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Testing seasonality and efficiency in commodity futures markets

by

Paul Newbold*
Tony Rayner*
Christine Ennew**
Emanuela Marrocu*

Abstract

Futures market efficiency has been one of the most researched topics for a number of years. The huge amount of results produced, highly dependent on the econometric techniques adopted and on the time period analysed, are often conflicting: for a given market, some authors find evidence of efficiency, others of inefficiency. Although some of the conclusions reached in the literature reflect genuine efficiency or inefficiency, some of them may reflect a lack of attention paid to the institutional aspects governing the functioning of futures markets and to the specific statistical characteristics of commodities time series price data, the most relevant of which, although not yet extensively investigated, are seasonality, overlapping data and unevenly spaced observations.

In this paper, we investigate thoroughly the effects of seasonality in testing efficiency over a range of commodities. An important question which is addressed is the extent to which strong and anticipated seasonal patterns can account for the inefficiency found in futures markets.

The efficiency testing procedure is carried out within a quasi-ECM model augmented with seasonal deterministic terms. At both short and long forecast horizons we find evidence that the seasonal terms are significant suggesting that the market inefficiencies are present since information about the seasonal pattern is not embodied in the basis and can be used by agents to predict future spot prices movements.

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*School of Economics, University of Nottingham, UK

**Nottingham Business School, University of Nottingham, UK

1. Introduction

Efficient futures markets provide a mechanism for managing the risk associated with the uncertainty of future events. The value of futures markets arises from their ability to predict the price of a given asset at a specified future date efficiently and without bias. Therefore, futures market efficiency is one of the most extensively researched topics in the empirical literature[1]. The huge amount of results produced are often conflicting: the efficiency hypothesis is supported only for certain markets and only over some periods. The rejections of the efficiency hypothesis have been interpreted as arguing that economic agents do not process rationally the information available and that the futures price is a biased predictor due to the presence of a constant or time-varying risk premium. It is worth stressing that the results produced so far are also highly dependent on the econometric techniques adopted.

Although some of the conclusions reached in the literature reflect genuine efficiency or inefficiency, some of them may reflect the lack of attention paid to the institutional aspects governing the functioning of futures markets and to the specific statistical characteristics of commodities time series price data, the most relevant of which, although not yet extensively investigated, are seasonality, overlapping data and unevenly spaced observations. In a previous paper (Newbold *et al*., 1999) we dealt with efficiency testing in the context of unevenly spaced contracts and we argued that failing to take into account this feature can lead to incorrect and inaccurate conclusions about efficiency and its related measures for the five markets analysed (corn, wheat, cocoa, coffee and cotton).

In this paper, we aim to investigate thoroughly the effects of seasonality in testing efficiency over a range of soft and hard commodities. An important question which is addressed is the extent to which strong and anticipated seasonal patterns can account for the inefficiency found in futures markets. As stated in Hylleberg (1992),

> *seasonality is the systematic, although not necessarily regular, intra-year movement caused by changes of the weather, the calendar and timing of decisions, directly or indirectly through the production and consumption decisions made by the agents of the economy. These decisions are influenced by the endowments, the expectations and the preferences of the agents, and the production techniques available in the economy.*

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[1] See, for example, Fama (1970, 1984), Malkiel (1992), Crowder and Hamed (1993), Krebiel and Adkins (1993), Beck (1994), Kellard *et al*. (1999)

As pointed out by Franses (1996), although seasonal variation can be deterministic because of weather or calendar effects, some seasonal fluctuations are the result of the economic agents behaviour and may therefore not be constant over time. For example, producers of commodities that are harvested seasonally smooth their output using inventories, which, in turn, will show a seasonal pattern. Thus, economic agents take into account the seasonality present in some variables when forming expectations for other variables. A change in their habits and utility functions may be mirrored in a changing seasonal pattern.

When seasonal effects are strong it is very likely that the contracts are unevenly spaced, but in order to disentangle the two effects, that is seasonality and unevenly spaced data *per se*, in this paper only time series sampled at regular intervals are examined. These are the futures and spot data for heating oil, live hogs, live cattle, soybeans and orange juice; all contract details are reported in Table A in the appendix. This paper is organised as follows: section 2 deals with estimation issues in testing market efficiency in the presence of seasonal effects and section 3 summarises the main findings and offers some concluding considerations.

2. Data and estimation

Since augmented Dickey-Fuller tests suggested that the series are characterised by an in-sample nonstationary behaviour, in order to avoid the spurious regression problem (Granger and Newbold, 1974) the efficiency testing procedure is carried out within the quasi-Error Correction Mechanism (ECM) framework as in Kellard *et al*. (1999),

Model 1

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

where s_t and f_t are the logarithms of spot and futures prices sampled on contract termination date, respectively; $s_{t-\tau}$ and $f_{t-\tau}$ are spot and futures prices sampled from a specific day less than a month for monthly contracts from the last trading day of the delivery month. Longer forecast horizons would cause autocorrelation problems because of informational overlap; autocorrelation, in turn, would lead to false rejections of the efficiency hypothesis even in efficient markets. The variables $s_{t\text{-}\tau}$ and $f_{t\text{-}\tau}$ are, therefore, selected by working backwards 28 days from the contract termination date for monthly contracts (heating oil) and also 56 days for two-monthly contracts (live hogs, live cattle, soybeans and orange juice).

The efficient market hypothesis requires that in (1) the constant term is not significantly different from zero and that the basis ($f_{t\text{-}\tau}$-$s_{t\text{-}\tau}$) coefficient is not significantly different from unity. The inclusion of lagged changes in spot and futures prices in (1) allows us to test whether additional information to the basis is optimally used in forecasting changes in the spot prices; thus, the statistical significance of such lags provides evidence of inefficiency. The lag order is selected through general-to-specific testing by initially setting k=12 and dropping lags that are not significant at the 5% level, but preserving the symmetry on the lag length for the change in spot and futures price.

In order to take into account the seasonal effects the above model (1) is augmented with seasonal dummies[2] (see box below) whose statistical significance can be considered an indication that the market is inefficient because information about the seasonal pattern is not embodied in the basis.

Model 2

$$s_t - s_{t-\tau} = \theta_0 + \theta_1\left(f_{t-\tau} - s_{t-\tau}\right) + \sum_{i=1}^{k}\lambda_i\left(s_{t-i} - s_{(t-\tau)-i}\right) + \sum_{i=1}^{k}\gamma_i\left(f_{t-i} - f_{(t-\tau)-i}\right) + \sum_{j=1}^{s-1}\delta_j D_{jt} + \upsilon_t \tag{2}$$

where j=1, 2,…,11 for heating oil contracts
and j=1,2,…,5 for live hogs, soybeans, live cattle and orange juice contracts.
j=1 refers to the first delivery month of the year; j=2 to the second delivery month and so on.

In the next paragraphs we discuss the results obtained for each commodity market separately.

[2] In empirical studies such as, for example, Miron (1996) and Franses (1996), it is found that seasonal dummy variables often can capture about 80% to 90% of the seasonal variation.

Heating Oil

Since the contracts have a monthly frequency, a 28 day forecast horizon could have been more appropriate, as mentioned above, but in that case we have for 32 termination prices[3] a problem of overlapping observations which, by inducing autocorrelation in the errors of (1) and (2), could lead to the finding of inefficiency even if the market is efficient. Thus, a 21 day forecast horizon is preferred. Data for heating oil futures and spot prices are graphed in fig.1 for the sample period January 1980 - May 1999. The series appear to be characterised by a large fall at the end of 1985 and by two peaks corresponding to the termination price of the 1989 December contract and 1990 September contract, when tight supply and unusual cold weather drove up crude and gas oil prices[4].

In order to avoid the undue influence of particular circumstances on the results, the analysis reported below is conducted for the subsample November 1990 - May 1999 (103 observations), when the data display a more regular behaviour.

Table 1A contains the results for the estimated models for the heating oil market. For comparison purposes we also report model 1 in the first column, where the efficiency tests are carried out by ignoring the seasonality issue. For this model, although the constant term is not significantly different from zero and no lags are necessary to account for the dynamic pattern of the change in the spot price, we have to reject the hypothesis that the basis coefficient is equal to unity (*p*-value=0.0019). Model 2 is the augmented version of the first model, the results suggesting that seven out of eleven seasonal terms are significant at the conventional 5% level and two (FEB, MAR) at 11%. As expected, the test for their joint exclusion from the estimated model generates a very low *p*-value of 0.0084. All dummies are positive and their average value is about 0.07. Since the November term is not significantly different from zero, in that month the seasonal pattern is not different from the December one, which represents the dummy base. For this model we can argue that the basis coefficient is equal to unity at a level of 5.5%.

[3] Of which 16 in the subsample.
[4] See Financial Times issues 5.12 1989 and 8.12.1989.

Table 1A contains also two alternative specifications, labelled model 3 and model 4. Model 3, as well as step seasonal dummies, includes also multiplicative seasonal terms which interact with the basis; the seasonal effects are now picked up by interactive terms and almost all step dummies are no longer significant. The two tests for the exclusion of each set of dummies suggest that they can be eliminated from the model; but their overall exclusion is not recommended on the grounds of the last test reported in Table 1A. Therefore, the results suggest that a seasonal pattern is indeed present, but in model 3 it is likely to have been overparemeterised. A more parsimonious specification alternative to model 2 is represented by model 4, which includes only multiplicative seasonal terms, all of which turn out to be significant and the unbiasedness hypothesis is generally not rejected. The only exceptions are related to the April and December contracts. According to the Schwarz (SC) and Hannan-Quinn (HQ) information criteria, apart from model 1 which ignores the seasonality issue, model 2 is the preferred model. As noticed before, the evidence provided by this model suggests that the seasonal pattern is dichotomous given that we can single out two groups of contracts showing similar features. The first consists of contracts from January to October and the second one is represented by November and December contracts. In order to achieve a parsimonious specification we model this feature of the heating oil data by including just one dummy variable (DUM) which takes value zero for November and December and the value one for all other contracts. The estimated model is reported in Table 2A (model 5). The results suggest that the seasonal term is highly significant and that we have to reject the hypothesis that the basis coefficient is equal to unity. Model 6 of Table 2A differs from the previous model because it also includes a multiplicative dummy. Model 7 is estimated with additional seasonal regressors (DUMNOV and DUMNOVb) which are dummies assuming value zero just in November and one for all the other contracts. Model 8 restricts to zero the coefficients on the DUM and DUMb variables. Across all the different specifications the seasonal terms are in general significant and the basis coefficient is always significantly different from unity. According to the information criteria the preferred model is model 5, which suggests that economic agents have an asymmetric loss function for their forecast errors: they associate a higher weight to errors caused by underestimation of the future spot price. In other words, they manage the risk that heating oil spot prices increase in November and December by locking-in in futures contracts whose price turns out to be higher than the actual spot price. This interpretation is supported by the evidence provided by the estimated models reported in

Table 4A. These models are univariate time series specifications for the change in the spot and futures prices, the basis, and the forecast error (s_t-$f_{t\text{-}\tau}$). The regressor variables are their own lags, included to get rid of autocorrelation, and seasonal dummy variables. The aim of these models is to unveil the major source of seasonality. For the change in the spot price, eleven lags are necessary to ensure white noise residuals, but all the seasonal terms, with the exception of the October dummy, turn out to be not significant. On the other hand, the change in the futures price is strongly influenced by seasonal effects. Although the dynamics are accounted for by just two lags, most of the dummy variables are significant. The test for their joint exclusion from the model yields a very low *p*-value (0.0154). In the model for the basis, only the March dummy is significant, although the test for the hypothesis that all the seasonal terms should be restricted to zero is significant at 6%. As expected, the forecast error series is characterised by highly significant seasonal effects; the model for the forecast error complements the analysis carried out within the framework of model 2 (Table 1A). In fact, consistent with this latter model, the dummies which significantly account for the behaviour of the forecast error series are the same which picked up the seasonal pattern detected in the quasi-ECM model for the change in the heating oil spot prices. The last column of Table 4A reports a parsimonious version for the univariate forecast error model. Although a much richer dynamic specification is necessary (10 lags), the seasonality is now captured only by the DUM variable, which is highly significant. For the heating oil markets it appears that the inefficiency is mainly due to the presence of seasonal effects that the agents do not systematically account for in the formation of their expectations about future spot prices.

Live hogs

The live hogs futures markets is analysed with respect to two different forecast horizons; given that the frequency of the contracts is two-monthly the estimated models refer to a 28 days and to a 56 days horizon. A common 28 days forecast horizon allows us to formulate comparisons across markets with contracts of different durations, while with two horizons for each market it is possible to check whether the results obtained are dependent, to a certain extent, on the length of the chosen forecast period.

Table 1B reports the models for the short forecast horizon of 28 days. Model 1 represents the benchmark model to assess the importance of any seasonal effect on the behaviour of the change in the spot price[5]. According to this model the live hogs market is inefficient since we can rule out that the basis coefficient is equal to unity. Model 2 includes the step seasonal dummy variables, which, with the exception of the one for the October contracts, turn out to be not significantly different from zero; on the grounds of the evidence provided by this model the unbiasedness hypothesis can be rejected. Moving from model 2 to a more general specification which allows for interactive dummy variables, the results suggest the presence of relevant seasonal effects. The slope seasonal terms are jointly significant and the unbiasedness hypothesis is not rejected for February and August contracts. In model 4 we account for the seasonal pattern only by means of the multiplicative dummies. Apart from the February one, they are all significant at the conventional levels and only the April contracts appear to be characterised by biased predictions.

In Table 2B we report the estimation of the univariate models for the change in the spot and futures prices, the basis and the forecast error series in order to detect the source of the seasonal effects we detected within the ECM framework. The univariate model for the change in the live hogs spot price suggests that the seasonal effects are not relevant[6]. All the dummies can be jointly excluded from the model, although the one related to October contracts is highly significant. For the forecast error series similar results are obtained, while the change in the futures prices and the basis series show a clear seasonal behaviour.

Table 3B reports the analysis for the 56 days forecast horizon. Again model 1 is estimated by ignoring the seasonality issue. We can claim that the live hogs market is efficient on the grounds that the lags can be jointly excluded from the model and that the basis coefficient is equal to unity (at 8% level). When we tackle the seasonality issue by estimating model 2 it turns out that the dummy variables are significant at the 6% level and that we cannot restrict to zero the coefficient on the second lag for the change in the futures price. Once we account for seasonal effects the unbiasedness hypothesis no longer holds true. Model 3 and model 4 allow for the presence of the multiplicative seasonal dummies[7], but their joint inclusion in both models can be ruled out. According to the SC and HQ information criteria the preferred model across the four estimated ones is model 2. From the univariate models reported in Table 4B we

[5] Note that a similar model is reported in Kellard et al. (1999), where the focus is not on the seasonality issue.
[6] Note that the test for their joint exclusion obtains a *p*-value of 0.073.

can argue that both the change in spot prices and the basis series show strong seasonal behaviour. As far as the change in futures prices is concerned, although none of the dummy variables is significant at the conventional 5% level, they cannot be excluded from the model on the basis of the test for their joint significant (*p*-value = 0.0485). The forecast error series shows no indication of seasonal effects, so it can be argued that, although the live hogs market is inefficient agents' predictions are not biased because agents fail to take seasonality into account. Although we always reject the presence of seasonality effects for the estimated ECM models, for the individual series the dummy variables are highly significant. A possible explanation for this finding is that seasonal variation in the change of the spot price is picked up by the same kind of seasonality affecting the basis series and the change in the futures price, thus ensuring white noise residuals from the ECM models.

Live cattle

Table 1C reports the analysis for the live cattle market for the 28 day forecast horizon; again in model 1, which is the same estimated by Kellard *et al.* (1999), the seasonality issue is ignored and the results suggest that the market is inefficient. The hypotheses that the intercept term does not significantly differ from zero and the basis coefficient from unity are both rejected; furthermore, the test for the joint inclusion of seven lagged terms for the change of the spot and the change of the futures prices is significant at 7% level. As for the previously analysed markets we estimate models 2, 3 and 4 in order to check if the inefficiency present in this market is due to lack of attention to seasonality effects. However, in all three models we cannot reject the hypothesis that the coefficient of the seasonal terms (additive, multiplicative or jointly) are equal to zero.

In Table 2C the above analysis is carried out with respect to a 56 day forecast horizon; for model 1 we select a lag order as high as nine and all the lags are jointly significant at 7% level. Although the constant is not significantly different from zero, the unity restriction on the basis coefficient is strongly rejected. Model 2 is estimated including step seasonal dummies which, although allowing for a more parsimonious dynamic specification (3 lags), are not significant and the market appears to be very inefficient at this horizon as well. In model 3 we introduce the set of regressors represented by the basis-multiplicative dummies; when the seasonality is

[7] The multiplicative dummy variables are the step seasonal dummies multiplied by the basis.

modelled by interactive terms, the results suggest that part of the variability in the change of the spot price is due to seasonal effects, which are particularly relevant for the April contracts. Given that the step dummies are not jointly significant in model 3, we restrict them to zero and estimate model 4 with only 3 lags and slope seasonal terms. These latter are jointly highly significant and the unity restriction on the basis coefficient is not rejected for February and October contracts.

Table 3C reports the univariate specifications for the variables involved in the estimation of the ECM models; the results obtained suggest that seasonality affects the change in the futures price (February dummy is significant) and the basis series (February and June dummies are significant), but not the change in the spot price or the forecast error series.

The evidence provided in this paper confirms that the live cattle market is very inefficient at both short and long forecast horizons, but the seasonal effect appears to account only marginally for such inefficiency. Our findings show some consistency with previous studies, in particular Beck (1994) and Kellard *et al*. (1999).

Soybeans

The analysis of the soybeans market is also carried out for two different forecast horizons. Table 1D reports model 1, which is the same estimated in Kellard *et al*. (1999); although the constant is significantly different from zero, we cannot reject the hypothesis that the basis coefficient is equal to unity. In model 2 we check whether any seasonal effect is determining the behaviour of the change in the spot price; when contract dummy variables are included a richer dynamics has to be specified, the eighth lag of spot and futures price change is now significant at the 6% level. However, the sixteen lags included in the model are not jointly significant. There is some evidence of seasonality since the dummy variables can be restricted to zero only at the 8.6% level; the basis coefficient does not differ significantly from one, as in the previously estimated model. Model 3 represents an extension of model 2, since we allow the seasonal effects to influence the change in the soybeans spot price through the basis as well. The estimation results indicate a stronger presence of seasonality when both sets of dummy terms are included, since the test for their joint exclusion from the model is highly significant. The hypothesis that the basis coefficient is equal to one is now rejected for July contracts. In fact, the overall significance of the seasonal variables is driven almost entirely by the significance of the additive and multiplicative July dummies. Therefore, we propose a more parsimonious specification of the estimated model by including only such seasonal terms (model 4). As expected, it turns out to be highly significant; within the new estimated model the dynamics are adequately described by the inclusion of only two lags, which, although not jointly significant are maintained in order to avoid misspecification problems and to ensure white noise residuals.

Table 2D reports the investigation of the source of seasonality for the soybeans market; both the variation in the change of spot and in the change of futures prices can be partly described by seasonal influences. The September term is highly significant for explaining the behaviour of the spot change, while the July dummy is determining the evolution of the futures price change. All the seasonal terms are significant in the modelling of the basis series. In order to get rid of non-normality problems in the estimated residuals we need to include some impulse dummies for some extreme observations. The forecast error series, on the other hand, does not appear to be determined by any seasonal variation.

Turning to the longer 56 days horizon (Table 3D), we find that the seasonal step dummies (model 2) highly improve the model fit; the overall significance of the seasonal terms is generated by the highly significant May contracts dummy. Eight lags of the change in spot and the change in futures price are included along with an impulse dummy in order to obtain well-behaved residuals. The unity hypothesis on the basis coefficient is not rejected and, therefore, it is consistent with the efficient market hypothesis. In model 3 the multiplicative seasonal dummies do not appear to be relevant in accounting for the variation of the dependent variable, even if when the additive dummies are restricted to zero (model 4) they are forced to pick up some of the seasonal effects. Again the May contracts are the only ones which display a little evidence of seasonality.

According to the SC ad HQ information criteria, model 2 appears to provide the most adequate specification for testing the soybeans market efficiency without overlooking the seasonal pattern embodied in the data.

The results obtained from the estimation of the univariate models for the change in the spot and futures prices, the basis and the forecast error series, reported in Table 4D, indicate that all variables show a seasonal pattern, although not the same dummies turn out to be significant for each variable examined.

From our analysis seasonality effects seem to considerably affect the soybeans market, particularly at the longer forecast horizon of 56 days. Although the hypothesis that the basis coefficient is equal to one is exceptionally rejected (for July contracts for the 28 days horizon and for May contracts at 56 days horizon), our results provide valuable information in an attempt to explain the mixed evidence produced in the empirical literature on commodity market efficiency testing (Beck, 1994).

Orange Juice

For the orange juice futures market no matching spot price series is available. Following Beck (1994), we assume that the spot price series is actually the futures price on the day of contract expiration. The two prices should be same since arbitrage will drive them together. Table 1E reports the analysis of the forecast error. Seasonal variation does not seem to affect this market. On the basis of the results obtained all the seasonal dummy terms can be restricted to zero.

3. Summary and concluding remarks

This paper has aimed to investigate thoroughly the effects of seasonality in testing market efficiency over a range of five different commodities, namely heating oil, live hogs, live cattle, soybeans and orange juice. The robustness of the results has been checked by carrying out the analysis with respect to a short (28 days) and a long (56 days) forecast horizon. The most relevant question we addressed is whether a strong and anticipated seasonal pattern can account for the inefficiency found in futures markets. In order to tackle the seasonality issue we propose an estimation procedures which involves the augmentation of the quasi-ECM model suggested in Kellard *et al*.(1999) with seasonal dummy terms. All the contracts examined in this paper have an equally spaced settlement pattern, so that the analysis is not influenced by the unequally spaced data problem (Newbold *et al*. 1999).

Our main findings are summarised for the short horizon analysis in Table 1 and for the long horizon in Table 2. Focusing on the short horizon analysis, the results suggest that the heating oil market is strongly affected by seasonality. Economic agents operating in this market appear to have an asymmetric loss function since they prefer to manage the risk of oil price increases in November and December by locking-in futures contracts whose price turns out to be higher than the actual spot price. This behaviour results in systematic negative forecast errors that make the market apparently very inefficient. The hypothesis that the basis coefficient is equal to unity is almost always rejected.

The seasonality present in the live hog market is adequately described by a model which includes just contract dummy variables interacting with the basis term; the hypothesis of a unit coefficient for the basis is rejected only for April contracts. For all the other estimated models, including the one in which we ignored the seasonality issue, the unbiasedness hypothesis was always rejected.

The live cattle market, confirming the results already obtained by Beck (1994) and Kellard *et al.* (1999), appears to be very inefficient. However, the tests on the significance of the seasonal terms suggest that this market for the short forecast horizon is not affected by seasonality.

Table 1 - Short Forecast Horizon

		HEATING OIL	LIVE HOGS	LIVE CATTLE	SOYBEANS
	Contracts	monthly	Feb, Apr, Jun, Aug, Oct, Dec	Feb, Apr, Jun, Aug, Oct, Dec	Jan, Mar, May, Jul, Sep, Nov
Model 1	Basis coeff. = 1 (No seasonal terms)	rejected	rejected	rejected	not rejected
Model 2	Zero restrictions on additive seas. terms	rejected	not rejected	not rejected	not rejected [0.09]
	Basis coeff. = 1	rejected [0.055]	rejected	rejected	not rejected
Model 3	Zero restrictions on additive seas. terms	not rejected	not rejected	not rejected	rejected
	Zero restrictions on multiplic. seas terms	not rejected	rejected	not rejected	rejected
	Zero restrictions on all seasonal terms	rejected	rejected	not rejected	rejected
	Basis coeff. = 1	not rejected (Aug at 9%)	not rejected in Feb and Aug	not rejected in Oct and Dec	rejected in Jul
Model 4	Zero restrictions on multiplic. seas terms	rejected	rejected	not rejected	rejected*
	Basis coeff. = 1	rejected in Apr, and Dec	rejected in Apr	not rejected in Oct and Dec	rejected
Model 5	Zero restriction on DUM	rejected	--	--	--
	Basis coeff. = 1	rejected	--	--	--
No seasonality in Δs_t		not rejected	not rejected [0.07]	--	rejected
No seasonality in Δf_t		rejected	rejected	--	rejected
No seasonality in the basis		not rejected [0.06]	rejected	--	rejected
No seasonality in the forecast error		rejected	not rejected	--	not rejected

*Note that for the soybeans market model 4 is estimated including only the additive and multiplicative seasonal term for July contracts.

The soybeans market is generally efficient; seasonal effects are confined to July contracts. The most parsimonious specification we propose is a model for the change in the spot price which includes only the additive and multiplicative dummy variable for July contracts; these turned out to be the only contracts characterised by inefficient and biased predictions.

Table 2 - Long Forecast Horizon

		LIVE HOGS	LIVE CATTLE	SOYBEANS
	Contracts	Feb, Apr, Jun, Aug, Oct, Dec	Feb, Apr, Jun, Aug, Oct, Dec	Jan, Mar, May, Jul, Sep, Nov
Model 1	Basis coeff. = 1 (No seasonal terms)	not rejected [0.08]	rejected	not rejected
Model 2	Zero restrictions on additive seas. terms	rejected [0.06]	not rejected	rejected
	Basis coeff. = 1	rejected	rejected	not rejected
Model 3	Zero restrictions on additive seas. terms	not rejected [0.09]	not rejected	not rejected [0.08]
	Zero restrictions on multiplic. seas terms	not rejected	rejected	not rejected
	Zero restrictions on all seasonal terms	not rejected	rejected	rejected
	Basis coeff. = 1	rejected in Jun (Apr [0.06])	not rejected in Feb and Oct	not rejected (in May [0.06], Jul [0.08]
Model 4	Zero restrictions on multiplic. seas terms	not rejected	rejected	not rejected
	Basis coeff. = 1	not rejected	not rejected in Feb and Oct	rejected in Mar [0.08] and May
No seasonality in Δs_t		rejected	not rejected	rejected
No seasonality in Δf_t		rejected	rejected	rejected
No seasonality in the basis		rejected	rejected	rejected
No seasonality in the forecast error		not rejected	not rejected	rejected

Turning to the long forecast horizon of 56 days, we can argue that our previous findings are quite robust; for this horizon as well there is evidence that the markets are influenced by seasonality.

For the live hog market spot price change an adequate specification is achieved when the seasonal step dummies are included; the seasonality effects are mainly due to June and August contracts.

The hypothesis that the basis coefficient is equal to unity is rejected. This contrasts with the result we obtained for the model where seasonal effects were ignored; the unbiasedness hypothesis was not rejected at the 8% level. Thus, it can be argued that a market can be considered inefficient when seasonality effects are accounted for.

At a longer forecast horizon the live cattle market too seems to be affected by seasonality. The preferred model is the one in which the seasonal features of the data are picked up by dummy terms interacting with the basis variable. The market is efficient only with respect to February and October contracts. Only for these contracts, in fact, is the basis coefficient not different from unity once we take into account the seasonal influences.

Although the efficiency hypothesis is not rejected for the soybeans market, seasonality is present for the 56 days forecast horizon as well. The behaviour of the change in the spot price is adequately described by a very rich dynamics which includes eight own lags for the spot price change and for the change in the futures price and step seasonal dummies, the most significant of which is the one related to May contracts.

Our analysis has shown that seasonality represents an important issue in testing for market efficiency in commodity markets. Although our results confirm those already presented in previous studies, they also point out that more rigorous and robust conclusions on the efficiency hypothesis can only be reached when the seasonality issue is not overlooked.

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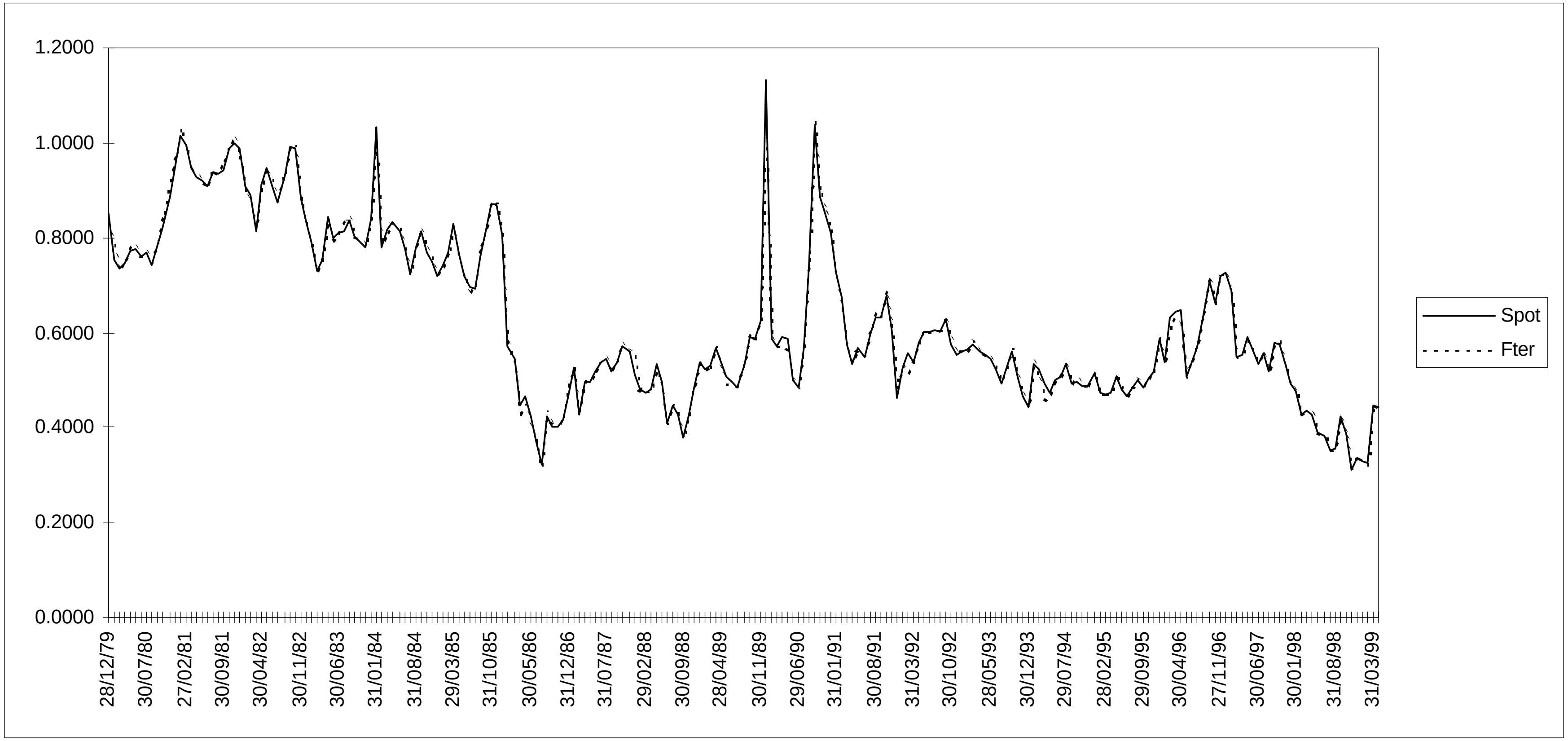
APPENDIX

Table A Contract Details

Commodity	Spot Exchange	Future Exchange	Contract Period	Contract Months	S_t	F_t	S_{t-28}	F_{t-28}	S_{t-56}	F_{t-56}
					mean (st.dev.)	mean (st.dev.)	mean (st.dev.)	mean (st.dev.)	mean (st.dev.)	mean (st.dev.)
HEATING OIL	New York	New York Mercantile Exchange	11/90 to 05/99	All months	0.539 $/gal (0.102)	0.538 $/gal (0.102)	0.539 $/gal* (0.113)	0.537 $/gal* (0.108)	-----	-----
LIVE HOGS	Omaha, Nebraska	Chicago Mercantile Exchange	05/82 to 10/96	Feb, Apr, Jun, Aug, Oct, Dec	47.90 c/lb (6.66)	48.24 c/lb (6.03)	47.92 c/lb (7.23)	48.69 c/lb (6.43)	47.62 c/lb (6.75)	48.14 c/lb (6.05)
LIVE CATTLE	Omaha, Nebraska	Chicago Mercantile Exchange	05/82 to 10/96	Feb, Apr, Jun, Aug, Oct, Dec	67.96 c/lb (6.96)	68.03 c/lb (6.58)	68.24 c/lb (7.19)	68.68 c/lb (6.86)	67.95 c/lb (7.00)	68.15 c/lb (6.55)
SOYBEANS	Chicago board of Trade	Chicago board of Trade	03/80 to 11/96	Jan, Mar, May, Jul, Sep, Nov	627.02 c/bu (98.34)	642.18 c/bu (101.59)	624.77 c/bu (100.37)	637.20 c/bu (103.60)	623.00 c/bu (93.18)	638.38 c/bu (96.53)
ORANGE JUICE	-----	New York Cotton Exchange (NYCE)	01/80 to 01/99	Jan, Mar, May, Jul, Sep, Nov	-----	124.25 c/lb (30.65)	-----	-----	-----	124.84 c/lb (29.53)

* For Heating Oil contracts the forecast horizon is 21 days.

Fig. 1



Futures price: NYM-HEATING OIL #2 CONTINUOUS - SETT. PRICE - U$/GL
Spot price: FUEL OIL, NO.2 (NEW YORK), CENTS/GAL

Table 1A HEATING OIL - sample period: Nov 1990-May 1999

	ΔS_t	Model 1	Model 2	Model 3	Model 4
θ_0	Constant	0.004 (0.614)	-0.054 (-2.636)	0.052 (1.177)	0.010 (1.241)
θ_1	Basis	0.540 (3.654)	0.689 (4.248)	-6.005 (-2.403)	-3.866 (-3.179)
δ_1	JAN		0.055 (1.924)	-0.036 (-0.719)	
δ_2	FEB		0.046 (1.603)	-0.065 (-1.328)	
δ_3	MAR		0.049(1.624)	-0.059 (-1.194)	
δ_4	APR		0.112 (3.680)	0.002 (0.039)	
δ_5	MAY		0.074 (2.472)	-0.033 (-0.663)	
δ_6	JUN		0.039 (1.318)	-0.060 (-1.222)	
δ_7	JUL		0.069 (2.332)	-0.024 (-0.449)	
δ_8	AUG		0.077 (2.587)	0.007 (0.124)	
δ_9	SEP		0.081 (2.743)	-0.037 (-0.661)	
δ_{10}	OCT		0.098 (3.297)	-0.038 (-0.660)	
δ_{11}	NOV		0.008 (0.267)	-0.122 (-2.252)	
ϕ_1	JANb			5.689 (2.135)	3.686 (2.610)
ϕ_2	FEBb			7.765 (2.837)	5.326 (3.270)
ϕ_3	MARb			6.636 (2.637)	4.611 (3.652)
ϕ_4	APRb			6.609 (2.627)	4.166 (3.307)
ϕ_5	MAYb			6.674 (2.650)	4.471 (3.529)
ϕ_6	JUNb			7.373 (2.888)	5.335 (3.986)
ϕ_7	JULb			5.228 (1.506)	4.143 (1.987)
ϕ_8	AUGb			3.161 (0.932)	3.690 (1.893)
ϕ_9	SEPb			7.420 (2.493)	5.480 (3.560)
ϕ_{10}	OCTb			8.416 (2.777)	6.461 (4.172)
ϕ_{11}	NOVb			7.896 (2.834)	3.326 (2.352)
	Obs.	103	103	103	103
	Var.	2	13	24	13
	RSS	0.437832	0.335012	0.278672	0.336642
	SC Inf Crit	-5.371	-5.143	-4.832	-5.138
	HQ Inf Crit	-5.401	-5.341	-5.198	-5.336
	H_0: θ_1=1	9.6515 [0.0019]	3.6784 [0.0551]		
	H_0: no step dummies		2.5111 [0.0084]	1.494 [0.1504]	
	H_0: no slope dummies			1.452 [0.1670]	2.4593 [0.0098]
	H_0: no seas. dummies			2.051 [0.0110]	

t-statistics are reported in parenthesis

Testing unbiasedness

Model 3			
H_0: $\theta_1+\phi_1=1$	2.0136 [0.1559]	H_0: $\theta_1+\phi_7=1$	0.5437 [0.4609]
H_0: $\theta_1+\phi_2=1$	0.4635 [0.4960]	H_0: $\theta_1+\phi_8=1$	2.8031 [0.0941]
H_0: $\theta_1+\phi_3=1$	1.5037 [0.2201]	H_0: $\theta_1+\phi_9=1$	0.0660 [0.7972]
H_0: $\theta_1+\phi_4=1$	1.8172 [0.1776]	H_0: $\theta_1+\phi_{10}=1$	0.6771 [0.4106]
H_0: $\theta_1+\phi_5=1$	1.0894 [0.2966]	H_0: $\theta_1+\phi_{11}=1$	0.5221 [0.4699]
H_0: $\theta_1+\phi_6=1$	0.4937 [0.4823]		
Model 4			
H_0: $\theta_1+\phi_1=1$	2.1406 [0.1434]	H_0: $\theta_1+\phi_7=1$	0.1617 [0.6875]
H_0: $\theta_1+\phi_2=1$	0.1682 [0.6817]	H_0: $\theta_1+\phi_8=1$	0.5193 [0.4711]
H_0: $\theta_1+\phi_3=1$	0.8780 [0.3487]	H_0: $\theta_1+\phi_9=1$	0.3359 [0.5622]
H_0: $\theta_1+\phi_4=1$	7.4644 [0.0063]	H_0: $\theta_1+\phi_{10}=1$	2.1914 [0.1388]
H_0: $\theta_1+\phi_5=1$	1.8414 [0.1748]	H_0: $\theta_1+\phi_{11}=1$	3.3358 [0.0678]
H_0: $\theta_1+\phi_6=1$	0.7927 [0.3733]		

Table 2A HEATING OIL - sample period: Nov 1990-May 1999

	ΔS_t	Model 5	Model 6	Model 7	Model 8
θ_0	Constant	-0.050 (-3.381)	-0.045 (-1.813)	-0.070 (-2.222)	-0.070 (-2.067)
θ_1	Basis	0.658 (4.667)	0.393 (0.345)	1.891 (1.520)	1.891 (1.413)
α_0	DUM	0.065 (4.010)	0.061 (2.360)	-0.036 (-0.807)	
α_1	DUMb		0.270 (0.235)	6.667 (2.641)	
β_0	DUMNOV			0.122 (2.233)	0.078 (2.280)
β_1	DUMNOVb			-7.898 (-2.809)	-1.314 (-0.976)
	Obs.	103	103	103	103
	Var.	3	4	6	4
	RSS	0.377187	0.376976	0.348299	0.411129
	SC Inf Crit	-5.475	-5.430	-5.419	-5.344
	HQ Inf Crit	-5.520	-5.491	-5.511	-5.404
	H_0: θ_1=1	5.8596 [0.0155]			
	H_0: $\theta_1+\alpha_1$=1		5.5749 [0.0182]		
	H_0: $\theta_1+\alpha_1+\beta_1$=1			5.912 [0.0150]	
	H_0: $\theta_1+\beta_1$=1				8.2307 [0.0041]
	H_0: $\alpha_0=\alpha_1$=0		7.9908 [0.0006]	8.749 [0.0003]	
	H_0: $\beta_0=\beta_1$=0			3.9933 [0.0215]	3.215 [0.0444]
	H_0: $\alpha_0=\alpha_1=\beta_0=\beta_1$=0			6.2337 [0.0002]	

$$\text{DUM} = \begin{cases} 1 \text{ for JAN, FEB, MAR, APR, MAY, JUN, JUL, AUG, SEP, OCT} \\ 0 \text{ for NOV, DEC} \end{cases}$$

$$\text{DUMNOV} = \begin{cases} 1 \text{ for JAN, FEB, MAR, APR, MAY, JUN, JUL, AUG, SEP, OCT, DEC} \\ 0 \text{ for NOV} \end{cases}$$

t-statistics are reported in parenthesis

Table 3

Testing the equality of the estimated error variances from model (1), (2), (3), (4), (5)

Model: (1) *Vs* (2): F(101,90) = 1.1646 [0.23090]

Model: (1) *vs* (5): F(101,100) = 1.1493 [0.24352]

Model: (5) *vs* (2): F(100,90) = 1.0133 [0.47587]

Model: (4) *vs* (3): F(90,79) = 1.0604 [0.39622]

Model: (4) *vs* (2): F(90, 90) = 1.0049 [0.49084]

Model: (5) *vs* (4): F(100,90) = 1.0084 [0.48526]

Table 4A HEATING OIL - sample period: Nov 1990-May 1999

	HEATING OIL	s_t-s_{t-21}	f_t-f_{t-21}	f_{t-21}-s_{t-21}	s_t-f_{t-21}	s_t-f_{t-21}
θ_0	Constant	0.005 (0.210)	-0.051 (-2.339)	0.004 (0.422)	-0.053 (-2.309)	-0.051 (-2.868)
λ_1	lag 1	-0.162 (-1.397)	-0.004 (-0.035)	0.791 (7.578)	0.076 (0.716)	0.152 (1.491)
λ_2	lag 2	-0.403 (-3.272)	-0.086 (-0.802)	-0.234 (-2.222)	-0.085 (-0.800)	-0.092 (-0.861)
λ_3	lag 3	-0.314 (-2.442)				-0.017 (-0.162)
λ_4	lag 4	0.043 (0.322)				0.089 (0.826)
λ_5	lag 5	-0.343 (-2.554)				-0.134 (-1.235)
λ_6	lag 6	0.069 (0.526)				0.192 (1.674)
λ_7	lag 7	-0.169 (-1.322)				-0.035 (-0.297)
λ_8	lag 8	-0.035 (-0.287)				-0.032 (0.278)
λ_9	lag 9	0.258 (2.125)				0.905 (0.790)
λ_{10}	lag 10	0.005 (0.042)				-0.215 (-1.969)
λ_{11}	lag 11	0.284 (2.441)				
δ_1	JAN	0.010 (0.299)	0.051 (1.669)	0.002 (0.139)	0.050 (1.563)	
δ_2	FEB	0.002 (0.069)	0.034 (1.100)	-0.008 (-0.538)	0.039 (1.201)	
δ_3	MAR	-0.009 (-0.259)	0.041 (1.390)	-0.043 (-2.933)	0.060 (1.950)	
δ_4	APR	0.038 (1.097)	0.108 (3.639)	-0.019 (-1.191)	0.124 (3.966)	
δ_5	MAY	-0.008 (-0.234)	0.076 (2.453)	-0.012 (-0.764)	0.078 (2.386)	
δ_6	JUN	-0.051 (-1.473)	0.045 (1.487)	0.005 (0.300)	0.044 (1.383)	
δ_7	JUL	-0.004 (-0.106)	0.067 (2.234)	0.003 (0.176)	0.069 (2.189)	
δ_8	AUG	-0.003 (-0.091)	0.072 (2.353)	-0.003 (-0.233)	0.070 (2.188)	
δ_9	SEP	0.043 (1.242)	0.078 (2.555)	0.006 (0.413)	0.074 (2.329)	
δ_{10}	OCT	0.076 (2.246)	0.096 (3.163)	0.001 (0.100)	0.091 (2.854)	
δ_{11}	NOV	0.006 (0.175)	0.018 (0.581)	0.006 (0.372)	0.009 (0.291)	
α_0	DUM					0.069 (3.566)
	SC Inf Crit.				-5.062	-5.011
	HQ Inf Crit.				-5.278	-5.206
	Obs.	92	101	101	101	93
	Var.	23	14	14	14	12
	RSS	0.250797	0.306290	0.079075	0.337263	0.345289
				Norm [0.0000]		
	H_0: no seas. dummies	1.6337 [0.1086]	2.3126 [0.0154]	1.8198 [0.0625]	2.4305 [0.0109]	

t-statistics are reported in parenthesis

Table 1B LIVE HOGS - sample period: Jun 1982-Oct 1996 - forecast horizon 28 days

	ΔS_t	Model 1	Model 2	Model 3	Model 4
θ_0	Constant	-0.005 (-0.597)	0.031 (1.336)	-0.057 (-1.557)	-0.017 (-1.686)
θ_1	Basis	0.489 (2.751)	0.420 (2.076)	1.957 (3.578)	1.444 (4.555)
λ_1	ΔS_{t-1}	-0.277 (-2.125)			
γ_1	ΔF_{t-1}	0.208 (1.760)			
δ_1	FEB		-0.037 (-1.276)	0.033 (0.759)	
δ_2	APR		-0.052 (-1.790)	0.054 (1.263)	
δ_3	JUN		-0.026 (-0.931)	0.077 (1.713)	
δ_4	AUG		-0.030 (-0.971)	0.059 (1.426)	
δ_5	OCT		-0.078 (-2.395)	-0.005 (-0.116)	
ϕ_1	FEBb			-0.966 (-1.281)	-0.542 (-1.086)
ϕ_2	APRb			-2.286 (-3.198)	-1.628 (-3.257)
ϕ_3	JUNb			-1.881 (-2.712)	-0.932 (-2.239)
ϕ_4	AUGb			-1.420 (-2.035)	-1.047 (-1.915)
ϕ_5	OCTb			-2.083 (-2.879)	-1.0235 (-1.856)
	Obs.	86	87	87	87
	Var.	4	7	12	7
	RSS	0.458500	0.446293	0.376895	0.420405
	SC Inf Crit	-5.027	-4.913	-4.826	-4.973
	HQ Inf Crit	-5.095	-5.032	-5.030	-5.092
	H_0: no lags	2.3995 [0.0971]			
	H_0: θ_1=1	8.2299 [0.0041]	8.1897 [0.0042]		
	H_0: no step dummies		1.4108 [0.2293]	1.7316 [0.1377]	
	H_0: no slope dummies			2.7619 [0.0241]	2.4829 [0.0383]
	H_0: no seas dummies			2.1640 [0.0293]	

t-statistics are reported in parenthesis

Testing unbiasedness

Model 3		Model 4	
H_0: $\theta_1+\phi_1=1$	0.0003 [0.9860]	H_0: $\theta_1+\phi_1=1$	0.0524 [0.8190]
H_0: $\theta_1+\phi_2=1$	8.3458 [0.0039]	H_0: $\theta_1+\phi_2=1$	7.9546 [0.0048]
H_0: $\theta_1+\phi_3=1$	4.6987 [0.0302]	H_0: $\theta_1+\phi_3=1$	2.3273 [0.1271]
H_0: $\theta_1+\phi_4=1$	1.1439 [0.2848]	H_0: $\theta_1+\phi_4=1$	2.0269 [0.1545]
H_0: $\theta_1+\phi_5=1$	5.6526 [0.0174]	H_0: $\theta_1+\phi_5=1$	1.9461 [0.1630]

Table 2B LIVE HOGS - sample period: Jun 1982-Oct 1996 - forecast horizon 28 days

	LIVE HOGS	s_t-s_{t-28}	f_t-f_{t-28}	f_{t-28}-s_{t-28}	s_t-f_{t-28}
θ_0	Constant	0.050 (2.074)	0.027 (0.997)	0.073 (7.793)	-0.001 (-0.058)
λ_1	lag 1	-0.016 (-0.123)	0.009 (0.077)	0.581 (6.348)	0.040 (0.355)
λ_2	lag 2	-0.244 (-1.886)	-0.009 (-0.077)		
λ_3	lag 3	-0.096 (-0.784)	-0.050 (-0.414)		
λ_4	lag 4	-0.069 (-0.547)	-0.013 (-0.109)		
λ_5	lag 5	-0.070 (-0.570)	0.055 (0.458)		
λ_6	lag 6	-0.020 (-0.168)	0.035 (0.292)		
λ_7	lag 7	-0.078 (-0.647)	-0.246 (-2.065)		
λ_8	lag 8	-0.038 (-0.314)			
λ_9	lag 9	-0.192 (-1.555)			
λ_{10}	lag 10	-0.237 (-1.938)			
λ_{11}	lag 11	0.029 (0.232)			
λ_{12}	lag 12	-0.289 (-2.189)			
δ_1	FEB	-0.030 (-0.859)	-0.076 (-1.913)	-0.075 (-5.051)	-0.022 (-0.747)
δ_2	APR	-0.059 (-1.655)	0.056 (1.316)	-0.067 (-4.835)	-0.032 (-1.102)
δ_3	JUN	-0.010 (-0.330)	-0.011 (-0.303)	-0.041 (-3.010)	-0.017 (-0.583)
δ_4	AUG	-0.050 (-1.411)	-0.134 (-3.285)	-0.114 (-8.051)	0.011 (0.380)
δ_5	OCT	-0.104 (-2.987)	-0.047 (-1.148)	-0.091 (-7.240)	-0.031 (-1.038)
	Obs.	75	80	86	86
	Var.	18	13	7	7
	RSS	0.296406	0.383415	0.090070	0.490702
	H_0: no seas. dummies	2.142 [0.0734]	5.2193 [0.0004]	18.057 [0.0000]	0.71493 [0.6141]

t-statistics are reported in parenthesis

Table 3B LIVE HOGS - sample period: Jun 1982-Oct 1996 - forecast horizon 56 days

	ΔS_t	Model 1	Model 2	Model 3	Model 4
θ_0	Constant	-0.002 (-0.136)	-0.059 (-1.478)	-0.07 (-1.583)	0.004 (0.329)
θ_1	Basis	0.566 (2.312)	0.348 (1.492)	0.659 (1.289)	0.522 (1.029)
λ_1	ΔS_{t-1}	-0.137 (-0.583)	-0.208 (-0.885)	-0.110 (-0.447)	-0.256 (-1.764)
λ_2	ΔS_{t-2}	0.125 (0.590)	0.348 (1.650)	0.458 (1.965)	
λ_3	ΔS_{t-3}	0.029 (0.157)			
λ_4	ΔS_{t-4}	0.066 (0.362)			
λ_5	ΔS_{t-5}	0.083 (0.460)			
λ_6	ΔS_{t-6}	0.413 (2.189)			
γ_1	ΔF_{t-1}	0.002 (0.008)	0.0004 (0.002)	-0.105 (-0.415)	0.139 (0.856)
γ_2	ΔF_{t-2}	-0.313 (-1.408)	-0.542 (-2.418)	-0.627 (-2.654)	
γ_3	ΔF_{t-3}	-0.089 (-0.439)			
γ_4	ΔF_{t-4}	-0.298 (-1.411)			
γ_5	ΔF_{t-5}	-0.015 (-0.079)			
γ_6	ΔF_{t-6}	-0.338 (-1.666)			
δ_1	FEB		0.121 (1.993)	0.118 (1.839)	
δ_2	APR		0.054 (0.995)	0.050 (0.897)	
δ_3	JUN		0.104 (2.373)	0.134 (2.223)	
δ_4	AUG		0.137 (1.910)	0.146 (1.984)	
δ_5	OCT		-0.052 (-0.861)	-0.063 (-0.811)	
ϕ_1	FEBb			0.279 (0.390)	0.047 (0.075)
ϕ_2	APRb			-1.051 (-1.166)	-0.689 (-0.776)
ϕ_3	JUNb			-0.442 (-0.720)	0.121 (0.247)
ϕ_4	AUGb			-0.502 (-0.636)	-0.268 (-0.343)
ϕ_5	OCTb			-0.263 (-0.357)	0.420 (0.728)
	Obs.	81	85	85	86
	Var.	14	11	16	9
	RSS	0.632355	0.635460	0.611323	0.721302
	SC Inf Crit	-4.093	-4.321	-4.098	-4.315
	HQ Inf Crit	-4.341	-4.510	-4.373	-4.468
	H_0: no lags	1.0276 [0.4347]	2.7143 [0.0362]	2.7914 [0.038]	1.7100 [0.1877]
	H_0: θ_1=1	3.1491 [0.0760]	7.7845 [0.0053]	0.4440 [0.5052]	0.8891 [0.3457]
	H_0: no step dummies		2.239 [0.0592]	2.0102 [0.0880]	
	H_0: no slope dummies			0.5449 [0.7416]	0.5490 [0.7385]
	H_0: no seas dummies			1.3575 [0.2187]	

t-statistics are reported in parenthesis

Testing unbiasedness

Model 3		Model 4	
H_0: $\theta_1+\phi_1=1$	0.0128 [0.9099]	H_0: $\theta_1+\phi_1=1$	0.9978 [0.3178]
H_0: $\theta_1+\phi_2=1$	3.4351 [0.0638]	H_0: $\theta_1+\phi_2=1$	2.4788 [0.1154]
H_0: $\theta_1+\phi_3=1$	3.8782 [0.0489]	H_0: $\theta_1+\phi_3=1$	1.6749 [0.1956]
H_0: $\theta_1+\phi_4=1$	1.8218 [0.1771]	H_0: $\theta_1+\phi_4=1$	1.5233 [0.2171]
H_0: $\theta_1+\phi_5=1$	1.1050 [0.2932]	H_0: $\theta_1+\phi_5=1$	0.0373 [0.8469]

Table 4B LIVE HOGS - sample period: Jun 1982-Oct 1996 - forecast horizon 56 days

	LIVE HOGS	s_t-s_{t-56}	f_t-f_{t-56}	f_{t-56}-s_{t-56}	s_t-f_{t-56}
θ_0	Constant	-0.014 (-0.442)	0.005 (0.140)	0.102 (3.312)	0.004 (0.128)
λ_1	lag 1	-0.336 (-2.936)	-0.244 (-1.953)	0.255 (2.100)	0.039 (0.329)
λ_2	lag 2	-0.122 (-1.040)	-0.342 (-2.563)	0.290 (2.380)	0.084 (0.715)
λ_3	lag 3	-0.098 (-0.832)	-0.123 (-0.921)	0.167 (1.365)	0.007 (0.057)
λ_4	lag 4	-0.147 (-1.251)	-0.206 (-1.497)	-0.020 (-0.161)	-0.087 (-0.739)
λ_5	lag 5	0.026 (0.217)	-0.021 (-0.152)	-0.145 (-1.062)	0.133 (1.136)
λ_6	lag 6	0.054 (0.456)	-0.058 (-0.435)	0.039 (0.290)	0.126 (1.076)
λ_7	lag 7	-0.204 (-1.781)	-0.268 (-2.050)	0.307 (2.283)	-0.213 (-1.806)
λ_8	lag 8		-0.280 (-1.969)	-0.141 (-1.122)	
λ_9	lag 9		-0.192 (-1.333)	-0.272 (-2.132)	
λ_{10}	lag 10		-0.310 (-2.119)		
λ_{11}	lag 11		-0.215 (-1.603)		
λ_{12}	lag 12		-0.300 (-2.297)		
δ_1	FEB	0.062 (1.324)	-0.039 (-0.731)	-0.064 (-1.453)	-0.013 (-0.326)
δ_2	APR	0.010 (0.207)	0.086 (1.452)	-0.122 (-2.454)	-0.009 (-0.225)
δ_3	JUN	0.119 (2.782)	0.038 (0.774)	0.006 (0.150)	0.005 (0.138)
δ_4	AUG	0.073 (1.458)	-0.098 (-1.678)	-0.182 (-3.491)	-0.011 (-0.276)
δ_5	OCT	-0.081 (-1.805)	-0.015 (-0.289)	-0.211 (-4.878)	-0.013 (-0.340)
	Obs.	80	75	78	80
	Var.	13	18	15	13
	RSS	0.581423	0.403896	0.120445	0.682910
	H_0: no seas. dummies	4.4501 [0.0015]	2.3952 [0.0485]	7.5709 [0.0000]	0.0754 [0.9957]

t-statistics are reported in parenthesis

Table 1C LIVE CATTLE- sample period: Jun 1982-Oct 1996 - forecast horizon 28 days

	ΔS_t	Model 1	Model 2	Model 3	Model 4
θ_0	Constant	-0.010 (-2.158)	-0.001 (-0.092)	-0.013 (-1.131)	-0.10 (-2.282)
θ_1	Basis	0.221 (1.919)	0.138 (1.101)	0.622 (1.485)	0.588 (1.611)
λ_1	ΔS_{t-1}	0.055 (0.320)	-0.019 (-0.108)	-0.013 (-0.081)	0.006 (0.041)
λ_2	ΔS_{t-2}	0.037 (0.239)	0.045 (0.272)	0.075 (0.482)	0.158 (1.103)
λ_3	ΔS_{t-3}	-0.071 (-0.466)	-0.055 (-0.351)		
λ_4	ΔS_{t-4}	-0.141 (-0.893)	-0.125 (-0.758)		
λ_5	ΔS_{t-5}	-0.015 (-0.094)	-0.051 (-0.310)		
λ_6	ΔS_{t-6}	0.044 (0.271)	0.048 (0.291)		
λ_7	ΔS_{t-7}	-0.285 (-1.840)	-0.318 (-1.964)		
γ_1	ΔF_{t-1}	-0.030 (-0.251)	0.017 (0.129)	0.040 (0.321)	0.020 (0.177)
γ_2	ΔF_{t-2}	-0.264 (-2.317)	-0.281 (-2.240)	-0.284 (2.424)	-0.317 (-3.117)
γ_3	ΔF_{t-3}	-0.083 (-0.727)	-0.007 (-0.053)		
γ_4	ΔF_{t-4}	0.014 (0.125)	0.007 (0.059)		
γ_5	ΔF_{t-5}	-0.034 (-0.308)	0.003 (0.022)		
γ_6	ΔF_{t-6}	0.033 (0.292)	-0.013 (-0.106)		
γ_7	ΔF_{t-7}	0.043 (0.393)	0.044 (0.354)		
δ_1	FEB		-0.003 (-0.198)	0.020 (1.325)	
δ_2	APR		-0.022 (-1.242)	-0.006 (-0.388)	
δ_3	JUN		-0.013 (-0.732)	-0.003 (-0.199)	
δ_4	AUG		-0.019 (-1.132)	0.002 (0.137)	
δ_5	OCT		0.007 (0.437)	0.007 (0.329)	
ϕ_1	FEBb			-1.013 (-1.458)	-0.783 (-1.219)
ϕ_2	APRb			-0.490 (-1.080)	-0.470 (-1.157)
ϕ_3	JUNb			-0.458 (-1.005)	-0.362 (-0.877)
ϕ_4	AUGb			-0.493 (-0.880)	-0.418 (-0.824)
ϕ_5	OCTb			-0.119 (-0.211)	0.032 (0.080)
	Obs.	80	80	85	85
	Var.	16	21	16	11
	RSS	0.070661	0.065276	0.077517	0.082526
	SC Inf Crit	-6.155	-5.961	-6.164	-6.362
	HQ Inf Crit	-6.441	-6.335	-6.438	-6.551
	H_0: no lags	1.7194 [0.0734]	1.2378 [0.2740]	2.1174 [0.0879]	3.0814 [0.0210]
	H_0: θ_1=1	45.707 [0.0000]	47.484 [0.0000]	0.8161 [0.3663]	1.2722 [0.2594]
	H_0: no step dummies		0.9734 [0.4416]	0.8918 [0.4916]	
	H_0: no slope dummies			0.6015 [0.6989]	0.9422 [0.4590]
	H_0: no seas dummies			0.9135 [0.5260]	

t-statistics are reported in parenthesis

Testing unbiasedness

Model 3		Model 4	
H_0: $\theta_1+\phi_1=1$	5.9952 [0.0143]	H_0: $\theta_1+\phi_1=1$	4.6195 [0.0316]
H_0: $\theta_1+\phi_2=1$	21.675 [0.0000]	H_0: $\theta_1+\phi_2=1$	22.62 [0.0000]
H_0: $\theta_1+\phi_3=1$	21.481 [0.0000]	H_0: $\theta_1+\phi_3=1$	21.03 [0.0000]
H_0: $\theta_1+\phi_4=1$	5.1839 [0.0228]	H_0: $\theta_1+\phi_4=1$	4.9810 [0.0256]
H_0: $\theta_1+\phi_5=1$	1.5582 [0.2119]	H_0: $\theta_1+\phi_5=1$	2.6943 [0.1007]

Table 2C LIVE CATTLE- sample period: Jun 1982-Oct 1996 - forecast horizon 56 days

	ΔS_t	Model 1	Model 2	Model 3	Model 4
θ_0	Constant	-0.002 (-0.409)	0.003 (0.184)	0.008 (0.561)	0.002 (0.302)
θ_1	Basis	0.092 (0.431)	0.175 (1.074)	-0.040 (-0.095)	-0.095 (-0.236)
λ_1	ΔS_{t-1}	-0.216 (-0.860)	-0.239 (-1.258)	-0.441 (-2.403)	-0.426 (-2.365)
λ_2	ΔS_{t-2}	-0.225 (-0.945)	-0.072 (-0.392)	-0.114 (-0.625)	-0.169 (-1.048)
λ_3	ΔS_{t-3}	-0.408 (-1.791)	-0.390 (-2.220)	-0.527 (-3.113)	-0.474 (-3.235)
λ_4	ΔS_{t-4}	-0.125 (-0.559)			
λ_5	ΔS_{t-5}	0.281 (1.282)			
λ_6	ΔS_{t-6}	0.096 (0.452)			
λ_7	ΔS_{t-7}	-0.318 (-1.524)			
λ_8	ΔS_{t-8}	0.200 (0.959)			
λ_9	ΔS_{t-9}	0.383 (1.889)			
γ_1	ΔF_{t-1}	0.095 (0.438)	0.169 (0.931)	0.305 (1.778)	0.400 (2.498)
γ_2	ΔF_{t-2}	-0.041 (-0.199)	-0.298 (-1.684)	-0.237 (-1.403)	-0.108 (-0.751)
γ_3	ΔF_{t-3}	0.108 (0.543)	0.116 (0.662)	0.348 (2.029)	0.304 (2.055)
γ_4	ΔF_{t-4}	-0.112 (-0.597)			
γ_5	ΔF_{t-5}	-0.195 (-1.110)			
γ_6	ΔF_{t-6}	-0.092 (-0.537)			
γ_7	ΔF_{t-7}	0.145 (0.818)			
γ_8	ΔF_{t-8}	-0.108 (-0.621)			
γ_9	ΔF_{t-9}	-0.365 (-2.156)			
δ_1	FEB		0.013 (0.651)	0.003 (0.137)	
δ_2	APR		-0.005 (-0.222)	0.016 (0.725)	
δ_3	JUN		-0.012 (-0.532)	-0.021 (-0.858)	
δ_4	AUG		-0.026 (-1.123)	-0.039 (-1.724)	
δ_5	OCT		0.010 (0.463)	-0.001 (-0.053)	
ϕ_1	FEBb			0.530 (0.944)	0.518 (0.956)
ϕ_2	APRb			-1.318 (-2.165)	-0.948 (-1.755)
ϕ_3	JUNb			-0.053 (-0.096)	0.178 (0.368)
ϕ_4	AUGb			0.400 (0.780)	0.500 (1.024)
ϕ_5	OCTb			0.760 (1.544)	0.785 (1.786)
	Obs.	78	84	84	84
	Var.	20	13	18	13
	RSS	0.145433	0.172744	0.134067	0.150174
	SC Inf Crit	-5.168	-5.501	-5.491	-5.641
	HQ Inf Crit	-5.530	-5.726	-5.802	-5.866
	H_0: no lags	1.6777 [0.0707]	2.8801 [0.0144]	4.0585 [0.0016]	3.7391 [0.0027]
	H_0: θ_1=1	18.064 [0.0000]	25.448 [0.0000]		
	H_0: no step dummies		0.9031 [0.4840]	1.5858 [0.1763]	
	H_0: no slope dummies			3.8081 [0.0043]	3.173 [0.0121]
	H_0: no seas dummies			2.4449 [0.0151]	

t-statistics are reported in parenthesis

Testing unbiasedness

Model 3		Model 4	
H_0: $\theta_1+\phi_1=1$	1.9306 [0.1647]	H_0: $\theta_1+\phi_1=1$	2.4312 [0.1189]
H_0: $\theta_1+\phi_2=1$	30.236 [0.0000]	H_0: $\theta_1+\phi_2=1$	28.384 [0.0000]
H_0: $\theta_1+\phi_3=1$	11.056 [0.0009]	H_0: $\theta_1+\phi_3=1$	10.996 [0.0009]
H_0: $\theta_1+\phi_4=1$	4.7402 [0.0295]	H_0: $\theta_1+\phi_4=1$	3.9963 [0.0456]
H_0: $\theta_1+\phi_5=1$	0.9303 [0.3348]	H_0: $\theta_1+\phi_5=1$	1.3340 [0.2481]

Table 3C LIVE CATTLE - sample period: Jun 1982-Oct 1996 - forecast horizon 56 days

	LIVE CATTLE	s_t-s_{t-56}	f_t-f_{t-56}	f_{t-56}-s_{t-56}	s_t-f_{t-56}
θ_0	Constant	0.007 (0.470)	0.002 (0.106)	0.022 (1.747)	-0.003 (-0.199)
λ_1	lag 1	-0.211 (-1.761)	-0.254 (-2.188)	0.540 (4.224)	0.275 (2.332)
λ_2	lag 2	-0.327 (-2.642)	-0.427 (-3.546)	0.172 (1.133)	0.005 (0.044)
λ_3	lag 3	-0.291 (-2.171)	-0.177 (-1.317)	0.149 (1.028)	0.071 (0.583)
λ_4	lag 4	-0.227 (-1.668)	-0.036 (-0.278)	-0.179 (-1.229)	0.135 (1.070)
λ_5	lag 5	0.085 (0.637)	0.239 (1.900)	0.184 (1.335)	0.246 (1.953)
λ_6	lag 6	-0.012 (-0.097)		-0.099 (0.712)	-0.121 (-0.939)
λ_7	lag 7	-0.253 (-2.031)		-0.094 (-0.679)	-0.263 (-2.107)
λ_8	lag 8			0.006 (0.042)	
λ_9	lag 9			0.081 (0.611)	
λ_{10}	lag 10			-0.369 (-2.778)	
λ_{11}	lag 11			0.064 (0.448)	
λ_{12}	lag 12			0.269 (2.092)	
δ_1	FEB	-0.0004 (-0.022)	0.056 (2.386)	-0.058 (-3.020)	0.013 (0.611)
δ_2	APR	0.005 (0.237)	-0.033 (-1.345)	-0.013 (-0.664)	-0.021 (-0.951)
δ_3	JUN	-0.034 (-1.556)	-0.032 (-1.347)	-0.049 (-2.703)	0.001 (0.067)
δ_4	AUG	-0.025 (-1.167)	-0.012 (-0.495)	-0.008 (-0.418)	0.003 (0.134)
δ_5	OCT	0.005 (0.236)	0.001 (0.038)	0.011 (0.572)	0.003 (0.168)
	Obs.	80	82	74	80
	Var.	13	11	18	13
	RSS	0.161646	0.191885	0.050133	0.194332
	H_0: no seas. dummies	1.2085 [0.3148]	4.0448 [0.0028]	5.0632 [0.0007]	0.53072 [0.7522]

t-statistics are reported in parenthesis

Table 1D SOYBEANS - sample period: Mar 1980-Nov 1996 - forecast horizon 28 days

	ΔS_t	Model 1	Model 2	Model 3	Model 4
θ_0	Constant	-0.020 (-2.623)	-0.018 (-0.804)	-0.029 (-0.897)	-0.014 (-1.821)
θ_1	Basis	1.246 (4.363)	1.090 (2.926)	1.460 (0.143)	0.974 (3.273)
λ_1	ΔS_{t-1}		-0.144 (-0.330)	-0.324 (-0.766)	-0.565 (-1.644)
λ_2	ΔS_{t-2}		-0.068 (-0.149)	-0.564 (-1.223)	-0.168 (-0.502)
λ_3	ΔS_{t-3}		-0.017 (-0.038)	-0.085 (-0.197)	
λ_4	ΔS_{t-4}		0.145 (0.327)	-0.040 (-0.093)	
λ_5	ΔS_{t-5}		0.035 (0.080)	-0.007 (-0.017)	
λ_6	ΔS_{t-6}		-0.419 (-0.959)	-0.201 (-0.491)	
λ_7	ΔS_{t-7}		-0.396 (-0.922)	-0.479 (-1.170)	
λ_8	ΔS_{t-8}		-0.775 (-1.816)	-0.922 (-2.211)	
γ_1	ΔF_{t-1}		-0.030 (-0.065)	0.181 (0.403)	0.527 (1.504)
γ_2	ΔF_{t-2}		-0.011 (-0.024)	0.525 (1.083)	0.092 (0.263)
γ_3	ΔF_{t-3}		0.048 (0.101)	0.075 (0.169)	
γ_4	ΔF_{t-4}		-0.100 (-0.218)	0.083 (0.186)	
γ_5	ΔF_{t-5}		0.035 (0.079)	0.075 (0.180)	
γ_6	ΔF_{t-6}		0.200 (0.454)	-0.061 (-0.147)	
γ_7	ΔF_{t-7}		0.222 (0.515)	0.334 (0.811)	
γ_8	ΔF_{t-8}		0.817 (1.903)	1.018 (2.423)	
δ_1	JAN		-0.017 (-0.580)	0.011 (0.274)	
δ_2	MAR		0.025 (0.974)	0.058 (1.551)	
δ_3	MAY		0.023 (0.903)	0.010 (0.251)	
δ_4	JUL		-0.022 (-0.866)	-0.121 (-2.597)	-0.120 (-3.709)
δ_5	SEP		-0.032 (-1.048)	-0.016 (-0.412)	
ϕ_1	JANb			-2.010 (-1.405)	
ϕ_2	MARb			-1.416 (-1.229)	
ϕ_3	MAYb			0.449 (0.377)	
ϕ_4	JULb			6.040 (2.726)	6.491 (3.617)
ϕ_5	SEPb			-0.650 (-0.527)	
	Obs.	101	93	93	99
	Var.	2	23	28	8
	RSS	0.284044	0.196108	0.155514	0.233516
	SC Inf Crit	-5.782	-5.041	-5.029	-5.678
	HQ Inf Crit	-5.813	-5.414	-5.483	-5.803
	H_0: no lags		0.9219 [0.5485]	1.3064 [0.2207]	0.9818 [0.4216]
	H_0: $\theta_1=1$	0.7442 [0.3883]	0.0579 [0.8098]	0.2184 [0.6402]	
	H_0: $\theta_1+\phi_4=1$				13.346 [0.0003]
	H_0: no step dummies		2.0222 [0.0860]	4.4817 [0.0014]	
	H_0: no slope dummies			3.3934 [0.0087]	
	H_0: no seas dummies			2.8807 [0.0049]	7.0618 [0.0014]

t-statistics are reported in parenthesis

Testing unbiasedness

Model 3	
H_0: $\theta_1+\phi_1=1$	2.1365 [0.1438]
H_0: $\theta_1+\phi_2=1$	2.3221 [0.1275]
H_0: $\theta_1+\phi_3=1$	1.9565 [0.1619]
H_0: $\theta_1+\phi_4=1$	10.708 [0.0011]
H_0: $\theta_1+\phi_5=1$	0.0640 [0.8003]

Table 2D SOYBEANS - sample period: Mar 1980-Nov 1996 - forecast horizon 28 days

	SOYBEANS	s_t-s_{t-28}	f_t-f_{t-28}	f_{t-28}-s_{t-28}	s_t-f_{t-28}
θ_0	Constant	0.012 (0.735)	0.016 (1.135)	0.029 (10.317)	-0.014 (-1.108)
λ_1	lag 1	-0.166 (-1.466)	-0.096 (-0.895)	0.430 (6.280)	-0.036 (-0.368)
λ_2	lag 2	-0.005 (-0.042)	-0.041 (-0.388)		-0.071 (-0.743)
λ_3	lag 3	0.076 (0.692)	0.062 (0.609)		-0.013 (-0.141)
λ_4	lag 4	0.091 (0.824)	-0.006 (-0.065)		0.016 (0.175)
λ_5	lag 5	0.118 (1.078)	0.083 (0.859)		0.132 (1.486)
λ_6	lag 6	-0.291 (-2.719)	-0.205 (-2.119)		-0.180 (-2.016)
λ_7	lag 7	-0.223 (-2.026)			
λ_8	lag 8	-0.037 (0.342)			
λ_9	lag 9	0.107 (1.047)			
λ_{10}	lag 10	-0.040 (-0.388)			
λ_{11}	lag 11	0.211 (2.081)			
	d40			-0.056 (-4.708)	
	d49			0.067 (5.511)	
	d5051			0.040 (4.756)	0.118 (3.423)
	d81				0.169 (3.545)
δ_1	JAN	-0.009 (-0.405)	-0.010 (-0.507)	-0.025 (-5.634)	-0.013 (-0.775)
δ_2	MAR	0.016 (0.645)	0.015 (0.750)	-0.0217 (-5.251)	0.014 (0.808)
δ_3	MAY	0.024 (0.997)	0.012 (0.622)	-0.020 (-4.932)	0.005 (0.299)
δ_4	JUL	-0.031 (-1.290)	-0.044 (-2.234)	-0.019 (-4.787)	-0.029 (-1.650)
δ_5	SEP	-0.069 (-3.134)	-0.027 (-1.366)	-0.025 (-6.253)	-0.022 (-1.309)
	Obs.	90	95	100	95
	Var.	17	12	10	14
	RSS	0.203259	0.228499	0.011914	0.169470
	H_0: no seas. dummies	4.6773 [0.0009]	2.8331 [0.0206]	10.178 [0.0000]	1.84 [0.1143]

t-statistics are reported in parenthesis

Table 3D SOYBEANS - sample period: Mar 1980-Nov 1996 - forecast horizon 56 days

	ΔS_t	Model 1	Model 2	Model 3	Model 4
θ_0	Constant	-0.036 (-2.893)	-0.035 (-1.701)	-0.041 (1.386)	-0.041 (-3.335)
θ_1	Basis	1.756 (3.639)	1.617 (3.633)	1.806 (1.922)	1.896 (2.734)
λ_1	ΔS_{t-1}	0.123 (0.259)	0.435 (0.963)	0.600 (1.239)	0.599 (1.246)
λ_2	ΔS_{t-2}	-0.813 (-1.802)	-0.733 (-1.690)	-0.550 (-1.218)	-0.641 (-1.402)
λ_3	ΔS_{t-3}	-1.385 (-3.116)	-1.284 (-2.993)	-1.120 (-2.352)	-1.185 (-2.484)
λ_4	ΔS_{t-4}	-0.243 (-0.538)	-0.258 (-0.592)	-0.106(-0.237)	-0.088 (-0.192)
λ_5	ΔS_{t-5}	-0.202 (-0.469)	-0.676 (-1.622)	-0.688 (-1.602)	-0.562 (-1.295)
λ_6	ΔS_{t-6}	-0.110 (-0.260)	-0.318 (-0.768)	-0.190 (-0.438)	-0.262 (-0.628)
λ_7	ΔS_{t-7}	-0.531 (-1.233)	-0.379 (-0.922)	-0.402 (-0.958)	-0.606 (-1.427)
λ_8	ΔS_{t-8}	-1.025 (-2.627)	-0.866 (-2.223)	-0.924 (-2.216)	-1.160 (-2.802)
γ_1	ΔF_{t-1}	-0.396 (-0.800)	-0.802 (-1.667)	-0.979 (-1.874)	-0.912 (-1.800)
γ_2	ΔF_{t-2}	0.687 (1.461)	0.620 (1.350)	0.442 (0.922)	0.519 (1.067)
γ_3	ΔF_{t-3}	1.399 (3.062)	1.330 (2.990)	1.152 (2.333)	1.179 (2.374)
γ_4	ΔF_{t-4}	0.357 (0.765)	0.413 (0.909)	0.290 (0.626)	0.255 (0.535)
γ_5	ΔF_{t-5}	0.114 (0.259)	0.617 (1.440)	0.668 (1.518)	0.514 (1.164)
γ_6	ΔF_{t-6}	-0.051 (-0.119)	0.125 (0.295)	-0.041 (-0.093)	0.025 (0.059)
γ_7	ΔF_{t-7}	0.510 (1.163)	0.292 (0.698)	0.308 (0.720)	0.542 (1.273)
γ_8	ΔF_{t-8}	0.984 (2.462)	0.854 (2.141)	0.910 (2.147)	1.120 (2.651)
	d22	0.332 (5.123)	0.379 (6.119)	0.391 (6.106)	0.379 (5.786)
δ_1	JAN		0.003 (0.099)	0.026 (0.560)	
δ_2	MAR		0.021 (0.869)	0.053 (1.186)	
δ_3	MAY		0.053 (2.138)	0.037 (0.979)	
δ_4	JUL		-0.017 (-0.713)	-0.035 (-0.953)	
δ_5	SEP		-0.044 (-1.589)	-0.029 (-0.751)	
ϕ_1	JANb			-1.085 (-0.661)	-0.489 (-0.511)
ϕ_2	MARb			-1.269 (-0.812)	0.390 (0.451)
ϕ_3	MAYb			0.911 (0.740)	1.639 (1.976)
ϕ_4	JULb			0.649 (0.503)	-0.342 (-0.392)
ϕ_5	SEPb			-1.029 (-0.751)	-1.793 (-1.618)
	Obs.	93	93	93	93
	Var.	19	24	29	24
	RSS	0.259365	0.201706	0.187625	0.217810
	SC Inf Crit	-4.956	-4.964	-4.792	-4.887
	HQ Inf Crit	-5.264	-5.353	-5.263	-5.277
	H_0: no lags	2.1609 [0.0138]	3.08 [0.0006]	3.0895 [0.0007]	2.9526 [0.0009]
	H_0: θ_1=1	2.4534 [0.1173]	1.9221 [0.1656]	0.7356 [0.3911]	
	H_0: $\theta_1+\alpha_1$=1				
	H_0: no step dummies		3.9448 [0.0033]	2.0592 [0.0821]	
	H_0: no slope dummies			0.9606 [0.4486]	2.6329 [0.0308]
	H_0: no seas dummies			2.4471 [0.0153]	

t-statistics are reported in parenthesis

Testing unbiasedness

Model 3		Model 4	
H_0: $\theta_1+\phi_1=1$	0.0428 [0.8360]	H_0: $\theta_1+\phi_1=1$	0.2204 [0.6887]
H_0: $\theta_1+\phi_2=1$	0.1437 [0.7046]	H_0: $\theta_1+\phi_2=1$	2.9817 [0.0842]
H_0: $\theta_1+\phi_3=1$	3.4330 [0.0639]	H_0: $\theta_1+\phi_3=1$	11.888 [0.0006]
H_0: $\theta_1+\phi_4=1$	2.9959 [0.0835]	H_0: $\theta_1+\phi_4=1$	0.6460 [0.4216]
H_0: $\theta_1+\phi_5=1$	0.0541 [0.8161]	H_0: $\theta_1+\phi_5=1$	0.9823 [0.3216]

Table 4D SOYBEANS - sample period: Mar 1980-Nov 1996 - forecast horizon 56 days

	SOYBEANS	s_t-s_{t-56}	f_t-f_{t-56}	f_{t-56}-s_{t-56}	s_t-f_{t-56}
θ_0	Constant	0.005 (0.252)	-0.012 (-0.570)	0.019 (4.403)	-0.054 (-3.286)
λ_1	lag 1	-0.042 (-0.398)	-0.141 (-1.255)	0.389 (3.713)	-0.315 (-3.283)
λ_2	lag 2	0.052 (0.500)	0.021 (0.181)	0.227 (2.200)	-0.051 (-0.569)
λ_3	lag 3	0.100 (0.967)	0.194 (1.706)		0.055 (0.629)
λ_4	lag 4	0.184 (1.775)	0.168 (1.455)		0.134 (1.564)
λ_5	lag 5	-0.138 (-1.302)	-0.077 (-0.662)		-0.080 (-0.960)
λ_6	lag 6	-0.340 (-3.161)	-0.532 (-4.610)		-0.231 (-2.719)
λ_7	lag 7	-0.152 (-1.483)	-0.145 (-1.288)		-0.112 (-1.286)
λ_8	lag 8	-0.028 (-0.270)	0.020 (0.177)		
λ_9	lag 9	0.019 (0.195)	0.023 (0.215)		
λ_{10}	lag 10	0.009 (0.092)	0.013 (0.128)		
λ_{11}	lag 11	0.006 (0.068)	0.005 (0.047)		
λ_{12}	lag 12	-0.217 (-2.307)	-0.294 (-2.941)		
	d223	0.234 (4.381)			
	d22				0.345 (5.445)
δ_1	JAN	0.009 (0.336)	0.031 (1.088)	-0.010 (-1.647)	0.024 (1.116)
δ_2	MAR	0.037 (0.028)	0.063 (2.126)	-0.10 (-1.931)	0.048 (2.198)
δ_3	MAY	0.046 (1.579)	0.069 (2.307)	-0.011 (-1.998)	0.059 (2.699)
δ_4	JUL	-0.031 (-1.058)	-0.041 (-1.349)	-0.10 (-1.828)	0.007 (0.327)
δ_5	SEP	-0.055 (-2.017)	-0.013 (-0.475)	-0.021 (-3.852)	-0.022 (-1.025)
	Obs.	89	89	99	94
	Var.	19	18	8	14
	RSS	0.318187	0.346822	0.020908	0.280402
	H_0: no seas. dummies	3.5823 [0.0061]	4.3393 [0.0017]	3.0163 [0.0145]	3.7056 [0.0046]

t-statistics are reported in parenthesis

Table 1E ORANGE JUICE - forecast horizon 56 days

	ORANGE JUICE	f_t-f_{t-56}	f_t-f_{t-56}
θ_0	Constant	-0.012 (-1.011)	0.020 (0.705)
λ_1	lag 1	-0.035 (-0.336)	-0.026 (-0.247)
λ_2	lag 2	0.057 (0.551)	0.074 (0.693)
λ_3	lag 3	-0.027 (-0.259)	-0.040 (-0.374)
λ_4	lag 4	0.046 (0.446)	0.060 (0.561)
λ_5	lag 5	-0.013 (-0.126)	-0.004 (-0.040)
λ_6	lag 6	-0.175 (-1.755)	0.206 (-2.024)
λ_7	lag 7	-0.190 (-1.920)	-0.184 (-1.820)
λ_8	lag 8	0.056 (0.557)	0.077 (0.749)
λ_9	lag 9	0.135 (1.339)	0.126 (1.223)
λ_{10}	lag 10	-0.040 (-0.390)	-0.034 (-0.331)
λ_{11}	lag 11	-0.040 (-0.390)	-0.032 (-0.314)
λ_{12}	lag 12	-0.192 (-1.876)	-0.211 (-2.035)
δ_1	JAN		-0.041 (-1.014)
δ_2	MAR		-0.02 (-0.448)
δ_3	MAY		-0.020 (-0.510)
δ_4	JUL		-0.072 (-1.775)
δ_5	SEP		-0.040 (-0.988)
	Obs.	103	103
	Var.	13	18
	RSS	1.187589	1.137484
	H_0: no seas. dummies		0.7488 [0.5892]

t-statistics are reported in parenthesis