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Target zones for futures prices regulated by limits

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Limits to Linear Price Behaviour:

Target zones for futures regulated by price limits

Abstract
This paper analyzes the random walk behaviour of futures prices when the exchange is regulated by price limits. Using a model analogous to exchange rate target zone models, the study tests for the existence of a nonlinear S-shape relation between observed and theoretical futures prices. This phenomenon reflects the adjustments in traders' expectations even when limits are not actually hit. The approach is illustrated for five agricultural futures contracts traded at the Chicago Board of Trade. There is some evidence of nonlinearity in quiet periods. In cases of fundamental realignments, that is volatile periods, this non-linearity disappears.

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I. Introduction

Price Limit Regulation and Trading Behaviour

Defaulting traders, market crashes, and asymmetric information problems provoke criticism of the integrity of derivatives exchanges. As a result, calls for further regulation arise with almost every large realignment of market values. Regulation thus clearly responds to the trading behaviour of market participants. Whether or not trading behaviour is also affected by regulation has so far largely been neglected [1].

When traders are confronted with market impediments they revise their expectations accordingly. This affects their order flow and, hence, the volatility of prices. These dynamic adjustments are ignored by evaluations of the impact of market regulations on the price discovery process that consider the trading process exogenous. If trades are diverted to other outlets (such as non-regulated options or the cash market), this may lead to increased volatility and a reduction in order flow. Thus, the 'integrity' of the exchange can even be further endangered due to the trading impediments invoked by regulation.

This paper focuses on price limit regulation and investigates how it affects the trading behaviour of market participants. Technical (i.e., statistical) consequences of price limits have been investigated in a number of other papers. For example, as Roll (1984) correctly notes, the use of possibly stale prices implied by limit moves will inevitably affect any informational efficiency study. Two studies that carefully account for the possibility of limit moves are Kodres

(1988,1993) which analyze the impact of price limits on tests of the unbiasedness hypothesis in foreign exchange futures markets. These studies restrict the impact of limits to actual limit move occurrences and thereby ignore any ‘intra’ limit dynamics. There are also a number of studies more directly focussing on the impact of price limits, in particular on measures of intraday volatility. Most of them perform this analysis in an event-study context. Ma et al. (1989), Greenwald and Stein (1991), and Kodres and O’Brien (1994), claim that trading halts mitigate price risk and enhance informational efficiency. Others, however, argue that limits obstruct informational efficiency and, in the process, tend to inflate volatility excessively (see inter alia, McMillan (1991), Lee et al. (1994), and Subrahmanyam (1994,1995)). So far, there has been no attempt to encompass the two conflicting models. This paper proposes a modeling framework able to discriminate between these conflicting findings.

Trading Behaviour Models

Underlying the study’s model is the notion that ex ante trading decisions incorporate the existence of trading zones bounded by price limits. For example, market makers may try to avoid or at least postpone the price hitting a boundary, since that would imply interrupted trading, and hence a loss of earnings/profits.

Kuserk and Locke (1996) investigate the impact of price limits on market making profitability and conclude that, on average, market makers profit from trading halts. This finding contrasts with Roll’s (1984) remark that limits do create informational inefficiencies, but not a profit opportunity. Kuserk and Locke focus on market maker behaviour immediately preceding and following limit moves, thus ignoring potential impacts further away from those limits.

Informed traders will similarly try to smooth their planned trading volume before the price hits a limit, after which the risk of a dissipation of their private information increases. Market makers protect themselves against these actions by increasing the bid-ask spread upwards when the market moves towards a limit. This may “exaggerate” volatility and lead to an incorrect inference that price limits cause increased volatility, an argument used by gravitation proponents. Gravitationists argue that limits are self-exciting, since they induce a strong drift in prices. Traders, allegedly, increase this drift by unwinding positions whenever the price gets close to the limits.

Empirical work in this area is rather limited; some examples are McMillan (1991) and Kuserk and Locke (1996). Some of these papers deal with circuit breakers, but their findings supposedly apply identically to price limits. A theoretical micro-structural analysis of these (opposing) dynamic trading adjustments is given in Greenwald and Stein (1991), Kodres and

O'Brien (1994) and Subrahmanyam (1994, 1995). Whereas the first two papers tend to support trade suspension rules as (second best) optimal, the latter clearly rejects these rules based on an informational inefficiency that arises because of traders advancing their trades in time as in the informed trader context above. Obviously, the theoretical specification has some impact on the subsequent results.

Influence of Limits on Price Expectations

This paper addresses the issue of how price expectations are influenced by limits, by using concepts recently developed for exchange rate target zones.

A seminal paper by Krugman (1991) shows that bounded exchange rates no longer exhibit a linear relationship with the underlying fundamentals of supply and demand. If, for example, there is a fixed and credible upper limit, and the exchange rate is close to that limit, then the probability of a further increase will be limited, while the probability of a decrease will be relatively larger. Thus, the probability distribution of the next price move will become increasingly skewed the closer it gets to the limit. This phenomenon implies a nonlinear relationship between the actually observed price and the fundamental price. In the absence of trade 'disruptions' the relationship between the two will be linear, but the presence of limits implies a nonlinear S-shape. The relationship will be convex for prices negatively drifting towards the lower limit, and concave for prices positively drifting towards the upper limit. Thus, the effect of limits will theoretically be to stabilize prices. Shocks (demand/supply driven) in the fundamental value will have a less than proportional impact on observed prices.

The statistical specification in this paper also allows for nonlinearity of a different (opposite) type. Instead of a smoothing impact, price limits may have an exacerbating impact. Shocks in the fundamental value will then have a more than proportional impact on the observed price. Thus, the authors nest the two competing models of mean reversion [2] versus gravitation.

Procedure of the Paper

The study investigates the existence of similar non-linear relationships in futures markets that are regulated by price limits. The target zone is then defined by the difference between the upper and lower limit prices. In this case the issue is not so much whether the target zone is credible (it may move the next day and is fully credible intraday), but whether its existence has an impact far away from the limits. This, in particular, distinguishes the paper from previous price limits literature. As suggested by Strongin (1995, p.205), work on the impact of price limits away from limit moves themselves is urgently needed and this issue is addressed.

The following hypothesis is postulated: *The relationship between theoretical and observed – that is, regulated by limits – futures prices is linear*. Rejection of this hypothesis would require analysis of the shape of the non-linearity. If the so-called S-shape familiar in exchange rate target zones is found, it can be concluded that 'target' reversion occurs. If, on the other hand, an inverse S-shape is observed, it can be concluded that gravitation occurs. The underlying theory and its relevance for this setting is discussed in the next section.

After developing the theoretical target zone model of price expectations, it is applied empirically to agricultural futures contracts traded at the Chicago Board of Trade. Daily limits apply to all of these contracts and are allegedly effective in the sense that they alter trading behaviour. The sample period, which extends from January 1988 through December 1988, was chosen because of the frequency of limit moves (when the market closes up- or down-limit) and limit hits (when the price hits the limit but bounces back before market close) in the months of June and July 1988.

II. Absorbing Limits: A Target Zone Model

This paper considers the existence of a non-linear relationship between fundamental (theoretical) futures prices and observed futures prices that are regulated by price limits.

The study adapts a procedure recently developed in the exchange rate literature. However, there is an important difference with the exchange rate target zones in that observed futures prices are regulated directly, whereas exchange rates are typically regulated indirectly by monetary authorities influencing the fundamentals (ie the supply and demand of foreign exchange). As well, unlike the well-known intramarginal regulations prevailing with exchange rate target zones, futures price limit regulation operates only at the limits. However, the main distinction with the target zone literature is the fact that futures price limits are valid for one day only. Except when the closing price coincides exactly with the opening price on a particular trading day, the next trading day will have a different target zone. The limits are not 'credible' on an interday basis, but are perfectly credible intraday. For this reason, the focus of this study is on intraday trading behaviour.

The observed intraday futures price f_{t+j} is prevented from taking values outside of the intraday price limits and should be treated as a censored variable,

$$f_{t+j} = \begin{cases} \overline{f} & \text{if} \quad (f_{t+j-1} + u_{t+j}) \geq \overline{f} \\ (f_{t+j-1} + u_{t+j}) & \text{if} \quad \underline{f} < (f_{t+j-1} + u_{t+j}) < \overline{f} \\ \underline{f} & \text{if} \quad (f_{t+j-1} + u_{t+j}) \leq \underline{f} \end{cases}, \qquad j = 1, \ldots, N \tag{1}$$

where $\overline{f}, \underline{f}$ are, respectively, the upper and lower limits on the N intraday futures prices for any particular day symmetrically specified around f_t, the previous days closing price that defines the 'target' futures price. The innovation u_{t+j}, is the j-th intraday innovation in the futures price (f_{t+j} - f_{t+j-1}), and the u_{t+j} are conditionally distributed according to a unimodal distribution function $\Phi(u)$ with mean zero and conditional variance s^2_{t+j}

Rose (1995) generalizes this conditional distribution problem in the context of doubly censored distributions. In the case of credible reflecting barriers (such as futures price limits on an intraday basis), the probability of f_{t+j} exceeding the barriers will be folded inwards. Thus, $\Phi(u)$ can hardly be expected to display normality. In fact, whereas it is likely to be unimodal, it will typically have excessive tail probability mass. Intuitively appealing estimation methods include the Tobit model by Yang and Brorsen (1995) and the Limited-Dependent Rational Expectations approach advocated by Pesaran and Samiei (1992) and Pesaran and Ruge-Murcia (1996), which model time-varying volatility as an increasing function of the distance from the target price. This is the key notion that we exploit in this paper, albeit with a different functional specification. In a commentary on McMillan (1991), A.S. Margulis Jr. (1991) wrote:

> *"[The existence of price limits] starts affecting trading decisions at some indeterminate level [well within the price limits] and it becomes stronger and stronger as the futures price approaches the limit price."*

If trading decisions are reflected in prices, a relationship will be observed between those prices and the distance from the boundaries on those prices (or alternatively, the distance from the target price). According to the target zone literature (and following from (1) above) this relationship is nonlinear due to the distortion in $\Phi(.)$. Typically the nonlinear specifications following from the target zone models are estimated in continuous time, but it is notoriously difficult to capture particular empirical characteristics like fat-tailedness and time-varying volatility in those models and the assumption of normality is frequently violated. In discrete time, a simple analytical solution for this target zone problem has been suggested by Koedijk et al. (1997) which permits modification of $\Phi(u)$ in line with the empirical characteristics.

First, note from (1) that the conditional expectation of intraday futures price f_{t+j} is bounded,

$$E\left(f_{t+j} \mid f_{t+j\text{-}1}\right) = f_{t+j\text{-}1} + \left(\bar{f} - f_{t+j\text{-}1}\right)\left[1 - \Phi\left(\bar{f} - f_{t+j\text{-}1}\right)\right] + \left(\underline{f} - f_{t+j\text{-}1}\right)\left[\Phi\left(\underline{f} - f_{t+j\text{-}1}\right)\right] + \int_{\underline{f} - f_{t+j\text{-}1}}^{\bar{f} - f_{t+j\text{-}1}} \left(u_{t+j}\right) f\left(u_{t+j}\right) du_{t+j} \qquad (2)$$

where $\Phi(.)$, $f(.)$ are, respectively, the probability distribution and probability density function of the innovations, u_{t+j}. Define the regression equation

$$f_{t+j} - f_{t+j\text{-}1} = E\left[u_{t+j} \mid f_{t+j\text{-}1}\right] + \varepsilon_{t+j} \qquad (3)$$

where e_{t+j} is orthogonal to the conditional expectation term. We know that for a credible target zone, E[.] follows an S-shape in $(f_{t+j\text{-}1} - f_t)$ (see Koedijk et al., 1997). The first three derivatives will then satisfy:

$$\frac{\partial E\left[u_{t+j} \mid f_{t+j\text{-}1}\right]}{\partial\left(f_{t+j\text{-}1} - f_t\right)} = \Phi\left(\bar{f} - f_{t+j\text{-}1}\right) - \Phi\left(\underline{f} - f_{t+j\text{-}1}\right) > 0 \qquad (4a)$$

$$\frac{\partial^2 E\left[u_{t+j} \mid f_{t+j\text{-}1}\right]}{\partial\left(f_{t+j\text{-}1} - f_t\right)^2} = -f\left(\bar{f} - f_{t+j\text{-}1}\right) + f\left(\underline{f} - f_{t+j\text{-}1}\right) \begin{cases} < 0 \ \ if \ \ f_{t+j\text{-}1} > f_t \\ > 0 \ \ if \ \ f_{t+j\text{-}1} < f_t \\ = 0 \ \ if \ \ f_{t+j\text{-}1} = f_t \end{cases} \qquad (4b)$$

$$\frac{\partial^3 E\left[u_{t+j} \mid f_{t+j\text{-}1}\right]}{\partial\left(f_{t+j\text{-}1} - f_t\right)^3} = f'\left(\bar{f} - f_{t+j\text{-}1}\right) - f'\left(\underline{f} - f_{t+j\text{-}1}\right) < 0 \qquad (4c)$$

and we can specify the following functional form, which captures these necessary requirements for an S-shape. One approach suggested in the literature is to use a Laguerre function (as in Miller and Weller, 1991), or one can take a Taylor series expansion around the target futures price f_t (see Rose and Svensson, 1995 and Koedijk et al., 1997), to obtain,

$$f_{t+j} - f_{t+j\text{-}1} = d_0 + d_1\left(f_{t+j\text{-}1} - f_t\right) + \sum_{i=1}^{2} d_{2i} I(.)\left(f_{t+j\text{-}1} - f_t\right)^2 + d_3\left(f_{t+j\text{-}1} - f_t\right)^3 + e_{t+j} \qquad (5)$$

where the residual e_{t+j} consists of ε_{t+j} and any omitted higher order Taylor-expansion terms. The indicator variable I(.) separates the positive from the negative deviations from the target futures price. The fact that the error term contains omitted higher order terms unfortunately implies that e_{t+j} is not necessarily orthogonal to the futures price change. This is a potential problem when estimating (5), which is addressed further on.

Testing the Hypothesis

Having estimated (5), the hypothesis can be tested. For a nonlinear relationship, i.e., to establish whether the limits have an impact on the observed futures prices, it needs to tested whether any of the parameters δ_1, δ_{21}, δ_{22} or δ_3 are significantly different from zero. In the case of non-credible limits (a finding of insignificant parameter estimates) it is expected – in the absence of market imperfections such as bid/ask spreads, infrequent trading etc. – that the random walk model for futures prices will prevail. If it is possible to reject a linear relationship, the study can proceed by investigating the shape of the non-linearity. It can be considered that the following parameter signs imply the theoretical S-shape. To find a mean-reverting target zone, δ_1 needs to be positive, δ_{21} (for positive deviations from f_t) to be negative, δ_{22} (for negative deviations from f_t) to be positive, and δ_3 to be negative. These conditions follow directly from (4a), (4b), and (4c).

Bleaney and Mizen (1996) model a target zone for exchange rates by specifying two models: a linear mean-reversion versus a cubic mean-reversion, both models being nested in (5) above, and conclude that the cubic model clearly outperforms the linear model. However, by ignoring the quadratic terms they may have a misspecified model and, by distorting the empirically desirable orthogonality of the error term in (5), this may have a pronounced effect on the outcome. The study does not restrict the regression model, but instead takes a pragmatic approach. After estimating (5), the function is investigated and it is concluded from its shape whether or not the mean-reversion hypothesis is to be rejected.

In general, the above mentioned signs of parameters capture the mean-reverting behaviour of the futures price, and any non-linearity involved in this behaviour. The first-order term indicates whether the futures price reverts to the target price f_t (positive sign), or gravitates towards the limits (negative sign). The second- and third-order terms indicate the speed at which this occurs, whereas the second-order terms also allow for asymmetric adjustments depending on the position (above or below the target price f_t) of the futures price.

Next, the error term in (5) needs to be addressed. Since time-varying conditional variance and fat tails most often characterize futures price changes, the innovations are modelled according to these two characteristics. Numerous authors have investigated the apparent non-normality of futures price changes. Typically, a fat-tailed alternative has been proposed with the evidence pointing towards the class of Student-t distributions (see Kofman, 1994). Allowance is made here for 'fatter-than-normal' distributions by assuming that the innovations in (5) follow a *t*-distribution:

$$e_{t+j} \sim t_n(0, h_{t+j}), \tag{6}$$

where e_t is assumed to follow a symmetric Student-*t* distribution with mean zero, variance h, and degrees of freedom n ($n > 2$). The n parameter measures the extent of fat-tailedness – the smaller n, the larger the probability mass in the tails. For $n = \infty$, the *t*-distribution converges to a normal distribution. For $n = 2$, the *t*-distribution no longer has finite variance.

Note that the normal distribution based on observed excess kurtosis cannot be rejected a priori. It is possible that the fat tails are driven by time-varying conditional variance. In that case, the standardized price changes may well be normal. Thus the conditional variance in (6) is allowed to have the following well known GARCH(1,1) specification.

$$h_{t+j} = b_0 + b_1 e^2_{t+j-1} + b_2 h_{t+j-1} \tag{7}$$

III. Price Limits in Agricultural Futures Contracts

Having introduced the approach, the methodology is now applied to a set of agricultural futures contracts that are regulated by price limits.

The dataset consists of five agricultural commodities traded at the Chicago Board Of Trade for 227 trading days in 1988. Contract descriptions and limit regulations for these contracts are given in Appendix B. The sample period is characterized by an unusual frequency of limit moves, in particular in the month of June. The dataset is based on the nearby futures contracts, which rollover two business days prior to the delivery month. This coincides with the date the price limits are lifted on the nearby contract. A 5-minute sampling interval has been chosen, based on a tradeoff between minimizing the number of no-trade intervals while using as much information as possible. To some extent this choice alleviates the noise to signal problem endemic in using high frequency data. If no price was recorded during this interval, the last previously recorded price was taken.

Price changes (called returns from now on) are constructed from the futures prices f_t: $R_{t+j} = f_{t+j} - f_{t+j-1}$. The overnight returns are omitted. The first return of each day is computed as the difference between the last recorded price during the first five minutes of trading and the first observed price during that interval. The rollover return is omitted and zero returns are imputed for empty intervals to obtain up to 10,215 observations per commodity for the time period January 5 through November 28, 1988.

The descriptive statistics for the five contracts' 5-minute returns are given in panel A of Table I. The number of limit-move days is given in the last row. It is obvious that Wheat forms an exception among these contracts since its limits have been hit on only 9 days as compared to between 25 and 32 limit moves for other contracts. The trading days on which the limits have been hit are eliminated because trading in limit-up (limit-down) contracts is usually interrupted for prolonged periods of time during a trading session. This implies an excessive number of – non-informative – zero price changes.

The information in Table I is rather homogeneous across commodities and can easily be summarized. There is clear evidence of skewness and excess kurtosis. It is therefore of no surprise that the Jarque-Bera tests for normality are overwhelmingly rejected. The significance of the Ljung-Box tests for serial correlation in the returns, and the reported first-order serial correlation coefficient (ρ), reflect either the impact of the bid-ask bounce, the discreteness of the data or the infrequent trading effect. When further investigating this phenomenon, it seems that the serial correlation can be characterized as first-order autocorrelation.

TABLE I ABOUT HERE

The Ljung-Box test statistic on the squared residuals and ARCH test for heteroskedasticity illustrate the time-varying conditionality in the variance of the returns. The ARCH test is based on an autoregression of the squared returns on lagged squared returns, whereas the Ljung-Box test is a serial correlation test on the squares of the returns.

A well-known characteristic of high frequency prices is the seasonality in intraday volatility, see Andersen and Bollerslev (1997). When intraday volatility is defined as the absolute price change over the 5-minute sampling interval, a similar U-shape pattern is found in the series. This seasonality implies large price changes during opening of the trading session, which then taper off during the middle of the trading session, before reverting to large price changes at the close of the trading session. This pattern may bias the target zone results. In Appendix A, it is explained how the series is deseasonalized to avoid that problem. This generates a new series of deseasonalized returns U_{t+j}. Table I, panel B, indicates that deseasonalization has major effects on the descriptive statistics. Skewness and kurtosis reduce to near-normal values (even though the Jarque-Bera test statistics still reject normality). The serial correlation in returns is not affected, but serial correlation in the squares of returns is considerably smaller (though still significant).

The next step involves an intertemporal analysis of the descriptive statistics. Since the frequency of limit hits and moves is clustered in the middle of 1988, interest centres on the stability over time of certain key descriptive statistics. These statistics allegedly illustrate the harmful aspects of price limits.

Table II is based on a three-fold sample split with reasonably comparable sample sizes: PRE from January 5 through May 1; LIMIT from May 2 through August 31; and POST from September 1 through November 28 [3]. The columns are sequentially ordered so that the first entry is PRE, the second entry is LIMIT, and the third entry is POST. The LIMIT period coincides with the months with the highest frequency of limit hits/moves during 1988. For Soybeans, Soybean Meal and Soybean Oil, a single limit hit/move is observed in the post-limit period.

A number of conclusions can be drawn from the reported measures.

Firstly, for all contracts except Corn, the standard deviation is marginally larger during the LIMIT period. However, this does not necessarily imply causality with limit moves. Increases in the 'fundamental' (cash price) volatility could also lead to a higher frequency of limit hits (and/or moves).

Secondly, skewness and/or kurtosis are similar across the periods. It can be observed that the first-order autocorrelation coefficient is significantly negative in PRE and POST samples, but much less so for the LIMIT sample (insignificant for Soybeans and Soybean Meal). Bid-ask spreads are known to increase with increasing variance. Despite the fact that variance is marginally larger in the LIMIT period, however, first order autocorrelation is much lower during that period. This may be due to infrequent trading which causes positive autocorrelation, thereby offsetting the bid-ask effect.

TABLE II ABOUT HERE

Having discussed the empirical characteristics of the data, the paper now estimates the target zone model for the deseasonalized returns U_{t+j}. For this purpose, equation (5) is slightly modified by including a lagged dependent variable as well as by including appropriate interactive dummy variables D_k, to allow for different parameters in each of the three periods PRE, LIMIT and POST.

$$U_{t+j} = \sum_{k=1}^{3} D_k \Big\{ \delta_{0k} + \delta_{1k}\left(f_{t+j-1} - f_t\right) + \sum_{i=1}^{2} \delta_{2ik} I(.)\left(f_{t+j-1} - f_t\right)^2 + \delta_{3k}\left(f_{t+j-1} - f_t\right)^3 + \delta_{4k} U_{t+j-1} \Big\} + e_{t+j}, \qquad (5a)$$

The autoregressive term captures the bid-ask bounce and discreteness effects typically characterizing high-frequency intraday prices, see Harris (1990) and Miller et al. (1994). For a dominating bid-ask effect, it is expected that δ_4 will be negative. Table III reports the log-likelihood obtained for a number of normal and Student-*t* distribution models. Likelihood Ratio tests are performed to determine which model is best. The study estimates the unrestricted model, where the coefficients are defined for each sub-period, and a restricted model where the coefficients are the same for the full sample period.

A sequence of likelihood ratio tests indicate that the Student-*t* distribution outperforms the normal distribution and that allowing for time-varying conditional variance results in improved performance for the Student-*t* distribution. Estimates of ν are found to be close to 11. In addition, the unrestricted model outperforms the restricted model, though marginally so for the Soybean complex and Wheat, so that splitting the sample into PRE, LIMIT and POST seems to be relevant.

TABLE III ABOUT HERE

The following discussion is restricted to the Student-*t* cum GARCH distributional model and to the unrestricted sub-period model. In the cubic functional forms for all commodities, all but one coefficient of the Taylor series approximation terms (ie the variables in $(f_{t+j-1} - f_t)$) are individually insignificant, and about half of the coefficients have the opposite sign to that suggested by the target zone model. Collinearity is clearly a problem in interpreting the model. A number of restrictions on the coefficients of this model were therefore considered. The log-likelihoods for these restricted models and likelihood ratio test statistics for testing these restrictions are presented in Table IV. For each commodity, the null hypothesis that the coefficients on the cubic terms are zero can be accepted. In the remaining quadratic functional form for the five commodities, while the majority of coefficients remain individually insignificant, it is notable that across the five commodities every coefficient has the correct sign as predicted by the target zone model.

TABLE IV ABOUT HERE

The coefficient estimates of this quadratic functional form are presented in Table V. In contrast with the cubic specification, there are consistent parameter estimates across commodities and across sub-periods for the target zone variables. Except for Soybeans, and Soybean Meal, in the LIMIT period, the constant, δ_0, is insignificantly different from zero. The first-order term, δ_1, is also frequently insignificantly different from zero. It is, however, significant for Corn, and does have the positive sign required for mean reversion. The second-order terms, δ_{21}, and δ_{22}, are occasionally significant (or close to significance), particularly in the PRE and POST period. The non-linear model apparently performs best (in terms of significance) for Corn. Formal statistical tests indicate that the random walk model is the preferred model for the Soybean complex and Wheat, whereas the quadratic functional form is the preferred model for Corn.

TABLE V ABOUT HERE

Concluding the parameter estimates discussion, it is found that there is some evidence of non-linearity in futures prices potentially driven by the existence of price limits.

The target zone coefficients indicate that even within the limits, there may be a discernible impact, in particular in the PRE and POST Corn samples. The consistency in the signs of these coefficients suggests a straightforward conclusion can be drawn with regard to the gravitation versus mean reversion theory. Even though conclusive evidence for mean reversion is not found, gravitation can clearly be rejected.

Given that linearity is rejected by the estimates, it would be expected that the S-shape implied by the target zone theory would be found. For this purpose, consider Figure 1 where the fitted model for Corn from Table V is plotted according to the target zone estimates. The dashed lines indicate the 95% confidence interval. Panel A is related to the PRE estimates; Panel B is related to the LIMIT estimates; and Panel C is related to the POST estimates.

If the target zone mean reverting model is the true model, a (increasing) negative deviation from the target futures price would be expected to generate a (increasing) positive futures return. If the gravitation model is the true model a (increasing) negative deviation from the target futures price would be expected to generate a (increasing) negative futures return. Analogous conclusions can be drawn for positive deviations from the target futures price.

A similar shape is observed for the three sub-periods. The PRE and POST graphs clearly display mean-reverting non-linear behaviour. The LIMIT graph also displays mean reverting behaviour, but the confidence bands indicate that it is much less 'impressive' in non-linear terms; there is hardly any reaction, or weak evidence of mean reversion. The cases where we cannot reject 'no reaction' correspond to the random walk model. The evidence for the other commodities corroborates these results. While all graphs indicate mean reversion, in most cases it is insignificant.

FIGURE I ABOUT HERE

Thus, when the fundamental cash price is strongly drifting upwards or downwards, so that it seems that limit hits (and moves) are imminent, the futures price process behaves like a random walk with drift. For 'normal' periods, price limits seem to have a mean-reverting impact on prices. As suggested in the introduction, it is tempting to conclude that price limits are not the preferred regulatory tool in case of fundamental market realignments. In the case of overreacting markets (when there is little evidence of fundamental realignments), limits do seem to have a moderating impact on price changes.

IV. Concluding Remarks

Price limit regulation is a hotly debated issue provoked by the occasional major realignment in prices. Despite their limited occurrence, antagonists argue that their very existence may deter prospective traders from entering futures trading. Protagonists, on the other hand, argue that the occasional mayhem and chaos sufficiently underline the need for even tighter price limits.

This paper has made an attempt to identify the impact of futures price limits on traders' expectations, and hence price discovery. The current literature on futures price limits can be divided between those that argue in favour of the gravitation of prices towards the limits versus those that claim mean-reverting behaviour of prices bouncing back from the limits. Both hypotheses imply non-linearities in futures returns. This study specifies a target zone model for intraday futures prices that allows proper testing for the existence of this non-linearity. By applying the model to a set of agricultural futures contracts, it is illustrated that, even without actual limit hits (or moves) for a prolonged period of time, there is some impact of the boundedness of prices.

All parameter estimates have signs consistent with the S-shape mean reversion hypothesis. For Corn futures, in particular, evidence is found of mean-reverting non-linearity in futures price returns. For the Soybean complex and Wheat, conclusive evidence for mean reversion is unable to be found, but the gravitation hypothesis can still be rejected. Hence, there is either no impact of price limits on traders' expectations, or there is some moderation impact.

It is therefore tentatively concluded that price limits might not be the preferred tool in case of major market realignments. For regular market behaviour, however, price limits seem to have a modifying impact on volatility.

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Footnotes

[1] As an example, Jorion (1995) mentions that the US repo market is a creature of Federal Reserve Regulation Q. A market with daily turnover in excess of $500 billion has been created as investors switched out of bank deposits as a result of Q.

[2] Note that the mean reversion hypothesis is not synonymous to its statistical counterpart. In this paper, mean reversion implies price movements towards the target price, i.e. the centre between upper and lower price limits.

[3] Note that the exact number of observations differs per commodity due to the number of (excluded) limit move days. The sub-sample sizes are given in the Appendix (contract specifications).

Table I. Descriptive Statistics

This table reports a range of descriptive statistics for the returns (ie. futures price changes) of five commodity futures contracts traded at the Chicago Board of Trade. The nearest delivery contract has been chosen and rollover to the next-to-nearest contract occurs two trading days prior to the delivery month. The last line indicates the number of five-minute sampling intervals for 1988 for each of these contracts (45 observations per trading day).

Statistics given in this table comprise the first four moments, and a set of tests for normality, serial correlation, and heteroskedasticity. A * indicates a significant rejection of the test at the 5%-level. The Jarque-Bera test is a normality test based on skewness and excess kurtosis measures. Autocorrelation ρ gives the first-order autocorrelation coefficient estimate. The Ljung-Box test is a test for up to 12th order serial correlation in the levels, respectively squares of price changes. The ARCH test is a Lagrange Multiplier test for conditional heteroskedasticity in the returns. Limit move days indicates the number of days on which the futures price closes at the limit (limit up or down) for each of the contracts individually.

Panel A: Raw Returns, R_{t+j}

	Corn	**Soybeans**	**Soybean Meal**	**Soybean Oil**	**Wheat**
Mean	-0.00	0.02	0.01	-0.00	-0.00
Standard deviation	0.58	1.69	0.59	0.06	0.88
Skewness	-0.87	-0.18	0.52	-1.17	-0.57
Excess kurtosis	31.37	16.49	28.91	26.24	24.64
Jarque-Bera test	296890.6*	67299.8*	250881.7*	208681.6*	193741.5*
Autocorrelation ρ	-0.073*	-0.004	-0.044*	-0.053*	-0.025*
Ljung-Box (12) –levels	165.63*	102.61*	80.86*	112.66*	58.44*
Ljung-Box (12) –squares	3404.46*	3712.17*	1333.98*	733.26*	2182.79*
ARCH test	457.99*	729.94*	754.93*	230.48*	908.48*
Number of observations	8820	8865	8955	9180	9900
Limit move days	31	32	30	25	9

Panel B: Deseasonalized Returns, U_{t+j}

	Corn	**Soybeans**	**Soybean Meal**	**Soybean Oil**	**Wheat**
Mean	-0.00	0.03	0.03	0.01	0.01
Standard deviation	1.37	1.30	1.32	1.34	1.36
Skewness	-0.03	-0.07	-0.00	-0.00	-0.02
Excess kurtosis	3.69	3.59	3.68	3.84	4.12
Jarque-Bera test	176.3*	135.16*	172.14*	267.34*	516.2*
Autocorrelation ρ	-0.143*	-0.052*	-0.045*	-0.058*	-0.056*
Ljung-Box (12) –levels	186.45*	72.42*	82.10*	94.30*	51.41*
Ljung-Box (12) –squares	36.33*	52.89*	136.03*	74.08*	70.51*
ARCH test	15.97*	38.28*	77.79*	46.64*	48.70*

Table II. Sample Split Statistics

This table reports a set of descriptive statistics for deseasonalised returns U_{t+j} and test statistics for three sub-samples. The sub-sample selection is based on the frequency of limit hits/moves. Limit hits/moves predominantly occur in the months of June and July 1988. Hence, we distinguish a PRE, a LIMIT, and a POST sample. These sub-samples correspond with respectively the first, second and third entry in each cell. The descriptive statistics are the first, second, third and fourth empirical moments, and the first-order serial correlation coefficient. A * indicates a significant rejection of the null hypothesis of normal distribution values for skewness and kurtosis and the null hypothesis of no autocorrelation, at the 5%-level.

		Mean	Standard Deviation	Skewness	Excess Kurtosis	First order autocorrelation	Limit moves
Corn	*PRE*	-0.00	1.42	-0.07	3.58	-0.206	0
	LIMIT	0.00	1.34	0.11	4.20	-0.077	31
	POST	-0.01	1.34	-0.07	3.37	-0.107	0
Soybeans	*PRE*	0.03	1.26	-0.13	3.65	-0.043	0
	LIMIT	0.06	1.34	-0.09	3.64	-0.013	31
	POST	0.01	1.32	-0.10	3.43	-0.102	1
Soybean Meal	*PRE*	0.01	1.26	-0.07	3.49	-0.042	0
	LIMIT	0.07	1.37	0.03	3.52	0.001	29
	POST	0.02	1.34	0.03	3.99	-0.096	1
Soybean Oil	*PRE*	0.04	1.31	0.03	3.72	-0.052	0
	LIMIT	0.03	1.37	-0.01	3.76	-0.044	24
	POST	-0.04	1.35	-0.04	4.03	-0.082	1
Wheat	*PRE*	-0.01	1.31	-0.10	4.07	-0.050	0
	LIMIT	0.01	1.39	-0.04	4.08	-0.040	9
	POST	0.04	1.37	0.10	4.16	-0.084	0

Table III. Target Zone Log-Likelihoods

This table reports the maximized log-likelihood for the following unrestricted equation:

$$U_{t+j} = \sum_{k=1}^{3} D_k \left\{ d_{0k} + d_{1k}\left(f_{t+j\text{-}1} - f_t\right) + \sum_{i=1}^{2} d_{2ik} I(.)\left(f_{t+j\text{-}1} - f_t\right)^2 + d_{3k}\left(f_{t+j\text{-}1} - f_t\right)^3 + d_{4k} U_{t+j\text{-}1} \right\} + e_{t+j},$$

where $I(.)$ is an indicator function separating positive from negative target deviations for $i = 1$, respectively $i = 2$; and a sample split dummy is indicated by $k = 1$ (PRE), 2 (LIMIT), and 3 (POST), and the restricted equation where the coefficients are constrained to be equal across each period, i.e., $d_{*1} = d_{*2} = d_{*3}$, i.e.

$$U_{t+j} = d_0 + d_1\left(f_{t+j\text{-}1} - f_t\right) + \sum_{i=1}^{2} d_{2i} I(.)\left(f_{t+j\text{-}1} - f_t\right)^2 + d_3\left(f_{t+j\text{-}1} - f_t\right)^3 + d_4 U_{t+j\text{-}1} + e_{t+j}$$

We estimate this model for the unconditional normal distribution, the unconditional Student-*t* distribution, and conditional versions of both models with GARCH(1,1) errors. Underlined entries indicate the 'best' model based on a likelihood ratio test with the appropriate degrees of freedom.

Error Distribution	**Model**	**Corn**	**Soybeans**	**Soybean Meal**	**Soybean Oil**	**Wheat**
Normal	unrestricted	-14,875.3	-14,544.6	-14,801.7	-15,319.7	-16,643.3
Normal	restricted	-14,898.2	-14,556.1	-14,811.8	-15,328.3	-16,652.6
Normal-GARCH	unrestricted	-14,869.6	-14,528.7	-14,751.2	-15,289.7	-16,608.4
Normal- GARCH	restricted	-14,892.7	-14,539.6	-14,759.6	-15,299.0	-16,616.3
Student-*t*	unrestricted	-14,825.3	-14,493.7	-14,740.6	-15,220.1	-16,478.3
Student-*t*	restricted	-14,847.7	-14,506.1	-17,751.2	-15,228.9	-16,488.1
Student-*t*- GARCH	unrestricted	<u>-14,821.5</u>	<u>-14,480.4</u>	-14,696.4	-15,190.3	-16,442.1
Student-*t*- GARCH	restricted	-14,844.1	-14,492.2	<u>-14,705.2</u>	<u>-15,199.5</u>	<u>-16,450.3</u>

Table IV. Tests of Restrictions

Panel A gives the log likelihood values of the unrestricted Student-*t* GARCH model of Table III and for a number of restricted versions of that model. Panel B presents likelihood ratio test statistics and *p-values* for the restrictions in parentheses. The conditional hypotheses are based on imposing the conditioning restrictions.

Panel A: Log-Likelihood Values

Restrictions	**Number of Coefficients**	**Corn**	**Soybeans**	**Soybean Meal**	**Soybean Oil**	**Wheat**
Unrestricted	22	-14,821.5	-14,480.4	-14,696.4	-15,190.3	-16,442.1
$\delta_{*1} = \delta_{*2} = \delta_{*3}$	10	-14,844.1	-14,492.2	-14,705.2	-15,199.5	-16,450.3
$\delta_{3*} = 0$	19	-14,821.7	-14,482.9	-14,697.2	-15,191.3	-16,443.7
$\delta_{2*} = \delta_{3*} = 0$	13	-14,832.2	-14,486.9	-14,700.0	-15,196.1	-16,448.0
$\delta_{1*} = \delta_{2*} = \delta_{3*} = 0$	10	-14,832.8	-14,490.6	-14,703.2	-15,198.6	-16,452.2
$\delta_{2*} = 0$	16	-14,825.6	-14,483.0	-14,697.0	-15,193.3	-16,446.5
$\delta_{1*} = 0$	19	-14,822.9	-14,482.2	-14,696.5	-15,192.8	-16,442.6

Panel B: Likelihood Ratio Test Statistics

Restrictions	**Degrees of Freedom**	**Corn**	**Soybeans**	**Soybean Meal**	**Soybean Oil**	**Wheat**
$\delta_{*1} = \delta_{*2} = \delta_{*3}$	12	45.2 (0.000)	23.6 (0.023)	17.6 (0.128)	18.4 (0.104)	16.4 (0.176)
$\delta_{3*} = 0$	3	0.4 (0.940)	5. 0 (0.172)	1.6 (0.659)	2.0 (0.572)	3.2 (0.362)
$\delta_{2*} = \delta_{3*} = 0$	9	21.4 (0.011)	13.0 (0.163)	7.2 (0.616)	11.6 (0.237)	11.8 (0.225)
$\delta_{1*} = \delta_{2*} = \delta_{3*} = 0$	12	22.6 (0.031)	20.4 (0.060)	13.6 (0.327)	16.6 (0.165)	20.2 (0.063)
$\delta_{2*} = 0$	6	8.2 (0.224)	5.2 (0.518)	1.2 (0.977)	6.0 (0.423)	8.8 (0.185)
$\delta_{1*} = 0$	3	2.8 (0.424)	3.6 (0.308)	0.2 (0.978)	5.0 (0.172)	1.0 (0.801)
$\delta_{2*} = 0 \mid \delta_{3*} = 0$	6	21.0 (0.002)	8.0 (0.238)	5.6 (0.469)	9.6 (0.143)	8.6 (0.197)
$\delta_{1*} = \delta_{2*} = 0 \mid \delta_{3*} = 0$	9	22.2 (0.008)	15.4 (0.081)	12.0 (0.213)	14.6 (0.103)	17.0 (0.049)
$\delta_{1*} = 0 \mid \delta_{3*} = 0$	3	14.2 (0.003)	2.4 (0.494)	3.4 (0.334)	6.2 (0.102)	1.6 (0.659)
$\delta_{1*} = 0 \mid \delta_{2*} = \delta_{3*} = 0$	3	1.2 (0.753)	7.4 (0.060)	6.4 (0.093)	5.0 (0.172)	8.4 (0.038)

Table V. Quadratic Target Zone Models

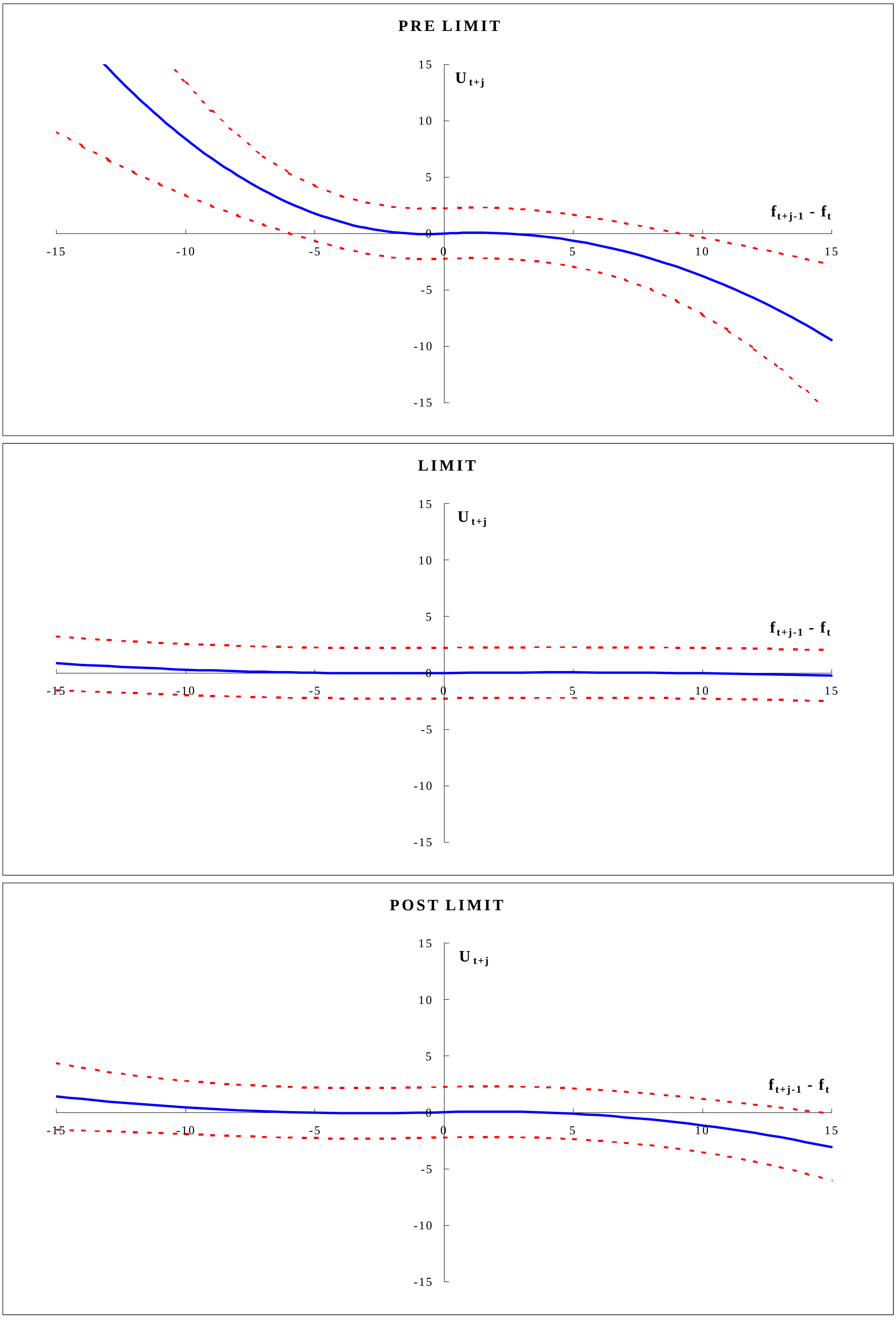
This table reports the parameter estimates for the Student-*t* cum GARCH error distribution:

$$U_{t+j} = \sum_{k=1}^{3} D_k \left\{ d_{0k} + d_{1k}\left(f_{t+j\text{-}1} - f_t\right) + \sum_{i=1}^{2} d_{2ik} I(.)\left(f_{t+j\text{-}1} - f_t\right)^2 + d_{4k} U_{t+j\text{-}1} \right\} + e_{t+j},$$

where the third order term coefficients are restricted to zero. The coefficient estimates are given for the three sub-samples PRE, LIMIT, and POST. The t-statistics are given in parentheses (for the degrees of freedom parameter, the null hypothesis is $n = 2$)

	Corn	Soybeans	Soybean Meal	Soybean Oil	Wheat
$d_{0,pre}$	-0.0022	0.0362	0.0155	0.0186	-0.0193
	(-0.077)	(1.595)	(0.649)	(0.727)	(-0.754)
$d_{0,limit}$	-0.0057	0.0725	0.0658	0.0285	0.0209
	(-0.181)	(2.287)	(2.116)	(0.993)	(0.823)
$d_{0,post}$	0.0239	0.0269	0.0313	-0.0510	0.0073
	(0.747)	(0.928)	(1.040)	(1.678)	(0.235)
$d_{1,pre}$	0.1266	0.0067	0.0135	0.5767	0.0089
	(2.568)	(0.728)	(0.466)	(2.362)	(0.468)
$d_{1,limit}$	0.0226	0.0087	0.0063	0.0328	0.0011
	(1.306)	(1.261)	(0.344)	(0.206)	(0.125)
$d_{1,post}$	0.0626	0.0044	0.0406	0.1863	0.0247
	(2.398)	(0.524)	(1.735)	(0.684)	(1.171)
$d_{21,pre}$	-0.0504	-0.0004	-0.0035	-0.9915	-0.0017
	(-2.545)	(-0.571)	(-0.449)	(-1.563)	(-0.531)
$d_{21,limit}$	-0.0025	-0.0008	-0.0037	-0.2662	-0.0009
	(-1.316)	(-2.667)	(-1.423)	(-0.996)	(-1.125)
$d_{21,post}$	-0.0180	-0.0006	-0.0094	-0.7621	-0.0040
	(-2.769)	(-0.857)	(-1.709)	(-0.854)	(-1.081)
$d_{22,pre}$	0.0964	0.0013	0.0057	1.9408	0.0123
	(3.110)	(1.182)	(0.445)	(2.582)	(1.864)
$d_{22,limit}$	0.0053	0.0008	0.0047	0.1653	0.0005
	(1.767)	(2.000)	(1.270)	(0.811)	(0.714)
$d_{22,post}$	0.0104	0.0002	0.0069	0.8150	0.0085
	(1.576)	(0.333)	(1.408)	(1.334)	(1.889)
$d_{4,pre}$	-0.2050	-0.0469	-0.0558	-0.0565	-0.0615
	(-12.275)	(-2.635)	(-3.100)	(-3.247)	(-3.534)
$d_{4,limit}$	-0.0827	-0.0155	-0.0070	-0.0401	-0.0464
	(-3.919)	(-0.760)	(-0.338)	(-2.046)	(-2.651)
$d_{4,post}$	-0.1160	-0.1168	-0.1069	-0.0859	-0.0953
	(-5.771)	(-5.869)	(-5.189)	(-4.295)	(-4.862)
b_0	0.8682	0.4827	0.6192	0.6212	0.7498
	(2.208)	(2.887)	(6.236)	(4.375)	(4.943)
b_1	0.0302	0.0416	0.0887	0.0732	0.0798
	(2.517)	(4.078)	(7.040)	(5.588)	(6.045)
b_2	0.4995	0.6719	0.5536	0.5828	0.5169
	(2.294)	(6.454)	(8.900)	(6.824)	(5.914)
n	12.1996	11.5559	11.0375	7.9738	6.7075
	(6.818)	(7.126)	(7.278)	(8.846)	(10.299)

Figure 1. Target Zone Functions for Corn Futures



APPENDIX A. DESEASONALIZING RETURNS

Theory:

As in Andersen and Bollerslev (1997) and Kofman and Martens (1997), the Flexible Fourier Form (FFF) specification originally introduced by Gallant (1981) is used to account for deterministic intraday volatility. The FFF models volatility as a sum of low-order polynomial and trigonometric terms:

$$\left|R_{t,d}\right| = \sum_{k=0}^{K} \sigma_d^k \left[\alpha_{0k} + \alpha_{1k}\left(\frac{t}{T}\right) + \alpha_{2k}\left(\frac{t}{T}\right)^2 + \sum_{j=1}^{J}\left(\tau_{jk}\cos\left(\frac{2jt\pi}{T}\right) + \gamma_{jk}\sin\left(\frac{2jt\pi}{T}\right)\right)\right] + \zeta_{t,d} \qquad \text{(A1)}$$

where absolute intraday futures returns are used as the volatility measure. The FFF is partly a quadratic function of time $t = 1,\ldots,T$ – to capture the intraday U-shape – and partly a trigonometric functions of time t – to capture any other smooth patterns (e.g., regularly timed agricultural news releases). The σ_d^k term measures the standard deviation of futures returns on day d. By including this interactive volatility term, allowance is made for the fact that daily volatility levels are commonly found to be correlated. Hence, inclusion will absorb level shifts in the volatility seasonal during the sample period. The number of (co-)sinusoids J and interactive volatility terms K is determined by the overall goodness of fit of the regression. The futures returns will then be deseasonalized by dividing them by their seasonal fitted value:

$$U_{t,d} = \frac{R_{t,d}}{\left|\hat{R}_{t,d}\right|} \qquad \text{(A2)}$$

Both raw returns and deseasonalized returns have been used in the target zone estimation.

Empirical Seasonal

Consider the absolute value of futures price changes as a measure of return volatility. These volatility measures are averaged for each 5-minute sampling interval across trading days. This generates an average sample volatility measure per 5-minute interval. Figure A.1 illustrates the well known intraday U-shape (the broken line) for the average sample volatility. Next it is investigated whether the interactive – interdaily – volatility level should be included in the estimation of the seasonal effect. Daily standard deviations are computed from the (45) intradaily price changes per day. Note that the opening interval uses the difference between the last and the first observed price within that interval. The remaining intervals use the difference between the last observed price in that interval and the last observed price in the previous interval. Figure A.2 plots this series. Whereas volatility is rather stable for the first four months, it clearly explodes in the following three months, after which it becomes more stable, but at a much higher level than before. These structural changes may have a substantial impact on intradaily volatility seasonals.

Figure A.1

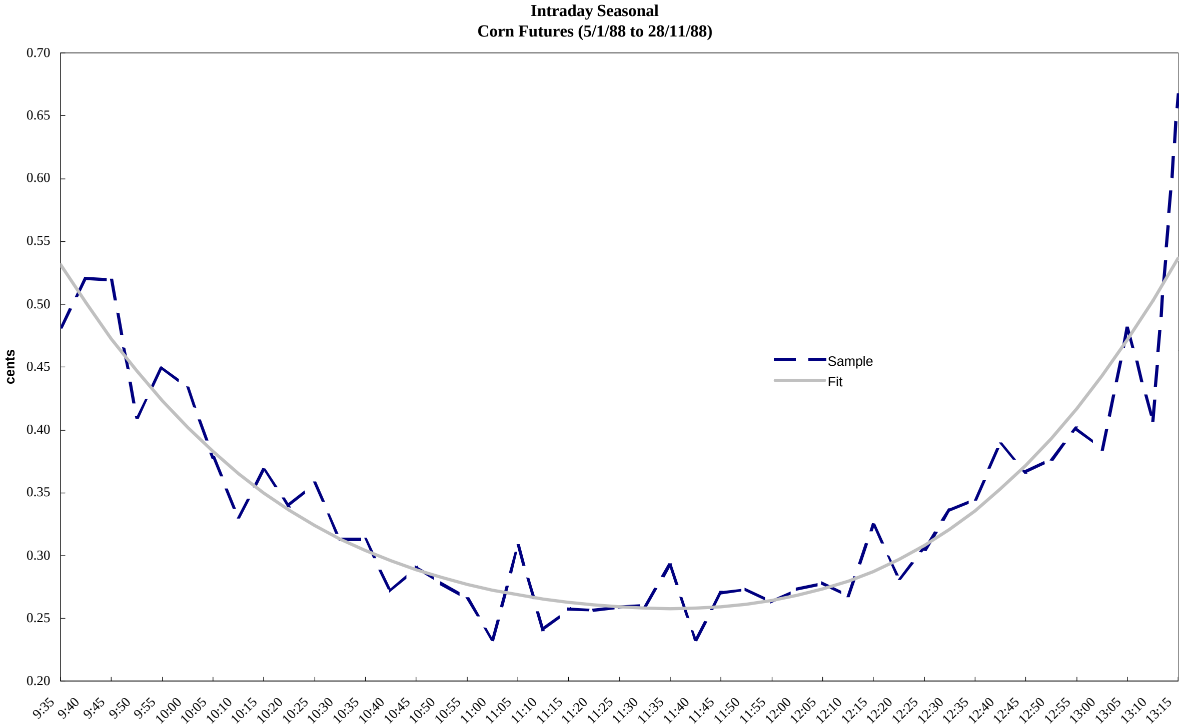


Figure A.2

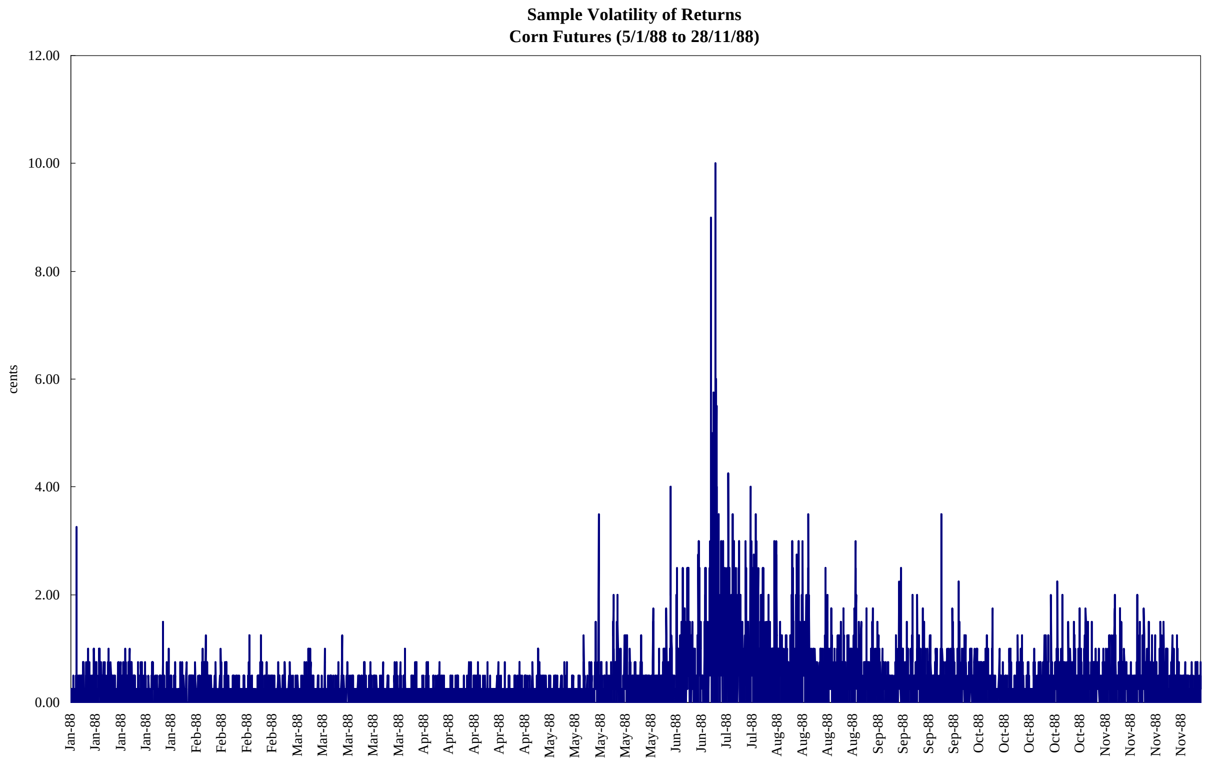


Table A.1, therefore uses the interactive volatility level in the estimation of the seasonal effects. Let J=K=1 in (A1). Higher order terms do not contribute to the shape and significance of the seasonal.

Table A.1. Seasonal Estimation Results

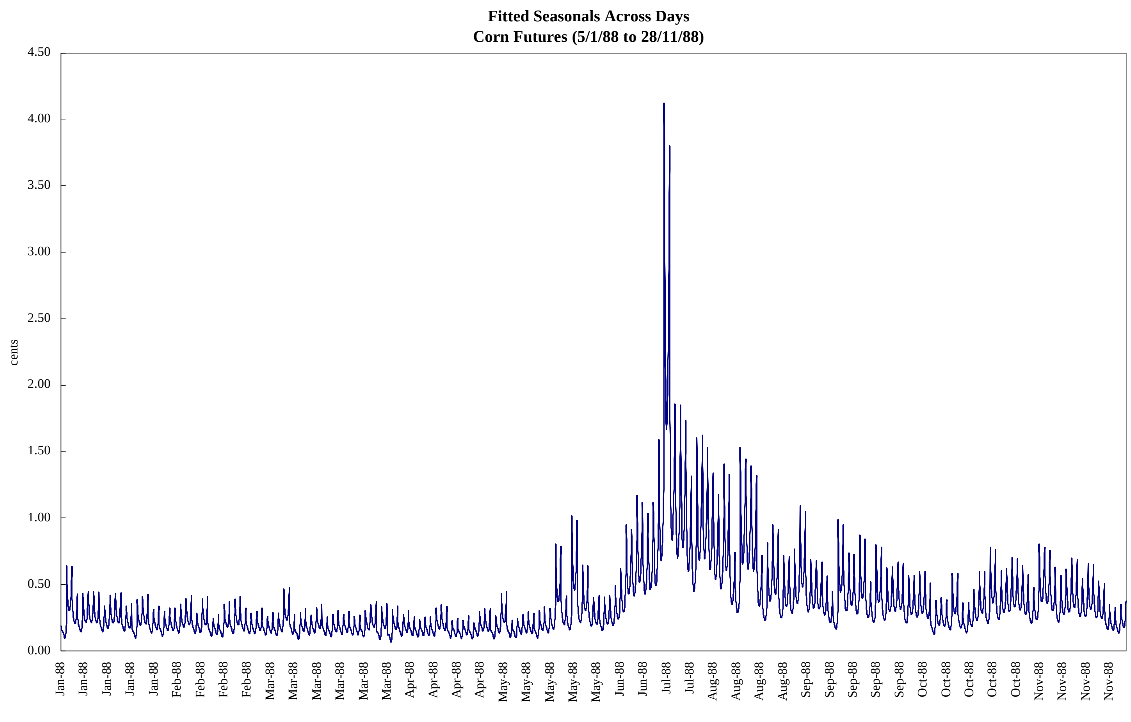
This table reports the estimation results for the seasonal in each of the five commodity futures price volatility series. The seasonal specification is given by:

$$|R_{t,d}| = \sum_{k=0}^{1} \sigma_d^k \left[\alpha_{0k} + \alpha_{1k}\left(\frac{t}{T}\right) + \alpha_{2k}\left(\frac{t}{T}\right)^2 + \left(\tau_k \cos\left(\frac{2t\pi}{T}\right) + \gamma_k \sin\left(\frac{2t\pi}{T}\right)\right)\right] + \zeta_{t,d}$$

The t-statistics are given in parentheses.

Variables	Corn	Soybeans	Soybean Meal	Soybean Oil	Wheat
C	-0.0368 (-0.60)	0.3877 (1.85)	-0.3011 (-4.09)	-0.0179 (-2.24)	-0.5340 (-5.04)
$\sigma \cdot C$	1.3912 (13.10)	1.1458 (9.26)	2.1925 (17.48)	1.9876 (15.52)	2.5311 (21.02)
$\frac{t}{T}$	0.0014 (0.01)	-2.3332 (-2.04)	1.3897 (3.45)	0.0338 (0.78)	2.4961 (4.31)
$\sigma \cdot \frac{t}{T}$	-3.3639 (-5.80)	-2.9991 (-4.43)	-7.7483 (-11.30)	-5.9372 (-8.49)	-9.3484 (-14.21)
$\left(\frac{t}{T}\right)^2$	0.0717 (0.22)	2.4651 (2.21)	-1.1148 (-2.85)	0.0065 (0.15)	-2.0366 (-3.62)
$\sigma \cdot \left(\frac{t}{T}\right)^2$	3.1422 (5.57)	3.1650 (4.81)	7.1178 (10.68)	5.0545 (7.43)	8.4181 (13.16)
$\cos(.)$	-0.0377 (-1.10)	-0.3028 (-2.59)	0.0791 (1.92)	-0.0040 (-0.90)	0.1364 (2.31)
$\sigma \cdot \cos(.)$	-0.0207 (-0.35)	-0.0240 (-0.35)	-0.4245 (-6.06)	-0.2058 (-2.88)	-0.4886 (-7.27)
$\sin(.)$	0.0517 (3.40)	0.1339 (2.57)	0.0994 (5.44)	0.0127 (6.39)	0.1547 (5.89)
$\sigma \cdot \sin(.)$	-0.0986 (-3.74)	-0.0369 (-1.20)	-0.2113 (-6.79)	-0.2897 (-9.12)	-0.2734 (-9.16)

The smooth solid line in Figure A.1 shows the fitted 'average' U-shape for Corn. Finally, Figure A.3 shows these seasonals across days, clearly capturing the interdaily volatility changes.



APPENDIX B. DATA

The data used in this study cover the time period 5 January 1988 through 28 November 1988. The intraday data (all frequencies) are derived from the Tick Data Inc. time and sales tapes. The details of the agricultural futures contracts traded at the Chicago Board Of Trade are given below. According to Regulation 1008.01 Trading Limits, the following rules have been active for our sample period:

> *Price Limits are symmetric above/below the previous business day's settlement price. Limits are lifted two business days before the cash month (=delivery month). For the first half of our sample period (until June 23, 1988) limits were expanded by 150% of the current level if, for two successive business days, the market closes at the limit for three or more simultaneously traded maturities for a contract year. If there are less than three maturities remaining, this rule is changed to all traded maturities. For the second half of our sample period (as of June 24, 1988) the sequential limit days requirement was reduced to a single business day. Expanded limits remain in action for three successive business days. Limits remain at 150% for successive three day periods unless at the end of such a period three or more maturities do not close at the limit. The limit expansion will operate concurrently on the Soybean complex futures. Limits will revert to 100% only if all futures in this complex meet the conditions for reversal.*

Contract Specifications

Contract	Corn	Soybeans	Soybean Meal	Soybean Oil	Wheat
Contract Size	5,000 bushels	5,000 bushels	100 tons	60,000 lbs	5,000 bushels
Delivery Months	Mar, May, Jul, Sep, Dec	Jan, Mar, May, Jul, Aug, Sep, Nov	Jan, Mar, May, Jul, Aug, Sep, Nov	Jan, Mar, May, Jul, Aug, Sep, Nov	Mar, May, Jul, Sep, Dec
Minimum Tick Size	0.25 ¢ / bushel	0.25 ¢ / bushel	10 ¢ / ton	0.01 ¢ / lb	0.25 ¢ / bushel
Initial Limit	12 ¢	30 ¢	$10	1 ¢	20 ¢
Expandable Limit	18 ¢	45 ¢	$15	1.5 ¢	30 ¢
Sample Periods	5Jan – 29Apr 2May - 31Aug 1Sep – 28Nov	5Jan – 29Apr 2May - 31Aug 1Sep – 28Nov	5Jan – 29Apr 2May - 31Aug 1Sep – 28Nov	5Jan – 29Apr 2May - 31Aug 1Sep – 28Nov	5Jan – 29Apr 2May - 31Aug 1Sep – 28Nov
Observations in Samples	3645 2475 2700	3690 2475 2700	3690 2565 2700	3690 2790 2700	3690 3465 2745