508 *(-1.264)*	0.444 *(0.847)*	0.268 *(0.592)*
γ_2	0.129 *(0.343)*	-0.944 *(-1.849)*	-0.830 *(-1.959)*
γ_3	0.176 *(0.498)*	0.942 *(1.857)*	0.534 *(1.415)*
γ_4	0.182 *(0.548)*	-0.746 *(-1.472)*	
γ_5	-0.938 *(-2.838)*	0.123 *(0.252)*	
	Norm. [0.0134]	ARCH [0.0173]	Norm. [0.0289]
			RESET [0.0444]
Obs.	52	33	35
Variables	12	12	8
RSS	0.9002787	0.3489797	0.4185770

F test for testing the equality of the estimated error variances for Regime 1 and Regime 2*a*: $F(40,21) = 1.3544$ [0.2309]

F test for testing the equality of the estimated error variances for Regime 1 and Regime 2*b*: $F(40,27) = 1.4518$ [0.1557]

t-statistics are reported in parenthesis

Table 5D OLS Regression for $s_t - s_{t-\tau} = \theta_0 + \theta_1 \left(f_{t-\tau} - s_{t-\tau} \right) + \varepsilon_t$

COFFEE	θ_0	θ_1	*p*-value	*p*-autoc.	*p*-heteros.
Regime 1	-0.018 *(-0.833)*	0.0968 *(0.493)*	0.0000	0.0208	0.0000
Regime 2	0.005 *(0.211)*	0.158 *(0.800)*	0.0000	--	--

t-statistics are reported in parenthesis; *p*-value refers to the hypothesis θ_1=1

Table 6D Efficiency Measures for 56 days forecast horizon

COFFEE_CSCE	Model 1 *(lags=7)*	Model 2 *(lags=7)*	Model 1a *(lags=7)*	Model 2a *(lags=7)*		
ϕ_c	0.685	0.677	0.267	0.157		
Degree of Ineff.	0.315	0.323	0.733	0.843		
$\bar{R}_1^2$	0.042	0.053	0.626	0.780		
$\bar{R}_2^2$	-0.400	-0.400	-0.400	-0.400		
COFFEE_CSCE	Regime 1 *(lags=5)*	Regime 2a *(lags=5)*	Combined Regimes	Regime 1 *(lags=5)*	Regime 2b *(lags=3)*	Combined Regimes
ϕ_c	0.593	0.631	0.605	0.593	0.619	0.601
Degree of Ineff.	0.407	0.369	0.395	0.407	0.381	0.399
$\bar{R}_1^2$	0.178	0.073	0.147	0.178	0.096	0.154
$\bar{R}_2^2$	-0.385	-0.468	-0.409	-0.385	-0.461	-0.407

Table 7D Unit root tests for COFFEE_CSCE series

Entire sample (95 obs.)						
	lags		t-adf	c.v.	dummies	diagnostics
s_t	6	const	-1.891	-2.894		norm. [0.0059]
s_t	2	const.	-1.116		d48, d65, d73, d8788	
f_t	0	const.	-2.803	-2.892		norm. [0.0026], ARCH [0.0237]
f_t	0	const.	-2.813		d73, d86	norm. [0.0264]
$s_{t-\tau}$	1	const.	-2.696	-2.893		norm [0.0000]
$s_{t-\tau}$	1	const.	-2.604		d31, d49, d73, d8889	norm. [0.0473]
$f_{t-\tau}$	1	const.	-3.042	-2.893		norm [0.0002], heter. [0.0315]
$f_{t-\tau}$	1	const.	-2.967		d31, d49, d73, d74, d8889	
s_t-$s_{t-\tau}$	5	const.	-4.080	-2.894		norm. [0.0001], ARCH [0.0142]
s_t-$s_{t-\tau}$	5	const.	-6.861		d48, d65, d73, d8788	norm. [0.0126]
f_t-$f_{t-\tau}$	6	const.	-5.323	-2.894		norm. [0.0001], ARCH [0.0252]
f_t-$f_{t-\tau}$	6	const.	-7.927		d30, d48, d73, d8788	
$f_{t-\tau}$-$s_{t-\tau}$	1	const.	-2.132	-2.893		RESET [0.0158]
Regime1 (57 obs.)						
	lags		t-adf	c.v.	dummies	diagnostics
s_t	0	const.	-2.345	-2.914		norm [0.0018], RESET [0.0387]
s_t	4	const.	-1.875		d19, d22, d44, d52	norm. [0.0254]
f_t	0	const.	-2.731	-2.914		norm [0.0005]
f_t	3	const.	-2.036		d19, d43, d44, d52	
$s_{t-\tau}$	2	const.	-2.469	-2.916		
$f_{t-\tau}$	6	const.	-1.630	-2.920		
s_t-$s_{t-\tau}$	3	const.	-3.906	-2.916		norm [0.0000], heter. [0.0292]
s_t-$s_{t-\tau}$	3	const.	-8.683		d29, d43, d44, d5253	
f_t-$f_{t-\tau}$	3	const.	-4.471	-2.916		norm [0.0001]
f_t-$f_{t-\tau}$	3	const.	-8.059		d29, d43, d44, d5253	
$f_{t-\tau}$-$s_{t-\tau}$	6	const.	-2.245	-2.920		
Regime 2 (38 obs.)						
	lags		t-adf	c.v.	dummies	
s_t	5	const.	-1.950	-2.956		
f_t	5	const.	-1.669	-2.956		
$s_{t-\tau}$	0	const.	-2.611	-2.942		norm. [0.0021]
$s_{t-\tau}$	3	const.	-0.692		d13, d20, d30	ARCH [0.0163]
$f_{t-\tau}$	0	const.	-2.719	-2.942		norm. [0.0009]
$f_{t-\tau}$	2	const.	-1.235		d13, d20, d30	sample 4-37
s_t-$s_{t-\tau}$	0	const.	-6.326	-2.942		
f_t-$f_{t-\tau}$	0	const.	-6.062	-2.942		
$f_{t-\tau}$-$s_{t-\tau}$	0	const.	-2.934	-2.942		norm. [0.0087]
$f_{t-\tau}$-$s_{t-\tau}$	0	const.	-3.694		d24	

COTTON_NYCE

Table 1E OLS Regression for Model 1 and Model 2

COTTON	Model 1 (lags=7)	Model 2 (lags=7)	Model 1a (lags=6)	Model 2a (lags=6)	Model 1b (lags=7)	Model 2b (lags=7)
θ_0	-0.023 *(-1.698)*	-0.030 *(-1.063)*	-0.033 *(-2.414)*	-0.040 *(-1.516)*	-0.009 *(-0.719)*	-0.002 *(-0.088)*
θ_1	0.681 *(3.530)*	1.192 *(3.830)*	0.797 *(4.232)*	1.377 (5.274)	0.324 *(1.715)*	0.467 *(1.241)*
λ_1	0.330*(1.761)*	-0.259 *(-0.468)*	0.273 *(1.452)*	-0.518 *(-1.047)*	0.429 *(2.628)*	0.258 *(0.486)*
λ_2	-0.019 *(-0.098)*	0.296 *(0.877)*	-0.087 *(-0.450)*	0.215 *(0.675)*	-0.106 *(-0.628)*	0.142 *(0.464)*
λ_3	-0.018 *(-0.093)*	-0.247 *(-0.387)*	0.064 *(0.338)*	0.062 *(0.111)*	-0.116 *(-0.705)*	-0.702 *(-1.155)*
λ_4	-0.089 *(-0.480)*	-0.726 *(-1.354)*	-0.102 *(-0.542)*	-0.453 *(-1.085)*	0.006 *(0.034)*	-0.603 *(-1.239)*
λ_5	-0.072 *(-0.375)*	-0.144 *(-0.437)*	0.009 *(0.048)*	-0.255 *(-0.882)*	0.020 *(0.121)*	0.154 *(0.502)*
λ_6	0.201 *(1.081)*	-0.530 *(-1.034)*	0.068 *(0.393)*	-0.707 *(-1.882)*	0.144 *(0.893)*	-0.322 *(-0.688)*
λ_7	-0.395 *(-2.228)*	-0.406 *(-1.145)*			-0.409 *(-2.664)*	-0.718 *(-2.173)*
γ_1	-0.072 *(-0.411)*	0.511 *(1.286)*	-0.028 *(-0.158)*	0.707 *(2.009)*	-0.178 *(-1.164)*	-0.052 *(-0.134)*
γ_2	-0.188 *(-1.084)*	-0.698*(-1.772)*	-0.100 *(-0.581)*	-0.483 *(-1.444)*	-0.175 *(-1.166)*	-0.653 *(-1.809)*
γ_3	0.110 *(0.646)*	0.395 *(0.861)*	0.054 *(0.315)*	0.146 *(0.373)*	0.258 *(1.711)*	0.814 *(1.890)*
γ_4	0.202 *(1.192)*	0.635 *(1.585)*	0.155 *(0.911)*	0.470 *(1.320)*	0.103 *(0.695)*	0.476 *(1.309)*
γ_5	-0.095 *(-0.546)*	0.228 *(0.720)*	-0.132 *(-0.757)*	0.229 *(0.756)*	-0.243 *(-1.589)*	-0.214 *(-0.695)*
γ_6	-0.136 *(-0.792)*	0.561 *(1.380)*	-0.051 *(-0.299)*	0.757 *(2.249)*	-0.087 *(-0.579)*	0.269 *(0.719)*
γ_7	0.224 *(1.321)*	0.489 *(1.121)*			0.182 *(1.236)*	0.721 *(1.812)*
δ_0		0.036 *(0.981)*		0.036 *(1.029)*		0.009 *(0.246)*
δ_1		-1.102 *(-2.345)*		-1.132 *(-2.710)*		-0.378 *(-0.767)*
α_1		0.606 *(1.016)*		0.878 *(1.633)*		0.089 *(0.157)*
α_2		-0.440 *(-0.855)*		-0.345 *(-0.700)*		-0.287 *(-0.616)*
α_3		0.287 *(0.419)*		-0.048 *(-0.080)*		0.741 *(1.148)*
α_4		0.774 *(1.322)*		0.519 *(1.090)*		0.651 *(1.228)*
α_5		-0.155 *(-0.322)*		0.129 *(0.297)*		-0.453 *(-1.032)*
α_6		0.986 *(1.724)*		1.004 *(2.287)*		0.779 *(1.493)*
α_7		0.348 *(0.698)*				0.661 *(1.446)*
β_1		-0.518 *(-1.058)*		-0.758 (-1.738)		0.045 *(0.096)*
β_2		0.484 *(0.969)*		0.324 *(0.726)*		0.439 *(0.965)*
β_3		-0.236 *(-0.459)*		0.019 *(0.041)*		-0.655 *(-1.367)*
β_4		-0.733 *(-1.588)*		-0.547 *(-1.332)*		-0.574 *(-1.372)*
β_5		-0.248 *(-0.598)*		-0.353 *(-0.886)*		0.194 *(0.496)*
β_6		-0.966 *(-2.000)*		-1.077 *(-2.563)*		-0.674 *(-1.525)*
β_7		-0.661 *(-1.223)*				-0.893 *(-1.820)*
d34					0.341 *(4.218)*	0.309 *(2.918)*
d76					0.218 *(2.914)*	0.235 *(2.513)*
	Norm. [0.0043]	RESET [0.031]	Autoc. [0.0339]	RESET [0.033]		
			Norm. [0.0229]			
Obs.	88	88	89	89	88	88
Var.	16	32	14	28	18	34
RSS	0.4581157	0.3487376	0.4937287	0.3734620	0.3327092	0.2727979

H_0: $\delta_0=\delta_1=\alpha_1=\alpha_2=\alpha_3=\alpha_4=\alpha_5=\alpha_6=\alpha_7=\beta_1=\beta_2=\beta_3=\beta_4=\beta_5=\beta_6=\beta_7=0$ F(16,56) = 1.0977 [0.3793]	H_0: $\delta_0=\delta_1=\alpha_1=\alpha_2=\alpha_3=\alpha_4=\alpha_5=\alpha_6=\beta_1=\beta_2=\beta_3=\beta_4=\beta_5=\beta_6=0$ F(14,61) = 1.4031 [0.1795]	H_0: $\delta_0=\delta_1=\alpha_1=\alpha_2=\alpha_3=\alpha_4=\alpha_5=\alpha_6=\alpha_7=\beta_1=\beta_2=\beta_3=\beta_4=\beta_5=\beta_6=\beta_7=0$ F(16,56) = 0.7412 [0.7403]
F test for testing the equality of the estimated error variances for Model 1 and Model 2: F(72,56) = 1.0217 [0.4704]	F test for testing the equality of the estimated error variances for Model 1a and Model 2a: F(75,61) = 1.0752 [0.3868]	F test for testing the equality of the estimated error variances for Model 1b and Model 2b: F(54,70) = 1.0629 [0.4019]

t-statistics are reported in parenthesis
F test for testing the equality of the estimated error variances for Model 1 and Model 1b: F(72,70) = 1.3387 [0.1112]

Table 2E Joint test of zero restrictions on the coefficients of lagged variables in short-run regressions

Commodity	F test	*p*-value
Model 1 (lags=7)	F(14,72) = 1.1617	0.3230
Model 1a (lags=6)	F(12,75) = 0.9003	0.5560
Model 1b (lags=7)	F(14,70) = 1.8669	0.0454

Table 3E Testing for Market Efficiency

COTTON	$q_0=0$	$q_1=1$	$q_0=0;\ q_1=1$	$q_0+d_0=0$	$q_1+d_1=1$	$q_0+d_0=0;\ q_1+d_1=1$
Model 1 (lags=7)	2.8817 [0.0896]	2.7348 [0.0982]	24.296 [0.0000]			
Model 2 (lags=7)				0.0692 [0.7925]	6.6824 [0.0097]	12.957 [0.0015]
Model 1a (lags=6)	5.829 [0.0158]	1.161 [0.2812]	24.998 [0.0000]			
Model 2b (lags=6)				0.0464 [0.8294]	5.3588 [0.0206]	15.782 [0.0004]
Model 1b (lags=7)	0.5163 [0.4724]	12.857 [0.0003]	46.576 [0.0000]			
Model 2b (lags=7)				0.0853 [0.7703]	8.2376 [0.0041]	15.972 [0.0003]

Table 4E OLS regression *by regime*

COTTON	Regime 1	Regime 2*a*	Regime 2*b*
	(May, July, December)	(March, October)	(March, October)
θ_0	0.044 *(1.435)*	-0.071 *(-1.155)*	-0.057 *(-2.760)*
θ_1	0.390 *(1.151)*	1.433 *(2.364)*	1.312 *(4.628)*
λ_1	-0.203 *(-0.552)*	0.478 *(0.840)*	0.260 *(1.141)*
λ_2	-0.558 *(-1.611)*	-0.934 *(-1.384)*	-0.211 *(-0.871)*
λ_3	-0.522 *(-1.490)*	-0.348 *(-0.496)*	-0.467 *(-2.054)*
λ_4	-0.670 *(-1.811)*	0.756 *(0.941)*	
λ_5	-0.694 *(-2.035)*	0.243 *(0.282)*	
λ_6	-0.655 *(-1.832)*	-0.389 *(-0.540)*	
λ_7	-0.439 *(-1.295)*	-0.129 *(-0.193)*	
λ_8	-0.268 *(-0.849)*	0.423 *(0.734)*	
λ_9	-0.706 *(-2.161)*	-0.316 *(-0.591)*	
γ_1	-0.031 *(-0.119)*	-0.163 *(-0.211)*	-0.066 *(-0.226)*
γ_2	0.239 *(0.905)*	1.003 *(1.116)*	0.126 *(0.426)*
γ_3	0.194 *(0.720)*	0.322 *(0.343)*	0.447 *(1.621)*
γ_4	0.300 *(1.089)*	-0.978 *(-1.143)*	
γ_5	0.397 *(1.563)*	0.106 *(0.123)*	
γ_6	0.529 *(2.063)*	0.155 *(0.202)*	
γ_7	0.084 *(0.327)*	0.181 *(0.257)*	
γ_8	-0.030 *(-0.109)*	-0.073 *(-0.101)*	
γ_9	0.387 *(1.392)*	0.897 *(1.171)*	
d31			0.230 *(2.916)*
			RESET [0.0211]
Obs.	48	29	35
Variables	20	20	9
RSS	0.1675366	0.1230408	0.1471186
F test for testing the equality of the estimated error variances for Regime 1 and Regime 2*a*: F(9,28) = 2.2848 [0.0456] F test for testing the equality of the estimated error variances for Regime 1 and Regime 2*b*: F(28,26) = 1.0574 [0.4448]			

t-statistics are reported in parenthesis

Table 5E OLS Regression for $s_t - s_{t-\tau} = \theta_0 + \theta_1\left(f_{t-\tau} - s_{t-\tau}\right) + \varepsilon_t$

COTTON	θ_0	θ_1	*p*-value	*p*-autoc.	*p*-heteros.	*p*-RESET
Regime 1	-0.018 *(-1.009)*	0.55261 *(2.047)*	0.0975	--	--	--
Regime 2	-0.040 *(-2.351)*	1.484 *(4.959)*	0.8189	0.0499	0.0031	0.0108

t-statistics are reported in parenthesis; *p*-value refers to the hypothesis θ_1=1

Table 6E Efficiency Measures for 56 days forecast horizon

COTTON	Model 1 *(lags=7)*	Model 2 *(lags=7)*	Model 1a *(lags=6)*	Model 2a *(lags=6)*	Model 1b *(lags=7)*	Model 2b *(lags=7)*
ϕ_c	0.979	0.958	1.018	0.947	0.731	0.777
Degree of Ineff.	0.021	0.042	-0.018	0.053	0.269	0.223
$\overline{R}_1^2$	0.244	0.260	0.211	0.267	0.435	0.399
$\overline{R}_2^2$	0.227	0.227	0.226	0.226	0.227	0.227
COTTON_NYCE	Regime 1 *(lags=9)*	Regime 2a *(lags=9)*	Combined Regimes	Regime 1 *(lags=9)*	Regime 2b *(lags=3)*	Combined Regimes
ϕ_c	0.960	1.863	1.336	0.960	0.843	0.908
Degree of Ineff.	0.040	-0.863	-0.336	0.040	0.157	0.092
$\overline{R}_1^2$	0.089	-0.040	0.019	0.089	0.504	0.321
$\overline{R}_2^2$	0.051	0442	0.265	0.051	0.412	0.253

Table 7E Unit root tests for COTTON_NYCE series

Entire sample (95 obs.)						
	lags		t-adf	c.v.	dummies	diagnostics
s_t	3	const.	-2.681	-2.893		norm. [0.0000]
s_t	3	const.	-3.992		D, d34, d76	
f_t	6	const.	-3.658	-2.894		norm. [0.0014]
f_t	6	const.	-4.181		d34	
$s_{t-\tau}$	4	const.	-2.830	-2.894		norm. [0.0000]
$s_{t-\tau}$	2	const.	-3.475		D, d34, d35, d76	heter. [0.0073]
$f_{t-\tau}$	0	const.	-4.005	-2.892		norm. [0.0000]
$f_{t-\tau}$	0	const.	-5.201		d34	norm. [0.0450]
s_t-$s_{t-\tau}$	6	const.	-4.491	-2.894		norm. [0.0000]
s_t-$s_{t-\tau}$	6	const.	-5.103		d34	
f_t-$f_{t-\tau}$	0	const.	-8.410	-2.892		norm. [0.0282]
f_t-$f_{t-\tau}$	0	const.	-8.876		d34	
$f_{t-\tau}$-$s_{t-\tau}$	4	const.	-2.371	-2.894		norm [0.0000], RESET [0.0331]
$f_{t-\tau}$-$s_{t-\tau}$	5	const.	-3.267		D, d34, d44, d79 d5960	heter. [0.0297]
Regime1 (57 obs.)						
	lags		t-adf	c.v.	dummies	diagnostics
s_t	5	const.	-2.719	-2.919		
f_t	0	const.	-3.960	-2.914		
$s_{t-\tau}$	7	const.	-1.927	-2.921		norm. [0.0001]
$s_{t-\tau}$	7	const.	-2.340		d21, d46	
$f_{t-\tau}$	7	const.	-2.184	-2.921		
s_t-$s_{t-\tau}$	0	const.	-7.958	-2.914		
f_t-$f_{t-\tau}$	0	const.	-8.158	-2.914		
$f_{t-\tau}$-$s_{t-\tau}$	2	const.	-2.392	-2.916		norm [0.0000]
$f_{t-\tau}$-$s_{t-\tau}$	2	const.	-2.518		d21	
Regime 2 (38 obs.)						
	lags		t-adf	c.v.	dummies	
s_t	7	const.	-1.295	-2.963		norm. [0.0231]
s_t	7	const.	-2.483		d14, d31	
f_t	4	const.	-2.572	-2.953		
$s_{t-\tau}$	4	const.	-2.251	-2.953		norm. [0.0000]
$s_{t-\tau}$	4	const.	-3.611		d14	
$f_{t-\tau}$	3	const.	-2.434	-2.950		norm. [0.0003]
$f_{t-\tau}$	0	const.	-5.659		d14, d31	
s_t-$s_{t-\tau}$	2	const.	-4.631	-2.947		norm. [0.0010]
s_t-$s_{t-\tau}$	2	const.	-7.368		d14, d31	
f_t-$f_{t-\tau}$	0	const.	-5.797	-2.942		norm. [0.0026]
f_t-$f_{t-\tau}$	1	const.	-6.448		d14, d31	
$f_{t-\tau}$-$s_{t-\tau}$	1	const.	-2.973	-2.945		norm. [0.0001]
$f_{t-\tau}$-$s_{t-\tau}$	1	const.	-4.139		d14, d32	norm. [0.0230]