Price Volatility in the U.S. Dairy Sector: Due to Week-of-Month Effects?

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Abstract

Under recent dairy policy reforms, farm-level milk prices are determined by a multiple component pricing scheme that derives monthly dairy product class prices from weekly NASS survey prices for only the first two weeks of each month. This pricing rule may provide incentives for strategic behavior by dairy sector participants that could induce dairy product price volatility. Empirical evidence is examined to test this and related hypotheses.

Introduction

Following recent regulatory reforms in the dairy sector, substantial intertemporal price variation has been cited as a concern for both producers and processors. Numerous explanations have been offered for this increased variation of prices over time. Reduced public stocks have been cited as increasing processor willingness to pay for products when processing procurements unexpected fall short of needs. Another hypothesis has been that the expansion of scale and scope by dairy cooperatives has afforded the larger cooperatives the ability to pursue strategic market behavior by managing their intra-month supply of dairy products to control their prices. In this paper, we examine evidence that prices may not be competitively determined and show evidence consistent with such an intra-month strategy.

Under the current multiple component (MC) dairy pricing system, use-class prices underlie the raw milk price paid to producers. These class prices are determined as functions of estimated dairy product prices. The logic is to extract from dairy product prices the implicit price of raw milk used in their manufacture. However, in implementation, the MC pricing system uses as estimates of dairy product prices only the estimates of dairy product prices received by manufacturing plants drawn from weekly National Agricultural Statistical Service (NASS) surveys for only the first two weeks of each month.

This focus on prices from only the first two weeks of the month, together with the technological feasibility of strategically shifting sales within each month, has led some to suggest that dairy product prices could be manipulated to strategically manage the class prices and the associated raw milk price. If this were feasible, dairy coops that purchase

and process raw milk for producer members, could enhance net returns available for distribution to members. By shifting product sales into the last weeks in each month, the class prices could be driven up reducing net returns, though enhancing the raw milk paid to producers. Alternatively, by shifting product sales into the first two weeks in each month, class prices could be driven down, enhancing net returns distributable to members. In either case, this practice could induce price variation. This paper examines evidence in historical weekly dairy product price series to determine its consistency with this strategic behavior hypothesis

Approach

The issue addressed in this paper is one that has drawn attention within an extensive literature that has considered the presence of day-of-week and intraday price timing effects in financial and commodity markets (see e.g. Rudel and McCamley 2000 and Bollerslev, Cai, and Song 2000). In general, the consensus emerging from this literature is that prices behave differently during specific trading periods (e.g. opening versus close). For example, Xu and Wu (1999) find that the effect of trading frequency on return volatility is much stronger during the opening of trading. Rudel and McCamley find that price changes for corn are greater from Friday to Monday than other day-to-day changes.

A standard approach to determine if an economic time series displays calendar effects is to incorporate dummy variables in an OLS regression (see e.g. Johnson *et al*. 1991, Chang *et al.* 1998, and Liano *et al.* 1999). The approach is analogous to accounting for seasonality in a time series where dummy variables are introduced into the conditional mean to account for recurrent seasonal variation. Say for example, there is an interest in determining if there is a "January effect" in equity prices. This can be explored by regressing equity prices on an *n x11* dummy variable matrix and a constant

$$P_t = a_0 + \sum_{m=1}^{11} a_m D_m + e_t \tag{1.1}$$

where D_1 takes the value of 1 to represent the second month and zero elsewhere. The intercept α_0 measures the average monthly price in January while the remaining parameters $(a_1,...,a_{11})$ provide a pairwise comparison between the January price and prices during the remaining months (Liano *et al.* 1999). If for example, it is found that $a_1 < 0$ then this implies that prices during February are significantly lower than the average price during January.

Clearly, in implementation, the efficacy of this approach relies on the existence of a common underlying data generation mechanism (DGM) from which the realization is drawn. Further, the approach can find evidence of monthly effects that are perfectly stable. That is, the January effect would have to be in effect during the same interval each year. Just as "harvest time" is not a precise temporal concept, it is often the case that in the context of a market, temporal intervals are not fixed in duration or placement in a time series. For these reasons, we consider nonparametric and other parametric approaches.

To begin, suppose we have realizations for weekly average, central market prices for a set of dairy products, i.e. $\{P_{i,t}\}$ for each product *i*. Conventionally, if these series were generated by competitive markets, we would suppose free entry into intertemporal arbitrage results in (dropping the product subscript):

$$\begin{aligned} P_t &= P_{t-1} + e_t \\ e_t &\sim g(0, s_t) \end{aligned} \tag{1.2}$$

We note the absence of any priors that a series of weekly prices is indeed drawn from a single DGM. Rather than examine evidence of stationarity for such a series, we first sort the sample of weekly prices for each commodity by week-of-month. Dropping the product subscript, the observations from the first week of each month were rearranged into a single "first week of month" series interpretable as a realization of a unique "first week of month" DGM. Similarly, a week of month realization is organized for each week. Disregarding the fifth week, we could write these new series as a 4 x m matrix, where *m* is the number of months in the weekly series, $\{P^m{}_t\}$:

$$\begin{bmatrix} P_t^1 & P_t^2 & P_t^3 & P_t^4 \end{bmatrix} \tag{1.3}$$

Based on this organization of the observations, two approaches can be taken to examine the consistency of the data with the hypothesis that prices have been manipulated within the month. First, if the weekly series is generated by competitive markets, then it should be free of arbitrage opportunities. That is, the difference between any pair of weekly prices should be null on average. Further, these differences should be generated by a common underlying DGM. In fact, that DGM would be expected to be a white noise process. A second perspective can be drawn by recognizing that if week-of-month effects exist, then each week-of-month series, $\{P^i{}_t\}$ would be distinguishable as a separate regime.

Week of Month Differences

To pursue the first approach, we sort the weekly product price series and create each of six possible "week of month difference series" defined as the difference between each possible pair of week-of-month series, i.e. for the first and second week of month difference:

$$\Delta P_t^{1,2} \equiv P_t^1 - P_t^2 \tag{1.4}$$

Grouping these into a matrix, we have:

$$\left[\Delta P_t^{1,2}\, \Delta P_t^{1,3}\, \Delta P_t^{1,4}\, \Delta P_t^{2,3}\, \Delta P_t^{2,4}\, \Delta P_t^{3,4}\right] \tag{1.5}$$

Under the null hypothesis that week of month series is generated by competitive market, each week of month difference $\Delta P_t^{j,k}$ will be a white noise process with zero mean. That is, suppose under the alternative hypothesis, each week of month series can be written:

$$\begin{aligned} P_t^{j} &= m_t^{j} + e_t^{j} \\ e_t^{j} &\sim \Phi^{j}(m^{j}_{e}, s_j^{2}) \end{aligned} \quad \text{for all } j\text{=1,..4} \tag{1.6}$$

Then, consistent with the null is the joint hypothesis that

$$\begin{aligned} m_t^{j} &= m_t^{k} \\ m^{j}_{e} &= m^{k}_{e} \\ s_j^{2} &= s_k^{2} \quad \forall j \neq k \end{aligned} \tag{1.7}$$

It would also follow under the null hypothesis that

$$\begin{aligned} \Delta P_t^{j,k} &= m_t + e_t^{j} - (m_t + e_t^{k}) \\ &= e_t^{j} - e_t^{k} \\ &= e_t^{j,k} = 0 \\ (given \quad & e_t^{j,k} \sim \text{g}(0, 0)) \end{aligned} \tag{1.8}$$

Alternatively, if week-of month effects are present, then there will exist a systematic component in the weekly price differences,

$$\begin{aligned} \Delta P_t^{j,k} &= m_t^{j} + e_t^{j} - (m_t^{k} + e_t^{k}) \\ &= m_t^{j,k} - e_t^{j,k} \end{aligned} \tag{1.9}$$

Stacked Week of Month Price Series

For the second approach, we recognize that if the weekly markets are arbitraged efficiently, then each week of month series would be generated by a common DGM. To proceed, stack the four, week-of-month price series into a *Tx1* vector where *T* is the total number of observations in the sample. For this analysis, *T*=539. The new price series is represented as,

$$P_t^{w} = \begin{bmatrix} P^1 \\ \cdots \\ P^2 \\ \cdots \\ P^3 \\ \cdots \\ P^4 \end{bmatrix} \tag{1.10}$$

The reorganization of the data allow for possible structural breakpoints to be identified. If breakpoints exist and coincide with an intrinsic switching point defined by the week of month, then this would suggest week-of-month effects. To highlight this point, let's assume a price series is generated from a single DGM:

$$\begin{aligned} P_t &= m_t + e_t \\ e_t &\sim \Phi(0, s^{2}) \end{aligned} \tag{1.11}$$

where μ_t is the conditional mean of P_t and e_t is distributed Φ with a mean of zero and a variance of σ^2. The distribution function Φ is assumed to be independent of time.

If (1.11) holds and prices are generated from a single DGP, then sample moments should be unaffected by reordering of sample data. Further, if each weekly series is drawn from the same underlying distribution, then samples drawn from any such common distribution can be arranged in any order with no affect on the underlying moments, and having no affect on expectations of sample moments. That is, each individual price represents a single draw from the distribution but the unconditional moments of the distribution remain unchanged. Alternatively, if the price data are characterized by week-of-month effects, then (1.11) no longer holds and the DGP can be described as

$$\begin{aligned} P_t^i &= m_t^i + e_t^i \\ e_t^i &\sim \Phi^i(0, s^{i2}) \quad \textit{for } i = 1,\ldots,4 \end{aligned} \tag{1.12}$$

Equation (1.12) motivates the use of breakpoint analysis (see e.g. Kim 2000 and Inclan and Tiao 1994) to examine week-of-month effects. That is, if structural breaks are found after sorting the data by week-of-month, then this would suggest the presence of a calendar effect. Implementation of this approach in a weekly series that follows a trend is problematic. Suppose the initial series follows a trend. Then, each week of month series will also follow a trend. If these series are stacked by week of month, then the resulting series will follow a sawtooth trend, reverting at each date when the series shifts to a new week. That is, suppose

$$P_t = a_0 t_t + e_t \tag{1.13}$$

then the week of month series can be written:

$$P_t^i = a_0 t_t^i + e_t^i \tag{1.14}$$

where the week number or trend is the date for each ith week, t_t^i. Given the trend index is increasing, we can define t^i_w as the week number for the wth occurrence of the ith week. Thus, for T occurrences of the ith week, we would have:

$$t_0^i < t_1^i < \ldots < t_T^i \tag{1.15}$$

If we concern ourselves only with the trend component, then (1.10) can be restated as,

$$P_t^w = \begin{bmatrix} t_t^1 \\ \cdot \\ \cdot \\ t_T^1 \\ \hline t_t^2 \\ \cdot \\ \cdot \\ t_T^2 \\ \hline \cdot \\ t_t^4 \\ \cdot \\ \cdot \\ t_T^4 \end{bmatrix} \tag{1.16}$$

It can be seen in (1.16) that when the weekly series are stacked into a vector, then a breakpoint in the trend will exist between t_T^i and t_1^{i+1}. Therefore, to avoid spurious week-of-month effects, the trend must be removed from the original price series.

This result also holds for the conditional variance. That is, since this analysis moves beyond the first moment of the distribution, any trend in higher moments will result in self-imposed structural breakpoints when the data are sorted by week-of-month. For example, let's suppose the variance of a series can be expressed as,

$$s_t^2 = s^2 + t_t \tag{1.17}$$

where s^2 represents some constant level of variance and once again, t_t is a trend term. If we further assume an increasing trend, then this implies,

$$s_1^2 < s_2^2 < \ldots < s_T^2 \tag{1.18}$$

Therefore, if the data series is characterized by a trending variance, then sorting the series by week-of-month will result in a self-imposed structural breakpoints.

Descriptive Statistics and Nonparametric Tests

Descriptive statistics for each week of month difference series $\Delta P_t^{j,k}$ were first examined. The Jarque-Bera (1980) statistic provides a test for normality

$$JB = \frac{n-1}{6}\left(S^2 + \frac{1}{4}(K-3)^2 \right) \tag{1.19}$$

In (1.19), n represents the number of observations of each $\Delta P_t^{j,k}$ series, S is the skewness, and K is the kurtosis. The JB test statistic is distributed $c^2_{(2)}$ under the null hypothesis of a normal distribution.

The normality test results motivate further nonparametric analysis. In particular, it is of interest to determine whether the series appear to have come from the same DGM. However, before considering this evidence we report results concerning the existence of common means and variances across the series. While evidence suggests the series are not normally distributed, it is of interest to determine inferences that would follow if normality were presumed. Under the maintained hypothesis of competitive markets and symmetry in distribution, there should be no significant difference in mean between any of the $\Delta P_t^{j,k}$ series. In other words, each series should be generated from a single DGM. Alternatively, if there exists a systematic difference in mean between specific weeks then under the maintained hypothesis of symmetry of distributions, we could reject the null hypothesis that weekly markets are competitively arbitraged.

To test for a constant mean under the maintained symmetry in distribution the analysis of variance (ANOVA) approach is employed (see e.g. Siegel and Castellan 1988 for a discussion of ANOVA). The equality-in-means F-statistic is defined as

$$F = \frac{SS_1/(G-1)}{SS_2/(N-G)} \tag{1.20}$$

where G is the number of subgroups (series) used in the analysis and N is the total number of observations for all G series. For example, in the current analysis, each of the six weekly series (G=6) has a total of 134 observations so N=(6x134)=804. Under the null of identical means, (1.20) has an F-distribution with G-1 degrees of freedom in the numerator and N-G in the denominator. Finally, the terms SS_1 and SS_2 represent the sum of squares defined as,

$$\begin{aligned} SS_1 &= \sum_{g=1}^{G}\left(\hat{m}_g - \hat{m}\right)^2 \\ SS_2 &= \sum_{g=1}^{G}\sum_{t=1}^{T_G}\left(\Delta P_{t,g} - \hat{m}_g\right)^2 \end{aligned} \tag{1.21}$$

where $\hat{m}$ is the sample mean of all N observations and $\hat{m}_g$ is the sample mean from each individual series.

Similar to the equality-in-mean test, we next test for equality-in-variance. Here, the Levene test (1960) is adopted which is based on ANOVA of the absolute difference from the mean. The test statistic in (1.20) is used but now (1.21) is redefined as

$$\begin{aligned} AD_1 &= \sum_{g=1}^{G}\left|\hat{m}_g - \hat{m}\right| \\ AD_2 &= \sum_{g=1}^{G}\sum_{t=1}^{T_G}\left|\Delta P_{t,g} - \hat{m}_g\right| \end{aligned} \tag{1.22}$$

so (1.20) becomes

$$F = \frac{AD_1/(G-1)}{AD_2/(N-G)} \tag{1.23}$$

We proceed by testing for equivalent data generating functions by utilizing the Wilcox signed ranks test (WSRT). The test involves first calculating the absolute difference

$$|D_i| = |P_t^{\,j} - P_t^{\,k}| \tag{1.24}$$

Next, the rank of 1 is given to the smallest absolute difference and a rank of 2 is given to the next smallest difference. This ranking is repeated until all pairs are considered. Then using the following results,

$$\begin{aligned} R_i &= 0 \qquad \text{if } D_i < 0 \\ R_i &= \text{Rank assigned to } D_i (D_i \text{positive}) \end{aligned} \tag{1.25}$$

the test statistic is constructed as

$$z = \sum_{i=1}^{n} R_i^{+} \tag{1.26}$$

Regime Identification

To implement the second approach described above, we attempt to identify regimes in the *Tx1* vector of stacked week-of-month data. A statistical regime is defined as a period where the moments of DGM are constant.

$$e_t \sim \Phi(m, s^2) \text{ for } t = 1, \ldots t\,T \tag{1.27}$$

In equation (1.27), $t \in (0,1)$ and T is the total number of observations. If $\tau = 1$, then the series is characterized by a single regime, otherwise the time series is characterized by multiple regimes. For this analysis, the focus will be on the first and second moments of the probability distribution. To identify possible changes in the mean, the approach proposed by Kim (2000) is used. Kim bases the test statistic used to identify change

points in persistence on the partial sum of the residuals (e_t). The test statistic is defi ned as

$$\Psi_T(t) = \frac{\left[(1-t)T\right]^{-2} \sum_{[tT]+1}^{T} S_{1,t}(t)^2}{\left[tT\right]^{-2} \sum_{1}^{[tT]} S_{0,t}(t)^2}. \tag{1.28}$$

$S_{i,t}$ is a partial sum defined as

$$\begin{aligned} S_{0,t}(t) &= \sum_{i=1}^{t} e_i \qquad \text{for t=1,...,}[tT], \\ S_{1,t}(t) &= \sum_{i=tT+1}^{t} e_i \qquad \text{for t=}[tT]\text{+1,...,T} \end{aligned} \tag{1.29}$$

To estimate a point change in a series, (1.28) is maximized with regard to τ. This approach is referred to as the maximum Chow test (Kim 2000).

To identify changes in regime expressed as changes in the second moment, we implement the iterative cumulative sum of squares (ICSS) test proposed by Inclan and Tiao (1994) is utilized. This approach is based on the partial sum

$$C_k = \sum_{t=1}^{k} e_t^2 \tag{1.30}$$

where it is assumed that the underlying process $\{e_t\}$ is a series of independent, random variables with $E[e_t] = 0$ and $E[e_t^2] = s_t^2$. When the variance of a time series is constant, then C_k is linear with a slope of e_t^2. However, if a change in variance occurs, then C_k will display 'jump' behavior.

Incorporating the partial sum from (1.30), the test statistic is derived which is referred to as a centered cumulative sum of squares (CSS). The test statistic is defined as:

$$D_k = \frac{C_k}{C_T} - \frac{k}{T}, \quad k = 1,...,T. \tag{1.31}$$

It is noted by Inclan and Tiao that test statistic D_k will fluctuate around 0 for a constant variance series but in the event of a structural change D_k will extend beyond some predetermined confidence interval. The critical values for this confidence interval were estimated by Inclan and Tiao through simulation.

The ICSS is an iterative approach because the process must be repeated over subsamples to identify multiple change points. For example, if a point change is observed at τT, then this point is used to partition the sample into two subsamples: t_0-τT and $(\tau T+1)$-T. The CSS is then estimated over both subsamples to identify additional point changes. The process is repeated until no new change points are identified.

Empirical Results

The data used in the analysis consists of weekly cash prices for key dairy products for the period January, 1990-March, 2001. The products include Grade AA butter, cheddar cheese, nonfat dry milk, and whey protein. A complete description of the data is provided in Table 1 and the data are presented graphically in Figure 1. From reviewing the graphics it worth noting that each series experiences considerable variation over the sample period. The variation appears to have increased for butter and cheese approximately around 1996. However, no such change is apparent for NFD milk or whey protein. It also appears to be no apparent trend in any of the data series, at least in price levels.

Provided in Figure 2 are the week-of-month price series plotted in a single graph. For example, the first graph presents the four week-of-month price series for cheddar cheese. From the graphs, there appears to be no apparent lead/lag relationships that persist over the entire sample period. Specifically, none of the weekly series appear to lead any of the other series, although there are periodic episodes. For example, the fourth week of Grade AA butter appears to lead the other weeks between 1997 and 1999. But for the most part, there appears to be no systematic margin between the series.

Weekly Price Difference Series

Provided in Tables 2-5 are the descriptive statistics for the weekly price difference series $\Delta P_t^{j,k}$. For example, Table 2 presents the results for Grade AA butter where the first row contains a description of the data series. For example, the heading **Butter 1-2** indicates the series

$$\Delta P_t^{1,2} = P_t^1 - P_t^2 \tag{1.32}$$

where the superscripts indicates the week of the month.

The most noteworthy result from reviewing the tables is that each series is described by a non-normal distribution. This conclusion is drawn from estimated Jarque-Bera test statistics, along with the estimated skewness and kurtosis values. Recall that a normal distribution is characterized by zero skewness but each weekly differenced series displays either positive or negative skewness. Consequently, the null hypothesis under the Jarque-Bera test of normality is rejected in all cases.

Next, to establish results that are consistent with approaches that maintain the hypothesis of symmetry in distribution, we move to Table 6 where the results are presented from testing the hypothesis that the first and second moments between the series are equal. From Table 6, it can be seen that for each commodity, the hypothesis of a constant mean cannot be rejected. This is consistent with a single DGP thereby suggesting no week-of-month effects.

However, the table also reveals that based on the Levene test the weekly price difference series are not characterized by a constant variance. This result holds for each commodity. Does a nonconstant variance indicate week-of-month effects? The answer appears to be no. To support this conclusion, insight can be gained by once again reviewing the results from Tables 2-5. If the standard deviation from each series is ordered by magnitude, then it can be seen that in all cases that the largest value is associated with the $\Delta P_t^{1,4}$ series. In other words, the series generated by differencing the first and fourth week of each month is characterized by having the largest standard deviation of all series generated. The next largest value is from either the series $\Delta P_t^{1,3}$ or $\Delta P_t^{2,4}$. This result is intuitive. The greater the temporal distance between the series (e.g. 3 or 2 weeks) the greater the variance in the series while the shortest distance (i.e. 1 week) has the smallest standard deviation.

This result is supported graphically in Figures 2 and 3. Figure 2 presents the week 1 minus week 2 series while Figure 3 present the week 1 minus week 4 series. While each series fluctuates around zero, the variation is greater for the $\Delta P_t^{1,4}$ series. Therefore, the results in Table 6 do not suggest that the data are characterized by week-of-month effects.

Because the results from the Jarque-Bera test indicate nonnormality, the WSRT was applied to each of the weekly price difference series. The results for Grade AA butter are presented in Table 8. In all cases N, the number of price difference pairs remaining after omitting the pairs with a difference of zero, is substantially greater than fifteen. Therefore, the distribution of the sum of the ranks can be approximated as normal with a mean of,

$$m_{R^+} = \frac{N(N+1)}{4} \tag{1.33}$$

and a variance of

$$s^2_{R^+} = \frac{N(N+1)(2N+1)}{24} \tag{1.34}$$

The test statistic is shown to be

$$z = \frac{R^+ - m_{R^+}}{s^2_{R^+}} \tag{1.35}$$

which is normally distributed with a mean of zero and unit variance (Seigel and Castellan 1988). The null hypothesis that there is no difference between the weekly price series cannot be rejected for all bivariate combinations. This indicates that the weekly data series are generated by observationally equivalent data generating functions. Given these results are free of maintained hypotheses conceming distribution, they are dominant over the suggestions of parametric results reported earlier.

Week of Month Stacked Series

The results from the Kim (2000) test for structural change are presented graphically in Figure 6. The graphs present the test statistic along with the corresponding critical value provided by Kim. Recall that if the maximum value of the test statistic exceeds the critical value, then this suggests a structural change in the mean of the series. In this analysis, the data is first sorted by week-of-month prior to applying the test. The objective is to determine if each series is characterized by structural changes and if so, whether the changes correspond to the week-of-month breakpoints. Based on the sample period, what we might call "definitional breakpoints", i.e. those between the 1st and 2nd week, 2nd and 3rd week, and 3rd and 4th week, correspond in the week of month stacked series to observation numbers 134, 268, and 402. For example, the break between week one observations and week two occurs at observation number 134.

Notice that for all commodities, with the exception of NFD milk, none of the commodities experienced a change that corresponds to any of the week-of-month breakpoints. For example, both cheddar cheese and whey protein share a common breakpoint but it was well past the fourth week-of-month breakpoint. Alternatively, the Grade AA butter price series does not appear to be characterized by any structural changes. The only commodity that experienced a change that possibly corresponds to a week-of-month definitional breakpoint is NFD milk but this occurred at observation 422. Considering the week-of-month point is at observation 402, we can not conclude this represents a week-of-month effect.

Turning our attention to the second moment of the series, the ICSS results are presented in Table 8. The results where produced by first estimating the following regression,[1]

$$\Delta P_t = b_0 \Delta P_{t-1} + e_t \qquad (1.36)$$

where P_t is the original price series. The ICSS testing procedure is conducted on $\{\hat{e}_t^2\}$ but since each series appeared to have a trend component, $\{\hat{e}_t^2\}$ was first detrended by regressing the squared residuals on a trend term.

$$\hat{e}_t^2 = a_0 t_t + m_t \qquad (1.37)$$

The analysis was then applied to $\{\hat{m}_t\}$.

[1] The analysis was conducted on price differences because price levels were found to be I(1). The results from the unit analysis can be provided upon request.

The results presented in Table 8 indicate that each stacked series is characterized by multiple changes in variance. Moreover, a few of the changes correspond to week-of-month breakpoints. For example, a change occurred for NFD milk at observation 268, which corresponds exactly to the week 3-4 definitional breakpoint. Similarly, change points were identified at observations 129 and 400 for Grade AA butter, corresponding roughly to definitional breakpoints for the 1st and 2nd week, and 3rd and 4th week, respectively. The change points identified for cheddar cheese and whey protein do not appear to be related to the week-of-month definitional breakpoints.

Overall, these results suggest that the series do not differ in levels. In fact, we find consistent evidence through a series of differing perspectives that the series are observationally equivalent. Based on weekly differences, we find some evidence that the extent of difference found expands as the temporal difference increases, that is 1st versus 4th week series appear more different than any adjacent pairs. The ICSS results suggest some difference may exist between 3rd and 4th week series for butter and NFD milk, though these weeks are not of interest with respect to the initial hypothesis that prices may be manipulated.

Conclusions

In this paper, state of the art nonparametric methods are applied to consider the hypothesis that dairy product prices have been manipulated to enhance producer or coop returns under the multiple component pricing plan. Under this rule, raw milk prices are derived from the weekly averages for the first two weeks of each month of dairy product prices reported as received by dairy processors. These prices are collected by NASS and used to derive a set of use class prices and the raw milk price. Throughout the perspectives taken, we find no evidence that the weekly average price series for dairy products have been distorted. Instead, we find consistent evidence that the week-of-month price series are generated by an observationally equivalent mechanism. It follows that week-of-month is not a relevant indicator of price, or equivalently, arbitrage across week-of-month dated markets appears to have eliminated all profit opportunities and rendered price manipulation infeasible.

Tables

Table 1. Chicago Mercantile Weekly Data Description

Commodity	Description	Units
Butter	Grade AA butter	Dollars/Pound
Cheese	#40 block cheddar cheese	Dollars/Pound
Nonfat Dry Milk	Extra Grade nonfat dry milk Central States, Low/Medium Heat	Dollars/Pound
Whey	Extra Grade dry whey 34% protein	Dollars/Pound

Table 2. Descriptive Statistics for Weekly CME Price Differences: Grade AA Butter

	Butter week 1-2	Butter week 1-3	Butter week 1-4	Butter week 2-3	Butter week 2-4	Butter week 3-4
Mean	0.007954	0.015281	0.003234	0.007328	-0.004720	-0.012048
Median	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	0.467500	0.805000	0.912500	0.425000	0.532500	0.280000
Minimum	-0.214200	-0.215000	-0.660000	-0.195000	-0.660000	-0.580000
Std. Dev.	0.075788	0.128384	0.161250	0.075309	0.116930	0.072540
Skewness	3.064238	3.045886	1.364622	2.861509	-0.338194	-3.378566
Kurtosis	18.98515	16.98685	13.11411	17.49663	13.60160	31.64949
Jarque-Bera	1636.382	1299.474	612.7378	1356.220	630.0874	4837.691
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Table 3. Descriptive Statistics for Weekly CME Price Differences: Cheddar Cheese

	Cheese week 1-2	Cheese week 1-3	Cheese week 1-4	Cheese week 2-3	Cheese week 2-4	Cheese week 3-4
Mean	-0.000619	0.001396	7.69E-05	0.002014	0.000696	-0.001319
Median	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	0.140000	0.487500	0.513500	0.347500	0.373500	0.098000
Minimum	-0.102500	-0.156000	-0.235200	-0.100000	-0.171000	-0.112500
Std. Dev.	0.035378	0.068955	0.082566	0.044998	0.060092	0.027299
Skewness	0.743308	2.646681	2.031488	4.075335	2.609980	-0.324971
Kurtosis	7.058223	21.01343	14.53742	31.21740	17.54964	7.919519
Jarque -Bera	104.2922	1968.143	835.3779	4816.491	1334.081	137.4845
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Table 4. Descriptive Statistics for Weekly CME Price Differences: Nonfat Dry Milk

	NFD week 1-2	NFD week 1-3	NFD week 1-4	NFD week 2-3	NFD week 2-4	NFD week 3-4
Mean	-0.000263	0.000730	-0.000807	0.000993	-0.000545	-0.001537
Median	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	0.085000	0.150000	0.182500	0.075000	0.162500	0.087500
Minimum	-0.043800	-0.152500	-0.267500	-0.108700	-0.223700	-0.229500
Std. Dev.	0.011609	0.025672	0.043548	0.016184	0.036662	0.026530
Skewness	2.123036	0.090407	-1.478495	-1.101908	-2.367442	-5.090581
Kurtosis	25.74157	20.74017	19.52944	22.32144	23.64809	45.83625
Jarque -Bera	2988.244	1757.333	1574.312	2111.475	2505.592	10823.85
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Table 5. Descriptive Statistics for Weekly CME Price Differences: Whey Protein

	Whey week 1-2	Whey week 1-3	Whey week 1-4	Whey week 2-3	Whey week 2-4	Whey week 3-4
Mean	0.002027	0.001895	0.001337	-0.000132	-0.000690	-0.000558
Median	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	0.236300	0.216300	0.196300	0.032500	0.097500	0.065000
Minimum	-0.055000	-0.070000	-0.082500	-0.047500	-0.067500	-0.030000
Std. Dev.	0.023107	0.026617	0.032176	0.009323	0.017928	0.009638
Skewness	7.806491	3.860329	2.011755	-0.735967	0.515561	1.753942
Kurtosis	80.66369	33.91444	15.61064	8.192302	10.23295	18.48276
Jarque -Bera	35037.73	5668.821	978.2947	162.6235	298.0312	1407.118
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Table 6. Equality of Moments Hypothesis Test Results

	Equality of Means Between Series[1] ANOVA Test			Equality of Variance Between Series[2] Levene Test		
	T-Stat.	**P-Value**	**Result**	**T-Stat.**	**P-Value**	**Result**
Grade AA Butter	1.0598	0.3814	Fail to Reject	6.7142	0.0000	Reject
Cheddar Cheddar	0.0651	0.9971	Fail to Reject	9.3230	0.0000	Reject
NFD Milk	0.1466	0.9811	Fail to Reject	5.5369	0.0001	Reject
Whey Protein	0.4504	0.8131	Fail to Reject	11.0874	0.0000	Reject

[1] Null hypothesis is that the means are equal between the series.
[2] Null hypothesis is that the variances are equal between the series.

Table 7. Wilcoxon Signed Ranks Test Results for Grade AA Butter
Null Hypothesis: The Two Distributions are Equivalent

Period	Sum of Ranks	N	Mean	Variance	T-Stat	P-Value[1]	Result
Week 1-2	351	54	742.5	13488.75	-0.02902	.4880	Fail to reject
Week 13	861	77	1501.5	38788.75	-0.01651	.4920	Fail to reject
Week 14	1081	85	1827.5	52083.75	-0.01433	.4960	Fail to reject
Week 23	496	62	976.5	20343.75	-0.02362	.4920	Fail to reject
Week 24	861	74	1387.5	34456.25	-0.01528	.4920	Fail to reject
Week 34	741	58	855.5	16682.25	-0.00686	.5000	Fail to reject

1 The P-value gives the one-tailed probability under the null hypothesis of the test statistic. For example, in the Week 1-2 case the one-tailed probability of t-stat≥ .02902 or t-stat≤-.02902 is .4880.

Table 8. Iterative Cumulative Sum of Squares Test Results

Commodity	Observation Week Number at Breakpoints[1]	Inference for Null Hypothesis
Cheddar Cheese	90, 215, 375, 387	Fail to reject
NFD Milk	20, 110, 210, 268	Fail to reject except for week 3-4
Grade AA Butter	90, 129, 374, 400	Fail to reject except for week 2-3 and week 3-4
Whey Protein	122, 350, 451	Fail to reject

[1] Week-of-month stacked price series involved break points at observations 134 (1st and 2nd week), 268 (2nd and 3rd week), and 402 (3rd and 4th week)
Null hypothesis is that there are no breakpoints at "definitional breakpoints".

Figures

Figure 1. Weekly CME Dairy Price Series

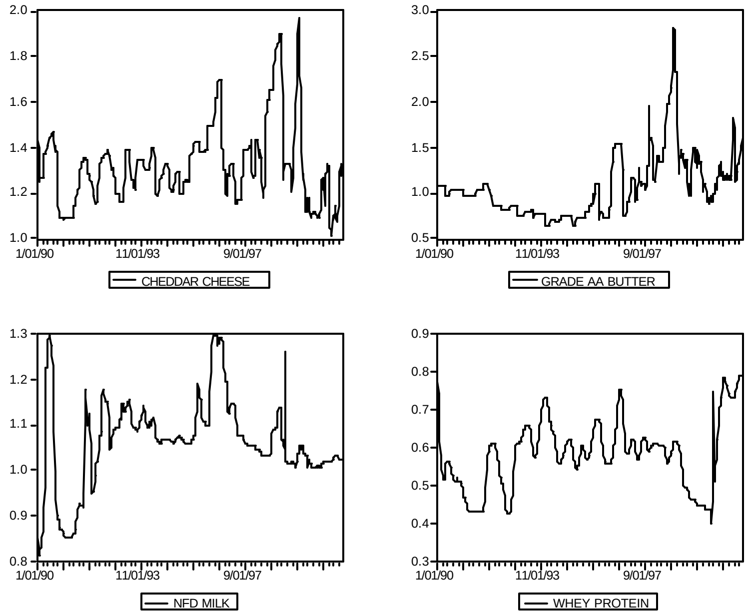


Figure 2. Week-of-Month CME Dairy Prices Series

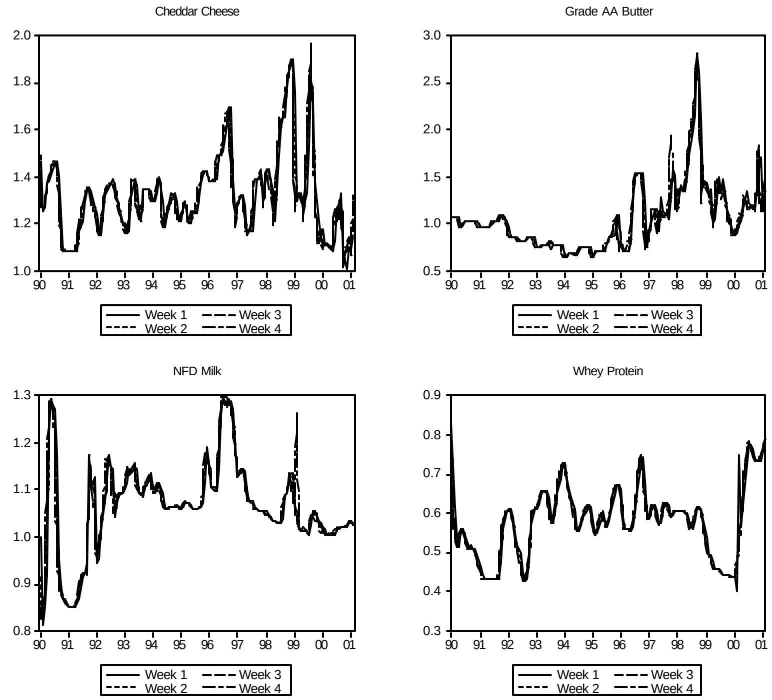


Figure 3. Weekly CME Dairy Price Difference Series: Week 1 minus Week 2

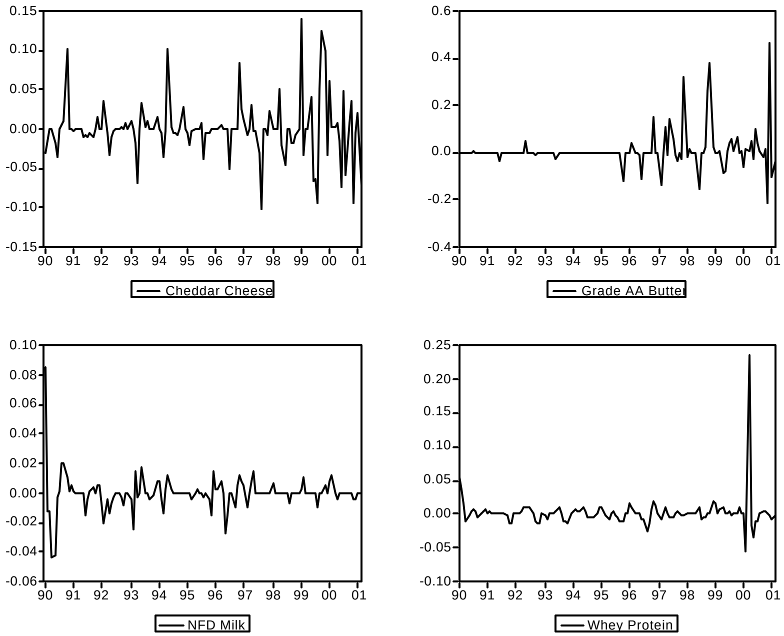


Figure 4. Weekly CME Dairy Price Difference Series: Week 1 minus Week 4

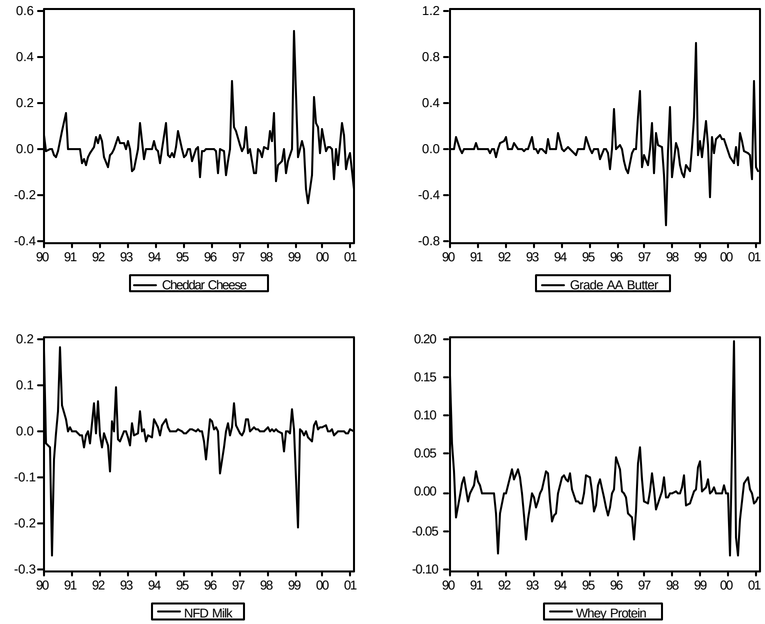


Figure 5. Weekly CME Dairy Prices Sorted by Week-of-Month

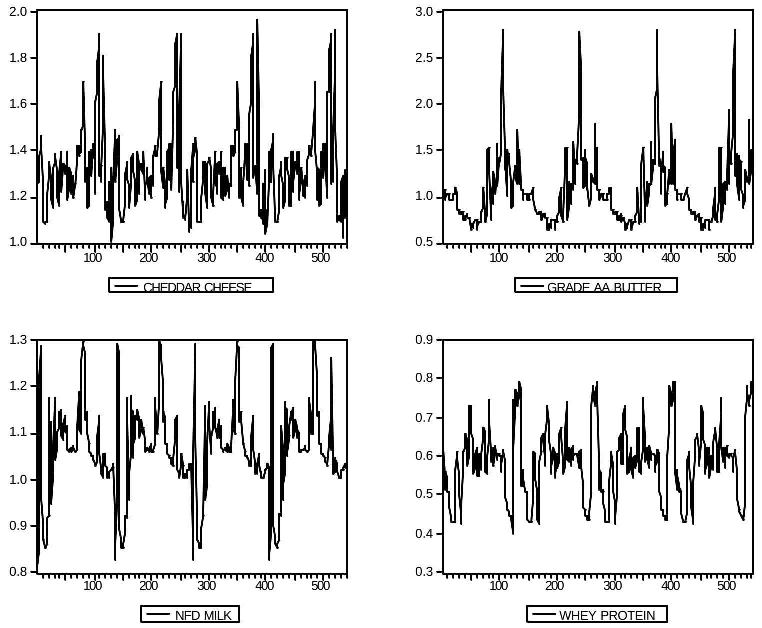
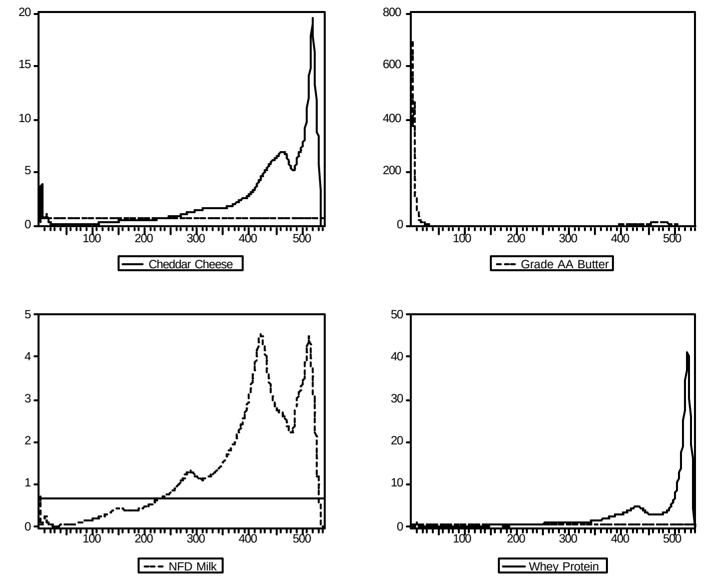


Figure 6. Regime Identification in the Conditional Mean Based on the Maximum-Chow Test



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