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# Measuring Price–Quantity Relationships in the Dutch Flower Market

Marie Steen

This research applies an inverse, almost ideal demand model with seasonal adjustments to estimate price–quantity relationships among major cut flower species traded at the Dutch flower auctions. Trigonometric functions are used as a flexible and efficient alternative to standard seasonal dummies. The estimated price and scale flexibilities were all found to be statistically significant with signs as expected. The demand for all flower groups is inflexible, and most of them are quantity substitutes. Based on the estimated values for price and scale flexibilities, a potential for market timing seems to exist, i.e., flower producers may use easily available calendar information to predict prices and quantities.

*Key Words:* cut flower production, inverse linear aids, market timing, risk management, seasonality, trigonometric functions

**JEL Classifications:** D12, Q11

The European market for cut flowers has shown a substantial growth over the last decade, and the growth seems likely to continue. The value of consumption of flowers in Europe in 2006 was more than €26 billion (approximately US\$31 billion [US\$1 = Euro 0.82]) and the highest in the world, which was more than twice the value of consumption in the United States. In the period 1995–2004, the value of imports of cut flowers to the European Union increased by approximately 40%, and from 2004 to 2007, the increase was 25% (International Association of Horticultural Producers, 1993, 2005, 2007, and 2008). Total imports from non-European countries to the European Union (EU) in 2007 were more than €800 million. Several countries have more than doubled their imports during this period. In particular, there has been a growth in imports from developing countries. More than

half of the imports to the EU came from Africa with Kenya as the dominating country. An overview of the international flower production, flower trade, and the Dutch Auctions is presented in Steen (2010).

In 1995, turnover at the Dutch Flower Auctions was approximately €1.2 billion. By 2008, the figure had reached some €4.1 billion (FloraHolland, 2009). The Dutch flower auctions represent the major marketplace in the European and global flower trade. More than half of Europe's flower imports go through the flower auctions in The Netherlands, and there is also a significant intra-European flower trade with The Netherlands as the focal point. Almost half of Germany's imports, more than 60% of Great Britain's imports, and roughly 40% of the flower imports to France, by value, stem from The Netherlands (Steen, 2010). As a result of these considerable volumes, the auction prices will to a large extent determine prices outside the auction premises. Hence, supply, demand, quantities, and prices at the auctions are highly

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relevant to European flower producers, importers, and traders.

Despite its increasing size, the demand for flowers has received relatively little attention in the literature. Abdelmagid, Wohlgenant, and Safley (1996) studied the demand for nursery plants. They found the demand to be affected more by prices than by income, demographic, and other variables. They found own-price elasticities to range from  $-0.71$  to  $-1.65$  and income elasticities from  $-0.78$  to  $0.41$ . Rhodus (1989) studied the demand for fresh flower bouquets in supermarkets in the United States, performing a controlled pricing experiment as a means of identifying consumer preferences for fresh flower bouquets. He found that urban and rural consumers have significantly different preferences for flower bouquets and that the demand during the week showed a great variation. Palma and Ward (2010) have studied the U.S. demand for cut flowers, potted flowering plants, and dry/artificial and outdoor flowers using simulation analysis to decompose demand into market penetration and buying frequency. Muhammad et al. have analyzed the effects of different tariff regimes on the EU demand for imported cut flowers (Muhammad, 2009; Muhammad, Amponsah, and Dennis, 2010; Muhammad, D'Souza, and Amponsah, 2013).

Studies on other aspects of the flower markets have been done by, e.g., Hall, Hodges, and Haydu (2006) who investigated trade flows within the U.S. Nursery Industry; Liu and Yue (2009) who studied nontariff barriers to trade in the Japanese cut flower market logistics; and Honma (1991) who studied Japanese flower trade with developing countries. The flower auctions in Holland have been investigated by Kambil and Van Heck (1998), Van den Berg, Van Ours, and Pradhan (2001), and Van Heck and Ribbers (1997). Beyond these studies, there are few economic analyses of the flower markets published in scientific journals.

In the section on data used in the econometric analysis, the functioning of the Dutch flower auctions is outlined, indicating why prices of cut flowers are very volatile. This is, of course, mainly the result of the fact that cut flowers are highly perishable. Changes in prices and volumes of 30–40% from one week to the

next are not unusual. Based on information regarding the price and quantity data generating processes and the underlying demand/supply schedules, producers' risk management and marketing behavior may generate less volatile prices (and higher producer use). Although there are many small price-taking producers in the flower industry, quantity variations over time may be such that on a particular day, even a relatively small producer may be big enough to influence prices. This is the result of the batch character of production and the problems connected to storing cut flowers. By applying more or less heat or light, it may be possible to shorten or delay the end of the production period (Larson, 1980). Assume, for instance, that there are three or four large producers of a given species of flowers and a large number of small ones. If the large producers happen to arrive at the market place with a bulk of their production simultaneously, small producers may during subsequent weeks be de facto large ones. Thus, market structure in the cut flower business is not a static function of aggregated market shares. Rather, it may vary considerably over time. Strategic marketing should therefore involve systematic surveillance of variations in traded volumes.

In this article, price–quantity relationships for cut flowers traded at the Dutch flower auctions are analyzed using an inverse, almost ideal demand (IAID) system based on weekly observations from 1993 to 2005 for four categories of cut flowers. An inverse demand system is a natural model for the price formation of quickly perishable goods like flowers, in which supply is fixed in the short run.

However, flower demand is highly seasonal. This creates an additional challenge when using high-frequency observations in that one would like a procedure that is parsimonious when representing the seasonality. To handle this, a trigonometric representation in the demand system following the general notion of Ghysels and Osborn (2001) will be applied. The trigonometric representation allows the seasonality to be represented with only two additional parameters in each demand equation. This approach will be compared with that of using a standard dummy representation.

The article proceeds as follows. First, the price and quantity data and some stylized facts from the Dutch flower auctions are presented. Then, the seasonally adjusted IAID system is described and estimated. The results are summarized before some concluding remarks regarding possible strategic behavior among producers are presented in the last section of the article.

### Dutch Flower Auction Data

Weekly price and quantity data for Week 1, 1993, through Week 21, 2005, were obtained from weekly editions of the Dutch *Vakblad voor de Bloemisterij* (1993–2005). Approximately 70 of the most important cut flower species, representing close to 100% of the total value of cut flowers traded at the Dutch flower auctions, are included in the data set. Approximately 9000 individual producers market their flowers at the auctions of FloraHolland, of whom 5000 are exchange members (Steen, 2010). In any given week, approximately 100 species of cut flowers are traded in Aalsmeer, which is the biggest auction site, and for many of the species, there are several varieties. As many as 30–40 different varieties of roses are traded with each variety having different colors and lengths. There are also quality differences. Therefore, in contrast to many agricultural and industry products, fresh flowers cannot be treated as a well-defined, homogeneous product. Cut flowers are very fragile, they cannot be stored, the supply is relatively unpredictable, and price variations over time and among cultivars are substantial.

The auction mechanism is the so-called Dutch auction. The auctioneer announces the flowers to be sold, and the bidding is controlled by a huge clock-like screen indicating the unit price. A blinking light on the screen marks the starting price, which then moves downward on the clock. A buyer will press the button at his or her desk in the auction room to stop the clock when the light hits the price he or she is willing to pay.

During the auction, each of the bidders must choose a reservation price, which is where the bidder would stop the clock if the price should

fall to that level without exhausting the offering. The bidder with the highest reservation price wins the object at his or her chosen price. This type of auction is often described as an “open first-price auction.” Each unit of flowers has a minimum price. If the minimum price is not achieved, the whole batch is withdrawn and destroyed immediately after the auction. A detailed description of the Dutch flower auctions can be found in Steen (2010).

The cut flowers were aggregated into four groups; the three major species, chrysanthemums, carnations, and roses; and a fourth aggregated category, “other cut flowers.” Table 1 shows the volume weighted prices and quantities, and as we can see, both prices and quantities vary substantially. The coefficients of variation (CVs), as regard weekly prices, range from approximately 21% (roses) to 34% (carnations), whereas the CVs of quantities are between 9% and 18% per week.

On an annual basis we have standard deviations of price and quantity changes from approximately 60% to 140%.<sup>1</sup> This makes cut flowers probably the most volatile agricultural commodity. Cereals, potatoes, and other agricultural commodities rarely show annual standard deviation of price changes beyond 20–30%. For instance, Pietola and Wang (2000) argue that the price of piglets are very volatile, reporting a CV of 11% on an annual basis.

There are clear seasonal patterns in prices and quantities as shown in Figure 1, but the patterns of the major cut flowers differ. For instance, the budget share of carnations is at its lowest in December to January and has a well-defined peak in the middle of the summer. Roses also have a low budget share in the winter rising to a high in the second and the third quarters. Chrysanthemums, on the other hand, show almost the opposite pattern as carnations, which is probably the result of different patterns of demand.

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<sup>1</sup> Annualized standard deviations of percent price changes are obtained by multiplying by the square root of 52; thus, independent changes are assumed. This is slightly incorrect as a result of serial correlations in the changes.

Table 1. Prices<sup>a</sup> and Quantities of Major Cut Flower Species, Week 1, 1993, to Week 21, 2005

	Prices, Weekly Observations			Weekly quantities (1000 stems)			Highest and Lowest Quantities Observed (weekly)	
	Mean	SD	Coefficient of Variation	Mean	SD	Coefficient of Variation	Highest	Lowest
Chrysanthemum	21.7	7.32	33.73	26,305	5,188	13.3	39,014	5,522
Carnations	12.4	2.94	23.70	12,319	6,063	18.0	33,693	1,130
Roses	19.3	5.53	28.65	58,867	12,121	10.5	115,551	16,194
Others	19.0	3.99	21.00	118,290	36,386	8.7	417,041	33,210

<sup>a</sup> Prices are measured in Eurocents per stem.  
SD, standard deviation.

The Model

Price–quantity relationships have been analyzed in an almost ideal demand (AID) system framework as developed by Deaton and Muellbauer (1980) in numerous studies. Although the AID model has worked well in several applications, there are commodities for which the assumption of predetermined prices at the market level may be untenable.

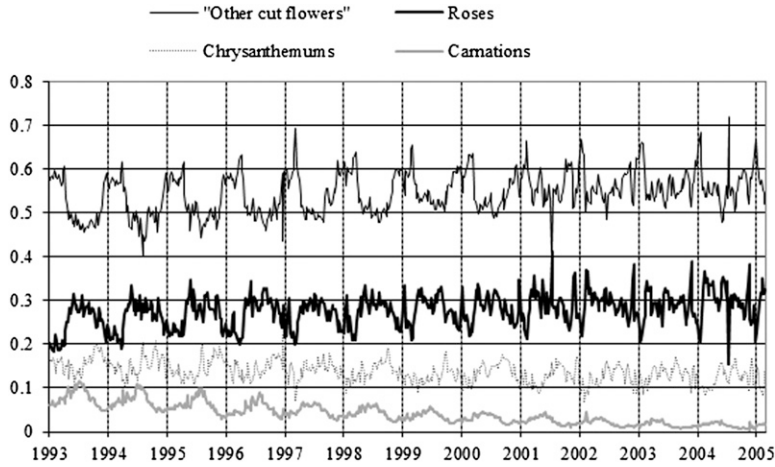
Typically, the consumer is a price-taker, and a regular demand system is then called for. For highly perishable goods, however, like fresh vegetables, fresh fish, or in this case, fresh flowers, supply is very inelastic in the short run and the producers are price-takers. At the Dutch flower auctions, the wholesale traders offer prices for the fixed quantities of the different flower species, which are sufficiently low to induce consumers to buy the available quantities, i.e., the prices are set as a function of the quantities.

Inverse demand functions, where prices are functions of quantities, provide an alternative and fully dual approach to the standard analysis of consumer demand. Inverse demand models have been applied to perishable products such as meat (Eales and Unnevehr, 1994), fish (Barten and Bettendorf, 1989), and vegetables (Rickertsen, 1998).

An inverse demand system can be derived from the direct utility function, e.g., Anderson (1980), or from the distance function (transformation function). The last approach is explained in detail in Moschini and Vissa (1992). The distance function and the cost function have some parallel features, which are useful because they imply that any standard functional form of the function can also be applied to the distance function. Eales and Unnevehr (1994) and Moschini and Vissa (1992) followed this approach and developed an inverse almost ideal demand system where the inverse almost ideal demand functions can be written in share form as:

(1)  $w_i = \alpha_i + \sum_j \gamma_{ij}(\ln q_j) - \beta_i \ln(Q)$

where  $w_i$  is the  $i$ th good’s budget share,  $q_j$  is the quantity of cut flower  $j$ , and  $\ln(Q)$  is a quantity index defined as:



**Figure 1.** Budget Shares of Chrysanthemums, Carnations, Roses, and Other Cut Flowers Out of the Total Expenditure of Cut Flowers from Week 1, 1993, to Week 21, 2005

$$(2) \quad \ln(Q) \equiv \alpha_0 + \sum_i \alpha_i \ln(q_i) + \frac{1}{2} \sum_i \sum_j \gamma_{ij} \ln(q_i) \ln(q_j)$$

In practice, given that quantities are properly scaled,  $\ln(Q)$  can be replaced by an index  $\ln(Q^*)$  constructed before estimation of the share system to yield:

$$(3) \quad w_i = \alpha_i + \sum_j \gamma_{ij} (\ln q_j) - \beta_i \ln(Q^*)$$

where

$$(4) \quad \ln(Q^*) = \sum_i w_i \ln(q_i)$$

is the linear approximate quantity index, which is a geometric aggregator. Eales and Unnevehr (1994) have shown that the linear inverse AID model produces results reasonably close to the nonlinear version.

Homogeneity and symmetry restrictions are imposed. These restrictions are:

$$(5) \quad \sum_j \gamma_{ij} = 0 \text{ (homogeneity)}$$

$$(6) \quad \gamma_{ij} = \gamma_{ji} \text{ (symmetry)}$$

$$(7) \quad \sum_i \alpha_i = 1, \sum_i \gamma_{ij} = 0, \sum_i \beta_i = 1 \text{ (adding up)}$$

Deaton and Muellbauer (1980) suggested that other variables could be included in the AID model by allowing the constant terms in equations (2)

and (3) to vary with them. Following this approach, seasonality is introduced into the model using seasonal dummy variables as shift variables where:

$$(8) \quad \alpha_i = \alpha_{i0} + \sum_j \theta_{ij} a_j$$

where  $j = 3, 12$ , and  $51$  for quarterly, four-weekly, and weekly seasons respectively. For the adding up condition to hold,  $\sum_i \alpha_{i0} = 1$  and  $\sum_i \theta_{ij} = 0$  for all  $j$ . As an alternative to seasonal dummy variables, an approach using trigonometric functions to handle seasonality is presented.

Following Ghysels and Osborn (2001), using weekly data and assuming one complete seasonal cycle within a year, a trigonometric representation of deterministic seasonality is given by the following expression:

$$(9) \quad \alpha_i = \alpha_{i0} + \omega_{i1} \sin(2\pi u/52) + \omega_{i2} \cos(2\pi u/52)$$

where  $u$  is the number of the week. For the adding up condition to hold,  $\sum_i \alpha_{i0} = 1$  and  $\sum_i \omega_{i1} = \sum_i \omega_{i2} = 0$ .

One advantage of the trigonometric functions is that they are continuous. This fact gives us parsimony in the use of regression variables. For instance, the weekly dummy variable model requires 51 variables per equation, one for each week, whereas the trigonometric approach only



uses two variables per equation. This is especially important when estimating systems of equations.

Price and scale flexibilities are the natural concepts of uncompensated elasticities for inverse demand. Price flexibilities are the price changes caused by a small change in the supplied quantity of a good and scale flexibilities are the analogs to the expenditure elasticities.

Following the approach of Moschini and Vissa (1992), we apply the flexibility formulas (which are consistent with taking  $\ln(Q^*)$  as given in estimation):

$$(10) \quad f_{ij} = \frac{\gamma_{ij}}{w_i} - \beta_i \frac{w_j}{w_i} - \delta_{ij}$$

Here  $\delta$  is the Kronecker delta ( $\delta_{ij} = \text{one for } i = j$  and  $\delta_{ij} = \text{zero otherwise}$ ).

The system consists of demand for chrysanthemums, carnations, roses, and "others species," respectively. The last equation was dropped in estimation as a result of singularity of the cross-equation covariance matrix. The system is estimated using seemingly unrelated regressions. The system is tested for autocorrelation using a Breuch-Godfrey Score Test, see, e.g., Ruud (2000). The  $H_0$  hypotheses were strongly rejected for all groups of cut flowers, and t-values were significant for the first two lags.

Berndt and Savin (1975) discuss alternative specifications of the lag structure of the residuals to include in the system to correct for autocorrelation. Here, an autoregressive model is applied and the inverse linear approximate AID model in equation (3) is replaced by:

$$(11) \quad w_i = \alpha_i^* + \sum_j \gamma_{ij}(\ln q_j) - \beta_i \ln(Q^*) + \sum_{j=1}^{n-1} \sum_{k=1}^p \rho_{ijk} \hat{\epsilon}_{j,t-k}$$

where  $\sum_{j=1}^{n-1} \rho_{ij} = 0$ , and  $n$  and  $p$  are the number of groups in the system and the order of lags to include, respectively. Because the score test indicates that the first two lags are the problem, two lags of the residuals are included in the corrected model. The error terms in a singular system must sum to zero. Therefore, the autoregressive (AR) covariance structure is singular

and cannot be identified without additional restrictions, as Berndt and Savin point (1975) out. In this case the restriction that the  $\rho$  parameter for each lag sums to zero is imposed for identification. The estimation method used to identify the model is a two-step procedure, identifying the error terms,  $\tau$  (called  $v$  in Berndt and Savin's paper), in the first step and the model, including the AR structure, in the second step, as shown in, e.g., Rickertsen, Kristofersson, and Lothe (2003).

Economic theory implies the following restrictions on the equation system: 1) adding up; 2) homogeneity; and 3) symmetry. The adding up conditions, which are automatically satisfied by the data, imply that the covariance matrix is singular. This problem can be avoided by deleting one equation from the system, and the deleted equation may be retrieved using the adding up conditions. Homogeneity and symmetry restrictions are imposed on the system.

The AR model was tested for seasonality using an F-test, and the hypothesis of no seasonality was strongly rejected. Seasonality was included in the AR model in four different ways: weekly, four-weekly, and quarterly dummy variables as well as the trigonometric approach. The results of the different models were compared using the Bayesian Information Criterion (BIC) (Greene, 2003).

## Econometric Results

The results from the estimation of the different seasonal models show that the trigonometric functions were superior to the standard seasonal dummy variable approach evaluated by the BIC values. The trigonometric model was therefore used for further estimations and for calculation of the flexibilities.

The estimated coefficients and the summary statistics from estimation of equation (11) are presented in Table 2.

We can see from Table 2 that all quantity coefficients as well as the coefficients of the quantity indices are highly significant. Seasonality coefficients show the presence of significant seasonality in the budget shares for all groups of cut flowers. The seasonal cycles differ across cut flower species. However, the demand

seems to follow cosine waves for most of the species. This implies that the constant in equation (1) can be predicted using the estimated parameters from equation (9) together with calendar information, i.e., week number.

Table 3 reports the price and scale flexibilities and the summary statistics. The price flexibilities show the percentage changes in the prices associated with a 1% change in the supplied quantity of a group of cut flowers. Goods are gross quantity substitutes if their uncompensated cross-price flexibility is negative and gross complements if it is positive. All own flexibilities (quantity elasticities) are statistically significant (at 1% level) and negative as expected, i.e., a price of a group of cut flowers is reduced when the supplied quantity of that group is increased. We, furthermore, see that the own flexibilities vary substantially across the different species, from -0.8 (chrysanthemums) to -0.3 (carnations). Thus, the demand for all cut flowers is inflexible with carnations as the least flexible. This implies that an increase in the supply of one group of cut flowers will result in lower prices paid for that group. Taken at face value, the estimates indicate different effects from market timing behavior across producers of different species. Although there are many different varieties and qualities within one group of cut flowers, some “concerted action” among chrysanthemum producers in terms of supply adjustments may have significant price effects; such behavior for producers of carnations seems to have less impact.

All cross-flexibilities are highly significant, and all but carnations versus chrysanthemums are negative, which means that the price of one group of cut flowers is reduced when the supplied quantity of another group of cut flowers is increased. That is, chrysanthemum and carnations seem to be quantity complements, whereas the other combinations appear to be quantity substitutes. For example, the own-price flexibility of chrysanthemums is -0.8 and the cross-price flexibility between the price of chrysanthemums and the quantity of roses is -0.046. These values imply that a 10% increase in the supplied quantity of chrysanthemums is associated with an 8% and 0.5% decline in the price of chrysanthemums and roses, respectively.

Table 2. Coefficients and Summary Statistics of the Linear Inverse Almost Ideal Demand System<sup>a</sup>

	$\gamma_{ij}$				SIN	COS	$\beta_i$
	Chrysanthemum, Carnations, Roses, Other Species						
Chrysanthemums	0.031*** (5.98)	0.007*** (6.74)	-0.016*** (-4.0)	-0.022*** (-5.65)	-0.006*** (-4.33)	0.012*** (9.40)	-0.032*** (-7.74)
Carnations (Dianthus)	0.007*** (6.74)	0.027*** (57.90)	-0.012*** (-10.41)	-0.021*** (-17.35)	0.001* (2.33)	-0.009*** (-18.27)	-0.011*** (-6.37)
Roses	-0.016*** (-4.0)	-0.012*** (-10.41)	0.093*** (15.80)	-0.065*** (-12.70)	0.003 (1.28)	-0.009*** (-5.05)	0.023*** (3.67)
Other species	-0.022*** (-5.65)	-0.021*** (-17.35)	-0.065*** (-12.70)	0.108*** (17.75)	0.002 (1.06)	0.005*** (2.68)	0.020*** (3.22)

<sup>a</sup> (T-values in parentheses).  $\beta_i$  is the coefficient of the quantity index of equation i, and  $\gamma_{ij}$  is the jth quantity coefficient of equation i (i and j = chrysanthemums, carnations [Dianthus], roses, other in that given order).  
\* Significant at 5% level, \*\* significant at 1% level, \*\*\* significant at 0.1% level.



**Table 3.** Uncompensated Price Flexibilities ( $f_{ij}$ ) and Scale Flexibilities ( $f_i$ ) Evaluated at Mean Shares of  $w_i$  (t-values in parentheses)

	$f_{ij}$				$f_i$
	Chrysanthemums	Carnations	Roses	Others	
Chrysanthemums	−0.810*** (−21.16)	0.040*** (5.13)	−0.179*** (−6.08)	−0.283*** (−10.79)	−1.232*** (−41.16)
Carnations	0.13*** (4.92)	−0.345*** (−27.76)	−0.387*** (−11.84)	−0.681*** (−20.96)	−1.284*** (−28.77)
Roses	−0.046** (−3.06)	−0.042*** (−8.86)	−0.640*** (−28.43)	−0.190*** (−9.57)	−0.917*** (−40.58)
Others	−0.034*** (−4.58)	−0.038*** (−15.19)	−0.109*** (−10.47)	−0.782*** (−72.85)	−0.962*** (−82.62)

\* Significant at 5% level, \*\* significant at 1% level, \*\*\* significant at 0.1% level.

Seasonality plays a central part in defining which flower groups are complements and substitutes.

Furthermore, for chrysanthemums, roses, and “others,” each of the cross-flexibilities is numerically smaller than the corresponding own-price elasticity, implying that an increase in supply of a given flower species mostly affects the price of that flower itself. For carnations, however, it actually seems to be the case that increased supply affects the prices of chrysanthemums, roses, and “others” more than it affects the price of carnations themselves. For instance, a 10% increase in the supply of carnations will, according to the estimation results, reduce the price of roses by more than 5%.

The scale flexibility shows the percentage change in the price of a species in response to a proportionate increase in the supply of all cut flowers. The scale flexibilities range from −0.9 (roses) to −1.3 (carnations), an indication that the hypothesis of homothetic preferences is rejected for all groups of flowers.

Conclusions

The aim of this article was to provide information on price–quantity relationships for cut flowers traded at the Dutch flower auctions. Flower producers continuously make decisions on when to harvest a given cohort. Harvesting may be postponed (or speeded up) by adding (or reducing) light and heat in the greenhouses. Once the decision to harvest has been made, the products have economic value only for a short

period of time. Consequently, flower prices are very volatile and individual producers may profit substantially from good timing of harvesting and marketing.

The major findings from the econometric analysis may be summarized as follows. Weekly cut flower consumption can be modeled using an inverse linear version of the almost ideal demand system. To handle seasonal patterns, we found that trigonometric functions clearly outperformed standard seasonal dummy models.

The estimated price and scale flexibilities were all found to be statistically significant with signs as expected. According to the estimated own flexibilities, the demand for all cut flower groups is inflexible with carnations as the least flexible species. Furthermore, given the estimated cross flexibilities, chrysanthemums and carnations seem to be quantity complements, whereas the rest appear to be quantity substitutes. The hypothesis of homothetic preferences is rejected for all groups of cut flowers.

Based on the econometric results, a potential for strategic marketing or market timing seems to exist, enabling individual producers to profit from adjusting light and temperature to hit short-term price peaks (or also avoid weeks with excess supply and depressed prices). Using information on the statistically significant seasonal parameters in combination with the estimated price–quantity relationships may give good predictions as regard short-term price changes. The differences in estimated flexibilities across species suggest that there are different

effects from strategic marketing behavior across different species. Although some “concerted action” among chrysanthemum producers in terms of supply adjustments may have significant price effects, such behavior for producers of carnations appears to have less impact. Most cross-flexibilities are negative; thus, the different cut flowers appear to be quantity substitutes. The results furthermore indicate that a futures market linked to the physical flower market might reduce the price volatility in spot prices. Through forward trading arrangements, more relevant information on planned supply and demand would, most likely, be revealed. In turn, this could dampen the short turn-ups and -downs and reduce risk for both flower producers and consumers.

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