

# Supply Response in the Northeastern Fresh Tomato Market: Cointegration and Error Correction Analysis

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This paper reexamines supply response in the Northeastern fresh tomato market during the 1949–94 period by employing cointegration and error correction technique. It tests whether there has been a long-run equilibrium relationship between Northeastern production and a set of price and nonprice factors that influence it. Findings suggest that wage rate, imports from competing regions, and urban pressure have had significant negative impacts on regional production. The negative relationship between price and production may have resulted from the strong negative effects exerted by the nonprice factors.

Fresh tomato production in the Northeastern United States continuously declined during the three decades following World War II. The drastic decline in production amid considerable increases in real price (figure 1) prompted the argument that price incentives were not sufficient for Northeastern producers to expand the supply of fresh tomatoes.<sup>1</sup> Given this argument, a few studies examined the impact of nonprice factors, such as urban pressure and imports from competing regions, on the supply of fresh tomatoes in the Northeast. Although these studies strongly support the hypothesis that urban pressure has played a major role in shifting the supply response of fresh tomatoes in the Northeast, the evidence on the role of imports is mixed (Lopez and Munoz 1987; Porter 1975).

A major shortcoming of all previous supply response studies of the Northeastern tomato market (Dunn 1981; Lopez and Munoz 1987; Wyson, Leigh, and Ganguly 1984) is that they failed to take into account the possible nonstationary behavior of the time series data used. Failure to account for the nonstationarity of the data invalidates standard statistical tests, resulting in what have become known

as “spurious regressions.” Cointegration techniques offer a means of identifying and hence avoiding spurious regressions associated with nonstationary time series. Also, the cointegration modeling procedure is a means by which long-run information concerning the relationship between the levels of the variables can be reincorporated into a regression equation.

This article reexamines the responsiveness of Northeastern fresh tomato production to changes in economic and demographic characteristics during the post-World War II period by taking into account the nonstationarity of time series involved in estimation. It addresses the question of whether a long-run equilibrium relationship has existed between fresh tomato production and a set of price and nonprice factors that influence it. In particular, the article tests whether there is a cointegrated relationship between tomato production and tomato price, prices of substitutes, wage rate, urban pressure, imports, and weather. Findings suggest that urban pressure, imports from competing regions, and increased wage rate have resulted in a decline in production. The error correction model used is a more general approach to modeling agricultural supply response than the commonly used Nerlove partial adjustment model.

## Nerlove Partial Adjustment Model

The Nerlove partial adjustment model has been the dominant method used in modeling agricultural supply response during the past three decades. According to Nerlove (1956, 1958), a simple partial

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<sup>1</sup> Production began to increase in 1972/73 and continued to increase afterward. Although this reversal in the production trend coincided with the energy crisis in the early 1970s, there is no strong evidence to support the argument that the energy crisis had a significant impact on the competitive position of Northeastern agriculture (Dunn 1981). See also Lopez and Munoz (1987) for more on this subject.

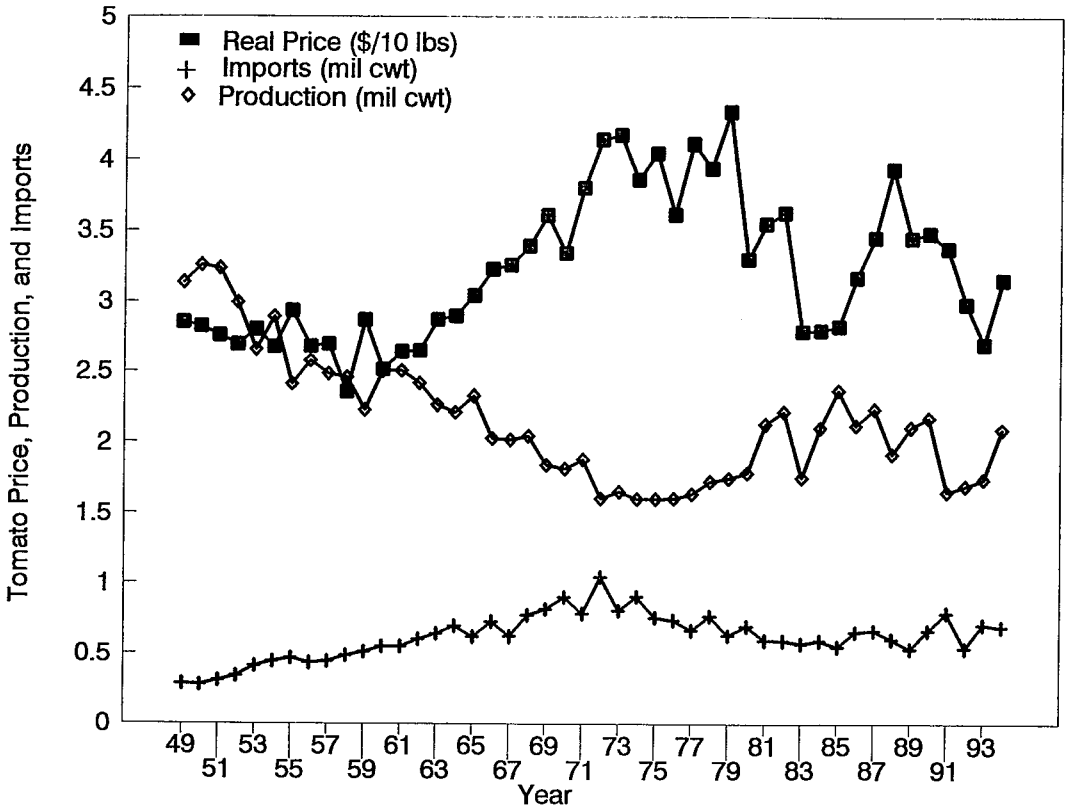


Figure 1. Tomato Price, Production, and Imports, 1949–94.

adjustment model will result from the minimization of a loss function that takes the form

$$(1) \quad L_t = \gamma_1(Z_t - Z_t^*)^2 + \gamma_2(Z_t - Z_{t-1})^2,$$

where  $L_t$  is the loss incurred by a producer in period  $t$  in the supply of an agricultural product,  $Z_t^*$  is the desired or long-run equilibrium level of some variable  $Z_t$ , and is defined according to stationary expectations of some conditioning variables toward which adjustments are made in the long-run. Minimization of  $L_t$  in equation (1) with respect to  $Z_t$  will yield the partial adjustment model

$$(2) \quad \Delta Z_t = Z_t - Z_{t-1} = \gamma(Z_t^* - Z_t),$$

where  $\gamma (= \gamma_1/\gamma_2)$  is the coefficient of adjustment,  $\Delta Z_t$  is the actual change,  $Z_t^* - Z_t$  is the desired change, and  $\Delta$  is the first-difference operator.  $Z_t$  is usually expressed in terms of expected product and input prices. The model assumes that there is an equilibrium toward which producers are moving in the long-run. This movement toward the long-run equilibrium is determined on the basis of a static theory of optimization, which assumes that future values of the exogenous variables (mainly prices) remain unchanged. These static expectations result

in a fixed target  $Z_t^*$  toward which the actual value  $Z_t$  adjusts in the long-run.

However, the notion of a fixed target has been criticized by many economists, including Nerlove himself (1979), as unrealistic in the context of optimization under dynamic conditions. A more realistic approach that has recently been proposed for analyzing supply response of agricultural products is the application of an error correction model that captures both short-run dynamics and adjustments toward long-run equilibrium. Following the work of Nickell (1985) and Hendry and von Ungern-Sternberg (1981), Hallam and Zanolì (1993) demonstrate that a more realistic, forward-looking partial adjustment model is nested within the error correction model that results from the minimization of a more general intertemporal quadratic loss function. It is in this spirit we are using the error correction model to examine the supply response of tomato production in the Northeast.<sup>2</sup>

<sup>2</sup> Hallam and Zanolì (1993) provide a formal demonstration showing that the partial adjustment model is only a special case of the error correction model. To avoid repetition, we do not present this derivation here.

**Error Correction Model**

In this section, we outline the empirical counterpart of the error correction model for the supply of fresh tomatoes in the Northeast. Following Hallam and Zanoli (1993), we write a dynamically unrestricted version of the error correction model for the tomato supply as

$$(3) \quad \Delta \ln OUT_t = \beta_0 + \beta_1 \Delta \ln OUT_t^* + \beta_2 (\ln OUT_{t-1}^* - \ln OUT_{t-1}),$$

where  $\ln OUT_t$  is the aggregate tomato production in the Northeast expressed in natural logarithms. The model in equation (3) is consistent with a wide array of possible processes that describe the movement of output toward the desired level (Hallam and Zanoli 1993). Following previous work, the desired production of fresh tomatoes in the Northeast ( $\ln OUT_t^*$ ) is assumed to be a linear function of expectations of a set of explanatory variables as in equations (4):

$$(4) \quad \ln OUT_t^* = \beta_0 + \beta_1 \ln TPR_t + \beta_2 \ln PRS_t + \beta_3 \ln UNL_t + \beta_4 \ln WAG_t + \beta_5 \ln POP_t + \beta_6 WEA_t + \epsilon_t,$$

where  $TPR_t$  is the real price of tomatoes,  $PRS_t$  is the real price of the substitute crop,  $UNL_t$  is tomato imports from competing regions,  $WAG_t$  is the hourly wage rate,  $POP_t$  is the suburban population pressure, and  $WEA_t$  is the effect of weather. All variables except weather are expressed in natural logarithms. Specific definitions of the variables are given in the data section.<sup>3</sup> The general error correction model (ECM) that evaluates the short-run behavior of the supply response in (4) is given by

$$(5) \quad \begin{aligned} \Delta \ln OUT_t = & \alpha_0 + \sum_{i=1}^{m_1} \alpha_{1i} \Delta \ln OUT_{t-i} \\ & + \sum_{i=0}^{m_2} \alpha_{2i} \Delta \ln TPR_{t-i} \\ & + \sum_{i=0}^{m_3} \alpha_{3i} \Delta \ln PRS_{t-i} \\ & + \sum_{i=0}^{m_4} \alpha_{4i} \Delta \ln WAG_{t-i} \end{aligned}$$

$$\begin{aligned} & + \sum_{i=0}^{m_5} \alpha_{5i} \Delta \ln UNL_{t-i} \\ & + \sum_{i=0}^{m_6} \alpha_{6i} \Delta \ln POP_{t-i} \\ & + \sum_{i=0}^{m_7} \alpha_{7i} \Delta WEA_{t-i} + \lambda \epsilon_{t-1} + \omega_t, \end{aligned}$$

where  $m_j$  ( $j = 1$  to  $7$ ) measures response of  $\ln OUT_t$  to changes in the regressors and  $\lambda$  is the error correction coefficient. If all the variables in equation (4) have unit roots and are cointegrated, then the ECM in (5) will represent the short-run behavior of the supply response in (4). Parameter  $\lambda$ , which is negative in general, measures the speed of adjustment toward the long-run equilibrium relationship between the variables in (4).

**Johansen and Juselius Cointegration Tests**

Following Johansen and Juselius (1990), consider the following vector autoregressive (VAR) model

$$(6) \quad \mathbf{X}_t = \Pi_1 \mathbf{X}_{t-1} + \Pi_2 \mathbf{X}_{t-2} + \dots + \Pi_k \mathbf{X}_{t-k} + \epsilon_t \quad (t = 1, \dots, T),$$

where  $\mathbf{X}_t$  is a column vector of  $m$  endogenous variables, i.e.,  $\mathbf{X}'_t = (X_{1t}, \dots, X_{mt})$ . The stochastic terms  $\epsilon_1, \dots, \epsilon_T$  are drawn from an  $m$ -dimensional *identically and independently* normally distributed covariance matrix  $\Lambda$ . Since most economic time series are nonstationary, VAR models such as equation (6) are generally estimated in their first-difference forms. First differencing of the series satisfies an important requirement in time series analysis, that is, the variables of concern are stationary. However, since first differencing removes much of the valuable information about the equilibrium relationships between the variables, applying least squares regressions to first-differenced variables is not a satisfactory alternative to estimating economic models with nonstationary variables.

Following Johansen and Juselius (1990), we rewrite equation (6) in its first-difference form as

$$(7) \quad \begin{aligned} \Delta \mathbf{X}_t = & \Gamma_1 \Delta \mathbf{X}_{t-1} + \Gamma_2 \Delta \mathbf{X}_{t-2} + \dots \\ & + \Gamma_{k-1} \Delta \mathbf{X}_{t-k+1} - \Pi \mathbf{X}_{t-k} \\ & + \boldsymbol{\mu} + \epsilon_t \quad (t = 1, \dots, T), \end{aligned}$$

where

$$(8) \quad \Gamma \pm_i = -(\mathbf{I} + \Pi_1 + \dots + \Pi_i) \quad (i = 1, \dots, k = 1),$$

and

<sup>3</sup> The cost of producing tomatoes is also an important factor that influences farmers' production decisions, but a consistent data series on the cost of production could not be obtained for a reasonable period of our sample. Lopez and Munoz (1987) use an extrapolation procedure to generate a cost of production series, but we feel that such an approximation is not appropriate for a time series analysis such as ours. Hence, we do not include cost of production as an explanatory variable in our model.

$$(9) \quad \Pi = I - \Pi_1 - \dots - \Pi_k$$

Equation (7) differs from a standard first-difference version of a VAR model only by the presence of the  $\Pi X_{t-k}$  term in it.<sup>4</sup> It is this term that contains information about the long-run equilibrium relationship between the variables in  $X_t$ . If the rank of  $\Pi$  matrix  $r$  is  $0 < r < m$ , then there are two matrices  $\alpha$  and  $\beta$ , each with dimension  $m \times r$  such that  $\alpha\beta' = \Pi$ .  $r$  represents the number of cointegrating relationships among the variables in  $X_t$ . The matrix  $\beta$  contains the elements of  $r$  cointegrating vectors and has the property that the elements of  $\beta'X_t$  are stationary.  $\alpha$  is the matrix of error correction parameters that measure the speed of adjustments in  $\Delta X_t$ .  $\mu$  is an  $m \times 1$  vector that contains linear time trends in the nonstationary process of  $X_t$ .

Johansen and Juselius (1990) demonstrate that  $\beta$  matrix, which contains the cointegrating vectors, can be estimated as the eigenvector associated with the  $r$  largest eigenvalues of the following equation:

$$(10) \quad \lambda S_{kk} - (S_{ko}S_{ok})/S_{oo} = 0,$$

where  $S_{oo}$  contains residuals from a least square regression of  $\Delta X_t$  on  $\Delta X_{t-1}, \dots, \Delta X_{t-k+1}$ ,  $S_{kk}$  is the residual matrix from the least square regression of  $X_{t-1}$  on  $\Delta X_{t-k+1}$ , and  $S_{ok}$  is the cross-product matrix. These eigenvalues can be used to construct a log likelihood ratio (LR) test statistic called a trace test, which is used to test the hypothesis that there are at most  $r$  cointegrating vectors in model (7). The trace test statistic is

$$(11) \quad -2\ln Q = -T \sum_{i=r+1}^m \ln(1 - \lambda_i),$$

where  $\lambda_{r+1}, \dots, \lambda_m$  are  $m - r$  smallest eigenvalues.

Johansen and Juselius (1990) also provide another LR statistic known as the maximum eigenvalue test, which is more powerful than the trace test. The maximum eigenvalue test is calculated as

$$(12) \quad \lambda_{\max} = -2 \ln(Q_{r/r+1}) = -T \ln(1 - \lambda_{r+1}).$$

With the maximum eigenvalue test, the null hypothesis that there are  $r - 1$  cointegrating vectors is tested against the alternative that there are only  $r$  cointegrating vectors. In the Johansen and Juselius procedure, we initially maintain the hypothesis that

time series contain linear trends but the cointegrating equations do not. This hypothesis can be evaluated by testing the null hypothesis that  $\mu = 0$  in equation (7) against the alternative that  $\mu \neq 0$  by an LR test statistic distributed as  $\chi^2$  with degrees of freedom equal to  $m - r$  (Lee and Chung 1995).

### Results

Before the cointegrating equation (7) is estimated, all the variables must be tested for the presence of unit roots. First, the ADF test was performed on the time series on  $\ln OUT$ ,  $\ln TPR$ ,  $\ln PRS$ ,  $\ln UNL$ ,  $\ln POP$ ,  $\ln WAG$ , and  $WEA$ . The ADF test procedure involves estimating the following regression:

$$(13) \quad \Delta Y_t = \alpha + \beta Y_{t-1} + \sum_{j=1}^m \gamma \Delta Y_{t-j} + \rho t + \epsilon_t,$$

where  $Y_t$  is the variable of concern and  $t$  is a time trend. The null hypothesis that  $Y_t$  has a unit root implies  $\beta = 0$  in equation (13). So, testing whether  $\beta = 0$  in (13) means testing the null hypothesis that  $Y_t$  has a unit root against the alternative that it is integrated of order zero. The optimum lag length  $m$  in (13) was chosen based on the Akaike's final prediction error (FPE) criterion. We first performed the ADF test on the levels of the variables both with and without the deterministic time trend ( $\rho t$ ). The results are presented in table 1. At the 95% significance level, the null hypothesis is accepted in all cases, with the exception of weather ( $WEA$ ). This result indicates that, except for  $WEA$ , all the time series are nonstationary and have unit roots. To confirm this, we also performed the ADF test on the first difference of the variables both with and without the deterministic time trend. With the first difference of the variables, the null hypothesis that a variable is integrated of order two is tested against the alternative that a variable is integrated of order one. At the 95% significance level, the null hypothesis is rejected in each case. The ADF test results, thus, suggest that all the time series, except  $WEA$ , have unit roots.

Perron (1988) and Phillips and Perron (1988) propose a series of nonparametric tests that have several advantages over the ADF test. The Phillips-Perron tests are more powerful than the ADF test, particularly with small samples, and are simpler to estimate. They require only estimating first-order autoregressions by OLS and incorporating a correction factor computed using errors from those regressions. Testing for the presence of a unit root

<sup>4</sup> To obtain equation (7) from (6), subtract  $X_{t-1}$  from both sides of equation (6) and collect terms on  $X_{t-1}$ . Then add zero to the right-hand side (RHS) of the equation: that is, add  $-(\Pi_1 - 1)X_{t-1} + (\Pi_1 - 1)X_{t-1}$ . Next, use  $\Delta X_{t-1} = X_{t-1} - X_{t-2}$  and rearrange terms to obtain the first RHS term of equation (7). Repetition of this procedure will yield equation (7).

**Table 1. Unit Root Test Results**

ADF Test Variable	Level		First Difference	
	ADF <sup>1</sup>	ADF <sup>2</sup>	ADF <sup>1</sup>	ADF <sup>2</sup>
ln <i>OUT</i>	-1.66	-2.48	-3.05*	-3.25
ln <i>TPR</i>	-1.48	-0.95	-2.98*	-3.56*
ln <i>PRS</i>	-1.69	-1.57	-3.59*	-3.63*
ln <i>UNL</i>	-1.63	-1.04	-4.17**	-4.74**
ln <i>WAG</i>	-1.29	-1.99	-3.15*	-3.08
ln <i>POP</i>	-0.85	-1.55	-3.07*	-3.07*
<i>WEA</i>	-0.35	-4.21*		

Phillips-Perron Test Variable	Z( $\tilde{\alpha}$ )	Z( $t_{\tilde{\alpha}}$ )	Z( $\Phi_3$ )	Z( $\Phi_2$ )	Z( $\alpha^*$ )	Z( $t_{\alpha^*}$ )	Z( $\Phi_1$ )
ln <i>OUT</i>	-8.48	-2.05	2.72	1.97	-6.44	-2.26	2.78
ln <i>TPR</i>	-9.09	-2.13	2.31	1.54	-7.01	-1.98	1.95
ln <i>PRS</i>	-37.75*	-5.72*	16.55*	11.04*	-37.90*	-5.82*	16.95*
ln <i>UNL</i>	-6.43	-2.26	3.65	3.01	-6.23	-2.79	4.75
ln <i>WAG</i>	-4.36	-1.46	1.08	1.78	-2.68	-1.15	2.29
ln <i>POP</i>	-5.15	-1.52	1.29	5.85*	-0.67	-0.84	8.07*
<i>WEA</i>	-32.49*	-4.93*	12.18*	8.27*	-5.67	-1.69	1.61

ADF<sup>1</sup> and ADF<sup>2</sup> are, respectively, the ADF test statistics when equation (12) was estimated with and without a deterministic time trend (pt).

\*\* and \* denote statistical significance at the 99% and 95% levels, respectively. Critical values for ADF<sup>1</sup>, ADF<sup>2</sup>, Z( $\tilde{\alpha}$ ), Z( $t_{\tilde{\alpha}}$ ), Z( $\alpha^*$ ), and Z( $t_{\alpha^*}$ ), are given in Fuller (1976), and those for Z( $\Phi_1$ ), Z( $\Phi_2$ ), and Z( $\Phi_3$ ) can be found in Dickey and Fuller (1981).

with the Phillips-Perron tests involves estimating the following OLS regressions:

$$(14) \quad Y_t = \mu^* + \alpha^* Y_{t-1} + u_t^*$$

$$(15) \quad Y_t = \tilde{\alpha} + \tilde{\beta} \left( t - \frac{T}{2} \right) + \tilde{\alpha} Y_{t-1} + \tilde{u}_t,$$

where  $u_t^*$  and  $\tilde{u}_t$  are error terms and  $T$  is the sample size. Using the regression results of equations (14) and (15), we compute the following test statistics:

$$(16) \quad (1) Z(\alpha^*) \text{ tests } H_0: \alpha^* = 1 \text{ in (14)}$$

$$(17) \quad (2) Z(t_{\alpha^*}) \text{ tests } H_0: \alpha^* = 1 \text{ in (14)}$$

$$(18) \quad (3) Z(\Phi_1) \text{ tests } H_0: \mu^* = 0 \text{ and } \alpha^* = 1 \text{ in (14)}$$

$$(19) \quad (4) Z(\tilde{\alpha}) \text{ tests } H_0: \tilde{\alpha} = 1 \text{ in (15)}$$

$$(20) \quad (5) Z(t_{\tilde{\alpha}}) \text{ tests } H_0: \tilde{\alpha} = 1 \text{ in (15)}$$

$$(21) \quad (6) Z(\Phi_2) \text{ tests } H_0: \tilde{\mu} = \tilde{\beta} = 0 \text{ and } \tilde{\alpha} = 1 \text{ in (15)}$$

$$(22) \quad (7) Z(\Phi_3) \text{ tests } H_0: \tilde{\beta} = 0 \text{ and } \tilde{\alpha} = 1 \text{ in (15)}$$

In each case, the  $H_0$  is tested against the alternative that  $Y_t$  is stationary. Since these statistics are asymptotically equivalent to the corresponding Dickey-Fuller tests, the critical values from Fuller (1976) and Dickey and Fuller (1981) can be used

in testing. According to the results presented in table 1, we reject the null hypothesis in both cases at the 95% significance level for both ln *PRS* and *WEA*. Since these results confirm that ln *PRS* and *WEA* do not have unit roots, only ln *OUT*, ln *TPR*, ln *UNL*, ln *WAG*, and ln *POP* can have any meaningful cointegrating relationship between them.

Before we estimate equation (7), we must also determine the optimum lag length  $k$ . Following the procedure adopted by Lee and Chung (1995), we first estimated equation (7) as the unrestricted model with  $k$  arbitrarily set equal to 5. This unrestricted model was then tested against a restricted model with  $k = 4$  by the LR test statistic which is distributed as  $\chi^2$  with degrees of freedom equal to 25. The test was repeated by reducing  $k$  by one at a time from both the unrestricted and restricted models. The LR statistic led us to reject the restriction of  $k = 3$  against the alternative of  $k = 4$ , indicating that the optimum lag length for the model in equation (7) is 4.

Table 2 presents the trace and maximum eigenvalue test statistics and the coefficients of the cointegrating vector that have been normalized on ln *OUT*. The trace test and the maximum eigenvalue test both reject the null hypothesis of no cointegration at the 99% significance level. Both tests confirm that there are at least two cointegrating vectors at the 99% significance level. Furthermore, both tests indicate a possibility of a third cointe-

**Table 2. Cointegration Tests and Regression Equation Normalized on  $\ln OUT$** 

Trace Test		Maximum Eigenvalue Test			
$H_0$		$H_0$			
$r = 0$	144.37**	$r = 0$		65.04**	
$r \leq 1$	79.34**	$r = 1$		45.71**	
$r \leq 2$	33.63*	$r = 2$		22.19*	
$r \leq 3$	11.44	$r = 3$		11.42	
$r \leq 4$	0.02	$r = 4$		0.02	

Cointegrated Vector Normalized on $\ln OUT$				
Constant	$\ln LTP$	$\ln WAG$	$\ln UNL$	$\ln POP$
11.29	-0.169** (-4.207)	-1.230** (-10.287)	-0.109** (-2.821)	-0.099** (-3.003)

Critical Values				Maximum Eigenvalue Test			
Trace Test				$H_0$			
$H_0$	90%	95%	99%	$H_0$	90%	95%	99%
$r = 0$	64.84	68.52	76.07	$r = 0$	30.90	33.46	38.77
$r \leq 1$	43.95	47.21	54.46	$r = 1$	24.73	27.07	32.24
$r \leq 2$	26.79	29.68	35.65	$r = 2$	18.60	20.97	25.52
$r \leq 3$	13.33	15.41	20.04	$r = 3$	12.07	14.07	18.63
$r \leq 4$	2.69	3.76	6.65	$r = 4$	2.69	3.76	6.65

Critical values for trace and maximum eigenvalue tests are from Osterwald-Lenum (1992), table 1. Figures in parentheses are  $t$ -ratios.

\*\* and \* indicate statistical significance at the 99% and 95% levels, respectively.

grating vector at the 95% significance level. Because we know that the more stable the specified relationship is, the greater the number of cointegrated vectors (Van den Berg and Jayanetti 1993), our cointegrating results indicate that a strong long-run equilibrium relationship exists between the five variables.

The normalized coefficients reported in table 2 are estimates of the long-run elasticities of Northeastern fresh tomato production with respect to tomato price, wage rate, imports from competing regions, and suburban pressure. The negative coefficients for the long-run supply elasticity confirms that tomato price and production have moved in opposite directions in the long run. It also implies that the negative impacts of suburban pressure, wage rates, and imports have been more significant than the positive effect of its own price in determining farmers' production decisions.

Several interesting findings emerge from our results. The coefficients obtained for wage rate, imports, and urban pressure are statistically significant and have negative signs. This finding indicates that these three variables have played significant roles in determining tomato production in the Northeast and that they all have had negative impacts on tomato production during the 1949-94 period. These results confirm the findings of Lopez and Munoz (1987) that urban pressure has played a

major role in shifting the supply response in Northeastern tomato production. But contrary to their findings that imports have had only a modest impact on regional tomato production during the post-World War II period, our results suggest that a strong long-run equilibrium relationship has existed between the decline in tomato production and the increase in tomato imports. Wage rate also seems to have had a significant negative impact on tomato production.

The most interesting finding of our study, however, is that there has been a strong negative correlation between tomato production and prices received by farmers during the post-World War II period. This finding does not support the argument made by some (e.g., Wysong, Leigh, and Ganguly 1984) that there are sufficient price incentives for Northeastern tomato producers to take on a bigger share of the market. Our results, however, do confirm the claim that nonprice factors such as imports and urban pressure have played significant roles in shifting the competitiveness of tomato production in the Northeast.

Next, we examine the short-run dynamics (or the direction of causality) between the variables in the cointegration equation by estimating the error correction model in equation (5). Estimating error correction models involve regressing the first difference of each variable in the cointegration equation

on the lagged values of the first-differences of all the variables and the lagged value of the error correction term ( $\epsilon_{t-1}$ ) obtained from the cointegrated regression. The appropriate lag length for each regressor in each model was chosen based on Akaike's FPE criterion. All possible combinations of one to four lags were examined. According to Granger (1980) and Engle and Granger (1987), as long as two or more variables are cointegrated, a causality has to exist in at least one direction. That is, for example, in the error correction model in (5), the Granger causality implies causality from the independent variables in levels to the dependent variable  $\ln OUT$ . Testing for Granger causality requires only testing whether  $\lambda$  in (5) is significantly different from zero. Even if the coefficients of the lagged changes in the independent variables are not statistically significant, Granger causality still can exist as long as  $\lambda$  is significantly different from zero (Choudhry 1995, p. 665).

The ECM estimations results are presented in table 3. The chi-square statistics in brackets show whether the sum of the coefficients is significantly different from zero. Although the Granger causality test in the output equation implies that price Granger causes production, this causation is not a statistically significant one. In other words, it implies that although there is a positive relationship between price and production in the short run, this relationship is not statistically significant. A similar interpretation can be given to the coefficients for wage rate, suburban pressure, and imports. Significance of  $\lambda$  is determined by the  $t$ -ratio given below the coefficient. The magnitude of the error correction coefficient indicates the speed of adjust-

ment of any disequilibrium toward a long-run equilibrium state. The error correction term is significant only in the output equation. Significance of  $\lambda$  in the output equation implies that tomato production adjusts to changes in prices, imports, wage rate, and population pressure, and its value of 0.96 indicates that the adjustments toward equilibrium take place almost instantaneously. Considering the fact that tomato is an annual crop, instantaneous adjustments in production imply that farmers adjust their production choices to changes in economic and demographic conditions almost on an annual basis.

### Summary and Conclusions

Past studies of agricultural supply response have been based mainly on the partial adjustment model, which assumes a fixed target supply toward which farmers adjust their production in the long run. In a recent article, Hallam and Zanolli (1993) demonstrate that the partial adjustment model is only a special case of the error correction model. They show that the error correction modeling technique is more relevant in modeling agricultural supply response than is the partial adjustment model. The error correction form is a useful modeling procedure to uncover long-run equilibrium relationships between macroeconomic time series and short-run dynamics associated with such relationships.

In this article, we have employed cointegration and error correction modeling procedure to examine the responsiveness of Northeastern tomato production to changes in economic and demographic

**Table 3. Coefficient Estimates of Error Correction Models**

Dependent variable	$\lambda_{t-1}$	$\Sigma \Delta \ln OUT$	$\Sigma \Delta \ln TPR$	$\Sigma \Delta \ln WAG$	$\Sigma \Delta \ln UNL$	$\Sigma \Delta \ln POP$
$\Delta \ln OUT$	-0.96* (-2.72)	-0.69 [1.61] {4}	0.17 [0.28] {2}	0.73 [0.45] {2}	-0.15 [0.32] {2}	-0.24 [0.02] {4}
$\Delta \ln TPR$	-0.88 (-1.48)	2.21* [3.37] {4}	0.28 [0.26] {4}	4.11* [2.58] {4}	1.28 [4.26] {4}	-0.22 [0.06] {1}
$\Delta \ln WAG$	-0.03 (-0.15)	-0.05 [0.01] {4}	-0.06 [0.23] {2}	0.40 [0.22] {4}	0.15 [0.67] {4}	-0.003 [0.00] {4}
$\Delta \ln UNL$	0.73 (1.05)	-0.17 [0.02] {4}	-0.67 [1.03] {3}	0.35 [0.02] {3}	-0.63 [0.68] {4}	0.57 [0.04] {4}
$\Delta \ln POP$	0.07 (0.49)	-0.14 [0.33] {3}	0.03 [0.06] {4}	-0.08 [0.02] {4}	-0.06 [0.16] {4}	-0.03 [0.01] {4}

$\lambda_{t-1}$  is the one period lagged error correction term from the cointegrating equation. Asymptotic  $t$ -ratios are in parentheses. Chi-square statistics are in square brackets, and figures in curly brackets are lag lengths.

characteristics during the post-World War II period. Our results suggest that a long-run equilibrium relationship has existed between Northeastern tomato production and tomato price, wage rate, shipments from competing regions, and urban pressure. The results suggest that wage rate, imports, and urban pressure have all had negative impacts upon tomato supply. These results lend support to findings of some of the previous studies. However, contrary to the findings of all previous studies, the results of the present paper show that an inverse long-run relationship has existed between tomato production and price. This finding suggests that the effect of the increase in price has been negated by population pressure and competition from other regions. These findings are further supported by error correction analyses that provide evidence that a causality has existed in the direction from the explanatory variables toward production.

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## Appendix

Annual data for the period 1949-94 for Connecticut, Delaware, Maryland, Massachusetts, New Jersey, New York, and Pennsylvania were used for estimation. The growing season for which price,



production, and import data were collected extends from July through September.

1. Northeastern tomato production (*OUT*): The annual tomato production in the seven states was summed.
2. Price of fresh tomato (*TPR*). The annual aggregate production and the average annual tomato price for the seven states were used to construct a weighted sum of state prices. The shares of total tomato receipts for individual states were used as weights. The data were obtained from the National Agricultural Statistics Service (NASS), a division of the USDA.
3. Price of substitute crops (*PRS*). Since there are many crops farmers can choose as alternatives to fresh market tomato production in the Northeast, a Divisia price index was used as the price of substitute crops. Annual prices and quantities of sweet corn and pepper, whose planting seasons coincide with that of fresh tomatoes, were used to construct the Divisia price index. Inclusion of these two crops is justified by the fact that their harvest labor requirements are quite similar to those of fresh market tomatoes. The production and price data are available from the NASS.
4. Urban pressure (*POP*). Pressure from suburbanization on farming was measured by the log of population in the Northeast excluding metropolitan statistical areas (MSA). The MSAs in the Northeast include Baltimore, Buffalo, New York City, Newark, Philadelphia, Pittsburgh, and Nassau-Suffolk-New York. This measure is used as a proxy for urban pressure on agriculture, and its use is justified because the process of suburbanization involves forces that diverge nonfarming economic activities away from urban centers into rural and farming areas (Lopez and Munoz 1987). Population figures for the states were obtained from *Historical Statistics of the United States* and *Statistical Abstract of the United States* (U. S. Department of Commerce, Bureau of the Census 1992, 1971-94). Since population data for MSAs are not available for the entire sample period, we interpolated the series.
5. Wage rate (*WAG*). Average wage rate for the Northeast was constructed using average state wage rates and labor quantity. Statewide average wage rates are reported in *Farm Labor* (USDA, Agricultural Marketing Service, various issues). To obtain statewide data on labor quantity, we divided the total expenditure on contract and hired labor by the average wage rate. The expenditure data were obtained from the NASS. We then used average state wage rate and the number of hours to construct the wage rate for the Northeast.
6. Stallings' weather index (*WEA*). Stallings' Index (Stallings 1960) was used to measure the effect of weather on fresh tomato yields. The Stallings' Index was constructed as the weighted ratio of actual to expected yields of sweet corn and processing tomatoes—two vegetables whose growing seasons coincide with that of fresh tomatoes in the Northeast. The predicted yields obtained from regressing yield on time were used as expected yields. Revenue shares of the two crops were used as weights.
7. Unloads from competing regions (*UNL*). *Fresh Fruits and Vegetable Unloads in Eastern Cities* (USDA, Agricultural Marketing Service 1962-86) reports annual shipments of fresh tomatoes from competing regions to major cities in the Northeast. These cities include Albany, Baltimore, Boston, Buffalo, New York City, Philadelphia, and Pittsburgh. But the data are available only for the period 1962-86. To estimate other data, we used a procedure similar to that used by Lopez and Munoz (1987); that is, we extrapolated the existing series to obtain the data for the 1949-61 and 1987-94 periods. For the period 1962-86, unloads were regressed on the ratio of U.S. personal income to Northeastern personal income (Bureau of the Census, *Historical Statistics* and *Statistical Abstract*), the ratio of U.S. tomato yields to Northeastern tomato yields (NASS), the price index for diesel as a proxy for transportation cost (*Historical Statistics* and *Statistical Abstract*), a time-trend, and Northeastern tomato price (NASS). We then extrapolated the series for the 1949-61 and 1987-94 periods using same regressors and regression coefficients. The tomato price (*TPR*), price of substitutes (*PRS*), and the wage rate (*WAG*) were deflated by the Consumer Price Index (1990 = 100, U.S. Department of Commerce, *Survey of Current Business*) to express them in real terms.