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Disciplines
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Q180 - Agricultural Policy; Food Policy

Keywords: cointegration, jump price process, organic crops, organic production, price analysis.

1. Introduction

Born (2005, p. 1) noted that "prices for organic grains and oilseeds were about double the conventional prices from 1995 to 2003". Such "doubling" in organic crop prices is a commonly held belief in the organic agriculture sector. But, does that "doubling" depict the true existing relationship between the conventional and organic grain and oilseed markets? Is there any other relationship that links those conventional and organic markets? Or, is it that they are not really related to each other? The present study provides information to answer these questions.

A priori, one would expect organic crop prices to closely follow conventional ones in the U.S., not only due to the thinness of organic markets, but also because organic crops account for a very small share of cropland. In 2008, only 0.57% of U.S. cropland was planted with organic crops; and although organic corn and soybeans are among the main organic crops in the U.S. in terms of acreage, they respectively account for only 0.21% and 0.20% of the total cropland devoted to such crops (USDA-ERS, 2008a). In addition, one might expect organic crops to sell at a premium because, as argued by Clarkson (2007) and exemplified by Loureiro, McCluskey and Mittelhammer (2001), some consumers strongly prefer them over their conventional counterparts. Organic price premiums are also expected because organic production involves additional risks (Klonsky and Greene, 2005) that help explain the lower yields (Porter 2003; Delate and Cambardella, 2004; Singerman, Hart and Lence, 2010). McBride and Greene (2008) also found that organic production involves higher costs. Therefore, price premiums act as a major incentive in encouraging conventional producers and processors to switch to organic agriculture, by making organic crop systems as profitable as, or outperform, conventional ones.[1]

Price dynamics in organic crop markets need not be the same as in conventional ones because they are less liquid. In many instances, it is difficult for organic producers to find spot markets for their crops to turn them into cash. This feature stimulates more complex relationships between producers and buyers in organic markets, and it makes contracting ahead of planting a key feature of crop marketing (Born, 2005). Dimitri and Oberholtzer (2008) found evidence that contracting is the primary method for selling in the organic sector, with organic handlers procuring 46% of their supply underwritten contracts, 24% under informal contracts, and only 27% through spot markets in 2004. In contrast, spot market transactions account for almost a 60% share for the agricultural sector as a whole (MacDonald *et al*., 2004).

The Agricultural Risk Protection Act of 2000 recognized organic farming as a “good farming practice”, making Federal crop insurance coverage available for organic crops taking into account the idiosyncrasies of their production system. However, the incorporation of organic production into the crop insurance rating structure has been limited. Organic producers are charged an arbitrary 5% premium surcharge over conventional crop insurance. The actuarial fairness of this premium is, at least, questionable [see Singerman, Hart, and Lence, 2010]. In addition, in the case of crop failure, organic farmers receive a compensation based on conventionally produced crop prices, so organic price premiums are not accounted for under the current insurance policy (Risk Management Agency (RMA), 2008).[2] In this regard, Chen, Wang, and Makus (2007) showed that crop insurance is an important risk management tool for apple growers; however, “the low price selection and low price premium setting do not provide enough indemnity [to organic growers] when losses occur”. Greene and Kremen (2003) further argue that limited access to crop insurance may discourage conventional farmers from switching to organic farming.

Having established the importance of price premiums for the organic agricultural sector, from producers to processors, as well as for governmental agencies and insurance companies, it should be evident that a better understanding of the relationship between organic and conventional crop markets is quite relevant. Interestingly, however, an extensive literature review resulted in a noticeable lack of rigorous studies focusing on the analysis of organic crop prices and their premiums over conventional ones. One possible exception is Streff and Dobbs (2004), but their work was limited to the northern plains and upper Midwest region, and provided no quantitative analysis of the organic price premiums depicted in their plots.

Given the relevance of the relationship between organic prices and conventional ones, and the absence of related quantitative studies, the present work aims at starting to fill this gap in the literature by analyzing organic price premiums. More specifically, this study investigates the dynamic relationship between organic and conventional prices for corn and soybean at the main U.S. organic markets. In addition, the dynamic relationships between organic prices across different geographic locations are analyzed and compared with their conventional counterparts. The study further contributes to the literature by introducing a simple discrete-time specification of a pure jump process that can be easily estimated using standard econometric methods. The advocated model is applied to study the behavior of organic prices.

Results may prove useful to identify the price risks that organic methods of production are subject to. The analysis is likely to yield useful information to improve the pricing provisions of RMA organic insurance rates, correct the insurance price determination by which organic producers get compensated for when losses occur, and offer additional price elections for organic crops. The present results may also help determine the potential usefulness of existing futures and option markets to cross hedge organic producers' price risks.

2. Data

Organic market data are scarce and difficult to obtain, so we are grateful to the Rodale Institute (Rodale) for providing us its unique historic time series of organic corn and soybean spot prices, and the procedures it follows to acquire them. Rodale's database comprises a number of market locations that roughly cover the entire U.S. and constitutes, to the best of our knowledge, the most complete, updated and extensive set of historic organic prices. Rodale has been collecting and comparing the prices of organic and conventional crops, in some cases as far back as 2003, and making them publicly available on the internet via their Organic Price Report.

The main data set used here consisted of organic corn and soybean feed price series. Such prices are provided to Rodale on a weekly basis by large elevators or handlers that specialize in organic grains and oilseeds, and reflect spot prices paid to organic producers. We focused on corn and soybean because they are among the organic crops with the largest area planted in the U.S. (USDA-ERS, 2008a). In addition, corn and soybean had the fewest number of missing observations relative to the other available series.[3] The main corn (soybean) series corresponded to the Dallas, Fargo, Minneapolis, and Omaha (Fargo, Minneapolis, and Omaha) markets, each involving 246 weekly price observations starting in late October 2004 and ending in early July 2009. Two additional price series for both corn (Detroit and San Francisco) and soybean (Detroit and Dallas) were also analyzed, but they covered a period about one year shorter. Table 1 shows additional information regarding period covered and number of observations for each series.

For comparative purposes, Rodale uses conventional crop prices gathered by the United States Department of Agriculture's (USDA) Agricultural Marketing Service (AMS), selecting AMS regions that handle product within the geographic location of the elevators or handlers (see http://www.rodaleinstitute.org/Organic-Price-Report). Here we used comparable conventional price series, obtained by applying the procedure described by Rodale to the data in the corresponding AMS reports (i.e., US GR 110, SF GR 110, MS GR 110, and WH GR 111 for Dallas, Fargo, Minneapolis, and Omaha, respectively).[4] The analysis was also conducted employing the conventional Rodale series instead. In the interest of space, the latter results are omitted because the main conclusions remained unchanged.

3. Methods

The dynamic relationships between organic and conventional prices were investigated using time series econometrics. To this end, following standard practice in the literature, all of the original price series were converted to natural logarithms. In a first stage, the stationarity properties of the series were explored by visual inspection of the sample autocorrelation (ACF) and partial autocorrelation (PACF) functions (Box and Jenkins, 1970), to determine the parameter of integration that would make them stationary. The visual analysis was supplemented with the Elliot, Rothenberg, and Stock (ERS) unit-root tests, which are formal statistical tests to determine the parameter of integration. The ERS test is a modified Augmented Dickey Fuller (ADF) test that can accommodate more general formulations of the error (Greene, 2002).

Maddala and Kim (2004, p. 99) point out that the ERS test dominates the ADF test and, therefore, should be used instead.

ERS's Dickey-Fuller GLS (DF-GLS) method is described in Maddala and Kim (2004). Succinctly, ERS tests the null hypothesis that $a_0 = 0$ in the following equation:

$$(1) \qquad \Delta y_t^d = a_0 \; y_{t-1}^d + a_1 \; \Delta y_{t-1}^d + \ldots + a_q \; \Delta y_{t-q}^d + \varepsilon_t,$$

where $\Delta \equiv (1 - L)$ denotes first differences, L is the lag operator, y_t^d is the locally detrended series y_t, as are regression parameters, and ε_t is an error term. A detrended series model with a linear trend is generally used, which takes the form $y_t^d \equiv y_t - \hat{\kappa}_0 - \hat{\kappa}_1 \; t$, where $\hat{\kappa}_0$ and $\hat{\kappa}_1$ are obtained by regressing $\overline{y} \equiv [\, y_1, (1 - L \; \overline{\alpha}) \; y_2, \ldots, (1 - L \; \overline{\alpha}) \; y_T \,]$ on $\overline{z} \equiv [\, z_1, (1 - L \; \overline{\alpha}) \; z_2, \ldots, (1 - L \; \overline{\alpha}) \; z_T \,]$, $z_t \equiv [1, t]'$, $\overline{\alpha} \equiv 1 + \overline{c} \,/T$, T is the number of observations in the time series, and $\overline{c}$ is a parameter fixed by ERS at −13.5.

A potentially important pitfall of the procedure just described for the present data is that, as shown later, the null hypothesis that the organic series behave as diffusions can be strongly rejected at any reasonable level of significance. In particular, organic prices are more realistically modeled as jump processes rather than diffusions. The ERS test (as well as the ADF test) is only asymptotically valid for non-normal errors (Elliot, Rothenberg, and Stock, 1996); hence, their applicability to a small sample like the one under study is questionable. For this reason, Monte Carlo experiments were conducted to compute appropriate critical values for this application. The advocated Monte Carlo experiments are explained next.

3.1. Monte Carlo Experiment to Test for Unit Roots in Organic Prices

Organic log-prices were simulated as a pure jump process (Neftci, Ch. 8; Pennacchi, Ch. 11), by means of the model consisting of equations (2)-(4) below. To the best of our knowledge, the proposed specification is an original simple representation of pure jump processes in discrete time that can be easily estimated using standard econometric methods, and it is a major contribution of the present study.

The dynamic behavior of organic log-prices is assumed to be represented by

$$(2)\qquad ln(P_t^O) = \begin{cases} ln(P_{t-1}^O) + J_t^O \text{ with probability } \pi_t^O, \\ ln(P_{t-1}^O) \text{ with probability } (1-\pi_t^O). \end{cases}$$

If the organic log-prices were stationary, they would have an unconditional mean equal to μ^O. Defining the difference between the log-price at date *t* and the unconditional mean as $e_t^O \equiv ln(P_t^O) - \mu^O$, for log-prices to tend to return back to their long-term mean both the jump probability (π_t^O) and the jump size (J_t^O) were assumed to be functions of the lagged residuals (e_{t-1}^O) as in (3) and (4):

$$(3)\qquad \pi_t^O = 1/\{1 + exp[-\gamma(\lambda_0^O + \lambda_1^O \; |e_{t-1}^O|) - (1-\gamma)\; \Lambda_0^O]\},$$

$$(4)\qquad J_t^O \sim \mathrm{N}(\gamma\, \theta^O\, e_{t-1}^O, \gamma^2\, (\theta^O\, \sigma^O)^2 + (1-\gamma)^2\, (\Sigma^O)^2).$$

Parameter $\gamma \in [0, 1]$ can be fixed so as to yield log-price autocorrelations of varying strength. The extreme scenario of $\gamma = 1$ results in the strongest possible mean reversion in log-prices, whereas $\gamma = 0$ leads to log-prices characterized by a unit root. In (3) and (4), λ_0^O, λ_1^O, Λ_0^O, θ^O, σ^O, and Σ^O are parameters whose values were calibrated to render the simulated series consistent with key features of the organic Minneapolis log-price data. Minneapolis was used as the baseline market because it is located in Minnesota across the border from Wisconsin, and the former was the state with the largest area devoted to organic soybean from 2000 to 2008 and to organic corn from 2003 to 2006, and the second largest area planted with organic corn in 2007 and 2008 after Wisconsin (USDA-ERS, 2008b-c).

Parameters λ_0^O and λ_1^O in (3) were set equal to the coefficient estimates from a logit regression in which the dependent variable took values of zero or one depending on whether an organic price change occurred, and the independent variables were a vector of ones and the absolute value of the lagged error e^O_{t-1}. However, since λ^O_0 and λ^O_1 are meant to represent the strongest autocorrelation possible consistent with the number of jumps and the estimated variance of the lagged errors e^O_{t-1} in the data, the values of the variables were reordered before fitting the logit so as to have the jumps aligned with the largest absolute lagged errors. Parameter Λ^O_0, on the other hand, is associated with the opposite case of no autocorrelation (i.e., the lagged error does not affect the occurrence of price changes). Therefore, Λ^O_0 was set equal to the point estimate of the coefficient of another logit regression in which the dependent variable was a binary variable taking values of zero or one depending on the occurrence of price changes, but where the independent variable was a vector of ones.

The log-jumps simulated according to (4) have a normal distribution with mean and variance consisting of a γ-weighted combination of jumps inducing autocorrelation and jumps not inducing autocorrelation. The former jumps are governed by parameters θ^O and σ^O, and their magnitudes are inversely related to the lagged errors e^O_{t-1} to the maximum extent possible consistent with the data. Jumps not inducing autocorrelation are driven by parameter Σ^O, and their size is independent of the lagged errors e^O_{t-1}. The value of θ^O was set equal to the ordinary least squares (OLS) estimates from a regression of the organic corn and soybean log-price jumps against the corresponding lagged errors e^O_{t-1}, previous rearrangement of the variable values so as to associate the largest (smallest) jumps with the smallest (largest) lagged errors. Parameter σ^O was set equal to the standard deviation of the residuals from such regression. The value of Σ^O was fixed at the standard deviation of the log-jump magnitudes in the data.

Importantly, because of the chosen parameterization, the Monte Carlo design allowed us to simulate series that depicted key features of the actual series (e.g., jump probabilities and jump sizes), while varying the strength of the simulated autocorrelation relationship by fixing the value of parameter γ in (3) and (4) anywhere between 0 and 1. Reported results correspond to simulations performed for the polar case of unit root ($\gamma = 0$) and a scenario of medium-strength autocorrelation ($\gamma = 0.5$). The unit-root case was used to compute the critical values for the unit root test in the presence of jumps, whereas the autocorrelation case enabled us to examine the power of the test. Both experiments consisted of 10,000 simulations of the organic log-price series following the aforementioned parameterizations.

Observations for each of the 10,000 simulated series were obtained by performing the following iterative procedure:

Step 1. Set $ln(P^O_{(0)})$ equal to the first observation from the actual organic log-price series for Minneapolis.

Step 2. Compute the *j*th lagged error $e^O_{(j)} = ln(P^O_{(j)}) - \mu^O$.

Step 3. Compute the (*j*+1)th probability of jump:

$$\pi^O_{(j+1)} = 1/\{1 + exp[-\gamma(\lambda^O_0 + \lambda^O_1 \, |e^O_{(j)}|) - (1-\gamma)\,\Lambda^O_0]\}.$$

Step 4. Generate an observation $U_{(j+1)}$ from a standard uniform distribution.

Step 5. If $U_{(j+1)} > \pi^O_{(j+1)}$, set $ln(P^O_{(j+1)}) = ln(P^O_{(j)})$ and go to Step 7. Otherwise, go to Step 6.

Step 6. Draw $J^O_{(j+1)} \sim \mathrm{N}(\gamma\,\theta_1\, e^O_{(j)}, \gamma^2 (\theta^O \sigma^O)^2 + (1-\gamma)^2 (\Sigma^O)^2)$, and set $ln(P^O_{(j+1)}) = ln(P^O_{(j)}) + J^O_{(j+1)}$.

Step 7. If $j < 10{,}000 + T$, go back to Step 2. Otherwise, stop.

The first 10,000 observations of each simulation were used as a "burning period" and discarded to ensure randomness and independence from starting values. The last *T* observations of each simulation were kept to compute critical values for the unit root test, by fitting regression (1) and then estimating the *t* statistic corresponding to the associated coefficient a_0 for each of the simulated series under $\gamma = 0$. For example, the critical residual test value at the *z*% significance level was set equal to the $(1 - z)^{\text{th}}$ percentile of the 10,000 *t* values obtained in this manner. To compute the power of the test, an additional 10,000 *t* statistics were estimated in the same way but for the series simulated under $\gamma = 0.5$. Then, the power corresponding to the *z*% significance test was calculated as the percentage of such *t* values that exceeded the *z*% critical value.

3.2. Cointegration Analysis

As shown in the "Results and Discussion" section, both the visual ACF and PACF inspection and ERS tests strongly supported the hypothesis that all log-price series are nonstationary and integrated of order one (I(1)), i.e., they were rendered stationary after taking first differences. Therefore, the relationship between organic and conventional log-prices was examined by means of cointegration analysis. Introduced by Granger (1981), cointegration is a concept involving long run relationships between integrated variables. In a bivariate case, for example, if x_t and y_t are both I(1) variables, they are cointegrated if there exists a β such that the linear combination $u_t = y_t - \beta x_t$ is stationary (i.e., u_t is I(0)), where β indicates the long-run equilibrium relationship between the two variables. However, if u_t is I(1), then it means that y_t and x_t are not cointegrated (Maddala and Kim 2004). Intuitively, if y_t and x_t are cointegrated, on average the difference between y_t and βx_t is the unconditional expectation of u_t ($E(u_t)$). At any point in time $y_t - \beta x_t$ may be different from $E(u_t)$, but y and x will evolve in such a way so as to bring the difference $y - \beta x$ back to $E(u_t)$. In contrast, if y and x are not cointegrated, the unconditional mean of u_t does not exist, and as y and x evolve over time they do not have a tendency to restore a long-run relationship between them.

With the cointegration concept in mind, the second step of the data analysis was to determine whether organic and conventional prices were linked by any long-run equilibrium relationship by testing for cointegration. For this purpose, OLS regressions of organic log-prices ($ln(P_t^O)$) on conventional log-prices ($ln(P_t^C)$) were fit for each market location:

$$ln(P_t^O) = b_0^{OC} + b_1^{OC} \; ln(P_t^C) + v_t^{OC}, \tag{5}$$

where b^{OC}s are parameters and v_t^{OC} is a residual. Then, the estimated residuals ($\hat{v}_t^{OC}$) were examined to determine whether they were stationary or not.

Residual-based cointegration tests have "no cointegration" as the null hypothesis and, thus, test $\hat{v}_t^{OC}$ for a unit root.[5] For this purpose it is common practice to apply Phillips' (1987) Z_α test (Maddala and Kim, 2004), which Phillips and Ouliaris (1990) advocate over the ADF or Z_t tests for having superior power properties. Phillips' $\hat{Z}_\alpha$ test statistic is calculated as

(6) $$\hat{Z}_\alpha = T(\hat{\alpha} - 1) - (1/2)(s_{Tl}^2 - s_k^2)(T^{-2} \sum_{t=2}^{T} (\hat{v}_{t-1}^{OC})^2)^{-1},$$

where $s_{Tl}^2 \equiv T^{-1} \sum_{t=1}^{T} \hat{k}_t^2 + 2\, T^{-1} \sum_{\tau=1}^{l} w_{\tau l} \sum_{t=\tau+1}^{T} \hat{k}_t \hat{k}_{t-\tau}$, $s_k^2 \equiv T^{-1} \sum_{t=1}^{T} \hat{k}_t^2$, $w_{\tau l} = 1 - \tau/(l+1)$, l is a window parameter, and $\hat{\alpha}$ and $\hat{k}_t$ are obtained by performing the regression $\hat{v}_t^{OC} = \hat{\alpha}\hat{v}_{t-1}^{OC} + \hat{k}_t$.

In addition to the relationship between organic and conventional prices, the extent to which organic prices at different locations are related in the long run was examined by fitting OLS regressions like (5) but using organic log-prices for two different markets at a time, and performing cointegration tests on their residuals. For comparative purposes, a similar procedure was also employed on conventional log-prices for different market locations.

Similar to the unit root tests discussed earlier, a potentially important shortcoming of applying cointegration to our data is that organic log-prices are better represented as jump processes, whereas existing critical test values have been generated from two series with independent and identically distributed (i.i.d.) normal errors with zero mean and constant variance (e.g., Phillip and Ouliaris, 1990, p. 168 eq. (3) and Engle and Yoo 1987, p.153). Hence, appropriate critical values were obtained from the Monte Carlo experiments described next.

3.3. Monte Carlo Experiment to Test for Cointegration Between Organic and Conventional Prices

Given the widespread belief that organic prices are twice as large as conventional prices, for simulation purposes the postulated cointegrating relationship between the two price series was

(7) $$ln(P_t^O) = ln(2) + ln(P_t^C) + v_t^{OC}.$$

Further, since the conventional market dwarfs the organic one, it was assumed that cointegration was due to the organic prices changing in response to changes in conventional prices, rather than the other way around.[6] That is, the simulated cointegrated series involved log-prices changing independently of organic log-prices, and the latter reacting so as to re-establish the long-term relationship between the two price series.

$I(1)$ log-price series for conventional corn and soybean were computed by letting $ln(P_t^C) = ln(P_{t-1}^C) + \varepsilon_t^C$, where $\varepsilon_t^C \sim N(0, s^2)$ and the values used for parameter s^2 matched the estimates from the original Minneapolis conventional log-price data. That is, conventional prices were assumed to follow a discrete-time limiting case of a geometric Brownian motion (Dixit and Pindyck, 1994).

Organic log-prices were simulated as a jump process like (2). However, consistent with the assumption of organic-conventional cointegration being driven by organic prices reacting so as to restore the long-run relationship with conventional prices, both the jump probability and the jump size were made functions of the lagged cointegration residuals (v_{t-1}^{OC}) as follows:

(8) $\pi_t^O = 1/\{1 + exp[-\gamma(\lambda_0^{OC} + \lambda_1^{OC} \, |v_{t-1}^{OC}|) - (1-\gamma) \, \Lambda_0^{OC}]\}$,

(9) $J_t^O \sim N(\gamma\, \theta^{OC} \, v_{t-1}^{OC}, \gamma^2 \, (\theta^{OC} \, \sigma^{OC})^2 + (1-\gamma)^2 \, (\Sigma^{OC})^2)$.

That is, (8) and (9) are functions analogous to (3) and (4), but involving v_{t-1}^{OC} instead of e_{t-1}^O. Parameters λ_0^{OC}, λ_1^{OC}, Λ_0^{OC}, θ^{OC}, σ^{OC}, and Σ^{OC} were estimated using sample data in a manner analogous to the estimation of λ_0^O, λ_1^O, Λ_0^O, θ^O, σ^O, and Σ^O described earlier.[7]

It should become clear that the design of the Monte Carlo experiment followed the reasoning behind an error correction model; hence, under the hypothesis of cointegration, the organic log-prices tended to change so as to bring the system back to the long-run equilibrium (7). In other words, in the cointegration case, the short-run dynamics of the organic prices were influenced by the departures from the long-run equilibrium, so that

(10) $\Delta ln(P_{t+1}^O) = \phi\,[\,ln(P_t^O) - ln(2) - ln(P_t^C)\,] + e_{t+1}^O$, $-2 < \phi < 0$,

whereas changes in conventional log-prices were exogenously driven.

Reported results correspond to simulations performed for scenarios with $\gamma = 0$ (used to compute the critical values for the residual test in the presence of jumps) and $\gamma = 0.5$ (used to examine the power of the test). Both experiments consisted of 10,000 simulated series, each of them computed by performing the following iterations:

Step 1. Set $ln(P^{O}_{(0)})$ and $ln(P^{C}_{(0)})$ equal to the first observation from the actual organic and conventional log-price series for Minneapolis, respectively.

Step 2. Compute the jth cointegration error $v^{OC}_{(j)} = ln(P^{O}_{(j)}) - ln(2) - ln(P^{C}_{(j)})$.

Step 3. Compute the (j+1)th probability of jump:

$$\pi^{O}_{(j+1)} = 1/\{1 + exp[-\gamma(\lambda^{OC}_{0} + \lambda^{OC}_{1} \,|v^{OC}_{(j)}|) - (1-\gamma)\,\Lambda^{OC}_{0}]\}.$$

Step 4. Generate an observation $U_{(j+1)}$ from a standard uniform distribution.

Step 5. If $U_{(j+1)} > \pi^{O}_{(j+1)}$, set $ln(P^{O}_{(j+1)}) = ln(P^{O}_{(j)})$ and go to Step 7. Otherwise, go to Step 6.

Step 6. Draw $J^{O}_{(j+1)} \sim \mathrm{N}(\gamma\,\theta^{OC}\,v^{OC}_{(j)},\ \gamma^{2}\,(\theta^{OC}\,\sigma^{OC})^{2} + (1-\gamma)^{2}\,(\Sigma^{OC})^{2})$, and set $ln(P^{O}_{(j+1)}) = ln(P^{O}_{(j)}) + J^{O}_{(j+1)}$.

Step 7. Draw $\varepsilon^{C}_{(j+1)} \sim \mathrm{N}(0, s^{2})$, and set $ln(P^{C}_{(j+1)}) = ln(P^{C}_{(j)}) + \varepsilon^{C}_{(j+1)}$.

Step 8. If $j < 10{,}000 + T$, go back to Step 2. Otherwise, stop.

The critical values and the power of the residual cointegration test were calculated from the final T simulated observations.

3.4. Monte Carlo Experiment to Test for Cointegration Between Organic Prices at Different Markets

Another Monte Carlo experiment was performed to determine the critical values and the power of the cointegration tests for the organic log-prices at different markets. This experiment differed from the previous one in that it involved the relationship between two series characterized by jump processes, so as to emulate the behavior of organic log-prices at different market locations.

The organic markets used to calibrate the cointegration errors were Minneapolis and Dallas for corn, and Minneapolis and Fargo for soybean. The Dallas market was chosen because among the other markets we had the longest series available for, its state ranked highest in terms of acreage devoted to organic corn. In the case of soybean we used Fargo because its series was about one year longer than the Dallas series (see Table 1). The postulated long-run equilibrium relationship (i.e., the analog of (7)) between the organic log-prices at the two markets (i.e., Minneapolis and Dallas for corn, and Minneapolis and Fargo for soybean) was (11):

$$(11) \qquad ln(P_t^{O_1}) = ln(P_t^{O_2}) + v_t^{O_1 O_2}.$$

The prices of both of the simulated organic series were assumed to change as defined by the analogs of expressions (8)-(9), so as to bring the system back to the long-run equilibrium (11). The parameterization of the (8)-(9) analogs and the simulations were performed by applying procedures similar to the ones used to analyze the organic-conventional relationship. Therefore, their description is omitted to save space.

4. Results and Discussion

The organic and conventional corn and soybean spot prices series for the Minneapolis market, as well as their ratio, are depicted in panels A and B of Figure 1; the plots for the other markets look similar and are omitted here in the interest of space. The first noticeable feature in Figure 1.A is the piecewise linear shape of the organic prices, denoting a constant price for several weeks before a price change or jump occurs. For the organic series, $\Delta y_t = 0$ was observed with frequencies ranging from 80.1% (for soybean in Minneapolis) to 94.3% (for corn and soybean in Fargo). In other words, on average, organic prices changed at most once every five weeks. Therefore, the null hypothesis that the organic series behave as diffusions is rejected at any reasonable level of significance.[8] Given the large frequency of occurrences with $\Delta y_t = 0$, organic prices are more realistically modeled as jump processes rather than diffusions (Neftci, Ch. 8; Pennacchi, Ch. 11).[9] Their step-shape pricing pattern is likely to be associated with the relative thinness of the organic markets and the impact of contracting on them. According to the lower plots of panels A and B in Figure 1, for the period analyzed the ratio of organic to conventional prices arguably oscillated around two for soybeans, but it was usually larger (and sometimes much greater) than two for corn.

Table 2 reports summary statistics for organic and conventional prices, price premiums, and price ratios for all of the market locations under study. Average ratios for all corn markets are above the "2×" threshold, denoting the persistence of substantial price premiums for organic corn. For soybean, average ratios are more closely aligned with the "doubling" rule. In all instances, however, the ratios vary substantially, as evidenced by the coefficients of variation of the ratios, and the minimum and maximum ratios in the series.

Additional information about the jump-like behavior of organic prices is furnished in Table 3. Minneapolis exhibited the largest number of jumps for both crops. Even for this market, organic corn (soybean) prices only changed 12.2% (19.9%) of the weeks. Alternatively, the average period between price jumps in Minneapolis was 8.2 (= 1/0.122) weeks for corn and 5.0 (= 1/0.199) weeks for soybean. When a price change did occur in Minneapolis, its average size (standard deviation) was \$0.22/bu (\$1.11/bu) for corn and \$0.31/bu (\$3.10/bu) for soybean.

The results of the ERS tests for the complete set of organic and conventional series are presented in Table 4. For log-price levels, all test statistics are substantially below the critical values corresponding to standard levels of significance, whereas the opposite is true for log-price first differences. Therefore, the empirical evidence is consistent with the assumption that both log-price series are $I(1)$.

Table 5 shows results for the cointegration regression (5) and the residual-based tests corresponding to (6). The *p*-values for the $\hat{Z}_{\alpha}$ test statistics are all larger than conventional levels of significance, with the smallest *p*-value equal to 0.116 (for soybean in Omaha). This indicates that the data fail to reject the null hypothesis of no cointegration for both crops in all markets. Importantly, the power of the tests is high, suggesting that the alternative of cointegration is not likely. In other words, there is not enough evidence to reject the null hypothesis that the residuals from the organic-conventional cointegrating regression contain a unit root, which means no cointegrating relationship between organic and conventional prices.

The absence of a long-run relationship does not preclude the existence of a short-run association. Hence, we examined short-run dependencies by means of impulse response function (IRF) and forecast error variance decomposition (FEVD) analyses based on VARs estimated using first-differenced log-prices. Succinctly, the data provide no evidence either of short-term dependencies between organic and conventional prices. Results are omitted in the interest of space, but are available from the authors upon request.

It is arguable whether the present results are surprising. On one hand, one might think that organic crop prices would reflect the additional cost of such method of production, making organic crops a "premium" commodity compared to their conventional counterparts, and allowing therefore for some degree of substitutability between them. In this regard, a close association between organic and conventional prices is more likely to be observed if the two types of crops are highly substitutable in production or consumption.

On the other hand, for some purposes organic and conventional crops cannot really be considered close substitutes, if substitutes at all. For example, for livestock to be considered organic it is required that it be fed with organic products as established by the National Organic Program regulations in section §205.237: "The producer of an organic livestock operation must provide livestock with a total feed ration composed of agricultural products, including pasture and forage, that are organically produced …"

Nonetheless, it could be argued that some degree of substitutability could exist even in this latter context if the producer switches his livestock to conventional feed, making it non-organic livestock because in section §205.236 (a) the National Organic Program regulations establishes that "Livestock products that are to be sold, labeled or represented as organic must be from livestock under continuous organic management from the last third of gestation or hatching". But such substitution is limited to a one-time event, since section §205.236 (b) states that "Livestock or edible livestock products that are removed from an organic operation and subsequently managed on a nonorganic operation may be not sold, labeled or represented as organically produced". Therefore, producers could switch their livestock to conventional but after that they could no longer switch it back to organic. Dairy producers eventually could, however, do the switch more than once because in section §205.236 (a) it is stipulated that "Milk or milk products must be from animals that have been under continuous organic management beginning no later than one year prior to the production of the milk or milk products that are to be sold, labeled or represented as organic", with some specific exceptions being also admitted.

Our findings of no cointegration between organic and conventional prices not only support the limited substitutability argument in production, but also exemplify the significant impact that the organic livestock feed requirements have in the organic crop market. Taking a closer look at Figure 1.A, it can be seen that in mid 2007 there was a sizable jump in organic corn prices in Minneapolis. Such a change is the largest in the series, with prices rising from \$6.75/bu to \$10/bu, that is, a 48% increase from the second to third week of July 2007. Importantly, Figure 1.A also reveals that conventional corn prices in Minneapolis did not experience a similar price change over the same period; in fact, they decreased by 13%. The behavior of corn prices in Minneapolis during mid 2007 is representative of the price dynamics in all other locations around that period.

Looking for an explanation of the contrasting behavior of the organic prices compared to the conventional ones, Born's (2005, p. 1) characterization seems to fit in: "Organic markets can be volatile, with periods of high demand and short supply for certain crops and periods of high supply and sluggish demand for others". Evidence on the matter can be found that not only supports Born's statement, but also provides further explanation with respect to the 2007 organic price jumps and their link to organic livestock requirements. For example, Clarkson (2007, p. 163) pointed out before the U.S. House of Representatives' Agriculture Committee that "demand is troubled by an increasing shortfall in the supply of organic raw materials" and then added that "U.S. demand for organic soy foods and feeds is growing so rapidly that processors probably consume twice as many organic soybeans as are produced in the U.S. Despite excellent prices and an abundance of land and great farmers, these U.S. processors find themselves importing organic soybeans from countries such as China, Brazil, Paraguay, Bolivia and Argentina".

Along the same lines, Lavigne (2007) argued that shortages of organic feed were due to the different growth pace of livestock feed demand and supply, and further added that imports of organic soybean had held its price steady while organic corn had not faced foreign competition and had, therefore, increased significantly.[10] Furthermore, Dimitri and Oberholtzer (2009, p. 8-9) stated that "Organic 'handlers' move nearly all organic products from the farm to the retailer" and they added that "sourcing organic ingredients has become even more challenging as demand for organic products has increased". In that study, the authors indicated that almost 60% of organic handlers faced limited supply of raw materials during 2007.

Examining the organic livestock growth trend in recent years (see Figure 2) and comparing it with the trend for acreage destined for organic corn and soybean production over the same period (Figure 3), the explanation for having short supply of organic feed crops and consequent increase in their prices (as the one we noted particularly for corn) is evident. From 2001 through 2007 the U.S. organic beef, dairy, and poultry production increased by 325%, 241%, and 143%, respectively, whereas over that same period the acreage destined in the U.S to organic corn production increased by only 84% and the one for organic soybean actually decreased by 42%. Such disparity in growth rates between livestock and acreage for feedstuff within the organic agriculture sector, along with the imports' explanation discussed above, helps better understand the significant 2007 organic corn jump in our data.

It is worth pointing out that it is evident from Table 2 that the data are consistent with the hypothesis that organic crops sell at a premium over conventional ones. This is true because all of the minimum organic/conventional price ratios in the table are greater than unity. This means that the relationship between organic and conventional prices may be characterized by threshold cointegration. Threshold cointegration refers to the case in which the adjustment towards the long-run equilibrium, like the one defined by equation (7), is discrete (Balke and Fomby, 1997; Maddala and Kim, 2004) rather than continuous as assumed in the present study. In our case, threshold cointegration would imply that the adjusting process would be triggered when the organic log-price minus the conventional log-price fell below a sufficiently small positive threshold, whereas no adjustment would occur above such threshold allowing organic and conventional prices to freely diverge. Threshold cointegration could be even more relevant in the context of spatial markets, due to the presence of transaction costs (Goodwin and Piggott, 2001).

To explore the possibility of threshold cointegration, we performed the test advocated by Li and Lee (2010) under the two alternative assumptions that (a) conventional prices lead organic prices, and (b) organic prices lead conventional ones. The Li-Lee test was used because Lee, Li, and Strazicich (forthcoming) found that it exhibits the most desirable properties among OLS-based tests of the null of no cointegration against the alternative of threshold cointegration under Gaussian noise. Succinctly, the results reported in Table 6 provide no evidence of threshold cointegration for any of the corn markets or some of the soybean markets. The instances where the null hypothesis is rejected should be interpreted with caution, as the Li-Lee test tends to over-reject the null, the more so the smaller the sample (Li and Lee, 2010). Furthermore, results under the assumption that conventional prices lead organic prices should be considered suggestive rather than formal evidence regarding threshold cointegration, because the Li-Lee test assumes Gaussian residuals. Extending the model presented here to analyze the case of threshold cointegration in the presence of jumps is beyond the scope of the present study, but it seems an interesting topic for future research.

The results in the present study are useful for several reasons. Firstly, they provide important information for designing organic insurance pricing provisions. In this regard, RMA should not only take into account that prices for organic corn and soybean are higher than the corresponding conventional prices (see Table 2), but also that the former do not follow the latter. It seems sensible that crop insurance policies be offered with additional price elections, compensating organic farmers so as to better reflect the idiosyncrasies of organic agriculture. Given that RMA currently calculates organic crops' insurance rates using conventional crop prices, this recommendation is particularly relevant for the determination of rates for the Actual Production History and Crop Revenue Coverage insurance products. Secondly, conventional producers evaluating whether to switch to organic production should be aware that organic corn and soybean prices have been about as volatile as their conventional counterparts. Further, they should also be aware that organic corn and soybean have sold at a premium, but that such premium has experienced substantial volatility in both absolute as well as relative terms. Finally, the historical data indicate that existing futures and option markets would be of little use to cross hedge the price risks of organic corn and soybean in any meaningful way.

4.1. Cointegration Between Organic Prices at Different Markets

Another dimension to the study consisted of analyzing whether organic prices in different locations are related to each other in the long run. In this way, we wanted to assess how idiosyncratic organic markets are. To this end, we fitted OLS cointegration regressions similar to (5) but for pairs of organic log-prices at different markets, so that the organic series for one location was regressed against its counterpart for a different location.

Results for the OLS regressions and the corresponding residual-based tests for location pairs for which we had at least T = 246 observations are reported in Table 7. It can be noticed that all of the pairs but one for corn (Omaha-Dallas) show evidence of cointegration. Since cointegration is transitive,[11] however, rejection of the null hypothesis of no cointegration for all pairs other than Omaha-Dallas means that non-rejection for the latter should be considered with some skepticism. It can also be seen that the evidence in favor of cointegration is strongest for pairs involving Minneapolis, suggesting that such market is the organic hub and that there could be some sort of price disagreement between the markets in the second tier.

To shed further light on the relationships between organic log-prices at different markets, we fitted the analogs of regressions (8) and (9). Results for the jump probability logit model and the jump size regression model are reported in Tables 8 and 9, respectively. The main insight from Table 8 is that departures from the cointegrating relationship between pairs of organic log-prices do not seem to induce changes in the probabilities of price changes. That is, jump probabilities do not appear to respond to deviations from the respective long-run relationships. However, Table 9 shows strong evidence that when organic price changes do occur, their magnitudes are significantly negatively related to the lagged cointegrating errors, so as to restore the corresponding long-run relationship between organic prices. This is true because all of the slope estimates $\theta_1^{O_i O_j}$ are negative and, with the exception of Omaha-Dallas corn, at least one of such estimates is statistically significantly negative for each location pair.[12] The significantly negative estimates $\theta_1^{O_{Minneapolis} O_j}$ also suggests that when prices in the Minneapolis organic market do change, the magnitude of such change is negatively related to the before-jump gap between the price in Minneapolis and the price in the other markets. Together, Tables 8 and 9 provide further support for the hypothesis that there are long-run relationships between log-prices at different U.S. organic markets.

For completeness, and as a way of comparing the relationship between organic log-prices at different locations with those between conventional log-prices, results for the cointegration regressions and residual-based cointegration tests for the conventional log-price series are shown in Table 10. According to this table, cointegration is present in all conventional market locations at any reasonable level of significance. The *p*-values reported in Table 10 are orders of magnitude smaller than the *p*-values in Table 7, suggesting that the long-run relationship between log-prices at different locations is stronger for conventional than for organic markets, in the sense that the probability of rejecting the null of no cointegration by chance alone (i.e.: type I error) is much smaller in the former than in the latter.

5. Conclusions

In recent years there has been a steady and significant growth of the organic sector (OTA, 2009). However, little economic research has been done on the subject likely due to the lack of data availability. The present study aimed at starting filling this gap; in particular at determining whether the organic corn and soybean prices in the U.S. follow their conventional counterparts. Our findings suggest that there is no basis for advocating the existence of a long-run relationship between organic and conventional prices.

Evidence of spatial price cointegration among organic markets was found, particularly between pairs of markets we had data for and the presumed organic hub, Minneapolis, indicating that such market is the leading one. Overall, spatial cointegration in organic markets seems weaker than the one present in conventional markets, suggesting that local market forces may exert a stronger effect on the determination of local prices for organic crops than for conventional ones. Departures from the long-term relationships across organic markets do not seem to increase the probability of price changes, however, whenever price changes do occur, they tend to restore such long-term relationships.

If our conclusions for the organic corn and soybean markets extend to other organic crop markets, it would imply that organic crop markets have unique characteristics when compared with their conventional counterparts. Such idiosyncrasies need to be taken into consideration, for example, by RMA when setting the Federal crop insurance policy for organic farmers. Our results also suggest that organic prices are as volatile as conventional ones, that the premiums paid for organic crops exhibit substantial variability, and that existing futures and derivatives markets do not provide effective tools to manage price risks for the organic sector.

Notes

1. It must be noted, however, that Welsh (1999) reported some Midwestern organic grain and soybean production systems to be more profitable than conventional ones, even without price premiums.

2. RMA is offering a pilot program with additional price elections in 2011 for four organic crops, including corn and soybean. For these two organic crops, contrarily to what our analysis will indicate as being a non-existent long run relationship, the additional price elections under the pilot program are based on the prices of conventional crops (RMA, 2010).

3. The results reported in this article were obtained by replacing missing observations by the values of the immediately preceding observations. To assess the robustness of the results to the method used to fill in missing observations, we performed the analysis for two additional scenarios. Missing observations were replaced by the values of the immediately following observations in one scenario, and by the average of the contiguous observations in the other one. Results were essentially the same regardless of the method used.

4. The SF GR 110 AMS report actually corresponds to East River South Dakota Grain Markets, but Rodale identifies it with Fargo, which is relatively close. For the San Francisco and Detroit corn series, and the Dallas and Detroit soybean series, both the organic as well as the conventional series were provided by Rodale because they were not available from AMS. There were 9 and 7 missing observations in the conventional corn series for San Francisco and Detroit, respectively, and 7 missing observations in each of the conventional soybean series for Dallas and Detroit; all of which were replaced by the average of the two contiguous observations.

5. Although a test with the null of cointegration instead might seem more appealing, Phillips and Ouliaris (1990) point out some major pitfalls associated with such an approach.

6. The data do not support the view that conventional prices follow organic prices for any of the markets under study. The hypotheses of conventional prices following organic prices, rather than the other way around, was tested by means of the cointegration test advocated by Banerjee, Dolado, and Mestre (BJM) (1998). The main advantage of the BJM test for the present

application is that it tests whether conventional prices adjust to restore a cointegrating relationship, assuming that organic prices are weakly exogenous (i.e., that organic prices do not respond to deviations in the cointegrating relationship, if there is any). Another useful feature of the BJM is that, since the dependent variable is the conventional price, the fact that organic prices are better represented as jumps rather than diffusions is irrelevant. Results of the BJM test are available from the authors upon request.

7. For example, appropriate values for λ_0^{OC} and λ_1^{OC} were obtained from a logit regression involving the re-ordered (so as to build the "ideal" logit) organic-conventional cointegrating errors for the Minneapolis market. Similarly, the value of θ^{OC} was obtained from an OLS regression of the re-ordered organic corn and soybean log-price jumps against the corresponding re-ordered lagged cointegration errors v_{t-1}^{OC}.

8. This is true because the probability of having $\Delta y_t = 0$ is zero if series y_t follows a diffusion.

9. The upper panels of Figures 1.A and 1.B provide clear graphical illustrations of the stark differences between the behaviors of diffusions and jump processes, exemplified respectively by the conventional and the organic price series. Diffusions are such that prices change every single period, typically by small amounts. In contrast, jump processes are characterized by extended periods of time where prices remain constant and, in the relatively infrequent occasions when prices do change, they "jump" (up or down) by relatively large amounts. Johannes (2004) estimated jump-diffusion processes using interest rate data, and Hilliard and Reis (1999) and Koekebakker and Gudbrandare (2004) applied jump processes to derivatives markets; however, we are not aware of any study fitting pure jump processes to commodity spot prices.

10. Our data confirm this line of thought because for all locations the jump in organic soybean prices over the period being discussed was much smaller; the biggest one being 18% for one location.

11. Suppose variables x, y, and z are $I(1)$, then x and z must be cointegrated if (i) x and y are cointegrated, and (ii) y and z are contegrated (Taylor and Tonks, 1989). However, on any sample, it is not uncommon to find test statistics indicating that one of the variable pairs is not

cointegrated while the other two variable pairs are cointegrated (e.g., Rapsomanikis and Karfakis, 2007). In fact, referring to estimated cointegrating relationships, Enders and Hurn (1994, pp. 186-187), state that "There is no reason to expect transitivity across the various cointegrating relationships." This is a sampling problem, i.e., a test statistic computed from a finite sample of a cointegrated process may incorrectly lead to no rejection of the null of no cointegration with probability greater than zero (except in the extremely unlikely case where the test has power equal to one). Ferré (2004) explains why this problem may arise, and Mishra (2007) shows how to generate simulated data characterized by it.

12. However, as pointed out in connection with Table 7, the finding that the slope for the Omaha-Dallas corn regressions is not significantly negative should be taken with care because cointegration is transitive.

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Table 1. Summary Information for Organic Prices Series

	Corn				Soybean			
	Date		Observations		Date		Observations	
	Start	End	Total	Missing	Start	End	Total	Missing
Minneapolis	10/26/04	7/9/09	246	13	10/26/04	7/2/09	246	13
Omaha	10/26/04	7/9/09	246	13	10/26/04	7/2/09	246	13
Fargo	10/26/04	7/9/09	246	15	10/26/04	7/2/09	246	13
Dallas	10/26/04	7/9/09	246	13	10/26/04	8/5/08	198	7
Detroit	10/26/04	8/5/08	198	7	10/26/04	8/5/08	198	7
San Francisco	11/9/04	7/8/08	193	6	n/a	n/a	n/a	n/a

Table 2. Summary Statistics for Organic and Conventional Prices, Price Premiums and their Ratio by Market

		Corn				Soybean			
		Organic	Conv.	Premium	Ratio	Organic	Conv.	Premium	Ratio
Minneapolis	Mean	7.21	3.05	4.17	2.52	16.29	7.84	8.45	2.09
	Std.dev.	2.32	1.23	1.63	0.63	6.42	2.61	4.75	0.49
	Coeff.var.	0.32	0.40	0.39	0.25	0.39	0.33	0.56	0.24
	Min.	4.00	1.30	1.47	1.45	9.50	4.74	3.66	1.37
	Max.	11.00	6.66	8.31	4.23	31.00	14.74	22.69	3.82
Omaha	Mean	7.24	3.18	4.05	2.38	15.09	8.02	7.07	1.96
	Std. dev.	2.70	1.33	1.83	0.56	3.92	2.79	2.26	0.35
	Coeff.var.	0.37	0.42	0.45	0.23	0.26	0.35	0.32	0.18
	Min.	4.00	1.47	1.09	1.28	11.00	4.89	3.36	1.29
	Max.	11.00	7.09	8.00	3.67	25.00	15.74	16.47	2.93
Fargo	Mean	7.16	3.11	4.05	2.47	15.53	7.79	7.74	2.02
	Std.dev.	2.29	1.34	1.42	0.60	5.97	2.74	3.95	0.41
	Coeff.var.	0.32	0.43	0.35	0.24	0.38	0.35	0.51	0.20
	Min.	4.50	1.46	1.23	1.33	10.00	4.78	3.39	1.35
	Max.	11.00	7.08	7.63	3.94	31.00	15.48	19.57	3.11
Dallas	Mean	7.72	3.59	4.13	2.17	14.39	7.11	7.28	2.13
	Std.dev.	3.02	1.25	2.11	0.45	3.15	2.61	1.32	0.36
	Coeff.var.	0.39	0.35	0.51	0.21	0.22	0.37	0.18	0.17
	Min.	4.35	2.07	0.58	1.13	11.25	4.30	4.50	1.42
	Max.	13.00	7.49	8.14	3.18	21.00	14.55	10.58	2.94
Detroit	Mean	6.99	3.07	3.92	2.40	14.10	7.60	6.51	1.95
	Std.dev.	2.61	1.34	1.77	0.58	3.14	2.83	1.23	0.33
	Coeff.var.	0.37	0.44	0.45	0.24	0.22	0.37	0.19	0.17
	Min.	4.15	1.58	1.11	1.29	11.25	4.95	3.65	1.31
	Max.	11.00	7.05	7.85	3.49	21.00	16.04	9.69	2.67
San Francisco	Mean	9.00	4.30	4.70	2.10	n/a	n/a	n/a	n/a
	Std.dev.	3.28	1.43	2.28	0.41	n/a	n/a	n/a	n/a
	Coeff.var.	0.36	0.33	0.48	0.20	n/a	n/a	n/a	n/a
	Min.	5.45	2.38	2.13	1.49	n/a	n/a	n/a	n/a
	Max.	14.00	8.79	9.74	3.29	n/a	n/a	n/a	n/a

Table 3. Summary Statistics for Jumps in Organic Prices, by Market

		Corn	Soybean
Minneapolis	Number of observations	246	246
	Number of jumps	30	49
	Frequency of jumps	0.122	0.199
	Average jump size	0.22	0.31
	Std. Dev. jump size	1.11	3.10
Omaha	Number of observations	246	246
	Number of jumps	19	24
	Frequency of jumps	0.077	0.098
	Average jump size	0.34	0.35
	Std. Dev. jump size	1.34	1.98
Fargo	Number of observations	246	246
	Number of jumps	14	14
	Frequency of jumps	0.057	0.057
	Average jump size	0.32	0.36
	Std. Dev. jump size	0.98	3.39
Dallas	Number of observations	246	198
	Number of jumps	20	17
	Frequency of jumps	0.081	0.086
	Average jump size	0.31	0.56
	Std. Dev. jump size	1.43	1.11
Detroit	Number of observations	198	198
	Number of jumps	16	18
	Frequency of jumps	0.081	0.091
	Average jump size	0.43	0.49
	Std. Dev. jump size	0.95	1.20
San Francisco	Number of observations	193	n/a
	Number of jumps	16	n/a
	Frequency of jumps	0.083	n/a
	Average jump size	0.53	n/a
	Std. Dev. jump size	1.12	n/a

Table 4. ERS DF-GLS Unit Root Test Statistics for Organic and Conventional Log-Prices

A. Log-Price Levels [$ln(P_t)$]

	Conventional		Organic					
	Corn	Soybean	Corn			Soybean		
	Test stat.[a]	Test stat.[a]	Test stat.	*p*-value	Power	Test stat.	*p*-value	Power
Minneapolis	-1.81	-2.16	-1.75	0.460	0.830	-1.30	0.737	0.990
Omaha	-1.37	-1.91	-1.64	0.525	0.877	-1.49	0.628	0.976
Fargo	-1.53	-1.87	-1.33	0.715	0.964	-0.93	0.893	0.998
Dallas	-1.63	-1.81	-1.47	0.630	0.934	-0.74	0.940	1.000
Detroit	-2.31	-1.49	-1.45	0.641	0.939	-0.65	0.957	1.000
San Francisco	-1.44	n/a	-1.72	0.477	0.843	n/a	n/a	n/a

[a]For the conventional series, critical values for the test statistics are -3.48 (-2.89, -2.57) at the 1% (5%, 10%) significance levels, respectively (Elliot, Rothenberg and Stock, 1996, p.825).

B. Log-Price First Differences [$\Delta ln(P_t) \equiv ln(P_t) - ln(P_{t-1})$]

	Conventional		Organic[b]			
	Corn	Soybean	Corn		Soybean	
	Test stat.[a]	Test stat.[a]	Test stat.	*p*-value	Test stat.	*p*-value
Minneapolis	-7.77***	-5.89***	-18.50***	0.000	-13.77***	0.000
Omaha	-4.39***	-12.17***	-16.07***	0.000	-16.30***	0.000
Fargo	-5.80***	-11.80***	-15.68***	0.000	-15.65***	0.000
Dallas	-7.12***	-6.73***	-15.71***	0.000	-14.30***	0.000
Detroit	-4.50***	-8.14***	-16.17***	0.000	-15.76***	0.000
San Francisco	-3.40**	n/a	-14.94***	0.000	n/a	n/a

*** (**, *) Denotes significance at the 1% (5%, 10%) level.

[a]For the conventional series, critical values for the test statistics are -3.48 (-2.89, -2.57) at the 1% (5%, 10%) significance levels, respectively (Elliot, Rothenberg and Stock, 1996, p.825).

[b]Power is omitted because the null is being rejected at standard levels of significance.

Table 5. Regression Results for Cointegration between Organic and Conventional Log-Prices, and Residual-Based Cointegration Tests

Model: $ln(P_t^O) = b_0^{OC} + b_1^{OC}\ ln(P_t^C) + v_t^{OC}$

						Residual-based test		
		b_0^{OC}	b_1^{OC}	R^2	# Obs.	$\hat{Z}_\alpha$	*p*-value	Power
Corn	Minneapolis	1.28	0.62	0.60	246	-14.62	0.186	0.99
		(35.89)	(19.15)					
	Omaha	1.14	0.71	0.67	246	-12.32	0.277	1.00
		(30.78)	(22.12)					
	Fargo	1.29	0.60	0.66	246	-7.60	0.555	1.00
		(41.77)	(21.74)					
	Dallas	0.88	0.89	0.65	246	-11.88	0.296	1.00
		(16.68)	(21.52)					
	Detroit	1.18	0.67	0.61	198	-8.00	0.526	1.00
		(27.68)	(17.37)					
	San Francisco	0.81	0.94	0.71	194	-10.56	0.363	1.00
		(12.85)	(21.66)					
Soybean	Minneapolis	0.86	0.93	0.64	246	-12.17	0.282	0.761
		(9.57)	(21.01)					
	Omaha	1.41	0.63	0.72	246	-17.19	0.116	0.466
		(27.20)	(25.02)					
	Fargo	0.92	0.88	0.70	246	-9.59	0.418	0.891
		(12.21)	(23.79)					
	Dallas	1.58	0.56	0.79	198	-10.22	0.381	0.863
		(39.43)	(26.75)					
	Detroit	1.53	0.56	0.79	198	-10.39	0.373	0.854
		(37.17)	(27.01)					

Note: *t* statistics are shown in parenthesis below the corresponding coefficients.

Table 6. Results for Li-Lee Threshold Cointegration Tests between Organic and Conventional Log-Prices at Different Corn and Soybean Markets

		Conventional Prices lead Organic Prices		Organic Prices lead Conventional Prices	
		BO_t	$\widetilde{BO}_t$	BO_t	$\widetilde{BO}_t$
Corn	Minneapolis	10.24	16.10	5.81	8.15
	Omaha	13.71	8.02	4.99	10.36
	Fargo	13.55	19.13	9.69	8.70
	Dallas	17.57	15.40	11.31	11.16
	Detroit	17.83	11.64	6.96	9.50
	San Francisco	7.82	5.37	11.16	6.41
Soybean	Minneapolis	24.34**	24.14**	10.28	25.44**
	Omaha	33.44***	16.85	6.71	18.50
	Fargo	36.46***	25.55**	9.77	9.86
	Dallas	12.94	14.34	8.36	11.80
	Detroit	35.55***	25.06**	16.66	9.41

*** (**, *) Denotes significance at the 1% (5%, 10%) level.

Note: The Li-Lee threshold BO test statistics are described in subsection 4.1 of Li and Lee (2010). Critical values for BO_t ($\widetilde{BO}_t$) are 26.98, 22.07, and 19.57 (26.15, 21.44, and 19.17) at the 1%, 5%, and 10% significance levels, respectively. The results reported in the table were obtained by assuming two lags for the differenced data.

Table 7. Regression Results for Cointegration between Organic Log-Prices at Different Markets, and Residual-Based Cointegration Tests[a]

Model: $ln(P_t^{O_i}) = b_0^{O_iO_j} + b_1^{O_iO_j}\ ln(P_t^{O_j}) + v_t^{O_iO_j}$

	O_i	O_j	$b_0^{O_iO_j}$	$b_1^{O_iO_j}$	R^2	Observ.	Residual-based test	
							$\hat{Z}_\alpha$	*p*-value
Corn	Minn.[b]	Omaha	-0.21	1.10	0.93	246	-44.82	0.001
			(-5.58)	(55.68)				
	Minn.[b]	Fargo	0.11	0.94	0.91	246	-44.93	0.001
			(2.87)	(49.94)				
	Minn.[b]	Dallas	-0.16	1.11	0.90	246	-30.07	0.010
			(-3.47)	(45.69)				
	Omaha	Fargo	0.37	0.81	0.89	246	-21.52	0.049
			(10.26)	(43.36)				
	Omaha	Dallas	0.04	1.01	0.98	246	-13.77	0.212
			(2.15)	(97.85)				
	Fargo	Dallas	-0.15	1.11	0.87	246	-20.54	0.058
			(-2.86)	(40.14)				
Soybean	Minn.[b]	Omaha	1.09	0.58	0.78	246	-26.22	0.020
			(20.30)	(29.84)				
	Minn.[b]	Fargo	0.34	0.86	0.82	246	-27.48	0.016
			(5.04)	(34.05)				
	Omaha	Fargo	-0.80	1.30	0.82	246	-22.26	0.042
			(-7.71)	(33.71)				

[a] *t* statistics are shown in parenthesis below the corresponding coefficients.
[b] "Minn." means Minneapolis.

Table 8. Logit Regression Results for Jump Probabilities between Organic Log-Prices at Different Markets[a]

Model: $\pi_t^{O_i} = 1/\{1 + exp[-(\lambda_0^{O_iO_j} + \lambda_1^{O_iO_j} \mid v_{t-1}^{O_iO_j} \mid)\}$

O_i	O_j	Corn $\lambda_0^{O_iO_j}$	Corn $\lambda_1^{O_iO_j}$	Corn *Mc-Fadden Pseudo-R^2*	Corn Observ.	Soybean $\lambda_0^{O_iO_j}$	Soybean $\lambda_1^{O_iO_j}$	Soybean *Mc-Fadden Pseudo-R^2*	Soybean Observ.
Minn.[b]	Omaha	-1.73***	-4.14	0.006	246	-1.46***	0.57	0.001	246
		(-5.65)	(-0.97)			(-6.66)	(0.46)		
Omaha	Minn.[b]	-2.83***	4.27	0.016	246	-2.39***	2.03	0.004	246
		(-8.20)	(1.58)			(-7.85)	(0.83)		
Minn.[b]	Fargo	-2.37***	4.99*	0.018	246	-1.42***	0.24	0.0001	246
		(-7.91)	(1.92)			(-6.15)	(0.16)		
Fargo	Minn.[b]	-2.92***	1.44	0.001	246	-3.12***	2.62	0.009	246
		(-6.60)	(0.32)			(-7.15)	(1.02)		
Minn.[b]	Dallas	-1.82***	-2.04	0.002	246	n/a	n/a	n/a	n/a
		(-5.97)	(-0.64)						
Dallas	Minn.[b]	-2.80***	3.64	0.013	246	n/a	n/a	n/a	n/a
		(-7.38)	(1.38)						
Omaha	Fargo	-2.99***	4.70*	0.024	246	-2.18***	-0.56	0.00001	246
		(-7.66)	(1.87)			(-5.97)	(-0.15)		
Fargo	Omaha	-2.18***	-8.80	0.022	246	-2.78***	-0.20	0.0001	246
		(-4.41)	(-1.34)			(-6.07)	(-0.06)		
Omaha	Dallas	-1.83***	-13.27	0.014	246	n/a	n/a	n/a	n/a
		(-3.65)	(-1.37)						
Dallas	Omaha	-1.93***	-10.41	0.011	246	n/a	n/a	n/a	n/a
		(-4.32)	(-1.22)						
Fargo	Dallas	-2.47***	-4.74	0.012	246	n/a	n/a	n/a	n/a
		(-6.39)	(-1.07)						
Dallas	Fargo	-2.70***	2.48	0.007	246	n/a	n/a	n/a	n/a
		(-7.26)	(1.04)						

[a] *t* statistics are shown in parenthesis below the corresponding coefficients.

[b] "Minn." means Minneapolis.

*** (**, *) Denotes significantly different from zero at the 1% (5%, 10%) level, based on the two-sided *t* statistic.

Table 9. OLS Regression Results for Jump Sizes between Organic Log-Prices at Different Markets[a]

Model:		$J_t^{O_i} = \theta_0^{O_iO_j} + \theta_1^{O_iO_j}\ v_{t-1}^{O_iO_j} + error_t^{O_iO_j}$							
O_i	O_j	Corn				Soybean			
		$\theta_0^{O_iO_j}$	$\theta_1^{O_iO_j}$	R^2	Observ.	$\theta_0^{O_iO_j}$	$\theta_1^{O_iO_j}$	R^2	Observ.
Minn.[b]	Omaha	0.01	-0.81***	0.41	30	0.03	-0.33***	0.22	49
		(0.57)	(-4.36)			(1.57)	(-3.63)		
Omaha	Minn.[b]	0.05	-0.13	0.005	19	0.02	-0.24	0.05	24
		(1.08)	(-0.29)			(0.79)	(-1.14)		
Minn.[b]	Fargo	0.02	-0.63***	0.26	30	0.03	-0.40***	0.26	49
		(1.00)	(-3.16)			(1.45)	(-4.08)		
Fargo	Minn.[b]	0.02	-0.70***	0.48	14	0.04	-0.56**	0.28	14
		(0.90)	(-3.39)			(1.06)	(-2.16)		
Minn.[b]	Dallas	0.01	-0.66***	0.32	30	n/a	n/a	n/a	n/a
		(0.66)	(-3.63)						
Dallas	Minn.[b]	0.04	-0.13	0.009	20	n/a	n/a	n/a	n/a
		(1.01)	(-0.41)						
Omaha	Fargo	0.03	-0.36	0.07	19	0.01	-0.55***	0.29	24
		(0.82)	(-1.15)			(0.56)	(-3.02)		
Fargo	Omaha	0.02	-0.91***	0.62	14	0.005	-0.56**	0.32	14
		(0.77)	(-4.44)			(0.14)	(-2.37)		
Omaha	Dallas	0.05	-0.28	0.006	19	n/a	n/a	n/a	n/a
		(1.30)	(-0.33)						
Dallas	Omaha	0.04	-0.70	0.04	20	n/a	n/a	n/a	n/a
		(1.07)	(-0.92)						
Fargo	Dallas	-0.03	-1.05***	0.68	14	n/a	n/a	n/a	n/a
		(-0.14)	(-4.41)						
Dallas	Fargo	0.028	-0.36	0.09	20	n/a	n/a	n/a	n/a
		(0.72)	(-1.34)						

[a] *t* statistics are shown in parenthesis below the corresponding coefficients.

[b] "Minn." means Minneapolis.

*** (**, *) Denotes significantly different from zero at the 1% (5%, 10%) level, based on the two-sided *t* statistic.

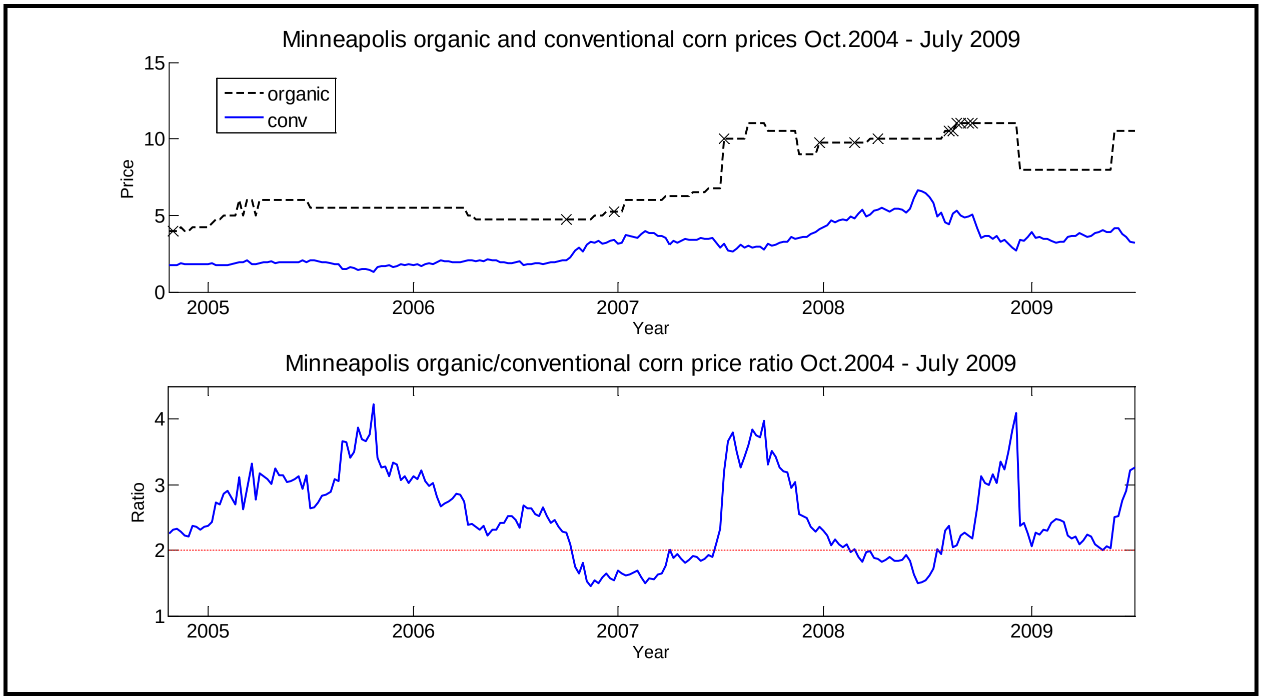
Table 10. Regression Results for Cointegration between Conventional Log-Prices at Different Markets, and Residual-Based Cointegration Tests[a]

Model: $ln(P_t^{C_i}) = b_0^{C_iC_j} + b_1^{C_iC_j} \; ln(P_t^{C_j}) + v_t^{C_iC_j}$

	C_i	C_j	$b_0^{C_iC_j}$	$b_1^{C_iC_j}$	R^2	Observ.	Residual-based test	
							$\hat{Z}_\alpha$	*p*-value[b]
Corn	Minn.[c]	Omaha	-0.002	1.04	0.98	246	-65.12	0.0000
			(-0.24)	(125.77)				
	Minn.[c]	Fargo	-0.05	1.06	0.98	246	-59.78	0.0000
			(-5.08)	(112.56)				
	Minn.[c]	Dallas	0.36	0.84	0.98	246	-83.65	0.0000
			(38.86)	(101.30)				
	Omaha	Fargo	-0.04	1.02	0.99	246	-23.91	0.0005
			(-6.82)	(166.38)				
	Omaha	Dallas	0.36	0.80	0.98	246	-49.80	0.0000
			(43.79)	(111.35)				
	Fargo	Dallas	0.40	0.79	0.99	246	-74.23	0.0000
			(59.34)	(130.83)				
Soybean	Minn.[c]	Omaha	-0.02	1.02	0.99	246	-34.43	0.0000
			(-1.31)	(132.05)				
	Minn.[c]	Fargo	-0.06	1.02	0.98	246	-31.80	0.0000
			(-3.66)	(128.43)				
	Omaha	Fargo	-0.04	1.00	0.99	246	-82.71	0.0000
			(-5.19)	(292.28)				

[a]*t* statistics are shown in parenthesis below the corresponding coefficients.
[b]Calculated based on McKinnon (1994).
[c]"Minn." means Minneapolis.

A. Corn



B. Soybean

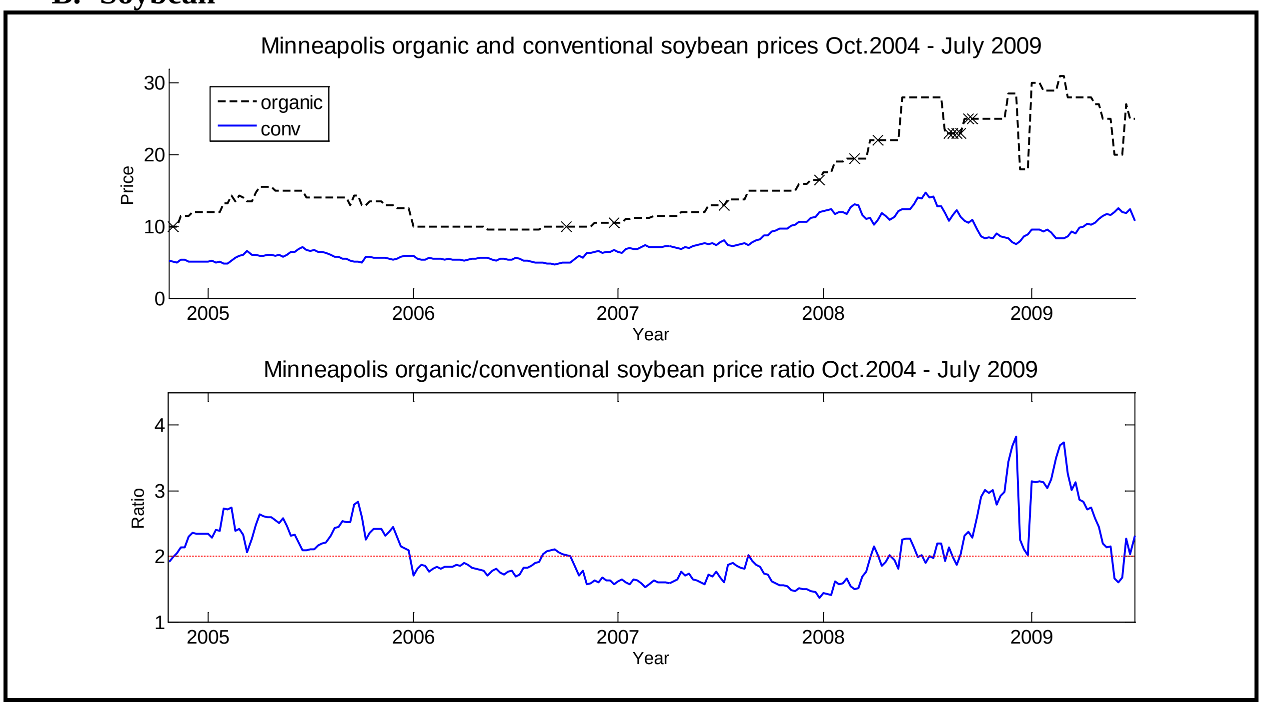
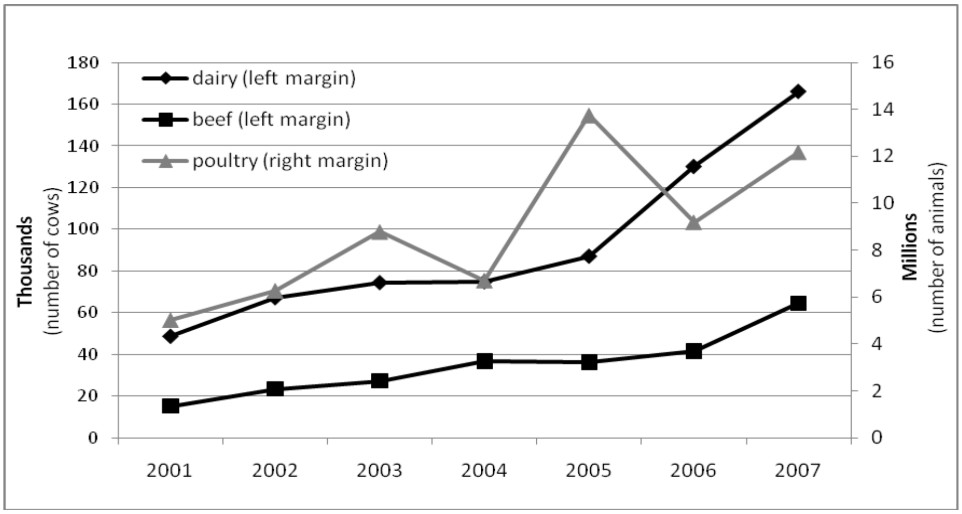


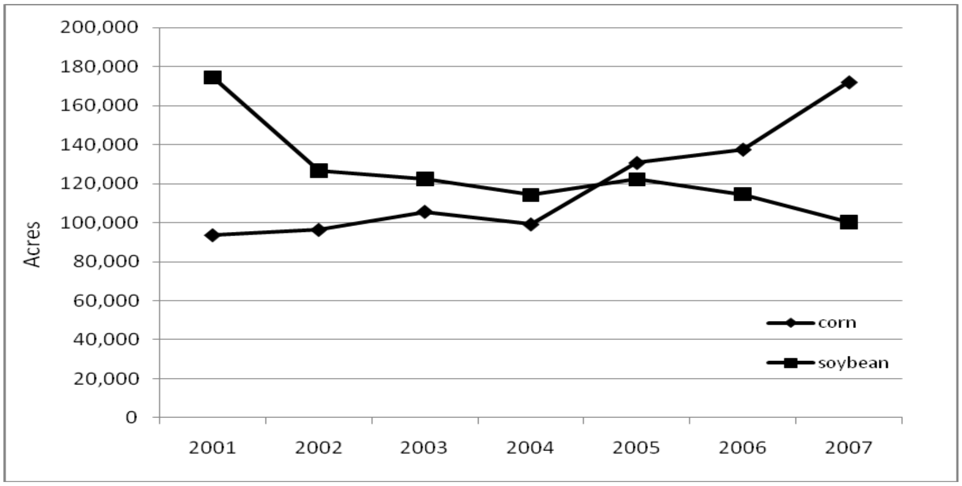
Figure 1. Organic and Conventional Prices and their Ratios for Minneapolis

Note: The crosses denote missing observations in the original series



Source: USDA-ERS (2008d).

Figure 2. Organic Dairy and Beef Cow Production, and Poultry Production in the U.S., 2001-2007



Source: USDA-ERS (2008b-c).

Figure 3. Organic Corn and Soybean Acreage in the U.S. 2001-2007