Impacts of Permanent and Transitory Shocks on Optimal Length of Moving Average to Predict Wheat Basis

Yoonsuk Lee
Department of Agricultural Economics
Oklahoma State University
Stillwater, OK 74078
Phone: 405-744-9809
Fax: 405-744-8210
Email: yoonsuk.lee@okstate.edu

B. Wade Brorsen
Department of Agricultural Economics
Oklahoma State University
Stillwater, OK 74078
Phone: 405-744-6836
Fax: 405-744-8210
Email: wade.brorsen@okstate.edu

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2012 AAEA Annual Meeting, Seattle, Washington, August 12-14, 2012

Abstract

A new stochastic process is introduced where permanent changes occur following a Poisson jump process and temporary changes occur following a normal distribution. The model is estimated using hard wheat basis data and is used to explain why the optimal length of moving average to forecast basis varies over time. The estimated probability of jumps is large and thus the optimal length of moving average is small.

Keywords: basis**,** jump-diffusion process, Monte Carlo simulation

Introduction

Forecasting basis is a requirement for many futures hedging strategies. Moving averages are the most common method of forecasting basis, but researchers have also applied various time series models. Jiang and Hayenga (1997) found 3-year moving averages worked relatively well, but were slightly outperformed by models that include current market information and seasonal ARIMA models. Sanders and Manfredo (2006) considered a variety of time series models and concluded that even when the time series models produced better forecasts than a five-year moving average, the accuracy gained from advanced time series models was relatively small. While there is agreement that moving averages compete well with time series approaches, there is much less agreement about the length of moving average to use. Hatchett, Brorsen, and Anderson (2010) argued that the longer moving averages are optimal when little or no structural change occurs, but shorter moving averages are optimal following structural changes. They suggested that when a structural change has occurred, the previous year's basis or an alternative approach should be used. Their approach is fine when a structural change can be easily identified. Otherwise, their approach suggests estimating the frequency of structural changes and using the estimated model to determine the optimal length of moving average rather than trying to determine the optimal length of moving average through simulation.

The paper proposes a new time series stochastic process and estimates the parameters of the model using wheat basis data. The proposed model allows two types of shocks: transitory shocks and permanent shocks. While the stochastic process is new, separating shocks into permanent and temporary ones has a long history. Nelson and Plosser (1982) argued, using statistical techniques developed by Dickey and Fuller (1979), that a portion of current shocks have a permanent effect on the long-run level of most macroeconomic and financial aggregates. Examples of shocks that had permanent effects on the long-run level of most macroeconomic aggregates are those related with the Great Depression and the first oil-price crisis. Campbell and Mankiw (1987) and Zivot and Andrews (1992) suggested that current shocks are a combination of temporary and permanent shocks, and that the long-run response of a series to a current shock depends on the relative importance or size of the two types of shocks.

A related set of literature is the structural breaks literature (e.g. Lee and Strazicich 2003) that typically only considers one or two structural breaks. These structural break models often have a completely different set of parameters before and after the break and the way they are identified will miss small breaks. Pesaran, Pettenuzzo, and Timmerman (2006) develop a Bayesian forecasting approach that considers the possibility of structural breaks when the number of structural breaks is known. We take a different approach in that we seek to find a single stochastic process that can estimate the probability of the break as well as a distribution for the size of the break.

The potential source of permanent shocks to wheat basis can be changes in storage cost, transportation cost, technological advances, building of ethanol plants, changes in farm policy and so on. In addition, the model allows transitory shocks that can affect local basis such as weather that can cause yields as well as wheat quality to vary. The proposed model uses a Poisson distribution to model the frequency of permanent shocks in which structural breaks, called jumps, occur independently of one another. Transitory shocks are exploited by an independent and identical normal distribution. The resulting model is similar to the jump-diffusion model of Merton (1976), except the presence of temporary shocks creates autocorrelation in the returns series. The model is estimated using generalized method of moments estimation. Based on the developed model, we determine effects of the relative importance of permanent and transitory shocks on an optimal length of moving average.

Theory

Basis predictions are important for evaluating prices being offered in cash contracts for later delivery, and for storage decisions for the storable commodities (Purcell and Koontz, 1998). The basis represents time, form, and space differences between cash and futures prices. Here, we are dealing with nearby basis so differences in time should be small and the changes in basis should be due to changes in values of form and space. Researchers have used a variety of variables to explain the basis (Dykema, Klein, and Taylor, 2002; Martin, Groenewegen, and Pigeon, 1980; Jiang and Hayenga, 1997). These explanatory models show that a wide variety of variables can influence basis. Examples include agricultural policy such as loan deficiency payments, introduction of ethanol plants, low protein in a region of the country, and increased cost of transportation. Some of these changes are permanent and some are temporary. Forecasts of basis, however, usually use either moving average or time series models.

Hatchett, Brorsen, and Anderson (2010) argued that the optimal length of moving average depended on the occurrence of structural change. With no structural change, a long moving average would be optimal, but the optimal length of moving average would decrease as the frequency of structural change increased. Hatchett, Brorsen, and Anderson do not offer a stochastic process for basis that is consistent with their arguments. This paper is an attempt to offer such a stochastic process. As they argue, one extreme is a random walk model where the optimal length of moving average would be one. If the mean is constant, then the optimal length of moving average is the entire data series. Empirical work that finds the optimal length of moving average is often one to five suggests that the mean is not constant, but that a random walk model is also not correct. Estimating the proposed stochastic process offers a means to determining the optimal length of moving average other than simply simulating alternative lengths of moving averages.

Model Development

Permanent-Jump and Transitory-Diffusion model

As an alternative model of commodity prices, the paper combines two different types of shocks: permanent impacts on the market from structural breaks and temporary impacts on the market. The assumption of discontinuities due to the discrete breaks may be consistent with the observed leptokurtosis in the distributions of many financial variables (Hall et al. 1989).

Merton (1976) added Poisson jumps to a standard Brownian motion process to approximate the movement of stock prices subject to occasional discontinuous breaks. The mixed jump-diffusion process has been applied successfully with stock and foreign currency prices displaying large price changes over a small time interval (Hilliard and Reis, 1998).

The model proposed in the paper includes permanent (structural breaks) and transitory shocks represented by Poisson and i.i.d normal distribution, respectively. The data generating process is a combination of the two different shocks:

$$(1) \qquad Basis_t = \alpha + \mu_0 t + \sum_{t=1}^{T}\sum_{q=1}^{Q_t} Jump_{qt} + \varepsilon_t,$$

where α is the initial basis, μ_0 is the time trend parameter, t is a time trend, $Jump_{kt}$ follows i.i.d $N(\mu_J, \sigma_J^2)$, Q_t is the number of permanent shocks in the time period and follows a Poisson (λ), and ε_t is the transitory shock and follows i.i.d $N(\mu_D, \sigma_D^2)$.

After first differences,

$$(2) \qquad \Delta Basis_t = Basis_t - Basis_{t-1} = \mu_0 + \sum_{q=1}^{Q_t} Jump_{qt} + \nu_t,$$

where the autocorrelated error ν_t is replaced by the uncorrelated error ε_t. The relationship between ν_t and ε_t is given by a moving average process, $\nu_t = \varepsilon_t - \varepsilon_{t-1}$.

Data

As a prime example of where both permanent and transitory shocks in prices are expected, hard wheat basis data are selected (Figures 1 and 2). Structural changes in grain markets change the relationship between cash and futures prices. The basis is the difference between the local cash price and the nearby futures price. Both harvest basis (June) and a storage basis (November) are considered in the paper. Harvest basis is calculated as the cash price in June minus the price of the July futures contract in June, while storage basis is calculated that the cash price in November minus the price of the December futures contract in November. Monthly average prices are used for cash and futures prices. Hatchett, Brorsen, and Anderson (2010) argued that there exist advantages and disadvantage of using average monthly basis rather than the basis from a single day. One disadvantage is that they will underestimate the basis risk a hedger will experience in practice. Another disadvantage is that it is not possible to adjust for limit days when using monthly averages. On the other hand, monthly averages may lead to slightly more powerful hypothesis tests. Cash prices for Oklahoma locations were taken from the Oklahoma Department of Agriculture, Food and Forestry's weekly "Oklahoma Market Report" from 1942 through 2009. The 5 production areas in Oklahoma for cash prices: Frederick, Medford, Weatherford, and Kingfisher and Okarche included since May 2003, are considered and then the prices collected from these areas are averaged. Futures prices reflect daily closing prices at the Kansas City Board of Trade (KCBT) for hard wheat. The study uses monthly time series data from 1942 to 2009 for June and December.

Procedure

Maximum likelihood estimation-based procedures achieve efficient estimators bound by relying on restrictive assumptions about the distribution, or data generating process, while the generalized method of moment (GMM) is relatively inefficient due to the largely arbitrary choice of unconditional moments that can be computed in closed form (Anderesn, Chung, SØrensne

(1999), and Hamilton (1994)). However, there are advantages to using GMM estimation. GMM estimation can be more computationally convenient than maximum likelihood. Hansen and West (2002) find that GMM techniques are most commonly used in nonlinear studies. The GMM adjustment to the covariance matrix can account for the moving average error. Therefore, the GMM procedure is used to estimate the proposed model. The data series are used as first differences.

The first five moment equations are the first-order conditions from the likelihood function of a diffusion-jump process. Gallant and Tauchen (1996) reported that the derivative of the log density of a stochastic model which does not necessarily require encompassing a structural model with respect to the parameters of the model could be used as the vector of moment conditions in order to generate moment conditions for the generalized method of moments (GMM) estimator.

The log-likelihood function of a diffusion-jump process can be written as:

$$(3) \qquad l(\theta, \Delta P_t) = \sum_{i=1}^{T} ln\left[\sum_{q=0}^{\infty} \frac{e^{-\lambda}\lambda^q}{q!} \frac{1}{\sqrt{2\pi\left(\sigma_D^2 + q\sigma_J^2\right)}} exp\left(\frac{-\left(\Delta P_t - \mu_D - q\mu_J\right)^2}{2\left(\sigma_D^2 + q\sigma_J^2\right)}\right)\right],$$

where $l(\theta, \Delta P_t)$ is the sum of the natural log of sums of exponentials weighted by the Poisson probabilities. θ is a vector of five parameters $(\mu_D, \sigma_D^2, \mu_J, \sigma_J^2, \lambda)$ considered in the permanent-jump and transitory-diffusion model. λ is a jump probability measuring the occurrence rate of discrete structural breaks by Poisson distribution, σ_J^2 is variance of structural breaks, μ_J is mean of structural breaks, and μ_D and σ_D^2 are diffusion mean and variance reflecting transitory shocks, respectively.

The five moment equations are the first order conditions of the log-likelihood function of a diffusion-jump process and can be expressed as:

(4) $$\bar{g}(\theta) = \frac{1}{T}\sum_{t=1}^{T}\frac{d}{d\theta} l(\theta, \Delta P_t),$$

evaluated at $\theta = (\mu_D, \sigma_D^2, \mu_J, \sigma_J^2, \lambda)$ and should be close to zero for large value of T. We also consider the presence of autocorrelation (ρ). The autocorrelation in basis changes due to transitory shocks could underestimate the standard errors of the parameter estimates. To handle autocorrelation, a sixth moment equation is created. The sixth moment equation for autocorrelation is computed by the difference between empirical autocorrelation estimated from actual data and theoretical autocorrelations. The sixth moment equation captures the autocorrelation created from overdifferencing the transitory shocks. With autocorrelation restriction, there are more moments equations (six) than parameters (five). Under the condition, GMM estimation is used to estimate the parameters of the proposed model. The GMM estimator is defined by choosing γ to minimize q:

(5) $$q = \bar{m}_T{}' W_T(\gamma)\bar{m}_T,$$

where γ is a vector of six parameters included autocorrelation (ρ),$\gamma = \left(\mu_D, \sigma_D^2, \mu_J, \sigma_J^2, \lambda, \rho\right)$,

$\bar{m}_T$ represents six moments equations; five moment equations derived from the first order conditions of the log-likelihoods function and the sixth moment equation in order for autocorrelation,$W_T(\gamma)$ is a positive-definite, symmetric weighting matrix that can depend on sample information, and $W_T(\gamma) = (\frac{1}{T}\sum_{t=1}^{T} \bar{m}_T(\gamma)\bar{m}_T(\gamma)')^{-1}$.

A bootstrap is used to estimate the standard error of the estimates since GMM methods are known to underestimate standard errors in small samples. A Monte Carlo study is used to validate the estimation procedure.

Based on the permanent-jump and temporary-diffusion model, an optimal moving average to use in forecasting can be determined. In order to measure the accuracy of forecasts, four different criteria could be used: mean absolute error (MAE), root mean squared errors (RMSE), two Theil's U statistics (Jiang and Hayenga, 1997). In this paper, root mean squared error is used to determine the accuracy of forecasts. The root mean squared error is

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Basis_t - \frac{1}{N}\sum_{i=1}^{N} Basis_{t-i})^2}, \quad (6)$$

where N is number of years, N=1, 2, 3, 4, 5, 10, 20. The lowest value of RMSE is selected as the optimal length of moving average.

Results

Table 1 contains parameter estimates from different estimation methods, maximum likelihood estimation (MLE) assuming no autocorrelation, the generalized method of moments (GMM), and GMM with bootstrap. The parameter estimates from MLE are of course similar to the parameters estimates from GMM, however, standard errors estimated from MLE and GMM are different. In table 1, the values of jump mean, jump variance, and jump frequency are from permanent-jump process in the developed model, and the values of mean and variance are from transitory-diffusion process in the model.

The paper estimated the permanent-jump and transitory-diffusion model without autocorrelation restriction and with autocorrelation restriction, using GMM estimation. In future research, we hope to estimate the full model with MLE where the autocorrelation is considered. The second and fourth columns in table 1 report results with autocorrelation and without autocorrelation, respectively. The parameter estimates with autocorrelation and without autocorrelation differ slightly from each other. A bootstrap is used to estimate the standard error of the estimates. Structural breaks in storage basis occur more often than in the harvest basis. Structural breaks are reflected by occurrences of jump frequency and size of jump variance. The jump frequency in storage basis is much higher than in harvest basis (table 1), but the jump variance in harvest basis is bigger than that in storage basis. For harvest basis, the series might be more related to the transitory shocks than to permanent shocks.

Based on the estimated parameters with autocorrelation restriction, we simulated stochastic basis series. The paper applies a simple moving average method based on the developed model. Table 2 reports length of moving average, using the hard wheat basis from 1942 to 2009. The 4-year moving average has the lowest RMSE for harvest basis forecasts, but for storage basis forecasts, the last year has the lowest RMSE. With the simulated data which include structural breaks and transitory shocks, the 2-year is optimal length for harvest basis forecasts, and the last year is optimal length for storage basis forecasts from table 3 and 4. In order to explain the effect of jump size and frequency on optimal length of moving average, the paper changes degree of jump size and frequency. The jump frequency is increased by 0.1 units from 0 through 1, and the size of jump is selected to values: closed to zero (0.0001), the estimated jump variance for both harvest basis and storage basis, and a unit (1). Tables 3-4 report the results. From table 3, when jump frequency is zero and size of jump changes, the longest length is the optimal length. When jump frequency and size of jump are large, one year is the optimal length. Table 4 represents the results using the parameters of storage basis. Harvest basis responds more to the changes in jump frequency and size of jump than storage basis from figure 3 and 4. The most important information about wheat prices is revealed during the growth and harvest season and thus the volatility of futures prices could be expected during such period. The forecast errors peak during the production period (Dhuyvetter and Kastens, 1998).

Summary and Conclusion

Hard wheat basis for harvest and storage are used to estimate relative impacts of permanent (structural breaks) and transitory shocks. The proposed model assumes the possibility of structural breaks in the basis. Several studies have approached various stochastic models to determine effects of permanent and temporary shocks. However, many researchers recognize the weaknesses of current unit-root assumptions used in ARIMA models, vector-autoregressions, cointegration, etc. In the paper we propose a new stochastic process. Discrete structural breaks are assumed to occur following a Poisson distribution process with temporary shocks following an i.i.d normal process. Maximum likelihood estimation (MLE) and generalized method of moments (GMM) are applied to estimate the developed model. Bootstrap is also used to estimate the standard errors of estimates. The proposed model shows the importance of existence of structural breaks to modeling wheat basis. Structural breaks are frequent in harvest basis and occur more often than in the storage basis. The frequent structural breaks suggest that a short moving average will be the optimal length for basis forecasts. For harvest basis, 4-year moving average is the optimal length with actual data. However, a 2-year moving average is the optimal length with the data generated using the estimated model. For storage basis, a one-year moving average is the optimal length with both actual data and the generated data. When jump frequency and size of jump are large, the optimal length of moving average is the previous year for both harvest and storage basis. The presence of structural breaks clearly reduces the optimal length of moving average.

Table 1. Parameter Estimates of Permanent-Jumps and Transitory-Diffusion Model for Hard Wheat Basis from 1942 to 2009

Parameters	MLE	GMM	Bootstrap	GMM	Bootstrap
	without Autocorrelation			with Autocorrelation	
Harvest Basis					
Mean	-0.00855 (0.0159)	-0.00856 (0.01663)	-0.00742 (0.08839)	-0.00842 (0.01382)	-0.00741 (0.01875)
Jump Mean	0.00474 (0.04540)	0.00470 (0.00909)	0.00335 (0.02601)	0.00438 (0.01958)	0.00329 (0.01754)
Variance	0.00630 (0.00251)	0.00630 (0.00617)	0.00699 (0.00965)	0.00645 (0.00011)	0.00705 (0.00549)
Jump Variance	0.03006 (0.02039)	0.03006 (0.01305)	0.02472 (0.01744)	0.02999 (0.00157)	0.02472 (0.02675)
Jump Frequency	0.40750 (0.29480)	0.40714 (0.04485)	0.36739 (0.14277)	0.39454 (0.04459)	0.36733 (0.17277)
Storage Basis					
Mean	0.00788 (0.00709)	0.00790 (0.01091)	0.00759 (0.00439)	0.00877 (0.00112)	0.00762 (0.00347)
Jump Mean	-0.02071 (0.01671)	-0.02073 (0.00800)	-0.01995 (0.01007)	-0.02043 (0.00232)	-0.01900 (0.01697)
Variance	0.00068 (0.00029)	0.00068 (0.00011)	0.00066 (0.00009)	0.00077 (0.00007)	0.00067 (0.00012)
Jump Variance	0.01273 (0.00460)	0.01286 (0.00269)	0.01324 (0.00429)	0.01193 (0.00264)	0.01229 (0.00452)
Jump Frequency	0.93560 (0.26560)	0.93557 (0.02544)	0.93470 (0.03678)	0.88958 (0.03701)	0.93028 (0.06190)

Note: numbers in parenthesis are standard errors.

Table 2. RMSE of Simple Moving Average models for June and December Wheat Basis from 1942 to 2009

Years	Value of RMSE
June Basis	
1-year	0.13494
2-year	0.13088
3-year	0.12711
4-year	0.12657
5-year	0.12864
10-year	0.12997
20-year	0.14897
November Basis	
1-year	0.11312
2-year	0.12283
3-year	0.13383
4-year	0.14790
5-year	0.14790
10-year	0.15138
20-year	0.17448

Note: RMSE is the root mean squared error. The lowest RMSE suggests the optimal length for basis forecasts.

Table 3. Optimal Length of Moving Average of Harvest Basis with Changes in Jump Frequency and Jump Size

Jump Frequency (λ)	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Jump Size (σ_j^2) = 0.0001											
Optimal Length (N)	20	20	20	10	10	10	10	9	8	7	7
Jump Size (σ_j^2) = 0.03006											
Optimal Length (N)	20	3	2	2	2	1	1	1	1	1	1
Jump Size (σ_j^2) = 1											
Optimal Length (N)	20	1	1	1	1	1	1	1	1	1	1

Note: N is number of average years. The values of five parameter estimates, $\mu_D, \sigma_D^2, \mu_J, \sigma_J^2, \lambda$, are used in order to simulate data, and frequency and jump size are changed. The length of moving average is estimated by RMSE and the lowest RMSE is selected.

Table 4. Optimal Length of Moving Average of Storage Basis with Changes in Jump Frequency and Jump Size

Jump Frequency (λ)	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	1.0
Jump Size (σ_j^2) = 0.0001										
Optimal Length (N)	20	4	3	3	2	2	2	1	1	1
Jump Size (σ_j^2) = 0.01273										
Optimal Length (N)	20	2	1	1	1	1	1	1	1	1
Jump Size (σ_j^2) = 1										
Optimal Length (N)	20	1	1	1	1	1	1	1	1	1

Note: N is number of average years. The values of five parameter estimates, $\mu_D, \sigma_D^2, \mu_J, \sigma_J^2, \lambda$, are used in order to simulate data, and frequency and jump size are changed. The length of moving average is estimated by RMSE and the lowest RMSE is selected.

Figure 1. Harvest Basis Trend, 1994-2008

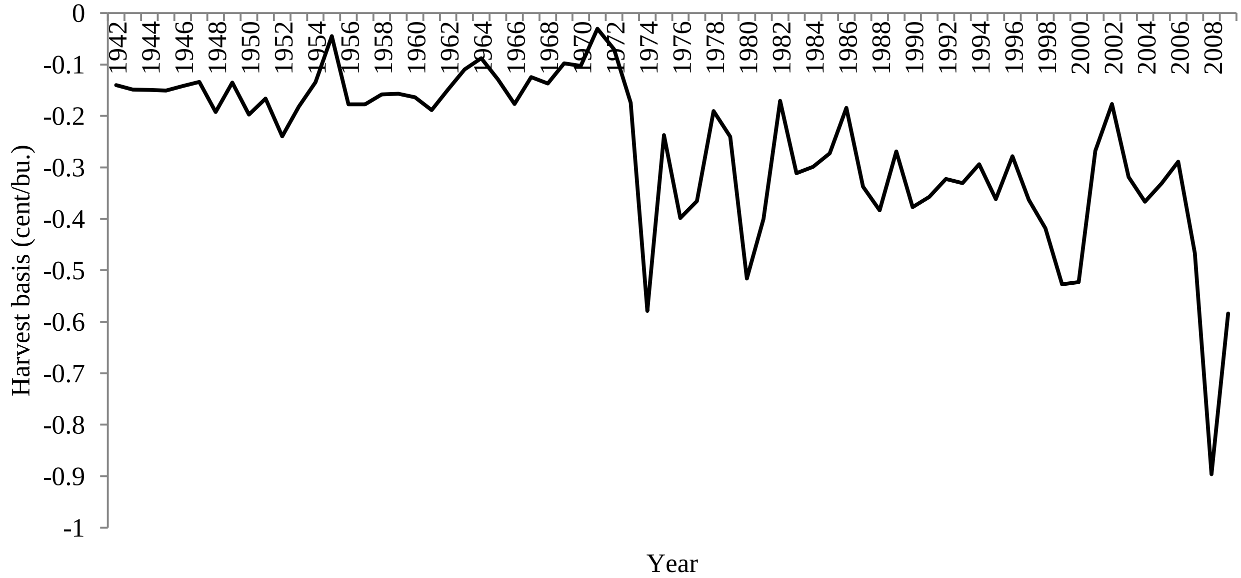


Figure 2. Storage Basis Trend, 1994-2008

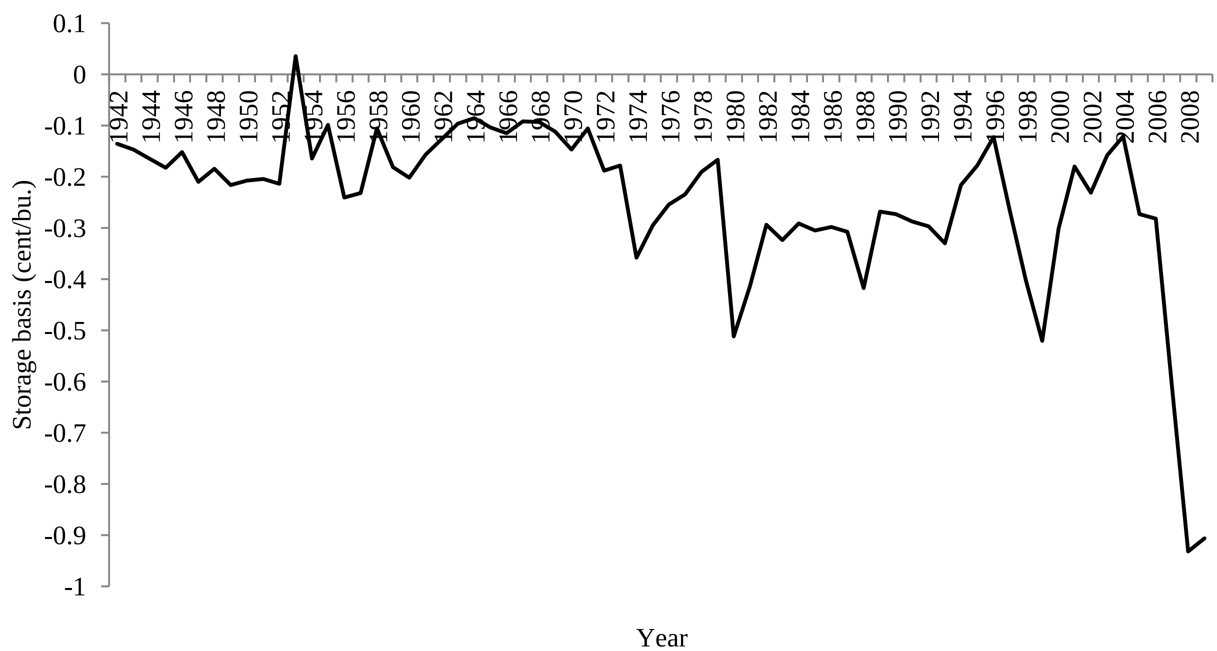


Figure 3. Optimal Length of Moving Average of June Basis for Hard Wheat with Simulated Data

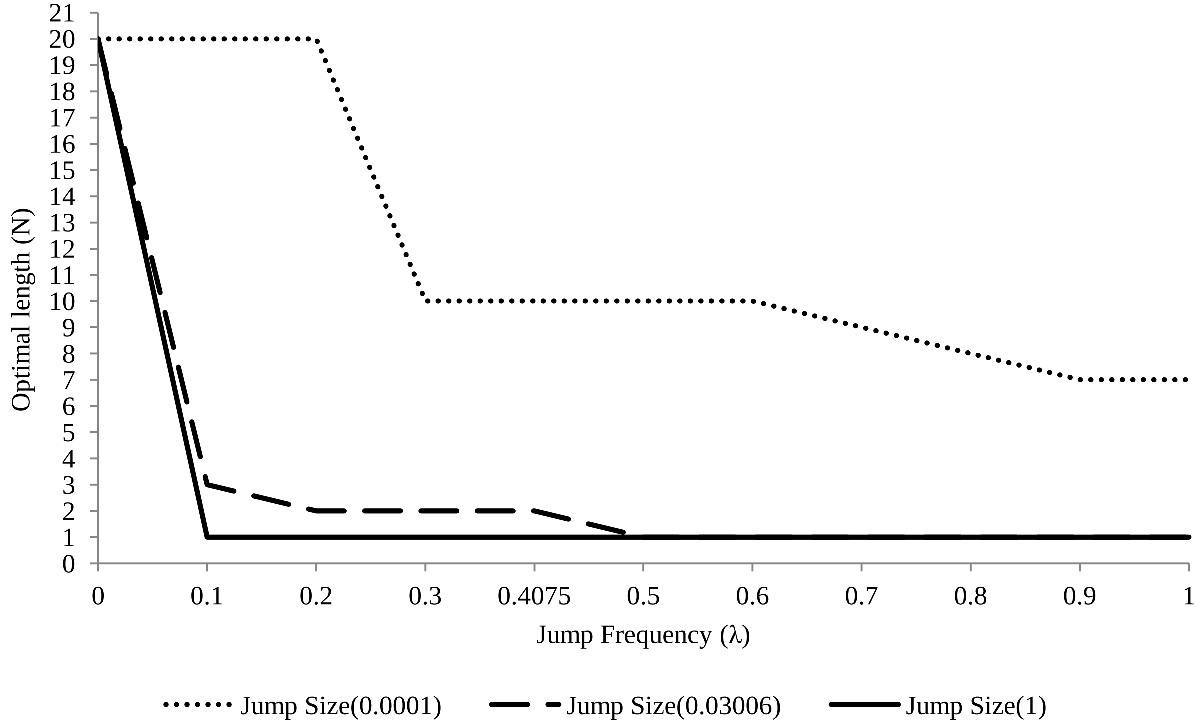
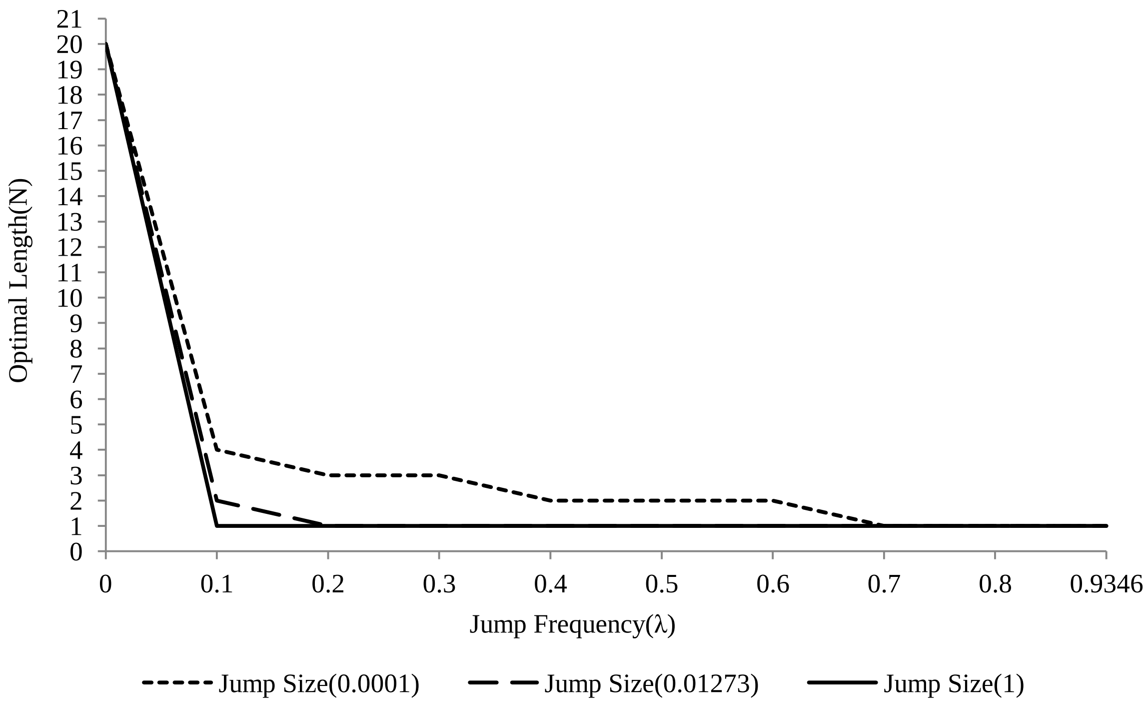


Figure 4. Optimal Length of Moving Average of June Basis for Hard Wheat with Simulated Data



References

Akgiray, V. and G. Booth. 1988. "Mixed Diffusion-Jump Process Modeling of Exchange Rate Movements." *The Review of Economics and Statistics* 70:631-637.

Andersen, T.G., H.J. Chung, and B.E. Sørensen. 1999. "Efficient Method of Moments Estimation of a Stochastic Volatility Model: A Monte Carlo Study." *Journal of Econometrics* 91:61-87.

Campbell, J. Y., and N.G. Mankiw. 1987. "Permanent and Transitory Components in Macroeconomic Fluctuations." *The American Economic Review* 77:111-117.

Dhuyvetter, K.C., and T.L. Kastens. 1998. "Forecasting Crop Basis: Practical Alternatives." *Applied Commodity Price Analysis, Forecasting, and Market Risk Management*, Proceedings of the NCR-134 Conference, pp.49-67.

Dykema, A., N.L. Klein, and G. Taylor. 2002. "The Widening Corn Basis in South Dakota: Factors Affecting and the Impact of the Loan Deficiency Payment." Paper presented at WAEA annual meeting, Long Beach, California, 28-31 July.

Dickey, D.A., and W.A. Fuller. 1979. "Distribution of the Estimators for Autoregressive Time Series with a Unit Root." *Journal of the American Statistical Association* 74:427-431.

Gallant, A.R., and G.E. Tauchen. 1996. "Which Moments to Match?" *Econometric Theory* 12: 657-681.

Hall, J. A., B. W. Brorsen, and S. H. Irwin, 1989. "The Distribution of Futures Prices: A Test of the Stable Paretian and Mixture of Normals Hypotheses." *Journal of Financial and Quantitative Analysis* 24(1):105-116.

Hamilton, J.D. 1994. *Time Series Analysis*, 1st. ed. New York: Princeton University Press.

Hansen, E. B and K.D. West. 2002. "Generalized Method of Moments and Macroeconomics." *Journal of Business and Economic Statistics* 20:460-469.

Hansen, L.P. 1982. "Large Sample Properties of Generalized Method of Moments Estimators." *Econometrica* 50:1029-1054.

Hatchett, R.B. 2009. "Optimal Length of Moving Average to Use When Forecasting Basis." M.S. thesis, Oklahoma State University.

Hatchett, B. R., B. W. Brorsen, and K. B. Anderson. 2010. "Optimal Length of Moving Average to Forecast Futures Basis." *Journal of Agricultural and Resource Economics* 5:18-33.

Hilliard, J.E., and J.A. Reis. 1998. "Valuation of Commodity Futures and Options under Stochastic Convenience Yields, Interest Rates, and Jump Diffusions in the Spot." *Journal of Financial and Quantitative Analysis* 33:61-86.

Jiang, B., and M. Hayenga. 1997. "Corn and Soybean Basis Behavior and Forecasting: Fundamental and Alternative Approaches." *Applied Commodity Price Analysis, Forecasting, and Market Risk Management*, Proceedings of the NCR-134 Conference, pp. 125-140.

Koekebakker, S., and G. Lien. 2004. “Volatility and Price Jumps in Agricultural Futures Prices Evidence from Wheat Options.” *American Journal of Agricultural Economics.* 86:1018-1031.

Lee, J., and M.C. Strazicich. 2003. “Minimum Lagrange Multiplier Unit Root Test with Two Structural Breaks.” *Review of Economics and Statistics* 85:1082-1089.

Nelson, C. P., and C.I. Plosser. 1982 “Trends and Random Walks in Macroeconomic Time Series.” *Journal of Monetary Economics* 10:139-162.

Martin, L., J.L. Groenewegen, and E. Pidgeon. 1980. “Factors Affecting Corn Basis in Southwestern Ontario.” *American Journal of Agricultural Economics* 62:107-112.

Merton, R.C. 1976. “Option Pricing When Underlying Stock Returns Are Discontinuous.” *Journal of Financial Economics* 3:125-144.

Perron, P. 1989. “The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis.” *Econometrica* 57:1361-1401.

Pesaran, M.H., D. Pettenuzzo, and A. Timmermann. 2006. “Forecasting Time Series Subject to Multiple Structural Breaks.” *The Review of Economic Studies* 73:1057-1084.

Purcell, W.D., and S.R. Koontz. 1998. *Agricultural Futures and Options: Principles and Strategies* 2nd ed. New Jersey: Prentice Hall.

Sanders, D.R., and M.R. Manfredo. 2006. “Forecasting Basis Levels in the Soybean Complex: A Comparison of Time Series Methods.” *Journal of Agricultural and Applied Economics* 38:513-523.

Zivot, E. and D. W. K. Andrews. 1992. "Further Evidence on the Great Crash, the Oil Price Shock, and the Unit-Root Hypothesis." *Journal of Business and Economic Statistics* 10:251-270.