

Organic Wheat Prices and Premium Uncertainty: Can Cross Hedging and Forecasting Play a Role?

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We compare the volatility of organic wheat prices to that of conventional wheat prices using historical measures. To reduce uncertainty, we examine the possibility of cross hedging using conventional wheat futures and the ability of futures to forecast the organic premium. Results provide evidence that conventional futures can be used to cross hedge organic wheat price risk, but results depend on the method used to impute the missing values. We also find a long-run equilibrium relationship between organic wheat prices and conventional wheat futures prices. Finally, futures prices contain some information useful in predicting organic prices in the short run.

Key words: cointegration, optimal hedge ratio, price volatility, wheat markets

Introduction

Agricultural production is inherently risky since yields are largely affected by factors outside of producers' control, such as weather, pests, and diseases. In addition, agricultural commodity prices and market conditions at harvest are unknown when production decisions are made. Producers who adopt organic production practices face additional challenges and restrictions from the National Organic Program (U.S. Department of Agriculture, 2002a), 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 (Seufert, Ramankutty, and Foley, 2012; de Ponti, Rijk, and van Ittersum, 2012) and higher total costs per bushel for organic production. While limits on fertilizer and pesticide use may decrease the per acre operating costs of organic compared to conventional grain production, the total per acre economic costs of producing organic grains may be higher when other costs—such as labor and land—are included (McBride et al., 2015). Lower per acre yields in organic production further increase total costs per bushel compared to conventional production.

For wheat production specifically, McBride et al. (2012) find that the additional costs of producing organic wheat were \$2–\$4/bu over conventional wheat in 2009, while the organic wheat premium at that time was \$3.79/bu, indicating that the higher costs of producing organic wheat could be offset with higher organic prices; thus, organic wheat production can be more profitable than conventional. In 2017, the estimated difference in production costs per bushel for organic and

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conventional wheat in North Dakota was around \$2.42 (Organic Center, 2017),¹ demonstrating that the cost difference remains in the \$2–\$4/bu range.

The relative profitability of organic wheat production depends on the organic premium, which in turn depends on how organic and conventional wheat prices develop over time. Unlike organic wheat production costs, organic wheat prices have changed rapidly in the past few years, leading to an overall increase in organic wheat pricing in excess of 140% between 2010 and 2017, positively affecting the organic premium. 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 affect their decision to begin or continue organic wheat production. This study evaluates the uncertainty associated with organic prices and premiums and explores options that growers may employ to manage this uncertainty.

This study has three primary objectives. First, we compare the risks associated with organic and conventional wheat prices by examining the historical volatilities. We hypothesize that organic wheat prices are more volatile than conventional wheat prices, making organic wheat production riskier from the perspective of growers and possibly affecting negatively growers' perceptions about organic wheat profitability. Higher volatility may act as a barrier to adopting organic wheat production practices. We also evaluate the organic premium risk directly and examine whether the organic premium can cover the additional cost of producing organic wheat. This allows for a better understanding of the risks associated with producing organic wheat.

Second, we explore options that growers considering conversion to or maintaining organic wheat production have to manage the price risk associated with organic wheat. More specifically, we investigate 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.

Our analysis is complicated by the limited availability of historical organic wheat price data and missing observations in the data that are available. Our third objective is to simulate missing organic wheat prices. We use three methods to add robustness to our analysis and to help determine whether our results are sensitive to the methods. This will allow us to highlight possible limitations and provide more validity to our results. In addition, we investigate which method is the optimal one by evaluating their accuracy at predicting randomly dropped observations.

As expected, we find that organic wheat prices are more volatile than conventional prices. In addition, our analysis shows that there are periods when organic premiums do not cover the additional costs of organic production, making organic wheat production riskier than conventional production. However, losses in one period can be more than offset with gains in another period. Depending on the cost of storage, growers might benefit from keeping organic crops until prices increase. We also find evidence that cross hedging organic wheat using conventional futures can be useful, but the evidence is limited and depends on the method used to impute the missing organic prices. Growers might be better off relying exclusively on the federal crop insurance program, since recent crop insurance changes have made it possible for growers to receive compensation for revenue losses using organic prices.²

Finally, we find that organic spot and conventional futures markets are somewhat connected, since long-run and short-run equilibrium relationships are found to exist. Growers can use futures

¹ Calculated as the difference between organic wheat cost per bushel equal to \$5.22 (given a cost of \$287.18/acre and a yield of 55 bu/acre) and conventional wheat cost per bushel equal to \$2.80 (given \$195.80/acre and 70 bu/acre).

² In the past, the crop insurance program did not consider the specific needs of organic growers, since the payouts to compensate growers for losses were calculated based on conventional price rates. However, organic growers can currently use prices either established in a purchase contract or organic price elections determined by the Risk Management Agency (RMA) to calculate their compensation.

prices to predict organic prices, but only in the short run. In the long run, we find some evidence that prices tend to move in the same direction.

Background and Literature Review

U.S. Organic Wheat Market and Demand Characteristics

Currently, less than 1% of wheat production in the United States is organic, but this number continues to increase over time. Organic wheat made up only 0.34% of U.S. wheat grown in 2000, but that share increased to 0.74% by 2008 and 0.76% by 2016 (U.S. Department of Agriculture, 2002c, 2018). In 2016, most U.S. organic wheat was produced in Montana (27.8%), Wyoming (10.1%), and Utah (10.0%), which jointly accounted for almost half of the organic wheat production in the United States. They have been the top three producing states since 2010 (U.S. Department of Agriculture, 2002c, 2018). Other states historically contributing at least 5% to total U.S. organic wheat production are Colorado (8.2%), California (7.3%), Texas (5.8%), and Nebraska (5.4%) in 2010 and Colorado (7.6%) in 2016. In 2017, 1,139 U.S. farms grew organic wheat, averaging 295 harvested acres and 9,264 bushels harvested (U.S. Department of Agriculture, 2017).

Consumer demand for organic foods continues to grow, increasing from \$3.4 billion spent on organic foods in 1997 to \$45.2 billion in 2017 (Organic Trade Association, 2018). Organic food demand is expected to continue to grow regardless of the relationship between the organic and conventional prices. In 2012, organic bread and grains accounted for approximately 9% of all organic food demand (U.S. Department of Agriculture, 2014). While consumers cannot distinguish whether organic or conventional wheat was used in final organic products using sensory evaluation, some prefer organic foods based on their perceived implications for health, the environment, etc. (Curtis and Cowee, 2011; Gumirakiza, Curtis, and Bosworth, 2017). Thus, consumers who strongly prefer products containing organic wheat will not switch to conventional products easily. The substitution from conventional to organic wheat products (assuming they are available in the market) is possible if the price differential between organic and conventional wheat products diminishes, potentially as a result of increased organic wheat supply, which will impact how prices evolve over time.

Price Volatility as a Measure of Price Uncertainty

Price volatility is defined as the deviation of a price from its mean value or price movements within a short period of time (Balcombe, 2010). Higher volatility makes it harder to predict future prices and creates more uncertainty associated with future price expectations. In general, commodity prices are highly volatile (Deaton and Laroque, 1992; Pindyck, 2004). McKay (2016) compares the price volatility of organic commodities and their conventional counterparts from 2007–2015 and finds that organic corn, soybeans, and oats prices were less volatile than conventional prices, while organic wheat and barley prices were more volatile. Higher price volatility for organic commodities can affect the risk perceptions associated with the relative profitability of organic production. We compare the volatilities of wheat prices using historical volatilities, while McKay (2016) uses a coefficient of variation as a measure of volatility.

Organic versus Conventional Production Profitability and Risk Perceptions

While some studies have found that organic production is less profitable than conventional production (Dobbs and Smolik, 1997), many studies have found the opposite. Mahoney et al. (2004) find that net returns for selected organic crops are significantly larger than those for conventional crops, and they are statistically equal when organic price premiums were not considered. Delbridge et al. (2013) consider the possible differences in the size of organic and conventional farms to evaluate whole-farm net returns for a corn–soybean rotation and find 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) find 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 generates lower net present values than do conventional systems. However, results for organic production are more positive when including organic premiums. These 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, higher volatility and uncertainty of organic prices, if found, can affect rates of adoption or continuation of organic production and confirms the value of having tools to manage the uncertainty associated with organic price premiums.

Hedging and Optimal Hedge Ratio

Hedging is one tool used to mitigate the risk associated with adverse price changes in agriculture. Often, the most efficient hedge is not a one-to-one hedge. In other words, not all of the spot risk is hedged in the futures market. Instead, hedgers apply an optimal hedge ratio (OHR), which 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:

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

OHRs can be estimated using regression analysis, but several techniques using different assumptions have been used in the literature. Some studies assume a constant (static) OHR over time (e.g., Rolfo, 1980; Wilson, 1982; Benninga, Eldor, and Zilcha, 1984; Figlewski, 1994). Other studies relax this assumption by allowing the distribution of spot and futures prices to vary over time, making it possible to estimate a time-variant (dynamic) OHR (Cecchetti, Cumby, and Figlewski, 1988; Baillie and Myers, 1991; Chang, McAleer, and Tansuchat, 2011; Revoredo-Giha and Zuppiroli, 2015).³ Although some studies show that assuming a time-invariant OHR is not appropriate (Baillie and Myers, 1991), others show that using more complex models to account for a time-variant OHR does not lead to significant reduction in portfolio variance (Lien, Tse, and Tsui, 2002; Lien and Tse, 2002; Cotter and Hanly, 2012). Hence, we start with the assumption that the OHR is constant over time and examine the validity of that assumption by performing specification tests.

Regardless of methodology, a majority of studies find that the 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) examines the efficiency of the U.S. wheat futures markets and finds that the time-invariant OHR is less than unity and the risk is reduced more if nearby futures contracts are used as opposed to those in the more distant future. Revoredo-Giha and Zuppiroli (2015) compare the effectiveness of short-term hedging of wheat price risk using U.S. and European futures markets, while considering time-varying OHRs. They find that U.S. futures markets can reduce the price variance of the portfolio by 77% with the OHR close to unity, while European markets reduce the variance by only 30% with the OHR significantly less than unity.

Cross Hedging

The organic wheat market is considered thin. Because of the lack of liquidity, there is no futures market for organic wheat, so 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 task is to find a related

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

commodity. According to Anderson and Danthine (1981), the correlation between prices of the hedged commodity and the related futures commodity must be significantly different from 0.

Several studies have examined the possibility of cross hedging price risk with no futures contract established for the spot commodity. Blake and Catlett (1984) simulate a routine cross hedge and find that using corn futures to manage the price risk of hay increased gross returns per ton of hay. Zacharias et al. (1987) apply a numerical simulation approach and 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) find 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, which is 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.

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 nonstationary prices share a stable long-run equilibrium, then the markets are said to be cointegrated⁴. 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.

Several 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 (Bessler and Covey, 1991; Lai and Lai, 1991; Wahab and Lashgari, 1993; Beck, 1994; Fortenbery and Zapata, 1997; McKenzie and Holt, 2002; Wang and Ke, 2005). Understanding the relationships between futures and cash markets can be helpful in determining how changes in futures markets can impact spot prices. If 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. Fewer studies have used cointegration specifically to estimate OHRs, and their overall aim was to compare the effectiveness of cointegration and conventional approaches in the process of OHR estimation (see the methodology section).

Data Description

We use monthly farm gate/FOB organic and conventional food grade wheat prices between January 2008 and August 2017 as spot prices (U.S. Department of Agriculture, 2002b, 2018). 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.

To add robustness to our analysis and to examine whether the results are sensitive to the methods used, we imputed values for the missing organic prices using three methods: (i) spline interpolation, (ii) exponential weighted moving average, and (iii) an expectation-maximization with

⁴ Maddala and Kim (1999) provide detailed review of cointegration. Rapsomanikis, Hallam, and Conforti (2006) offer a brief review of cointegration and testing for cointegration.

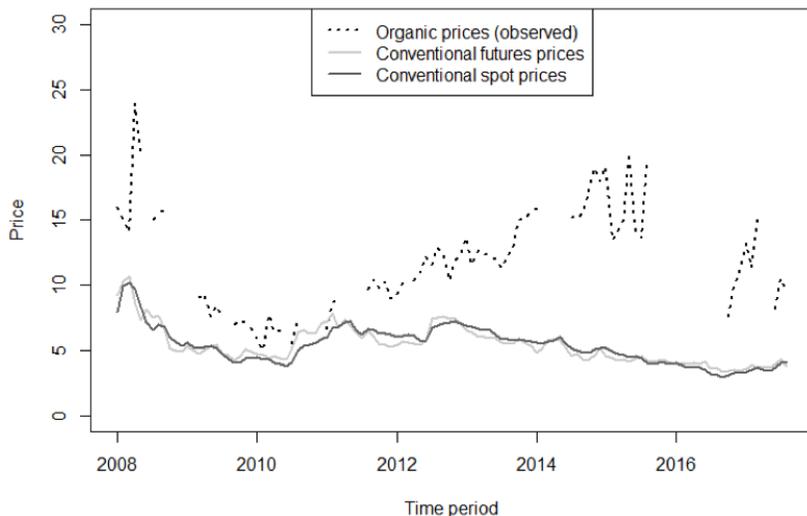


Figure 1. Observed Monthly Organic Wheat Spot Prices, and Conventional Wheat Spot and Futures Prices, January 2008–August 2017 (\$/bu)

bootstrapping (EMB) algorithm (Honaker and King, 2010).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.

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) with monthly frequency. Futures contracts are available for 5 delivery months in each year—March, May, July, September, and December. The futures price series is a collection of nearby futures prices between January 2008 and August 2017, with a total of 116 observations. We roll 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 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. Organic and conventional wheat prices tend to move in the same direction, suggesting a potential long-run relationship between the price series. But the difference between the prices (i.e., the organic premium) varies over time. Lastly, the plots suggest that organic prices are less stable than conventional prices. Figure 2 depicts observed organic prices as well as prices obtained using the three imputation methods. There are some differences in the imputed organic prices across the three methods, particularly around 2016, when no data were observed for several consecutive months.

⁵ The spline interpolation method fills in missing values by connecting observed values immediately before and after the missing values 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 apply the EMB algorithm, we use the Amelia II package developed by Honaker, King, and Blackwell (2011). We choose $m = 10$ in our analysis, but Honaker, King, and Blackwell note that $m = 5$ is usually adequate.

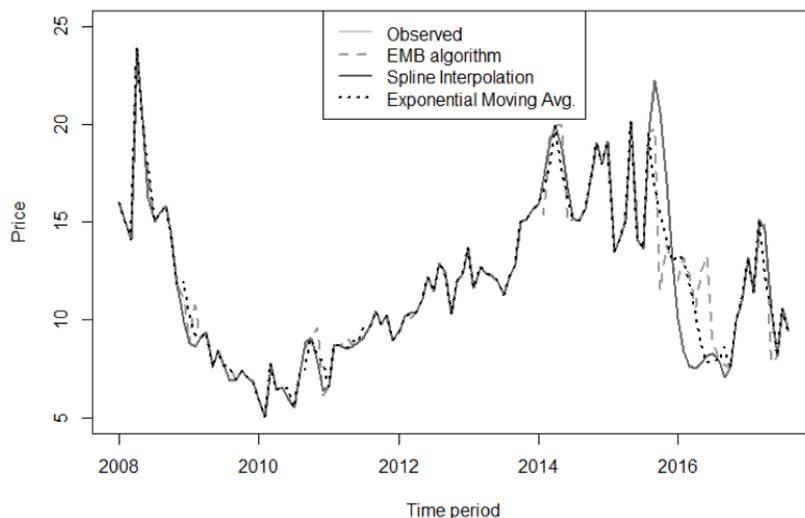


Figure 2. Observed Monthly Organic Wheat Prices Compared to Complete Organic Prices Obtained Using Three Imputation Methods (\$/bu)

Table 1. Summary Statistics for Conventional Wheat Futures and Spot Prices, Organic Wheat Spot Prices, and Organic Premium, January 2008–August 2017 (\$/bu)

	No. of Obs.	Mean	St. Dev.	Min.	Max.	Range
Conventional futures prices ^a	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 weighted 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 weighted moving avg.	116	6.48	3.67	0.55	15.66	15.11

Notes: ^a Nearby futures prices (soft red winter variety); that is, prices for the nearest futures contract. The contract is rolled over to the second-nearest contract the day before an actual delivery period.

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. Organic wheat prices are on average double conventional wheat prices. The standard deviation for each organic price series is relatively large 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 previously, 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

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

	Conventional Futures	Organic EMB Algorithm	Organic Spline Intervention	Organic Exponential Weighted Moving Avg.
Conventional futures	1.000	0.152*	0.157*	0.166*
Organic EMB algorithm		1.000	0.940***	0.968***
Organic spline interpolation			1.000	0.963***
Organic exponential weighted moving avg.				1.000

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

prices of the two commodities be significantly different from 0 (Anderson and Danthine, 1981). Table 2 reports the correlations between conventional futures prices and the three organic spot price series. We find the correlations to be significant at the 90% confidence level and between 0.15 and 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 the time, implying that hedging could be risk-reducing.

Methods

Organic Premium Risk and Price Risk Evaluation

To evaluate the risk associated with the organic premium, we first find the best-fitting probability density for the organic premium. Since four organic wheat price series are available (one observed and three imputed using the three imputation methods), we obtain four organic premium series. We use kernel density to fit each organic premium 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 the probability that the organic premium falls below the additional costs of producing organic.

In addition to calculating probabilities of observing a premium below cost of producing organic, we also calculate historical volatilities of organic and conventional prices. This enables us to compare how much prices change from one period to another and how much uncertainty is associated with change. Since we have monthly data, we calculate monthly historical volatilities and calculate the moving volatilities over a period of 12 months. To calculate the volatilities, we follow the standard procedure (described, e.g., in Figlewski, 1994).

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:

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

where OHR is the slope coefficient λ . However, 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

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 and 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).

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 including lags of futures and spot prices that may play a role in explaining the movements in spot prices. We also incorporate the cointegration relation, when it exists, between spot and futures 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) have found that this cointegration approach performs better than the simple OLS approach in equation (2). If cointegration is not found, we estimate

$$(3) \quad \Delta OS_t = \mu + \lambda \Delta CF_t + \sum_{i=1}^k \beta_i \Delta OS_{t-i} + \sum_{i=1}^k \gamma_i \Delta CF_{t-i} + \varepsilon_t,$$

as proposed by Myers and Thompson (1989). If cointegration is found, we add the error correction term to obtain

$$(4) \quad \Delta OS_t = \mu + \lambda \Delta CF_t + \sum_{i=1}^k \beta_i \Delta OS_{t-i} + \sum_{i=1}^k \gamma_i \Delta CF_{t-i} + \alpha Z_{t-1} + \varepsilon_t,$$

as described in Lien and Tse (2002). In each case, the OHR is the estimate of the slope coefficient λ . 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-i} is the i th lag of the conventional futures price difference. The number of lags, k , is determined by the Akaike Information Criterion (AIC), and Z_{t-1} in equation (4) is the lagged error correction term, obtained from the regression between OS_t and CF_t :

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

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, estimating 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 of these two equations. Given our interest in estimating the OHR, we only consider equations with organic price set as the dependent variable. Following the theory behind OHR calculation, we include the contemporaneous effect of conventional futures prices in the equation.

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. 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 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, estimated using prices in levels. 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).

Results

Risks Associated with the Organic Premium and Prices

Figure 3 presents the best-fitting kernel densities for organic premiums. Densities of organic premiums are far from being normal, as they are visibly skewed to the left, indicating that an organic

Table 3. Mean, Standard Deviation, and Probabilities Calculated Using Simulated Premiums

	Mean (\$/bu)	St. Dev. (\$/bu)	Pr(<\$2) (%)	Pr(<\$4) (%)	Pr(>\$8) (%)
Observed	6.52	3.97	10.44	30.64	32.37
EMB algorithm	6.62	3.92	9.37	30.24	34.83
Spline interpolation	6.47	4.21	11.40	33.31	31.85
Exponential weighted moving avg.	6.63	3.98	10.86	30.45	35.18

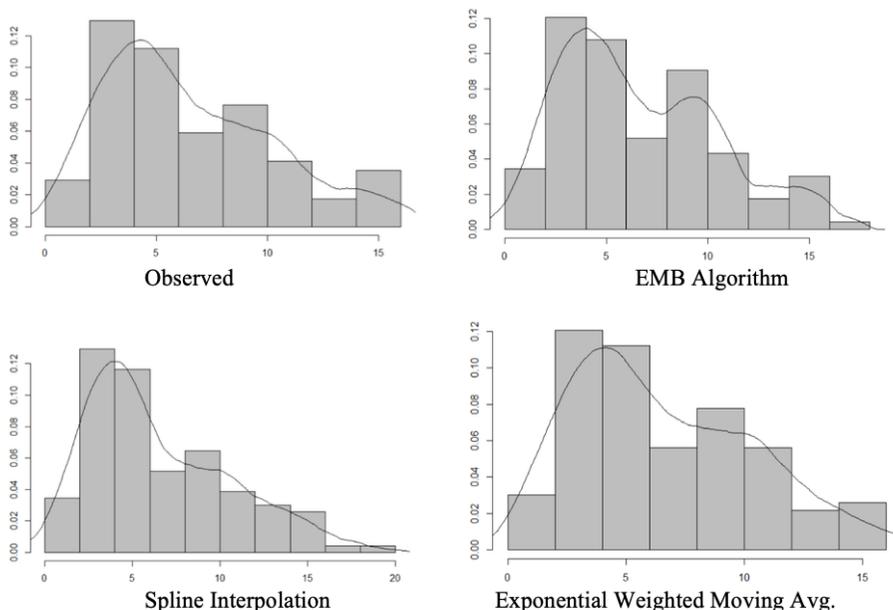


Figure 3. Histogram of Data and Kernel Density for Organic Premiums

premium of lower value is more likely to occur. 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 probability of the premium being less than \$4/bu as an upper limit and less than \$2/bu as a lower limit (the estimated increased costs for organic wheat, following McBride et al., 2012).⁷ We also obtain the probability of organic premiums above \$8/bu. This allows growers to cover organic costs across two periods. Table 3 reports the mean values and risk measures. With a simulated mean organic premium value of \$6.47–\$6.63/bu, organic wheat growers would more than offset the higher cost per bushel by producing organic wheat. However, the calculated probabilities need to be examined to understand the risk associated with the premium.

The probability of observing an organic premium below the maximum additional cost of \$4/bu is 30.2%–33.3%. In other words, if the premium falls below \$4/bu, which happens approximately one-third 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/bu is 9.4%–11.4%, which means that in 10% of the time, wheat growers will not receive

⁷ 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/bu, the count of all drawn values below or equal to \$x was divided by 10,000.

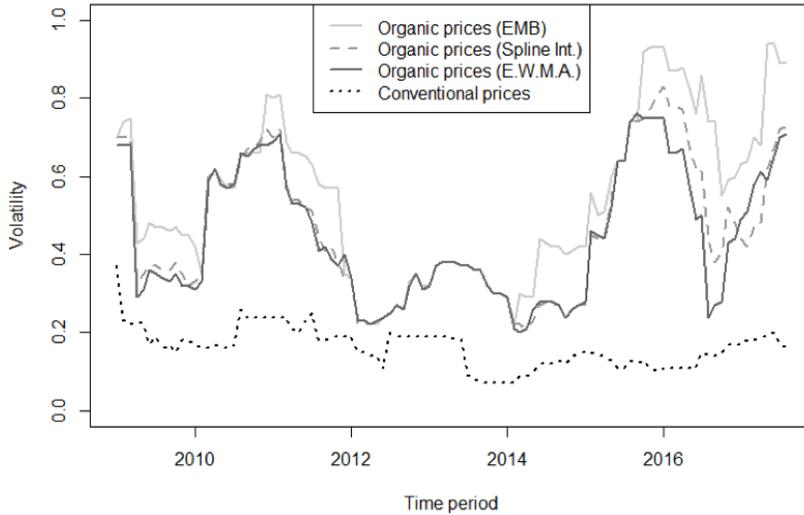


Figure 4. Annualized Historical Volatilities

organic premiums sufficient to cover costs. However, the lower relative profitability in one period is likely compensated by higher profitability in other periods. As results in Table 3 show, the probability of organic premiums being above \$8/bu, which is enough to cover the additional costs of producing organic for two periods, is 31.9%–35.2%.

It is important to note that all calculated probabilities are unconditional, which means they represent the probability of a particular event occurring over the entire observed period, not taking into consideration specific values observed today. For example, if a premium below \$4/bu is observed today, the probability of observing a premium below \$4/bu in the next month is more than 30% 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 to be observed.

We also calculated annualized historical volatilities of organic and conventional wheat prices (Figure 4). Annualized volatilities of conventional prices are 7%–37%, while the annualized volatilities of organic prices are 20%–94%. This shows that organic prices tend to change more dramatically and are less stable over a short horizon. The plots also show that periods of higher volatility are followed by periods of lower volatility in the case of organic prices, while the volatilities of conventional prices are relatively stable over time. This suggests that if more organic wheat production is desired, more risk-averse growers may need tools that will enable them to efficiently manage the risk associated with organic prices and premiums.

Time Series Properties of the Data

As a first step in any regression analysis involving time series, it is necessary to examine whether the time series are stationary using unit root tests. We apply three commonly used tests to determine whether the price series used in the analysis are stationary: the Augmented Dickey–Fuller (1979) ADF test, the Phillips–Perron (1988) PP test, and the Kwiatkowski–Phillips–Schmidt–Shin (1992) KPSS test. We use all three since some tests perform better in certain circumstances.⁸

For each set of organic cash and conventional futures prices, we confirm that the prices are nonstationary in levels and stationary after first differencing.⁹ This leads us to test for cointegration

⁸ For example, some studies suggest that the Augmented Dickey–Fuller test may perform poorly and be biased toward accepting the null of nonstationarity in the presence of serial correlation or heteroskedasticity (Rapsomanikis, Hallam, and Conforti, 2006; Esposti and Listorti, 2013).

⁹ Unit root test results are available from the authors upon request.

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 weighted moving avg.)	$r = 0$	$r = 1$	20.71**	14.87*
	$r = 1$	$r = 2$	5.85	5.85

Notes: Single and double asterisks (*, **) indicate significance at the 10% and 5% level.

between cash and futures prices. We apply the maximum likelihood method developed by Johansen (1988, 1991). We use the AIC to determine the number of lags, k . We estimate the trace and maximum eigenvalue statistics using a constant in the cointegrating equation. Table 4 reports trace test statistics, λ_{trace} , and maximum eigenvalue test statistics, λ_{max} , for each pair of prices. 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; we therefore estimate equation (4) for each pair.

Cross Hedge for Organic Wheat Using Conventional Wheat Futures

Table 5 reports the results of estimating the regressions. The AIC selected 3 lags, 1 lag, and 1 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 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, ΔCF_t , 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 Models 2 and 3, the coefficient estimate is statistically significant and large, but negative. Based on the calculation of OHR shown in equation (1), the covariance between organic spot prices and conventional futures prices is negative, after controlling for lags 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 price decreases 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 they can offset the loss in the spot market with gains in the futures market if spot prices decline and futures prices increase. Nevertheless, we find only limited evidence for the possibility of cross hedging organic prices using conventional futures, since only two of the three estimated models show an OHR significantly different from 0.

Relationships between Organic Spot and Conventional Futures Prices

The significance of the lagged price variables in Table 5 suggests that there are short-run relationships between organic spot and conventional futures prices. The results differ slightly based

Table 5. Regression Results: $\Delta OS_t = \mu + \lambda \Delta CF_t + \sum_{i=1}^k \beta_i \Delta OS_{t-i} + \sum_{i=1}^k \gamma_i \Delta CF_{t-i} + \alpha Z_{t-1} + \varepsilon_t$

	Model 1 (EMB Algorithm)		Model 2 (Spline Interpolation)		Model 3 (Exponential Weighted Moving Avg.)	
	Estimate	SE	Estimate	SE	Estimate	SE
μ	-0.041	0.194	-0.007	0.192	-0.062	0.180
ΔCF_t	0.276	0.456	-0.841**	0.408	-0.879**	0.381
ΔOS_{t-1}	-0.272***	0.097	0.024	0.092	-0.219**	0.090
ΔOS_{t-2}	-0.290***	0.095	-	-	-	-
ΔOS_{t-3}	-0.145	0.089	-	-	-	-
ΔCF_{t-1}	0.793*	0.403	1.385***	0.382	1.092***	0.358
ΔCF_{t-2}	0.518	0.408	-	-	-	-
ΔCF_{t-3}	0.095	0.409	-	-	-	-
Z_{t-1}	-0.022	0.039	-0.008	0.017	0.000	0.014
Autocorrelation						
Q-stat (lags = 2)	0.186		0.912		1.006	
Conditional heteroskedasticity						
$Q(m)$	6.093		12.771		11.591	
Rank test	18.653**		29.037***		24.369***	
$Q_k(m)$	45.049		53.059*		46.221	
$Q'_k(m)$	52.473*		46.040		45.799	
Q-stat (lags = 2)	7.036***		3.238		0.803	

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

Table 6. Short-Run Granger Causality Tests

	No. 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 weighted 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 weighted moving avg.	2	3.2	0.200

Notes: Triple asterisks (***) indicate significance at the 1% level. H_0 : X does not Granger-cause Y (= dependent variable in VAR model). Number of lags in VAR models is determined based on AIC.

on the method used to impute missing organic prices, but there is agreement across the three models that past futures prices affect organic prices. The results of the Wald test to examine short-run Granger causality (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 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, 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 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. 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 the performance of each imputation method based on how accurately it predicts the values for the missing observations. First, 10% of the originally observed organic prices (9 of 85 total observations) are dropped randomly. 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. We therefore 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.

Further Examination of OHRs

Since we find negative OHR, which had not been expected given the positive unconditional correlations between the conventional futures and organic spot prices (reported in Table 2), we further examine the unconditional correlations and OHRs in selected subperiods to determine the significance of the obtained result and whether it is driven by any particular time period. We split the sample in two subperiods: (i) January 2008–December 2012 and (ii) January 2013–August 2017. We choose to split the data in this way for two reasons. First, the initial, pooled sample is relatively small, with only 116 observations; splitting it into two subsamples of similar sizes (60 and 56 observations) will yield estimates of comparable statistical validity. Second, based on the plot of organic spot and conventional futures prices in Figure 1, the development of prices appears to become more divergent in the second half of 2013.

Table 7 reports the unconditional correlations between the conventional futures and organic spot prices in the two subperiods. All correlations are positive and statistically more significant than correlations found for the pooled prices series. For each subperiod, we estimate the same models in terms of number of lags and presence of cointegration as those estimated using the whole sample, with the justification that all observations come from the same data-generating process.

Table 8 reports models estimated for the 2008–2012 subperiod. The magnitude of the estimated OHR remains negative and significant in Models 2 and 3, despite strong positive unconditional correlations. In contrast with results obtained for the whole period, 2008–2017, there is a clear indication that there is no short-run relationship between organic spot and conventional futures prices in 2008–2012, regardless of the methods used to impute missing prices. However, organic

¹⁰ These results are based on the specification of the cointegrating relationship in equation (5), where organic spot price is set as dependent variable. However, the results are robust to the specification of the cointegrating relationship.

¹¹ We repeated the whole analysis using hard red winter futures, finding similar results in terms of negative OHRs and the 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: $RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (P_{i, imputed} - P_{i, observed})^2}$.

Table 7. Correlations between Conventional Futures Prices and Organic Spot Prices

	EMB Algorithm	Spline Interpolation	Exponential Weighted Moving Avg.
January 2008–December 2012	0.63***	0.64***	0.63***
January 2013–August 2017	0.35***	0.34**	0.36***

Notes: Double and triple asterisks (**, ***) indicate significance at the 5% and 1% level.

Table 8. Regression Results, January 2008–December 2012

	Model 1 (EMB Algorithm)		Model 2 (Spline Interpolation)		Model 3 (Exponential Weighted Moving Avg.)	
	Estimate	SE	Estimate	SE	Estimate	SE
μ	-0.005	0.152	-0.066	0.192	-0.065	0.190
ΔCF_t	0.022	0.281	-0.692**	0.331	-0.654*	0.329
ΔOS_{t-1}	-0.165	0.105	-0.092	0.111	-0.234**	0.111
ΔOS_{t-2}	-0.063	0.098	–	–	–	–
ΔOS_{t-3}	-0.159*	0.084	–	–	–	–
ΔCF_{t-1}	0.278	0.298	0.415	0.396	0.035	0.382
ΔCF_{t-2}	0.279	0.294	–	–	–	–
ΔCF_{t-3}	0.066	0.294	–	–	–	–
Z_{t-1}	-0.207***	0.071	-0.264***	0.074	-0.276***	0.071
Autocorrelation						
Q-stat (lags = 2)	1.012		0.442		0.151	
Conditional heteroskedasticity						
Q-stat (lags = 2)	0.496		1.032		0.464	

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

prices are now found to adjust to the deviations from long-run equilibrium, and the speed of adjustment is significantly high. Table 9 reports the results of models estimated for the 2013–2017 subperiod. The OHR is positive but insignificant, regardless of the method used to impute missing prices. Additionally, there is no clear pattern of short-run and long-run relationships across the three methods.

To summarize, considering the results obtained using the exponential weighted moving average method—found to be the most accurate in predicting missing organic prices—the possibility of cross hedging organic wheat price risk is dependent on the time period. However, there is evidence of short-run and/or long-run relationships between the prices regardless of the time period.

Summary and Conclusions

In this study, we examine the profitability risk associated with organic wheat, focusing on organic prices and premiums. As expected, we find organic prices to be more volatile than conventional wheat prices, indicating there is more uncertainty associated with organic wheat prices. Simulating 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/bu, assumed to be the maximum additional cost of producing organic wheat, and a 9%–11% probability that the premium will be below \$2/bu, assumed to be the minimum additional cost of producing organic wheat. 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.

Table 9. Regression Results, January 2013–August 2017

	Model 1 (EMB Algorithm)		Model 2 (Spline Interpolation)		Model 3 (Exponential Weighted Moving Avg.)	
	Estimate	SE	Estimate	SE	Estimate	SE
μ	-0.363	0.420	-0.164	0.315	-0.149	0.289
ΔCF_t	1.255	1.394	0.524	1.093	0.229	0.998
ΔOS_{t-1}	-0.360**	0.148	0.140	0.135	-0.159	0.131
ΔOS_{t-2}	-0.431***	0.141	-	-	-	-
ΔOS_{t-3}	-0.165	0.148	-	-	-	-
ΔCF_{t-1}	2.541**	1.253	1.640	1.090	2.185**	0.986
ΔCF_{t-2}	0.812	1.372	-	-	-	-
ΔCF_{t-3}	-1.827	1.424	-	-	-	-
Z_{t-1}	-0.032	0.025	-0.165**	0.069	-0.132*	0.068
Autocorrelation						
Q-stat (lags = 2)	0.485		0.559		0.868	
Conditional heteroskedasticity						
Q-stat (lags = 2)	3.689		5.550*		1.389	

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

We also find that the probability of observing an organic premium above \$8/bu is 32%–35%. Based on the probabilistic simulation of organic premiums only, it appears that organic wheat production is more attractive than conventional wheat production; growers may be tempted to switch to organic wheat production. However, growers wishing to switch will face several issues that make organic wheat production less attractive and may discourage some from switching, including lower yields in organic wheat production and transition costs (certification costs, inability to obtain the organic premium in the first three years, learning curve, etc.). Additionally, if many wheat growers switch to organic production, increased supplies may dampen the organic premium over time. We also note that the reported probabilities are unconditional, not taking into consideration the observed premium in a particular time period. For example, if the observed premium is low in one period, it is likely to be low in the next time period as well. This analysis suggests that tools that can be used to manage the risk associated with the organic premium may be needed if more organic wheat production is desired.

Since the organic premium results in the organic wheat price, we examine the possibility of hedging the organic price risk using conventional wheat futures contracts. Using cointegration we estimate OHRs. Results suggest that the coefficient representing OHR is significantly different from 0 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 conventional futures contracts as their hedge. However, the statistical significance of the estimated OHRs 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, we find that the possibility of cross hedging is dependent on the time period. We conclude that a cross hedge is not likely to be overall risk-reducing because the organic premium itself appears quite volatile and not closely linked to change in conventional wheat prices. Recent changes in the federal crop insurance program, which allow wheat growers to use prices agreed to in a contract or organic wheat price election established by USDA in calculating their compensation, make the crop insurance program likely a better option.

In addition to examining OHRs, the estimated models allow us to investigate the short-run and long-run dynamics between the organic spot and conventional futures prices. We find complex

relationships between the two prices. Considering the entire studied time period, 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. Further examination of the dynamic relationships in different time periods reveals that their nature changes over time. The organic wheat market was developing in the studied period and its lack of maturity and stability could have affected the dynamic relationships.

In summary, the uncovered relationships between organic spot prices and conventional wheat futures are not as strong as one might expect. This may provide some evidence that organic and conventional wheat represent separate markets responding to separate demand centers, but it may also be the result of the small share of organic wheat production in overall wheat production. A shock to the price of the market representing less than 1% of production might not be expected to impact the price in the remaining 99% if they are not perfect substitutes, even if they share some demand-center characteristics. The findings are useful in providing direction for future research to examine in more detail how conventional wheat futures prices might affect the movement of organic prices in the short run. This information would be important to growers and food manufacturers as they attempt to predict the movement of organic wheat prices for their production and purchasing decisions. Future research might also examine other commodities, which may be more closely correlated with organic wheat prices, for cross-hedge possibilities.

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