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Economies of Scale in the Floriculture Industry

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This study investigated the cost structure of the floriculture industry in the United States. Economies of scale and input elasticities were estimated with a normalized quadratic cost function. Results suggest that economies of scale exist in the floriculture industry. As producers become large and more automated, they have a cost advantage relative to smaller producers who are producing the same output product mix. The existence of economies of scale suggests that average grower size can increase in the future as growers increase in size to take advantage of cost efficiencies.

Key Words: duality, economies of scale, floriculture, nonprice variables

JEL Classifications: Q12, C31, D20

Floriculture is a thriving and dynamic part of production agriculture in the United States. However, from 1996 to 2001 the number of small- and medium-size firms (growers) declined by 16.0 and 2.0%, respectively, and the number of large growers increased by 1.0% (USDA 2002). This trend suggests that there could be a cost advantage associated with firm size. However, there is limited information about cost and input demand relationships in the floriculture industry. A study of the production technology of floriculture producers can help determine the existence and the magnitude of economies of size and how floriculture producers fit in the changing structure of the industry. Knowledge of scale economies, as well as price and substitution elasticities, can be used to assist growers in planning better for the future and by policymakers in formulating policy or regulations for the floriculture industry. Growers can use information from this study as a comparison to their operations to assist in their decision of whether to expand and to determine optimal levels of inputs.

Prior literature relating to cost relationships for greenhouse ornamentals is sparse and inadequate and provides limited evidence of scale economies in floriculture production. Most research for the floricultural industry has been devoted to calculating a cost per square foot or a cost per pot using partial budget or historical information (Brumfield et al.; Christensen 1978a,b,c; Hodges, Satterhwaite, and Haydu). Other studies have reported a cost per square foot that varies by firm size, market channel, or both (Brumfield et al.; Hodges, Satterhwaite, and Haydu). No research has been uncovered that explicitly estimated a cost function or resulting scale economies for floriculture production, which is vital knowledge for this industry. Information on economies of

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scale and elasticities in floriculture production is vital in assisting with long-term planning to increase cost efficiency either through size or productivity improvements from use of labor and other inputs.

The objective of this study was to estimate cost relationships for floriculture producers, including the cost function, input demands, price elasticities, and scale economies. The cost analysis was conducted with an original data set obtained from a survey of greenhouse firms conducted in the fall of 2000. In the analysis, we first estimate a standard cost model of the floriculture industry and then re-estimate it considering nonprice variables that are included to capture differences in the cost structure and output product mix among growers. Performance of the estimated models is compared out-of-sample, and results for the selected model are reported and discussed.

Theoretical Cost Model

Using duality theory, cost is modeled as a function of output and input prices under the neoclassical assumption of competitive markets with respect to input prices. A general cost function is specified as

$$(1)\qquad C = f(\mathbf{Y}, \mathbf{P}),$$

where C is the total cost of a firm, and $\mathbf{Y}$ and $\mathbf{P}$ are vectors of output and input prices, respectively. The corresponding input demand functions can be derived using Shephard's lemma, in which $\mathbf{X} = f(\mathbf{Y}, \mathbf{P})$, where $\mathbf{X}$ is a vector of inputs.

For this study, we assume the cost function is weakly separable in inputs. Weak separability of inputs from an empirical perspective implies a two-stage cost minimization process. In the first stage, the cost of producing a single unit of an aggregate input with the prices of the inputs in the subgroups is estimated. In the second stage, the aggregate input prices obtained from stage 1 is used to estimate the final cost function. Despite the restrictions imposed on input elasticities, an assumption of weak separability is flexible enough to estimate the economies of scale, price, and substitution elasticities (Chambers). As noted by Chambers, many published studies that involve empirical estimation of a cost function assume weak separability of inputs because of data limitations. In our circumstances, we do not have sufficient information on capital. However, this is not necessarily a major limitation because capital prices often have little variation across firms in a cross-sectional data set such as that used in our study. Hence, we assume weak separability of inputs and examine cost as a function of labor, materials, and energy.

In a multiproduct firm, several outputs that are separable from each other often can be accounted for accurately. However, because most greenhouse growers produce many types of floriculture but do not maintain or are not willing to provide this type of information, the use of multiple outputs is not possible. To capture the multiple products component, we propose a single output and specify the cost model as

$$(2)\qquad C = f(\mathbf{Y}, \mathbf{P}, \mathbf{H}),$$

with the related input demands as $\mathbf{X} = f(\mathbf{Y}, \mathbf{P}, \mathbf{H})$, where $\mathbf{H}$ is a vector of firm characteristics. This specification can be viewed as a cost function that is conditional on a vector of firm characteristics.

Empirical Model

A normalized quadratic cost function is chosen as the functional form because it is a second-order Taylor series approximation of a monotonic transformation of the true underlying function. Additionally, it is flexible, in that the value of its first- and second-order derivatives equal those of the underlying (true) function at the point of approximation (Diewert). The quadratic form was chosen because it is consistent with cost minimization theory and it accommodates the imposition of curvature, homogeneity, and symmetry. The normalized quadratic cost function and the related input demands are specified as

$$(3)\qquad C = A_0 + \sum_i A_i w_i + \sum_i B_i y_i + \left(\frac{1}{2}\right)\left(\sum_i \sum_j A_{ij} w_i w_j + \sum_i \sum_j B_{ij} y_i y_j\right) + \sum_i \sum_j \delta_{ij} w_i y_j,$$

$$(4)\qquad x_i = A_i + \sum_j A_{ij} w_{ij} + \sum_j \delta_{ij} y_j,$$

where C is normalized cost, the w_i are normalized input prices; y_i are output; x_i are quantities of inputs; and A_0, A_i, A_{ij}, B_i, B_{ij}, and δ_{ij} are parameters to be estimated. Symmetry conditions are imposed by restricting $A_{ij} = A_{ji}$ and $B_{ij} = B_{ji}$. To impose curvature (concavity in input prices and convexity in output), the matrix of coefficients of the quadratic terms of input prices and output quantities are reparameterized into semidefinite matrices (Lau). This method is described in detail by Kohli.

To incorporate nonprice variables into the cost function, Equation (3) is modified as in Equation (5),

$$(5)\qquad C = A_0 + \sum_i A_i w_i + \sum_i B_i y_i + \left(\frac{1}{2}\right)\left(\sum_i \sum_j A_{ij} w_i w_j + \sum_i \sum_j B_{ij} y_i y_j\right) + \sum_i \sum_j \delta_{ij} w_i y_j + \sum_k \sigma_k h_k + \sum_k \sum_l \phi_{kl} h_k h_l + \sum_i \sum_l \gamma_{il} w_i h_l + \sum_i \sum_l \psi_{il} y_i h_l,$$

where the h are firm characteristics; σ_k, ϕ_{kl}, γ_{il}, and ψ_{il} are parameters to be estimated; and all remaining variables are defined as in Equation (3). The input demands that result from Equation (5) are specified by Equation (6),

$$(6)\qquad x_i = A_i + \sum_j A_{ij} w_{ij} + \sum_j \delta_{ij} y_j + \sum_l \gamma_{il} h_l.$$

Equations (3) and (4) constitute a complete system of cost and demand equations, whereas Equations (5) and (6) make up a complete system augmented with nonprice variables.

Elasticities

Cost elasticities can be calculated from parameters estimated in the cost model specified in Equation (5). The elasticity of cost with respect to output, y (assuming only one output), results in the measure of scale economies in Equation (7),

$$(7)\qquad \varepsilon_{Cy} = \left(B_1 + B_{11} y + \sum_i \delta_i w_i + \sum_i \psi_i h_i\right)\left(\frac{y}{C}\right).$$

The term $B_1(y/C)$ is the direct effect of output on the cost elasticity for growers at the mean of the data. The second term, $B_{11}(y/C)$, measures how the elasticity varies as sales (output) increase or decrease from the sales sample mean. The term $\delta_i(y/C)$ measures the change in elasticity as input prices change. The last term $\psi_i(y/C)$ measures the change in elasticity due to changes in grower characteristics.

Similarly, the elasticity of cost with respect to grower characteristics that are measured as continuous variables can be calculated as in Equation (8),

$$(8)\qquad \varepsilon_{Ch_k} = \left(\sigma_k + \sum_l \phi_{kl} h_l + \sum_i \gamma_{ik} w_i + \psi_k y\right)\left(\frac{h_k}{C}\right).$$

The term $\sigma_k(h_k/C)$ is a direct effect of the grower characteristic, h_k, on costs at the sample means for all variables. The term $\phi_{kl}(h_k/C)$ measures how the elasticity varies as the grower characteristic, h_l moves away from the sample mean. The term $\gamma_{ik}(h_k/C)$ measures how the elasticity varies as the input price deviates from the sample mean. The last term, $\psi_k(h_k/C)$, measures how the elasticity changes as output moves away from the sample mean.

Elasticity estimates cannot be calculated for binary variables; however, the following expression measures the shift in the cost function when the respective binary variable is equal to 1:

$$(9)\qquad \xi_{Ch_k} = \sigma_k + \sum_l \phi_{kl} h_l + \sum_i \gamma_{ik} w_i + \psi_k y.$$

The term σ_k is a direct effect of the grower characteristic, h_k, on costs at the sample means for continuous variables. The term $\phi_{kl} h_l$ measures the combined effects of the grower characteristics, h_l and h_k, on costs. The term $\gamma_{ik} w_i$ measures the combined effect of input prices and grower characteristic, h_k, on costs. The last term $\psi_k y$ measures the effect of the interaction of output and the grower characteristic, h_k, on costs.

In addition to cost elasticities, we also define input price elasticities as

$$(10) \quad \varepsilon_{ij} = A_{ij}\left(\frac{w_j}{x_i}\right),$$

where all variables are as previously defined. Morishima elasticities of substitution, which measure the effect on the optimal quantity ratio, x_i/x_j given a percentage change in the price ratio, w_i/w_j, are given by

$$(11) \quad M_{ij} = \varepsilon_{ji} - \varepsilon_{ii}.$$

The derivation of Morishima elasticities are described in detail in Blackorby and Russell.

Price and Nonprice Inputs

Three inputs that are considered in this study are labor (x_1); materials (x_2), which includes production costs such as plants, seeds, fertilizer, and chemicals; and energy (x_3). The prices for labor, materials, and energy are denoted by w_1, w_2, and w_3, respectively.

To account for differences in cost structure not captured by input prices, we include nonprice variables in the cost function defined by Equations (3) and (4). Augmenting the cost function as in Equations (5) and (6), we add a vector of characteristics, **H**, that serves as a proxy to account for differences in product mix and cost structure. The nonprice variables we consider include sales per square foot, firm location, percentage of sales that are wholesale, technology, the age of management, production practices, and two different pest management practices. Further explanation of the variables included in the **H** vector follows. See Table 1 for a summary of the nonprice variables with their definitions.

The first nonprice variable, sales per square foot (h_1), captures differences in product mix, which varies by firm. Ornamental crops of the same size but of different type vary in sales price. For example, a 10-inch hanging basket of petunias would typically sell for less than a 10-inch hanging basket of geraniums or guinea impatiens. Therefore, a grower producing predominantly petunias would have lower sales per square foot than a grower producing primarily guinea impatiens. Sales per square foot serve as a proxy to account for the difference in product mix among firms. The second nonprice variable, h_2, is a binary variable representing the region in which the firm is located. The binary variable is a proxy to account for differences in cost due to location of the firm and human capital intensity. In the floriculture industry, certain crops can be produced more efficiently in specific regions because of more favorable environmental conditions, particularly weather. Additionally, the location variable serves as a proxy for a measure of human capital intensity. Clusters of growers in the Midwest, Northeast, and South are more experienced and might have superior human capital in greenhouse production. The use of a location binary variable is consistent with the theory of location and the spatial dispersion of human capital and technology in clusters (Ormrod).

An additional variable (h_3) measures the percentage of sales that are wholesale (versus

Table 1. Definitions of Nonprice Variables

Variable	Definition
h_1	Sales per square foot
h_2	A binary variable equal to 1 if the grower is located in the Midwest, Northeast, or South; 0 otherwise (other regions include the Midatlantic and the West)
h_3	Percentage of sales that are wholesale (versus retail)
h_4	Percentage of production area that is hand-watered
h_5	Age of the principal manager
h_6	A binary variable equal to 1 if the grower fertilizes with each watering; 0 otherwise
h_7	A binary variable equal to 1 if the grower uses scouting as a method of pest management; 0 otherwise
h_8	A binary variable equal to 1 if the grower uses preventive application of chemical pesticides; 0 otherwise

retail) and is included to capture differences in costs from selling in two different markets. The cost structure of a firm selling primarily wholesale can be substantially different from the cost structure of a grower selling primarily retail. Ornamentals that are sold directly to the retail market are typically under production longer; therefore we would expect firms that sell primarily to retail to have a higher cost structure than firms that sell primarily to wholesale outlets.

The variable selected to capture cost differences due to technology is the percentage of production area that is hand-watered (h_4). The percentage of production area that is hand-watered is an inverse measure of whether a grower uses the latest technology in production. A producer who hand-waters a large percentage of crops has not adopted some of the latest technology available in automated watering systems. Furthermore, a grower who hand-waters a large percentage of production area has a different cost configuration than a grower who predominantly uses an automated watering system. We have no prior expectation as to whether this measure has a positive or negative effect on cost.

Four additional nonprice variables are considered in the cost model to depict differences in cost composition due to management and cultural and pest management production practices. These variables include the age of management (h_5) and the binary variables h_6 ($=1$ if the grower fertilizes with each watering), h_7 ($=1$ if the grower uses scouting), and h_8 ($=1$ if the grower uses preventive application of chemical pesticides).

Data, Estimation, and Testing

Total sales, total cost, quantity of labor, and square footage data used in this research are obtained from a greenhouse grower survey conducted in the fall of 2000 for the year 1999. A mailing list of floriculture producers was obtained from the Ohio Florists Association targeting states with the largest number of growers in their membership. With two mailings, we surveyed 1,336 growers in 21 states, which resulted in a response rate of 18% (245 responses). Of the 245 responses, 98 are complete enough to include in this study and provide a unique high-quality data set in which to analyze economies of scale in the greenhouse floriculture industry. Primarily because of lack of sales information, cost information, or both, 147 of the survey responses are excluded from this study. Prices for labor by geographic region are obtained from the USDA (1999). Prices for materials ($/ft.²) by region and size are obtained from a survey conducted by Greenhouse Product News, a publication dedicated to greenhouse production (Cosgrove). Energy prices ($/ft.²) by state are obtained from the 1998 USDA Census of Horticultural Specialties. All prices and costs are stated in 1999 dollars. During estimation, cost and prices are normalized on the price of energy. Summary statistics of the variables used in the estimation are presented in Table 2.

Descriptions of 10 models are reported in Table 3. Five distinct models are estimated that vary by the restrictions placed on nonprice variables to determine whether they are significant in the cost estimation. Each of these five variations is estimated with and without curvature, for a total of 10 models. All models are estimated by the iterative seemingly unrelated regression (ITSUR) procedure in SHAZAM. We select an out-of-sample framework to compare competing models by the Ashley, Granger, Schmalensee (AGS) approach, which is described in more detail below. Cost and input elasticities for the selected model are calculated with parameter estimates from the model at mean values for continuous variables, and binary variables are set to 1. The elasticity of energy is recovered with the homogeneity condition. This restriction requires that the own-price elasticity and cross-price elasticities for an input sum to zero. The Hessian terms for energy are recovered from the corresponding elasticity estimates.

Confidence intervals for cost and input elasticities are calculated with a jackknife approach. It has been shown that the jackknife resampling method of calculating confidence intervals is a viable alternative for inference (Judge et al.). A jackknife confidence interval is calculated by eliminating one observation,

Table 2. Summary Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Sales ($000s)	654.88	600.82	25.00	2,725.30
Labor (no. of employees)	11.06	11.69	1.20	50.50
Materials (000s sq. ft.)	92.53	136.76	3.00	715.00
Labor Price ($/employee/yr.)	18,763.26	3,607.82	14,086.80	25,348.38
Materials Price ($/sq. ft.)	7.14	1.38	5.10	11.42
Energy Price ($/sq. ft.)	0.93	0.55	0.42	2.12
Cost ($000s)	559.54	466.39	35.00	1,500.00
Sales per sq. ft. ($)	12.68	11.04	1.08	91.67
Region (MW, NE, SO)[a]	0.82	0.39	0.00	1.00
Percent Wholesale	57.00	40.13	0.00	100.00
Percent Hand-Watered	59.02	33.51	0.00	100.00
Age of Principal Manager	48.62	12.15	24.00	75.00
Fertilize with Each Watering	0.69	0.46	0.00	1.00
Scouting	0.85	0.36	0.00	1.00
Preventive Application of Pesticides	0.58	0.50	0.00	1.00

[a] Binary variable = 1 if grower is located in the Midwest, Northeast, or South; 0 otherwise.
Note: Number of observations = 98.

estimating the cost model, and then using the estimates to calculate the input and output elasticities. This estimation process is completed for all $n = 98$ observations. Confidence intervals (90%) are estimated with the jackknife elasticity estimates and endpoints associated with the ordered jackknife estimates numbered 6 and 93.

To compare performance of the models, the out-of-sample root mean squared error (RMSE) is calculated for each model and formally compared with the AGS approach. For models that are not significantly different as determined by the AGS test (out-of-sample), we use the log-likelihood ratio (LR) test (in-sample) to test between models. The AGS test provides a method to test for the statistical significance of the difference between RMSEs of

Table 3. Results of AGS Test

Model	Restrictions Imposed	Nonprice Variables Included	Out-of-Sample RMSE ($000s)	Log-Likelihood Function
IA	Homogeneity, symmetry, and curvature	None	171.7**	−2,905
IB	Homogeneity and symmetry	None	152.7	−2,896
IIA	Homogeneity, symmetry, and curvature	All terms of h_1–h_8	637.6**	−2,833
IIB	Homogeneity and symmetry	All terms of h_1–h_8	756.9**	−2,821
IIIA	Homogeneity, symmetry, and curvature	Slope terms of h_1–h_8	178.6*	−2,900
IIIB	Homogeneity and symmetry	Slope terms of h_1–h_8	159.3	−2,876
IVA	Homogeneity, symmetry, and curvature	All terms of h_2 and h_4	179.9*	−2,884
IVB	Homogeneity and symmetry	All terms of h_2 and h_4	153.2	−2,869
VA	Homogeneity, symmetry, and curvature	Slope and interaction Terms of h_2 and h_4	188.3**	−2,894
VB	Homogeneity and symmetry	Slope and interaction Terms of h_2 and h_4	151.5	−2,871

Notes: RMSE is higher than model VB RMSE at the ** .01 and * .05 significance levels. RMSEs are compared out-of-sample with the Ashley, Granger, Schmalensee approach. For a description of variables h_1 thru h_8, see Table 1.

two competing forecasts. This out-of-sample comparison is chosen because determining effects of changes in cost by changes in dependent variables can be made directly by calculating a predicted cost given a change in output quantity or input prices. The predicted cost can be compared to the actual cost to see how changes in one or more dependent variables affect cost. This method of analyzing the effects of changes in quantities or input prices is dependent on the ability of the model to accurately predict out-of-sample.

To calculate RMSEs out-of-sample, a jackknife approach is used to predict cost out-of-sample. A jackknife prediction is made by eliminating one observation, estimating the cost model, and then using the eliminated observation and the parameter estimates to obtain an out-of-sample prediction of cost. This estimation and prediction process is completed for all 98 observations. The out-of-sample RMSE is calculated as

$$(12)\quad \text{RMSE} = \left\{\left[\sum_{i=1}^{n-1} (c_i^T - c_i^P)^2\right] \Big/ (n-1)\right\}^{1/2},$$

where c_i^T is the true cost and c_i^P is the predicted cost for out-of-sample observation i, where $i = 1, \ldots, n$.

The AGS test statistic is obtained by regressing the difference between forecast errors on the sum of the forecast errors less the mean of the sum of the forecast errors, as specified in the following equation,

$$(13)\quad D_t = B_0 + B_1(S_t - Smean) - e_t,$$

where D_t is the difference between forecast errors (the forecast errors associated with the lower RMSE forecast are subtracted from those of the higher RMSE forecast), S_t is the sum of the forecast errors, *Smean* is the sample mean of S, and e_t is a white noise residual. An F-test of the joint hypothesis that $B_0 = 0$ and $B_1 = 0$ is appropriate when both parameter estimates are positive. However, the significance levels are one-fourth of what is reported in an F-distribution table because the F-test does not consider the sign of the coefficient estimate (Kastens and Brester).

Model Selection, Results, and Discussion

Model Testing

To test performance of the 10 different models estimated, first the AGS test is applied to determine which cost model has the lowest RMSE out-of-sample. Second, we use the likelihood ratio test (in-sample) to choose between the alternative models that are not significantly different on the basis of the results of the AGS test out-of-sample. Third, for the cost and each demand equation of the selected model, we perform the Wald-Wolfowitz (WW) runs test (Mittelhammer), which under the null hypothesis assumes independent, identically distributed (*iid*) residuals and has an asymptotic normal distribution.

The out-of-sample RMSEs, results of the AGS tests, and values for the log-likelihood functions are reported in Table 3 for 10 models that are estimated. The most restrictive model that we estimate is model IA, which includes imposition of homogeneity, symmetry, and curvature but does not include any nonprice variables (all the h terms in Equation (5) are dropped and all the σ, ϕ, γ, and ψ coefficients are set to 0). Model IA ranks fifth in terms of performance out-of-sample, with an RMSE of 171.7. Model IB, which is similar to model IA, except it does not include the imposition of curvature, results in an out-of-sample RMSE of 152.7, which ranks second. The least restrictive models (IIA and IIB) that we estimate include all terms of variables h_1–h_8, with model IIA including the imposition of homogeneity, symmetry, and curvature and model IIB including the imposition of homogeneity and symmetry. The least restrictive model (IIB) performs the worst out-of-sample, with an RMSE of 756.9. This model has a large number of parameters that are statistically insignificant. We estimate more restrictive versions of models IIA and IIB by restricting nonprice coefficients on the interaction terms of input prices (γ), outputs (ψ), and other nonprice inputs (ϕ) to 0. The resulting models IIIA and IIIB perform better than models IIA and IIB out-of-sample with RMSEs of 178.6 and 159.3, respectively, but none of the nonprice coefficients are significant. Additionally, we estimate two sets of eight models, each with a single nonprice variable (Table 1), varying the imposition of curvature between the two sets. Results from these 16 estimations are not included in Table 3. However, from these estimations, we determine that significant nonprice variables include the binary location variable and percentage of production area that is hand-watered. Of these 16 models that we estimate with a single nonprice variable, none have a lower RMSE than model IB.

With the two significant nonprice variables, we estimate models IVA and IVB, which result in out-of-sample RMSEs of 179.9 and 153.2, respectively. The interaction of the nonprice variables with input prices and output are not significant in models IVA and IVB. We modify model IVA and IVB by restricting the coefficients γ and ψ to 0. The resulting models VA and VB, which include two nonprice variables, location and percentage of production area that is hand-watered, have out-of-sample RMSEs of 188.3 and 151.5, respectively. The model with the lowest out-of-sample RMSE is VB, which includes imposition of homogeneity and symmetry and the nonprice variables location and percentage of production area hand-watered.

With the AGS test, we determine the RMSE of model VB is statistically different from models IA, IIA, IIB, IIIA, IVA, and VA at the .05 significance level or better.[1] The RMSE of models IB, IIIB, and IVB are not statistically different from model VB; therefore, we perform the likelihood ratio test (in-sample) to compare models IB and IVB to model VB.

Comparing model VB to model IB under the null hypothesis that nonprice parameters in model VB are 0, the LR test statistic is estimated to be 48.66 with a chi-square critical value of 9.49 at the .05 significance level. Therefore, we reject the more restrictive model IB in favor of model VB. Comparing model VB to IVB under the null hypothesis that the interaction terms of the nonprice variables and prices are 0 in model IVB, the LR test statistic is estimated to be 4.72 with a chi-square critical value of 12.59 at the .05 significance level. Therefore, we fail to reject the more restrictive model VB. We cannot compare models VB and IIIB using the likelihood ratio test, but because the parameters of the nonprice variables are not significant in model IIIB, we select model VB over IIIB.

The WW test statistics for model VB are estimated to be 1.3895, 0.9796, and 0.0668 for the cost, labor demand, and materials demand equations, respectively. We therefore fail to reject the null hypothesis that the residuals are *iid* for each equation at the .05 significance level. This is encouraging because non-*iid* residuals are often symptomatic of model misspecification.

The preferred model VB is estimated imposing homogeneity and symmetry and includes the binary variable location and a measure of percentage of production area that is hand-watered. The coefficients and *t*-statistics for model VB are reported in Table 4. Ten of the 13 parameters are statistically significant at the .10 level or better. The coefficients for labor squared and sales squared are opposite in sign of what we expect, but neither is statistically significant. Consistent with our expectations, the coefficient on the location slope term is negative, implying that growers located in the Midwest, Northeast, or South have a lower cost *ceteris paribus.*

Cost Elasticities

The mean cost elasticities, calculated with the estimates from model VB by Equation (7), are reported in Table 5. The output elasticity is estimated to be 0.8267 with 90% lower and upper confidence intervals (calculated with the jackknife approach explained in the data and estimation section) of 0.8218 and 0.8313, respectively. This implies that at mean values of output, a 1.0% increase in output results in a cost increase of 0.83%. This result is consis-

[1] In addition to performing the AGS tests on the cost equation, we perform the same out-of-sample test on the input demand equations. The demand equations out-of-sample RMSE for model VB are not significantly lower than any other models listed in Table 3. Because economies of scale are the primary interest in this study, we use the AGS test results from the cost equation to compare the models listed in Table 3.

Table 4. Parameter Estimates and *t*-Statistics for Model VB

Parameter	Estimate	*t*-statistic
Constant	−350,469.7000***	−3.0355
Price of Labor	−0.3760	−0.3746
Price of Materials	63,971.7200***	5.8961
Sales	686.6895***	6.5738
Price of Labor Squared	−0.0001	−1.6004
Price of Materials Squared	−6,042.8833***	−5.9422
Sales Squared	−0.5911	−0.3924
Price of Labor × Price of Materials	0.2394*	1.7134
Price of Labor × Sales	0.0163***	22.7160
Price of Materials × Sales	49.3235***	9.2624
Location	−193,764.6000**	−2.2113
Percent Hand-Watered	5,174.9880**	2.2395
Location × Percent Hand-Watered	2,491.2940**	1.9994
Percent Hand-Watered Squared	−62.6284***	−3.2271

Notes: Significant at the *** .01, ** .05, and * .10 levels. The R^2 for the cost, labor, and SF equations are .91, .89, and .52, respectively.

tent with Brumfield et al., who reported annual overhead costs per square foot of $3.65, $2.43, and $2.31 for small, medium, and large growers, respectively. We also estimate the cost elasticity setting the location variable to 0 (rather than 1), which results in a lower cost elasticity of 0.7884 for growers not located in the Midwest, Northeast or South. Regardless of location, on the basis of the data used in this study, there appears to be an incentive in the form of a lower average cost for growers at or below mean sales of $654.88 × 10³ to increase in size.

By Equation (8), we estimate the elasticity of cost with respect to a change in the percentage of production area that is hand-watered at 0.0168. This implies a change in the percentage area that is hand-watered has little effect on cost. In addition, by Equation (9), we estimate the effect of location on cost to be −$43,296, which implies that at mean values, a grower located in the Midwest, Northeast, or South has a lower cost than growers in other locations *ceteris paribus.* This finding is consistent with the theory of location and of spatial human capital dispersion. Clusters of experienced growers in these regions (Midwest, Northeast, and South) might have superior locations and human capital for greenhouse production.

Table 5. Cost Elasticities

	Output Elasticity ε_{Cy}	Percent Hand-Watered ε_{Ch_k}
Estimate	0.8267*	0.0168*
Lower	0.8218	0.0115
Upper	0.8313	0.0239

Notes: Significant at the * .10 level. Elasticities are calculated at mean values for continuous variables and binary variables equal to 1. Lower and upper numbers are 90% confidence intervals of the elasticities calculated with the jackknife approach.

Input Elasticities

Input price elasticity estimates (Equation [10]) are computed at mean values for continuous variables and with the binary variable location to 1 (Table 6). Additionally, lower and upper critical values for 90% confidence intervals for all input price elasticities are computed with the jackknife approach. All inputs have downward-sloping demand curves at the mean. Note that the labor own-price elasticity is inelastic, whereas materials and energy are elastic, implying that the demand for materials and energy is more sensitive to changes in own price than in labor.

Table 6 also reports Morishima elasticities of substitution using mean values for continuous variables and the binary variable location

Table 6. Mean Input Elasticities

	Labor	Materials	Energy
ε_{ii}	−0.2445*	−1.4440*	−1.9626*
Lower	−0.2633	−1.4810	−2.0377
Upper	−0.2217	−1.4063	−1.8997
σ_{ij} (Morishima)			
Labor		0.3921*	0.2531*
Lower		0.3577	0.2182
Upper		0.4250	0.2788
Materials	1.6794*		3.3980*
Lower	1.6317		3.2976
Upper	1.7334		3.4984
Energy	1.9717*	3.2590*	
Lower	1.9118	3.1656	
Upper	2.0456	3.3643	

Note: Significant at the *.10 level. Elasticities are calculated at mean values for continuous variables and the location binary variable equal to 1. The own-price input demand elasticities (ε_{ii}) are calculated holding output and other variables constant, whereas the elasticities of substitution (σ_{ij}) are calculated with Blackorby and Russell's Equation (8). Lower and upper numbers are 90% confidence intervals of the elasticities calculated with the jackknife approach.

set to 1. Note that the elasticity of substitution for labor with respect to materials and energy is less than 1, which means there is little substitutability of materials or energy for labor. In contrast, the elasticity of substitution for materials with respect to labor is greater than 1, implying that labor is more substitutable for materials than the reverse. This could reflect an opportunity for growers to use labor to recycle some materials used in greenhouse production from one period to another, rather than purchasing new materials. The substitutability of energy with respect to materials and labor could be the result of more intense use of materials and labor to produce higher yields.

Conclusion

In this study, we find economies of scale in the floriculture industry, which is consistent with findings from other greenhouse studies (Brumfield et al.; Hodges, Satterhwaite, and Haydu). On the basis of data used in our study, large greenhouse growers can produce ornamental crops at a cost per square foot that is 18% lower than growers half their size. As horticultural producers become larger and more automated, they have a cost advantage because of size over smaller producers who are producing the same output mix. Small- and medium-size growers wanting to increase their cost efficiency might consider expanding their current operation to take advantage of these scale economies. Additionally, we provide measures of own-price elasticities and Morishima elasticities of substitution. The demand for labor is found to be inelastic; implying that growers' demand for labor is not very responsive to changes in labor prices, which is supported by the small labor elasticities of substitution. Because labor is typically a large portion of a growers' production costs, the low elasticity for labor suggests that growers might want to concentrate on efficiency improvements in labor. Depending on a grower's regional labor market, another opportunity for increased efficiency could be increasing investment in capital-intensive improvements that are labor saving. In contrast to labor, the demand for materials and energy are more elastic, and these two inputs can be substituted more easily with other inputs, as denoted by their elasticities of substitution. Although the results suggest that energy is elastic, growers might want to invest in energy-saving devices that could result in increased efficiency.

Although this study was conducted with only 1 year of cross-sectional data, it provides cost information that is important to greenhouse producers. Mean output elasticity is estimated to be 0.83, which suggests that growers with sales at or below 654.88×10^3 would benefit by increasing their size. These results suggest that average grower size could increase in the future through expansion, consolidation, or both as growers reap benefits associated with cost efficiencies of larger producers. Although this is the first study to provide empirical research in the area of cost relationships in the greenhouse ornamental business, the authors hope the work presented here will encourage additional applied research in this industry.

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