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Tatiana Drugova, Veronica F. Pozo, Kynda R. Curtis and T. Randall Fortenbery*

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*Tatiana Drugova is a Graduate Research Assistant, Veronica F. Pozo is an Assistant Professor and Kynda R. Curtis is a Professor in the Department of Applied Economics at Utah State University, T. Randall Fortenbery is a Professor in the School of Economic Sciences at Washington State University.

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Growers considering organic conversion or maintaining current organic wheat production face uncertainties due to large variations in organic wheat prices over time. In this study, the risk associated with organic premiums is evaluated using 5% VaR, and the probability that the additional costs of producing organic wheat will not be covered is calculated. To reduce the uncertainty associated with organic wheat prices, the possibility of cross hedging using conventional wheat futures is examined, as well as the ability of futures to forecast the organic premium. This is done by estimating an optimal hedge ratio using cointegration that at the same time identifies long-run and short-run price relationships between conventional and organic wheat. The data used are monthly wheat prices from USDA AMS, USDA ERS and the Commodity Research Bureau between January 2008 and July 2017. Since organic prices are not completely observed, three methods are used to impute missing values and add robustness to the analysis. Results provide some evidence that conventional futures can be used to cross hedge organic wheat price risk, but results are dependent on the method used to impute the missing values. Similarly, it is found that there is a long-run equilibrium relationship between organic wheat prices and conventional wheat futures prices. In addition, futures prices contain some information useful in predicting organic prices in the short run.

Key words: cointegration, cross hedging, optimal hedge ratio, organic wheat.

Introduction

The organic wheat market represents a market that has experienced increased scarcity as demand for organic wheat products has grown. For example, organic wheat acreage, including both food and feed production, represented just 6.7% of total organic acreage in 2016 (U.S. Department of Agriculture National Agricultural Statistical Service (USDA NASS) Certified Organic Survey, 2017), while the share of bread and grains in overall organic food consumption totaled 9% by 2012 (USDA Economic Research Service (ERS), 2017). In addition, organic wheat acreage represents less than 1% of total wheat acreage in the US. The Organic Trade Association (OTA) found from their Organic Industry Survey that growth in the market of organic grains in general "could have been even more robust in 2015 if greater supply had been available" (OTA, 2016). This suggests that demand growth in the organic grain market has outpaced the supply growth in recent years.

Agricultural production is inherently risky since yields are largely affected by factors outside of producers' control such as weather, pests and diseases. In addition, prices of agricultural commodities and market conditions at harvest are not known at the time production decisions are made. Producers who adopt organic production practices face additional challenges due to the restrictions resulting from the National Organic Program (NOP 2002) which defines national standards for the organic production system. These restrictions include limited use of chemical inputs such as fertilizers and pesticides, and usually lead to reduced yields (Lotter 2003; Korsaeth 2008; Seufert, Ramankutty and Foley 2012; De Ponti, Rijk, and Van Ittersum 2012). They also lead to higher total costs per bushel for organic production. Limits on fertilizer and

pesticide use decrease the operating costs of the organic grain production per acre compared to conventional production, and the total economic costs of producing organic grains per acre may be only marginally higher when other costs such as labor and land costs are included (McBride et al. 2015). Adding to that lower yields per acre in organic production results in higher total costs per bushel compared to conventional production.

Looking at wheat specifically, McBride et al. (2012) found that in 2009 the additional operating, capital and economic costs of producing organic wheat were \$2-\$4 per bushel[2], while the organic wheat premium was \$3.79 per bushel, indicating that the higher costs of producing organic wheat can be offset with higher organic prices. Thus, organic wheat production can be more profitable than the conventional production, assuming the transition period to organic production is over. But it also indicates that the relative profitability of the organic wheat production depends on the organic premium, which in turn depends on how organic and conventional wheat prices develop over time. Organic wheat prices have been changing rapidly in past years, leading to an overall increase in excess of 140% between 2010 and 2017, and affecting the organic premium positively. Although current organic wheat prices allow for profitable organic wheat production in the West, growers face uncertainties regarding the length of favorable market conditions, which potentially affects their decision to begin or continue dryland organic wheat production. This study evaluates the uncertainty associated with organic prices and organic premiums and explores options that growers may have to manage this uncertainty.

In this study we consider three primary objectives. The first is to compare risks associated with organic and conventional wheat prices and evaluate the organic premium risk by calculating the probability that the organic premium falls below costs of producing organic. This allows for a better understanding of the risks associated with producing organic wheat.

Next, we explore some options that growers considering conversion to or maintaining organic wheat production have to manage the price risk associated with organic wheat. More specifically, the second objective investigates whether hedging in conventional wheat futures mitigates the organic wheat price risk and whether conventional futures prices can be used to predict organic cash prices. Since the number of cash transactions on the organic wheat market is likely not large enough to support trading in organic wheat futures, we consider the alternative of using conventional wheat futures to cross hedge organic price risk. To estimate the optimal hedge ratio, we use a cointegration approach which is based on the concept of market integration.

Our analysis is complicated by the limited availability of historical organic wheat price data, as well as missing observations in the data that is available. Thus, our third objective is to simulate missing organic wheat prices through the use of three separate methods. We use three methods to add robustness to our analysis and to help us determine if our results are sensitive to the methods used. This will allow us to highlight possible limitations and provide more validity to our results.

[2] The authors used data from the 2009 Agricultural Resource Management Survey (ARMS) of organic and conventional wheat growers. The higher cost per bushel of organic wheat production was driven by lower yields of organic wheat production (30 bushels per acre) when compared to conventional wheat production (44 bushels per acre). The authors also accounted for the cost of transitioning to organic wheat production.

In addition, we investigate which method is the most optimal one by evaluating the accuracy predicting randomly dropped observations.

Background and Literature Review

Organic vs. Conventional Production Profitability

Some studies found that organic production is less profitable than conventional production (Dobbs and Smolik 1997), while others found the opposite. For example, Mahoney et al. (2004) found that net returns for selected organic crops were significantly larger compared to conventional crops, and they were statistically equal when organic price premiums were not considered. Delbridge et al. (2013) considered the possible differences in the size of organic and conventional farms to evaluate whole-farm net returns for a corn-soybean rotation and found that risk averse growers would be better off adopting organic production practices. However, this result is sensitive to the changes in the organic premium and yields. Similarly, Archer et al. (2007) found that during the period of transitioning to organic, when growers do not receive organic premiums for their crops, the rotation systems of corn, soybean and wheat generated lower net present values than conventional systems. However, results for organic production were more positive when organic premiums were included.

Previous studies suggest that the profitability of organic production depends on the price premiums which in turn depend on how organic and conventional prices develop over time. Thus, the higher uncertainty of organic prices, if found, can affect rates of adoption or continuation of organic production, and confirm the value of having tools to manage the uncertainty associated with organic price premiums.

Hedging and Optimal Hedge Ratio

Investments in agricultural production generally occur well before harvest, and during the interim prices usually change. Hedging is one of the tools used in agriculture to mitigate the risk associated with adverse price changes. Typically, if a futures market is established for a commodity, hedging from the producer's perspective involves selling a futures contract (expected to expire just after harvest) for the commodity first. Then at or near harvest the producer buys the futures contract back and delivers his/her production to a local buyer. As long as prices in the spot and futures markets move together, the producer will offset the losses in one market by gains in the other and the original expected sales price is protected.

Often the most efficient hedge is not a one-to-one hedge. In other words, all the spot risk is not hedged in the futures market. Instead, hedgers apply an optimal hedge ratio (OHR). The OHR is traditionally calculated as the ratio of the covariance of spot price S_t and futures price F_t at time t to the variance of the futures price F_t, with the goal of minimizing the variance of the portfolio:

$$(1) \qquad \lambda^* = \frac{Cov(S_t, F_t)}{Var(F_t)}$$

Because this version of the OHR is one of the most widely used, it is applied in this study. However, there are other ways to estimate OHR's that support other objective functions (Chen, Lee and Shrestha 2013).

OHR can be estimated using regression analysis, but several techniques based on different assumptions have been used in the literature. Some studies assume a constant (static) OHR over time, which can be estimated using ordinary least squares (OLS) estimation methods (e.g. Rolfo 1980; Wilson 1982; Benninga, Eldor and Zilcha 1984). Other studies relax this assumption by allowing the distribution of spot and futures prices to vary over time, making it possible to estimate time-variant (dynamic) OHR using variations of generalized auto-regressive conditional heteroscedasticity (GARCH) and stochastic volatility models (Cecchetti, Cumby and Figlewski 1988; Baillie and Myers 1991; Park and Switzer 1995; Chang, McAleer and Tansuchat 2011; Revoredo-Giha and Zuppiroli 2014).[3] Although some studies show that assuming time-invariant OHR is not appropriate (Baillie and Myers 1991), others show that using more complex models to account for the time-variant OHR does not lead to a significant reduction in the variance of the portfolio (Lien, Tse and Tsui 2002; Lien and Tse 2002; Cotter and Hanly 2012). This indicates that the costs of using more complicated models can outweigh the benefits. In this study, we start with the assumption that OHR is constant over time. We also examine the validity of the assumption of constant OHR by performing specification tests.

Regardless of the methodology used, a majority of studies find that OHR is less than unity, meaning that the naïve method of hedging all expected production using futures contracts is usually not appropriate**.** Looking at wheat specifically, Wilson (1982) examined efficiency of the U.S. futures markets for several wheat varieties. He found that the time-invariant OHR is less than unity and the risk is reduced more if the nearby futures contracts are used as opposed to the futures contracts in the more distant future. In addition, using portfolio analysis he found that the price risk was reduced more when two different wheat futures contracts were used, with little additional risk reduction using three contracts. Revoredo-Giha and Zuppiroli (2014) compared the effectiveness of short-term hedging of wheat price risk using U.S. and European futures markets, while considering time-varying OHR. They found that U.S. futures markets can reduce the price variance of the portfolio by 77% with OHR close to unity, while European markets reduce the variance by only 30% with OHR significantly less than unity. They also found that the hedging effectiveness has improved slightly since 2007, despite concerns that increased volatility in the markets due to increased speculation might have decreased hedging effectiveness.

Cross Hedging

The organic wheat market is considered a thin market. Because of the lack of liquidity, there is no futures market for organic wheat, thus other options need to be explored to hedge organic wheat price risk. In this study, the possibility of cross hedging, which involves reduction of price risk through hedging in a futures market for a related commodity, is evaluated. The challenging

[3] Lien and Tse (2002) provide a thorough review of the traditional (static) and recently developed (dynamic) hedging frameworks.

task is to find a related commodity. According to Anderson and Danthine (1981) the condition that needs to be met is that the correlation between prices of the hedged commodity and the related futures commodity be significantly different from zero.

Several studies have examined possibility of cross-hedging price risk with no futures contract established for the spot commodity. Blake and Catlett (1984) simulated a routine cross hedge to find that use of corn futures to manage the price risk of hay leads to increases in gross returns per ton of hay. Zacharias et al. (1987) applied a numerical simulation approach to find that growers can benefit from cross hedging the price risk of rough rice using wheat futures. On the other hand, Coffey, Anderson and Parcell (2000) found in their study that cross hedging the price risk of grain by-products (corn gluten feed, hominy, distiller's dried grain) using corn futures fails to perform efficiently.

This study builds on the previous literature by examining the possibility of cross-hedging organic wheat price risk using conventional wheat futures. To estimate the OHR we use the cointegration approach, based on the concept of market integration. Understanding market integration not only allows us to estimate cross-hedge OHR, but also investigate the dynamics between organic spot prices and conventional futures prices. This, in turn, can be used to evaluate the potential of conventional futures prices to predict organic spot prices.

Concept of Market Integration

If the same information is used to form expectations about supply and demand in two different markets, these markets and their prices become linked. The strength of the linkage between prices can be examined by investigating their long-run and short-run relationships. If non-stationary prices share a stable long-run equilibrium, then the markets are said to be cointegrated. In this case, if one of the prices deviates from this equilibrium due to a shock in the market, an adjustment will take place to re-establish the equilibrium relationship.

For the cointegration between two markets to exist, the prices need to be non-stationary in levels. Given two non-stationary series x_t and y_t, if a unique β_1 exists that renders the difference $y_t - \beta_0 - \beta_1 x_t = u_t$ stationary, the series are said to be cointegrated. β_1 is a cointegrating parameter and the difference $y_t - \beta_0 - \beta_1 x_t$ is a cointegrating regression. Put another way, if the price series x_t and y_t are non-stationary, they each contain a stochastic trend. If these stochastic trends are proportional to each other so that they are eliminated after applying the difference $y_t - \beta_0 - \beta_1 x_t$, then there is a cointegrating relationship between the series.[4]

Traditionally, market integration has been examined between spot markets for the same commodity connected horizontally across space (Gonzalez-Rivera and Helfand 2001; Rapsomanikis, Hallam and Conforti 2006; Asche et al. 2012; Rosa, Vasciaveo and Weaver 2014) or vertically along the supply chain (Cramon-Taubadel 1998; Pozo, Schroeder and Bachmeier 2013), and between different commodities acting as substitutes (Campiche et al. 2007; Rosa, Vasciaveo and Weaver 2014). Some studies have examined market integration specifically

[4] A detailed review of cointegration is provided in Maddala and Kim (1999). A brief review of cointegration and testing for cointegration can be found in Rapsomanikis, Hallam and Conforti (2006).

between spot markets for organic and conventional commodities, which are qualitatively differentiated, but can potentially act as substitutes to some extent. No integration has been found between markets for organic and conventional pineapple (Kleemann and Effenberger 2010), nor for corn and soybeans (Singerman, Lence and Kimble-Evans 2014). On the other hand, evidence of market integration has been found between organic and conventional markets for wheat (in Germany, Würriehausen, Ihle and Lakner 2015), apples (Nemati and Saghaian 2016) and salmonids (Ankamah-Yeboah, Nielsen, and Nielsen 2017).

Other studies have used the cointegration concept to investigate whether futures prices can be used to forecast spot prices, and to examine the efficiency of futures markets in transmitting price signals to spot markets. Understanding the relationships between futures and cash markets can be helpful in determining how changes in futures markets can impact spot prices. If it is found that current futures prices are unbiased forecasts of future spot prices, then the futures markets are said to be efficient and can be used to forecast future spot prices. In this process, some studies recognize that cointegration is a necessary condition for the efficiency of futures markets (Lai and Lai 1991; Bessler and Covey 1991; Wahab and Lashgari 1993; Beck 1994; Fortenbery and Zapata 1997; Aulton, Ennew and Rayner 1997; McKenzie and Holt 2002; Wang and Ke 2005; Carter and Mohapatra 2008).

Fewer studies have used cointegration specifically to estimate OHR's, and their overall aim was to compare the effectiveness of cointegration and conventional approaches in the process of OHR estimation. Ghosh (1993) used data for three indexes (S&P 500, NYSE, and DJIA) to conclude that use of cointegration methods results in a significantly improved OHR that appears to reduce the price risk more efficiently. Similarly, Chou, Denis and Lee (1996) used Japan's Nikkei Stock Average index and index futures data to find that cointegration performs better than conventional approaches in the estimation of OHR. Following these studies, we use a cointegration approach to examine whether organic wheat price risk can be hedged by taking a position on the conventional wheat futures market. This approach also allows us to gain insights into the dynamic long-run and short-run relationships between organic spot and conventional futures prices.

Data

In this section, we describe the data used in the analysis and the methods for imputing the missing organic wheat pricing. The spot prices used are monthly farm gate/FOB organic and conventional food grade wheat prices between January 2008 and August 2017. The data were obtained from the U.S. Department of Agriculture Agricultural Marketing Service (USDA AMS) and Economic Research Service (USDA ERS). In total, 116 pricing observations were obtained for conventional wheat, and 85 observations for organic wheat with 26.7% of the organic wheat prices missing.

Values for the missing organic prices were imputed using three different methods, incluidng 1) spline interpolation, 2) exponential weighted moving average, and 3) an expectation-maximization with bootstrapping (EMB) algorithm. We used all three methods to add robustness

to our analysis and to examine whether the results are sensitive to the methods used.[5] While the first two methods consider only observations in the proximity of the missing values, the EMB algorithm utilizes the whole distribution of the data in the imputation process. In addition, it accounts for the time series nature of the data.

The futures prices for conventional wheat correspond to the soft red winter variety traded at the Chicago Board of Trade (CBOT) and are collected from the Commodity Research Bureau (CRB). The futures contracts are available for five delivery months in each year – March, May, July, September and December. Due to limited availability of organic spot prices, we only obtain the futures prices with monthly frequency. The futures price series is a collection of nearby futures prices in each month between January 2008 and August 2017, with a total of 116 observations. We rolled over to the contract with the next available delivery month the day before an actual delivery period. For example, for the futures contract with a maturity date in March, we record the futures prices up to February. In March, we use the price of the May contract.

All spot and futures prices used in the analysis are deflated using the seasonally adjusted consumer price index for cereals and bakery products. Figure 1 shows the plot of observed organic wheat spot prices, and conventional wheat spot and nearby futures prices. The plots show that organic and conventional wheat prices tend to move in the same direction, suggesting that there might be a long-run relationship between the price series. But the difference between the prices (i.e. the organic premium) is not stable and varies over time. The plots show there is no clear trend in the development of prices, as periods of price increases and decreases follow one another. Lastly, the plots suggest that organic prices are less stable than conventional prices. Also, as expected, conventional futures and spot prices follow each other closely. To summarize, the plots in Figure 1 provide visual evidence that there is some level of uncertainty associated with organic premiums, and there is more uncertainty associated with organic prices than conventional prices. Figure 2 depicts observed organic prices, as well as prices obtained using the three imputation methods. It can be seen from the plots that there are some differences in the imputed organic prices across the three methods, in particular around year 2016 when no data were observed for several months in a row.

Table 1 reports summary statistics for all price series and the organic premium calculated as the difference between organic spot prices (observed and imputed) and conventional spot prices. A quick look at the summary statistics reveals that organic wheat prices are on average double

[5] The spline interpolation method is best explained using a plot of all observed data points. This method fills in the missing value(s) by connecting observed values immediately before and after the missing value(s) using a smooth curve. The exponential weighted moving average method calculates a missing value by taking the average of several observed values before and after the missing value, with the observations immediately before and after the missing observation receiving the highest weight. Weights decline exponentially with more distant observations. The EMB algorithm works under the assumption that the complete data (observed and unobserved) follow a multivariate normal distribution with the distribution parameters $(\mu, \Sigma) = \theta$, and that the data are missing at random. First, the algorithm finds the posterior distribution of the complete-data parameters θ given the observed data, and then it takes m draws of θ from this posterior distribution. In the next step, missing data are obtained by drawing values from the complete-data distribution conditional on the observed data and the draws of θ, creating m sets of complete data. In the last step, we combine m imputed values by taking a simple average. To do this, we utilize the Amelia II package developed by Honaker, King and Blackwell (2011). In our analysis we choose m=10, but the authors mention that m=5 is usually adequate.

conventional wheat prices. Similarly, the range of the organic prices is double of the range of conventional prices. The standard deviation is relatively large for each organic price series compared to conventional wheat (spot and futures) prices, indicating higher uncertainty associated with organic prices. Using an F test, we find that the differences in variance between organic prices, and conventional spot and futures prices are statistically significant.

As mentioned earlier, the price risk of a commodity can be cross hedged by taking a position on the futures market for a related commodity, under the condition that the correlation between the prices of the two commodities be significantly different from zero (Anderson and Danthine 1981). In general, the stronger the correlation the more effective the hedge.

The correlations between conventional futures prices and the three organic spot price series are reported in Table 2. The correlations are found to be significant at 90% confidence level and between 0.15 – 0.17, depending on the method used to impute missing organic prices. Positive correlations indicate that the spot and futures prices move in the same direction more than half of the time, meaning there is a possibility that hedging could be risk reducing.

Methods

Price Risk and Organic Premium Risk Evaluation

To evaluate the risk associated with organic and conventional wheat (spot) prices and the organic premium, we first find the best fitting probability density for each. Since we have four organic wheat price series available (one observed and three imputed using the three imputation methods), we obtain four organic premium series. Kernel density is used to fit each price set, because it does not impose any potentially limiting assumptions about the distribution of the data.[6]

In the next step, we sample 10,000 values from each kernel density. The values are drawn from each fitted kernel density with the probability that is attached to each value of the fitted density, so that the density of the simulated values comes close to the fitted kernel density. The simulated values are then used to calculate two risk measures – 5% value-at-risk (VaR) for the prices and organic premium and probability that the organic premium falls below the additional costs of producing organic.[7]

[6] The Epanechnikov (quadratic) kernel is chosen for the kernel function, since it can be shown that it is an optimal kernel, but in general the choice of kernel is not critical (Cameron and Trivedi 2005). The unbiased cross validation method is used for the bandwidth selection, as it is entirely data-driven while it minimizes the integrated squared error, which is a global measure evaluating the performance of the kernel smoothing at all data points (Cameron and Trivedi 2005).

[7] Standard deviation is a risk measure that can be used when evaluating the uncertainty associated with prices of agricultural commodities. However, the known issue with using standard deviation as a risk measure is that it is two-sided, penalizing also upper tail of the distribution. Thus, we use 5% VaR, which is one-sided, lower-tail-specific risk measure and in this study, it represents a price or organic premium point at which there is 5% probability that the observed price or organic premium will be lower.

Estimation of Optimal Hedge Ratio

Historically, a simple OLS regression of spot prices S_t on futures prices F_t at time *t*, with both prices expressed either in levels, differences, or as percentage changes, has been used to estimate the OHR, which is the slope coefficient λ in the equation (2):

$$(2) \qquad S_t = \mu + \lambda F_t + \varepsilon_t$$

However, it has been shown that the effectiveness of this approach is limited since the OHR obtained from equation (2) does not account for the past information available to the hedger at time *t* (Myers and Thompson 1989), and it likely yields an unreliable OHR if the relationships between the spot and futures prices are not specified correctly (Ghosh 1993). In this study, we apply a method that extends this simple OLS approach by incorporating the cointegration relation, when it exists, between spot and futures prices. We also include lags of futures and spot prices that may play a role in explaining the movements in spot prices. As summarized in Lien and Tse (2002), several studies (e.g. Lien and Luo 1994; Ghosh 1993; Wahab and Lashgari 1993; Chou, Denis and Lee 1996) found that this cointegration approach performs better than the simple OLS approach from equation (2). If cointegration is not found, we estimate equation (3), as proposed in Myers and Thompson (1989). If cointegration is found, we add the error correction term to obtain the equation (4), as described in Lien and Tse (2002). In each case, the OHR is the estimate of the slope coefficient λ.

$$(3) \qquad \Delta OS_t = \mu + \lambda \Delta CF_t + \sum_{i=1}^{k} \beta_i \Delta OS_{t-i} + \sum_{j=1}^{l} \gamma_j \Delta CF_{t-j} + \varepsilon_t$$

$$(4) \qquad \Delta OS_t = \mu + \lambda \Delta CF_t + \sum_{i=1}^{k} \beta_i \Delta OS_{t-i} + \sum_{j=1}^{l} \gamma_j \Delta CF_{t-j} + \alpha Z_{t-1} + \varepsilon_t$$

In these equations, ΔOS_t is the difference between the organic wheat spot prices in two time periods $OS_t - OS_{t-1}$, ΔCF_t is the difference between the conventional wheat futures prices in two time periods $CF_t - CF_{t-1}$, ΔOS_{t-i} is the *i-th* lag of the organic spot price difference, and ΔCF_{t-j} is the *j-th* lag of the conventional futures price difference. The number of lags *k* and *l* are determined by the AIC, and Z_{t-1} in equation (4) is the lagged error correction term, obtained from the regression between OS_t and CF_t:

$$(5) \qquad OS_t = \alpha + \beta CF_t + z_t$$

The regression analysis applied is a part of either a structural vector autoregressive (SVAR) or a structural vector error correction (SVEC) model, depending on whether equation (3) or equation (4) is estimated, respectively. Typically, estimation of SVAR and SVEC models in the case of a bivariate price analysis involves a simultaneous estimation of the system of two equations, where each price variable is in function of its own lags and lags of the other price variable, and the contemporaneous effect is captured in one equation only. We only consider equation with organic price set as the dependent variable given our interest in estimating the OHR. Following

the theory behind OHR calculation, we include the contemporaneous effect of conventional futures prices in the equation.

Examination of Dynamic Relationships

In addition to estimating the OHR, equations (3) and (4) also allow us to examine long-run and short-run relationships between organic spot and conventional futures prices. Understanding these relationships provides insights concerning the possibility to predict organic spot prices using conventional futures prices. Following Rapsomanikis, Hallam, and Conforti (2006), we perform short-run and long-run causality tests to determine whether futures prices can be used to predict organic prices or vice versa. Short-run causality is examined using Granger causality tests, following the procedure proposed by Toda and Yamamoto (1995). Using this procedure, we apply a Wald test to determine whether prediction of one price variable improves if lags of the other price variable are included in the vector autoregressive (VAR) model. It is estimated using prices in levels. If the joint effect of past lags of price series x_t is significantly different from zero in the equation with the price series y_t as the dependent variable, then x_t is said to Granger cause y_t, and past values of x_t can be used to improve the prediction of y_t.

If cointegration is found between the prices, then we examine long-run causality by applying a standard t-test to the coefficient of the error correction term estimated using equation (4). If the coefficient on the error correction term is significantly different from zero in the equation with price series y_t as dependent variable, then the long-run causality runs from x_t to y_t.

Results

Risks Associated with Prices and Organic Premium

To evaluate the risks associated with organic wheat prices, conventional wheat prices, and organic premiums, we first find the best fitting kernel density for each. Figure 3 shows histograms of the data with plots of the best fitting kernel densities. It can be seen that fitted densities of imputed organic prices using the EMB algorithm and the exponential weighted moving average are similar to the fitted density of the observed organic prices. The fitted density of imputed organic prices using the spline interpolation is skewed to the left, meaning that lower organic prices are more frequent. Densities of organic prices (except those imputed using spline interpolation) and conventional prices are approximately normally distributed. Densities of organic premiums are far from being normal, as they are visibly skewed to the left, indicating that organic premium of lower value is more likely to occur. Again, the fitted density of organic premium calculated with organic prices imputed using the exponential weighted moving average is closest to the fitted density of the observed organic premium.

In the next step, 10,000 draws are taken from each estimated kernel density to obtain the risk measures 5% VaR and, for the organic premium only, the probability of the premium being less than \$4/bushel as an upper limit, and less than \$2/bushel as a lower limit (the estimated increased

costs for organic wheat).[8] We also obtain the probability of organic premiums above $8/bushel. This allows growers to cover organic costs across two periods. Table 3 reports the mean values and risk measures.

The means of the 10,000 drawn values for organic and conventional spot prices are close to those calculated from the observed data, reported in the Table 1. Again, on average, organic prices are double conventional prices. With the simulated mean value of the organic premium between $6.47 and $6.63 per bushel, organic wheat growers would more than offset the higher cost per bushel producing the organic wheat. Similar to the actual data, the standard deviation of simulated organic prices and organic premiums is more than double the standard deviation of the simulated conventional prices. This suggests there is more uncertainty associated with organic prices than conventional prices.

The 5% VaR values are not directly comparable across organic and conventional wheat prices since the observed minimum values are different for each. However, the results show that there is a 5% chance that the organic wheat price will fall below $5.42 - $6.04 per bushel, depending on the method used to impute missing organic wheat prices. This is slightly above the average simulated price for conventional wheat at $5.46 per bushel. It is more interesting to look at the 5% VaR values for the organic premiums, which are between $1.03 and $1.38 per bushel. Considering McBride et al. (2012) argued it takes an additional $2 to $4 per bushel to produce organic wheat, there is a greater than 5% chance that the minimum additional cost of $2/bushel will not be covered by the organic premium. The probability of observing an organic premium below the maximum additional cost of $4/bushel is between 30.2% and 33.3%. In other words, if the premium falls below $4/bushel, which happens approximately 1/3 of the time, the grower may be unable to cover costs, resulting in lower profitability of the organic wheat compared to conventional.

Results also show that the probability of organic premiums below $2/bushel is between 9.4% and 11.4%, which means that in 10% of the time, wheat growers will not receive organic premiums sufficient to cover costs. However, the lower relative profitability in one period is likely compensated for with the higher profitability in other periods. As results in Table 3 show, the probability of organic premiums being above $8/bushel, which is enough to cover the additional costs of producing organic for two periods, is between 31.9% and 35.2%. However, it is important to note that all calculated probabilities are unconditional, which means they represent probability of a particular event occurring over the entire observed period, not taking into consideration specific values observed today. For example, if premium below $4/bushel is observed today, the probability of observing premium below $4/bushel in the next month is more than just 30%. This is due to the time series nature of the data and strong dependence between observations in two adjacent time periods. However, as the time passes, the dependence weakens, and higher premiums may be more likely observed.

[8] The probabilities were calculated as follows. First, all 10,000 values were ordered from the lowest to the highest and then, to calculate the probability of organic premium being below $x/bushel, the count of all drawn values below or equal to $x was divided by 10,000.

Time Series Properties of the Data

Unit Root Tests

As a first step in any regression analysis involving time series, it is necessary to examine whether the time series are stationary (integrated of order zero, denoted $I(0)$) or non-stationary (integrated of order d, denoted $I(d)$, with d being an integer greater than 0) using unit root tests. We apply three tests to determine whether the price series used in the analysis are stationary. They include the Augmented Dickey-Fuller (1979) ADF test, the Phillips-Perron (1988) PP test, and the Kwiatkowski-Phillips-Schmidt-Shin (1992) KPSS test. These tests are commonly used in the literature. We use all three since it is known that in some circumstances some tests perform better than the others[9]. We find all price series are non-stationary in levels, and stationary in first differences. Unit root test results are available from the authors.

Johansen Cointegration Test

For each set of organic cash and conventional futures prices we confirm that the prices are non-stationary in levels and stationary after first differencing. This leads us to test for cointegration, i.e. long-run relationship, between the cash and futures prices. We apply the maximum likelihood method developed by Johansen (1988, 1991). The Akaike Information Criterion (AIC) is used to determine the number of lags k to be used. We estimate the trace and maximum eigenvalue statistics using a constant in the cointegrating equation. Trace test statistics λ_{trace} and maximum eigenvalue test statistics λ_{max} for each pair of prices are reported in Table 4. The null hypothesis of no cointegrating relationship ($r = 0$) is rejected for all three pairs of conventional futures prices with organic spot prices using at least one of the two estimated statistics, and thus equation (4) is estimated for each pair.

Cross Hedge for Organic Wheat Using Conventional Wheat Futures

The results of estimating the OHR's reported in Table 5. The AIC selected three lags, one lag, and one lag as optimal for the regressions involving organic prices imputed using the EMB algorithm (Model 1), the spline interpolation (Model 2), and the exponential weighted moving average (Model 3), respectively. Table 5 also reports results of performed misspecification tests. We fail to reject the null of no autocorrelation using the Box-Ljung test for all three models. This means the models are well specified in terms of the number of included lags.

The coefficient estimate on the differenced futures price in the current period ΔF_t is of primary interest, because it represents the OHR. In Model 1, the coefficient estimate is not statistically significant, implying that organic wheat price risk cannot be cross hedged using conventional futures. In Model 2 and Model 3, the coefficient estimate is statistically significant and large, but negative. Based on the calculation of OHR shown in equation (1), it means the covariance between organic spot prices and conventional futures prices is negative, after controlling for lags

[9] For example, some studies suggest the Augmented Dickey-Fuller test may perform poorly and be biased towards accepting the null of non-stationarity in the presence of serial correlation or heteroskedasticity (Rapsomanikis, Hallam and Conforti 2006; Esposti and Listorti 2013).

and the error correction term included in the estimated regressions based on equation (4). Thus, if there is an increase in futures prices, the organic spot prices decrease and vice versa. Typically, spot and futures prices for the same commodity are positively correlated. In that case, growers first sell futures contracts and later, when both spot and futures prices decline, losses in the spot market can be offset with a gain in the futures market. But a negative OHR coefficient means that spot and futures prices move in opposite directions, making a typical strategy of first selling futures contracts not applicable. However, if growers purchase futures contracts first, then if spot prices decline and futures prices increase, growers can offset the loss in the spot market with gains in the futures market. This means that cross hedging organic price risk using conventional futures prices can be applied in practice, even if spot and futures prices move in the opposite direction. However, we find only limited evidence for the possibility of cross hedging organic prices using conventional futures, since only two out of three estimated models show an OHR that is significantly different from zero.

Relationships between Organic Spot and Conventional Futures Prices

Although the results reported in Table 5 do not provide strong evidence that taking a position in the conventional futures market can cross hedge organic price risk, the significance of the lagged price variables suggests that there are short-run relationships between organic spot and conventional futures prices. The results differ slightly based on the method used to impute missing organic prices, but there is agreement across the three models that past futures prices affect organic prices. Following the procedure by Toda and Yamamoto (1995), we perform short-run Granger causality tests to determine if one price variable can be used to predict the other in the short run.

The results of the Wald test reported in Table 6 provide some evidence that futures prices Granger-cause organic prices, meaning that past futures prices contain information that helps predict current organic prices in the short run. On the other hand, results show clearly that organic prices do not affect futures prices in the Granger sense, regardless of the method used to impute the organic prices.

Results further show that coefficients from the error correction term in all three models are not significant, although a cointegrating relationship has been found between organic spot and conventional futures prices. The presence of a cointegrating relationship implies that there is a long-run equilibrium relationship between prices. The insignificance of the error correction term in the models with organic prices as dependent variables suggests that if there is a shock to the system, the futures prices adjust to the deviation from the long-run equilibrium. This has been confirmed by the significance of the error correction term in the regressions with the conventional wheat prices as the dependent variable (not reported)[10]. Results indicate that although the long-run relationship from organic prices to futures prices means that futures prices adjust to the deviation from the long-run equilibrium, it happens slowly, over a longer period of time. Therefore, the effect of changes in organic prices on futures prices is fully exerted over a

[10] The results discussed are based on the specification of the cointegrating relationship in equation (5), where organic spot price is set as dependent variable. However, it is found that the results are robust to the specification of the cointegrating relationship.

longer period. On the other hand, the short-run effect from futures prices to organic prices means that information from the conventional futures market is passed to the organic spot market quickly, in a relatively short time. Thus, we find some evidence that futures prices can be used to predict organic prices, but only for short horizons.[11]

Evaluation of Imputation Methods

Since we find that results are not robust to the methods used to impute missing organic prices, we evaluate performance of each imputation method based on how accurately they predict the values for the missing observations. First, 10% from the originally observed organic prices (85 observations) are dropped randomly. In total, nine observations are dropped. Then, each method is applied to impute the values of the observations dropped from the dataset. Lastly, the root mean squared error (RMSE)[12] is calculated using the imputed and observed values and compared across the three methods.

The lowest RMSE=2.45 is found for the exponential weighted moving average method. The RMSE value for the EMB algorithm method is 2.75, and the largest RMSE=2.87 is found for the spline interpolation method. Based on that, we consider the results obtained using the exponential weighted moving average method to have the highest validity and to be the most appropriate to conclude with.

Summary and Conclusions

In this study we examine the profitability risk associated with organic wheat, focusing on the organic prices and premiums. As expected, there is more uncertainty associated with organic wheat prices. The simulation of organic premiums reveals that, depending on the method used to impute missing prices, there is a 30-33% probability of observing a premium below $4 per bushel, assumed to be the maximum additional cost of producing organic wheat, and 9-11% probability that the premium will be below $2 per bushel, assumed to be the minimum additional cost of producing organic. Thus, there are occasions when organic wheat production is relatively less profitable per bushel than conventional wheat production. On the other hand, there are twice as many occasions when organic wheat production is more profitable per bushel, and the gains from organic premiums cover the additional costs. It is found that the probability of observing an organic premium above $8/bushel is 32-35%. However, these probabilities are unconditional, not taking into consideration observed premium in a particular time period. For example, if the observed premium is low in one period, it is very likely it will be low in the next time period as well, but the calculated probabilities do not reflect that. This analysis suggests that if more

[11] We repeated the whole analysis using hard red winter futures as well, finding very similar results in terms of negative OHR's and existence of dynamic relationships.

[12] The RMSE is the root of the mean of the squared deviations between the imputed and observed values of the organic prices, $RMSE = \sqrt{\frac{1}{N}\sum_1^N \left(P_{imputed} - P_{observed}\right)^2}$

organic wheat production is desired, tools that can be used to manage the risk associated with the organic premium may be needed.

Since the organic premium results in the organic wheat price, we examine the possibility to hedge the organic price risk using conventional wheat futures contracts. Using cointegration we estimate OHR's. Results suggest that after accounting for the effects of lagged prices and the error correction term, the coefficient representing OHR is significantly different from zero, but negative. This means that there is an inverse relationship between changes in organic spot and conventional futures prices. In this case, growers looking to mitigate losses from a decrease in spot prices could cross hedge using conventional futures prices, but they need to purchase the conventional futures contracts as their hedge. However, the statistical significance of estimated OHR's is sensitive to the methods used to impute the missing organic prices, providing only limited evidence that organic price risk can be cross hedged using conventional futures prices.

In addition to the examination of OHR's, the estimated models allow us to investigate the short-run and long-run dynamics between the organic spot and conventional futures prices. It is found that there are complex relationships between the two prices. Tests of short-run Granger causality reveal that futures are weakly exogenous, meaning that they contain some information to help predict organic spot prices in the short run. Our analysis also provides some evidence of cointegration between organic spot and conventional futures markets. However, organic prices are found to be weakly exogenous in the long run, meaning that futures prices adjust to the deviations from the long-run equilibrium relationship rather than organic prices, but the speed of adjustment is slow.

We conclude that cross hedging the risk associated with organic prices using conventional futures market might be useful to growers, but the evidence is limited. Recent changes in the federal crop insurance program that allow wheat growers to use prices agreed to in a contract or organic wheat price election established by USDA in the calculation of their compensation, make the crop insurance program likely a better option. Conventional futures prices can be used to predict organic wheat prices, but only within a short timeframe based on the examination of the dynamic relationships in the more recent years.

These findings are useful in providing direction for future research to examine in more detail how conventional wheat futures prices might be affecting the development of the organic prices in the short run. This can be of great importance to growers and food manufacturers as they attempt to predict the movement of organic wheat prices. Also, there might be other commodities that are more closely correlated with organic wheat prices and could potentially be examined for cross hedge possibilities.

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Table 1. Summary Statistics for Conventional Wheat Futures and Spot Prices, Organic Wheat Spot Prices, and Organic Premium between January 2008 and August 2017

	Number of obs.	Mean $/bu.	St. Dev. $/bu.	Min. $/bu.	Max. $/bu.	Range $/bu.
Conventional Futures Prices*	116	5.41	1.44	3.38	10.70	7.32
Conventional Spot Prices	116	5.38	1.44	2.93	10.19	7.27
Organic Spot Prices						
Observed	85	11.96	3.96	5.02	23.91	18.89
EMB Algorithm	116	11.92	3.92	5.02	23.91	18.89
Spline Interpolation	116	11.80	4.18	5.02	23.91	18.89
Exponential Moving Avg.	116	11.85	3.85	5.02	23.91	18.89
Organic Premium						
Observed	85	6.41	3.72	0.55	15.66	15.11
EMB Algorithm	116	6.54	3.77	0.29	15.86	15.57
Spline Interpolation	116	6.42	4.00	0.50	18.27	17.77
Exponential Moving Avg.	116	6.48	3.67	0.55	15.66	15.11

*Nearby futures prices (soft red winter variety), i.e. prices for the nearest futures contract. The contract is rolled over to the second nearest contract the day before an actual delivery period.

Table 2. Correlations between Conventional Futures Prices and Organic Spot Prices

	Futures	Organic EMB A.	Organic S.I.	Organic E.W.M.A.
Futures	1.000	0.152 .	0.157 .	0.166 .
Organic EMB A.		1.000	0.940***	0.968***
Organic S.I.			1.000	0.963***
Organic E.W.M.A.				1.000

. = significant at 90% confidence level, * = significant at 95% confidence level, ** = significant at 99% confidence level, *** = significant at 99.9% confidence level

Table 3. Mean, Standard Deviation, and Risk Measures Calculated Using Simulated Values

	Mean $/bu.	St. Dev. $/bu.	5% VaR $/bu.	Pr(<$2) %	Pr(<$4) %	Pr(>$8) %
Conventional Spot Prices	5.46	1.53	3.21	-	-	-
Organic Spot Prices						
Observed	12.17	4.45	5.42	-	-	-
EMB algorithm	12.14	4.21	6.04	-	-	-
Spline Interpolation	11.93	4.40	5.91	-	-	-
Exponential Moving Avg.	12.06	4.29	5.67	-	-	-
Organic Premium						
Observed	6.52	3.97	1.14	10.44	30.64	32.37
EMB algorithm	6.62	3.92	1.38	9.37	30.24	34.83
Spline Interpolation	6.47	4.21	1.03	11.40	33.31	31.85
Exponential Moving Avg.	6.63	3.98	1.08	10.86	30.45	35.18

Table 4. Johansen Cointegration Test Results

	Number of Cointegrating Vectors = Rank (r)			
	Null	Alternative	λ_{trace}	λ_{max}
Conventional futures and organic spot prices (EMB algorithm)	$r = 0$	$r = 1$	16.65	13.99*
	$r = 1$	$r = 2$	2.65	2.65
Conventional futures and organic spot prices (spline interpolation)	$r = 0$	$r = 1$	22.07**	15.03*
	$r = 1$	$r = 2$	7.04	7.04
Conventional futures and organic spot prices (exponential moving avg.)	$r = 0$	$r = 1$	20.71**	14.87*
	$r = 1$	$r = 2$	5.85	5.85

* = significant at 90% confidence level, ** = significant at 95% confidence level, *** = significant at 99% confidence level

Table 5. Regression Results

$$\Delta OS_t = \mu + \lambda \Delta CF_t + \sum_{i=1}^{k} \beta_i \Delta OS_{t-i} + \sum_{j=1}^{l} \gamma_j \Delta CF_{t-j} + \alpha Z_{t-1} + \varepsilon_t$$

	Model 1 (EMB Algorithm)		Model 2 (Spline Interpolation)		Model 3 (Exp. Moving Avg.)	
	Estimate	SE	Estimate	SE	Estimate	SE
ΔCF_t	0.276	0.456	-0.841*	0.408	-0.879*	0.381
Z_{t-1}	-0.022	0.039	-0.008	0.017	0.000	0.014
ΔCF_{t-1}	0.793.	0.403	1.385***	0.382	1.092**	0.358
ΔOS_{t-1}	-0.272**	0.097	0.024	0.092	-0.219*	0.090
ΔCF_{t-2}	0.518	0.408	-	-	-	-
ΔOS_{t-2}	-0.290**	0.095	-	-	-	-
ΔCF_{t-3}	0.095	0.409	-	-	-	-
ΔOS_{t-3}	-0.145	0.089	-	-	-	-
μ	-0.041	0.194	-0.007	0.192	-0.062	0.180
Misspecification tests						
Autocorrelation						
Q-stat (lags=2)	0.186		0.912		1.006	
Conditional het.						
$Q(m)$	6.093		12.771		11.591	
Rank test	18.653*		29.037**		24.369**	
$Q_k(m)$	45.049		53.059.		46.221	
$Q_k^r(m)$	52.473.		46.040		45.799	
Q-stat (lags=2)	7.036*		3.238		0.803	

. = significant at 90% confidence level, * = significant at 95% confidence level, ** = significant at 99% confidence level, *** = significant at 99.9% confidence level

Q(m), Rank test, $Q_k(m)$ and $Q_k^r(m)$ tests developed by Tsay (2014).

Table 6. Short-run Granger Causality Tests

	# of lags in VAR model	χ^2 statistic	p-value
Futures prices Granger cause organic prices			
EMB Algorithm	4	5.3	0.260
Spline Interpolation	1	10.3**	0.001
Exponential Moving Avg.	2	12.5**	0.002
Organic prices Granger cause futures prices			
EMB Algorithm	4	2.0	0.740
Spline Interpolation	1	0.8	0.380
Exponential Moving Avg.	2	3.2	0.200

* = significant at 95% confidence level, ** = significant at 99% confidence level, *** = significant at 99.9% confidence level

H0: X does not Granger cause Y. Number of lags in VAR models (in levels) is determined based on AIC.

Figure 1. Observed Monthly Organic Wheat Spot Prices, and Conventional Wheat Spot and Futures Prices, Between January 2008 and August 2017 (USD per Bushel)

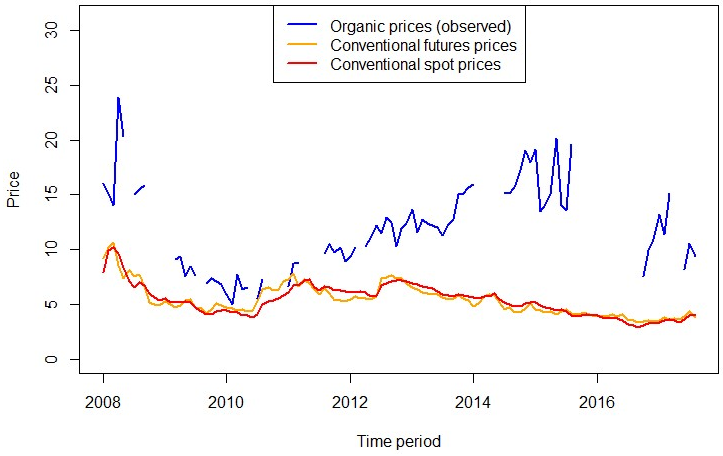


Figure 2. Observed Monthly Organic Wheat Prices Compared to Complete Organic Prices Obtained Using Three Imputation Methods (USD per Bushel)

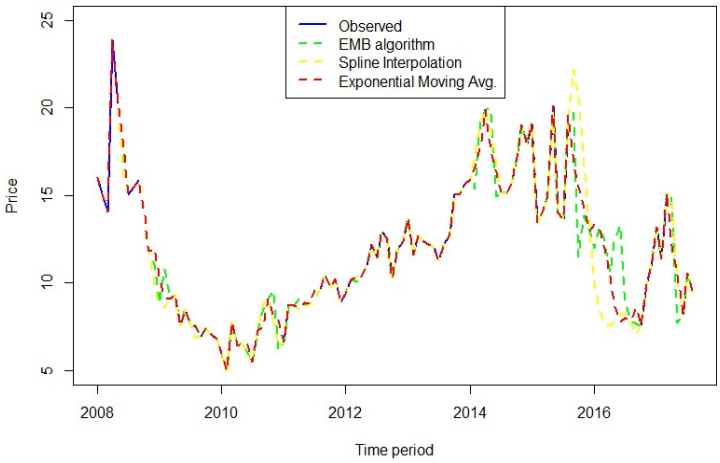
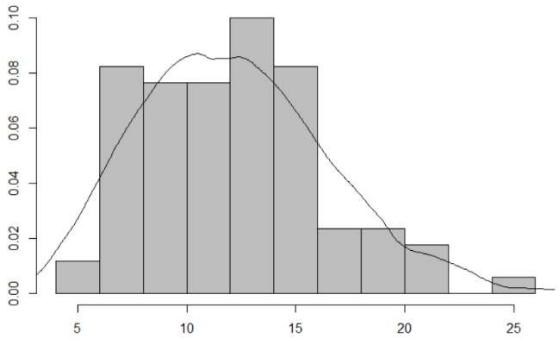
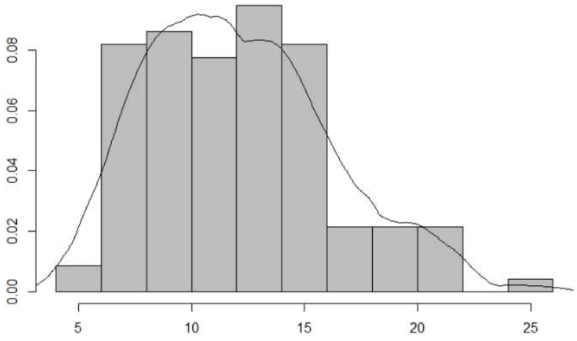


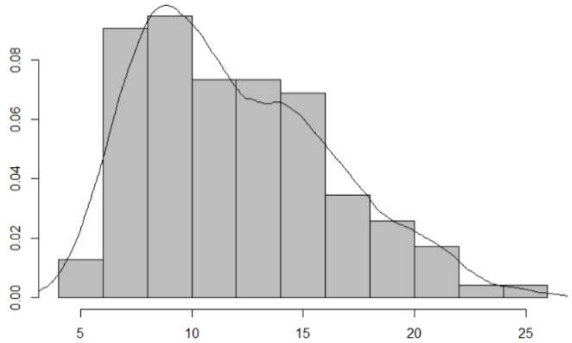
Figure 3. Histogram of Data and Kernel Density for (a) Organic Prices, (b) Conventional Prices, and (c) Organic Premiums



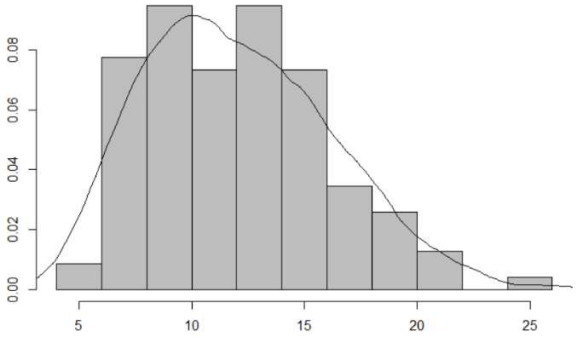
(a) Observed



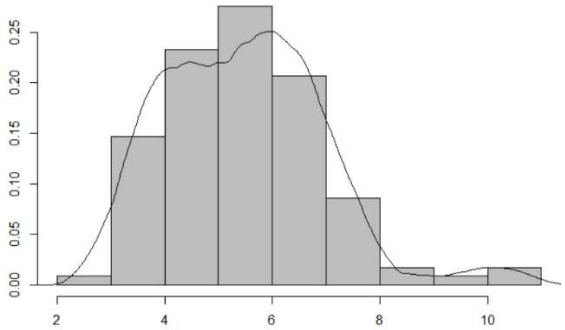
(a) EMB Algorithm



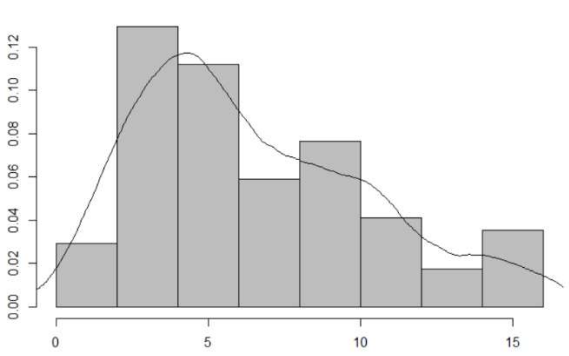
(a) Spline Interpolation



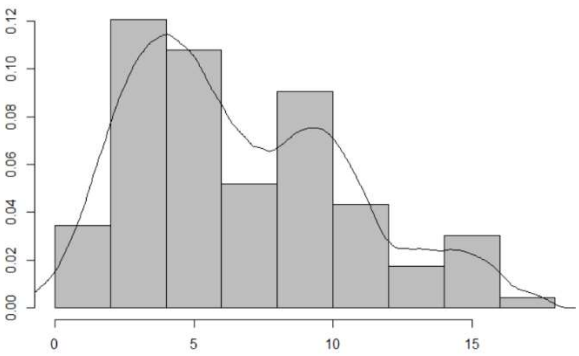
(a) Exponential Weighted Moving Avg.



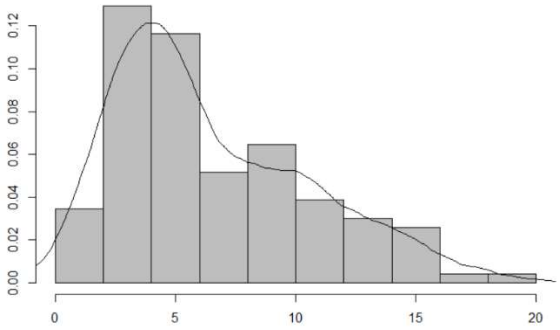
(b)



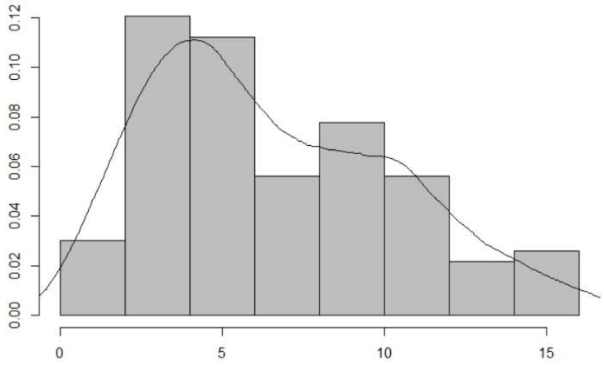
(c) Observed



(c) EMB Algorithm



(c) Spline Interpolation



(c) Exponential Weighted Moving Avg.