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Cointegration among regional corn cash prices

Xiaojie Xu
North Carolina State University

Abstract

This study investigates cointegration among daily corn cash prices from seven Midwestern states for January 2006 ~ March 2011, using both time invariant and time varying models. Changing cointegration is captured by time varying models, especially for the second half of the sample. The result identifies time periods for which a time invariant or time varying model is appropriate for further policy analysis.

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Contact: Xiaojie Xu - xxu6@ncsu.edu.
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1. Introduction

Cointegration has been widely adopted to model long-run economic relationships, typically through a time invariant (TI) vector error correction model (VECM)[1]. For example, financial and commodity price analysis is an area with many empirical studies that determine cointegration among different series as a model specification step before conducting further policy analysis such as causality identification and forecasting. However, it may be too restrictive to assume TI parameters because economic relationships tend to change over time. This could become more obvious for studies using a large sample size or a long time span and may cause failure to identify cointegration even among well-postulated economic relationships, which is likely to lead to uninformative or even misleading policy implications.

Considering the possibility that economic relationships, and thus model parameters, are time varying (TV), the introduction of structural breaks or other forms of nonlinearities in cointegration is one way to estimate a model, especially when instability is caused by abrupt shocks. Separate from incorporating structural breaks, two recently developed TV models suggest promising ways to model cointegration that possibly changes over the whole time period under consideration, especially when mutations of cointegration among associated variables are gradual and smooth. This pattern is common among changes of commodity prices. One model by Bierens and Martins (2010), BM-TVCM, treats the TV cointegration vector(s) in a VECM as expansions in terms of Chebyshev time polynomials, the other model by Koop *et al.* (2011), KLS-TVCM, takes a Bayesian perspective and divides parameters of a VECM into different blocks to determine whether each of them is TV. These two methods are applied to daily corn cash prices from seven Midwestern states – Iowa, Illinois, Indiana, Ohio, Minnesota, Nebraska, and Kansas – for January 2006 $\sim$ March 2011 to investigate TV cointegration that possibly inhabits the different series. As a comparison, a TI model also is considered as the benchmark. The empirical result identifies time periods for which a time invariant or time varying model is appropriate. It could be of interest to market participants by expanding their knowledge set of price dynamics among regional cash markets and sever

[1] Abbreviations: TI - time invariant; TV - time varying; BM - Bierens and Martins; KLS - Koop, Leon-Gonzalez, and Strachan; TVCM - time varying cointegration model; VECM - vector error correction model.

as the starting point for further policy analysis.

Combined applications of TV and TI models and comparisons of empirical results based on different models, in a broader sense, shed light on price analysis of other agricultural commodities such as wheat and soybean. Investigations of resource and financial markets are natural extensions as well. It is important for researchers to explore policy implications based on appropriate approaches to cointegration modeling. For example, the result in the current study suggests that TV or TI modeling of cointegration should match specific sample periods for further policy analysis such as causality tests, impulse responses, variance decompositions, and price forecasts. Further, the sensitivity of policy implications to cointegration modeling, TV or TI, could be investigated. Because heavy computing is involved in applications of TV models, TI models might be empirically taken as approximations to TV models for policy analysis when variations in cointegration over time are minor to moderate. TV cointegration that inhabits economic variables for certain periods of a sample also indicates that a closer examination of these periods for driving forces of variations in cointegration is worthwhile provided with necessary data.

The reminder of this study is organized as follows. Section 2 describes the data used for analysis. Section 3 reports cointegration tests based on the BM-TVCM and KLS-TVCM. A TI-VECM also is estimated. Section 4 discusses the results and Section 5 concludes.

2. Data

The data are obtained from GeoGrain Inc. They make daily calls to a large number of market locations and record and verify associated prices. As a result, they comprise an unbalanced panel of daily corn cash prices because different market locations have different dates for which data can be missing. Those missing observations are caused by failures to reach a market to get data. The complete raw data include over 4,000 markets (see Figure 1). More than 3.5 million daily prices are observed in total. The first observation in the raw data is recorded on September 1, 2015 and the last one on March 24, 2011. So, the raw data cover a 7-year period. Before January 3, 2006, data missing ratios are high across markets, this study thus focuses on the sample extending from January 3, 2006 to March 24, 2011.

However, the problem of missing observations still exists across markets.

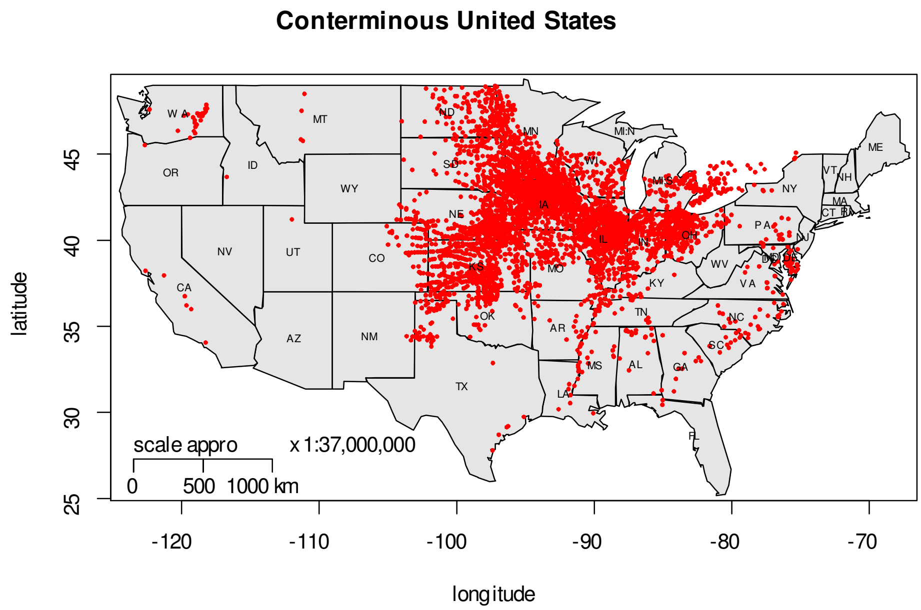

Figure 1: All Markets

To select markets with large numbers of observations and low data missing ratios, Figure 2 illustrates the 182 markets used in this study. The percentage of missing observations across these markets ranges from 0.3% to 5.2%. These sporadic and idiosyncratic missing prices are approximated by cubic spline interpolation with reasonable results which can be seen from plots of each individual price series of the 182 markets that are omitted here for brevity. Other markets are eliminated and not considered in the current study due to high data missing ratios and/or data missing patterns for which cubic spline interpolation does not produce reasonable approximations. Please note that on days such as holidays, for example weekends, where prices are not available in all markets, the associated missing observations are omitted and a smooth continuity of prices is assumed (Goodwin and Piggott, 2001). As a result, the 182 markets considered cover seven states, which are Iowa, Illinois, Indiana, Ohio, Minnesota, Nebraska, and Kansas. They represent seven of eight largest corn harvest states in the U.S. (South Dakota not considered in the current study is the sixth largest corn harvest state) and contribute to 67.4% of the national harvest acres (National Agricultural Statistics Service, 2010). They thus are the most important and relevant states for corn cash price analysis. Other states are not considered because individual markets in these states are all eliminated with the aforementioned market selection procedure.

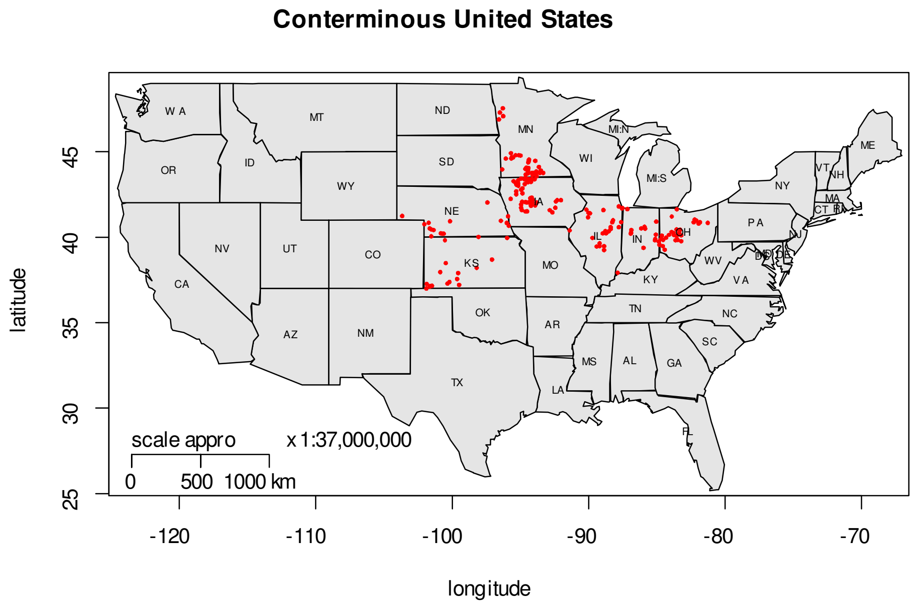

Figure 2: The 182 Cash Markets

The final data set analyzed covers a six-year period from January 3, 2006 to March 24, 2011, totaling 1316 observations for each of the 182 markets. A balanced panel is constructed to focus on regionwide cointegration; for each state, its price is calculated as the average of the prices of observed markets in it[2]. As a result, I have seven state-level daily price series for Iowa, Illinois, Indiana, Ohio, Minnesota, Nebraska, and Kansas. For the rest of this study, prices (cents per bushel) are converted to their natural logarithms. Descriptive information of the price series of each state is exhibited in Table 1 and Figure 3. As one might expect, these series are close to each other and are slightly left-skewed and platykurtic.

[2]There are other ways to aggregate the data. For example, it may be interesting to aggregate the data based on the distance of a cash market to the Illinois River, where many corn futures contract delivery points locate. Further, it is also interesting to include specific individual cash price series in a model and investigate their spatial features rather than examine the aggregated data. These topics are beyond the scope of this study and thus not considered.

Table 1: Summary Statistics for All Price Series

State	Nob	Mean	Med	Min	Max	Std	Skew	Kurt
IA	1316	5.851	5.845	5.112	6.559	0.336	-0.254	2.838
IL	1316	5.889	5.869	5.230	6.561	0.309	-0.064	2.773
IN	1316	5.916	5.898	5.230	6.587	0.313	-0.139	2.834
OH	1316	5.893	5.876	5.207	6.577	0.317	-0.139	2.839
MN	1316	5.830	5.821	5.097	6.542	0.339	-0.242	2.820
NE	1316	5.866	5.853	5.150	6.555	0.313	-0.182	2.815
KS	1316	5.901	5.887	5.253	6.586	0.299	-0.004	2.680

To test for non-stationarity, two tests are used that set the null hypothesis of a unit root: the augmented Dickey-Fuller test (Dickey and Fuller, 1981) and the Phillips-Perron test (Phillips and Perron, 1988). Because failure to reject the null of a unit root does not imply that a unit root exists, unit root tests may not behave well in telling apart unit roots and weakly-stationary alternatives. Hence, the Kwiatkowski-Phillips-Schmidt-Shin test (Kwiatkowski *et al.*, 1992), with the null hypothesis of stationarity, also is applied. These three tests are implemented for both price levels and their first differences. The results omitted here for brevity show that the price series are stationary in differences but not in levels.

3. Cointegration Tests

3.1. The TI-VECM

Before investigating cointegration with TV models, it is first determined using Johansen's trace and maximum eigenvalue tests (Johansen, 1988, 1991) based on a TI-VECM: $\Delta Y_t = \gamma_0 + \alpha\beta' Y_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta Y_{t-j} + \varepsilon_t$ for $t = 1, \ldots, T$, where T is the number of observations, p is the number of lags selected by the Bayesian information criterion, $Y_t = (Y_{IA,t}, Y_{IL,t}, Y_{IN,t}, Y_{OH,t}, Y_{MN,t}, Y_{NE,t}, Y_{KS,t})'$ is a vector that contains price series of Iowa, Illinois, Indiana, Ohio, Minnesota, Nebraska, and Kansas at time t, and $\beta = (\beta_{IA}, \beta_{IL}, \beta_{IN}, \beta_{OH}, \beta_{MN}, \beta_{NE}, \beta_{KS})'$

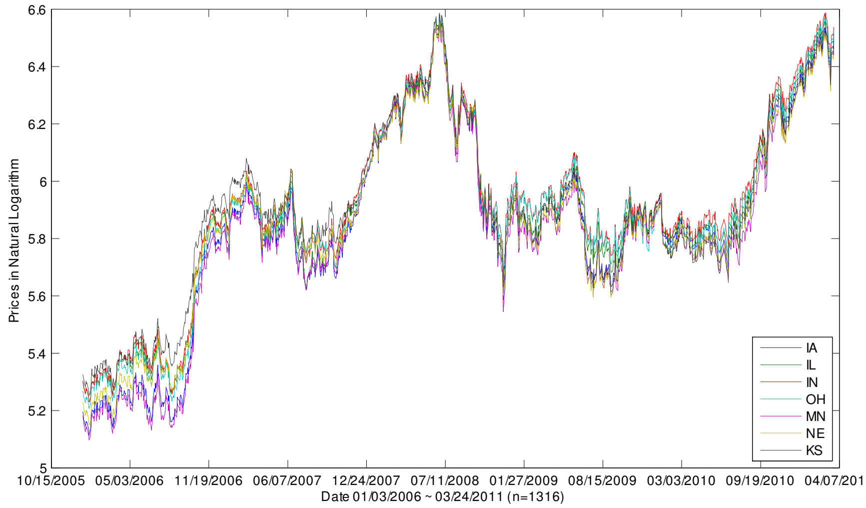

Figure 3: Price Series of Each State

is a vector that contains cointegration coefficients associated with different series[3]. Given that the cointegration rank is one, the estimated result of β, $(0.632,-0.762,1.000,-0.580,-0.187,-0.629,0.520)'$, will be used to provide a comparison with those based on TV models. Further, the application of Hansen and Johansen's recursive cointegration method (Hansen and Johansen, 1999) reveals that the identified cointegration rank of one is stable. Figure 4 shows the normalized trace test statistics calculated at each data point between March 9, 2006 (point 46) and March 24, 2011 (point 1,316). The first 45 data points ranging from January 3, 2006 to March 8, 2006 are used as the base period. As shown in Figure 4, the test statistics are scaled by the 5% critical values. Therefore, we can reject the null hypothesis at a data point if its corresponding entry in the figure is greater than 1. It is obvious that we have at least one and almost never more than one cointegration vector, especially for the R-representation.

[3] β is a vector because the cointegration rank is found to be one with Johansen's trace and maximum eigenvalue tests (Johansen, 1988, 1991). Numerical results of the tests are available upon request.

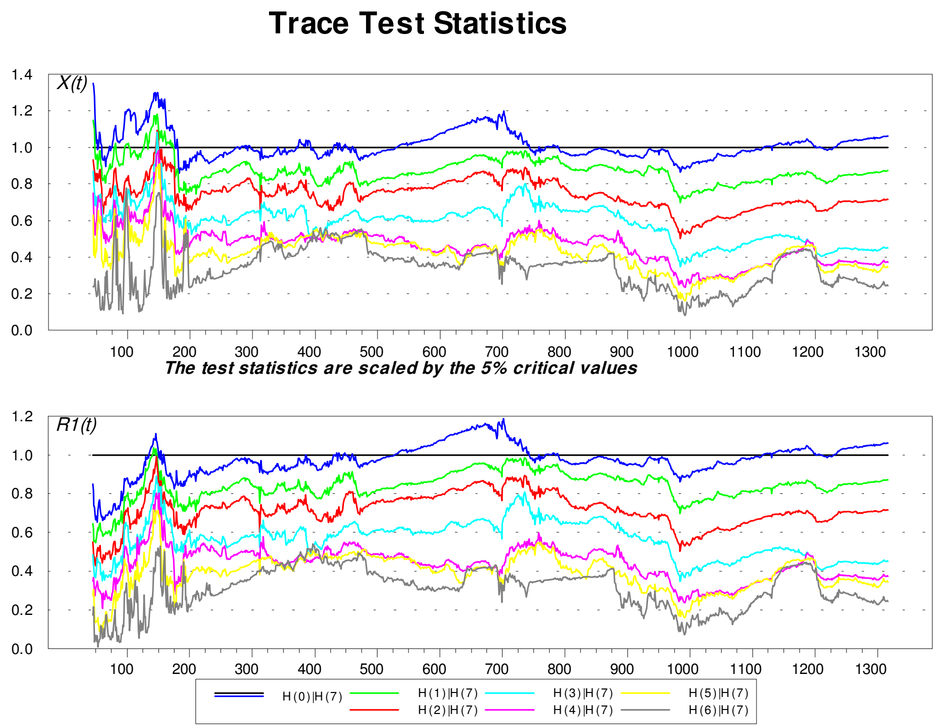

Figure 4: Recursive cointegration analysis: plots of trace test statistics ($H(0)$, $H(1)$, ..., $H(7)$ correspond to null hypotheses of the cointegration rank being 0, 1, ..., 7)

3.2. The BM-TVCM

The first TV model considered is the BM-TVCM. Before reporting the corresponding empirical results, a brief introduction of this model is given as follows. Consider a k-variate TV-VECM with Gaussian errors: $\Delta Y_t = \gamma_0 + \alpha\beta_t^{'} Y_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta Y_{t-j} + \varepsilon_t$ for $t = 1, \ldots, T$, where $\varepsilon_t \sim i.i.d.\ N_k(0, \Omega)$. The BM-TVCM tests the null hypothesis of TI cointegration, $\beta_t^{'} = \beta$, against the alternative of TV cointegration for rank $r \in [1, k-1]$ by modeling the TV cointegration vectors via expansions in terms of Chebyshev time polynomials defined as: $P_{0,T}(t) = 1$ and $P_{i,T} = \sqrt{2}\cos(i\pi(t-0.5)/T)$ for $t = 1, \ldots, T$ and $i = 1, 2, 3, \ldots$. The model can be rewritten as: $\Delta Y_t = \gamma_0 + \alpha(\sum_{i=0}^{m} \xi_i P_{i,T}(t))^{'} Y_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta Y_{t-j} + \varepsilon_t$, which is: $\Delta Y_t = \gamma_0 + \alpha\xi^{'} Y_{t-1}^{(m)} + \Gamma X_t + \varepsilon_t$, where $\xi^{'} = (\xi_0^{'}, \xi_1^{'}, \ldots, \xi_m^{'})$ is an $r \times (m+1)k$ matrix of rank r, $\Gamma = (\Gamma_1, \ldots, \Gamma_{p-1})$ is a $k \times k(p-1)$ matrix, $Y_{t-1}^{(m)} = (Y_{t-1}^{'}, P_{1,T}(t)Y_{t-1}^{'}, \ldots, P_{m,T}(t)Y_{t-1}^{'})^{'}$, $X_t = (\Delta Y_{t-1}^{'}, \ldots, \Delta Y_{t-p+1}^{'})^{'}$, and m can be selected based on the Hannan-Quinn information criterion (Hannan and Quinn, 1979). The null hypothesis thus corresponds to

$\xi' = (\beta', O_{r\times km})$, which implies that $\xi' Y_{t-1}^{(m)} = \beta' Y_{t-1}^{(0)}$, where $Y_{t-1}^{(0)} \equiv Y_{t-1}$. And the likelihood ratio test of the null hypothesis against the alternative given m and r is represented as: $LR^{tvc} = -2(\hat{l}_T(r,0) - \hat{l}_T(r,m))$, where $\hat{l}_T(r,0)$ and $\hat{l}_T(r,m)$ are log-likelihoods of the VECM in cases $m = 0$ and $m \geqslant 1$, respectively. Let $\hat{\lambda}_{m,1} \geqslant \hat{\lambda}_{m,2} \geqslant \cdots \geqslant \hat{\lambda}_{m,r} \geqslant \cdots \geqslant \hat{\lambda}_{m,(m+1)k}$, where $\hat{\lambda}_{m,k+1} = \cdots = \hat{\lambda}_{m,(m+1)k} \equiv 0$, be the ordered solutions to the generalized eigenvalue problem defined by Bierens and Martins (2010), the test statistics is represented as: $LR_T^{tvc} = T\sum_{j=1}^{r} \ln((1-\hat{\lambda}_{0,j})/(1-\hat{\lambda}_{m,j}))$. Under proper assumptions, LR_T^{tvc} is asymptotically χ^2_{mkr} distributed given $m \geqslant 1$ and $r \geqslant 1$.

In empirical applications, p-values of the BM-TVCM test for different combinations of the Chebyshev polynomial order $m \in [1, \lceil \max(T/10) \rceil] = [1, 132]$ and the VECM order $p \in [2, 20]$ based on $r = 1$ are first calculated and strong evidence of TV cointegration relationships among the seven price series are identified, i.e., the null hypothesis of TI cointegration is rejected. The plots of the TV cointegration coefficients $\beta_{IA,t}$, $\beta_{IL,t}$, $\beta_{IN,t}$, $\beta_{OH,t}$, $\beta_{MN,t}$, $\beta_{NE,t}$, and $\beta_{KS,t}$ are thus presented in Figure 5, for which the Chebyshev polynomial order $m = 2$ is selected according to the Hannan-Quinn criterion (Hannan and Quinn, 1979) and the VECM order is fixed at $p = 2$ as in the TI case. It is obvious from Figure 5 that these coefficients vary over time. Further, relative variations of the coefficients against each other are more obvious over time for the second half of the sample.

3.3. The KLS-TVCM

The second TV model considered is the KLS-TVCM. Again, a brief introduction of this model is provided before proceeding to empirical results. Consider a k-variate TV-VECM: $\Delta Y_t = \gamma_t + \alpha_t \beta_t' Y_{t-1} + \sum_{j=1}^{p-1} \Gamma_{j,t} \Delta Y_{t-j} + \varepsilon_t$ for $t = 1, \ldots, T$, where ε_t are independent $N_k(0, \Omega_t)$. The parameters are divided into three blocks: the VECM coefficients block $\{\gamma_t, \alpha_t, \Gamma_{1,t}, \ldots, \Gamma_{p-1,t}\}$, the error covariance block $\{\Omega_t\}$, and the cointegration block $\{\beta_t^*\}$[4]. The parameters in $A_t = \{\gamma_t, \alpha_t^*, \Gamma_{1,t}, \ldots, \Gamma_{p-1,t}\} = \left\{\gamma_t, \alpha_t \kappa_t^{-1}, \Gamma_{1,t}, \ldots, \Gamma_{p-1,t}\right\}$ follow a state

[4] β_t is specified to be semi-orthogonal and identified with $\beta_t' \beta_t = I_r$ imposed accordingly. $\beta_t = \beta_t^* (\kappa_t)^{-1}$, where $\kappa_t = (\beta_t^{*'} \beta_t^*)^{1/2}$. β_t^* is thus the unrestricted matrix of cointegrating vectors with no imposed identification.

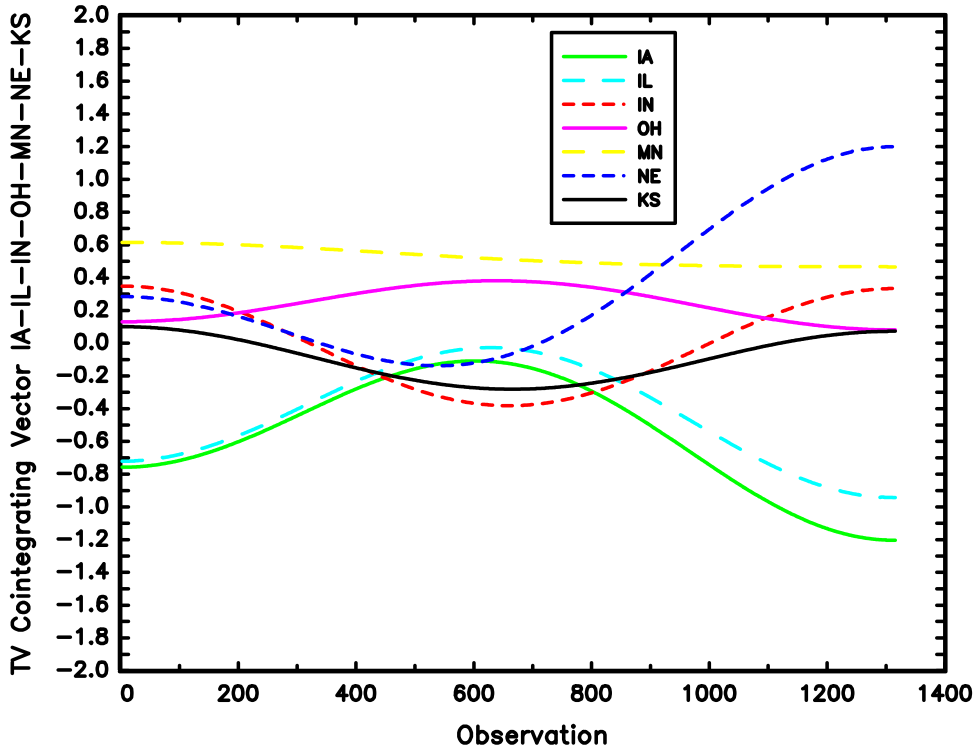

Figure 5: Plots of TV Cointegration Coefficients based on the BM-TVCM

equation specified as: $a_t = a_{t-1} + \zeta_t$, where $a_t = vec(A_t)$, $\zeta_t \sim N(0, Q)$, $a_1 \sim N(0, 2V_{a_1})$, V_{a_1} is the identity matrix except for diagonal elements corresponding to α_t^* whose values are $(1-\rho^2)$, and $Q^{-1} \sim Wishart(\dim(a_t) + 2, (0.0001I)^{-1})$. The TV error covariance Ω_t is transformed via a triangular reduction specified as: $\Omega_t = \Lambda_t^{-1}\Sigma_t\Sigma_t'(\Lambda_t^{-1})^{-1}$, where $\Sigma_t = diag(\sigma_{1,t}, \ldots, \sigma_{k,t})$ and Λ_t is a lower triangular matrix with ones on the diagonal and lower diagonal elements $\lambda_{ij,t}$. The evolution in Σ_t is modeled as: $h_t = h_{t-1} + u_t$, where $h_t = (\ln(\sigma_{1,t}), \ldots, \ln(\sigma_{k,t}))'$, $u_t \sim N(0, W)$, $h_1 \sim N(0, 2I_k)$, and $W^{-1} \sim Wishart(k+2, (0.0001I)^{-1})$, and that in Λ_t is modeled as: $\lambda_t = \lambda_{t-1} + \xi_t$, where $\lambda_t = (\lambda_{21,t}, \lambda_{31,t}, \lambda_{32,t}, \ldots, \lambda_{n1,t}, \lambda_{n2,t}, \lambda_{n(n-1),t})'$, $\xi_t \sim N(0, C)$, $\lambda_1 \sim N(0, 2I_{k(k-1)/2})$, and $C^{-1} \sim Wishart(k(k-1)+2, (0.0001I)^{-1})$. The state equation for β_t^* is defined as: $b_t^* = \rho b_{t-1}^* + \eta_t$, where $b_t^* = vec(\beta_t^*)$, $\eta_t \sim N(0, I_{kr})$, r is the usual cointegration rank, $b_1^* \sim N(0, I_{kr}/(1-\rho^2))$, and ρ is a scalar that controls the dispersion of the state equation with its absolute value being smaller than 1 and prior being uniform over $\rho \in [0.999, 1)$[5]. MCMC draws follow Durbin and Koopman (2002) for the VECM coefficients block, Primiceri (2005) for the error covariance block, Koop *et al.* (2010) for the cointegration block, and a Metropolis-within-Gibbs step as in Koop *et al.* (2011) for ρ. In empirical applications, variants of the KLS-TVCM are compared based on Geweke's predictive likelihood (Geweke, 1996). Specifically, whether each of the three blocks is TV is considered for $r = 0, 1, \ldots, k$[6].

Setting p to 2 as in the TI case, the number of replications to 3000, and the number of replications to be discarded to 1000, the model that results in the highest predictive likelihood for the last 100 observations is the one with a TV cointegration block and a TV error covariance block, but a TI-VECM coefficients block under $r = 1$. Therefore, it does not seem to be important to have coefficients controlling the short-run dynamics to vary over time (Koop *et al.*, 2011). This finding is consistent with that by Koop *et al.* (2011), although different empirical applications are pursued. The distance between the TV cointegration space and the space spanned by H_1=(0.632,-0.762,1.000,-0.580,-0.187,-0.629,0.520)$'$, which is estimated using the TI-VECM, is thus plotted in Figure 6 based on the selected model. It is evident that the cointegration space is TV because the distance shown in Figure 6 changes over time (Koop *et al.*, 2008), especially for the second half of the sample.

4. Discussion

If transportation costs are stationary, the law of one price (LOP) implies that efficient trade and arbitrage activities should result in equalization of prices for a homogeneous commodity in spatially separated markets such that price differentials never exceed transaction costs (Kuiper *et al.*, 1999). In other words, for p markets operating under pure competition (i.e.,

[5]It is possible to change the scalar ρ to a diagonal matrix $diag(\rho_1, \rho_2, \ldots, \rho_r) \otimes I_k$ and adjust the model properly to allow different vectors to move at different speeds by setting $\rho_i \neq \rho_j$ for $i, j = 1, 2, \ldots, r$ and $i \neq j$ if it is believed that some vectors in β_t^* evolve faster than others (Koop *et al.*, 2011). With limited prior knowledge about interrelationships of regional markets, this modification is not adopted.

[6]For $r = 0$, whether each of the VAR coefficients block $\{\gamma_t, \Gamma_{1,t}, \ldots, \Gamma_{p-1,t}\}$ and the error covariance block $\{\Omega_t\}$ is TV is considered.

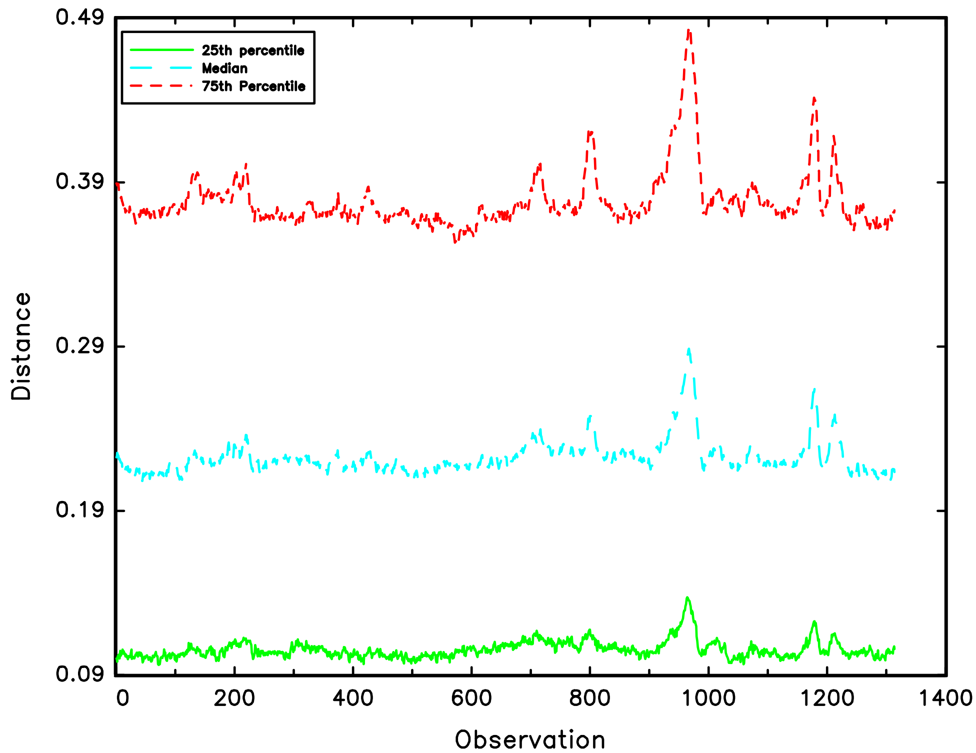

Figure 6: The Posterior Median and the 25^{th} and 75^{th} Percentiles of the Distance between the Cointegration Space and the Space Spanned by H_1=(0.632,-0.762,1.000,-0.580,-0.187,-0.629,0.520)$'$

with only stationary costs of transport between market pairs), $p-1$ cointegration vector(s) among p price series should be observed (Kuiper *et al.*, 1999).

The result of one cointegrating vector among the seven series is inconsistent with this hypothesis for two reasons. First, the pure competition assumption of the LOP may be violated. As described in Section 2, the price of each state is calculated as the average of the prices of observed markets in it. Some markets in different states are owned by the same firm and do not have an arms-length competitive relationship. Moreover, a relatively high ratio of markets operated by large firms, which usually play price leadership roles, for some states could lead to imperfect competition among the seven states under study. Second, transportation costs may be nonstationary. As a result, even if the perfect competition assumption holds, the $p-1$ cointegration vector(s) among p price series implied by the LOP may not hold (Bessler *et al.*, 2003). In the absence of perfect competition, however, certain cointegration relationships are possible through other factors such as government policies, similar influences of climate on harvest (Awokuse, 2007), and practices of price leadership (Bessler *et al.*, 2003).

Based on the two TV models, changing cointegration over time is more obvious in the second half of the sample as compared to the first half. This result indicates that a TI model may be appropriate for further policy analysis for the first half of the sample while a TV perspective should be taken for the second half.

5. Conclusion

This study investigates cointegration among daily corn cash prices from seven Midwestern states for January 2006 $\sim$ March 2011 through a time invariant vector error correction model and two time varying models. It is found that the time varying models capture changing cointegration that inhabits the price series under the same cointegration rank discovered using the time invariant model, especially for the second half of the sample. With the data used in the current work, future policy involved studies such as Granger causality tests, impulse response functions, and variance decompositions based on different models are of interest.

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