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Modeling Fresh Tomato Marketing Margins: Econometrics and Neural Networks

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This study compares two methods of estimating a reduced form model of fresh tomato marketing margins: an econometric and an artificial neural network (ANN) approach. Model performance is evaluated by comparing out-of-sample forecasts for the period of January 1992 to December 1994. Parameter estimates using the econometric model fail to reject a dynamic, imperfectly competitive, uncertain relative price spread margin specification, but misspecification tests reject both linearity and log-linearity. This nonlinearity suggests that an inherently nonlinear method, such as a neural network, may be of some value. The neural network is able to forecast with approximately half the mean square error of the econometric model, but both are equally adept at predicting turning points in the time series.

Retail-farm margins are of interest to agricultural economists for many reasons. First, wider margins mean that growers obtain a smaller share of the retail dollar. During periods when retailers are unable to raise their prices, this means lower grower revenue. Second, the extent to which margin growth is not due to higher marketing costs can suggest inefficiencies somewhere in the marketing channel (Kinnucan and Nelson 1993). Typically, such inefficiencies are due to the exercise of market power, on either the buying or the selling side, downstream from the farm. Third, market power and informational asymmetries are often cited as reasons for slow margin adjustment in response to change in underlying supply and demand conditions (Powers 1995; Kinnucan and Forker 1987). Whereas retail prices respond quickly to price increases, farm prices often take time to adjust. Fourth, margins are known to widen in the degree of uncertainty in returns to a crop—whether risk arises through prices or yields (Brorsen et al. 1985). This risk is of particular concern to growers who may not have access to future markets or crop insurance. Although all of these issues are important to growers of virtually all commodities, they are of particular concern to produce growers, who often face many planting and harvesting decisions

throughout a typical growing season, face many alternatives for their land, and have relatively few means by which they can manage risk. However, these issues are rarely explored in fruit and vegetable markets.

In particular, the performance of the fresh tomato marketing channel continues to be an issue to growers in both California and Florida.¹ However, typical methods of estimating the determinants of retail-farm price spreads may not be the best way to approach this problem. Econometric analysis of marketing margins has become a popular and important way of investigating the effects of many different factors on the efficiency of price transmission for a variety of commodities (Heien 1980; Brorsen et al. 1985; Wohlgenant and Mullen 1987; Thompson and Lyon 1989; Brester and Musick 1995). By developing reduced-form models that reflect more complete structural underpinnings of a particular market (Waugh 1964; Gardner 1975; Holloway 1991), empirical studies often concern themselves with non-nested tests that compare alternative empirical representations of various competing margin theories (Lyon and Thompson 1993). Kastens and Brester (1996), however, argue that such tests are often inconclusive. They argue that an alternative method of model selection, a comparison of out-of-sample forecasting ability, is conceptually preferable because “it is difficult to imagine how a model that provides less accurate in-sample and out-of-sample forecasts . . . could still be deemed the ‘better’ model” (p. 302). If the common goal among margin studies is to find the

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best fit to margin data by this criterion, given different data frequencies, different levels of geographic aggregation, or different commodities, but to include similar sets of explanatory variables, perhaps an approach other than an econometric one can better serve the purpose.

Artificial neural network (ANN) models provide one such alternative. Increasingly popular among financial and commodity analysts for their ability to forecast short-run price movements, neural networks can also provide an alternative way to determine the "best" model of retail-farm margins. ANN models are nothing more than nonlinear least squares estimators of highly nonlinear functional forms. The unfortunate name, however, derives from the analogy often drawn of their ability to emulate the biological processes of the human brain in "recognizing" patterns in the data and thereby "learning" relationships between sets of independent variables, or inputs and dependent variables, or outputs. Although economic theory can suggest the elements of the input and output sets, significant nonlinearities in the relationship introduced through the inclusion of risk preferences, imperfect competition, or dynamic margin behavior may mean that a neural network modeling approach provides a better fit to the data than do traditional econometric approaches.

Consequently, the primary objective of this paper is to compare the advantages and disadvantages to investigating an important empirical problem through neural network versus econometric methods. In doing so, the paper also attempts to derive a better empirical explanation of the retail-farm price spread in fresh-market tomatoes. The first section of the paper develops an economic model of fresh tomato marketing margins. This model guides the specification of an econometric model in the second section of the paper and is used to determine the set of input variables in the neural network model, as discussed in the third section. The fourth section describes the data used in making the comparison, while the fifth section presents and compares the forecast results from each model. Prior to drawing some conclusions and implications for model selection, this section also interprets the econometric parameter estimates and suggests how equivalent information can be taken from the neural network results.

Economic Model of Marketing Margins

For purposes of this study, the marketing margin, or retail-farm price spread, is defined as the difference between an average U.S. monthly retail price

and a grower price for fresh tomatoes. This section derives a conceptual model of marketing margins that, while working toward a reduced form solution, maintains theoretical consistency with an equilibrium model of margin determination.

Following the work of Gardner on the determination of farm-retail price spreads in competitive agricultural markets, Wohlgenant and Mullen (1987) develop a "relative price spread (RPS)" model. In this model, the price spread is a linear function of the retail price, marketing costs, and industry retail revenue. Both Lyon and Thompson (1993) and Faminow and Laubscher (1991) provide empirical support for the superiority of the RPS model in aggregate monthly data over a more restrictive markup specification. Extensions to this basic model consider the effect of lagged adjustment of prices at one level to changes in demand or supply at the other level (Heien 1980; Powers 1995), the effect of risk on the farm-retail price spread (Brorsen et al. 1985; Schroeter and Azzam 1991; Holt 1993), product quality (Parker and Zilberman 1993), market power (Cotterill 1986; Schroeter and Azzam 1991; Durham and Sexton 1992; Stiegert, Azzam, and Brorsen 1993; Brester and Musick 1995), vertical integration (Kinnucan and Nelson 1993), and changes to farm policy (Thompson and Lyon 1989). Of this set of considerations, dynamic margin adjustment, tomato price risk, market structure, and quality are likely relevant to the tomato margin problem. This section begins with a dynamic extension of the RPS model and then incorporates the other factors in turn.

Particularly in studies using data with a frequency of less than a year, the current retail-farm margin is often found to be a function not only of current supply and demand conditions, but also of those of previous weeks or months. Often, this conclusion follows from empirical studies that show prices downstream adjust at a different rate whether the upstream price is rising or falling (Heien 1980; Ward 1982; Kinnucan and Forker 1987; Powers 1995). Such asymmetry may be due either to incomplete information on the part of buyers or sellers, or to market power by downstream interests (Powers 1995). While primarily concerned with prices at only one level, dynamic margin adjustment in these models is implicit. Heien (1980), for example, develops a model of retail price adjustment to changes in wholesale prices that relies upon an assumption that retailers adopt a naive inventory adjustment rule. Similarly, Wohlgenant (1985) demonstrates that retail and wholesale prices may adjust at different rates because of retailer inventory behavior. However, because of the perishability of fresh tomatoes, inven-

tory adjustment is not a likely explanation for sluggish margin adjustment.

Alternatively, Wohlgenant and Mullen (1987) also show that a marketing margin must equal the marginal cost, and hence the marginal value in competition, of a bundle of marketing services. This marginal value must also include the value expected to accrue through all future periods of investing in brand equity today. Increasingly, tomato sellers are investing in brand equity through trade promotions, trade media advertising, and merchandising materials (*The Packer* 1996–97). Because obtaining brand recognition is a long-term asset to the seller, dynamic margin adjustment results from the dynamics of demand for these services, rather than retail inventory adjustment. This dynamic demand specification, however, must also take into consideration several other factors that influence the price spread.

One factor in particular—imperfect competition in the fresh tomato market—appears to have a significant influence on aggregate tomato margins. It is well known that the exercise of market power, whether on the buying or selling side, results in wider retail-farm margins (Holloway 1991). Using the “new empirical industrial organization” (NEIO) (Bresnahan 1989; Applebaum 1982; Azzam and Schroeter 1991) framework, Durham and Sexton (1992) show that processing tomato buyers exercise considerable monopsony power in sourcing raw product, while Jordan and Van Sickle (1995) show that, in aggregate, the U.S. and Mexico are imperfect competitors in the winter fresh tomato market. However, Holloway (1991), using data from Wohlgenant (1989), finds that the assumption of perfectly competitive behavior in fresh vegetables cannot be rejected in aggregate data. Given that Mexico provides competition only during the winter season, it is likely that U.S. growers are able to exercise some degree of market power—market power that will be evident only in monthly or seasonal data. Although the NEIO approach admits a formal test of this hypothesis, implementing a complete structural model of the tomato market is beyond both the scope and the data of this paper. Arnade and Pick (1996), however, show that measures of market share may be suitable proxies for more formal market power indicators. Brester and Musick (1995) employ a similar measure of concentration in the lamb-packing industry to determine the effect of market structure on marketing margins. Given identical market structures, however, many argue that variability of the output price is likely to be an important determinant of retail-farm margins.

This is particularly true in the case of fresh veg-

etables. If growers face what they perceive to be low market prices at harvest, their only options are to harvest and sell into a depressed market or to abandon the crop to avoid harvesting costs. Storage is not an option. While the latter choice is viewed as extreme by most growers, the former causes prices to fall further. Given the inflexibility of retail prices documented by Powers (1995), margins will widen if many choose to harvest. Brorsen et al. (1985), Holt (1993), and Schroeter and Azzam (1991) provide both theoretical justifications and empirical support for the contention that margins widen with uncertainty. The following section extends their approach by including uncertainty and market power in a dynamic model of marketing margins.

Suppose that a firm invests in a stock of marketing services (think of such investments as efforts to create brand equity) to facilitate both current and future sales. Brand equity accumulates over time directly with the level of sales, but deteriorates at a rate proportional to the current stock. Because investment in a brand is costly, the equilibrium rate of adjusting the stock of equity will be less than instantaneous. Further, assume that retailers face a Leontief technology where output is a fixed proportion of the farm input, but they can employ various amounts of marketing services:

$$(1) \quad y = \min[x/k, g(S)],$$

where y is monthly shipments from one firm, x is the amount of farm input, k is a constant of proportionality, and S is the stock of marketing services. Brorsen et al. (1985) show that this technology leads to an indirect cost function of the form:

$$(2) \quad C(w, p^f, y, t) = kp^f y + h(w, y, t),$$

where p^f is the farm input price, w is a rental price for marketing services, t is a time trend variable, and C is linearly homogeneous, increasing and concave in prices, and convex in output. If the stock of brand equity evolves as described above, the equation of motion constraining S is given by: $dS/dt = (y - \delta S)$, where δ is the constant rate of depreciation (suppressing the time subscript). Assuming tomato retailers choose output in order to maximize the expected utility of the present value of their firm, the dynamic optimization problem is given by a current value Hamiltonian:

$$(3) \quad H(\theta) = (p_t^r - kp_t^f)y_t - C(w_t, y_t, t) + \mu_t(y_t - \delta S_t),$$

where p_t^r is the retail price and μ_t is the dynamic multiplier, or the equilibrium cost of adjusting the stock of brand equity.

Application of the maximum principle to equation (3) first requires differentiating the Hamiltonian with respect to the control variable, or output. Assuming a representative utility function that reflects constant absolute risk aversion and normally distributed output prices, maximizing expected utility of firm value produces first order conditions that require the current value of an additional unit of brand equity to be equal to the difference between the marginal cost of production and the sum of three elements—the retail-farm margin, the effect of market power on retail prices, and the effect of price variability on the margin (Schroeter and Azzam 1991). In terms of the value of marketing services, the first order condition is given by:

$$(4) \quad \mu_t = C_{yt} - (p_t^r - kp_t^f) - \epsilon_d^{-1} \theta p_t^r ms_t - \lambda y \sigma_{pt}^2 \\ = C_{yt} - m_t - \Phi p_t^r ms_t - \lambda y \sigma_{pt}^2,$$

where C_{yt} is marginal cost, m_t is the margin, ϵ_d^{-1} is the inverse demand elasticity, θ is the conjectural variation, defined as $\theta = \partial Y / \partial y$ where Y is total market shipments, ms is the share of total market shipments due to one firm, λ is the coefficient of absolute risk aversion, and σ_{pt}^2 is the variance of retail prices. Further, the costate equation requires:

$$(5) \quad \dot{\mu}_t - r\mu = -\partial H / \partial S = \delta \mu,$$

or, $\dot{\mu}_t = (r + \delta)\mu_t$, where r is the rate of interest, assumed to be constant for this problem.²

Differentiating (4) with respect to time, assuming marginal costs change linearly with time at a rate τ , and assuming that neither the market power nor risk aversion terms vary with time, and then substituting the result into (5) provides an expression for the time path of margins:

$$(6) \quad \dot{m}_t = (r + \delta)(m_t + \Phi p_t^r ms_t + \lambda y \sigma_{pt}^2 - C_{yt}) + \tau.$$

As with most economic problems, the data are discrete rather than continuous. Expressing (6) in discrete time and solving for m_t gives a first order difference equation for the retail-farm margin:

$$(7) \quad m_t = \alpha m_{t-1} \\ + (r + \delta)\alpha(\Phi p_t^r ms_t + \lambda y \sigma_{pt}^2 - C_{yt}) + \alpha \tau,$$

where $\alpha = 1/(1 - r - \delta)$. Equation (7) implies that the current margin is a linear function of the previous margin, the marginal cost of marketing tomatoes, an interaction term between retail price and market share, an interaction term between firm shipments and price variability, and a time trend. The following section describes an empirical model of fresh tomato retail-farm margins based on this theoretical framework.

Econometric Model Specification

Although the economic model above is derived in general terms, it does not imply a specific functional form of relationship between the margin and its determinants. Given the presence of terms representing tomato sellers' risk attitudes, aggregate market power, and dynamic adjustment, it may indeed be far from linear. Tests of model misspecification determine whether a linear model is valid as compared with some nonlinear alternative. These tests consist of Ramsey's RESET test (Ramsey 1969), Davidson and Mackinnon's Pe test (Davidson and Mackinnon 1981), and tests of different λ values in a Box-Cox specification (Box and Cox 1964). Although the latter two tests posit either a double-log or flexible alternative model, respectively, failure of the RESET test does not suggest an alternative. Under the null hypothesis of linearity, the dynamic RPS model, augmented with a set of monthly dummy variables, becomes:

$$(8) \quad m_t = \beta_1 m_{t-1} + \beta_2 p_t^r + \beta_3 p_t^r \cdot y_t \\ + \beta_4 p_t^r \cdot ms_t^{us} + \beta_5 y_t \cdot \sigma_{pt}^2 \\ + \beta_6 t + \beta_7 w_t + \sum_k^{12} \gamma_k mn_k + e_t,$$

where ms^{us} is the U.S. share of total monthly shipments, σ_{pt}^2 is a five-month moving measure of retail price variation, t is a time trend, w_t is the average hourly wage of workers in food and kindred industries, mn_k are binary monthly indicator variables, and e is an independent, identically distributed normal error term.³ Although U.S. market share is primarily included as an indicator of tomato market structure, its influence may also reflect differences in quality between U.S. and Mexican tomatoes.⁴

The neural network model includes each of these variables and interaction terms but need not specify a functional form. In fact, failure of each of the above specification tests suggests that a wide variety of nonlinear specifications may be preferable to the maintained model. If so, then an ANN model can represent this unspecified nonlinear alternative, the exact form of which is found through experimenting with alternative designs and structures.

Designing a Neural Network for Margin Forecasting

ANN models are systems of interconnected nodes (neurons) that map input data, or explanatory vari-

ables in econometric usage, into outputs, or dependent variables. Based upon the presentation of several input patterns and their associated outputs, or examples, the network is able to autonomously learn the map from inputs to outputs (Beltratti, Margarita, and Terna 1996). In emulating the neural processes of the human brain, ANNs in general, and those using the backpropagation algorithm of this study in particular, have several desirable properties as forecasting tools. In particular, because ANNs do not rely on prior specification of either a functional form or an error distribution, they are able to approximate any nonlinear input-output relationship and are robust estimators even under conditions of extreme non-normality. Furthermore, the iterative solution algorithm prevents overfitting so they can generalize extremely well beyond the estimating, or training sample (Hiemstra 1996).

The ability of ANN to forecast out-of-sample at least as well as existing methods is well known in corporate finance (Trippi and DeSieno 1992; Bansal, Kauffman, and Weitz 1993; Refenes, Zaprakis, and Francis 1994; Hiemstra 1996), commodity price forecasting (Mendelsohn and Stein 1991; Chakraborty et al. 1992; Grudnitski and Osburn 1993), and macroeconomics (Moody 1995), but it is only now emerging as an analytical tool in agricultural economics (Joerding, Li, and Young 1994; Kohzadi et al. 1995; Kastens and Featherstone 1996). This section provides a brief description of the structure of a feed-forward network that uses the standard backpropagation learning algorithm and then describes the application of this model to tomato margin data.

The node, or neuron, is the basic element of any ANN. Data are first transformed with a scaling function before submission to the network. Next, the scaled data pass from neurons in the input layer, through one or more hidden layers, to an output layer. Neurons in each layer receive inputs (I_i) from those in the layer below, compute a weighted sum of these inputs (n_j), and pass the result to all neurons in the next layer through an activation function. The activation function, commonly approximated by a sigmoid form, maps the weighted sums into outputs (O_k) that are bound by zero and one. Mathematically, the feed-forward structure to the k th output neuron appears as:

$$(9) \quad O_k = [1 + \exp(-n_k)]^{-1},$$

where $n_k = \sum_j w_{kj} H_j$ and H_j is the output from the hidden layer j given by:

$$(10) \quad H_j = [1 + \exp(-n_j)]^{-1}.$$

As in the previous step, the value of n_j in equation (10) is a weighted sum from the input layer: $n_j = \sum_i w_{ji} I_i$. Consequently, in determining the "best" fit to the data, the ANN algorithm must estimate each of the w_{kj} values. With a data set consisting of M observations, or patterns, each is presented to the network through this feedforward process, resulting in a series of outputs O_{mk} . Comparing these outputs with the observed target values, T_{mk} , generates a series of errors that forms the basis for the backpropagation learning algorithm.

Backpropagation (BP) refers to the way in which the ANN updates the parameters of the system, w_{ij} , in order to move the outputs closer to the target values. Updating, or learning, proceeds by either an unsupervised or a supervised algorithm. Supervised learning uses a fixed set of inputs and outputs. As opposed to unsupervised learning, the example described here compares the network output with a known target in computing the prediction error. Specifically, supervised learning implies that BP updates the weights between each layer in order to minimize the sum of squared errors between the outputs and targets (Beltratti, Margarita, and Terna 1996):

$$(11) \quad E(w_{ij}) = (1/2) \sum_{m=1}^M \sum_{k=1}^K (T_{mk} - O_{mk})^2.$$

Offline, or batch, learning updates the weights after presenting all examples in the data set, whereas online learning updates after each presentation. Updates are made according to the rule:

$$(12) \quad \Delta w_{ji} = -\alpha \frac{\partial E}{\partial w_{ji}},$$

where α is the learning-rate parameter. In order to reduce the oscillation of the weights between iterations, it is possible to include a momentum term $\beta \Delta_{t-1} w_{ji}$ such that changes in one presentation, or epoch, persist to the next. The learning rate and momentum represent the two parameters under the control of the researcher. Consistent with the notation above, this rule implies $J \times K$ updating equations between the hidden and output layers, and $I \times J$ between the input and hidden. Taking advantage of the relative simplicity of the logistic function, the partial derivative in equation (12) becomes:

$$(13) \quad \frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial n_j} \frac{\partial n_j}{\partial w_{ij}} = H_j(1 - H_j)I_j \sum_k (T_k - O_k)O_k(1 - O_k)w_{kj}.$$

for updating weights between the input and hidden layers, while the equivalent term between the hidden and output layers is:

$$(14) \quad \frac{\partial E}{\partial w_{jk}} = \frac{\partial E}{\partial O_k} \frac{\partial O_k}{\partial w_{jk}} = -(T_k - O_k)O_k(1 - O_k)H_j.$$

Repeating the feedforward process with the new weights generates a new error vector, so unless these errors fall within the selected convergence criterion, the weights are again updated according to the rule in (12). Iterating this procedure until convergence provides an optimal set of weights and, if globally optimal, the minimum mean square error weight pattern. However, there are many other considerations that determine whether the optimum is local or global, and the rate at which it is achieved.

Although there are other ANN structures and learning algorithms (see Cheng and Titterton 1994 for a review), the feedforward/backpropagation method is well understood. Different methods of specifying and solving an ANN problem share a set of decisions that are made by the network designer. Principal among these are the network architecture (number of hidden layers and neurons per layer), the gradient descent terms (learning rate and momentum term), the training time (number of presentations or iterations), the type of activation function, and the selection of training, test, and production data sets. As there is little theoretical guidance in making these choices, the final form of the model results from trial and error. In the current example, therefore, the economic model of tomato margins determines the input and output sets, but the other considerations evolve from experimentation.⁵

The first step involves partitioning the data set. Dividing the data into training, test, and production components is meant to achieve the best tradeoff between in-sample estimation precision and out-of-sample performance. However, there is little guidance in choosing these partitions. Conscious of the relatively limited number of observations available in the tomato margin data set, this study defines the production set as consisting of observations from January 1992 to December 1994. The rest of the data, from January 1980 to December 1991, forms the training set and test set. Estimation

uses only the training data, but the ability of the current estimates to generalize, or to forecast out-of-sample, is continually evaluated on the test set. Continuous testing is necessary to keep the network from memorizing the training set and simply creating a lookup table. In cases where the problem set is finite, a test set is not necessary since the training set will include all possible patterns, and memorization of all these patterns by the network will generate the best results. After considerable experimentation, data from 1988–91 make up the test set, while the remaining years (1980–87) form the training set.

In determining the best network architecture for the tomato problem, this study also considers recurrent networks, general regression neural networks, and Ward NetsTM. Each of these has its own particular advantages, but none performed as well as the chosen algorithm. With the feedforward/backpropagation approach, a three-layer network will, in general, provide the best results for most of the problems in economics (Gorr, Naglin, and Szczypula 1994). In very complex and data-intensive problems, more layers add precision to the model, but adding layers to a simple problem (such as the tomato margin example) harms the network's ability to generalize. In the tomato example, a three-layer feedforward network considerably outperforms networks with more layers.

Within the hidden layer, a larger number of nodes allows the network to learn more structures in the patterns and, as such, will learn the training set better. Too many hidden layer nodes can, however, lead to poor out-of-sample performance. Kastens, Featherstone, and Biere (1995) cite recent theoretical research that determines mathematically the required number of nodes in the hidden layer that allows a three-layer network to exactly represent a continuous activation function (Salchenberger, Cinar, and Lash 1993). With n input nodes, the required number of nodes in the hidden layer is $2n + 1$. In the tomato example, we begin with an alternative rule of thumb that suggests the number of neurons in the hidden layer should be approximately 1.5 times the number of input layer neurons—18 in the tomato problem. After experimenting with hidden layers of different sizes (from 10 to 40 nodes), the network performed best with 27 nodes in the hidden layer. These nodes are connected to the output and input layers with the activation function.

The tomato margin neural network uses the symmetric logistic activation function between the input and hidden layers and between the hidden and output layers. The scaling function, which is

applied within the input layer, is linear, mapping the data into the $[-1, 1]$ interval. Some studies choose a linear activation function between the hidden and output layers, but this can reduce the power of the network to generalize, so this practice is not adopted here. The forecasting ability of the network is also determined by the parameters of the backpropagation process.

The factors that control the learning algorithm consist of the learning rate, momentum term, presentation pattern, weight initialization, and training time. As with the network structure, experimentation is a valuable tool in selecting these training criteria. Backpropagation essentially adjusts the weights of each link in order to apportion "blame" for the error to various nodes. As equation (12) shows, the learning rate controls the rate of weight adjustment as a function of current error values. As a general guideline, large values (>0.6) lead to better results in simple problems, while small values (<0.1) are more appropriate for complex problems with noisy data. In the current study, the network converges rapidly if the learning parameter is held constant. Including a momentum term in (12) causes the weight updates to depend on a proportion, determined by the momentum term (β), of previous weight changes. A higher momentum term (0.6 – 0.9) is useful in noisy data, or in combination with a high learning rate. In the final tomato margin model, the learning rate is 0.05 , while the momentum term is 0.3 .

The sequence in which the patterns are presented to the network can also influence the outcome. Of the two choices, rotational and random, the former is more appropriate when similar data points are equally dispersed through the data set, while the latter is preferable in seasonal or cyclical data. In the tomato example, the rotational pattern is chosen, as it provides slightly better performance, irrespective of the solution algorithm used.

Because the backpropagation algorithm uses a gradient descent solution method, convergence is often sensitive to both the initial values for the weights and the number of iterations. After varying the initial weight values between 0.05 and 0.7 , a value of 0.5 provided the best forecast accuracy. In determining how many iterations, or epochs, the network uses to learn the training set, the tradeoff is again between fit and a loss of generalization. However, by calibrating the network, the subjective element of stopping time is avoided. Calibration involves computing an average error for both the test and training sets. As training progresses, the training error falls monotonically, while the test error reaches a minimum and then rises. Stopping the learning process at the minimum test error,

after fewer than 300 iterations, optimizes the out-of-sample performance of the network. Once the neural network converges, the results are saved and the "optimal" network is applied to the production set. These results are then compared with the forecasts from the econometric model. The next section describes the data used in estimating each model.

Data and Estimation Methods

This study uses a series of monthly retail prices, grower prices, and shipment levels for the period January 1980 to December 1994. These data are obtained from *Tomato Statistics* (USDA-NASS 1995). Both price series are national averages and are converted to common units of dollars per hundredweight (\$/cwt). Monthly tomato shipments are in units of thousand hundredweights. The average weekly wage of workers in the "food and kindred industries" as reported by the Bureau of Labor Statistics (BLS) serves as a proxy for tomato packing costs. Data for aggregate Mexican tomato shipments are also found in *Tomato Statistics*.

The econometric margin model is estimated using an instrumental variables procedure in order to account for the endogeneity of tomato prices. Instruments include all of the exogenous variables described above in addition to a monthly retail lettuce price (BLS, *Consumer Price Index, Average Price Data* 1997), and annual measures of U.S. population and personal disposable income (WEFA Group 1997) converted to monthly series using the cubic spline EXPAND procedure in SAS. The neural network is trained using Ward Systems' Neuroshell 2 software. For both models, all prices and wages are in real values. The sample period consists of the monthly observations from January 1980 to December 1991. This subsample is equivalent to the training and test sets used by the neural network.

Comparisons of the forecasting performance of the econometric and neural net models are made on the basis of three alternative measures. First, the mean square error is calculated for both forecasts over the January 1992 to December 1994 period. Second, Theil's U provides a similar measure of forecast error that is independent of the units with which the margin is measured (Theil 1961). For practical purposes, however, methods that are successful in predicting changes in direction may be more useful than those with superior forecast accuracy as measured by the mean square forecast error. Consequently, the third test consists of Henriksson and Merton's test (1981) of the relative

ability of different models to forecast turning points in a time series. The results of each of these tests, and the estimation results from each model, are presented in the next section.

Results and Discussion

In order to address the objectives of this paper, this section presents the results obtained by testing for misspecification of the econometric model, followed by measures of forecast performance for each model, and then an interpretation of the model coefficients. Although the parameters of the econometric model have the usual interpretation as marginal impacts of the right-hand-side variables on the margin, derivation of analytical expressions that show similar marginal effects of each input node on the output node in the neural network is beyond the scope of this paper. However, sensitivity analysis of the margin to numerical changes in each of the input values provides a valuable approximation. While this exercise demonstrates the potential value for neural network modeling as a

policy tool, its strength clearly lies in forecasting noisy time series.

As discussed above, rejection of the maintained linear RPS model by any of the misspecification tests implies that an alternative, nonlinear model should be considered. First, the linear model fails Ramsey's RESET test using both squared and cubic terms for the fitted margin.⁶ Second, the Pe test of Davidson and Mackinnon (1981) rejects both the linear model and a double-log alternative.⁷ Given the indecisiveness of these tests, conducting likelihood ratio tests for $\lambda = 1$ (linear) or $\lambda = 0$ (double-log) against a variable λ alternative in a Box-Cox regression may suggest a more flexible alternative. This method yields a value of $\hat{\lambda} = 0.73$, rejecting both the linear and double-log alternatives. Consequently, this section compares the neural network and Box-Cox estimates of the structural econometric model.

Figure 1 provides a graphical representation of the forecasted margins from each model against the actual tomato margins. Close inspection of this figure shows that both models miss many of the same turning points, but the neural network forecasts appear to be much closer to the actual values.

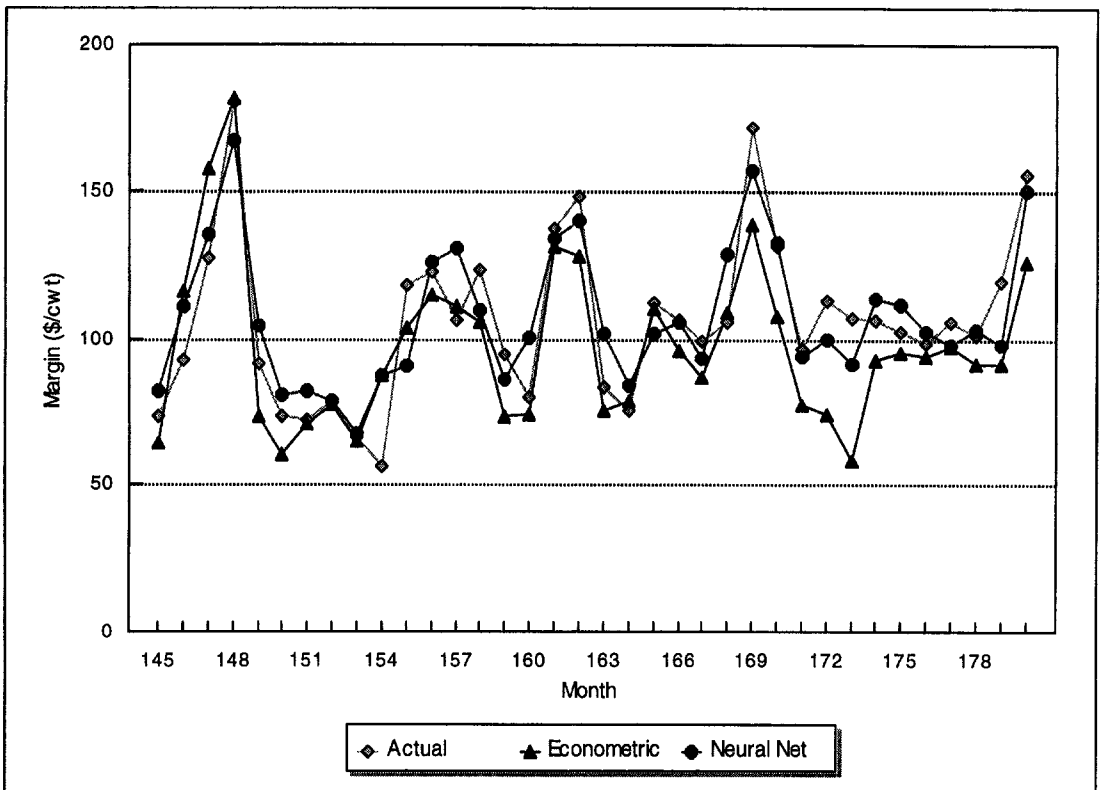


Figure 1. Neural Network and Econometric Models, Forecasts versus Actuals, U.S. Fresh Tomato Margins (January 1992 to December 1994)

In particular, both approaches miss the sharp downturns in months 154 and 160, while both miss the upturn in month 158. Quantitative measures of forecast accuracy provide an alternative basis for comparison.

Both the mean square error and Theil's U statistic provide similar measures of forecast accuracy. Table 1 shows each of these statistics for both models. Clearly, the neural network outperforms the econometric model by a considerable margin according to these measures. Other summary statistics, however, provide some opposing evidence. While the neural network predictions are within 5% of the actual value 25.0% of the time, forecasts with the econometric model are within 5% only 16.7% of the time. However, the error range for the econometric is smaller than for the neural network, erring by 1.0% at a minimum and 56.4% at a maximum, while the neural network errors range from 0.2% to 62.8%. Whereas the average absolute error by the econometric model is 14.2%, the average error by the neural network is 11.3%. Therefore, these measures provide some evidence for the superiority of the neural network model, but they are not conclusive. As Henriksson and Merton (1981) argue, however, often the ability to correctly forecast changes in the direction of a series is more important than obtaining accuracy by these quantitative measures.

Dorfman and McIntosh (1990) describe an application of the Henriksson and Merton (HM) test that compares alternative methods of forecasting the price of an agricultural commodity. The null hypothesis in the HM test is that the forecast contains no informational value, that is, the forecast predicts downturns correctly only 50% of the time, and upturns correctly 50% of the time. In such a case, a naive forecast would do just as well on average. Comparing the confidence level at which the null hypothesis is rejected between two alternative forecast models constitutes a test of their forecast accuracy. Dorfman and McIntosh explain the HM test method in some detail so is not repeated here. In this example, the neural network forecasts 14 downturns, 12 of which are correct,

while there are 19 actual downturns in the margin series. Applying the HM test to the neural network forecast gives a confidence value of 0.9972, which suggests rejecting the null hypothesis at levels of significance greater than 0.0028. According to the HM test, however, the econometric model performs marginally better, as it makes 24 downturn forecasts, 18 of which are correct. Although the econometric model predicts 6 downturns that do not occur, its ability to accurately forecast 18 of 19 actual turning points still implies a higher confidence level of 0.9996. Therefore, if the research objective is to forecast changes in the direction of a series, the econometric approach provides a slight improvement over the purely data-based neural network model.⁸ Often, however, researchers are interested in estimates of structural parameters. In this case as well, an econometric approach may prove more useful.

Table 2 presents parameter estimates from the econometric model. In this table, t-tests are used to evaluate each of the hypotheses derived from the theoretical model above.

First, despite questions as to the functional form of the RPS model, the significance of both the price and total revenue terms fail to reject the common specification of the relative price model. Second, the significance of the lagged margin value indicates that the price spread adjusts slowly toward its equilibrium level. Third, the coefficient on the trend variables shows that the margin not only is slow to adjust but is narrowing over time. Fourth, the margin rises in wages—a result that is consistent with prior expectations. Fifth, the price-variance parameter supports Brorsen et al. (1985) in showing that margins rise in price uncertainty. Finally, whether the U.S. market share variable measures quality factors or oligopsony in the fresh tomato market, the results in table 2 show that it is a significant determinant of tomato margins. Whereas increasing price spreads between the farm and retail are commonly attributed entirely to retailer concentration and market power (*The Packer* Nov. 11, 1997), these results show that risk, increased demand for marketing services, labor costs, and rigidity in margin adjustment all explain a statistically significant proportion of the difference in prices. Uncovering parameters that allow such direct interpretation of the neural network results are difficult to derive analytically, but there are two options for extracting similar information indirectly.

First, because the weights of all the links in the network are known, they may be used to calculate the economic significance of each factor through successive application of the chain rule (Refenes,

Table 1. Two Measures of Forecast Performance: RMSE and Theil's U, 1992–94

	Neural Net	Econometric
Root mean square error	13.674	19.186
Theil's U ^a	0.252	0.341

^aTheil's U statistics is calculated as

$$U = \sqrt{\sum_i (y_i - \hat{y}_i)^2 / \sum_i y_i^2}.$$

Table 2. Box-Cox Estimates of Retail-Farm Price Spread in Fresh Tomatoes, 1980–91

Variable ^a	Estimate	T-Ratio ^b	Variable	Estimate	T-Ratio
m_{t-1}^c	0.124	4.215*	April	-0.889	-1.968
p^r	0.067	5.369*	May	-0.936	-2.199*
$p^r y$	0.003	8.105*	June	-0.903	-2.040*
t	-0.003	-3.9141*	July	-0.855	-1.848
$p^r ms^{us}$	0.024	2.535*	Aug.	-0.802	-1.636
$y \sigma_p^{2d}$	0.119	3.501*	Sep.	-0.796	-1.614
w	0.072	3.304*	Oct.	-0.846	-1.779
Jan.	-0.877	-3.991*	Nov.	-0.831	-1.789
Feb.	-0.842	-3.825*	Dec.	-0.805	-1.660
March	-0.888	-4.005*	λ	0.730	
R^2	0.877		D.W.	2.034	

^aVariable definitions: m = retail-farm margin; p^r = retail price, y = shipment amount, t = time trend, ms^{us} = U.S. market share, σ_p^2 = five-year moving standard deviation of retail price, w = wage rate per hour of workers in food and kindred industries, Jan.–Dec. = monthly binary variables.

^bAsterisk indicates significance at a 5% level.

^cData sources: Retail prices and wages are from the Bureau of Labor Statistics (1997); all other data are from USDA *Tomato Statistics* (1995).

^dThis parameter and the monthly dummies have been scaled by a factor of 10^3 for presentation purposes.

Zapranis, and Francis 1994). Second, and perhaps most valuable, holding each of the variables at their mean and performing sensitivity analysis with respect to a factor of interest provides a pattern of response in the output variable. This approach is both a useful and a practical way to conduct policy analysis with a neural network.

For example, consider the effect of changing U.S. market share on fresh tomato margins. Figure 2 shows that the margin, in fact, falls in the U.S. market share, reaches a minimum, and only then begins to rise. This result suggests one possible source of the failed misspecification tests conducted with the linear econometric model above. In

fact, the correct form may indeed be quadratic in the U.S. market share. It also indicates that the results from the econometric model above may not, in fact, be true for all values of the U.S. share. Whereas margins may widen for increases in share when the U.S. is already dominating the market, a higher U.S. share when Mexico is the dominant producer may cause margins to narrow.

Combining the forecast performance and “parametric” results using this method presents another perspective on one issue of importance to Florida tomato growers—the effect of Mexican imports on the performance of the winter tomato market. First, note from figure 1 that spikes in the margin tend to

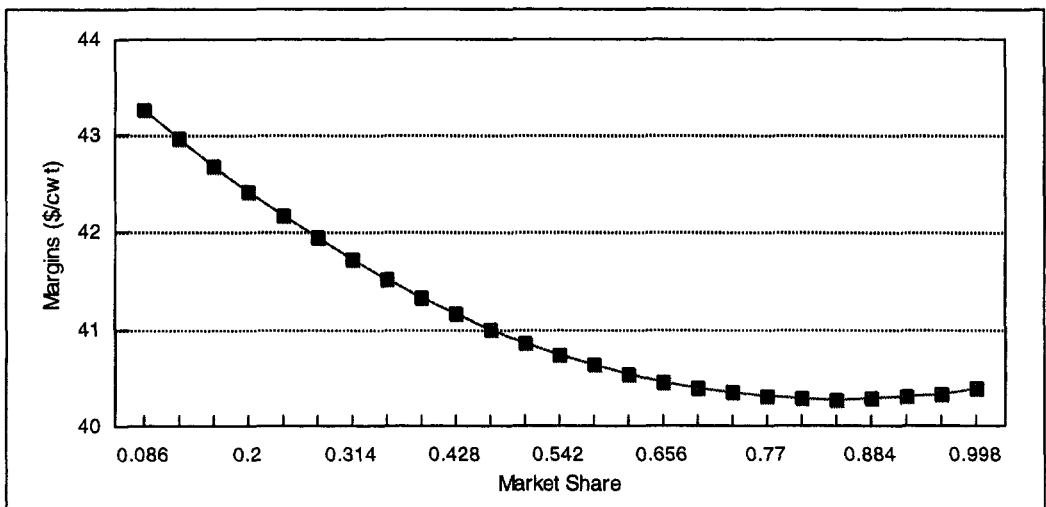


Figure 2. Sensitivity Analysis with Neural Network: U.S. Market Share and Margin Level

coincide with periods of seasonal decline in Mexican imports, suggesting that the market is less than efficient and may indeed be affected by imperfect competition. This result is supported by both the estimated effect of U.S. market share in the econometric model and the behavior of margins in the neural network model. Second, figure 1 shows that the econometric model tends to consistently understate the severity of these margin spikes. To the extent that existing policy models use econometric methods, the cost borne by U.S. growers and consumers is understated and policy recommendations are similarly misinformed. In this respect, a neural network approach to policy modeling would provide better measures of the economic significance, rather than the statistical significance, of a perceived problem.

Conclusions and Implications

This paper seeks to determine the factors that influence fresh tomato retail-farm margins and to compare the ability to model these margins using econometric and neural network methods. The set of possible factors, explanatory variables in the econometric model and inputs to the neural network, is determined by developing a dynamic relative-price spread margin model subject to output price uncertainty and imperfect competition.

The econometric model is estimated, and the neural network is trained using monthly margin observations from 1980 to 1991. Parameter estimates from the econometric model fail to reject the relative price spread (RPS) model as specified by Wohlgenant and Mullen (1987). A nonlinear Box-Cox specification of their RPS model supports including considerations for packing cost, imperfect competition, lagged margin adjustment, output price variability, and trends in the retail-farm margin. The choice of a Box-Cox model is based upon the results of several misspecification tests, each of which reject both linear and nonlinear margin models. Neural networks, however, are able to represent highly nonlinear relationships, so rejection of the linear econometric model in particular suggests that a neural network approach may be a viable alternative in both forecasting and conducting policy analysis.

As an example of using a neural network for this purpose, the study conducts sensitivity analysis by fitting the retail-farm margin for various levels of the U.S. market share. Whereas the econometric model indicates that retail-farm margins widen monotonically in U.S. market share, the neural network model instead shows that the relationship is

convex in U.S. share. Therefore, it is not necessarily true that maintaining a minimum U.S. market share through trade protection or minimum import prices is likely to cause margins to widen. In fact, if the U.S. market share is below 85%, rising market share is consistent with narrower retail-farm margins. In addition to policy analysis, various measures of forecast performance compare the ability of the neural network and econometric models to explain the margin data.

Specifically, model selection is made on the basis of mean square forecast error, Theil's U statistic, and the Henriksson-Merton (HM) test for the ability to predict turning points. The neural network outperforms the econometric model by the first two criteria, but the models are indistinguishable according to the HM test. Comparing the neural network and econometric forecasts also shows that the latter consistently understates the extent of margin spikes—spikes that typically occur when Mexican imports begin their seasonal decline. Such errors are critical as it is during these periods when complaints from grower groups typically occur. Understating the severity of changes in the margin may both trivialize grower concerns and misattribute shocks to factors other than U.S. market power.

Further research in this area is needed to find additional methods of deriving results from neural network models that are comparable to parametric results obtained from econometric models. Because most of the applied economic research using neural networks concerns their power as forecasting tools, comparatively little work has been done in bringing general comparative static results to the literature. As forecasting tools, neural networks may play a valuable role in policy simulation and welfare analysis, such as calculating lost economic welfare from implementing some of the trade policies discussed herein. Additional research on alternative network architectures may also be of interest in testing the sensitivity of the conclusions to network design.

References

- Appelbaum, E. 1982. "The Estimation of the Degree of Oligopoly Power." *Journal of Econometrics* 19:287–99.
- Arnade, C., and D. Pick. 1996. "Effects of Seasonality on Market Behavior: The Case of U.S. Fresh Fruit Market." Paper presented at AAEA meetings, San Antonio, TX. July.
- Azzam, A.M., and J.R. Schroeter. 1991. "Implications of Increased Regional Concentration and Oligopsonistic Coordination in the Beef Packing Industry." *Western Journal of Agricultural Economics* 16:374–81.
- Bansal, A., R.J. Kauffman, and R.R. Weitz. 1993. "Comparing

- the Modeling Performance of Regression and Neural Networks as Data Quality Varies: A Business Value Approach." *Journal of Management Information Systems* 10: 11-32.
- Beltratti, A., S. Margarita, and P. Terna. 1996. *Neural Networks for Economic and Financial Modelling*. London: International Thompson Computer Press.
- Box, G., and D. Cox. 1964. "An Analysis of Transformations." *Journal of the Royal Statistical Society, series B*, 26:211-64.
- Bresnahan, T. 1989. "Empirical Studies of Industries with Market Power." In *Handbook of Industrial Organization*, vol. 2, ed. R. Schmalensee and R.D. Willig. New York: North-Holland.
- Brester, G.W., and D.C. Musick. 1995. "The Effect of Market Concentration on Lamb Marketing Margins." *Journal of Agricultural and Applied Economics* 27:172-83.
- Brorsen, B.W., J.-P. Chavas, W.R. Grant, and L.D. Schnake. 1985. "Marketing Margins and Price Uncertainty: The Case of the U.S. Wheat Market." *American Journal of Agricultural Economics* 67:521-28.
- Chakraborty, K., K. Mehrotra, C.K. Mohan, and S. Ranka. 1992. "Forecasting the Behavior of Multivariate Time Series Using Neural Networks." *Neural Networks* 5:961-70.
- Cheng, B., and D.M. Titterton. 1994. "Neural Networks: A Review from a Statistical Perspective." *Statistical Science* 9:2-54.
- Cotterill, R.W. 1986. "Market Power in the Retail Food Industry: Evidence from Vermont." *Review of Economics and Statistics* 68:379-86.
- Davidson, R., and J. MacKinnon. 1981. "Several Tests for Model Specification in the Presence of Alternative Hypotheses." *Econometrica* 19:781-93.
- Dorfman, J.H., and C.S. McIntosh. 1990. "Results of a Price-Forecasting Competition." *American Journal of Agricultural Economics* 72:804-10.
- Durham, C.A., and R.J. Sexton. 1992. "Oligopsony Potential in Agriculture: Residual Supply Estimation in California's Processing Tomato Market." *American Journal of Agricultural Economics* 74:962-72.
- Faminow, M.D., and J.M. Laubscher. 1991. "Empirical Testing of Alternative Price Spread Models in the South African Maize Market." *Agricultural Economics* 6:49-66.
- Gardner, B. 1975. "The Farm-Retail Price Spread in a Competitive Food Industry." *American Journal of Agricultural Economics* 57:399-409.
- Goldberger, A.S. 1968. "The Interpretation and Estimation of Cobb-Douglas Functions." *Econometrica* 35:464-72.
- Gorr, W.L., D. Naglin, and J. Szczypula. 1994. "Comparative Study of Artificial Neural Network and Statistical Models for Predicting Student Grade Point Averages." *International Journal of Forecasting* 10:17-34.
- Grudnitski, G., and L. Osburn. 1993. "Forecasting S&P and Gold Futures Prices: An Application of Neural Networks." *Journal of Futures Markets* 13:631-43.
- Heien, D.M. 1980. "Markup Pricing in a Dynamic Model of the Food Industry." *American Journal of Agricultural Economics* 62:10-18.
- Henriksson, R.D., and R.C. Merton. 1981. "On Market Timing and Investment Performance. II. Statistical Procedures for Evaluating Forecasting Skills." *Journal of Business* 54: 513-33.
- Hiemstra, Y. 1996. "Linear Regression versus Backpropagation Networks to Predict Quarterly Stock Market Excess Returns." *Computational Economics* 9:67-76.
- Holloway, G.J. 1991. "The Farm-Retail Price Spread in an Imperfectly Competitive Food Industry." *American Journal of Agricultural Economics* 73:979-89.
- Holt, M.T. 1993. "Risk Responses in the Beef Marketing Channel: A Multivariate Generalized ARCH-M Approach." *American Journal of Agricultural Economics* 75:559-71.
- Joerding, W.H., Y. Li, and D.L. Young. 1994. "Feedforward Neural Network Estimation of a Crop Yield Response Function." *Journal of Agricultural and Applied Economics* 26:252-63.
- Jordan, K., and J. VanSickle. 1995. "Market Structure and Behavior in the U.S. Winter Market for Fresh Tomatoes." Paper presented at the AAEA meetings, Indianapolis. August.
- Kastens, T., and G.W. Brester. 1996. "Model Selection and Forecasting Ability of Theory-Constrained Food Demand Systems." *American Journal of Agricultural Economics* 78:301-12.
- Kastens, T., and A. Featherstone. 1996. "Feedforward Back-propagation Neural Networks in Prediction of Farmer Risk Preferences." *American Journal of Agricultural Economics* 78:400-415.
- Kastens, T., A. Featherstone, and A.W. Biere. 1995. "A Neural Networks Primer for Agricultural Economists." *Agricultural Finance Review* 55:54-73.
- Kinnucan, H.W., and O.D. Forker. 1987. "Asymmetry in Farm-Retail Price Transmission for Major Dairy Products." *American Journal of Agricultural Economics* 69:285-92.
- Kinnucan, H.W., and R.G. Nelson. 1993. "Vertical Control and the Farm-Retail Price Spread for Eggs." *Review of Agricultural Economics* 15:473-82.
- Kohzadi, N., M.S. Boyd, I. Kaastra, B.S. Kermanshahi, and D. Scuse. 1995. "Neural Networks for Forecasting: An Introduction." *Canadian Journal of Agricultural Economics* 43:463-74.
- Kosko, B. 1992. *Neural Networks and Fuzzy Systems*. Englewood Cliffs, N.J.: Prentice-Hall.
- Lucier, G., C.S. Plummer, D. Johnson, and J. Love. 1996. "Vegetables and Specialties: Situation and Outlook." Washington, D.C.: Economic Research Service, USDA. November.
- Lyon, G.D., and G.D. Thompson. 1993. "Temporal and Spatial Aggregation: Alternative Marketing Margin Models." *American Journal of Agricultural Economics* 75:523-36.
- Mendelsohn, L., and J. Stein. 1991. "Fundamental Analysis Meets the Neural Network." *Futures* 20:22-24.
- Moody, J. 1995. "Economic Forecasting: Challenges and Neural Network Solutions." Paper presented at the International Symposium on Artificial Neural Networks, Hsinchu, Taiwan. December.
- NeuralWare, Inc. 1993. *Using NeuralWorks: A Tutorial for NeuralWorks Professional II/PLUS and NeuralWorks Explorer*. Pittsburgh, Pa.
- Packer, The. 1996-97. Various issues. Lenexa, Kansas.
- Parker, D.D., and D. Zilberman. 1993. "Hedonic Estimation of

- Quality Factors Affecting the Farm-Retail Margin." *American Journal of Agricultural Economics* 75:458-66.
- Powers, N.J. 1995. "Sticky Short-Run Prices and Vertical Pricing: Evidence from the Market for Iceberg Lettuce." *Agribusiness* 11:57-75.
- Ramsey, J. 1969. "Tests for Specification Errors in Classical Linear Least Squares Regression Analysis." *Journal of the Royal Statistical Society, series B*, 31:350-71.
- Refenes, A.N., A. Zapranis, and G. Francis. 1994. "Stock Performance Modeling Using Neural Networks: A Comparative Study With Regression Models." *Neural Networks* 7:375-88.
- Salchenberger, L.M., E.M. Cinar, and N.A. Lash. 1993. "Neural Networks: A New Tool for Predicting Thrift Failures." In *Neural Networks in Finance and Investing*, ed. R.R. Trippi, and E. Turban. Chicago: Probus.
- Schroeter, J., and A. Azzam. 1991. "Marketing Margins, Market Power, and Price Uncertainty." *American Journal of Agricultural Economics* 73:990-99.
- Stiegert, K.W., A. Azzam, and B.W. Brorsen. 1993. "Mark-down Pricing and Cattle Supply in the Beef Packing Industry." *American Journal of Agricultural Economics* 75: 549-58.
- Theil, H. 1961. *Economic Forecasts and Policy*. Amsterdam: North-Holland.
- Thompson, G.D., and C.C. Lyon. 1989. "Marketing Order Impacts on Farm-Retail Price Spreads: The Suspension of Prorates on California-Arizona Navel Oranges." *American Journal of Agricultural Economics* 71:647-60.
- Trippi, R.R., and D. DeSieno. 1992. "Trading Equity Index Futures with a Neural Network." *Journal of Portfolio Management* 19:27-33.
- U.S. Department of Agriculture, National Agricultural Statistics Service. 1995. *Tomato Statistics: 1960-94*. Washington, D.C.
- U.S. Department of Labor, Bureau of Labor Statistics (BLS). 1997. *Consumer Price Index: Average Price Data*. Washington, D.C.
- Ward, R.W. 1982. "Asymmetry in Retail, Wholesale, and Shipping Point Pricing for Fresh Vegetables." *American Journal of Agricultural Economics* 64:205-12.
- Ward Systems Group, Inc. 1996. *NeuroShell 2*. Frederick, Md.
- Waugh, F.V. 1964. "Demand and Price Analysis: Some Examples from Agriculture." USDA Technical Bulletin no. 1316.
- WEFA Group. 1997. *Long Term U.S. Economic Outlook*. Ed-dystone, Pa.
- Wohlgenant, M.K. 1985. "Competitive Storage, Rational Expectations, and Short-run Food Price Determination." *American Journal of Agricultural Economics* 67:739-48.
- Wohlgenant, M.K. 1989. "Demand for Farm Output in a Complete System of Demand Functions." *American Journal of Agricultural Economics* 71:241-52.
- Wohlgenant, M.K., and J.D. Mullen. 1987. "Modeling the Farm-Retail Price Spread for Beef." *Western Journal of Agricultural Economics* 12:119-25.
- Lucier et al. 1996). California production occurs mainly from May to October, while the Florida deal extends from October to late April. Growers in both regions, however, are concerned over the possible impact on their share of the retail tomato dollar if Mexican growers have indeed violated the November 1996 suspension agreement, as has been alleged.

2. While a constant rate of interest is clearly a strong assumption, in the empirical model to follow scaling all arguments by the same value has no effect on the estimated parameters.

3. As a reviewer suggests, the summer and winter fresh tomato markets may differ significantly because the summer market is supplied by California and Baja-Mexico, while the winter is supplied by Florida and Sinaloa-Mexico. Including monthly dummy variables will account for differences in the average margin by month and season, but this model maintains that the marginal effects of each explanatory variable are constant across seasons. Although the sources of supply differ by season, behavior of the marketing channel does not necessarily have to follow because the set of buyers and buying practices remain the same throughout the year.

4. In recent years, consumers have begun to regard Mexican tomatoes as a higher quality product, so a high U.S. share may suggest that the average quality on the market is relatively low. As Parker and Zilberman (1993) show, quality is an important determinant of the retail-farm margin, but it is especially difficult to measure. Including a market share variable may also capture some of the impact of increased imports of greenhouse and hydroponic tomatoes. Imports of these products, up 87% in the first eight months of 1996, sell for between two and three times the price of domestically grown field tomatoes (Lucier et al. 1996).

5. Beltratti, Margarita, and Terna (1996) describe the process of evaluating the experimentation results in terms of "performance evaluation . . . based on some statistical indicator such as the coefficient of determination computed over the targets and the outputs of the network" (p. 16). When this is done in-sample, it is a measure of the training performance or fit of the network, whereas when it is done out-of-sample, it is an evaluation of the ability of the model to generalize, or to forecast. In our research, we use the mean square error (MSE) to similar purpose.

6. The calculated F-statistics are $F_{1,120} = 11.511$, and $F_{2,119} = 12.714$, respectively. The critical F statistics are 3.92 and 3.07 at a 5% level.

7. The Pe test consists of estimating a linear margin model that also includes a variable representing the difference between the fitted margin values

Notes

1. In 1996, California growers produced 31% of U.S. tomato output and Florida growers 39% (Lu-

from a log-log regression and the log of the fitted margin values from the linear regression. If the coefficient on this variable is significantly different from zero, then the linear model is rejected. A test of the log-log model uses the reverse of this procedure, where the included variable consists of the difference between the fitted margins from a linear regression and $\exp(\log \hat{y})$. The t-ratios on these variables are 1.97 and 2.06, respectively. An anonymous reviewer points out that transforming fitted log values to fitted level values in this man-

ner induces bias in the predicted value. However, Goldberger (1968) shows that "the alternative estimates are virtually identical . . . no payoff appears to the use of the minimum variance unbiased estimators rather than their approximate counterparts" (p. 471). Furthermore, this bias is confined to the intercept of the regression, so it does not affect the parameter of interest in the Pe test.

8. In fact, the difference in the performance of the two models is not statistically significant at any reasonable level of confidence.