SPECIFICATION SELECTION ISSUES IN MULTIVARIATE THRESHOLD AND SWITCHING MODELS

2002 AAEA-WAEA Annual Meeting

Teresa Serra*

Agricultural, Environmental and Development Economics Department, The Ohio State University
Economics Department, University of Vic

and

Barry K. Goodwin*

Agricultural, Environmental and Development Economics Department, The Ohio State University

May 10, 2002

In this paper we consider two general approaches to the selection of thresholds in multivariate threshold models. The first criteria ignores the cross equation correlation while the latter explicitly accounts for it. We focus on how model selection may be influenced by these alternative approaches and consider simulations of the alternative approaches.

Keywords: threshold selection, market integration, transactions costs
JEL codes: Q110, F150, C320, R320

---

*219 Agricultural Administration Bldg., Agricultural, Environmental and Development Economics Department, The Ohio State University, Columbus, OH 43210-1067. Tel: (614) 688 41 53. Fax: (614) 292 47 49. E-mail: serra.10@osu.edu.

Teresa Serra gratefully acknowledges research support from the Caja Madrid Foundation.

*229 Agricultural Administration Bldg., Agricultural, Environmental and Development Economics Department, The Ohio State University, Columbus, OH 43210-1067. Tel: (614) 688 41 38. Fax: (614) 292 47 49. E-mail: goodwin.112@osu.edu.

SPECIFICATION SELECTION ISSUES IN MULTIVARIATE THRESHOLD AND SWITCHING MODELS

A promising avenue of research in time-series analysis that considers structural change, regime switching, and threshold-type models has developed in recent years. Such models arise in situations where the underlying economic structure changes in a manner that is unknown a priori to the analyst. Examples include gradual switching models, threshold error-correction models, smooth threshold autoregressive (STAR) models, regime switching models, and threshold cointegration models. These models often occur when some "forcing-variable" is driving the switching among regimes. In the case of standard (Chow-type) structural change models, the forcing variable is time, such that any t greater than a break point forces the model into a new regime and the change is permanent. In threshold models, the size of a particular variable (i.e., whether the forcing variable is large enough to exceed a threshold) determines the regime and switching can occur back and forth among regimes. Different regimes are typically represented by different parameter estimates for the underlying model.

The literature has described two general approaches to the selection of thresholds or break points. In the overwhelming majority of applied analyses, the criterion for selecting the break point or threshold has involved minimization of the sum of squared errors for the model (see, for example, Balke and Fomby (1997) and Goodwin and Piggott (2001)). Alternatively, one may choose to choose the break point or threshold that maximizes a likelihood function (see, for example, Obstfeld and Taylor (1997)). In cases where normality and homoscedasticity are assumed, these alternative criteria are asymptotically equivalent and are fully analogous to maximizing a sup-Chow test of the difference between regimes.

This equivalence may break down in multivariate models involving systems of equations (e.g., demand systems and vector error correction models). Multivariate analogs to the criteria discussed above are obvious. In the first case, one could choose to minimize the system sum of squared errors (i.e., the trace of the covariance matrix for the system's residual errors). In the case of maximum likelihood estimation, the kernel of the likelihood function involves the logged determinant of the residual covariance matrix. These two criteria are by no means equivalent since the former ignores cross equation correlation while the latter explicitly accounts for it. It is thus possible that the two different approaches, both of which are certainly reasonable, could lead to very different answers in terms of regime switching or threshold effects. It is even possible that one could obtain negative test statistics for evaluating the statistical significance of the threshold or switching behavior. Of course, these test statistics, though assuming the form of a conventional chi-square test, are non-standard and thus must be simulated under the null hypothesis.

Our paper focuses on how model selection may be influenced by these alternative approaches, both of which have been applied in the literature. We conduct a simulation exercise involving a bivariate threshold vector error correction model. We examine the extent to which ignorance of cross-equation correlation influences the correct estimation of the threshold variable. Simulated data over varying levels of error variation and correlation are utilized in the simulation. The results from our Monte Carlo experiments suggest, contrary to the initial hypothesis, that the consideration of the cross-equation correlation does not increase the accuracy of small sample parameter estimates.

We then apply the methods discussed to a historical analysis of the regional integration of U.S. markets for eggs. Our application is to 31 years of monthly egg prices quoted at nine important wholesale markets: Atlanta, Baltimore, Boston, Cincinnati, Dubuque, Indianapolis, Memphis, Minneapolis and New York. Prices cover the historical period that goes from 1880 to 1911. Our results suggest that threshold behavior characterizes spatial price linkages between the markets analyzed.

Threshold vector error correction models

Tong (1978) originally introduced nonlinear threshold time series models. Tsay (1989) developed a method to test for threshold effects in autoregressive models and to model threshold autoregressive processes. Balke and Fomby (1997) extended the threshold autoregressive models to a cointegration framework, thus combining non-linearity and cointegration.

Threshold vector error correction models (TVECM) allow nonlinear and threshold-type adjustments to long-run equilibrium. These models occur when the size of the (lagged) error correction term allows one to distinguish between different regimes and the variables in the model exhibit different types of behavior in each regime.

We start our analysis by considering a general two-regime bivariate threshold vector error correction model. Let

$$x_t = \begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix} \qquad (1)$$

be a two-dimensional I(1) time series which is cointegrated with the cointegrating vector a (2x1). Let $n_t = ax_t$ be the I(0) error-correction term. A two-regime TVECM can be compactly written in the following way:

$$\Delta x_t = \begin{cases} b_1^{'} X_{t-1} + u_t & if \quad v_{t-1} \leq g \\ b_2^{'} X_{t-1} + u_t & if \quad v_{t-1} > g \end{cases} \qquad (2)$$

where:

$$X_{t-1} = \begin{bmatrix} \Delta x_{t-1} \\ \Delta x_{t-2} \\ . \\ . \\ . \\ \Delta x_{t-l} \\ n_{t-1} \end{bmatrix}$$

n_{t-1}= variable relevant to the threshold[1]; g = threshold parameter; and b_1 and b_2 = vectors of coefficients. We assume that there is no constant in the model, which is equivalent to assuming that the variables do not contain linear trends. The TVECM may also be written as:

$$\Delta x_t = b_1^{'} X_{t-1} d_1(g) + b_2^{'} X_{t-1} d_2(g) + u_t \qquad (3)$$

where:

$$d_1(g) = 1(n_{t-1} \leq g)$$
$$d_2(g) = 1(n_{t-1} > g)$$

[1] The lag of the error correction term, the variable relevant to the threshold, is assumed to be equal to 1.

Estimation of the threshold points

As has been explained above, there are two general approaches to the selection of thresholds in multivariate threshold models. In a first approach, the criterion for selecting the threshold involves minimization of the logarithm of the determinant of the variance-covariance matrix of the residuals (Σ). Under this first approach, the TVECM can be estimated using sequential multivariate least squares in two steps. In the first step, a grid search is carried out to estimate the threshold parameter (g). Conditional on g, the parameters b_1 and b_2 can be estimated through the OLS regressions of Δx_t on X_{t-1} for the sub-samples for which $n_{t-1} \leq g$ and $n_{t-1} > g$, respectively. From this estimation the logarithm of the determinant of the Σ matrix is derived:

$$S(g) = \ln\left|\hat{\Sigma}(g)\right| \tag{4}$$

where $\hat{\Sigma}(g)$ is a multivariate least squares estimate of $\Sigma = \mathrm{var}(u_t)$ conditional on g. In the second step, the least squares estimate of g is obtained as:

$$\hat{g} = \arg \quad \min \quad S(g) \tag{5}$$

This approach is equivalent to maximizing a likelihood function:

$$L(b_1, b_2, \Sigma, g) = -\frac{n}{2}\log\left|\Sigma\right| - \frac{1}{2}\sum_{t=1}^{n} u_t(b_1, b_2, g)'\Sigma^{-1}(b_1, b_2, g) \tag{6}$$

The MLE estimates $(\hat{b}_1, \hat{b}_2, \hat{\Sigma}, \hat{g})$ are the values that maximize $L(b_1, b_2, \Sigma, g)$. Holding g fixed, the following concentrated likelihood function can be derived (Hansen and Seo 2001):

$$L(g) = -\frac{n}{2}\log\left|\hat{\Sigma}(g)\right| - \frac{np}{2} \tag{7}$$

where:
p = number of variables.

Hence, the MLE$(\hat{g})$ estimates thus minimize $\log\left|\hat{\Sigma}(g)\right|$

Under a second approach, the TVECM estimation method differs in the grid search process. While the fist proposal minimizes the log determinant of the variance-covariance matrix of the residuals, the second minimizes the trace of the Σ matrix:

$$S(g) = trace(\hat{\Sigma}(g)) \tag{8}$$

As has been noted above, in finite sample estimation of multivariate models, the two approaches may not be not equivalent. While the maximum likelihood estimation accounts for cross equation correlation, the second approach ignores it. Hence, it is possible that the two different approaches could lead to different answers in terms of threshold effects. It is even possible that one could obtain negative test statistics for evaluating the significance of the threshold effects.

A common approach to test for the significance of the differences in parameters across regimes is the sup-LR statistic. The sup-LR statistic tests for a linear vector error correction model (VECM) against the alternative of a TVECM. The model under the null is $\Delta x_t = b' X_{t-1} + u_t$, while the model under the alternative can be expressed as $\Delta x_t = b_1' X_{t-1} d_1(g) + b_2' X_{t-1} d_2(g) + u_t$. The sup-LR statistic can be computed in the following way:

$$LR = n\left[\ln\left|\hat{\Sigma}\right| - \ln\left|\hat{\Sigma}(g)\right|\right] \tag{9}$$

where:

$\hat{\Sigma}$ = is the variance-covariance matrix of the residuals of the VECM;

$\hat{\Sigma}(g)$ = represents the variance-covariance matrix of the residuals of the TVECM; and n = is the number of observations.

The sup-LR statistic has a non-standard distribution because the threshold parameter is not identified under the null hypothesis and thus simulation of the test statistics under the null is needed in order to conduct hypothesis testing.

A simulation exercise

In order to evaluate how parameter estimation and model selection may be influenced by the two alternative approaches to the selection of the threshold, Monte Carlo experiments are conducted in this section. The experiments are based on the following bivariate TVECM with two regimes:

$$\begin{aligned}\Delta x_{1,t} &= 0.8\Delta x_{1,t-1}d_1(0) - 0.6\Delta x_{1,t-1}d_2(0) - 0.2\Delta x_{2,t-1}d_1(0) + 0.1\Delta x_{2,t-1}d_2(0) - 1.0 n_{t-1}d_1(0) - 0.5 n_{t-1}d_2(0) + u_{1t} \\ \Delta x_{2,t} &= -0.2\Delta x_{1,t-1}d_1(0) + 0.0\Delta x_{1,t-1}d_2(0) + 0.5\Delta x_{2,t-1}d_1(0) - 0.6\Delta x_{2,t-1}d_2(0) + 0.6 n_{t-1}d_1(0) + 0.5 n_{t-1}d_2(0) + u_{2t}\end{aligned} \tag{10}$$

We generate the errors u_{1t} and u_{2t} from a multivariate normal distribution ($N(0,\Sigma)$) and consider four different parameter sets for the variance-covariance matrix of the residuals (Σ), corresponding to no cross equation correlation, positive cross equation correlation, negative cross equation correlation and a positive cross equation correlation with different degrees of error variation[2]:

$$\Sigma = \begin{bmatrix} 0{,}4 & 0 \\ 0 & 0{,}1 \end{bmatrix} \text{ case 1} \qquad \Sigma = \begin{bmatrix} 0{,}4 & 0{,}1 \\ 0{,}1 & 0{,}1 \end{bmatrix} \text{ case 2}$$

$$\Sigma = \begin{bmatrix} 0{,}4 & -0{,}1 \\ -0{,}1 & 0{,}1 \end{bmatrix} \text{ case 3} \qquad \Sigma = \begin{bmatrix} 0{,}5 & 0{,}158 \\ 0{,}158 & 0{,}2 \end{bmatrix} \text{ case 4}$$

Two sample sizes are considered n=100 and n=250. Our simulations are divided into two main groups. First, we estimate the parameters of the TVECM under the two described approaches. The grid searches to find the optimum threshold are restricted to ensure an adequate number of observations for estimating the parameters in each regime. The thresholds are searched between 1% and 99% percentiles

[2] The Σ matrices correspond to 0 (case 1), 0.5 (case 2), -0.5 (case3) and 0.5 (case 4) correlation coefficients.

of the error correction term[3]. We asses the finite sample distribution of the estimators using 1000 simulation replications. Second, by using 100 simulation replications and focusing on one sample size, n=100, we also consider the sup-LR test and its associated probability-value. To determine the p-value of the sup-LR statistic, we run 100 simulations for each model whereby the dependent variables Δx_t are replaced by iid N(0,1) draws (see Hansen (1997) for a detailed discussion of this approach). The proportion of simulations under the null for which the simulated sup-LR statistic exceeds the observed sup-LR statistic gives the asymptotic p-value of the sup-LR test.

In table 1 we report the mean, root mean squared error (RMSE) and mean absolute error (MAE) of each estimator[4] of the parameters of the TVECM in 1000 simulation replications. In table 2 we report the same statistics for each estimator of the parameters of the TVECM, as well as the mean of the sup-LR test and its p-value[5] in 100 simulation replications.

The results indicate that, contrary to our initial expectations, choosing the threshold parameter through minimizing the logged determinant of the covariance matrix does not improve the accuracy of the estimates, at least for the sample size and simulation terms that we consider.

An Empirical application: Regional integration of Nineteenth Century U.S. egg markets

The last decades of the nineteenth century have been identified as an era of increased economic integration. Improvements in transportation, refrigeration and communication mechanisms made it easier for buyers and sellers to contact each other, yielding a higher level of market integration. Economic integration resulted in an increase in trade, a more efficient use of resources and an increase in productivity and overall production (Goodwin, Grennes and Craig 2002).

Economic integration was not limited to capital or labor markets. It also characterized the evolution of some agricultural markets such as grain markets (O'Rourke, 1997). Mechanical refrigeration played a key role in the spatial integration of markets for short shelf life commodities such as meat, butter and cheese (Williamson 1995 and Goodwin, Grennes and Craig 2002).

With the exception of the analysis of Goodwin, Grennes and Craig (2002), there are no econometric estimations of the effects of the technological improvements mentioned above on the level of market integration of agricultural commodities. In this empirical application, we study the effects of transport, refrigeration and communication improvements on the level of integration of regional markets for eggs.

Though the adoption of technical improvements at the end of the XIX century, specially the introduction of the mechanical refrigeration, contributed to a significant increase in the regional price convergence of perishable commodities, these changes may not have substantially affected egg markets. By the end of the nineteenth century, the egg industry was still at a very early stage of its development. Freezing egg operations were only at an experimental phase. The industry was mainly operating at a small scale, due to the fact that eggs were manually separated until 1912, when the hand separator was invented. Additionally, the egg industry was struggling to solve relevant sanitary and refrigeration problems affecting egg products. Another drawback precluding the expansion of the egg industry was the lack of demand for its products, mainly due to the low quality of the final outcome. The use of dried eggs, prior to the freezing of eggs, was scarce and principally limited to army camps. The consumption of frozen eggs, also limited, was mainly coming from bakers and other food manufacturers. It was not until World War II that the U.S. egg industry, specially the egg drying industry, considerably expanded as a result of both public programs to encourage an increased production of eggs through government purchases at supported prices and an increased demand from the Armed Services (Koudele and Heinsohn). Due to the lack of a high scale operating egg industry, along with the high perishability of fresh refrigerated eggs,

[3] When more than one optimum threshold is found, we take the median of the range.
[4] Selected percentiles of each estimator of the parameters are also available from the authors upon request.
[5] No measure of error can be computed for the sup-LR test and its p-value.

arbitrage operations of egg products may have been limited during the period of analysis, thus limiting the integration of markets through price convergence for this commodity.

Econometric methods

In order to study how technical developments at the end of the nineteenth century affected the level of market integration of eggs in the U.S., we focus on the transmission of price shocks across space using threshold vector error correction models. These nonstructural models allow us to estimate bands within which regional prices might not be linked to one another due to transactions costs, recognizing that deviations must exceed a certain amount to provoke equilibrating price adjustments and lead to regional market integration.

We define pairs of prices composed by a central market price – we choose New York– and another wholesale market price. For each pair of markets, we estimate a TVECM (eq. 3) with two thresholds (γ_1 and γ_2) in order to allow for asymmetries in the process of price adjustment. We include lagged price differentials to represent short-run price dynamics. The error correction term is given by the lagged residuals derived from the OLS regression that represents the equilibrium between each pair of prices. We conduct the two grid searches described above in order to estimate the thresholds. In particular, in each grid search, the thresholds are searched over 1% and 99% of the largest (in absolute values) negative and positive lagged error correction terms. The searches are restricted to ensure an adequate number of observations for estimating the parameters in each regime. We then estimate the TVECM conditional on the threshold parameters.

Our specific estimation strategy can be summarized as follows. First, in order to determine whether the price series are stationary, standard Dickey-Fuller unit root tests are applied on individual price series. Second, we test for cointegration among the pairs of prices using the Johansen cointegration test. We then follow the general approach of Engle and Granger and utilize ordinary least squares estimates of the cointegration relationships among the pairs of prices. The lagged residuals derived from these relationships are used to define the error correction terms. The next step consists of determining whether the dynamics of the long-run relationships among prices are linear or whether they exhibit threshold-type nonlinearities. We use Tsay's (1989) nonparametric test.

We then estimate a three-regime multivariate TVECM for each pair of prices. Finally, we test for the significance of the differences in parameters across relative regimes using the sup-LR test statistic (eq. 9). As we have mentioned above, the sup-LR statistic has a non-standard distribution because the threshold parameters are not identified under the null hypothesis. To determine the p-value of the sup-LR statistic, we run 100 simulations for each model whereby the dependent variables (ΔX_t) are replaced by iid N(0,1) draws (see Hansen (1997) for a detailed discussion of this approach)[6]. The proportion of simulations under the null for which the simulated LR statistic exceeds the observed LR statistic gives the asymptotic p-value of the sup-LR test.

[6] To keep calculations manageable, we reduce the number of gridpoints in these simulations.

Data and empirical application

Our empirical analysis utilizes U.S. monthly egg prices[7], observed from October 1880 to October 1911. Prices were quoted at nine relevant wholesale markets: Atlanta, Baltimore, Boston, Cincinnati, Dubuque, Indianapolis, Memphis, Minneapolis and New York. The monthly prices are taken from Holmes (1913)[8]. As explained above, we formulate the hypothesis that the technological developments at the end of the nineteenth century, especially the adoption of mechanical refrigeration, may not have exerted a strong influence on the level of market integration for eggs.

Standard unit-root tests confirm the presence of a unit root in all price series[9]. Johansen cointegration tests (table 3) indicate that there is no long run relationship between the prices[10], a result which is expected in light of the scarce development of the egg industry in the period analyzed[11].

We compute the OLS estimates of the error correction terms for all pairs of variables using the New York price as the regressor. Contrary to the Johansen cointegration tests, the DF and ADF cointegration tests of Engle and Granger (1987) indicate the existence of a long run relationship between the pairs of prices[12].

Tsay's test is conducted using the error correction term derived form the OLS cointegration regression. Tsay's test supports nonlinearity at the 10% significance level in all models except for the Dubuque – New York model (see table 4). The thresholds derived from the two dimensional grid searches and the sup-LR statistics are presented in table 4. Our results suggest that, with the exception of Indianapolis-New York model, threshold effects are statistically significant at the 10% level for all pairs of prices. If we select the thresholds by minimizing the natural log of the determinant of the Σ matrix, we find the transactions costs bands to be maximum for Atlanta-New York, Memphis-New York and Minneapolis-New York, indicating a high variability in egg prices between these cities. Atlanta, Memphis and Minneapolis markets are close to major production areas and likely to have been net exporters of the product analyzed. New York, as is the case for other major cities like Boston and Baltimore, is likely to have been a net importer of eggs. Hence, prices in New York, as well as prices in Boston and Baltimore, do probably include a significant transactions costs charge. In light of the previous argument, transactions costs bands are expected to be wider between an exporter and an importer market, than between importing markets. Bands for importing markets should be narrower to reflect the smaller price differentials usually observed for these pairs of prices, since both prices will include transactions cost components. In accordance to the previous argument, our results suggest much more lower transactions costs bands for Boston-New York and Baltimore-New York than for Atlanta-New York, Memphis-New York and Minneapolis-New York. The finding that bands for Cincinnati-New York and Dubuque-New York are the smallest is difficult to explain in terms of the above argument, though, as it is noted in Goodwin, Grennes and Craig (2002), because we have not restricted the price transmission cointegration parameter to be equal to 1, the interpretation of the thresholds as transactions costs is somewhat complicated.

We find the threshold estimates to be more reasonable when the estimation aims at minimizing the natural log of the determinant of the Σ matrix than when the trace of this matrix is minimized: the

[7] We conduct the analysis for prices in levels.
[8] A detailed description of the price data is available from the authors upon request.
[9] Monthly dummies to allow seasonality are introduced in the model specification. It should be noted here that the standard unit-root tests are very sensitive to the model specification. We use the SBC information criteria to select the deterministic components introduced in the model.
[10] The specification of the model estimated to carry out the Johansen test is determined according to the SC and HQ information criteria.
[11] It should be noted here that, in spite of their limitations (Barrett 1996), cointegration tests have been widely used to evaluate the degree of market integration.
[12] Results are available from the authors upon request.

distance between the thresholds for Boston-New York and Baltimore-New York models is much smaller if the first method is utilized.

As the Monte Carlo results presented above suggest, the two grid search techniques that have been used do not lead to significant differences in the results. Both techniques yield the same LR test result, though there are some differences in the threshold parameters estimates.

In order to better interpret the dynamic relationships among prices, impulse response functions are considered for the models with significant threshold effects. In threshold models, responses to a shock depend on the history of the series, as well as on the size and sign of the shock. As a consequence, many different impulse response functions can be computed. We chose a single observation (the last observation of our data) to evaluate the responses to one standard deviation positive and negative price shocks in each of the markets. We adopt Koop, Pesaran and Potter's (1996) proposal, which defines responses (I_{t+k}) on the basis of the observed data (z_t, z_{t-1}, …) and a shock (v) as:

$$I_{t+k}(v, Z_t, Z_{t-1}, \ldots) = E\left[Z_{t+k} \middle| Z_t = z_t + v, Z_{t-1} = z_{t-1}, \ldots\right] - E\left[Z_{t+k} \middle| Z_t = z_t, Z_{t-1} = z_{t-1}, \ldots\right]$$

Because the prices are not stationary, we may find transitory as well as permanent responses. Specifically, for those pairs of variables with a nonstationary error correction term, shocks may provoke a permanent alteration of the variables' time path.

Figure 1 illustrates the impulse-response functions[13]. The responses appear to be highly consistent with long-run market integration. Shocks in one market generate responses in the other markets, leading to a tendency for prices to equalize. The long run price convergence takes, in the majority of cases analyzed, 4-6 months following the shock, though in some cases a longer adjustment period is required. These adjustment periods are very similar to the findings of Goodwin, Grennes and Craig (2002) for butter markets in the same historical period. In most models the shocks originate permanent adjustments in the price series, reflecting the nonstationary nature of the price data.

The impulse-response functions also suggest an important role for net importer cities, in this case New York, to determine prices. While price changes in net exporter markets follow the price shocks in New York, New York prices do not always imitate price changes in the producing areas. When the producer regions register a price decline, New York prices end up experiencing a higher drop[14]. On the other hand, when producing areas register a positive shock, New York prices do not follow the movement. Instead, they generally register price decreases that force the producing market to correct the initial modification.

As Goodwin, Grennes and Craig (2002) note, TVECM suffer from an important limitation when analyzing periods of relevant changes because they assume constant transactions costs. Our period of analysis was characterized by relevant technical changes that may have modified transactions costs. In order to allow for these changes, we split the sample into two subsets (1880-1895 and 1896-1911)[15]. The results are presented in table 5. Though the results do not yield a clear conclusion, in the majority of cases, a reduction in the transactions costs band is observed. This result is in accordance with our initial expectations and with the results for butter markets in Goodwin, Grennes and Craig (2002). These authors find refrigeration mechanisms to increase the distance between the thresholds. As they explain, prior to the adoption of refrigeration, wholesalers mainly arbitraged through space as they were willing to ship the product to another city, even the price differences were low, to avoid being left with an spoiled product. After the adoption of refrigeration, butter could be hold locally requiring a larger price differential to motivate spatial trade. Contrary to Goodwin, Grennes and Craig results (2002), our analysis mainly indicates a reduction in the bands. As we have previously explained, in spite of the technical

---

[13] The TVECM that minimizes the natural log of the Σ matrix has been used to compute the impulse response functions.

[14] This pattern is not appreciated in the New York – Boston model, as they are two net importer regions.

[15] We use the TVECM that minimizes the natural log of the Σ matrix.

developments that occurred in the period analyzed, the egg freezing and drying techniques were still at an initial stage. This fact along with the highly perishability of fresh refrigerated eggs was precluding temporal arbitrage in the egg sector. Hence, the evolution of transactions costs for eggs does probably only reflect improvements in transportation and communication techniques that reduced the costs of moving the eggs from one market place to another. But these transactions costs do not reflect the advantages of mechanical refrigeration because eggs, even refrigerated, are too perishable to trigger a significant temporal arbitrage.

Concluding Remarks

We compare two general approaches to the selection of thresholds in multivariate threshold models. The first criteria ignores the cross equation correlation while the latter explicitly accounts for it. We conduct a Monte Carlo exercise involving a bivariate threshold vector error correction model. We simulate data over different degrees of error variation and correlation. Contrary to the initial hypothesis, our results suggest that the consideration of the cross-equation correlation does not increase the accuracy of the parameter estimates.

We then apply the methods discussed to the analysis of regional integration of U.S. markets for eggs during the period that goes from 1880 to 1911. Our analysis is of a pairwise nature. We compare monthly prices quoted at several wholesale markets to a central market price – New York. Our results suggest that threshold behavior characterizes spatial price linkages between the markets analyzed. Impulse response functions indicate that price shocks in one market generate responses in the other markets, leading to a tendency for prices to equalize. The long run price convergence takes, in the majority of the cases studied, 4-6 months following the shock. These adjustment periods are very similar to the findings of Goodwin, Grennes and Craig (2002) for butter markets in the same historical period.

Results also suggest an important role for net importer cites in the determination of egg prices. While the price in producer areas mimics the movements of the price in net importing regions, the inverse is not true. We observe that when producer areas register a positive shock, net importer areas do not follow the movement. Instead, they generally register price decreases that force the producing market to correct the initial modification. We also observe that when producer areas experience a price decline, the importer market price registers a higher drop.

When we allow for changes in transactions costs motivated by the relevant technical improvements during the period analyzed, results suggest a reduction in these costs in the majority of cases. These findings suggest that, during the period analyzed, eggs trade mainly benefited from an improvement in transportation and communication mechanisms. This allowed a reduction in transactions costs and an increased spatial arbitrage. Refrigeration techniques, on the other hand, did not allow a temporal arbitrage contrary to what it has been observed in other agricultural markets, because eggs, even refrigerated, are too perishable to trigger a significant temporal arbitrage .

References

Balke, N.S. and T.B. Fomby. "Threshold Cointegration." *International Economic Review*, vol. 38, no 3 (1997): 627-645.

Barrett, C.B. "Market Analysis Methods: Are Our Enriched Toolkits Well-Suited to Enlivened Markets?". *American Journal of Agricultural Economics* 78 (1996): 825-829.

Engle, R.F. and C.W.J. Granger. "Cointegration and Error Correction: Representation, Estimation and Testing." *Econometrica* 55 (1987): 251-276.

Goodwin, B. K. and N. Piggott. "Spatial Market Integration in the Presence of Threshold Effects." *American Journal of Agricultural Economics* May 2001.

Goodwin, B. K., T. Grennes, Lee Craig. "Mechanical Refrigeration and the Integration of Perishable Commodity Markets." *Explorations in Economic History* 39 (2002): 154-182.

Hansen, B.E. "Inference in TAR Models." *Studies in Nonlinear Dynamics Econometrics* 2(1) (April 1997): 1-14.

Holmes, G. K. "Cold Storage and Prices". *Bureau of Statistics Bulletin* 101. United States Department of Agriculture, Washington D.C. (1913).

Johansen, S. "Statistical Analysis of Cointegrating Vectors." *Journal of Economic Dynamics and Control* 12 (1988): 231-254.

Koop, G., M.H. Pesaran, and S.M. Potter. "Impulse Response Analysis in Nonlinear Multivariate Models." *Journal of Econometrics* 74 (1996): 119-146.

Koudele, J.W. and E.C. Heinsohn. "The Egg Products Industry of the United States. Part I Historical Highlights, 1900-59". Kansas State University. Publications of the Agricultural Experiment Station. Historical Bulletin nº 423.

Obstfeld, M., and A.M. Taylor. "Nonlinear aspects of Goods-Market Arbitrage and Adjustment: Hecksher's Commodity Points Revisited." *Journal of the Japanese and International Economies* 11 (1997): 441- 479.

O'Rourke, K.H. "The European Grain Invasion, 1870-1913." *Journal of Economic History* 57 (1997): 775-801.

Tong, H. *On a Threshold Model in Pattern Recognition and Signal Processing*. In C. Chen (Ed.), Amsterdam: Sijhoff and Noonhoff (1978).

Tsay, R. "Testing and Modelling Threshold Autoregressive Processes." *Journal of the American Statistical Association* 84 (1989): 231-240.

Williamson, J.G. "The Evolution of Global Labor Markets Since 1830: Background Evidence and Hypotheses", *Explorations in Economic History* 32 (1995): 141-196.

TABLE 1. Monte Carlo Results

	n = 100. Replications = 1000. $\Sigma = \begin{bmatrix} 0,4 & 0 \\ 0 & 0,1 \end{bmatrix}$						**n = 100. Replications = 1000.** $\Sigma = \begin{bmatrix} 0,4 & 0,1 \\ 0,1 & 0,1 \end{bmatrix}$					
	MEAN		RMSE		MAE		MEAN		RMSE		MAE	
	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ
T	0.15636	-0.02068	0.67090	0.64422	0.52225	0.50503	0.21051	0.17009	0.51341	0.50919	0.40583	0.40695
B1	0.53074	0.54661	0.45914	0.46778	0.33128	0.31409	0.63241	0.64693	0.26673	0.25818	0.19786	0.19107
B2	-0.50183	-0.50793	0.35312	0.35991	0.26762	0.27156	-0.44510	-0.45819	0.32735	0.31121	0.25204	0.23150
B3	-0.06714	-0.09423	0.40569	0.43770	0.30623	0.30292	-0.05998	-0.05972	0.26014	0.26443	0.20506	0.20978
B4	0.21870	0.18831	0.42851	0.46350	0.31635	0.34215	0.24139	0.23758	0.32408	0.32481	0.24830	0.24783
B5	-1.14635	-1.17958	0.24063	0.26925	0.19783	0.22512	-1.19899	-1.22097	0.25242	0.26947	0.21721	0.23407
B6	-0.36592	-0.37603	0.26044	0.24948	0.21774	0.20444	-0.41165	-0.40059	0.24257	0.24411	0.19860	0.19953
B7	-0.03452	-0.05067	0.28056	0.28049	0.20415	0.19075	-0.09774	-0.10759	0.16729	0.15832	0.12443	0.11858
B8	0.21227	0.23727	0.29657	0.32520	0.24521	0.26337	0.17347	0.17903	0.23521	0.24237	0.19407	0.20238
B9	0.41392	0.41201	0.25247	0.27629	0.18940	0.19012	0.40883	0.39438	0.16922	0.17873	0.13093	0.13998
B10	-0.44706	-0.37258	0.34382	0.40567	0.25757	0.30024	-0.53498	-0.49502	0.20728	0.23162	0.15869	0.17088
B11	0.66399	0.68205	0.14113	0.15353	0.11556	0.12597	0.70071	0.70460	0.14353	0.14455	0.12288	0.12432
B12	0.20931	0.22409	0.31932	0.30560	0.29502	0.28219	0.20091	0.21548	0.32709	0.31702	0.30116	0.29057

Where:
T = threshold parameter
B_i, i= 1,…,6 correspond to the parameters of the first equation of model (10).
B_i, i=7,…,12 correspond to the parameters of the second equation of the model (10).

TABLE 1. Monte Carlo Results (continuation)

	n = 100. Replications = 1000. $\Sigma = \begin{bmatrix} 0,4 & -0,1 \\ -0,1 & 0,1 \end{bmatrix}$						**n = 100. Replications = 1000.** $\Sigma = \begin{bmatrix} 0,5 & 0,158 \\ 0,158 & 0,2 \end{bmatrix}$					
	MEAN		RMSE		MAE		MEAN		RMSE		MAE	
	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ
T	0.03732	-0.09970	0.74353	0.74243	0.58578	0.57837	0.28234	0.23177	0.59299	0.57930	0.47613	0.47039
B1	0.36612	0.43274	0.73308	0.70726	0.54190	0.49261	0.65671	0.66999	0.22791	0.22480	0.17178	0.16763
B2	-0.77438	-0.75838	0.56890	0.60060	0.40995	0.42343	-0.44886	-0.43352	0.32780	0.31557	0.24125	0.23307
B3	-0.23662	-0.20933	0.69593	0.71014	0.51201	0.50287	-0.04295	-0.05293	0.25825	0.25083	0.20505	0.20000
B4	-0.16351	-0.18075	0.86798	0.93038	0.59883	0.64004	0.24031	0.24833	0.30195	0.31791	0.22910	0.24401
B5	-1.11847	-1.15057	0.25395	0.25674	0.20485	0.21328	-1.21582	-1.23925	0.26185	0.28080	0.22832	0.24777
B6	-0.30563	-0.33353	0.28147	0.27979	0.24173	0.23423	-0.40798	-0.41795	0.25978	0.23413	0.21386	0.19220
B7	0.06121	0.00763	0.43978	0.41511	0.32188	0.28735	-0.10254	-0.11858	0.15632	0.14967	0.12061	0.11428
B8	0.38425	0.41383	0.53256	0.56370	0.41997	0.45024	0.14173	0.14129	0.21507	0.21354	0.17634	0.17758
B9	0.51685	0.48004	0.40752	0.41736	0.29777	0.29688	0.39380	0.38639	0.17862	0.18255	0.13711	0.14351
B10	-0.16040	-0.06830	0.73871	0.80864	0.54268	0.61029	-0.56837	-0.54432	0.19209	0.19141	0.14672	0.14777
B11	0.65745	0.67611	0.15580	0.15166	0.12580	0.12586	0.70015	0.71094	0.14109	0.15128	0.12036	0.12982
B12	0.20772	0.23459	0.31856	0.30067	0.29705	0.27522	0.21057	0.22477	0.32722	0.31320	0.29501	0.28259

Where:
T = threshold parameter
B_i, i= 1,…,6 correspond to the parameters of the first equation of model (10).
B_i, i=7,…,12 correspond to the parameters of the second equation of the model (10).

TABLE 1. Monte Carlo Results (continuation)

	n = 250. Replications = 1000. $\Sigma = \begin{bmatrix} 0,4 & 0 \\ 0 & 0,1 \end{bmatrix}$						**n = 250. Replications = 1000.** $\Sigma = \begin{bmatrix} 0,4 & 0,1 \\ 0,1 & 0,1 \end{bmatrix}$					
	MEAN		RMSE		MAE		MEAN		RMSE		MAE	
	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ
T	0.47164	0.39687	0.67268	0.59062	0.55482	0.48319	0.41102	0.39385	0.52238	0.51367	0.44892	0.43932
B1	0.67732	0.68079	0.21355	0.21477	0.15956	0.15875	0.70233	0.70818	0.15034	0.14609	0.11810	0.11361
B2	-0.60219	-0.58120	0.17374	0.17163	0.13333	0.13119	-0.55619	-0.55840	0.17151	0.16817	0.13429	0.12789
B3	-0.09600	-0.10067	0.20375	0.20345	0.16522	0.16365	-0.09575	-0.09355	0.15770	0.16143	0.13195	0.13400
B4	0.16061	0.17071	0.20368	0.20551	0.16102	0.15704	0.18628	0.18846	0.18733	0.18440	0.14698	0.14586
B5	-1.23717	-1.24371	0.26359	0.27153	0.24024	0.24648	-1.24862	-1.25054	0.26937	0.26986	0.24911	0.25123
B6	-0.29408	-0.30828	0.23908	0.22626	0.21553	0.20204	-0.32760	-0.32559	0.21768	0.21729	0.18875	0.19074
B7	-0.13074	-0.13512	0.12611	0.12543	0.09462	0.09125	-0.14501	-0.14846	0.09041	0.08754	0.06944	0.06808
B8	0.17746	0.18370	0.21606	0.22035	0.18410	0.18972	0.15903	0.16435	0.19142	0.19500	0.16406	0.16874
B9	0.42878	0.42422	0.12522	0.13006	0.09986	0.10578	0.42433	0.41792	0.10618	0.11508	0.08647	0.09314
B10	-0.49680	-0.46691	0.18822	0.20481	0.14167	0.15921	-0.53663	-0.52221	0.12880	0.13654	0.09897	0.10529
B11	0.73709	0.73896	0.15365	0.15704	0.13972	0.14229	0.74031	0.73939	0.15344	0.15238	0.14174	0.14043
B12	0.22433	0.23357	0.28782	0.27899	0.27582	0.26643	0.21843	0.22033	0.29598	0.29431	0.28175	0.27979

Where:
T = threshold parameter
B_i, i= 1,…,6 correspond to the parameters of the first equation of model (10).
B_i, i=7,…,12 correspond to the parameters of the second equation of the model (10).

TABLE 1. Monte Carlo Results (continuation)

	n = 250. Replications = 1000. $\Sigma = \begin{bmatrix} 0,4 & -0,1 \\ -0,1 & 0,1 \end{bmatrix}$						**n = 250. Replications = 1000.** $\Sigma = \begin{bmatrix} 0,5 & 0,158 \\ 0,158 & 0,2 \end{bmatrix}$					
	MEAN		RMSE		MAE		MEAN		RMSE		MAE	
	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ
T	0.56384	0.42479	0.78010	0.68387	0.63542	0.53954	0.51195	0.45411	0.62857	0.60050	0.54529	0.51064
B1	0.65401	0.64344	0.30864	0.31142	0.22421	0.22858	0.71489	0.71880	0.13329	0.12654	0.10380	0.09915
B2	-0.70294	-0.68669	0.23839	0.23721	0.18916	0.18742	-0.54625	-0.54346	0.15835	0.15749	0.11760	0.12211
B3	-0.12979	-0.15793	0.30507	0.31231	0.22753	0.23467	-0.10375	-0.09929	0.14346	0.14381	0.11709	0.11870
B4	0.02486	0.02328	0.30673	0.30306	0.23478	0.23285	0.18690	0.18944	0.17466	0.17605	0.13930	0.13843
B5	-1.24655	-1.25037	0.28013	0.27894	0.25278	0.25325	-1.26522	-1.26322	0.28572	0.28301	0.26547	0.26341
B6	-0.27330	-0.28876	0.25185	0.24300	0.23154	0.22065	-0.33868	-0.33829	0.20550	0.20413	0.17951	0.17648
B7	-0.11761	-0.11424	0.18235	0.18023	0.13301	0.13255	-0.14886	-0.15138	0.08457	0.08068	0.06618	0.06234
B8	0.23321	0.24667	0.28751	0.29201	0.24060	0.25149	0.12637	0.13854	0.16429	0.17562	0.13802	0.14650
B9	0.44822	0.45955	0.18104	0.18280	0.13524	0.13853	0.43002	0.42420	0.10122	0.10467	0.08125	0.08492
B10	-0.39888	-0.35080	0.31531	0.33909	0.23673	0.26870	-0.57002	-0.54958	0.11040	0.12314	0.08484	0.09537
B11	0.74542	0.74756	0.16601	0.16505	0.15021	0.14979	0.74976	0.74774	0.16307	0.16224	0.15023	0.14894
B12	0.22859	0.24108	0.28241	0.27148	0.27144	0.25957	0.23087	0.22895	0.28705	0.28852	0.26932	0.27122

Where:
T = threshold parameter
B_i, i= 1,…,6 correspond to the parameters of the first equation of model (10).
B_i, i=7,…,12 correspond to the parameters of the second equation of the model (10).

TABLE 2. Monte Carlo Results

	n = 100. Replications = 100. $\Sigma = \begin{bmatrix} 0,4 & 0 \\ 0 & 0,1 \end{bmatrix}$						**n = 100. Replications = 100.** $\Sigma = \begin{bmatrix} 0,4 & 0,1 \\ 0,1 & 0,1 \end{bmatrix}$					
	MEAN		RMSE		MAE		MEAN		RMSE		MAE	
	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ
LR	76.26100	71.49931					88.78760	84.07158				
p-val	0.00410	0.00620					5.00e-04	1.00e-04				
T	0.33207	-0.03942	0.76745	0.65494	0.60773	0.51160	0.17048	0.03997	0.53181	0.48937	0.40450	0.38968
B1	0.56682	0.55258	0.40389	0.44416	0.30737	0.31491	0.63418	0.65359	0.29880	0.26109	0.20648	0.19287
B2	-0.53811	-0.52022	0.34133	0.39768	0.26083	0.29268	-0.48072	-0.43776	0.27823	0.33803	0.22451	0.26193
B3	-0.02200	-0.08185	0.36798	0.40742	0.28498	0.31949	-0.03643	-0.07812	0.28343	0.30074	0.22454	0.23741
B4	0.23811	0.18834	0.41429	0.54480	0.32145	0.38982	0.22384	0.24444	0.28543	0.35854	0.22190	0.27483
B5	-1.13985	-1.18382	0.25278	0.26639	0.21761	0.22151	-1.19112	-1.24974	0.24327	0.29319	0.21246	0.25893
B6	-0.31646	-0.36226	0.29647	0.24049	0.24596	0.20673	-0.38961	-0.42346	0.23200	0.23576	0.18977	0.19810
B7	-0.06084	-0.06407	0.25110	0.26077	0.19075	0.18938	-0.09159	-0.10783	0.20192	0.16070	0.13338	0.12617
B8	0.19853	0.26772	0.29909	0.36773	0.23641	0.29480	0.18949	0.19606	0.24947	0.25989	0.21218	0.21774
B9	0.37607	0.39926	0.22856	0.25461	0.17562	0.19690	0.41906	0.40966	0.17603	0.20040	0.13921	0.14897
B10	-0.49004	-0.33654	0.33152	0.47172	0.22750	0.33981	-0.52670	-0.46548	0.23826	0.26086	0.17134	0.20416
B11	0.66408	0.69025	0.15023	0.15926	0.12395	0.13086	0.70218	0.71626	0.14689	0.14987	0.12641	0.13216
B12	0.20865	0.20942	0.32890	0.31622	0.29383	0.29430	0.19163	0.20494	0.33401	0.32158	0.31069	0.29752

Where:
T = threshold parameter
B_i, i= 1,…,6 correspond to the parameters of the first equation of model (10).
B_i, i=7,…,12 correspond to the parameters of the second equation of the model (10).

TABLE 2. Monte Carlo Results (continuation)

	n = 100. Replications = 100. $\Sigma=\begin{bmatrix}0,4 & -0,1\\ -0,1 & 0,1\end{bmatrix}$						**n = 100. Replications = 100.** $\Sigma=\begin{bmatrix}0,5 & 0,158\\ 0,158 & 0,2\end{bmatrix}$					
	MEAN		RMSE		MAE		MEAN		RMSE		MAE	
	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ	Min ln|Σ|	Min trΣ
LR	68.18626	67.71671					82.69171	83.08769				
p-val	0.01000	0.00610					4.00e-04	2.00e-04				
T	-0.00925	-0.22862	0.85214	0.82488	0.69235	0.61788	0.17344	0.20063	0.59796	0.55875	0.47576	0.45243
B1	0.39582	0.46271	0.79312	0.66369	0.52821	0.46732	0.64293	0.66629	0.26225	0.21932	0.18147	0.16232
B2	-0.79241	-0.79055	0.61598	0.60203	0.43167	0.46939	-0.43328	-0.41973	0.33033	0.31473	0.24175	0.23550
B3	-0.23282	-0.21619	0.76334	0.69779	0.53758	0.48047	-0.07101	-0.05610	0.25446	0.26118	0.20975	0.21181
B4	-0.21357	-0.24808	0.96544	0.86935	0.66399	0.67103	0.28883	0.28143	0.35551	0.33514	0.28844	0.25723
B5	-1.12934	-1.19290	0.24255	0.28946	0.20461	0.24742	-1.22401	-1.24399	0.26185	0.28257	0.23498	0.24693
B6	-0.32281	-0.34385	0.29680	0.27229	0.25649	0.23460	-0.41333	-0.41116	0.26428	0.23951	0.20510	0.19781
B7	0.05103	-0.01788	0.47153	0.38911	0.31332	0.26964	-0.09175	-0.12525	0.17447	0.14034	0.12836	0.10806
B8	0.41802	0.43365	0.57635	0.57419	0.44843	0.48494	0.13907	0.13287	0.20712	0.20221	0.17612	0.16815
B9	0.51886	0.47120	0.42677	0.40926	0.30445	0.28356	0.40262	0.38726	0.18080	0.18211	0.14345	0.14957
B10	-0.08881	-0.02374	0.82279	0.79714	0.59734	0.63708	-0.55229	-0.56281	0.19086	0.18706	0.14383	0.14788
B11	0.66117	0.69911	0.14746	0.17059	0.12290	0.14349	0.69615	0.72519	0.12943	0.15568	0.11220	0.13611
B12	0.21860	0.23553	0.31751	0.29854	0.29510	0.27823	0.21917	0.22003	0.32137	0.31250	0.28853	0.28645

Where:
T = threshold parameter
B_i, i= 1,…,6 correspond to the parameters of the first equation of model (10).
B_i, i=7,…,12 correspond to the parameters of the second equation of the model (10).

TABLE 3. The Johansen cointegration tests

Model	l max (sig. value 90%) r = 0	l max (sig. value 90%) r = 1	l trace (sig. value 90%) r = 0	l trace (sig. value 90%) r = 1
Atlanta-New York	227.53 (10.29)	37.53 (7.50)	265.06 (17.79)	37.53 (7.50)
Baltimore -New York	168.19 (10.29)	39.41 (7.50)	207.59 (17.79)	39.41 (7.50)
Boston-New York	221.99 (10.29)	31.45 (7.50)	253.43 (17.79)	31.45 (7.50)
Cincinnati-New York	165.90 (10.29)	37.32 (7.50)	203.21 (17.79)	37.32 (7.50)
Dubuque-New York	221.48 (10.29)	60.18 (7.50)	281.67 (17.79)	60.18 (7.50)
Indianapolis -New York	192.69 (10.29)	38.25 (7.50)	230.94 (17.79)	38.25 (7.50)
Memphis -New York	143.65 (10.29)	34.99 (7.50)	178.65 (17.79)	34.99 (7.50)
Minneapolis -New York	167.77 (10.29)	40.45 (7.50)	208.22 (17.79)	40.45 (7.50)

where:
λ MAX = Maximum eigenvalue test statistic;
λ TRACE = Trace test statistic;
r = number of cointegrating vectors being tested under the null hypothesis.

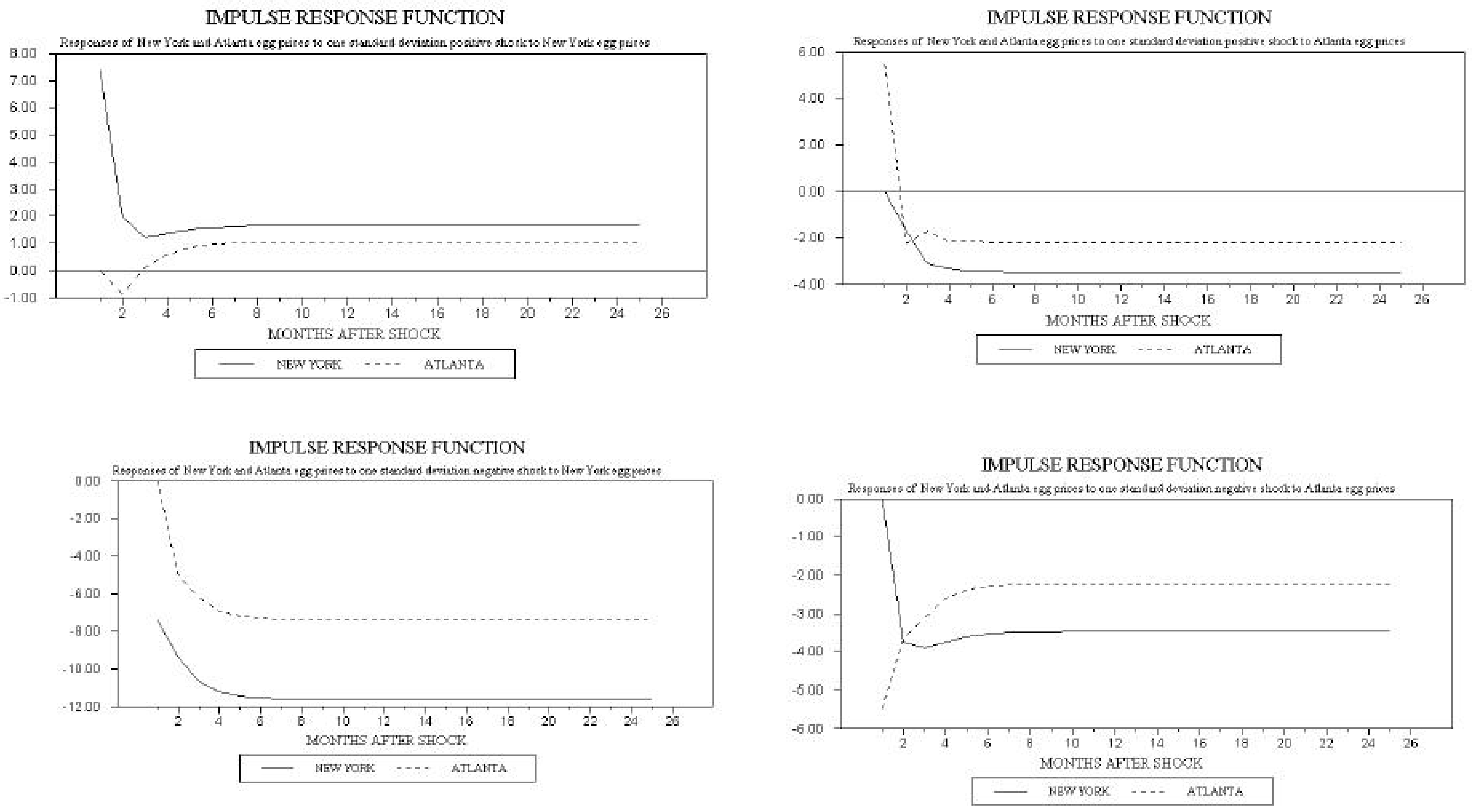
TABLE 4. Tsay's test, thresholds and the sup-LR test

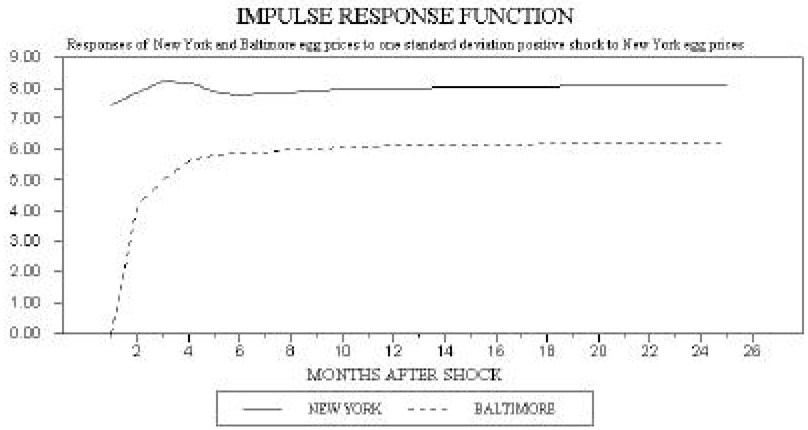
Variables	Tsay's test (p-value)	Minimum ln|S|			Minimum trace(S)		
		C1: Negative threshold	C2: Positive threshold	Sup-LR test (p-value)	C1: Negative threshold	C2: Positive threshold	Sup-LR test (p-value)
Atlanta-New York	4.36958 (0.03726990)	-4.21847	4.70471	35.82876 (0.03000)	-4.11347	4.70471	35.77480 (0.03000)
Baltimore -New York	5.54600 (0.01904593)	-0.41302	3.65352	48.10246 (0.00000)	-1.54302	4.04352	41.01023 (0.00000)
Boston-New York	2.78421 (0.09607421)	-2.16453	1.99346	53.02925 (0.00000)	-2.56453	3.91346	52.06534 (0.00000)
Cincinnati-New York	3.40618 (0.06575343)	-0.37792	3.62298	50.14700 (0.00000)	-0.37792	3.62298	50.14700 (0.00000)
Dubuque-New York	0.02541 (0.87343826)	-0.42392	2.68334	51.54597 (0.00000)	-0.40392	2.68334	50.63417 (0.00000)
Indianapolis -New York	3.37622 (0.06697451)	-2.36443	1.55603	31.21481 (0.12000)	-0.50943	0.05103	29.36951 (0.14000)
Memphis -New York	5.03133 (0.02573216)	-3.37125	4.84961	43.35183 (0.00000)	-3.45125	4.84961	40.93464 (0.00000)
Minneapolis -New York	8.48748 (0.00381766)	-2.28567	3.57694	41.45080 (0.02000)	-1.46567	3.76194	30.34356 (0.08000)

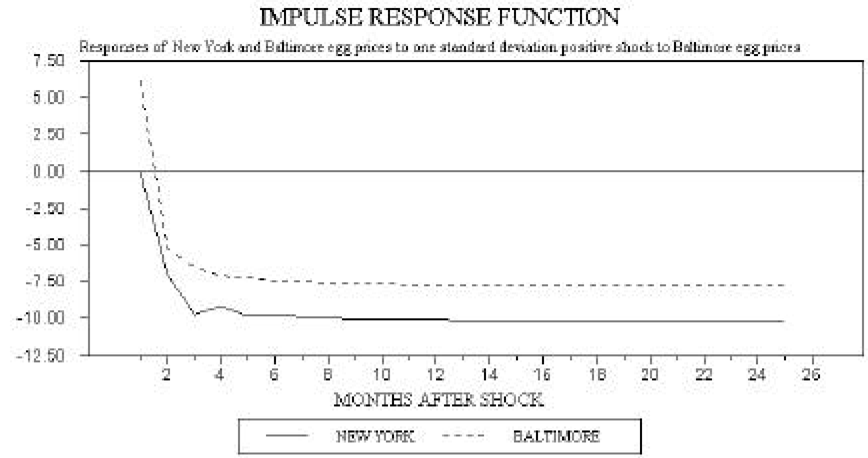
TABLE 5. Split-sample analysis of TVECM

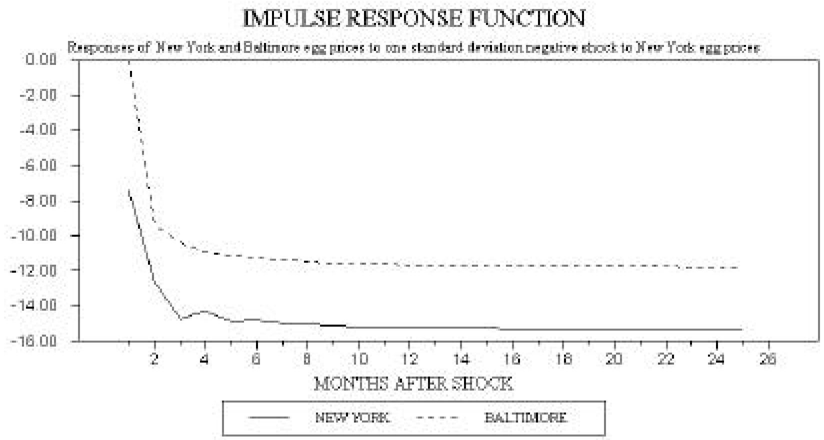
Variables	Minimum ln|S| 1880-1895		Minimum ln|S| 1896-1911	
	C1: Negative threshold	C2: Positive threshold	C1: Negative threshold	C2: Positive threshold
Atlanta-New York	-1.55546	1.45993	-1.30101	2.23548
Baltimore -New York	-0.48756	2.35695	-0.96415	2.99993
Boston-New York	-2.36966	3.04362	-1.30268	1.83689
Cincinnati-New York	-1.16718	2.17853	-0.06935	1.65395
Dubuque-New York	-2.63292	3.38760	-0.43701	2.92077
Indianapolis -New York	-2.17227	2.24428	-0.09240	0.25017
Memphis -New York	-3.91461	4.14149	-0.08173	1.31914
Minneapolis -New York	-1.30290	0.16400	-2.06985	3.17009

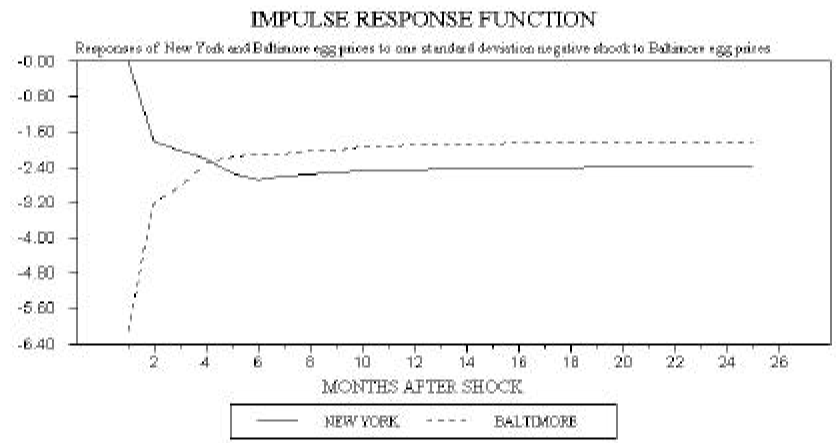
Figure 1. Nonlinear Impulse-response functions

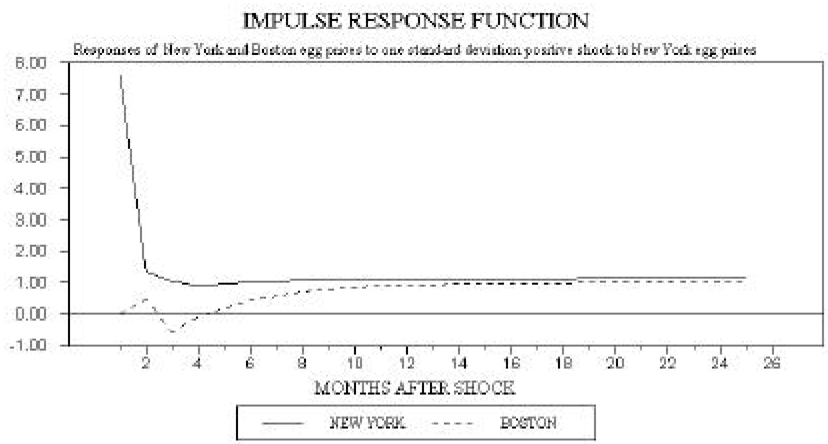


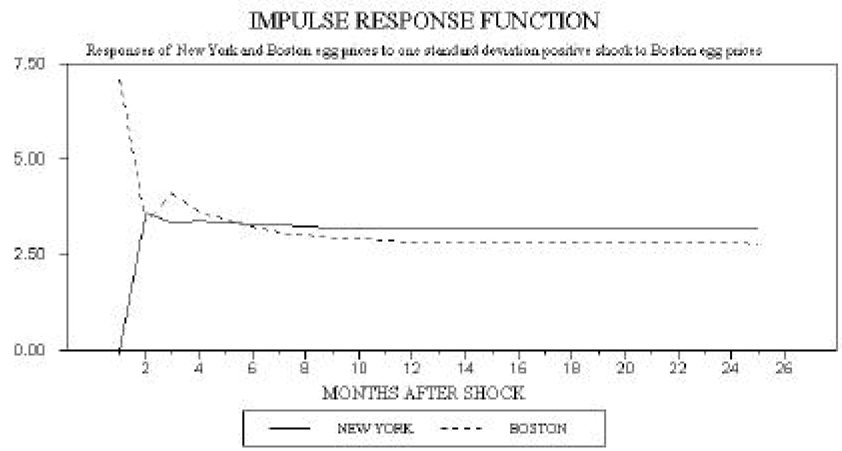

IMPULSE RESPONSE FUNCTION
Responses of New York and Baltimore egg prices to one standard deviation positive shock to New York egg prices
MONTHS AFTER SHOCK
NEW YORK
BALTIMORE

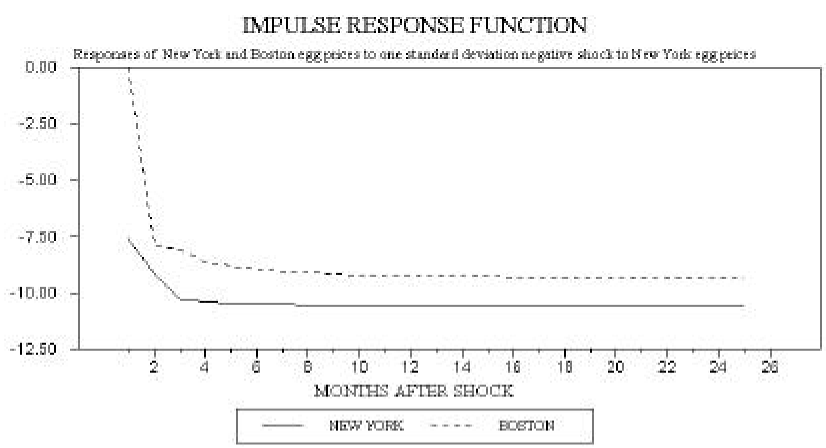

IMPULSE RESPONSE FUNCTION
Responses of New York and Baltimore egg prices to one standard deviation positive shock to Baltimore egg prices
MONTHS AFTER SHOCK
NEW YORK
BALTIMORE

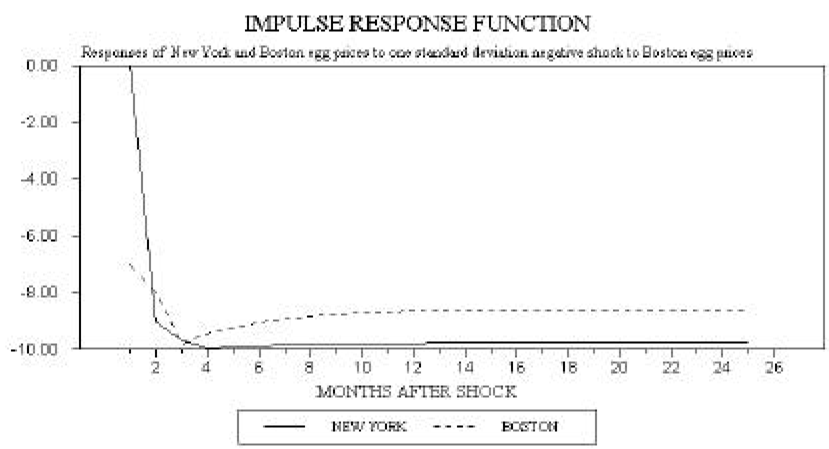

IMPULSE RESPONSE FUNCTION
Responses of New York and Baltimore egg prices to one standard deviation negative shock to New York egg prices
MONTHS AFTER SHOCK
NEW YORK
BALTIMORE

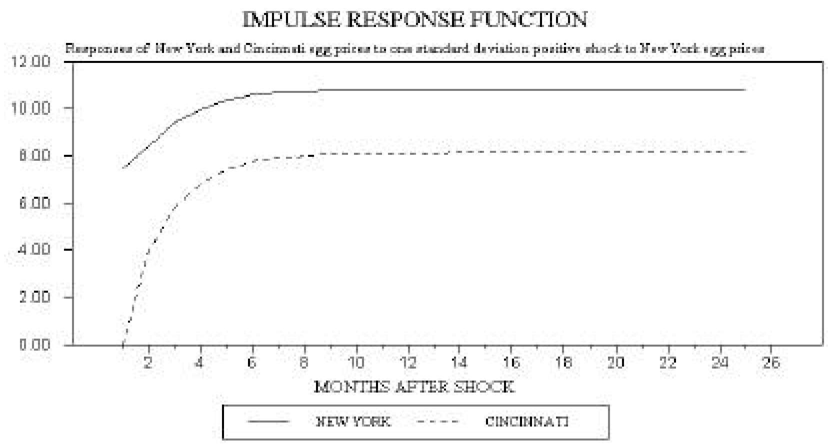

IMPULSE RESPONSE FUNCTION
Responses of New York and Baltimore egg prices to one standard deviation negative shock to Baltimore egg prices
MONTHS AFTER SHOCK
NEW YORK
BALTIMORE

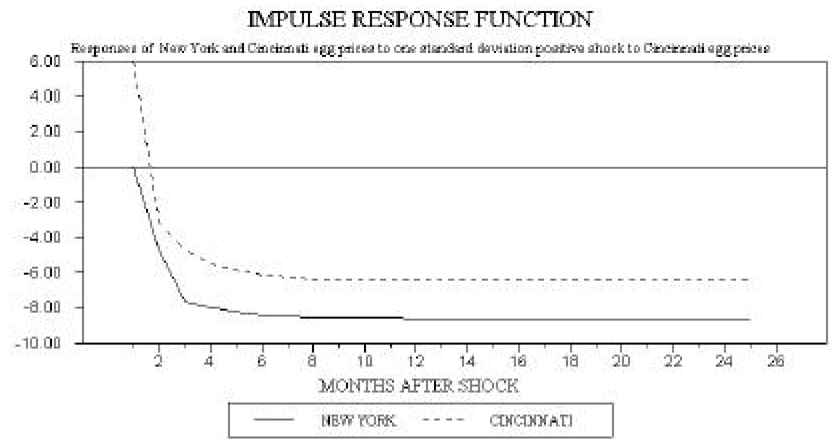

IMPULSE RESPONSE FUNCTION
Responses of New York and Boston egg prices to one standard deviation positive shock to New York egg prices
8.00
7.00
6.00
5.00
4.00
3.00
2.00
1.00
0.00
-1.00
2 4 6 8 10 12 14 16 18 20 22 24 26
MONTHS AFTER SHOCK
NEW YORK
BOSTON

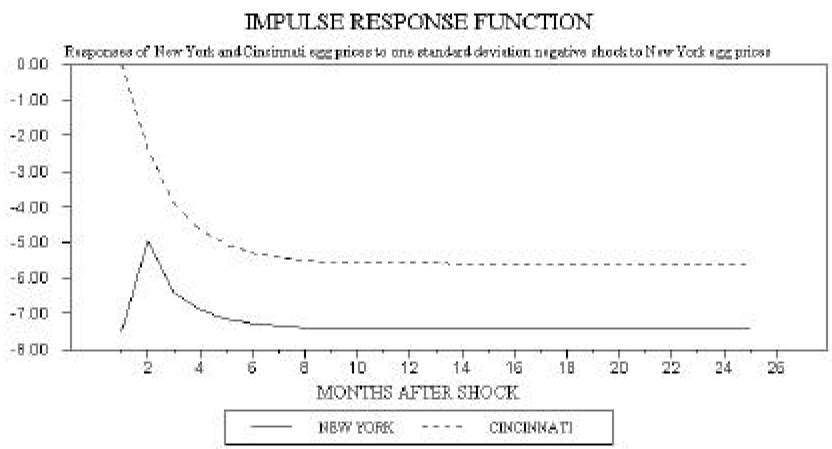

IMPULSE RESPONSE FUNCTION
Responses of New York and Boston egg prices to one standard deviation positive shock to Boston egg prices
7.50
5.00
2.50
0.00
2 4 6 8 10 12 14 16 18 20 22 24 26
MONTHS AFTER SHOCK
NEW YORK
BOSTON

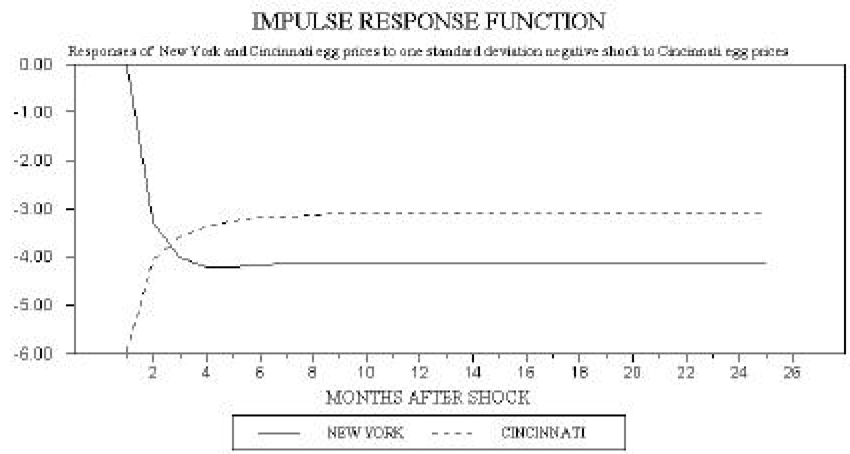

IMPULSE RESPONSE FUNCTION
Responses of New York and Boston egg prices to one standard deviation negative shock to New York egg prices
0.00
-2.50
-5.00
-7.50
-10.00
-12.50
2 4 6 8 10 12 14 16 18 20 22 24 26
MONTHS AFTER SHOCK
NEW YORK
BOSTON

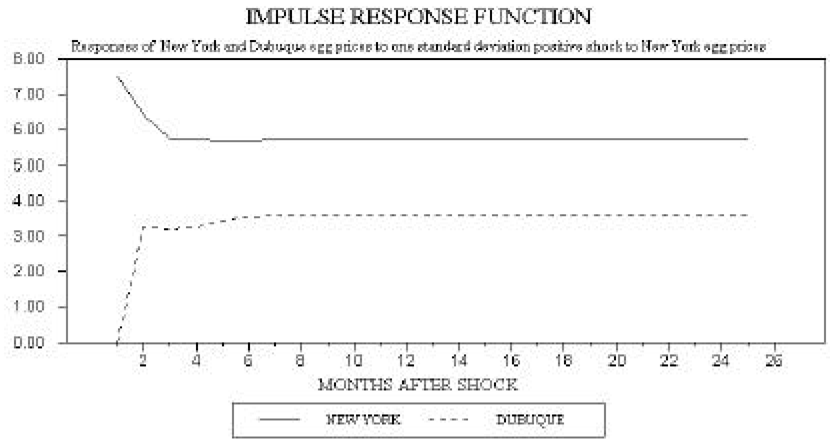

IMPULSE RESPONSE FUNCTION
Responses of New York and Boston egg prices to one standard deviation negative shock to Boston egg prices
0.00
-2.00
-4.00
-6.00
-8.00
-10.00
2 4 6 8 10 12 14 16 18 20 22 24 26
MONTHS AFTER SHOCK
NEW YORK
BOSTON

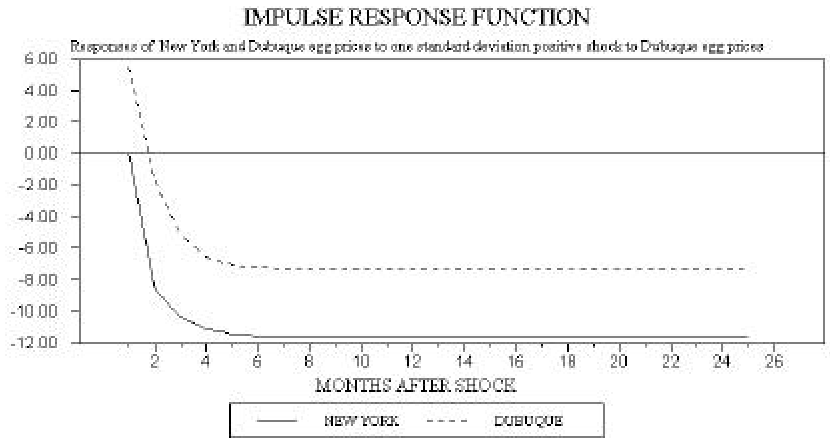

IMPULSE RESPONSE FUNCTION
Responses of New York and Cincinnati egg prices to one standard deviation positive shock to New York egg prices
MONTHS AFTER SHOCK
NEW YORK
CINCINNATI

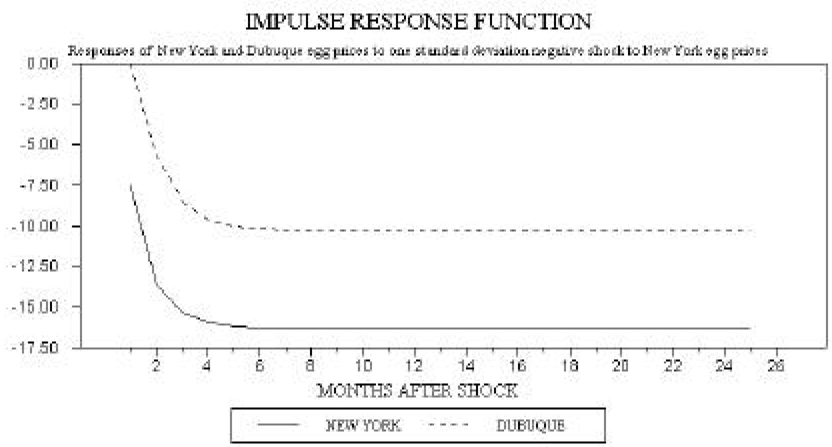

IMPULSE RESPONSE FUNCTION
Responses of New York and Cincinnati egg prices to one standard deviation positive shock to Cincinnati egg prices
MONTHS AFTER SHOCK
NEW YORK
CINCINNATI

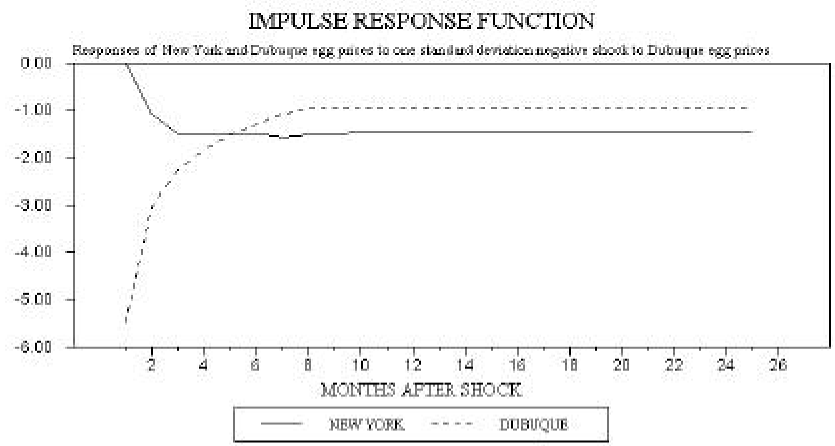

IMPULSE RESPONSE FUNCTION
Responses of New York and Cincinnati egg prices to one standard deviation negative shock to New York egg prices
MONTHS AFTER SHOCK
NEW YORK
CINCINNATI

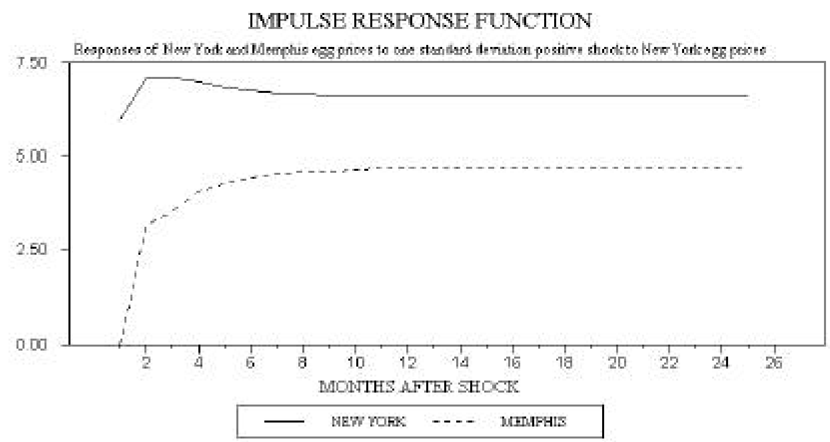

IMPULSE RESPONSE FUNCTION
Responses of New York and Cincinnati egg prices to one standard deviation negative shock to Cincinnati egg prices
MONTHS AFTER SHOCK
NEW YORK
CINCINNATI

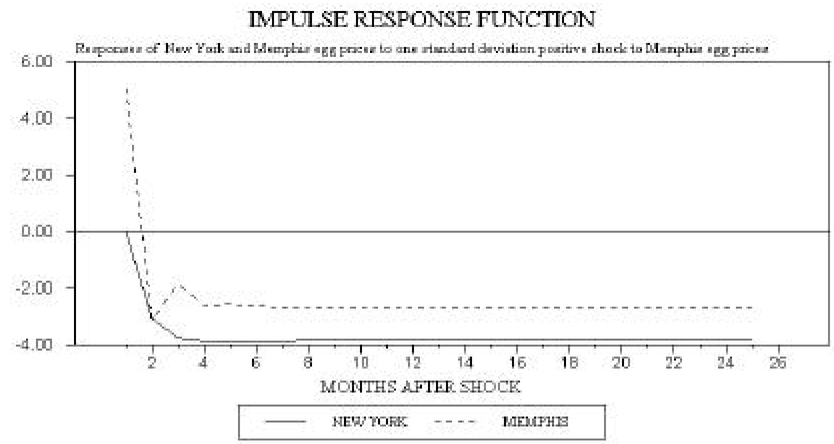

IMPULSE RESPONSE FUNCTION
Responses of New York and Dubuque egg prices to one standard deviation positive shock to New York egg prices
8.00
7.00
6.00
5.00
4.00
3.00
2.00
1.00
0.00
2 4 6 8 10 12 14 16 18 20 22 24 26
MONTHS AFTER SHOCK
NEW YORK
DUBUQUE

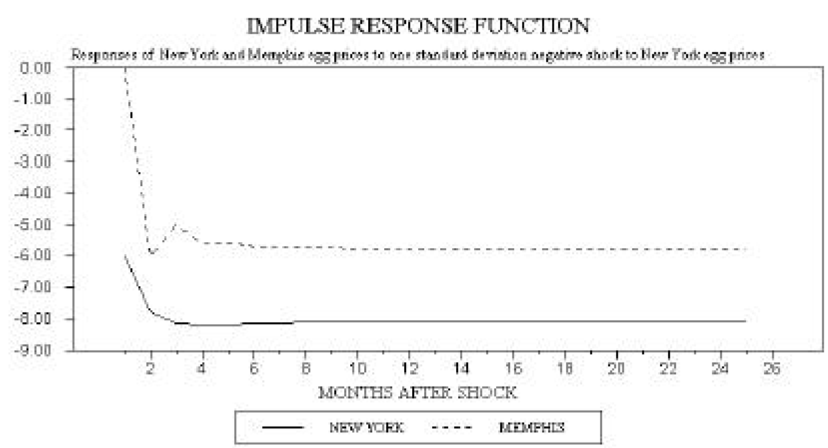

IMPULSE RESPONSE FUNCTION
Responses of New York and Dubuque egg prices to one standard deviation positive shock to Dubuque egg prices
6.00
4.00
2.00
0.00
-2.00
-4.00
-6.00
-8.00
-10.00
-12.00
2 4 6 8 10 12 14 16 18 20 22 24 26
MONTHS AFTER SHOCK
NEW YORK
DUBUQUE

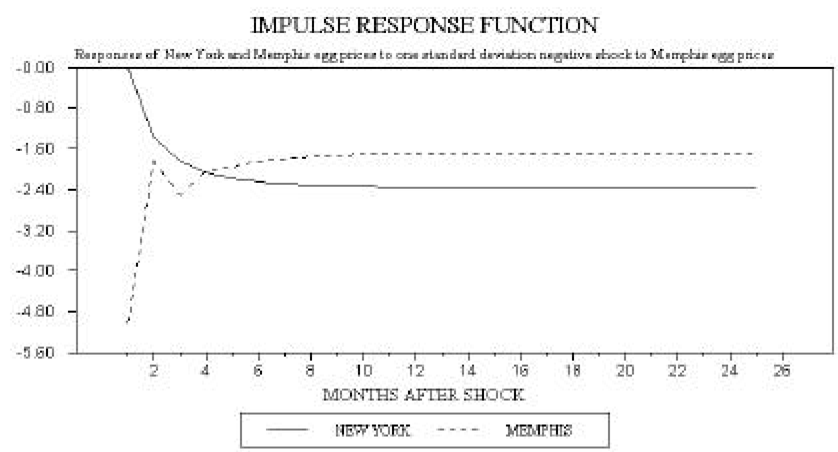

IMPULSE RESPONSE FUNCTION
Responses of New York and Dubuque egg prices to one standard deviation negative shock to New York egg prices
0.00
-2.50
-5.00
-7.50
-10.00
-12.50
-15.00
-17.50
2 4 6 8 10 12 14 16 18 20 22 24 26
MONTHS AFTER SHOCK
NEW YORK
DUBUQUE

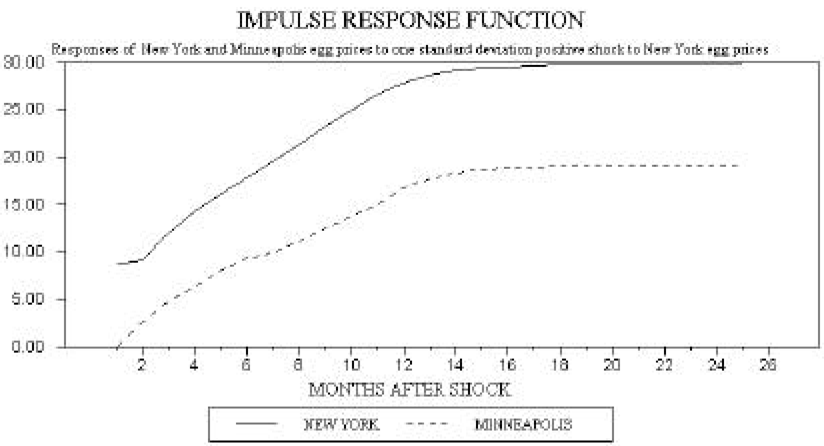

IMPULSE RESPONSE FUNCTION
Responses of New York and Dubuque egg prices to one standard deviation negative shock to Dubuque egg prices
0.00
-1.00
-2.00
-3.00
-4.00
-5.00
-6.00
2 4 6 8 10 12 14 16 18 20 22 24 26
MONTHS AFTER SHOCK
NEW YORK
DUBUQUE

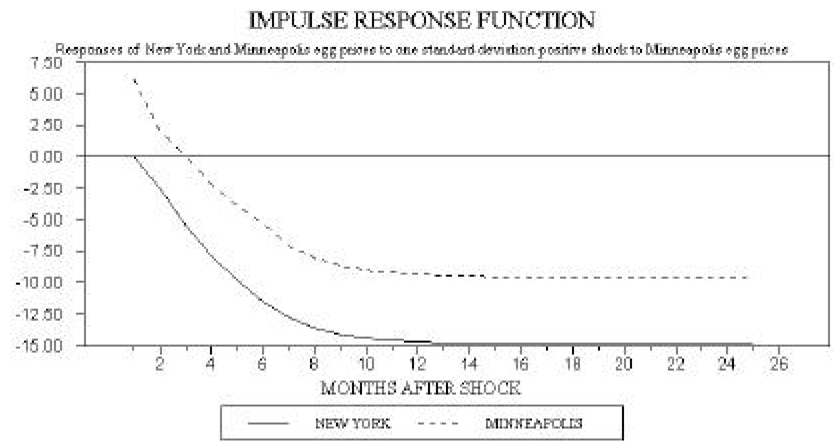

IMPULSE RESPONSE FUNCTION
Responses of New York and Memphis egg prices to one standard deviation positive shock to New York egg prices
7.50
5.00
2.50
0.00
2 4 6 8 10 12 14 16 18 20 22 24 26
MONTHS AFTER SHOCK
NEW YORK
MEMPHIS

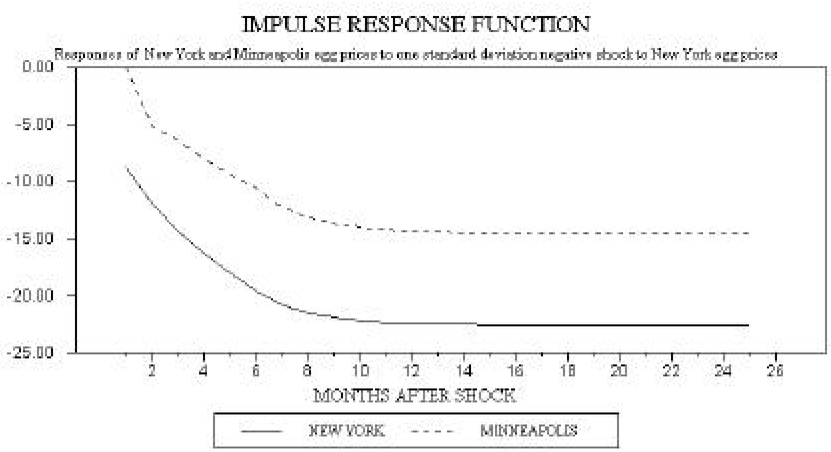

IMPULSE RESPONSE FUNCTION
Responses of New York and Memphis egg prices to one standard deviation positive shock to Memphis egg prices
6.00
4.00
2.00
0.00
-2.00
-4.00
2 4 6 8 10 12 14 16 18 20 22 24 26
MONTHS AFTER SHOCK
NEW YORK
MEMPHIS

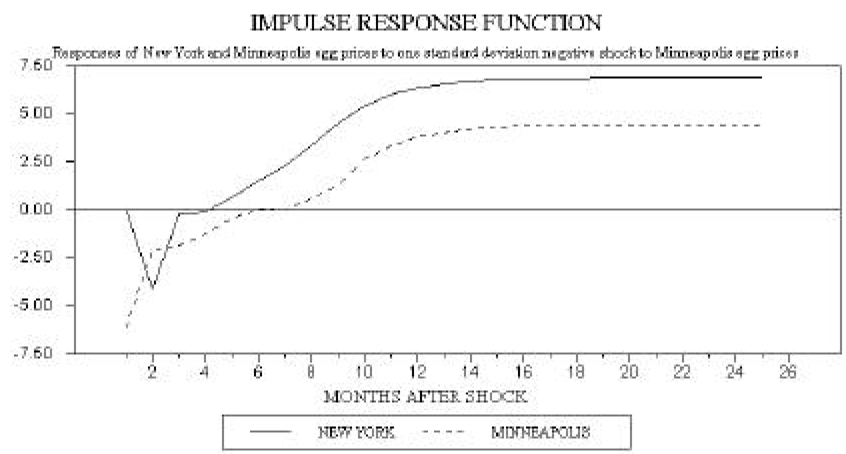

IMPULSE RESPONSE FUNCTION
Responses of New York and Memphis egg prices to one standard deviation negative shock to New York egg prices
0.00
-1.00
-2.00
-3.00
-4.00
-5.00
-6.00
-7.00
-8.00
-9.00
2 4 6 8 10 12 14 16 18 20 22 24 26
MONTHS AFTER SHOCK
NEW YORK
MEMPHIS


IMPULSE RESPONSE FUNCTION
Responses of New York and Memphis egg prices to one standard deviation negative shock to Memphis egg prices
-0.00
-0.80
-1.60
-2.40
-3.20
-4.00
-4.80
-5.60
2 4 6 8 10 12 14 16 18 20 22 24 26
MONTHS AFTER SHOCK
NEW YORK
MEMPHIS


IMPULSE RESPONSE FUNCTION
Responses of New York and Minneapolis egg prices to one standard deviation positive shock to New York egg prices
30.00
25.00
20.00
15.00
10.00
5.00
0.00
2 4 6 8 10 12 14 16 18 20 22 24 26
MONTHS AFTER SHOCK
NEW YORK
MINNEAPOLIS


IMPULSE RESPONSE FUNCTION
Responses of New York and Minneapolis egg prices to one standard deviation positive shock to Minneapolis egg prices
7.50
5.00
2.50
0.00
-2.50
-5.00
-7.50
-10.00
-12.50
-15.00
2 4 6 8 10 12 14 16 18 20 22 24 26
MONTHS AFTER SHOCK
NEW YORK
MINNEAPOLIS


IMPULSE RESPONSE FUNCTION
Responses of New York and Minneapolis egg prices to one standard deviation negative shock to New York egg prices
0.00
-5.00
-10.00
-15.00
-20.00
-25.00
2 4 6 8 10 12 14 16 18 20 22 24 26
MONTHS AFTER SHOCK
NEW YORK
MINNEAPOLIS


IMPULSE RESPONSE FUNCTION
Responses of New York and Minneapolis egg prices to one standard deviation negative shock to Minneapolis egg prices
7.50
5.00
2.50
0.00
-2.50
-5.00
-7.50
2 4 6 8 10 12 14 16 18 20 22 24 26
MONTHS AFTER SHOCK
NEW YORK
MINNEAPOLIS