Forecasting Retail-Farm Margins for Fresh Tomatoes: Econometrics vs. Neural Networks

by

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This study compares the forecasting ability of an econometric and a neural-network model of fresh tomato retail-farm margins over the period 1980-94. Tests of forecast accuracy show that the neural-network significantly outperforms the econometric model, while the latter is better able to predict turning points in the series.

Introduction

While grower prices are often cited as an indicator of producer well-being, using farmer returns to guide public policy ignores the role of consumers. One simple measure that takes both interests into account is the retail-farm margin. While consumers benefit from lower retail prices, farmers are harmed to the extent that price reductions are passed through to the farm, and vice versa. The margin, however, is an indirect measure of the efficiency of the marketing system - if the price spread widens, then both consumers and growers are worse off. This paper focuses on the retail-farm margin as an indicator of marketing efficiency, and develops two, complementary models to explain and predict this measure.

Most empirical studies of retail-farm margins estimate reduced-form models (Heien, 1980; Brorsen, et al., 1985; Wohlgenant and Mullen, 1987; Thompson and Lyon, 1989; Lyon and Thompson, 1993; Brester and Musick, 1995). Although ad hoc, these models include variables intended to proxy more complete structural models such as those of Waugh (1964), Gardner (1975), or Holloway (1991). These theoretical models are, however, not in complete agreement as to what factors determine retail-farm margins. Consequently, the empirical studies often concern themselves with non-nested testing among empirical representations of the various competing margin theories. However, the low power of many of these tests brings into question the value of making these comparisons. Rather, Kastens and Brester (1996) argue that a better test of the usefulness of a model is its ability to forecast. If this is indeed the case, then perhaps an approach other than an econometric one can serve the same purpose.

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Neural network models provide one such alternative. Neural network models are increasingly popular among financial and commodity analysts for their ability to forecast short-run price movements. Neural network models 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 non-linearities in the relationship may mean that a neural network modeling approach provides a better fit to the data than traditional econometric approaches. Despite this advantage, many feel that neural network models are inferior due to the difficulty of recovering parameters from the network. While it is true that estimating parameters analogous to those generally available through other methods is a difficult task, this paper demonstrates that equivalent qualitative information can be recovered with little difficulty.

The primary objective of this paper is to compare the forecast performance of a reduced-form econometric model and a neural network model of the fresh tomato retail-farm margin. The paper first develops an economic model of fresh tomato margins to determine the variables that comprise each. Applying each method to a monthly data set provides both structural and forecast comparisons of the two approaches.

Econometric Model of Retail-Farm Margins

While early work on margin determination assumed essentially ad hoc rules in setting retail prices above cost, more recent research casts the problem in terms of a competitive market equilibrium for output, farm inputs, and marketing services. Wohlgenant and Mullen (1987) argue that traditional models (Waugh, 1960; George and King, 1971) fail to account for the effect on margins of simultaneous changes in supply and demand in their belief that margins are combinations of percentage and constant absolute markups on cost. Their "relative price spread" (RPS) model specifies the margin as 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 similar to the data used in this study. 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 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 variables, lagged adjustment, risk, market structure, and quality are relevant to horticultural crops in general, and fresh tomatoes in particular (Jordan and Van Sickle, 1995).

Incorporating each of these arguments into a reduced-form RPS model of the fresh tomato retail-farm margin provides an estimable model:

$$(1) \quad M_t = \beta_1 M_{t-1} + \beta_2 RP_t + \beta_3 RP_t \cdot Q_t + \beta_4 MSUS_t + \beta_5 RISK_t + \beta_6 T + \beta_7 W_t + \sum_{k}^{12} \gamma_k MN_k, t + e_t;$$

where M is the retail price less the farm price, RP is the retail price, Q is the quantity shipped, $MSUS$ is the domestic share of the fresh tomato market, $RISK$ is a five-year moving standard deviation of the retail price, T is a time trend, W is a measure of input prices, the average hourly wage of workers in food and kindred industries, MN_k is a series of binary monthly indicator variables, e is a vector of independent and identically distributed normal error terms, and t indexes monthly observations. Equation (1) embodies several assumptions that require further explanation.

First, U.S. market share provides a proxy for the effect of seasonality-induced imperfect competition on margins in the absence of Mexican data necessary to estimate a more complete model of fresh tomato market structure (Arnade and Pick, 1996). Beyond the market power effects, this variable may also capture the effect of quality on margins. A high U.S. market share may indicate a poor Mexican harvest and, because Mexican tomatoes are recognized as higher quality than U.S. tomatoes, a high U.S. share may suggest the average quality on the market is relatively low. Third, the time trend represents an attempt to proxy changes in quality over time. Development of new vine-ripened varieties, introduction of genetically engineered tomatoes, and advances in distribution technology are all arguments for a trend towards higher quality fresh tomatoes. Fourth, Brorsen et al. discuss several alternative ways of measuring risk. In the margin equation above, RISK is a five-year moving standard deviation of retail price - similar to the specification suggested by Brester and Musick (1995).

Although previous studies determine the appropriate econometric specification through a variety of non-nested tests (Wohlgenant and Mullen, 1987; Lyon and Thompson, 1993; Faminow and Laubscher, 1991), this study maintains the validity of the RPS model, focusing on a comparison of the forecasting performance of the econometric and neural network models.

Designing a Neural Network for Margin Forecasting

Artificial neural networks (ANN) are systems of interconnected nodes, that map input data, or explanatory variables 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 specific 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, Zapranis, and Francis, 1994; Hiemstra, 1996), commodity price forecasting (Mendelsohn and Stein, 1991; Chakraborty, et al., 1992; Grudnitski and Osburn, 1993), and in macroeconomics (Moody, 1995), but is only now emerging as an analytical tool in agricultural economics (Kohzadi, et al. 1995; Kastens and Featherstone, 1996). Khozadi, et al. provide a detailed description of the feedforward-backpropagation algorithm used in this study.

Although there are other ANN structures and learning algorithms (see Cheng and Titterington for a review), the feedforward-backpropagation method is well understood and is common among financial and economic applications. 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 functional form choices like the network architecture (number of hidden layers and neurons per layer) and the type of activation functions, and estimation algorithm choices like the gradient descent terms (learning rate and momentum term), the training time (number of presentations or iterations), 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[2].

The first step involves partitioning the data set. Dividing the data into training, test, and production components is meant to achieve the best trade-off between in-sample estimation precision and out-of-sample performance. Calculating measures of forecast precision for the production set provides a method of evaluating network performance. In the monthly tomato margin data, this consists 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 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. After considerable experimentation, data from 1988-91 comprise the test set, while the remaining years (1980-87) form the training set.

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[2] Beltratti, Margarita, and Terna 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 if 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.

With the feedforward-backpropagation approach, a three layer network will, in general, provide the best results for most of the problems in economics. After experimenting with hidden layers of different sizes (from 10-40 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 network performs best with a sigmoidal function between the input and hidden layers, and between the hidden and output layers.

The factors that guide the learning algorithm consist of the learning rate, momentum term, presentation pattern, weight initializations, and training time. Backpropagation adjusts the weights of each link in order to apportion 'blame' for the error to various nodes, with the learning rate controlling 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. With the inclusion of a momentum term, the weight updates depend not only on the current error value but by a proportion, determined by the momentum term, 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.

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 (out of sample). 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. 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 optimizes the out-of-sample performance of the network. For the tomato margin problem, less than 300 iterations were enough to reach the minimum. Once the neural network converges, the results are saved and the "optimal" network is applied to the production set and compared to the econometric 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 the *Tomato Statistics* publication (USDA-NASS). Both price series are national averages and are converted to common units of dollars per hundred weight ($/cwt). Monthly tomato shipments are in units of 1000 cwt. The average weekly wage of workers in the "food and kindred industries" as reported by the Bureau of Labor Statistics serves as a proxy for tomato packing costs. Data on aggregate Mexican tomato shipments are also provided by the USDA publication.

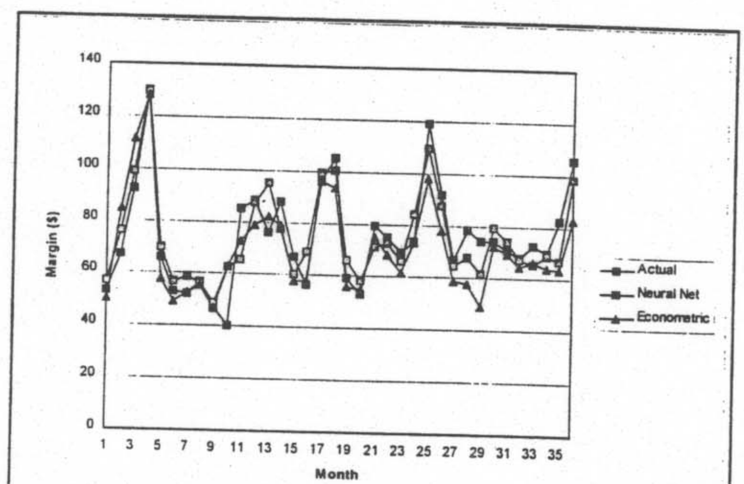
The econometric margin model is estimated using the two-stage least squares procedure in SHAZAM 7.0 over the period January 1980 to December 1990. This sub-sample is equivalent to the training and test sets used by the neural network. Instruments for the 2SLS model include all of the exogenous variables described above in addition to a monthly green pepper price (USDA/NASS, *Vegetables and Specialty Crops*), and annual measures of U.S. population and personal disposable income (WEFA Group) converted to monthly series using the cubic spline procedure in SAS. The neural network is trained using Ward Systems' Neuroshell2 software.

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 1991 to December 1994 period. Second, Theil's U provides a similar measure of forecast error, but 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. Henriksson and Merton (1981) describe a statistic that tests the ability of each approach to reliably predict turning points in the production set.

Results and Discussion

As the objective of this study is primarily a comparison of the forecasting ability of the two empirical methods, this section presents the measures of forecast performance first, and then follows with 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.

Figure 1. Forecasts vs Actuals: Neural Network and Econometric Models: U.S. Fresh Tomato Margins; January 1992 to December, 1994.



However, sensitivity analysis of the margin to numerical changes in each of the input values provides a valuable approximation of the marginal effects. While this exercise demonstrates the potential value for neural network modeling as a policy tool, its strength clearly lies in forecasting noisy time series.

Figure 1 provides a graphical representation of the forecast results from each model against the actual tomato margins. Closer inspection of this figure shows that both models miss many of the same turning points, but the neural network forecasts tend to be much closer to the actual values. In particular, both approaches miss the sharp downturns in months ten and thirteen, while both mistakenly forecast a rise in month thirty. 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 one shows each of these statistics for both models.

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

	Neural Net	Econometric
Mean Square Error	**79.29**	**131.90**
Theil's U[a]	**0.115**	**0.148**

[a] Theil's U statistics is calculated as: $U = \sqrt{\sum_i (y_i - \hat{y}_i)^2 / \sum_i y^2_i}$

Clearly, the neural network outperforms the econometric model by a considerable margin according to these measures. Other summary statistics also favor the neural network. While the neural network predictions are within 5% of the actual value 36.1% of the time, forecasts with the econometric model are within 5% only 27.8% of the time. The range of errors values is quite similar, as the minimum from the neural network and econometric models are 0.490 and 0.449, respectively, and the maximum from each are 22.815 and 23.070. Therefore, the range measure is an inconclusive indicator of forecast performance. As Henriksson and Merton 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.

McIntosh and Dorfman describe an application of the Henriksson and Merton (HM) test to 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, i.e., the forecast predicts downturns correctly only 50% of the time, and upturns correctly 50% of the time. In this case, a naive forecast will do just as well on average.

The neural network forecasts 15 downturns, 13 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 0.9989, which suggests rejecting the null hypothesis at levels of significance greater than 0.0011. According to the HM test, however, the econometric model performs marginally better as it makes 23 downturn forecasts, 18 of which are correct. Although the econometric model predicts five downturns that do not occur, its ability to accurately forecast 18 of 19 actual turning points implies a confidence level of 0.9999. If the objective of the research is to forecast changes in the direction of the series, rather than achieve a high degree of quantitative accuracy, the econometric model may outperform a neural network.

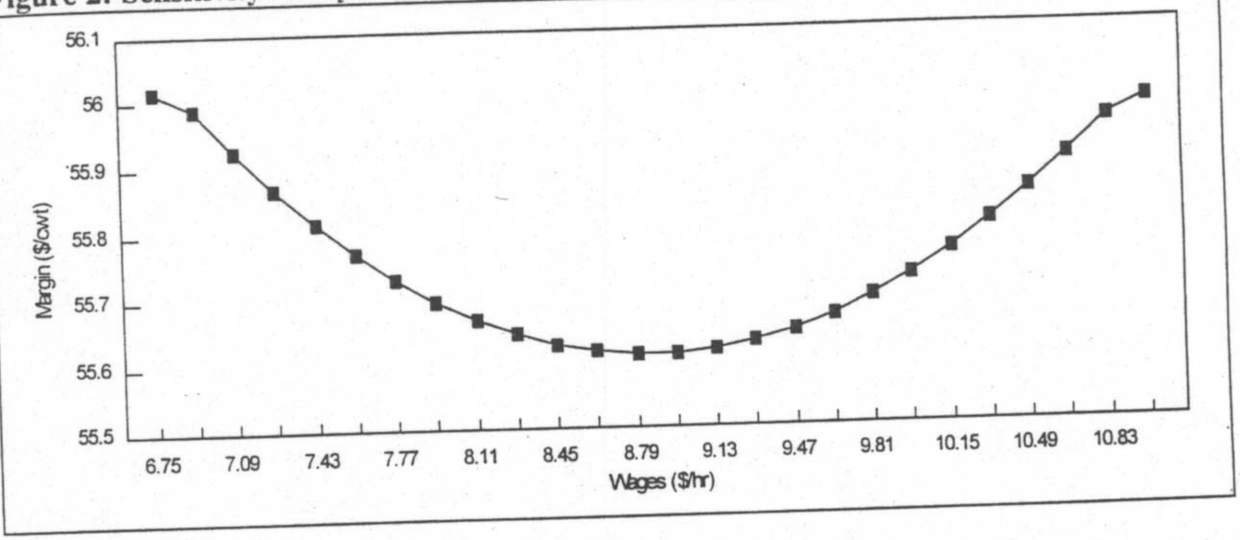
The objective of many forecasting studies is to improve the timing of market trades. While most find that neural networks forecast with greater accuracy than econometric or times series (Box-Jenkins) models, their usefulness may be limited if the result of the HM is generally true (Zaremba, 1990; Mendelsohn and Stein, 1991; Grudnitski and Osburn, 1993; Kohzadi, et al., 1995). Often, money is made or lost as much on the direction of price movements as it is on the extent of the move in any direction. In the tomato case, growers always have the option of abandoning a crop in a poor price year to avoid harvest costs, or in not growing tomatoes again in a short (90 day) planting and harvesting cycle, so the ability to predict turning points is potentially of great financial value. If the structural parameters of an econometric model are of interest, the ease of interpreting regression coefficients is another advantage.

Although space limitations prevent presentation of the full set of parameter estimates, tests of the theoretical margin model can be conducted with the econometric results. First, the significance of both the price and total revenue terms fail to reject the relative price spread specification. Second, the significance of the lagged margin value indicates that the price spread adjusts slowly towards its equilibrium level. Third, the coefficient on the TREND variable shows that the margin is not only slow to adjust, but it is narrowing over time. Fourth, while the margin rises in the labor-cost proxy variable, risk is only significant at an 18% level. Whether the U.S. market share variable measures quality factors or market imperfections, the estimation results show that it is a significant determinant of tomato margins. Uncovering similar parameters with neural networks is, in general, very difficult, but there are options for extracting equivalent information indirectly.

Qualitative conclusions can be drawn from analyzing the weights of each factor, the relative contribution of each, or through a sensitivity analysis procedure. Figure 2 shows the results of the latter, using the wage as an example. This procedure holds all variables constant at their mean and varies the variable of interest (wage) over its range. This exercise is useful not only in forming policy simulations, but can also help in selecting the functional form of variables in an econometric model. For example, Figure 2 shows that the margin, in fact, falls in the wage rate, reaches a minimum, and only then begins to rise. This suggests that there may be value in further specification tests of the econometric model to investigate the possibility that the correct form may indeed be quadratic in wages.

Performing a similar procedure with each of the input-variables can provide a complete structural interpretation of the neural network model, but does not indicate the relative importance of each factor. The second approach, ranking the factors according to their contribution, at least partially ameliorates this weakness of using neural networks to model economic phenomenon.

Figure 2. Sensitivity Analyis with Neural Network: Wage Rates and Margin Level



The contribution values can be interpreted in some sense as "partial R^2" values, or the percentage of explainable variation in the output variable attributable to each input variable. With this interpretation, both the price and revenue terms from the relative price spread specification are the most important margin determinants. It is also interesting to note that wages, lagged margin, and trend were relatively unimportant compared to many of the dummy variables. With the current econometric estimates, a direct comparison of the rankings between the neural network and econometric approach is not possible because t-statistics and the contribution values measure two different things. Although it is unacceptable as a model selection device, stepwise regression provides information that is more directly comparable to these contribution values. This approach suggests a ranking of the variables that is distinctly different from the neural network. In particular, the neural network finds the trend variable the fifth least important, whereas the stepwise regression suggests that is the fifth most important. Further, the lagged margin is one of the least important variables to the network, but enters the stepwise regression second only to the retail price. Finally, the econometric approach also shows the wage rate to be far more important than the network suggests, but risk as one of the least important. Clearly, the two methods not only forecast with different degrees of accuracy, but also provide a different rank-ordering of the variables.

Combining the forecast performance and "parametric" results from both methods presents another perspective on the policy problems mentioned in the introduction. First, note from figure 1 that spikes in the margin tend to coincide with periods of seasonal decline in Mexican imports, suggesting the market is less than efficient and may indeed be affected by imperfect competition. This result is supported by both the significance of U.S. market share in the econometric model, and the relative importance of market share in the neural network. 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 compares the performance of a reduced-form econometric model with a neural network model in forecasting fresh tomato retail-farm price spreads. Each model uses monthly margin observations from 1980 to 1991. Comparisons of forecast performance are made on the basis of mean square error, Theil's U statistic, and the Henriksson-Merton test for the ability to predict turning points. While the neural network outperforms the econometric model using the tests of forecast precision, the econometric model is better able to predict changes in direction of the series. This result is of interest to market-timers who bet on the direction of price movements rather than their magnitude. Qualitative comparisons of the econometric parameter estimates and the contribution factors from the neural network show a distinct difference in the importance of each variable within the alternative models. Simulating the neural network model with all but one variable held constant shows that the response of margins to wage rates is, in fact, quadratic and not linear as is often suggested. This result implies that neural networks may have value in helping economists determine the appropriate functional forms for econometric models.

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