A New and Dynamic Look at Forecasting MPP Margin Price

by

Hernan A. Tejeda and Dillon M. Feuz

Suggested citation format:

Tejeda, H. A., and D. M. Feuz. 2015. "A New and Dynamic Look at Forecasting MPP Margin Price." Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, MO. [http://www.farmdoc.illinois.edu/nccc134].

A New and Dynamic Look at Forecasting MPP Margin Price

Hernan A. Tejeda and Dillon M. Feuz*

Paper presented at the NCCC-134 Conference on Applied Commodity Price

Analysis, Forecasting, and Market Risk Management

St. Louis, Missouri, April 20-21, 2015

---

*Hernan Tejeda and Dillon Feuz are Research Fellow and Professor, respectively; in the Department of Applied Economics at Utah State University

A New and Dynamic Look at Forecasting MPP Margin Price

The recent Agricultural Act (Farm Bill) of 2014 considers a new insurance program for Dairy producers. The Margin Protection Program (MPP) accounts for the difference between the national average price of milk and feed, which includes corn, soybean meal and alfalfa. If this national dairy margin is below a threshold selected by the producer in their insurance contract, the producer receives an indemnity. A web-based tool available for access by dairy producers and/or dairy related stakeholders utilizes a method which forecasts this dairy margin, by making use of extensive futures and options market data. The method considers shocks to futures prices as the difference between a commodity's expected price - given by its futures contract price at a certain date - and its eventual settled (terminal) price at expiration. These unexpected shocks are calculated monthly for each commodity according to their time-to-maturity, from one month ahead up to one year ahead (i.e. 12 different periods of price shocks). The inter-relationship (rank correlation) between the different 'time-to-maturity' shocks from these commodities is maintained when forecasting the futures (and subsequently cash) prices. However, these correlations are static - depending only on time-to-maturity of the different shocks - without incorporating additional information obtained from a growing crop season (e.g. method considers price deviates from March Corn futures expiring in September same as for September Corn futures expiring in March). Our method takes into account the arrival of new information during the farming season by incorporating time-varying (dynamic) correlations in the forecast method. In addition, we make use of dynamic copulas to model the joint time-varying interrelationship among these price shocks. Results obtained are of relative improvement in forecasting the actual margin, especially during the 1st three months. Discussion and remarks for future venues are provided.[1]

Keywords: MPP Dairy Margin, Dairy Margin Forecast, Time-Varying Correlations, Dynamic Conditional Correlation (DCC) Copulas.

Introduction

The recent Agricultural Act (Farm Bill) of 2014 includes a new insurance program for Dairy producers. The Margin Protection Program (MPP) for dairies explicitly considers a national dairy 'average' margin - accounting for the difference between milk and feed prices - and compares it to a producer's selected preference of a certain margin threshold for their yearly

[1] We thank Scott Irwin and participants at the meeting for valuable comments and suggestions.

dairy production. If the national market margin is below the threshold selected by the producer in their insurance contract, the producer receives an indemnity.

The national margin considered by the USDA for this insurance program is defined by an equation making use of national monthly average prices for all milk, corn, alfalfa and soybean meal. The first three values are obtained with (monthly) transaction data directly from NASS, and the last one from monthly prices reported at Decatur Illinois, through the USDA Market News-Monthly Soybean Meal Price report. (USDA, Notice MPP-1). The following equation pertains to the national Actual Dairy Producer Margin (ADPM), expressed in \$/cwt of milk:

$$\text{ADPM \$/cwt of milk} = \text{All Milk \$/cwt} - \{ [1.0728 \times \text{Corn \$/bu}] + [0.0137 \times \text{Alfalfa \$/ton}] + [0.00735 \times \text{SBM \$/ton}] \};$$

Figure 1 below illustrates this margin from 2000 onwards, which considers prices since the implementation of the Federal Milk Marketing Order Reform onwards.[2] Dairy producers have been experiencing increased volatility in the prices of these feed commodities, which in turn has directly resulted in higher variability in their margin returns (without considering other production factors). Figure 2 shows the prices of each of these commodities considering the product of its specific factor. As may be seem from the figure, there is varying correlations among these, both during the year and through the years. Given the (prior) equation for the national dairy margin and its direct effect on determining eligibility of an indemnity, dairy farmers are able to estimate forward potential dairy margin values using up-to-date futures contracts for most of the markets.[3]

Presently, there is a web-based tool that has developed a method which forecasts this margin by making use of extensive futures (and options) markets data (Newton et al., 2013 and Newton and Nicholson, 2014). This method applies commodities futures prices and options for milk (class 3 and class 4), corn and soybean meal, as well as historic cash prices of these and of alfalfa to predict the margin price. The futures prices are used to predict the cash prices, and alfalfa uses its historic prices to predict its cash prices. The method takes into consideration differences between a commodity's expected price - given by its futures contract price at a certain date - and its eventual settled (terminal) price at expiration. These differences are noted as shocks to a commodities' market. They are unexpected price deviates for each commodity occurring at different periods during the year (e.g. September contracts expiring in December, or December contracts expiring in March), and with different span of time or time-to-maturity, (e.g. 3 months, 12 months, etc.). The inter-relationship between the futures price deviates of these commodities with respect to their time-to-maturity is calculated via rank correlation, in similar manner to Bozic et al (2014). These correlations are incorporated in the tool's forecasting method which

[2] A report by Jesse and Crop (2001) provides details on policy decisions made and implications.
[3] Alfalfa does not have a futures contract. For a future study we consider the effect from varying inter-relationships between this and other two feed commodities.

applies the Iman and Connover (1982) procedure,[4] maintaining the ranking correlation order among the price deviation series.

The tool presently does not account any differently for the correlation between price deviates of two commodities with the same time-to-maturity (e.g. 6 months) that occur at a different period during the year. That is, the tool considers in the same manner a correlation which may be calculated by the deviation price from a contract in March which expires in September, than the price deviation from a contract in September which expires in March. This however, seems to leave out the additional information available for corn and indirectly to soybean meal (derived from soybean) during the spring as harvest is already under way, in comparison to the prior end of winter which may be in the sowing stage.

This paper seeks to address this matter by considering the effect of dynamic correlations during different periods of the year among these price shocks, and its eventual impact on the margin forecast. Our forecasting method uses a similar approach in regards to the commodities' futures markets data and the computation of their price shocks, in conjunction with dynamic copula methods[5] that identify the time-varying correlations among the markets, to provide estimates for the prices considered in the Dairy Producer Margin. We briefly explain the method from the web-based tools currently in use, as well as some of its parameter estimates being applied. We then present our methodology and contrast some parameter estimates with those from the current tool. We provide some margin forecasts and compare with current forecasts, as well as future lines of study.

Methods

The objective is to forecast the national average cash prices for all milk, corn, soybean meal and alfalfa that are part of the ADPM margin. Employing futures markets for this purpose enables to apply up-to-date market information of transactions that are to be completed in the nearby future, making use of current readily available information. Efficient markets are assumed. As mentioned before, the current method considers futures prices for milk (class III and IV), corn and soybean meal. In order to establish the (basis spread) relationship between the cash prices and the futures prices, the national cash average prices for milk, corn and soybean are regressed (via OLS) with the respective closing futures prices of the prior mentioned futures prices. The alfalfa cash prices are modeled as a function of prior alfalfa prices.[6]

[4] Procedure similar to applying a Gaussian Copula (Mildenhall, 2006)
[5] Woodard et al. (2011) argue that copulas permit the use of broader and more flexible tools for modeling the relationship or dependence configuration among series in probabilistic settings, in comparison to more conventional methods used such as Iman and Conover (1982) or Phoon, Quek and Huang (2004).
[6] In this study, and for forecast comparison purposes, we consider these estimations as given and taken from Table 2 in Newton (2013). We leave for future study addressing the correlations

For the three commodities with futures contracts, shocks or price deviates are constructed according to their time to maturity. The shocks or price deviates are the difference between the expected price of a futures contract and its realized (terminal) price at expiration. E.g., a September 8 price of a futures contract of corn with expiration in December is subtracted to that contract's December 8 price. The deviation period (time-to-maturity) here would be of three months. This is done for each commodity's contracts for up to one year ahead. There is a futures contract for Milk Class III every month for up to one year ahead and for Milk Class IV up to six months ahead,[7] which produces 18 price deviates per year (i.e., one month ahead, two months ahead, etc.). Additionally, corn has six nearby futures contracts per year, and soybean meal has nine.

The relationship between the series of shocks is estimated via Spearman correlation. The method thus accounts for 33 different price deviate series of futures contract price data, considering the period from January 2000 onwards;[8] and then a Spearman ranking correlation is calculated among each of these series. E.g. a corn contract with 12 month deviates (corn 6th nearby contract) would have a rank correlation calculated with each Class III deviate (1st nearby (month) contract to 12th nearby contract), with each Class IV deviate (1st nearby thru 6th), each Soybean Meal deviates (1st nearby till 9th), and finally with each of its other 5 corn contract deviates (1st nearby until 5th). This is repeated for each series deviate for a total of 528 rank correlations.

Despite the large number of correlations computed, it is relevant to re-emphasize that these correlations are static. That is, these correlations depend only on the time-to-maturity horizon for each pair of futures price deviates, not taking into consideration the period during the year when this happens. Figures 3a and 3b show results of Pearson correlation between price shocks of two different series. The method overlooks timely market information that may affect the correlation between deviates of the same nearby time-to-maturity but which are at a distinctly different point in time of the year. E.g. deviates for a crop at sowing periods may be substantially different from those near harvesting periods, given the more recent crop information available. Our study takes this into consideration by applying a Dynamic Conditional Correlation (DCC) model (Engle, 2002) among the price deviations, for each particular time-to-maturity period.

The current method likewise estimates the probability distribution function for each commodity by applying a log-normal distribution to the futures prices. The method identifies

---

between cash prices of alfalfa and the other commodities with their past and futures prices, and its effect on the margin forecast.

[7] Class IV contracts have years with very low or no activity beyond six month time-to-maturity; thus only the deviations within the 1st six months were considered.

[8] In their paper, Newton et al. have data until September 2012 (i.e. 142 observations); however the web-tool keeps updating its data till present.

each distribution variance from calculating the implied volatilities of at-the-money option premiums by inverting the binomial option pricing model (Cox et al., 1979; Miranda and Fackler, 2002). With each commodity's marginal distribution, the authors then use the Iman and Conover (I&C, 1982) method to simulate futures prices.

The Iman and Conover method incorporates each marginal distribution and maintains the respective (previously computed) rank correlations among them. Simulated draws of 5000 futures prices for each commodity according to their time-to-maturity are obtained, preserving the respective rank relationship among the commodity's marginal distribution. Moreover, for months were a commodity does not have a CME contract, a weighted average of nearby months is used to extrapolate its prices. With these simulated future prices, the corresponding cash prices are obtained by using the parameter estimates of the OLS equations initially estimated (Table 2, Newton et al. 2013). This then leads to calculating the Dairy Margin. Figures 4a, 4b and 4c below contain some margin projections obtained directly from the web tool. These were accessed from http://dairymarkets.org/MPP/Tool/ and project the dairy margin onwards from September 30, 2013; September 28, 2012; and September 28, 2007; respectively.

Our method begins by estimating the time-varying correlations for the different pairs of price deviates, likewise considering separately the time-to-maturity (i.e. 1st nearby contract, 2nd nearby contract, etc). In our case, we directly interpolate futures prices for months in which a commodity does not have a futures contract, and incorporate the deviations from these in our time-varying correlations among price deviations. Thus we have price deviations series for each commodity for one month, two months, etc. until twelve months. The data was obtained from Brian Gould's "Understanding Dairy Markets" website (http://future.aae.wisc.edu/). We apply the DCC model to these series of deviations of futures price considering data from January 2000 to February 2015.

The Dynamic Multivariate GARCH model specifies the dynamic conditional covariance matrix $\boldsymbol{H_t}$ as a non-linear combination of univariate conditional variances. More specifically,

$$\boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t \qquad (1)$$

Where D_t is a diagonal matrix of time-varying standard deviations $\sqrt{h_{iit}}$ with i =1,2…k (number of variables), and $\boldsymbol{R}_t$ is a matrix of time-varying conditional correlations. Estimation is in two-steps and consistent and asymptotically efficient estimates are obtained. First each series may be estimated individually with an AR, ARMA or other, e.g. $\boldsymbol{y}_t = \emptyset_o + \sum \emptyset_i \boldsymbol{y}_{t-i} + \boldsymbol{\varepsilon}_t$ where then the residuals for the ith series in y_t can be obtained by using a univariate GARCH specification $h_{it} = a + b\varepsilon_{it-1} + ch_{it-1}$ for i = 1,2,…..k. The estimated standard deviations $\sqrt{h_{it}}$ are used to calculate the standard residuals $u_{it} = {}^{\varepsilon_{it}}\!/\!\sqrt{h_{it}}$. Moreover, the standard deviations are used to construct the k x k diagonal matrix $\boldsymbol{D}_t(\boldsymbol{\theta}_D)$ of time-varying standard deviations, where $\boldsymbol{\theta}_D$ refers to parameters$a$, b and c.

Following the estimation of the dynamic volatilities for each series, $\sqrt{h_{it}}$, the correlation matrix among the series is estimated. The time-varying conditional correlations are expressed as follows:

$$\boldsymbol{Q}_t = (1 - \alpha - \beta)\overline{\boldsymbol{Q}} + \alpha \boldsymbol{u}_{t-1}\boldsymbol{u}'_{t-1} + \beta \boldsymbol{Q}_{t-1} \tag{2}$$

$$\boldsymbol{R}_t(\boldsymbol{\theta}_R) = diag(\sqrt{q_{11t}}, \dots \dots \dots \sqrt{q_{kkt}})\boldsymbol{Q}_t diag(\sqrt{q_{11t}}, \dots \dots \dots \sqrt{q_{kkt}}\ ) \tag{3}$$

where $\boldsymbol{Q}_t$ is a kxk dynamic covariance matrix of standardized residuals, $\overline{\boldsymbol{Q}} = E[u_t u'_t]$ is a k x k unconditional variance matrix of u_t, and α and β are non-negative parameters such that their estimate $(\alpha + \ \beta) < 1$.

Estimation of (3) provides a consistent but inefficient parameter of $\boldsymbol{\theta}_R$, which is the parameter set that specifies the dynamic conditional correlation (DCC) matrix $\boldsymbol{R}_t$. Full efficient estimates of $\boldsymbol{\theta}_D$ are obtained by a single optimizing iteration of the following log-likelihood function:

$$ll_t(\boldsymbol{\theta}_D) = -\frac{1}{2}\sum_{t=1}(nlog(2\pi) + log\,|\boldsymbol{D}_t|^2 + \boldsymbol{\varepsilon}'_t\boldsymbol{D}_t^{-2}\boldsymbol{\varepsilon}_t) + [-\frac{1}{2}\sum_{t=1}(\log|\boldsymbol{R}_t| + \boldsymbol{u}'_t\boldsymbol{R}_t^{-1}\boldsymbol{u}_t - \boldsymbol{u}'_t\boldsymbol{u}_t)\,] \tag{4}$$

Efficient estimates of $\boldsymbol{D}_t$ and $\boldsymbol{R}_t$ are then used to obtain $\boldsymbol{H}_t$ per (1).

We then estimate time-varying copulas, specifically using DCC models as function marginals applied to our series of price deviations. For this we make use of Patton (2006a and 2006b), who extended and proved the validity of Sklar's (copula) theorem (Sklar, 1959) under time-varying conditions. Copulas have been well documented in the literature, including many applications in the agricultural markets. A non-comprehensive list includes Tejeda and Goodwin (2008), Power and Vedenov (2008), Vedenov (2008), Woodard et al. (2011), Goodwin and Hungerford (2015).

Copulas are a useful tool for modeling the relationship among different variables, without restricting the distribution of these variables. Sklar (1959) states that any continuous multivariate distribution can be uniquely described by the variables' univariate marginals and a multivariate dependence structure - which is represented by a copula. Let $\boldsymbol{F}$ be an n-dimensional distribution function with marginals $F_1, \dots \dots F_n$; then there exists an n-dimensional copula $\boldsymbol{C}$ defined as a multivariate distribution function in the unit $[0,1]^n$ with uniform $U[0,1]$ marginal distributions such that for all x in $\mathcal{R}^n$:

$$\boldsymbol{F}(x_1, \dots \dots \dots \dots, x_n) = \boldsymbol{C}(F_1(x_1), \dots \dots, F_1(x_n); \theta) \tag{5}$$

where θ is a vector of copula parameters called dependence parameters, measuring the dependence (relationship) between the marginal. The density function of a multivariate distribution defined by a copula function is obtained by differentiating the prior equation (5), resulting in:

$$\boldsymbol{f}(x_1, \dots \dots .., x_n; \theta) = \boldsymbol{c}(F_1(x_1), \dots \dots . F_n(x_n)) \prod_{i=1}^{n} f_i(x_i) \tag{6}$$

where f_i represents the marginal density function of x_i and $\boldsymbol{c}$ is the density function of the copula function $\boldsymbol{C}$ in (5).

In particular, two common types of Copulas used are the Gaussian and the t-Student, which belong to the elliptical class and both have radial symmetry (Nelsen, 1999). However, the t-Student Copula has the flexibility advantage of identifying tail dependence among the variables, and the Gaussian not. Either the Spearman or Kendall's Tau rank correlation is usually applied as measures of dependence, given that they are both measures of concordance and invariant to monotonic transformations.

Time-varying copulas have recently been applied in financial fields (Patton, 2006b; Chollete et al., 2009; Ausin and Lopes, 2010), and we apply to our series a DCC Gaussian copula and a DCC t-Student copula, and compare their results. Let $\boldsymbol{d}_t = d_{1t}$,……..$d_{nt}$ be and n-dimensional random vector of price deviations which follow a copula GARCH model with joint distribution:

$$\boldsymbol{F}(\boldsymbol{d}_t | \boldsymbol{u}_t, \boldsymbol{h}_t) = \boldsymbol{C}\big(F_1(d_{1t} | u_{1t}, h_{1t}), \dots \dots \dots F_n(d_{nt} | u_{nt}, h_{nt})\big) \tag{7}$$

where F_i, $i = 1 \dots . n$ is the conditional distribution of the ith marginal series density and $\boldsymbol{C}$ is the n-dimensional copula. The conditional mean is $E(d_{it} | \zeta_{t-1}) = u_{it}$, where $\zeta_{t-1}$is the σ-field generated by past realizations of $\boldsymbol{d}_t$. The conditional variance h_{it} follows a GARCH (1,1), such that $d_{it} = \sqrt{h_{it}} z_{it}$ and $h_{it} = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{it-1}$, where z_{it} are i.i.d. random variables which may follow a Normal or a standardized skew Student distribution - with shape and skew parameters ν and ξ, respectively. The dependence structure is then assumed to follow a Copula with conditional correlation $\boldsymbol{R}_t$ and constant shape parameter η. The joint density at time t is as follows:

$$f(\boldsymbol{d}_t | \boldsymbol{u}_t, \boldsymbol{h}_t, \boldsymbol{R}_t, \eta) = c_t(u_{1t}, \dots \dots \dots .., u_{nt} | \boldsymbol{R}_t, \eta) \prod_{i=1}^{n} \frac{1}{\sqrt{h_{it}}} f_{it}(z_{it} | \nu_i, \xi_i) \tag{8}$$

Again estimation is in a two stage process via maximum likelihood, where the DCC marginals are estimated first, followed by the copula estimation of the joint marginals. For this we make use of an R package 'rmgarch' developed by A. Ghalanos (2014).

Results

The dynamic (monthly) correlations obtained among the price deviations of the commodities, for each nearby period varied extensively per month and per years.[9] Figures 5a, 5b and 5c show the monthly correlations among price deviates - for nearby 12 months - of Class III and corn, and then these correlations were averaged accordingly by months and by years, respectively. It can be seen the large differences not only per month, but through the years given significant different yearly yields for corn during this period. Likewise, Figures 6a, 6b and 6c show the case of corn and soybean meal with 'average' near-to-maturity six months,[10] and have similar results. i.e., there is sizeable monthly and yearly variability of the correlations among these series.

We then applied a DCC Gaussian copula and a DCC t-Student copula to each of our joint series, separated by time-to-maturity. That is, for the 1st month to maturity, we estimated the two DCC copulas considering the marginals of the four commodities' price deviations previously modeled as DCC. We then calculated the two copulas considering price deviations with two months-to-maturity and repeated these copula estimations for the joint series up until twelve months-to-maturity. After the 6th month of maturity, Class IV was dropped because of lack of trade or liquidity in the market (thin market) for this time-to-maturity horizon onwards. Once we modeled the two DCC copulas for each time-to-maturity, we opted for the t-Student since it arrived at a slightly lower AIC and BIC coefficient.[11]

We simulated 5000 different price deviates for each of the twelve copula's series and added these to each corresponding expected futures price. Thus we obtained 5000 simulated futures prices for each commodity, depending on the time-to-maturity horizon, resulting in each commodity having 12 different sets of 5000 simulated prices (one for each month-to-maturity, up to one year ahead). With these futures prices, we then calculated our estimated cash prices by using the OLS parameters from Table 2 previously estimated by Newton et al. (2013).

---

[9] The data considered here is from the 12th, 13th or 14th of the month in comparison to the web-tool projections dated September 28 or 30. Thus our case considers a September Corn or Soybean Meal contract expiring in the same month, and a one month ahead contract being in 'October'. This may result in different information than in the case of a September 30 Corn contract considered for expiration in December as the web-tool applies. We subsequently calculated results for end of month contracts and obtained dynamic correlations of similar variation among series.

[10] We considered the weighted average of futures prices from contracts of nearby months for those months were the commodities had no contracts.

[11] This however was not the case when subsequently modelling the price deviates with futures price data of each commodity at the end of September. In which case the Gaussian copula had a minor edge over the t-Student copula. In any case, results among estimated copulas are not substantially different.

As mentioned previously (and in footnote 6), we applied our method to two different data sets of price deviates. The first set considered data at the middle of the month, i.e., September 12, 13 or 14, resulting in the settled (terminal) price for corn or soybean meal during that same month. So periods of one month ahead (time-to-maturity) and onwards begun with October settled (terminal) prices for corn and soybean meal.[12] The second data set considered prices at the end of month (similar to that of the projections in the web-tool method). i.e. September, 28 or 30, in which case the settled (terminal) price for corn or soybean meal was from December or October, respectively. Here one month ahead and onwards begins with January and November settled prices for corn and soybean meal, respectively. This latter case provides different prices than the first case since it is accounting for (a further) future setting with further-in-time expected prices.

Results in Figures 7a, 7b and 7c compare the projections from our dynamic method using mid-September, and end-of-September data from 2013 to the projections obtained from the web-tool, respectively. We can see that there may be negligible improvement in the first months forecasted over the current method, since all three methods have the actual margin contained within the bands until December of that year and all three miss entirely from January onwards. There is a decrease in the gap among the bands for initial months projected when using end-of-month data over middle-of-month data as seen in 7b and 7a. This may respond to the 'further down the road' data used for the different months ahead (i.e. time-to-maturity) of each commodity, specifically corn and soybean meal, as described previously in the case of data at end-of month. This characteristic is repeated on all our yearly projections.

Results in Figures 8a, 8b and 8c compare the projections obtained using mid-September, and end-of-September data from 2010 to the projections obtained from the web-tool, respectively. Here we see that our method - in both 8a and 8b – has improved the forecast after mid- January, over the current method in 8c. The actual dairy margin falls slightly off our projected +- 25% bands from December to January. However, after mid-February, the actual margin increases and retakes its place within the projected price bands. The current method forecasts a steady decline in the margin until about July, where a slight projected rise occurs yet still remains below the actual margin.

Results for Figures 9a, 9b and 9c compare the projections obtained using mid-September, and end-of-September data from 2007 to the projections obtained from the web-tool, respectively. In these projections we see that our method in both cases 9a and 9b has improved a bit the forecast during the initial months - over the current method. The actual dairy margin stays within our projected +- 25% bands from the day it is forecasted until the next three months ahead, i.e. December. Conversely, the web-tool method is able to capture the actual margin within its +-

[12] October corn settled futures prices would be a weighted average from September and December contracts.

25% bands from the beginning of December until mid-February; however, it also anticipates a downward trend.

We likewise compare in Figures 10a, 10b and 10c the projections from mid and of September of last year, 2014 to the current method. In this case the actual margin is only identified until March of 2015. Here the projection considering the data from mid-September onwards contains the actual dairy margin - within its +- 25% bands - for the next two months, i.e. until November. This is neither the case for our projections from September 30 onwards, nor from those of the web-tool as seen in Figures 10b and 10c, respectively. Thus it seems in this case that the latter information provided by the feed contracts for end of September data inadvertently 'throws-off' the projection. It is relevant to point out that the web-tool projection again does forecast a down-turn of the dairy margin, which our forecast misses. Comparison among the methods, for all the remaining years not mentioned above is located in Appendix 1.

We now proceed by considering only the actual futures prices at each forecasted September date, in lieu of findings by Irwin and Good (2015) and Westhoff (2015). Their studies compared ten year price projections for corn, wheat and soybean from WASDE-USDA and the futures markets, as well as those from FAPRI-MU, respectively. Despite these studies being yearly projections instead of monthly projections as is our case, they found that these futures markets forecasts tend towards a 'steady state'. This is in conformity with the theory of futures markets for storable commodities, where the positive difference between current and deferred futures prices is limited by the cost of carry and thus verging prices towards a steady-state. This may help explain a bit why the projected prices and bands did not fluctuate too far off from its initial value - even though it's to be noted that the margin's milk component is a non-storable commodity. Moreover, when the actual margin did deviate substantially from a relative steady-state (fluctuating substantially away from the forecasted margin bands), it may be most likely responding to supply or demand shocks - as mentioned by Irwin and Good (2015). In Figures 11a and 11b the margin forecasts are for September, 2013. Here the forecasted margin considering actual futures prices is the dotted line, and from January onwards it's moving within the lower bands of our projected price. The actual margin moves much higher above than our projected bands.

Figures 12a, 12b display the projected margin with the actual futures prices for mid and end of September, 2010. In both cases the forecast (dotted line) with actual futures prices dips below our forecasted bands from January onwards. This forecast does trace the actual margin from September to January; however, after January the actual margin turns upward and stays within our projected bands but the forecast with actual futures values remains lower. Revisiting the current method's projections in Figure 12c, we see that the projections and its bands are quite similar to those forecasted with the actual futures values. Thus these projections are missing the upturn from the actual margin occurring from January onwards, plausibly tending towards a steady state.

The margin forecasts - when accounting for the actual futures prices - at mid and end of September, 2007 are in Figures 13a and 13b, respectively. Here it can be seen that the latter margin forecast (in dotted line) traces better the actual margin as of December/January onwards, than our projected forecast within its +-25% bands. I.e. despite being a lower projection in the first three months, and out-forecasted by our method in this initial time-period, subsequently it does follow a (downward) path more in line with the actual margin. This is also the case for the projection with the current method as seen (again) in Figure 13c. The present method doesn't capture the actual margin path in the initial months, as in previous 13a and 13b, but it does portray its downward tendency.

Figures 14a and 14b include the margin forecasted - with the actual futures prices - for mid and end of September, 2014 respectively (dotted line). Here the latter forecast again traces better the overall actual margin over the projections made with our method. The present method of forecasting the margin in Figure 14c likewise follows a similar trajectory to that computed with the actual futures prices. However, it misses the initial months captured in our estimated bands with mid-September data, but again it does estimate the margin's downward tendency. Comparison of the methods, including the naïve forecast, that were not mentioned previously is in Appendix 2.

Conclusions

It is difficult to compare the resulting advantages from our dynamic relationship method over the current forecasting method, and even over the naïve (using the actual futures prices) method. It seems that for the initial two to three months, there may be a clear advantage of the dynamic method, since the actual margin is generally captured within its +25% bands. After December or January, this may not necessarily be the case as seen for the years 2007 and 2014 where neither our or the current method was better; and yet, the current method was able to portray the future (downward) tendency of the actual margin. This latter however, is not necessarily the norm, as seen in year 2010, where the current method portrayed a downward margin from December onwards, and our method was able to properly portray the bands in which the actual margin did fluctuate.

It is relevant to mention that often, the naïve forecast with just the actual futures prices was on the path of emulating the actual margin. However, there were some cases in which this forecast path was also quite far from the actual margin. Once again most notably in 2010 – forecasted correctly by our method – and in 2013, where all methods fell short. All in all, it does seem that considering the dynamic relationships may provide some advantage in the initial months.

Going forward, more data will be available which provides more degrees of freedom when estimating these models. This should improve the precision of the procedure, and other copula models may be considered. In addition, incorporating the relationship of alfalfa prices and the closing futures prices of the other commodities, as well as considering these relationships in estimating the commodities' cash prices may assist in improving the outcome. I.e., estimating (potential) new relationships, different than those from Table 1.2 in Newton et al. (2013) and taken here as given.

References

Ausin, M.C. and H.F. Lopes. (2010), Time-varying joint distribution through copulas, *Computational Statistics and Data Analysis*. 54: 2383–2399.

Bozic, M., J. Newton, C.S. Thraen, and B.W. Gould. (2014). "Tails Curtailed: Accounting for Non-Linear Dependence in Pricing Margin Insurance for Dairy Farmers." *American Journal of Agricultural Economics* 96(4): 1117-1135

Chollete, L., A. Heinen, and A. Valdesogo (2009). Modeling international financial returns with a multivariate regime-switching copula. *Journal of Financial Econometrics*, 7(4): 437-480.

Cox, J.C., Ross, S.A., Rubinstein, M. 1979. "Option Pricing: A Simplified Approach." *Journal of Financial Economics* 7: 229-263

Engle, R.F. (2002). Dynamic conditional correlation —a simple class of multivariate GARCH models. *Journal of Business and Economic Statistics*, 20: 339 –350

Ghalanos, A. (2014).The rmgarch models: Background and properties.(version1.2-6). http://cran.r-project.org/web/packages/rmgarch/index.html

Goodwin, B.K., and A. Hungerford.(2015) "Copula-Based Models of Systemic Risk in U.S. Agriculture: Implications for Crop Insurance and Reinsurance Contracts." American Journal of Agricultural Economics, 97(3):879-896

Gould, B. (2015). Understanding Dairy Markets – Your Source for Market Information and Price Risk Management Principles: http://future.aae.wisc.edu/

Iman, R. L. and Conover, W. J., (1982). "A Distribution-Free Approach to Inducing Rank Correlation Among Input Variables." *Communications in Statistics - Simulation and Computation* 11:311-334

Irwin, S., and D. Good. "Long-Term Corn, Soybeans, and Wheat Price Forecasts and the Farm Bill Program Choice." *farmdoc daily* (5):20, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, February 4, 2015

Jesse E, R. Cropp. Federal milk marketing order reform (continued). Marketing and Policy Briefing Paper No. 73. Madison (WI): Department of Agricultural and Applied Economics, University of Wisconsin–Madison; 2001.

Mildenhall, S.J. (2006). Correlation and Aggregate Loss Distributions with an Emphasis on the Iman-Conover Method. Casualty Actuarial Society Forum.

Miranda, M.J., Fackler, P.L., (2002). Applied Computational Economics and Finance. MIT Press, Cambridge

Nelsen, R.B. (1999). An Introduction to Copulas, Lecture Notes in Statistics, 139, New York: Springer-Verlag.

Newton, J., C.S. Thraen, and M. Bozic. (2013). "Actuarially Fair or Foul? Asymmetric Information Problems in Dairy Margin Insurance" Paper presented at NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting and Market Risk Management, St Louis MO, 22-23 April.

Newton, J. and Nicholson, C. (2014). Milk, Feed and MPP Margin Forecasting. Program on Dairy Markets and Policy; available at: http://dairymarkets.org/MPP/PowerPoint/TtT%20Newton%20Nicholson.pptx

Patton, A.J. (2006), Estimation of multivariate models for time series of possibly different lengths, *Journal of Applied Econometrics* 21 147–173.

Patton, A. (2006). Modelling asymmetric exchange rate dependence. *International Economic Review* 47(2), 527-556.

Phoon, K., S. T. Quek, and H. Huang. (2004). "Simulation of Non-Gaussian Processes Using Fractile Correlation." *Probabilistic Engineering Mechanics* 19:287-292

Power, G.J. and Vedenov, D.V. (2008). The shape of the optimal hedge ratio: Modeling joint spot-futures prices using an empirical copula-GARCH model. In Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St Louis MO, 21-22 April.

Sklar, A. (1959): Fonctions de repartition a n dimensions et leur marges. *Publications de l' Institut de Statistique de l'Universite de Paris*, 8: 229-231

Tejeda HA, Goodwin BK (2008). Modeling Crop prices through a Burr distribution and Analysis of Correlation between Crop Prices and Yields using a Copula method. Paper presented at the American Agricultural Economics Association Annual Meeting, Orlando, FL.

USDA, Notice MPP-1 (2014): Agricultural Act of 2014 (2014 Farm Bill), Title I Information About the Margin Protection Program for Dairy Producers (MPP-Dairy) Accessed at: http://dairymarkets.org/MPP/ResourceMaterial/mpp_1.pdf

Vedenov, D., 2008. Application of copulas to estimation of joint crop yield distributions. American Agricultural Economics Association Annual Meeting, Orlando, FL.

Westhoff, P. "Price Projections and Farm Bill Program Choices: Adding FAPRI-MU Projections to the Mix." *farmdoc daily* (5):26, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, February 12, 2015

Woodard, J.D., N.D. Paulson, D. Vedenov, G.J. Power, (2011). Impact of copula choice on the modeling of crop yield basis risk. *Agricultural Econonomics* 42, 101–112

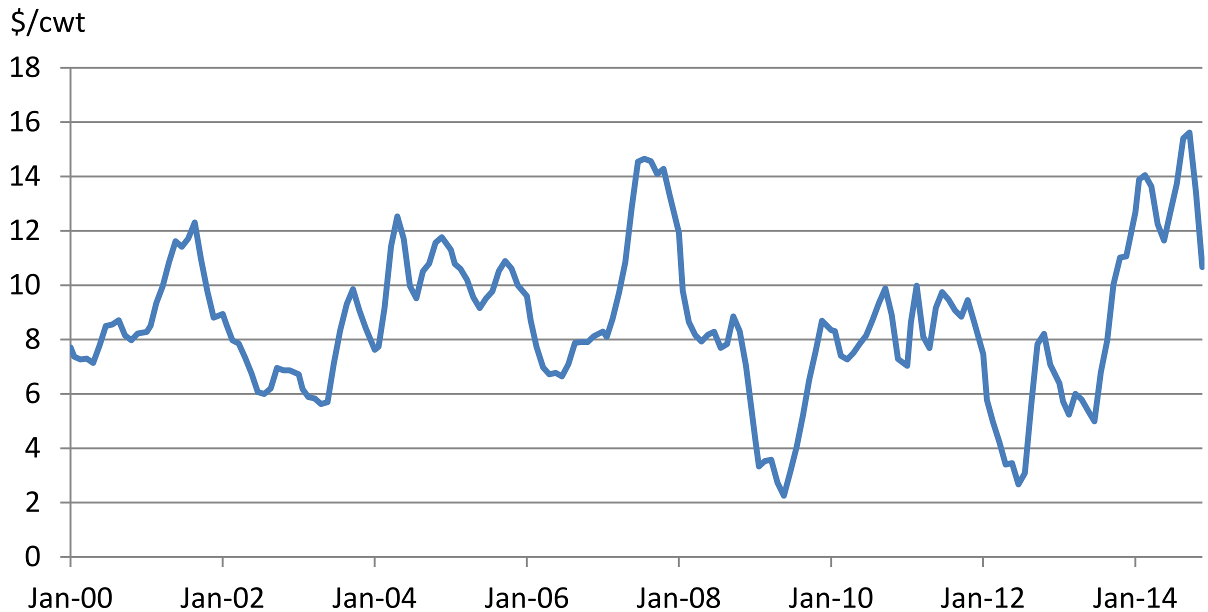


Figure 1: Actual Dairy Producer Margin for MPP Dairy program

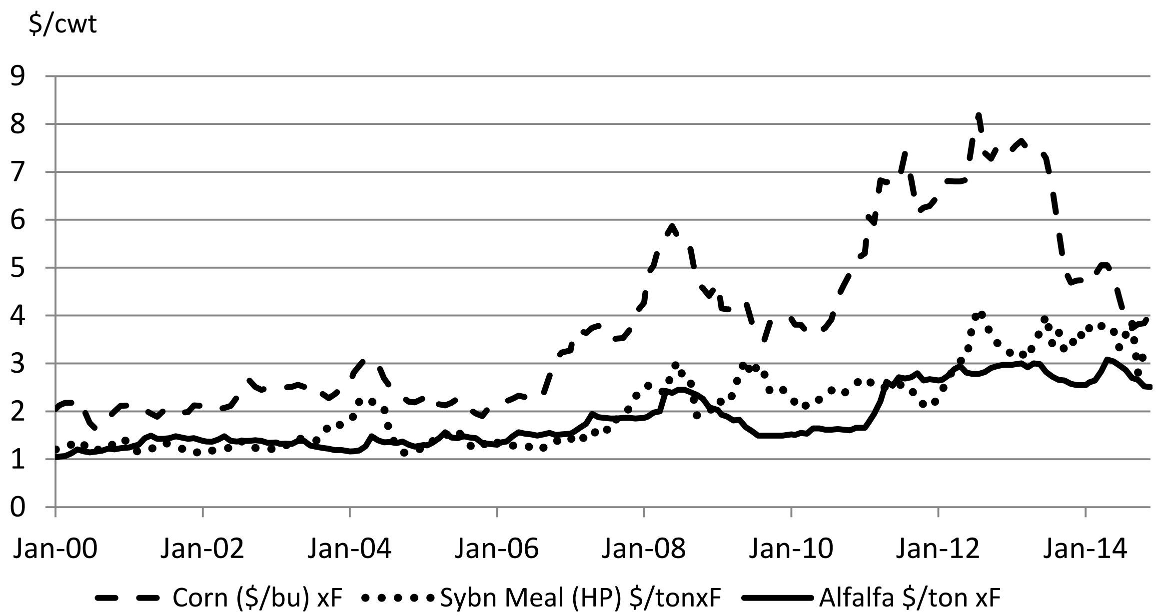
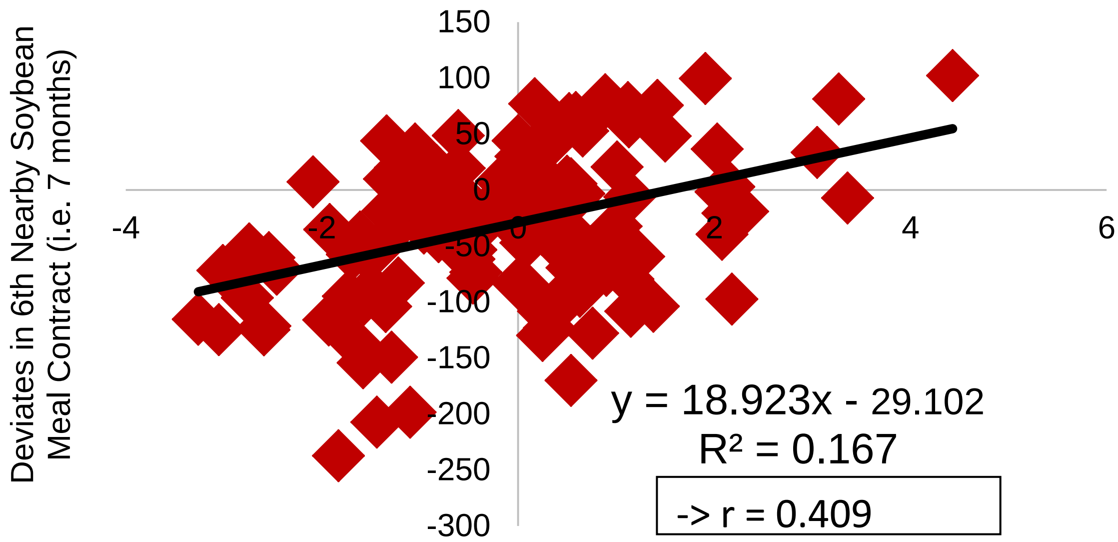
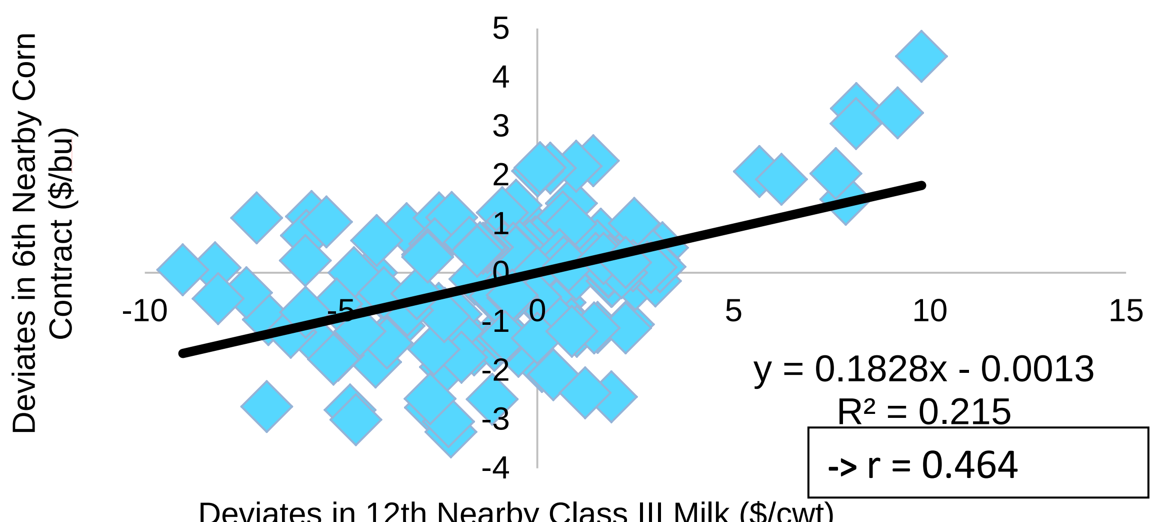


Figure 2: National Average Feed Prices for MPP Dairy program, multiplied by its specific factor.



(Newton & Nicholson, 2014)

Figure 3a: Pearson correlation between price deviates of the 6th nearby futures contracts for corn (12 months) and 6th nearby futures contract for soybean meal (~8 months)



(Newton & Nicholson, 2014)

Figure 3b: Pearson correlation between price deviates of the 12th nearby futures contracts for milk (12 months) and 6th nearby futures contract for corn (12 months)

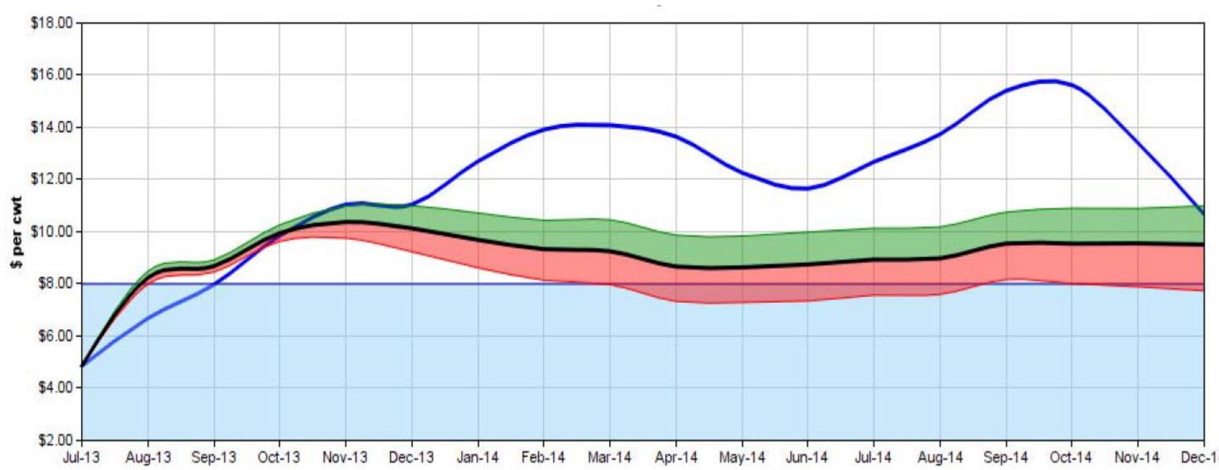


Figure 4a: Margin Forecast from September 30, 2013. Bands include +-25% probability of containing margin. Actual margin is blue line

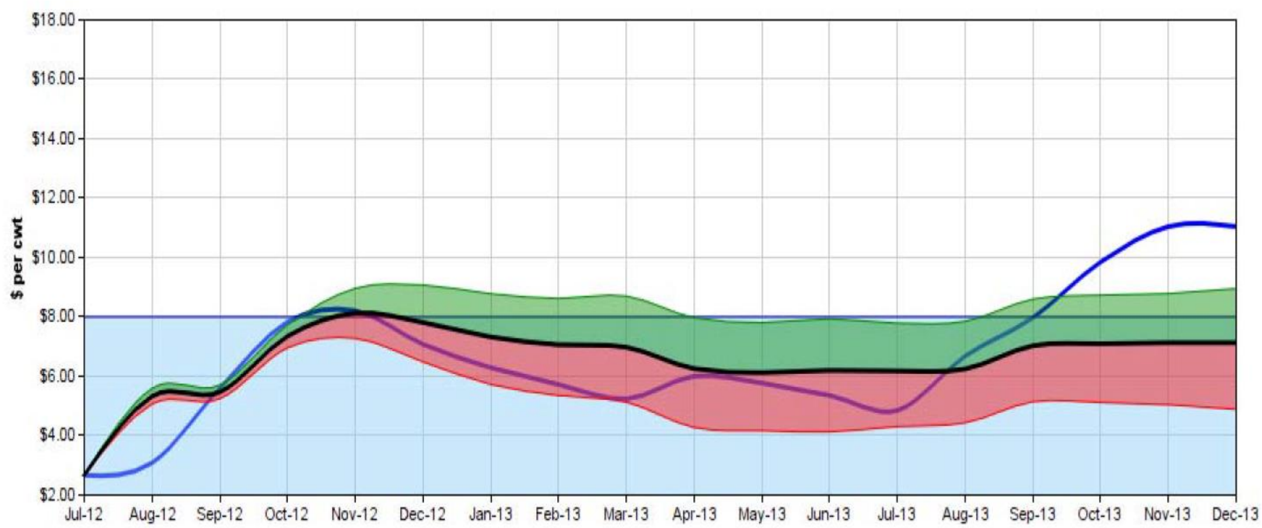


Figure 4b: Margin Forecast from September 28, 2012. Bands include +-25% probability of containing margin. Actual margin is blue line

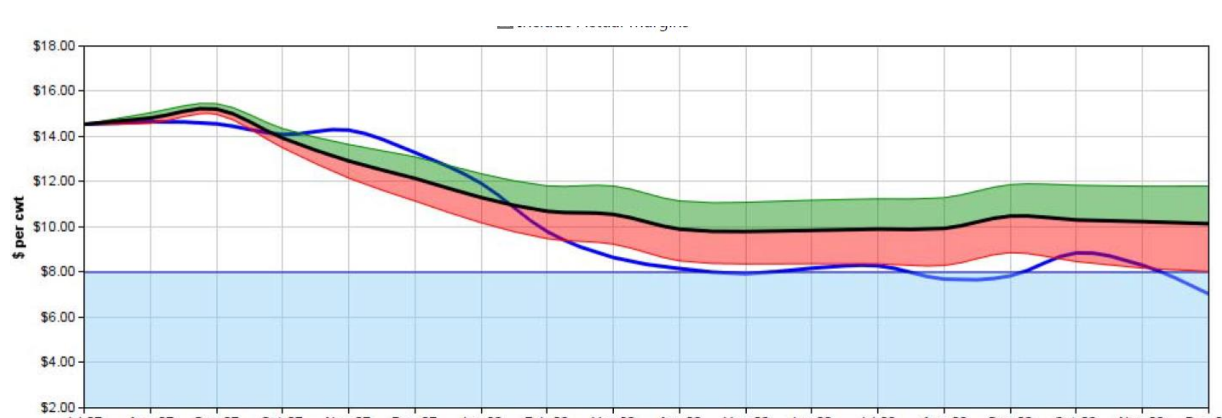


Figure 4c: Margin Forecast from September 28, 2007. Bands include +-25% probability of containing margin. Actual margin is blue line.

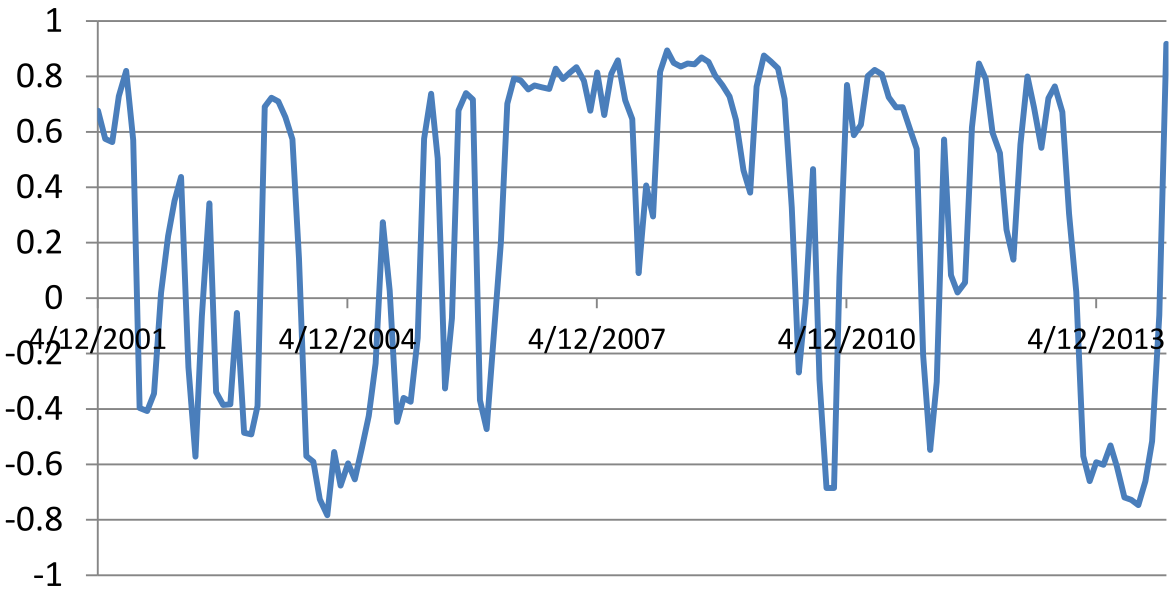


Figure 5a: Dynamic Monthly correlations between price deviates of the 12th nearby future contracts for Milk Class III (12 months) and 6th nearby futures contract for corn (12 months)

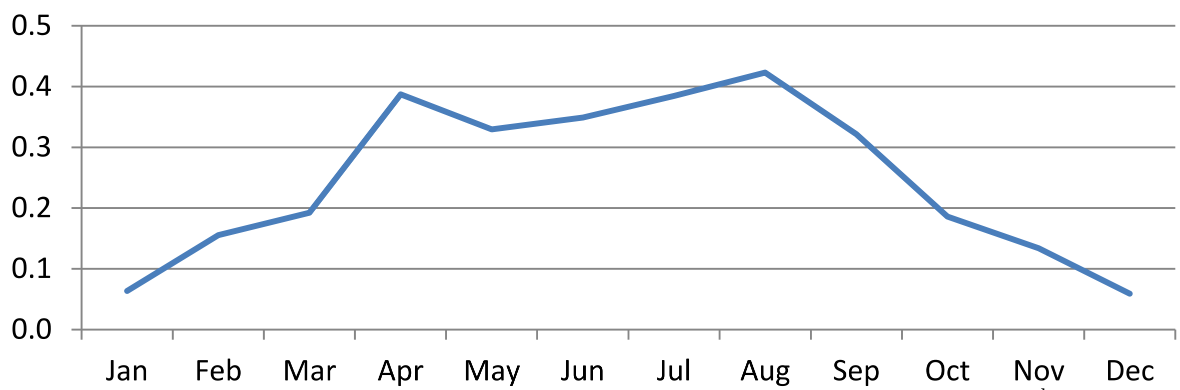


Figure 5b: Dynamic Average Monthly correlations between price deviates of the 12th nearby futures contracts for Milk Class III (12 months) and 6th nearby futures contract corn (12 months)

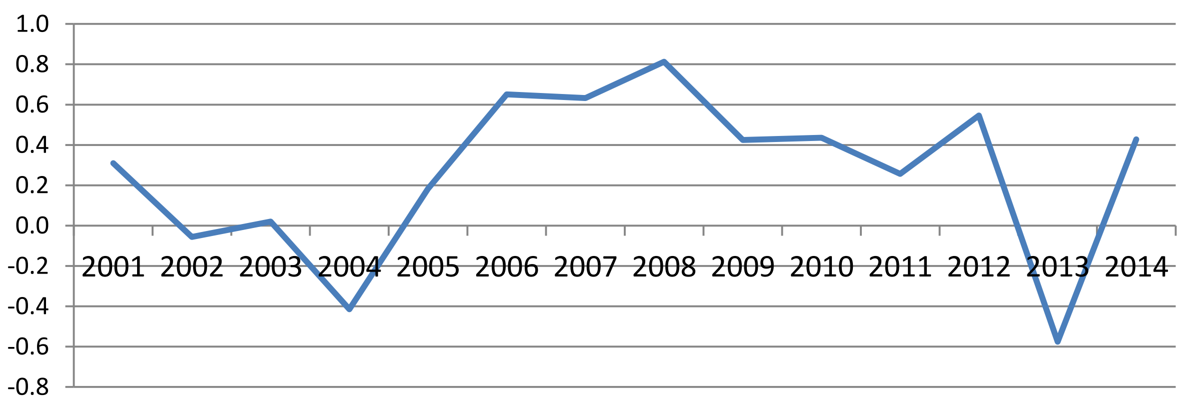


Figure 5c: Dynamic Average Yearly correlations between price deviates of the 12th nearby futures contracts for Milk Class III (12 months) and 6th nearby futures contract corn (12 months)

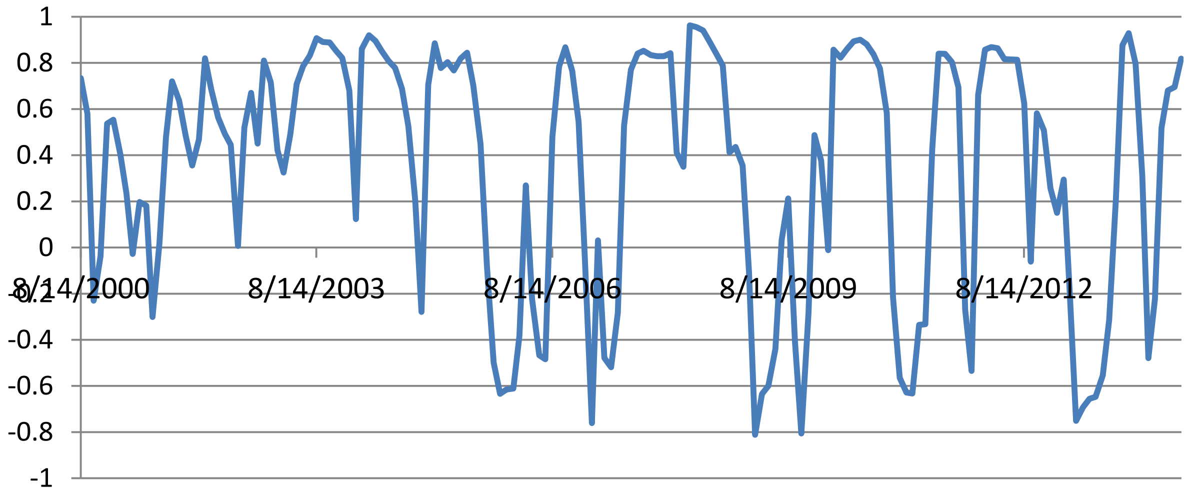


Figure 6a: Dynamic Monthly correlations between price deviates of the "nearby" futures contracts of Corn with 'average' 6 months-to-maturity, and "nearby" futures contract of Soybean Meal with 'average' 6 months-to-maturity

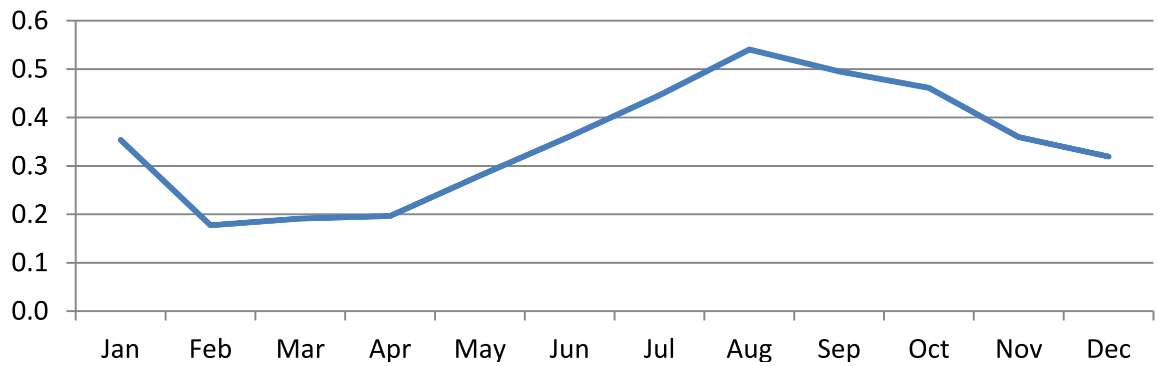


Figure 6b: Dynamic Average Monthly correlations between price deviates of the "nearby" futures contracts of Corn with 'average' 6 months-to-maturity, and "nearby" futures contract of Soybean Meal with 'average' 6 months-to-maturity.

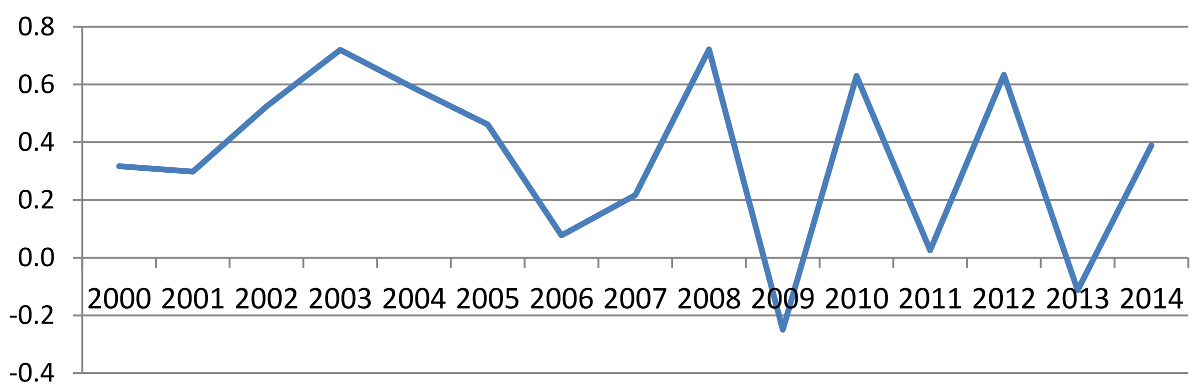


Figure 6c: Dynamic Average Yearly correlations between price deviates of the futures contracts of Corn with 'average' 6 months-to-maturity, and "nearby" futures contract for Soybean Meal with 'average' 6 months-to-maturity.

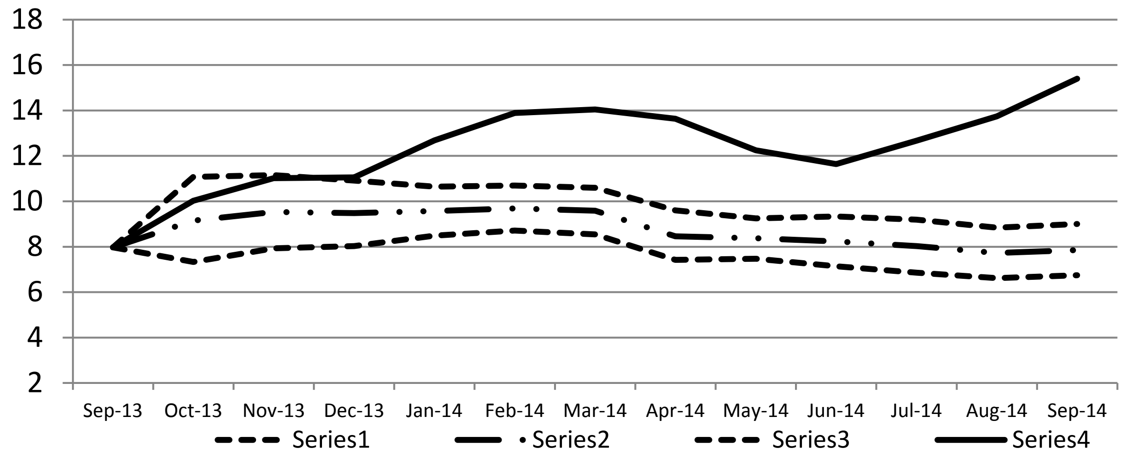


Figure 7a: Margin Forecast from September 13, 2013. Bands include +-25% probability of containing margin. Actual margin is solid line

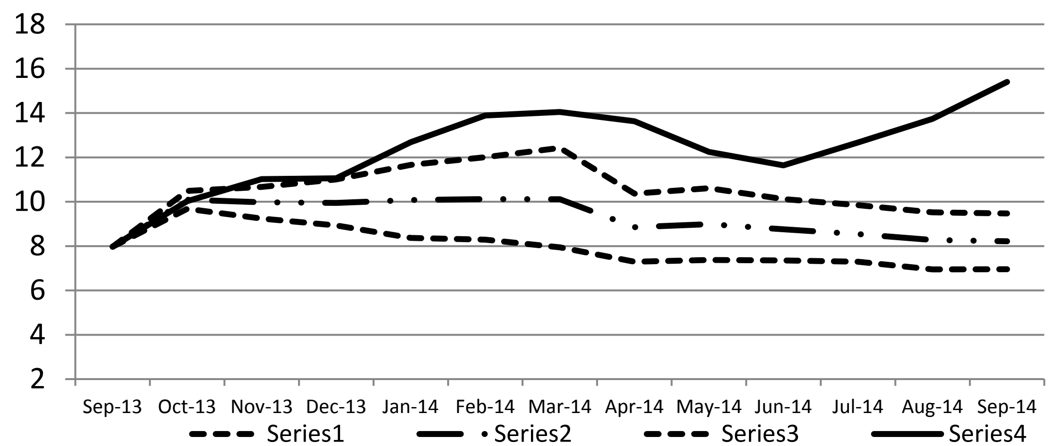


Figure 7b: Margin Forecast from September 30, 2013. Bands include +-25% probability of containing margin. Actual margin is solid line

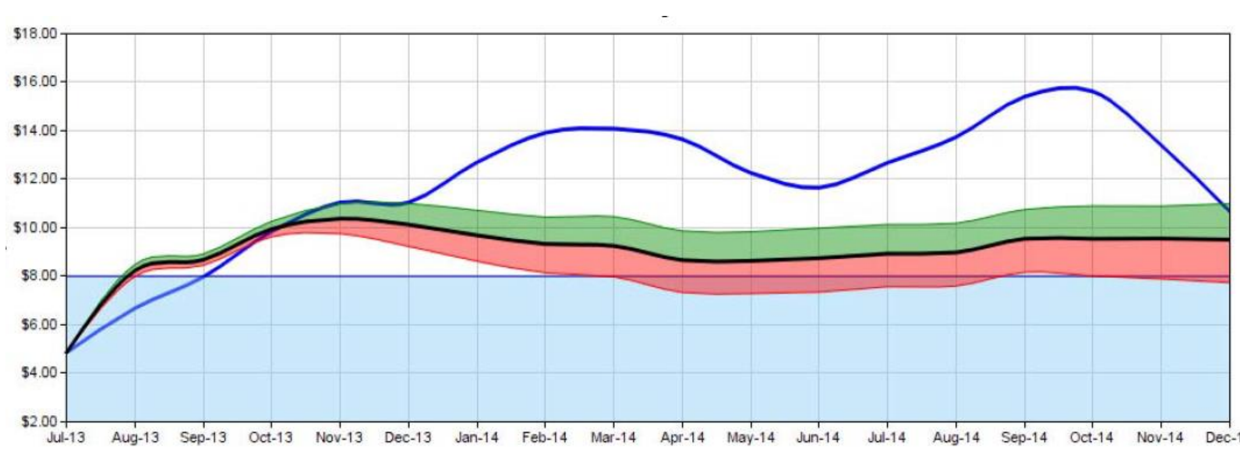


Figure 7c: Margin Forecast from September 30, 2013. Bands include +-25% probability of containing margin. Actual margin is blue line

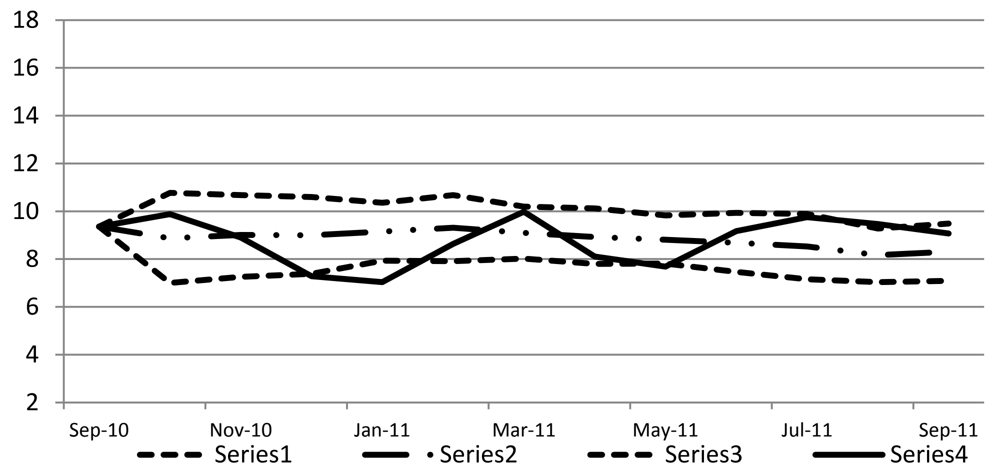


Figure 8a: Margin Forecast from September 14, 2010. Bands include +-25% probability of containing margin. Actual margin is solid line

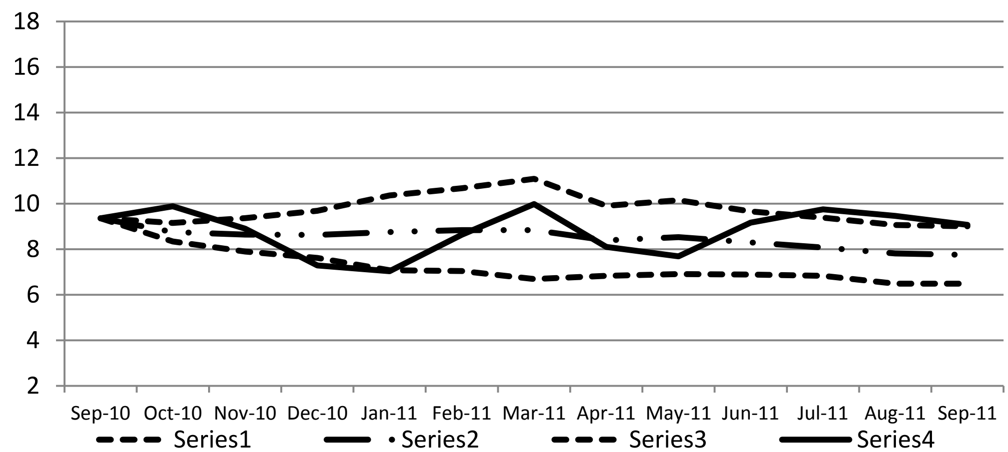


Figure 8b: Margin Forecast from September 30, 2010. Bands include +-25% probability of containing margin. Actual margin is solid line

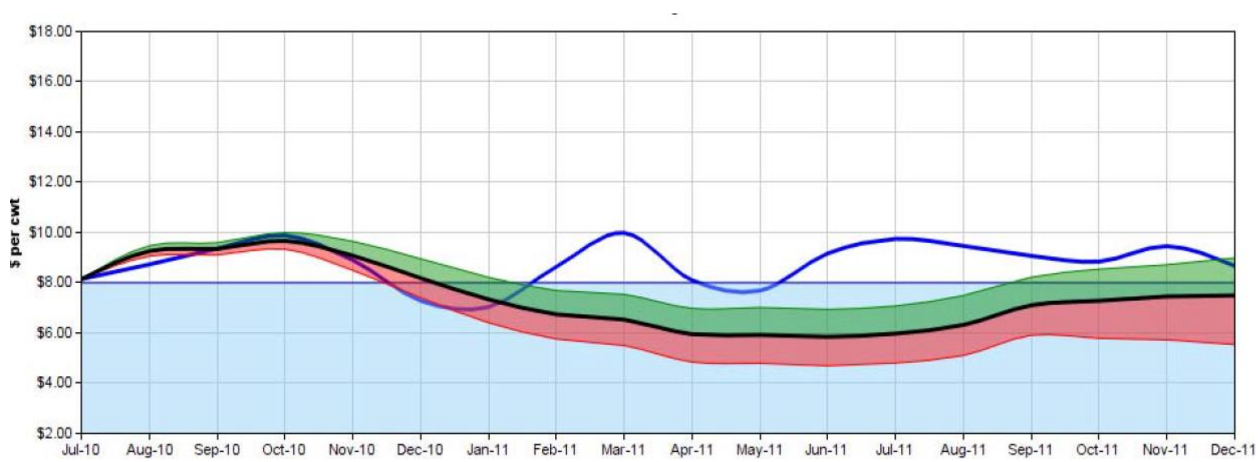


Figure 8c: Margin Forecast from September 30, 2010. Bands include +-25% probability of containing margin. Actual margin is blue line

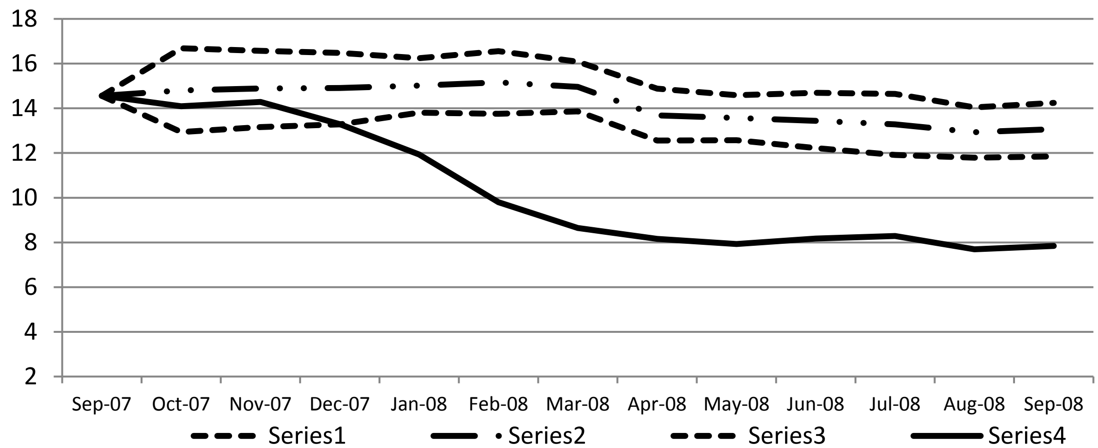


Figure 9a: Margin Forecast from September 14, 2007. Bands include +-25% probability of containing margin. Actual margin is solid line

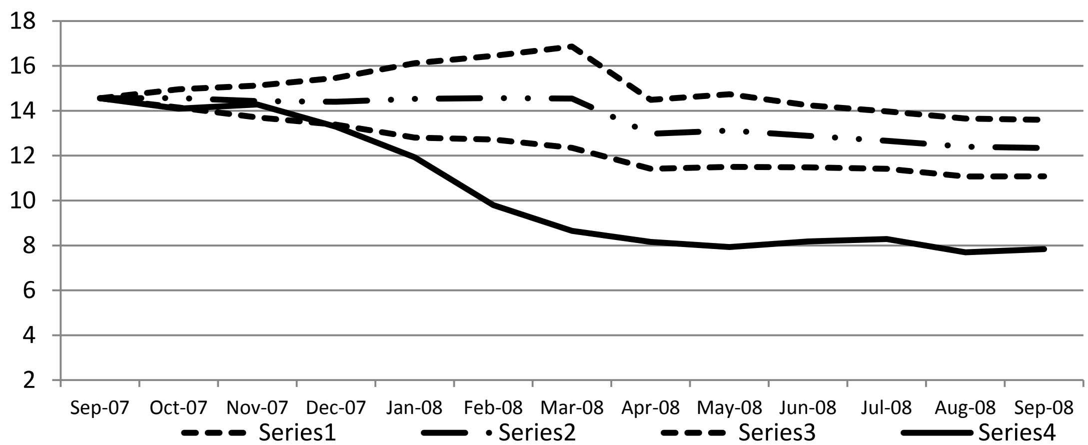


Figure 9b: Margin Forecast from September 28, 2007. Bands include +-25% probability of containing margin. Actual margin is solid line

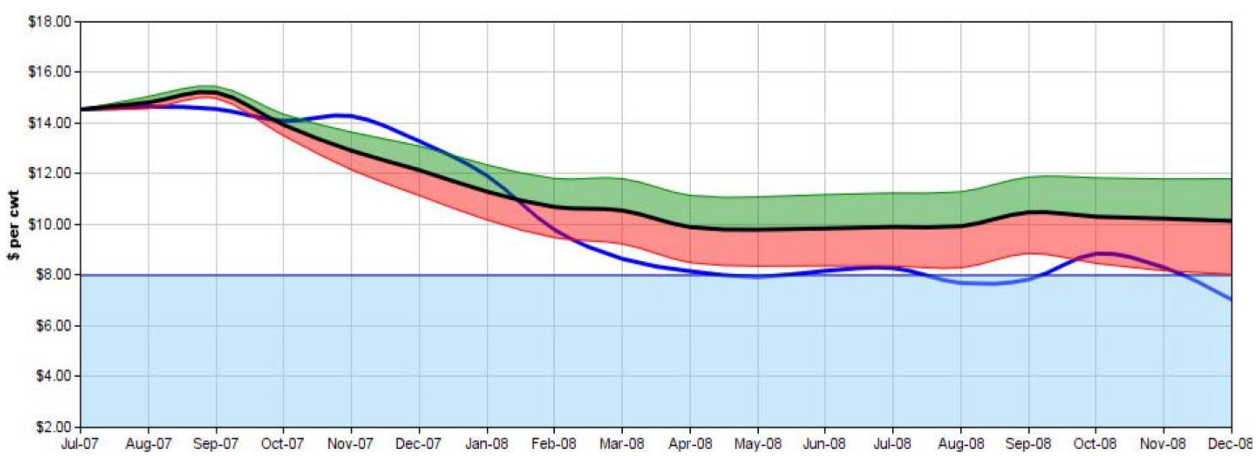


Figure 9c: Margin Forecast from September 28, 2007. Bands include +-25% probability of containing margin. Actual margin is blue line

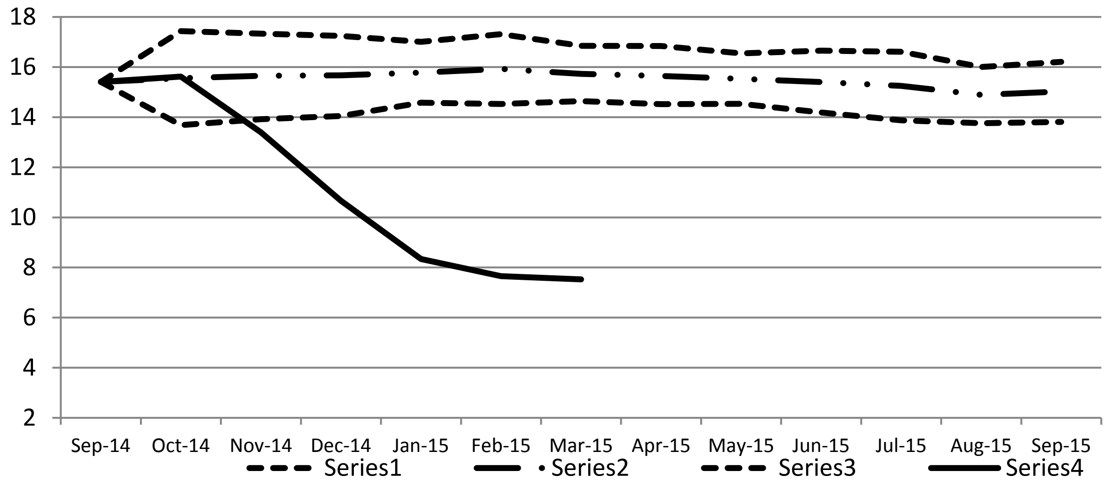


Figure 10a: Margin Forecast from September 12, 2014. Bands include +-25% probability of containing margin. Actual margin is solid line

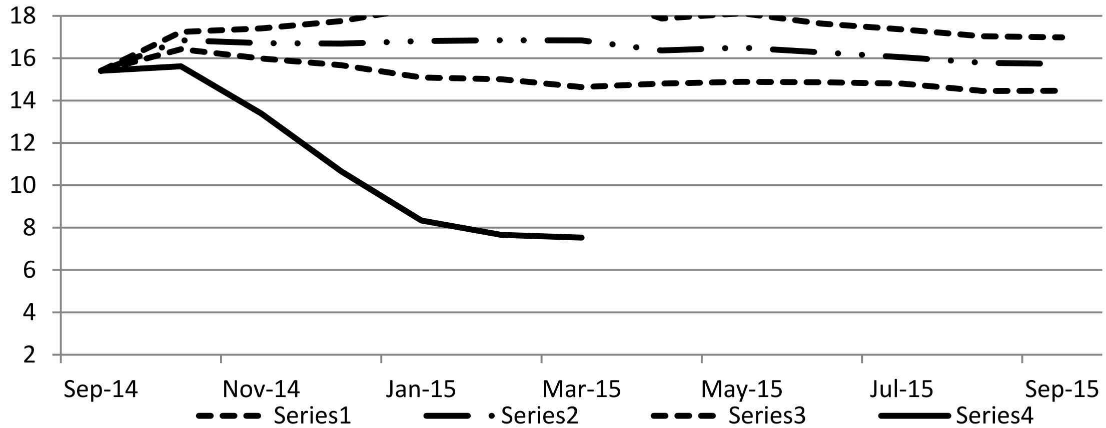


Figure 10b: Margin Forecast from September 30, 2014. Bands include +-25% probability of containing margin. Actual margin is solid line

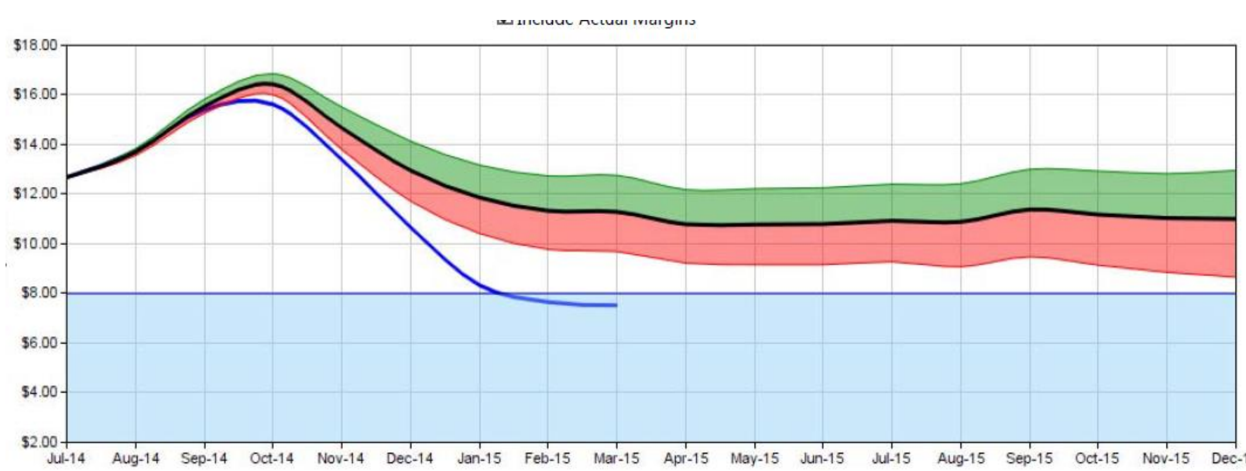


Figure 10c: Margin Forecast from September 30, 2014. Bands include +-25% probability of containing margin. Actual margin is blue line

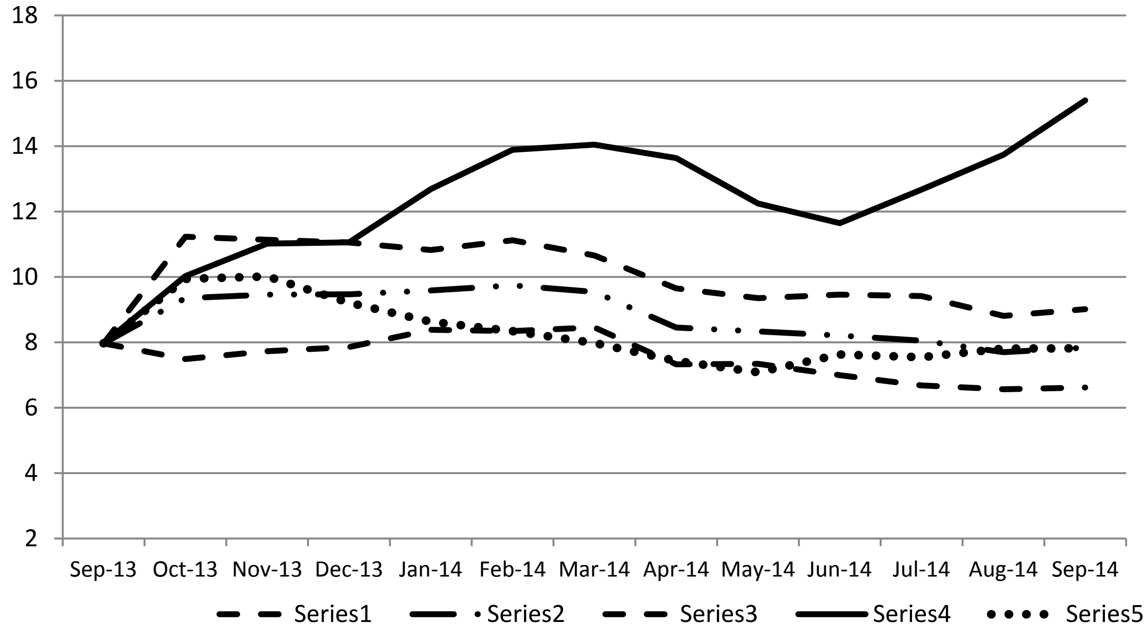


Figure 11a: Margin Forecast from September 13, 2013. Bands include +-25% probability of containing margin. Actual margin is solid line. Dotted line is forecast with Actual futures prices.

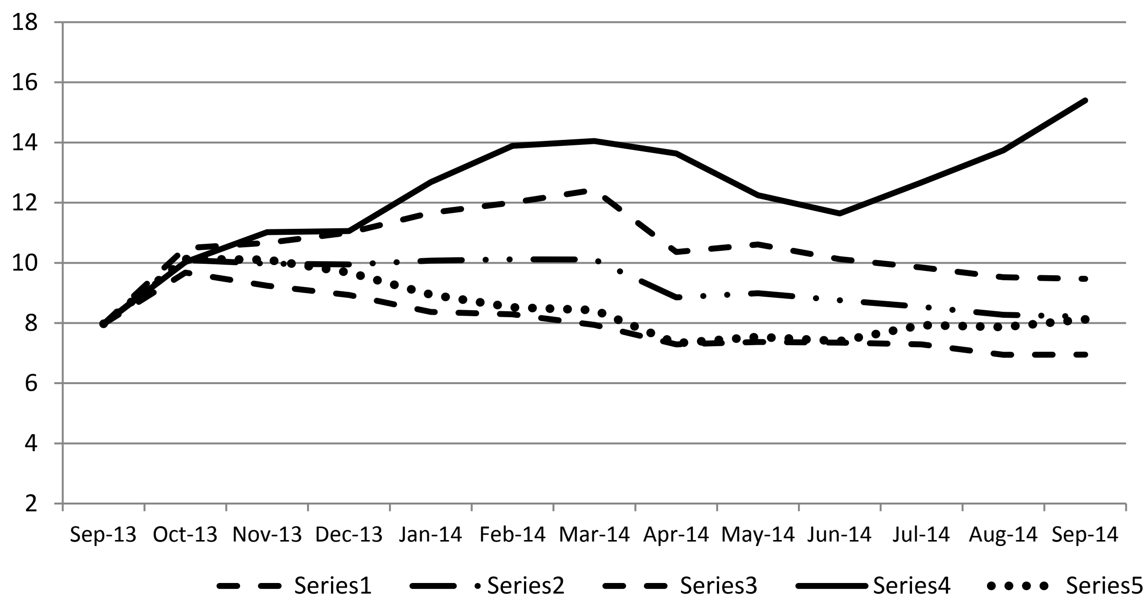


Figure 11b: Margin Forecast from September 30, 2013. Bands include +-25% probability of containing margin. Actual margin is solid line. Dotted line is forecast with Actual futures prices

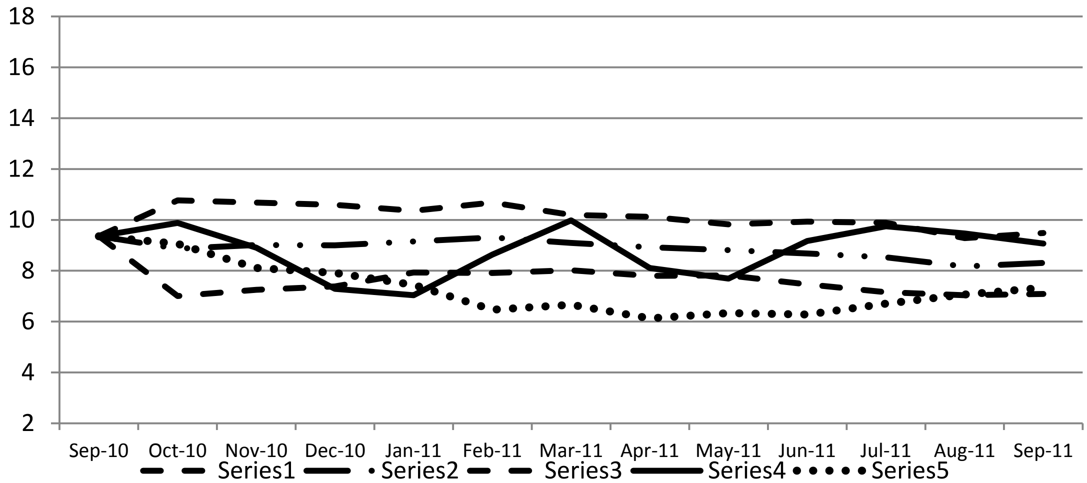


Figure 12a: Margin Forecast from September 14, 2010. Bands include +-25% probability of containing margin. Actual margin is solid line. Dotted line is forecast with Actual futures prices.

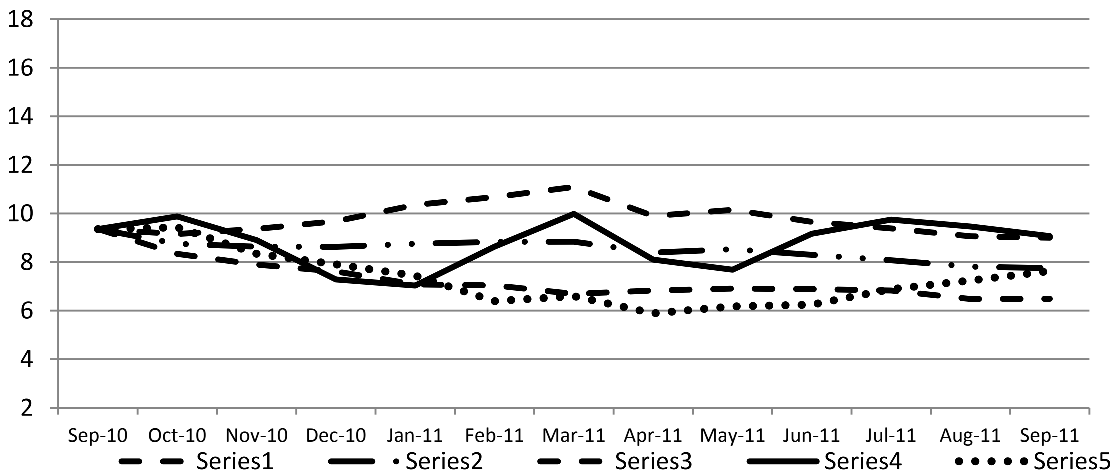


Figure 12b: Margin Forecast from September 30, 2010. Bands include +-25% probability of containing margin. Actual margin is solid line. Dotted line is forecast with Actual futures prices.

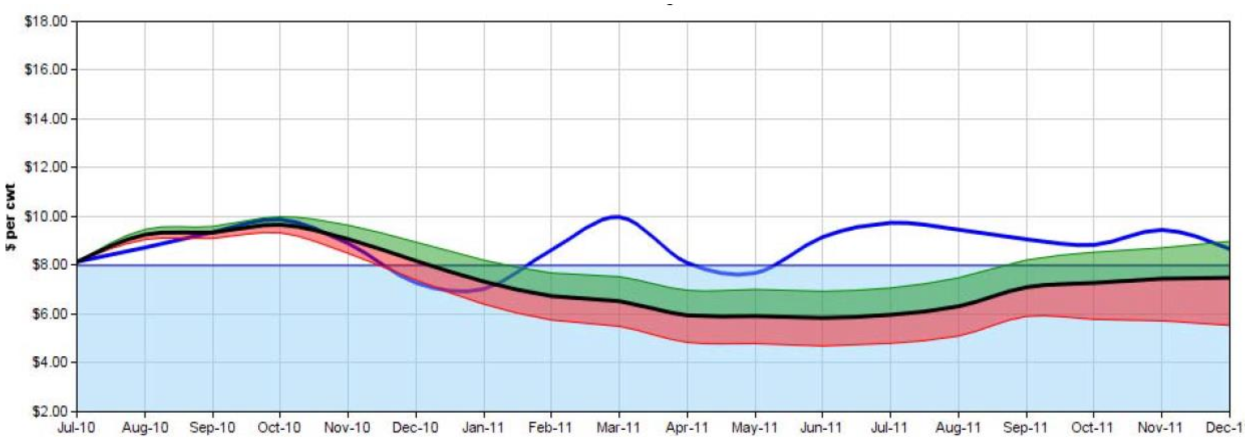


Figure 12c: Margin Forecast from September 30, 2010. Bands include +-25% probability of containing margin. Actual margin is blue line

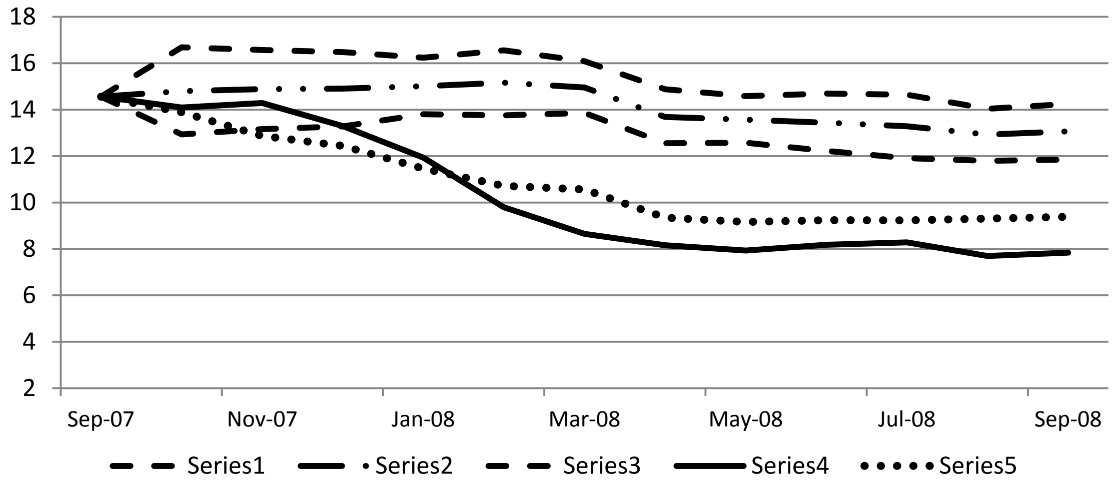


Figure 13a: Margin Forecast from September 14, 2007. Bands include +-25% probability of containing margin. Actual margin is solid line. Dotted line is forecast with Actual futures prices

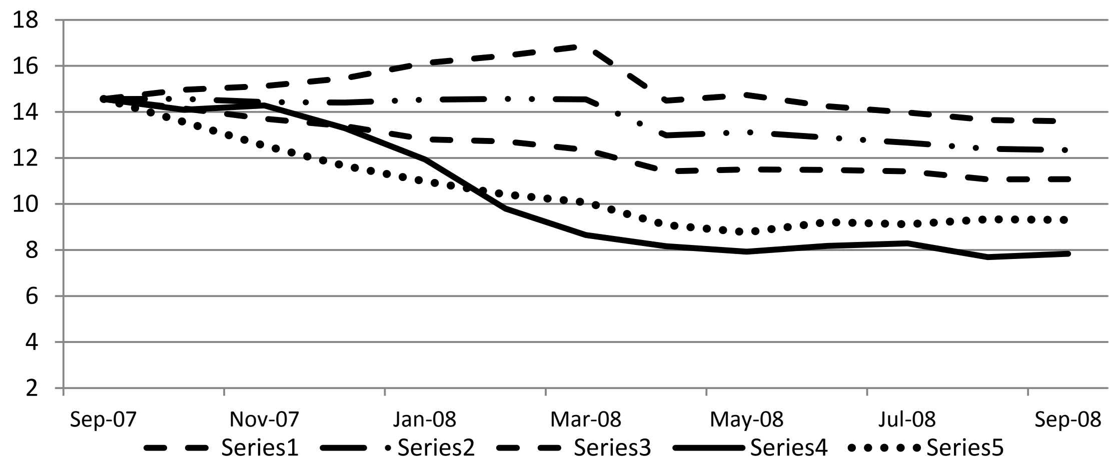


Figure 13b: Margin Forecast from September 28, 2007. Bands include +-25% probability of containing margin. Actual margin is solid line. Dotted line is forecast with Actual futures prices

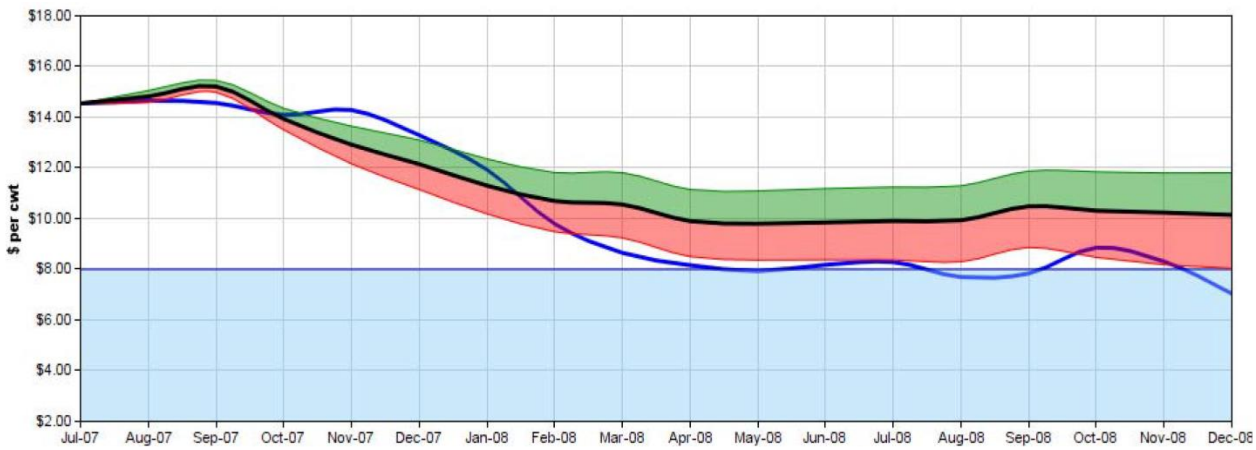


Figure 13c: Margin Forecast from September 28, 2007. Bands include +-25% probability of containing margin. Actual margin is blue line

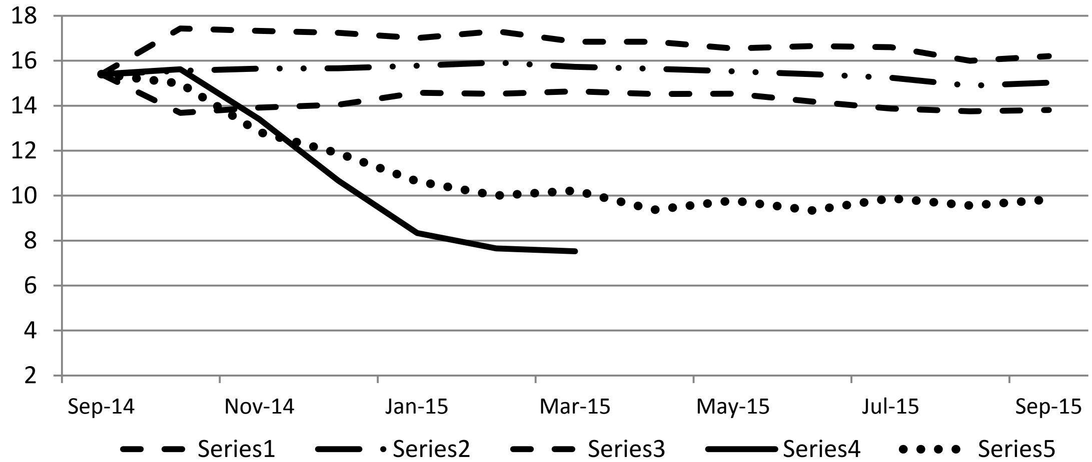


Figure 14a: Margin Forecast from September 12, 2014. Bands include +-25% probability of containing margin. Actual margin is solid line. Dotted line is forecast with Actual futures prices.

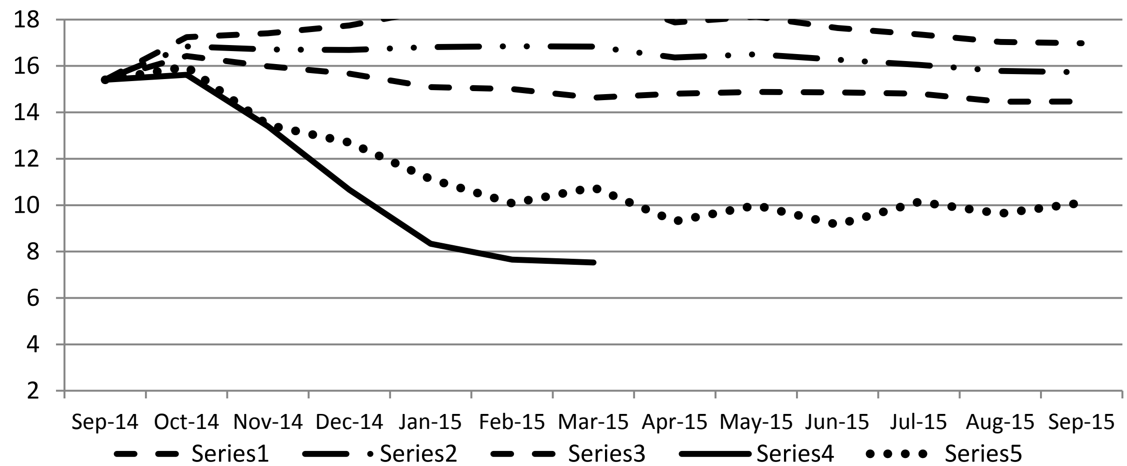


Figure 14b: Margin Forecast from September 30, 2014. Bands include +-25% probability of containing margin. Actual margin is solid line. Dotted line is forecast with Actual futures prices.

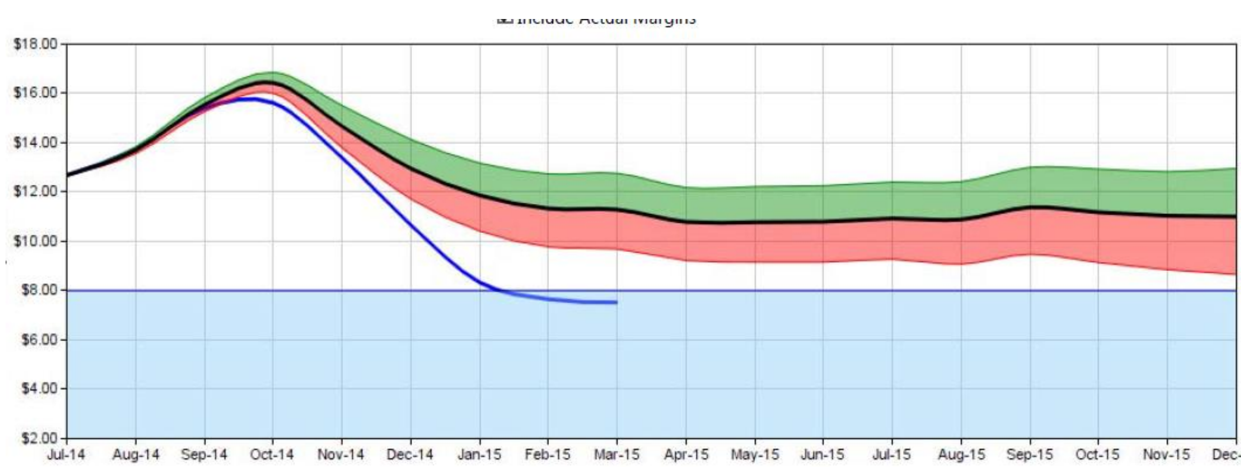
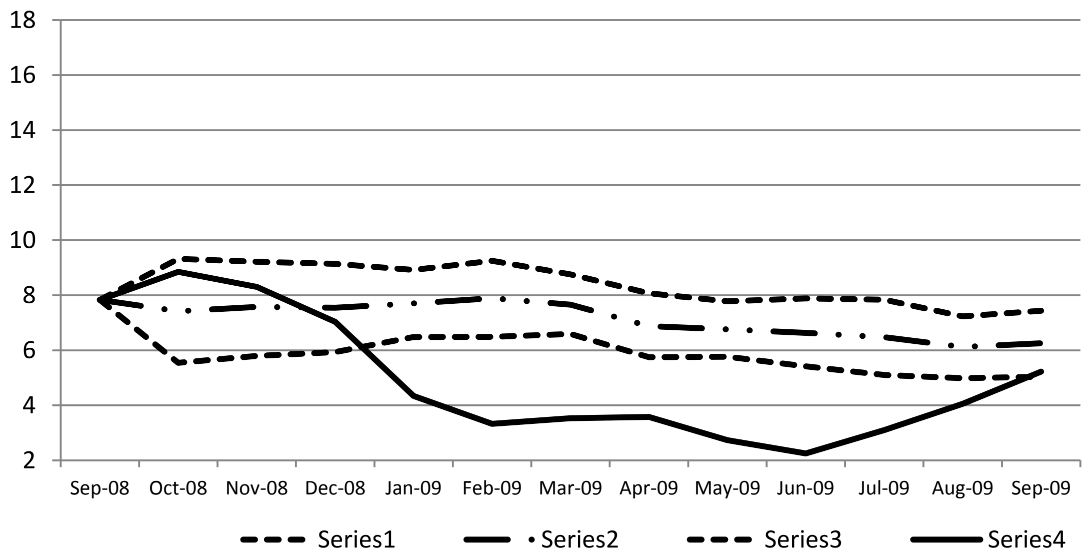
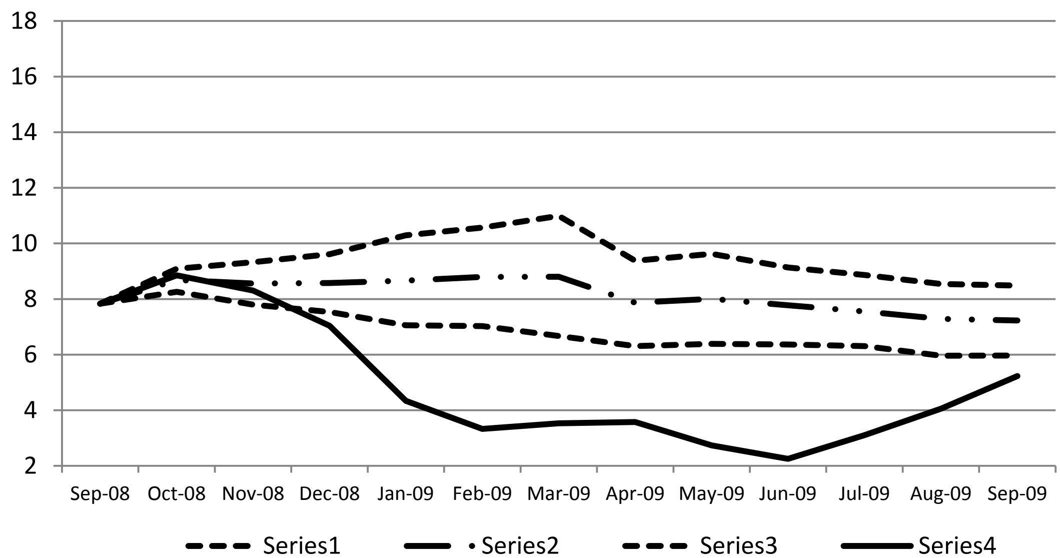
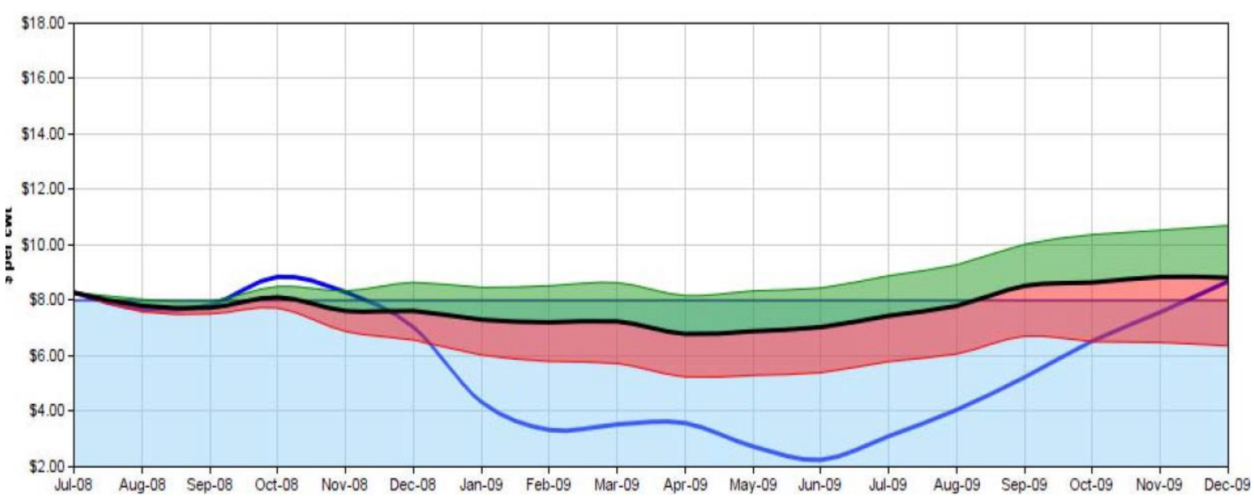


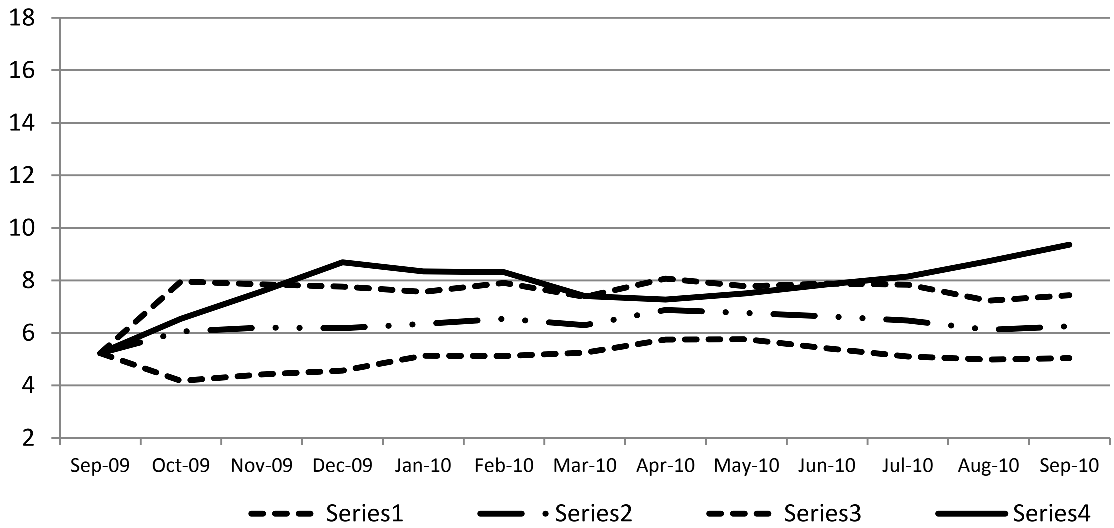
Figure 14c: Margin Forecast from September 30, 2014. Bands include +-25% probability of containing margin. Actual margin is blue line.

Appendix 1

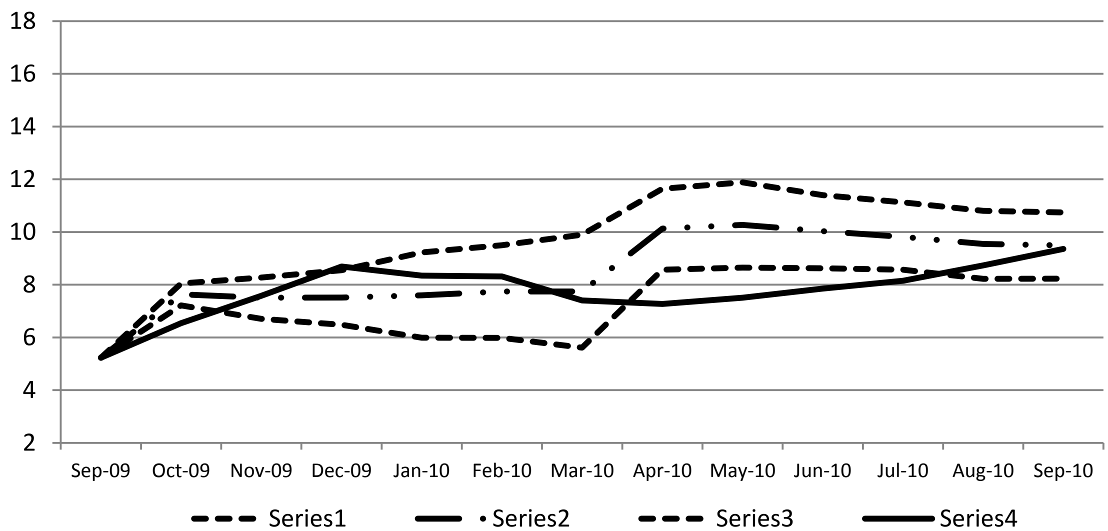

18
16
14
12
10
8
6
4
2
Sep-08
Oct-08
Nov-08
Dec-08
Jan-09
Feb-09
Mar-09
Apr-09
May-09
Jun-09
Jul-09
Aug-09
Sep-09
Series1
Series2
Series3
Series4


18
16
14
12
10
8
6
4
2
Sep-08
Oct-08
Nov-08
Dec-08
Jan-09
Feb-09
Mar-09
Apr-09
May-09
Jun-09
Jul-09
Aug-09
Sep-09
Series1
Series2
Series3
Series4

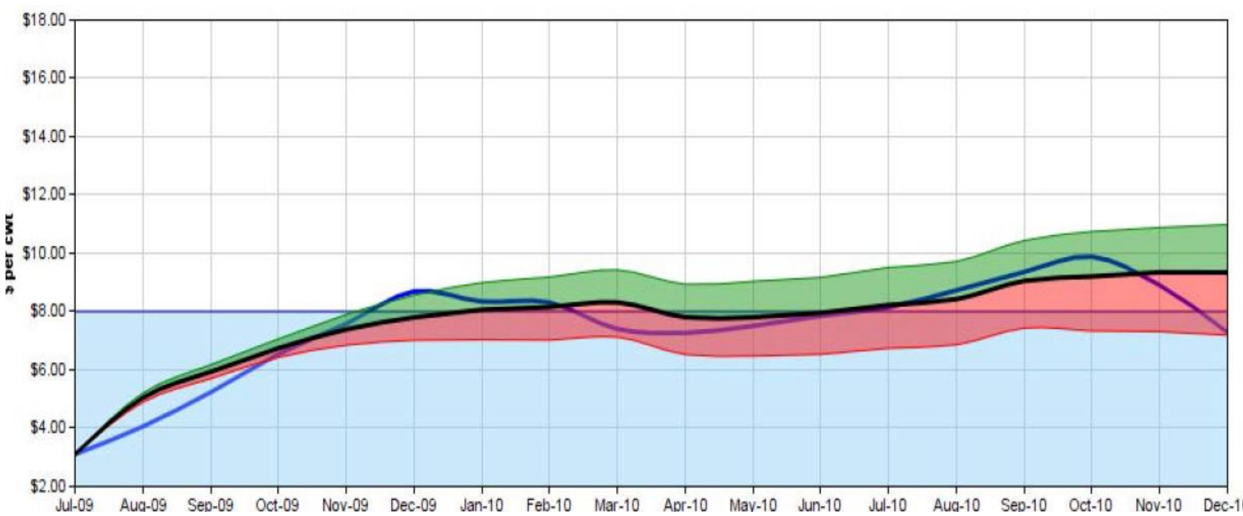

$18.00
$16.00
$14.00
$12.00
$10.00
$8.00
$6.00
$4.00
$2.00
Jul-08
Aug-08
Sep-08
Oct-08
Nov-08
Dec-08
Jan-09
Feb-09
Mar-09
Apr-09
May-09
Jun-09
Jul-09
Aug-09
Sep-09
Oct-09
Nov-09
Dec-09



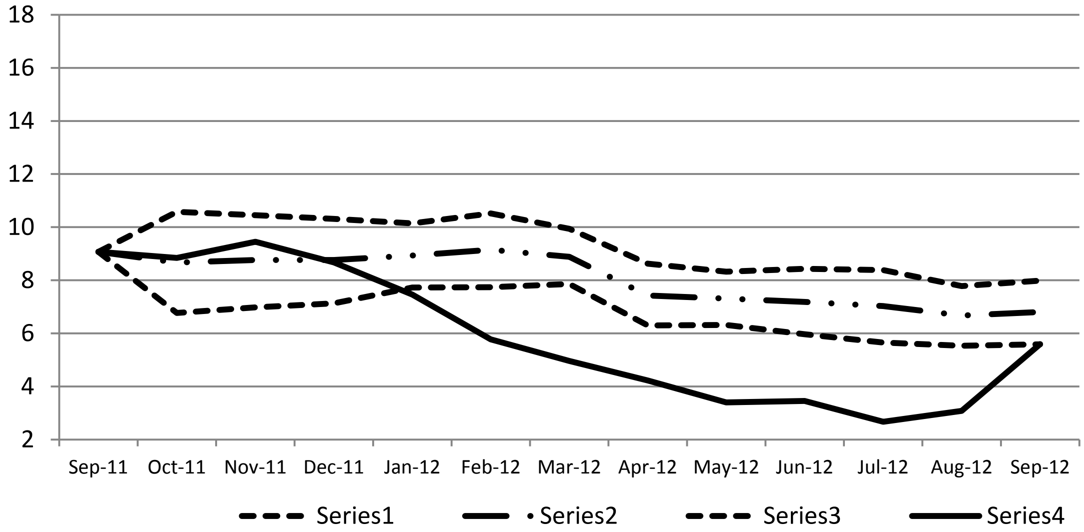
18
16
14
12
10
8
6
4
2
Sep-09
Oct-09
Nov-09
Dec-09
Jan-10
Feb-10
Mar-10
Apr-10
May-10
Jun-10
Jul-10
Aug-10
Sep-10
Series1
Series2
Series3
Series4

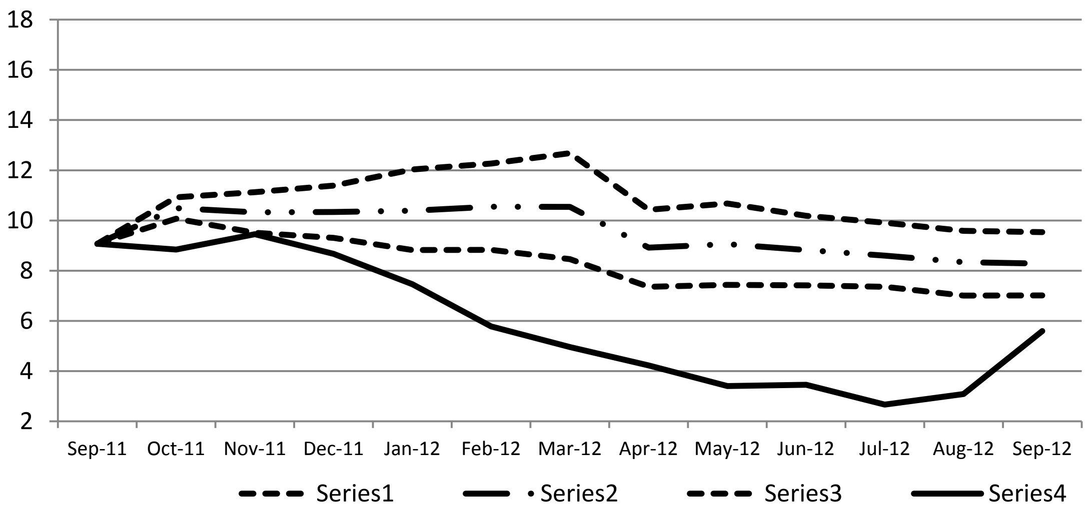


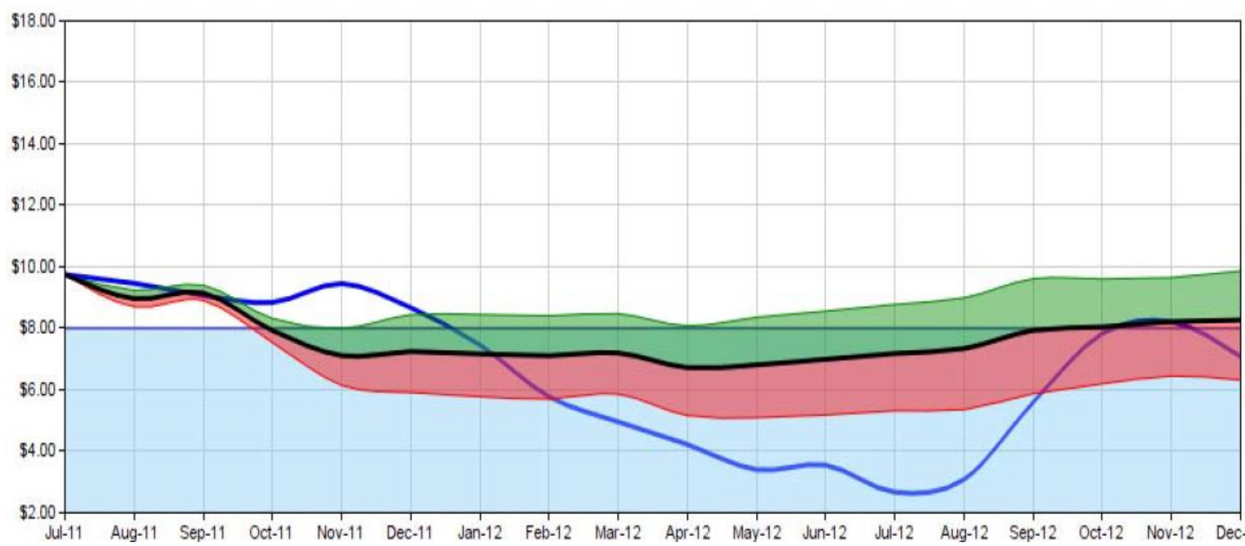
18
16
14
12
10
8
6
4
2
Sep-09
Oct-09
Nov-09
Dec-09
Jan-10
Feb-10
Mar-10
Apr-10
May-10
Jun-10
Jul-10
Aug-10
Sep-10
Series1
Series2
Series3
Series4

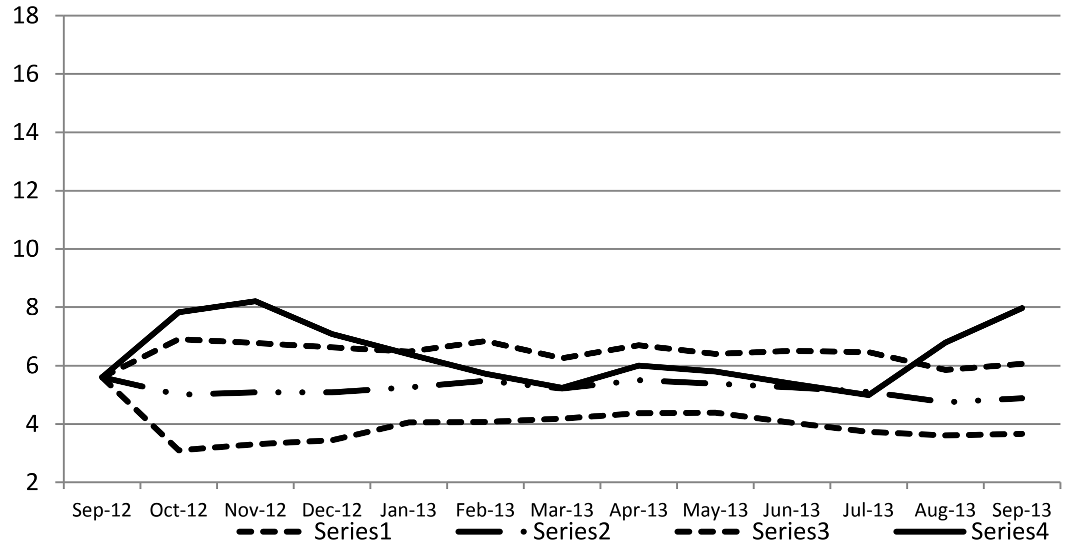


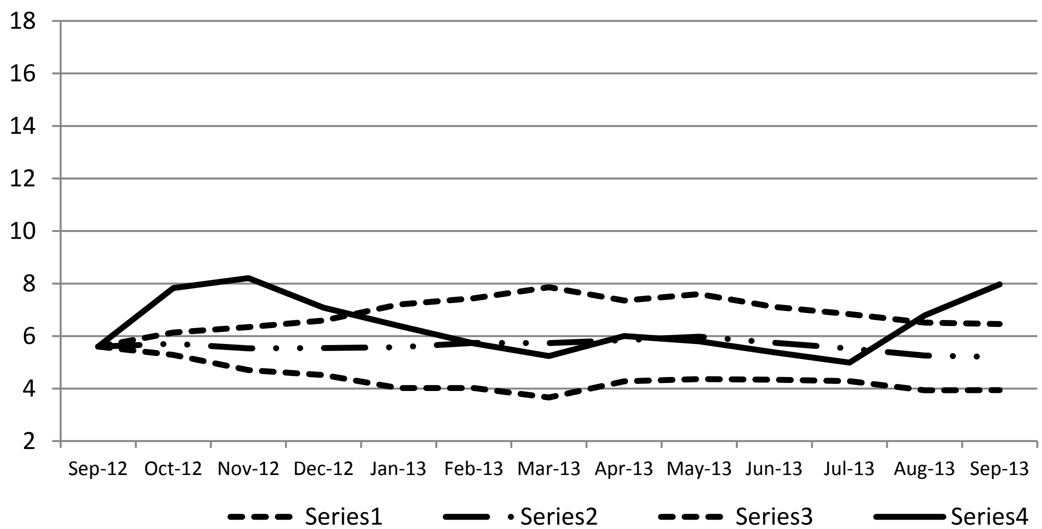
$18.00
$16.00
$14.00
$12.00
$10.00
$8.00
$6.00
$4.00
$2.00
per cwt
Jul-09
Aug-09
Sep-09
Oct-09
Nov-09
Dec-09
Jan-10
Feb-10
Mar-10
Apr-10
May-10
Jun-10
Jul-10
Aug-10
Sep-10
Oct-10
Nov-10
Dec-10

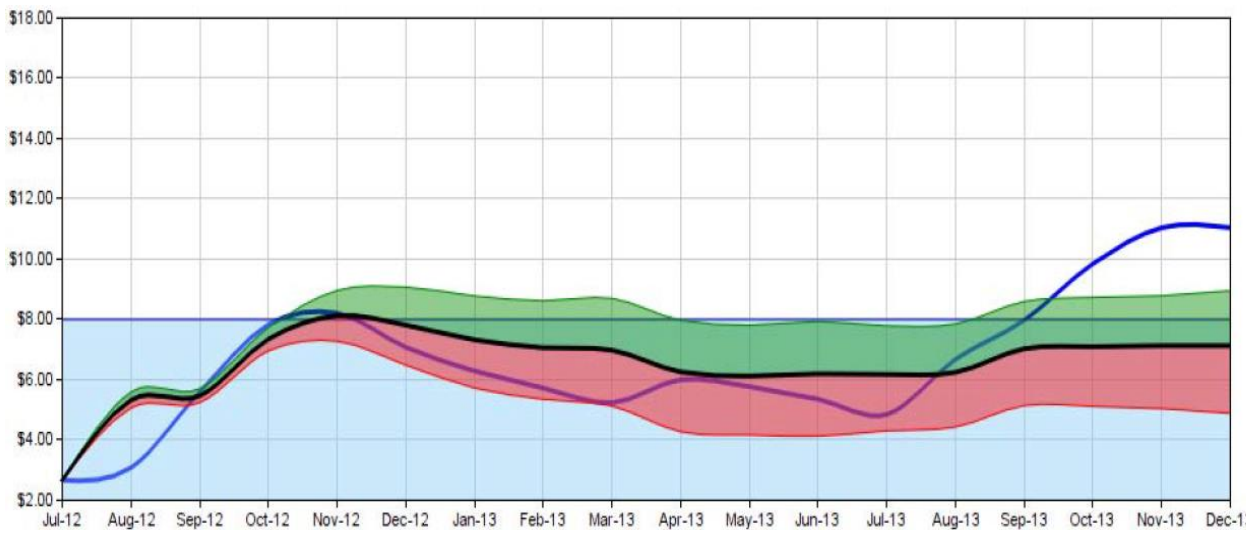

18
16
14
12
10
8
6
4
2
Sep-11 Oct-11 Nov-11 Dec-11 Jan-12 Feb-12 Mar-12 Apr-12 May-12 Jun-12 Jul-12 Aug-12 Sep-12
Series1
Series2
Series3
Series4


18
16
14
12
10
8
6
4
2
Sep-11 Oct-11 Nov-11 Dec-11 Jan-12 Feb-12 Mar-12 Apr-12 May-12 Jun-12 Jul-12 Aug-12 Sep-12
Series1
Series2
Series3
Series4

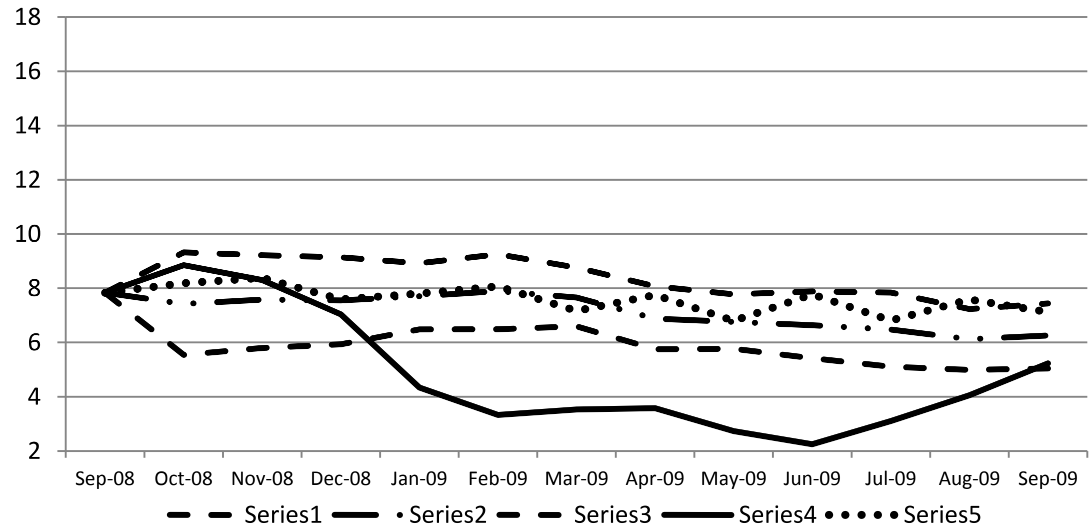

$18.00
$16.00
$14.00
$12.00
$10.00
$8.00
$6.00
$4.00
$2.00
Jul-11 Aug-11 Sep-11 Oct-11 Nov-11 Dec-11 Jan-12 Feb-12 Mar-12 Apr-12 May-12 Jun-12 Jul-12 Aug-12 Sep-12 Oct-12 Nov-12


18
16
14
12
10
8
6
4
2
Sep-12 Oct-12 Nov-12 Dec-12 Jan-13 Feb-13 Mar-13 Apr-13 May-13 Jun-13 Jul-13 Aug-13 Sep-13
Series1
Series2
Series3
Series4

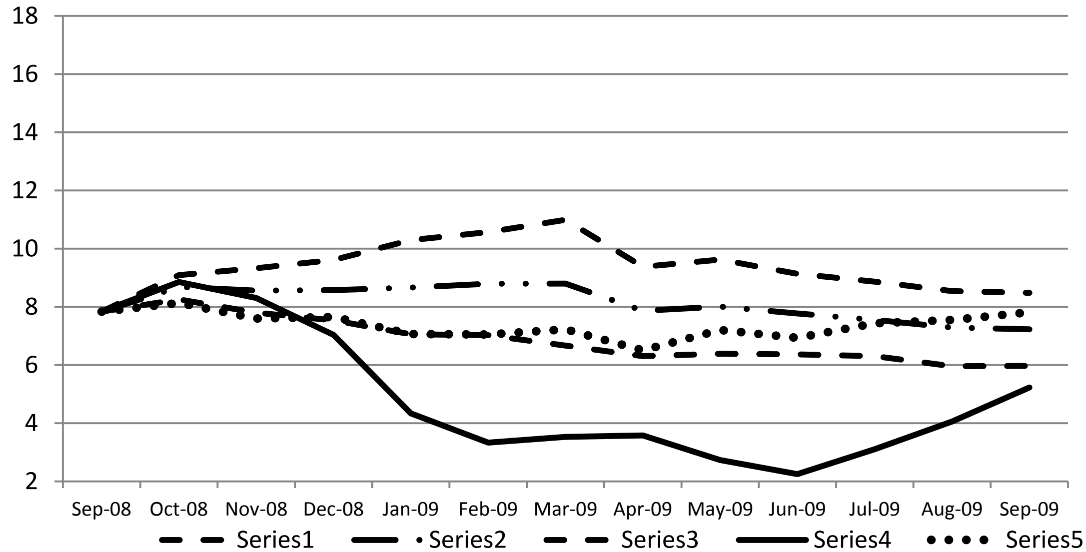

18
16
14
12
10
8
6
4
2
Sep-12 Oct-12 Nov-12 Dec-12 Jan-13 Feb-13 Mar-13 Apr-13 May-13 Jun-13 Jul-13 Aug-13 Sep-13
Series1
Series2
Series3
Series4


$18.00
$16.00
$14.00
$12.00
$10.00
$8.00
$6.00
$4.00
$2.00
Jul-12 Aug-12 Sep-12 Oct-12 Nov-12 Dec-12 Jan-13 Feb-13 Mar-13 Apr-13 May-13 Jun-13 Jul-13 Aug-13 Sep-13 Oct-13 Nov-13 Dec-13

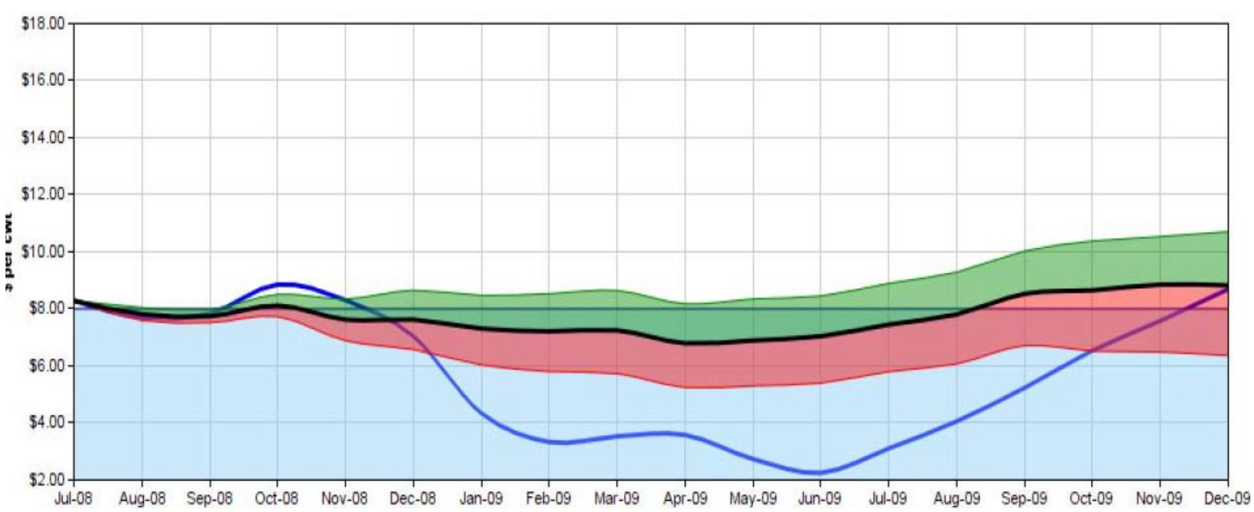
Appendix 2



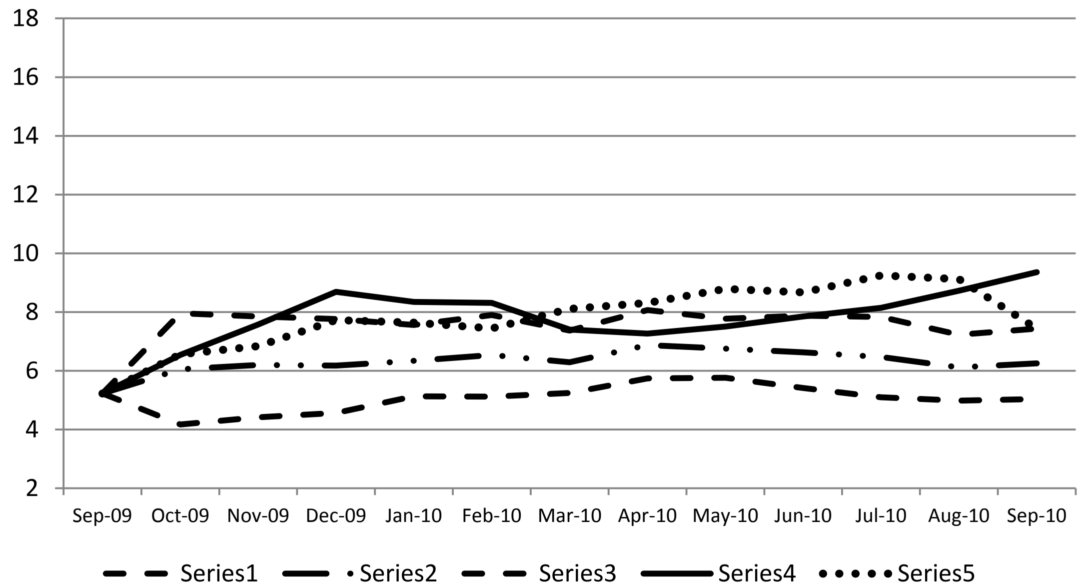
18
16
14
12
10
8
6
4
2
Sep-08 Oct-08 Nov-08 Dec-08 Jan-09 Feb-09 Mar-09 Apr-09 May-09 Jun-09 Jul-09 Aug-09 Sep-09
Series1 Series2 Series3 Series4 Series5

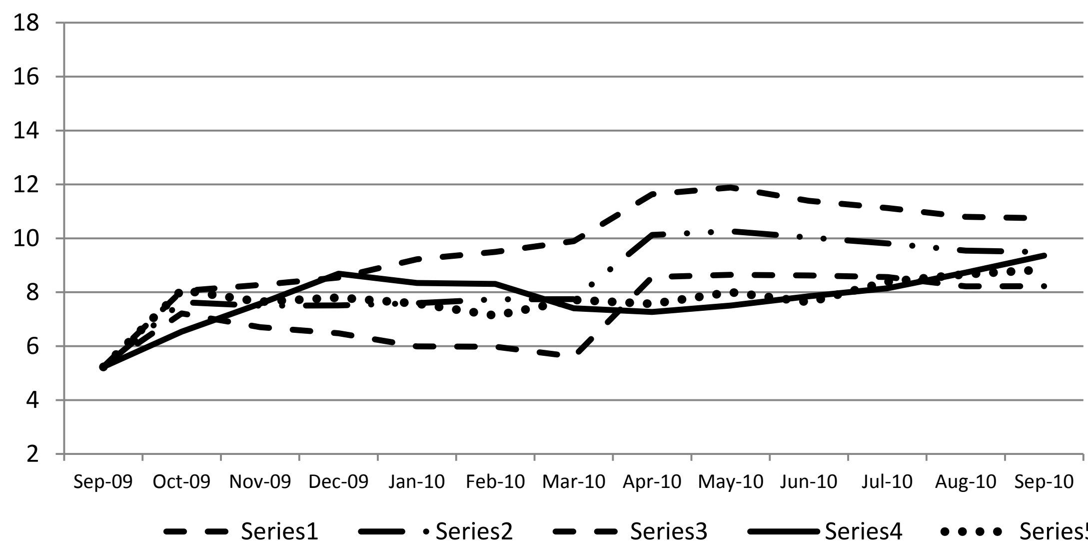


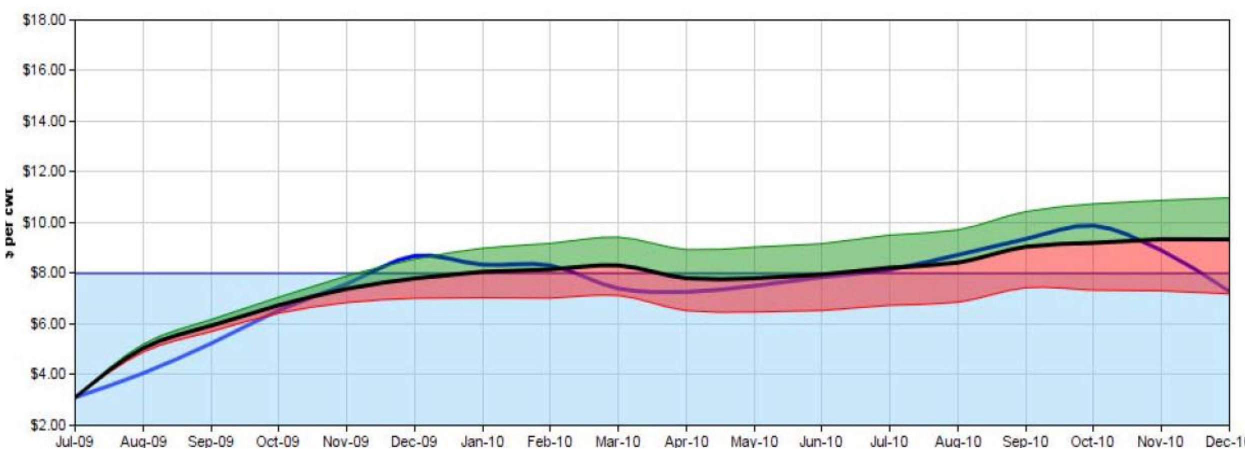
18
16
14
12
10
8
6
4
2
Sep-08 Oct-08 Nov-08 Dec-08 Jan-09 Feb-09 Mar-09 Apr-09 May-09 Jun-09 Jul-09 Aug-09 Sep-09
Series1 Series2 Series3 Series4 Series5

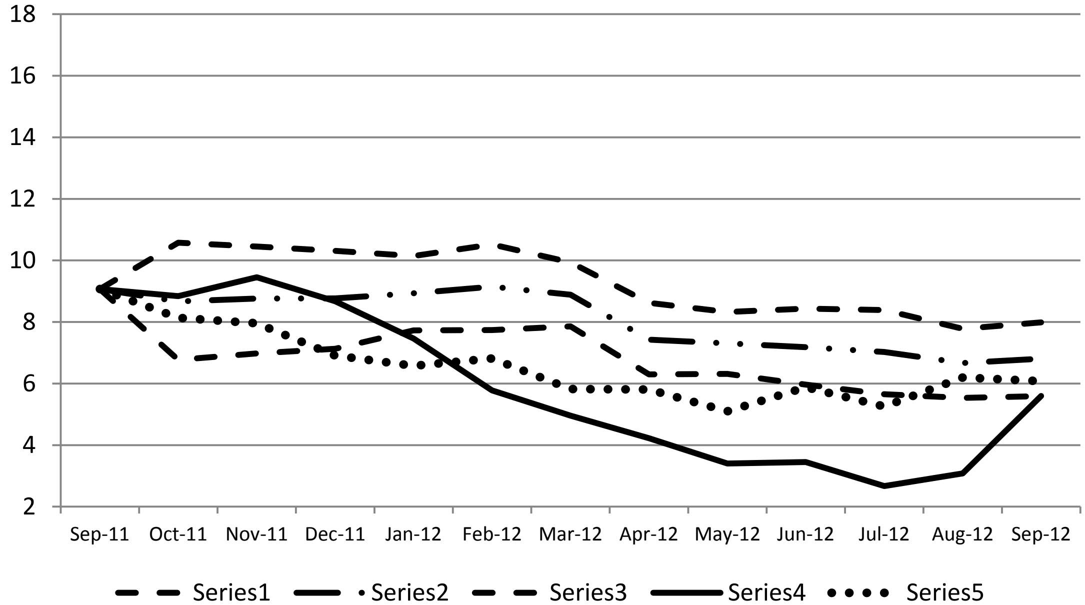


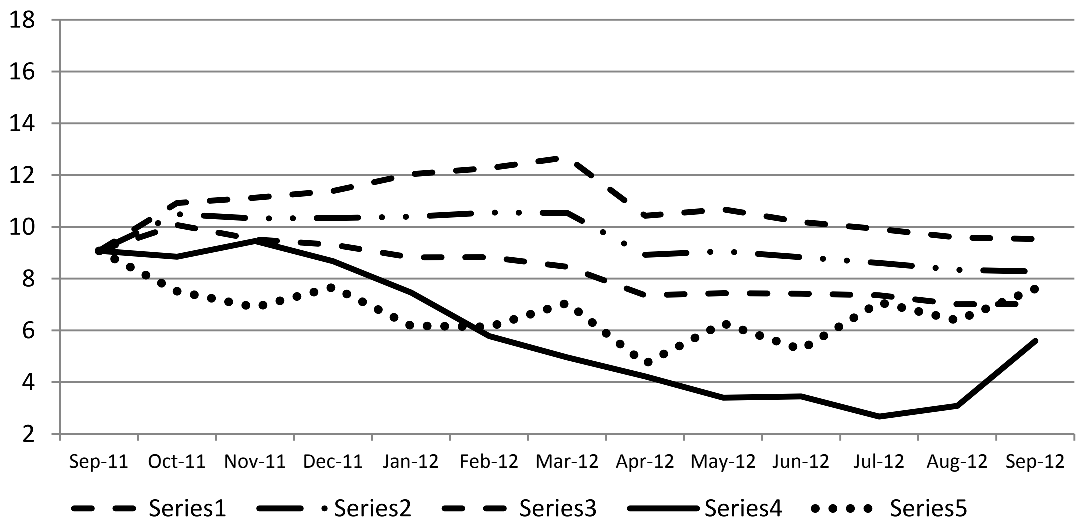
$18.00
$16.00
$14.00
$12.00
$10.00
$8.00
$6.00
$4.00
$2.00
Jul-08 Aug-08 Sep-08 Oct-08 Nov-08 Dec-08 Jan-09 Feb-09 Mar-09 Apr-09 May-09 Jun-09 Jul-09 Aug-09 Sep-09 Oct-09 Nov-09 Dec-09

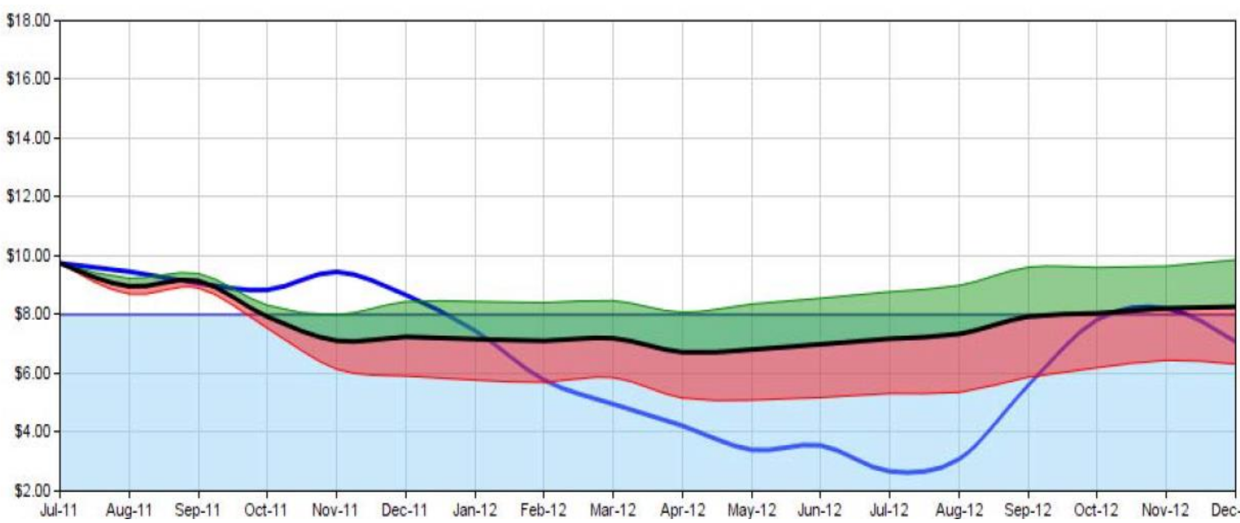

18
16
14
12
10
8
6
4
2
Sep-09 Oct-09 Nov-09 Dec-09 Jan-10 Feb-10 Mar-10 Apr-10 May-10 Jun-10 Jul-10 Aug-10 Sep-10
Series1 Series2 Series3 Series4 Series5

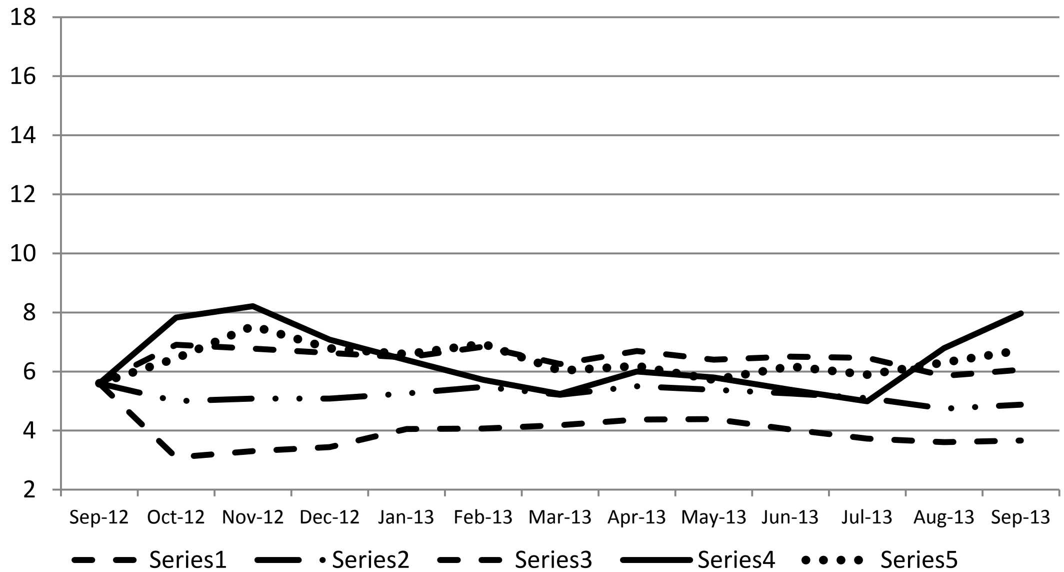

18
16
14
12
10
8
6
4
2
Sep-09 Oct-09 Nov-09 Dec-09 Jan-10 Feb-10 Mar-10 Apr-10 May-10 Jun-10 Jul-10 Aug-10 Sep-10
Series1 Series2 Series3 Series4 Series5


$18.00
$16.00
$14.00
$12.00
$10.00
$8.00
$6.00
$4.00
$2.00
$ per cwt
Jul-09 Aug-09 Sep-09 Oct-09 Nov-09 Dec-09 Jan-10 Feb-10 Mar-10 Apr-10 May-10 Jun-10 Jul-10 Aug-10 Sep-10 Oct-10 Nov-10 Dec-10

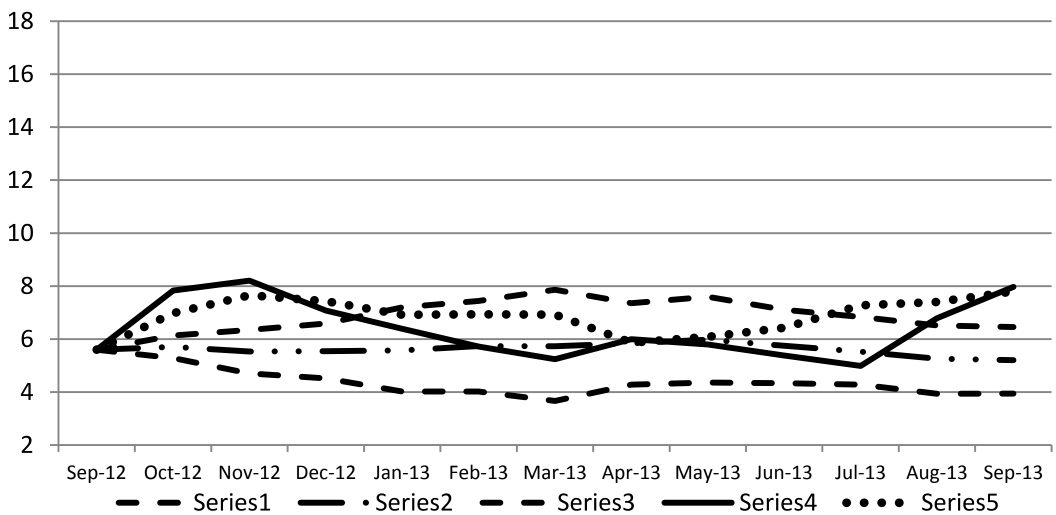

18
16
14
12
10
8
6
4
2
Sep-11 Oct-11 Nov-11 Dec-11 Jan-12 Feb-12 Mar-12 Apr-12 May-12 Jun-12 Jul-12 Aug-12 Sep-12
Series1 Series2 Series3 Series4 Series5


18
16
14
12
10
8
6
4
2
Sep-11 Oct-11 Nov-11 Dec-11 Jan-12 Feb-12 Mar-12 Apr-12 May-12 Jun-12 Jul-12 Aug-12 Sep-12
Series1 Series2 Series3 Series4 Series5

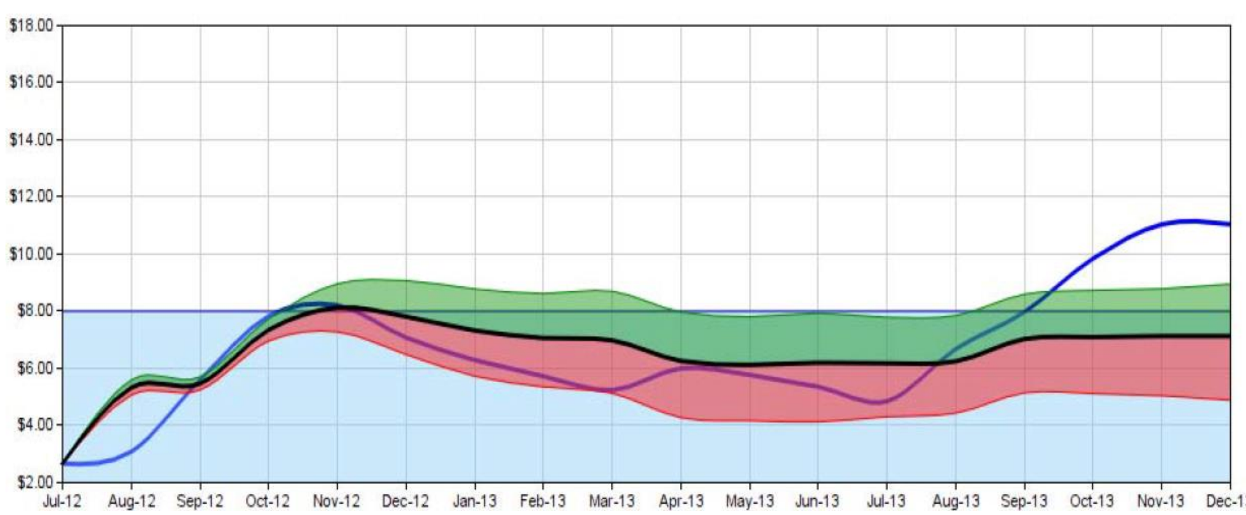

$18.00
$16.00
$14.00
$12.00
$10.00
$8.00
$6.00
$4.00
$2.00
Jul-11 Aug-11 Sep-11 Oct-11 Nov-11 Dec-11 Jan-12 Feb-12 Mar-12 Apr-12 May-12 Jun-12 Jul-12 Aug-12 Sep-12 Oct-12 Nov-12



18
16
14
12
10
8
6
4
2
Sep-12
Oct-12
Nov-12
Dec-12
Jan-13
Feb-13
Mar-13
Apr-13
May-13
Jun-13
Jul-13
Aug-13
Sep-13
Series1
Series2
Series3
Series4
Series5



18
16
14
12
10
8
6
4
2
Sep-12
Oct-12
Nov-12
Dec-12
Jan-13
Feb-13
Mar-13
Apr-13
May-13
Jun-13
Jul-13
Aug-13
Sep-13
Series1
Series2
Series3
Series4
Series5



$18.00
$16.00
$14.00
$12.00
$10.00
$8.00
$6.00
$4.00
$2.00
Jul-12
Aug-12
Sep-12
Oct-12
Nov-12
Dec-12
Jan-13
Feb-13
Mar-13
Apr-13
May-13
Jun-13
Jul-13
Aug-13
Sep-13
Oct-13
Nov-13
Dec-13