ISBN 978-82-575-0950-7
ISSN 1503-1667

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Philosophiae Doctor (PhD) Thesis 2010:40

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Department of Economics and Resource Management
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The Flower Markets: Five essays on flower prices 1993-2008

Blomstermarkedene: Fem essays om blomsterpriser 1993-2008

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Acknowledgements

This is the end of a long journey. It has taken quite a few years to get to this point, partly due to the fact that I have given birth to, and raised four children while writing my dissertation.

I would like to thank everybody who has helped me in different ways at various stages of this work.

First, and foremost, I would like to thank my advisor, Professor Ole Gjølberg, for all the guidance, encouragement, motivation and inspiration, and for never giving up on me. I would not have been able to complete this work without his continuous support. Further, I would like to give a special thanks to Dr. Dadi Már Kristófersson for valuable comments on two of the essays. I would also like to thank my colleagues at the Department of Economics and Resource Management at UMB, for valuable comments on earlier versions of a number of drafts and papers, and for moral support, and the faculty at Department of Agricultural Economics at University of California, Davis, for your inspiration.

Thanks also to the Norwegian Research Council for financial support.

Last, but not least, I would like to thank Göran and my children for their love, support and understanding.

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Introduction

"But if any man think that he behaveth himself
uncomely toward his virgin, if she pass the
flower of her age, and need so require, let him
do what he will, he sinneth not: let them marry".

1 Corinthians 7:36. The Holy Bible

Business decisions in floriculture

Introduction

This dissertation deals with business decisions within cut flower production and trade. The focus is on trade, prices, price forecasting and price risk management.

The production of cut flowers has become a large business during the last decades. However, production and marketing of ornamental flowers date back to (at least) the 17th century[1], and cut flowers have become a ceremonial and a sentimental token for several occasions in daily life. Flowers are used for decoration of homes and for expression of love, sympathy or gratitude.

The combination of cut flowers' extreme perishability and their being demanded for multiple emotional and aesthetic reasons makes the market for cut flowers an interesting and challenging object for economic analysis.

Decision-makers occupied with production planning and marketing in the cut flower business are faced with a number of rather challenging problems, one being similar to that of the traditional "newsboy's problem". Orders are placed, i.e. flowers are rooted, several months prior to marketing. Once blossoming takes place, decay occurs rapidly. Just like yesterday's newspaper, there is little demand for last week's fresh flowers. True, cut flowers can be stored at reduced temperatures for a few days and blossoming can be delayed by regulating the level of temperature and the amount of light exposure during the weeks prior to cutting.

[1] E.g. carnations have been cultivated by man for more than 2000 years as described by Aristoteles' student Theophrastus about 300 b. c.

Beyond this, little can be done in terms of adjusting to stochastic demand once the plants are rooted.

Further, cut flowers are usually produced in greenhouses, at least in Europe and the US. Investing in new greenhouses is a major decision. Capital costs amount to approximately 40 % in European greenhouse flower production. The decision to invest in a new greenhouse has three important characteristics. First, it is almost completely irreversible. There is no market for used greenhouses. Also, many greenhouses are custom made to fit the rest of the production system like the other greenhouses, the heating system, the fertilizer system and the ground. So, the investment cannot be recovered if the manager should change his mind. Second, there is uncertainty regarding the future payoff from the new greenhouse, mostly due to uncertain output prices. And third, there is a possibility to postpone the investment to get more information.

The simple theory of investment under uncertainty calculating the net present value (NPV) and concluding that the investment is profitable if NPV is greater than zero, does not recognize the important qualitative and quantitative implications between irreversibility, uncertainty and the choice of timing. The net present value rule is based on the assumption that either the investment is reversible, or, if it is irreversible, it's a "now or never" proposition. This might be true for some investment decisions but it is not true in the case of greenhouse investment.

This problem of opportunity to invest can be seen as holding an "option" analogous to a financial call option. The holder has the right, but not the obligation to buy an asset at some future time of its choosing. This again means that the NPV rule must be modified such that the value of the investment must exceed the purchase and installation cost plus the value of keeping the option value alive (Pindyck, 1988). The opportunity cost of investing can be large, and investment rules that ignore it can be grossly in error. Also the opportunity cost is highly sensitive to uncertainty over the future value of the project, so that riskiness in the future cash flows can have a larger impact than for instance a change in interest rates. This is not the direct focus of this dissertation, but is merely presented to show the complexity of the greenhouse producer's decision problem. An important part of this problem is how to evaluate future flower prices, which is the main topic of this dissertation.

The main commercial cut flower varieties

Roses, chrysanthemums and carnations are the most important cut flowers (year-round production) on an international scale. Of these, roses are produced in the largest number. Commercial cut production of roses in Europe started around 1850. Today, hybrid tea and floribunda types are prominent in the cut flower trade, and are produced by most rose growers. Traditionally roses are produced directly in ground beds with soil. Lately, especially when artificial lighting is used, rock wool and buckets are used to keep a better control with the temperature in the growth medium, and with diseases. Roses can be propagated from seeds, cuttings, buddings and graftings. Budded plants have been the most popular type used by commercial rose cut flower growers. In traditional production without artificial lighting, planting (in the northern hemisphere) is usually done from January to June. Usually it takes 4-5 months before the first cropping can start, and depending of the growth conditions, especially light and temperature, one can harvest 2-5 crops during the season. The plants are cut back or pruned once a year, usually at winter-time because of the natural light conditions. After a low-temperature resting period of 1-2 months the plants are pruned, i.e. the tops of the plants are removed. In the last few years year there has been an increasing research on and interest in year round production, by using artificial light. In year round production the pruning takes place approximately once a year, usually in the summer, when there is a lot of roses marketed and prices are low. It can, however, be done at any time during the year. The cropping (harvesting) periods can be controlled by controlling the input factors, i.e. temperature, light, time of pruning, and choice of types of roses.

Figure 1, adapted from Strømme and Moe (1988), gives an illustration of the complexity of the relationship between the temperature level and different quality characteristics of roses.

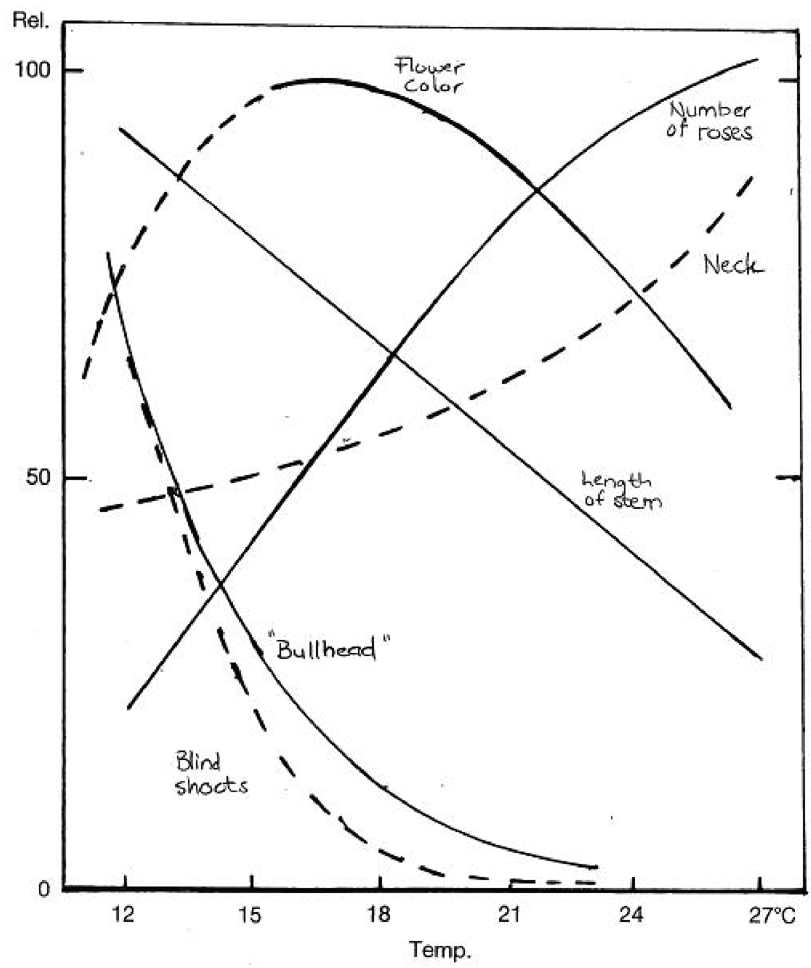

Figure 1. Effects of temperature on different quality characteristics in roses, relative values (adapted from Strømme and Moe, 1988, p. 68).

As the temperature increases, the number of blind shoots (shoots without flowers) and "bullheads" (flower deformation) decreases, and the total number of roses increases. These are all positive characteristics. But at the same time, higher temperatures cause the stems to shorten and the length of the necks (between the top leaf and the flower) to increase. Long stems are preferred to short stems, and a long neck increases the possibility of the neck cracking. When it comes to flower color, the intensity of the color decreases when the temperature is too high or too low. To make it even more complicated, the different varieties of roses respond differently to temperature. In addition, the photosynthesis of the plants increases with an increasing amount of light (Zieslin and Mor, 1990) and carbon dioxide (to a certain level), which affects both the quantity and the quality of the production. Similar relationships hold for the other cut flowers.

The carnation has been cultivated for more than 2000 years. Areas of natural climates for carnations occur near 30° North or South latitude, and on the western edges of the continents. E.g. Southern California, the Mediterranean area, Chile and South Africa. Previously, carnations were grown in local greenhouses near the market, but since the 1950's we have seen a continuous shift from the local production in the Northern sector both in the US and in Europe, to areas of natural climates. There are several reasons for this shift. Of course, the natural light and temperature conditions makes production less expensive, i.e. the use of inexpensive plastic film structures instead of more expensive greenhouses, and no need for heating and artificial light. Also, carnations are among the most labor-intensive of the cut flower productions, and, labor-costs in developing countries are very low compared to the labor-costs in the developed countries in the Northern sector. But the single most important reason for the shift is the use of airfreights for export especially to northern Europe where there is a high level of consumption.

The main groups of carnations used for commercial production are standard and miniature or spray carnations and the approximate length of the production cycle is one to two years, with two yields a year. Planting schedule for carnations are the basic means of production planning for market demand. The timing of flowering from various planting dates is quite predictable under ideal environmental conditions. The time between planting and peak flowering is about 110-150 days, with the shortest period when planting in late April (Larson, 1980). Planting schedules vary because of photoperiods, differences in temperatures and also variations in light intensity. If producing in a regulated environment, the time of flowering can be controlled by choice of planting time, day length, level of artificial light and temperature, and the time and method of pinching. Carnations are what we call “long-day” flowers, which means that they need a certain period of time with more than 12 hours daylight per day to initiate and develop flowers. The carnation grower who has good projections of his market demand by volume and flower colors throughout the year has the best basis for the planting schedules for number of plants and cultivars. Despite good planning, the vagaries of weather can throw predicted production cycles off schedule by several weeks, especially if producing in an uncontrolled light and temperature environment.

Chrysanthemum is the third major cut flower in commercial production. In contrast to carnations, much of the production still takes place in Europe. The varieties grown commercially today originate from species from the Far East. The main groups of varieties are “Dendranthema Indicum tros cas” and “Dendranthema Indicum tros santini”, each group including several hybrids. Chrysanthemums are grown in two basic ways for cut flowers, i.e. disbudded or standard (all buds but the terminal one are removed) and spray (several smaller flowers on each stem), depending on the market demand.

Starting in the early 17th century, the British and the Dutch were hybridizing chrysanthemums. In the United States Elmer D. Smith started hybridizing chrysanthemums for the florist trade in 1889. In his career he hybridized and named more than 500 varieties or cultivars, some of which are presently being grown (Larson, 1980). Commercial hybridization to improve cultivars continues today in Europe, America, Asia and Africa, based on floral shape, color, suitability for year-round production and post-harvest qualities.

In Europe, chrysanthemums are produced in greenhouses as year-round production. Depending on the variety grown, and the combination of input factors, it takes approx. 10-20 weeks from cuttings are planted until harvesting takes place. Chrysanthemum is a "short-day" plant, which means that after a few weeks in a vegetative growth stadium, it needs a certain amount of time (approx. 8-14 weeks) with less than 12 hours of daylight per day to initiate and develop flowers. This means that during periods of natural long day, the plants must be covered to make sure that the day length is appropriate. The temperature has a large influence on the time of flowering. Both high and low temperatures will inhibit the process of flower development, and the temperature sensitivity depends highly on the variety grown.

Economic decisions in flower production

Since stocks are limited by the size of the green house, the "newsboy problem" for decision makers in this case is also a question of which product to order or which portfolio ("bouquet") of flowers to start growing at a given space and time. The space for inventories is limited and represents a major cost in production. Therefore, the opportunity cost from having planted too many of a certain variety, e.g. chrysanthemums, given the demand subsequently observed is not simply the costs from producing an excess amount of this specific flower. The space allocated to (e.g.) chrysanthemums obviously could have been used for growing another variety, e.g. carnations. Theoretically, the demand for the two may be negatively correlated. Thus, having planted what turns out to be a too large area of chrysanthemums means an even greater loss from not having planted more carnations. Consequently, decision-makers are confronted with both a decision problem related to portfolio composition and a "real option" problem related to flexibility and irreversibility.

Planting X square meters of roses means that one forsakes the option of planting carnations on that very acreage for a given period of time. This is an irreversible decision for the subsequent production period, and to some extent also for production later on.

As outlined above, different flower varieties have widely different growth cycles. Roses can be harvested several times a year, depending on temperature and the amount of light applied. Before the first generation is harvested, however, there is a rather long gestation period. Other varieties, like for instance chrysanthemums, enter very fast into the harvesting stage. However, once the first production phase is started, there are biological restrictions as to when the second, third etc. cohort can be harvested. To the extent that demand follows systematic calendar patterns during the year, the problem facing the decision-maker is that of phasing biological and business cycles together. Price peaks and troughs do, however, occur at different times for different species. Skimming the cream in the market by planning for systematic deliveries at the peaks is not easy since production periods very often differ widely from the business cycles. In addition, production costs vary during the year. In greenhouse production, energy is a major cost. The energy input for heating and light depends partly on fairly deterministic seasonal factors, but also on unpredictable temperature fluctuations. Stochastic energy prices add to the cost uncertainty.

Pricing of cut flowers

The main data for this dissertation are prices and quantities obtained from the Dutch flower auctions 1993-2008. The Dutch flower auctions represent the major market place in European and global flower trade. A substantial volume of trade passes through these auctions. More importantly, the auction prices to a large extent determine prices outside the auction premises. Hence, supply, demand, quantities and prices at the auctions are relevant to all European flower producers, importers and traders.

The data used in the subsequent papers have been collected from weekly editions of *Vaakblad voor de Bloemisterij*, 1993-2008. Approximately 70 of the most important cut flower varieties, representing close to 100 per cent of the total value of cut flowers traded at the Dutch flower auctions are included in the data set. The cut flowers were aggregated into four groups, the three major varieties, i.e. chrysanthemums, carnations and roses, and a fourth aggregated category, “other” cut flowers.

The unifying theme of all essays is the challenge of producing and marketing cut flowers under price uncertainty. Prices and traded quantities represent the empirical material, and time series econometrics is the methodological basis for the analyses.

The purpose of the dissertation can be summarized in the following three points:

1. Forecasting prices in the short and medium term
2. Revealing price relationships that can be utilized to reduce price risk
3. Revealing price-quantity relationships that can be used for establishing marketing strategies

The results based on 1-3 can then, hopefully, be used for solving further decision problems not covered in this dissertation, such as optimal rotations, greenhouse investments etc.

Organization of the dissertation

The dissertation consists of five independent, but related essays. The aim of the first essay, “A world of flowers: Dutch flower auctions and the market for cut flowers (in print in *Journal of Applied Horticulture,* 2010)” is to give an overview of international flower production, consumption and trade. The paper describes the functions of the Dutch flower auctions in Aalsmeer, the world’s leading flower trading center. It also draws lines back into the history, viz. the Dutch flower trade and production in the 17th century. The so-called tulip mania 1636-37 is often referred to as history's first financial bubble. With the tulip mania as a backdrop the recent history of the flower markets is presented, showing some vital statistics on production, exports, imports, consumption and prices since the 1990's. The last two decades since 1990 represents the globalization of floriculture.

Flower production requires labor and capital, in particular energy (heat and light) and fertilizer. Energy for heating comes as oil, gas or electricity, or alternatively as heat generated by the sun. The latter is more available in the southern countries, and increasing oil prices have gradually reduced the relative production costs of flowers in countries like Kenya and other African countries. This process will be illuminated through some simple statistical relationships between flower prices and oil prices. Data from the Dutch flower auctions on prices and traded volumes for the three major varieties of cut flowers (roses, chrysanthemums and carnations) for the period 1993–2008 are analyzed.

Flower prices and traded volumes are extremely volatile. Although part of this volatility is predictable because of regular seasonal variations in demand, a large proportion of the observed volatility is due to sudden shifts in supply. The real prices of cut flowers have declined during the last two decades, and there has been a clear shift in consumer preferences toward roses and away from carnations. In addition, consumption of roses and carnations has shifted from clearly seasonal toward more year-round consumption, while consumption of chrysanthemums followed consistent seasonal cycles throughout the period. Non-European producers have increased their market shares. This development can be traced to a significant decrease in cut flower prices relative to energy prices, especially after 2003. While production in Europe has been stable or declining, it has increased rapidly in Africa, Asia and South America, and many Asian countries have experienced strong growth in consumption. This shift can also be traced as a decrease in cut flower prices relative to energy prices, especially during the last five years of the study period, due to strong growth in exports of flowers from Africa, notably Kenya, to Europe.

Production planning in the flower business offers a complicated variation over the Newsboy Problem. Decisions include which product to order or which portfolio of flowers to plant at a given time. Given the extremely high short-term price volatility in this business, good timing may yield substantially higher returns. Good price forecast could improve the necessary decisions, and therefore may be of great commercial interest. The purpose of the second essay, “Forecasting prices at the Dutch flower auctions” is to establish short-term price forecasting models which can be applied in the production and marketing of flowers. This essay is written with my supervisor Ole Gjølberg as the co-author, and has been published in *Journal of Agricultural Economics* (Steen and Gjølberg, 1999). The essay analyzes weekly prices for three major species of cut flowers, chrysanthemums, carnations and roses, 1993 - 1996. We found that were that there are strong calendar regularities in prices for all varieties. Establishing a model where we combine information on seasonal regularities and autoregressive price patterns, we manage to explain a substantial amount of the short-term price variability for all three species. Measured in terms of accuracy (defined by mean square error and mean absolute deviation) as well as direction (using ratio of correct signs) of price changes, the forecasts were superior compared to a naïve model (i.e. that the price will be equal to the price the same week one year earlier) as a benchmark. The model was tested in an out-of-sample dynamic forecasting experiment during the first 35 weeks of 1997.

The third essay “Forecasting prices at the Dutch flower auctions: A partial least squares approach” is a follow-up on the second paper in two important ways. First, the dataset now includes 11 additional years of weekly data on prices of the same varieties of cut flowers, which gives a much stronger basis for making conclusions. Second, this paper offers an alternative methodological approach. Forecasts are established based on partial least squares (PLS) regressions. There are two main purposes of this essay. One, to establish forecasting models that can be applied in the production planning and marketing of cut flowers. Second, to investigate whether partial least squares (PLS) can be recommended as a better forecasting method compared to alternative models. PLS bears some relation to principal components regression; it finds a linear regression model by projecting the predicted variables and the observable variables to a new space.

Partial Least Squares (PLS) regression is originally a method proposed by Herman Wold (1966) as an econometric technique, but PLS first became popular in chemometrics partly due to Herman's son Svante, e.g. (Wold et al., 2001). Until recently there have been few PLS-applications in economics. During the last decade, though, the method has been applied to macroeconomic data, e.g. Stock and Watson (1999); Stock and Watson (2002); Bernanke and Boivin (2003); Marcellino et al. (2003); Groen and Pesenti (2009) and Franses and Legerstee (2009). On the other hand, in chemometrics PLS regression has emerged as the leading forecasting method (e.g. Geladi and Kowalski (1986); Martens et al. (2001), and Helland (2001)).

A PLS model will try to find the multidimensional direction in the X space that explains the maximum multidimensional variance direction in the Y space. PLS-regression is particularly suited when the matrix of predictors has more variables than observations, and when there is multicollinearity among X values. In these cases, standard regression will easily fail.

This essay focuses on the short and medium run. Specifically, price forecasts 1-2, and up till 8-14 weeks ahead are established. Forecasting in the short run is interesting because it is possible for flower producers to shorten or delay the end of the production period using more or less heat or light. Forecasting the medium run is interesting in a production planning setting, e.g. when making decisions on whether or not to start a new cohort, and which varieties to plant. The forecasts are evaluated out-of-sample for the weeks 2007-26 to 2008-25 (52 weeks). In order to benchmark the results, the PLS forecasts are compared to the results from univariate time series (AR(1) and AR(5)) models, structural economic models and a naïve model. The main conclusions from this essay are as follows. Firstly, cut flower producers should be able to benefit from applying forecasting models in the production planning and marketing of cut flowers. Secondly, a partial least squares (PLS) regression model can be recommended as a successful forecasting method compared to more standard forecasting models. Both measured in quantitative (RMSE) and qualitative (predicting the right direction of price changes) PLS outperforms the other forecasting models.

International flower production and trade has grown into a multi-billion business with the Dutch flower auctions as its focal point of price and market information. Despite the size of the flower business and its increasing importance, the issues related to consumer behavior in the flower markets have received little attention in the literature. Abdelmagid et. al. (1996) studied the demand for nursery plants, Rhodus (1989) studied the demand for fresh flower bouquets in the US. Beyond these studies little systematic analysis of the price-quantity relationships has been published. Essay four, "Price-quantity relationships in the Dutch flower market: Is there a potential for strategic behavior?", submitted for publication in "*Journal of International Food & Agribusiness Marketing"*, is a contribution to bridge that gap, presenting econometric evidence on price-quantity relationships for three major varieties of cut flowers at the Dutch flower auctions.

Since cut flowers are, indeed, highly perishable, prices are volatile. The salvage value of yesterday's unsold cut flowers is close to zero. Based on information regarding the price and quantity data generating processes and the underlying demand/supply schedules, producers' risk management and strategic marketing behavior may generate less volatile prices (and higher producer utility). 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 due to the batch character of production and the problems connected to storing cut flowers. Assume, for instance, that there are three or four large producers of a given variety 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 market behavior should therefore involve systematic surveillance of variations in traded volumes.

We raise the question whether the producers can behave strategically by utilizing information on demand patterns. An inverse linear approximate almost ideal demand model (IAIDS) with seasonality is estimated. The system approach is chosen to model the demand as compared to a single equation approach since demand for close substitutes like different cut flowers most likely are interrelated. A system approach provides more information, as the interaction between the demands for different products can be accounted for, and therefore yields more efficient estimates. An inverse demand system is a natural model for the price formation of quickly perishable goods like flowers, where supply is fixed in the short run.

The flower demand typically follows seasonal cycles. This creates an additional challenge when using high frequency data such as weekly data, in that one would like a procedure that is parsimonious when representing the seasonality. A trigonometric representation in the demand system following the general notion of Ghysels and Osborn (2001) is introduced. The trigonometric representation allows the seasonality to be represented with only two additional parameters in each demand equation. This approach is compared to a standard dummy representation.

The results show that weekly cut flower consumption can be modeled using an inverse linear version of the almost ideal demand system. To handle seasonal patterns, trigonometric functions can be recommended as a flexible and inexpensive alternative, which in this study clearly outperformed standard seasonal dummy models. The parsimony in use of regression variables is especially important when estimating systems of equations. The estimated price and scale flexibilities are all strongly statistically significant, with the expected signs.

Based on the estimated values for price and scale flexibilities, a potential for strategic marketing or market timing seems to exist. The flexibility estimates vary across different species. While 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.

Finally, essay 5 "Risk management in the flower business" is addressing price risk. This is a substantially revised version of a previous paper, "A Portfolio Approach to Cooperative Risk Management", published in *Journal of Cooperatives*, **14** (1):21-29 (Gjolberg and Steen, 1999) . Flower producers face significant price risk, as do producers of other biological products. However, while producers of wheat, corn, hogs etc. may hedge price risk in well functioning futures markets, no such risk management instrument is readily available in the flower business. This essay suggests that flower producers take a portfolio approach to reduce risk. This means that individual producers diversify across different flower varieties. Since, however, such an individual multi-product approach may be costly; an alternative might be to achieve the diversification effect by pooling risk in a joint ("co-operative"), multi-variety portfolio. The aim of the essay is to analyze the risk reduction potential from such diversification, individually or in a pool of producers. Two different models, the Markowitz portfolio selection model and Sharpe's single-index model are used to create risk-minimizing portfolios based on minimizing the risk of return as well as minimizing price level risk. Weekly price data for cut flowers 1993-2008 were used for portfolio selections. It is shown that price risk can be substantially reduced through establishing some quite simple portfolios. These portfolios appear to be quite stable over time.

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Essay 1

"I beg your pardon,

I never promised you a rose garden.

Along with the sunshine,

there's gotta be a little rain sometimes.

When you take, you gotta give, so live and let live,

or let go.

I beg your pardon,

I never promised you a rose garden".

Lynn Anderson,
lyrics from "Rose garden"

A World of Flowers:

Dutch flower auctions and the market for cut flowers

Abstract

This article gives an overview of international flower production, consumption and trade, focusing on the Dutch flower auctions in Aalsmeer, the world's leading flower trading center. Data on prices and traded volumes for three important species of cut flowers (roses, chrysanthemums and carnations) for the period 1993–2008 are analyzed. Flower prices and traded volumes are extremely volatile. Although part of this volatility is predictable, because of regular seasonal variations in demand, a large proportion of the observed volatility is due to sudden shifts in supply. The real prices of cut flowers declined during this period, and there was a clear shift in consumer preferences toward roses and away from carnations. In addition, consumption of roses and carnations shifted from clearly seasonal toward more year-round consumption, while consumption of chrysanthemums followed consistent seasonal cycles throughout the period. During this period, non-European producers increased their market shares. This development can be traced to a significant decrease in cut flower prices relative to energy prices, especially after 2003.

Introduction[i]

Cut flowers belong to a very special class of commodities. Flowers, like newspapers, electricity or fresh bread, are extremely perishable. Furthermore, the intrinsic value of flowers differs from that of most other commodities. While almost all agricultural commodities are produced and bought to satisfy nutritional or energy requirements, flowers are demanded solely to satisfy emotional needs. As such, flowers are in the same category as the arts, e.g., a theater performance or a music concert[ii]. Furthermore, flowers are bought to convey sentiments of different, sometimes completely opposite, types. Flowers are used both to signal sympathy in times of grief and as a token of joy and happiness; they are given at weddings, funerals, anniversaries or other occasions, with the messages such as "I wish you all the best", "My deepest sympathy", "I love you", or "Please forgive me". Flowers are used to cheer up people suffering from illness and to decorate homes. If a man gives a woman expensive flowers it is considered a strong signal that he likes her, or more than that; that signal is understood independently of whether the man likes flowers or not[iii]. The combination of flowers' extreme perishability and their being demanded for multiple emotional and aesthetic reasons makes the market for cut flowers an interesting and challenging object for economic analysis.

The aim of this paper is to give an introduction to the international flower markets, with a focus on the Dutch flower auctions. First, we put flower prices in a historic perspective. The so-called tulip mania in the 16th century is often referred to as history's first financial bubble. With the tulip mania as a historic backdrop, we move to the recent history of flower markets, presenting some vital statistics on production, exports, imports, consumption and prices since the 1990's. The two decades since 1990 represent the globalization of floriculture. Flower production requires labor and capital, in particular energy (heat and light), and fertilizer. Energy comes as oil, gas or electricity, or alternatively generated by the sun. The latter is more available in the southern countries, and increasing oil prices have gradually reduced the relative production costs of flowers in countries like Kenya and other African countries. This process will be illuminated through some simple statistical relationships between flower prices and oil prices.

Flower prices: 500 years of roller coaster

The history of Holland as a flower-trading and flower-producing country dates back to the end of the 16th century[iv]. In 1594, botanist Carolus Clusius (1526–1609) planted the first tulips in Dutch soil, only to see the whole collection stolen from the university garden that same year (van Lier, 2005). From then on, exotic plants were imported in increasing quantities from the Dutch East and West Indies to merchants in Amsterdam, who acted as suppliers to the great gardens of Europe. Some of the merchants also commissioned drawings and paintings of the flowers they had for sale, which were published in books. By 1630, dozens of books existed depicting flowers, especially tulips; these served as catalogs of the flowers for sale (van Lier, 2005).

The demand for tulips rose dramatically and between 1610 and 1637 the tulip trade developed into a so-called “fever”, affecting the whole country. Garber (2000) gives an extensive analysis of the development, subsequently labeled “the tulipmania”.

The mania soon reached the middle classes and, according to Mackay (1841), a popular tulip could cost as much as an Amsterdam townhouse[v]. It has been suggested (e.g., Garber, 2000) that the fact that the tulip was difficult to grow and susceptible to disease made its cultivation a challenge at which only the best succeeded (Pavord, 1999). In addition, some of the tulips developed striped flowers, where the pattern of stripes was unique for each bulb; this became the focus of great attention. At that time, it was not known that the stripes were due to mosaic virus attacks[vi].

What makes tulips different from most flowers is that they can be harvested and moved only between June and September; consequently, spot market trading could take place only in this period. During the rest of the year, futures contracts were made before a notary. In 1636, these contracts were formalized, but no deliveries were made, as the market collapsed in February 1637.

However, as a result of the tulip trade, the Dutch developed many of the techniques used in modern finance. In 1636, regular markets were opened in many Dutch cities. Foreigners entered the market and money flooded into Holland. Eventually, it became obvious that the capital inflow and rising prices would come to an end. Confidence vanished and panic spread. Prices fell abruptly and bulbs could not be sold at even a fraction of their previous value.

The price differences across the different bulb cultivars were huge. Therefore Thompson (2007) has developed a standardized, quality-weighted price index for tulip bulbs in the period from November 12, 1636, to May 1637. The bulbs were sold by weight, and prices were calculated as guilders per aas[vii]. The price per aas increased from less than 10 guilders to approximately 200 in less than three months. From February 3 to February 9, 1637 (i.e. seven days), the price decreased by 50 guilders, and by the beginning of May 1637, the price had returned to the November 12 level.

According to Mackay (1841), several public meetings were held to try to pressure the government to bail out the unfortunate traders but without success. The problem ended up at the Provincial Council at The Hague, but a remedy was beyond the power of the government. The judges assumed this to be debt contracted in gambling, and therefore not debts in law.

So, according to Mackay (1841), the story ended. The final buyers had to carry their losses as best they could, and those who had gained from the high prices were allowed to keep their profit. The Dutch flower business suffered a severe shock, and it took years to reestablish confidence.

Until the 1980s, Mackay's presentation of the tulipmania, or "bubble", went unchallenged and mostly unexamined. More recent studies suggest that Mackay's research was incomplete and inaccurate. Goldgar (2007) argues that the tulipmania phenomenon was far more limited than previously thought, that only a handful of people experienced severe economic problems in this period, and that even for these people it could not be proven that the problems were due to the tulip trade. Even if prices had increased enormously, money had not changed hands. Therefore, profits were not realized and, unless they had made other deals on credit, the price collapse did not incur losses to traders.

Garber (1989) claims that one reason for the extreme price increase at the end of 1636 was that the bulbs had already been planted by then, which meant that the producers could not increase production as a response to the price increase.

Thompson (2007) argues that Garber's model cannot explain the abrupt price decrease. He believes that the dramatic price movements can be explained by changes in laws related to the futures contracts. According to Thompson, the essence of these changes was that futures contracts written after November 30, 1636, were to be interpreted as options. This meant that whereas the buyers were previously legally obliged to buy the bulbs, they could now choose to compensate the sellers with a fixed small percentage of the contract price (Thompson, 2007). Thompson argues that the mania was a rational response to legal changes. In any case, the tulipmania is still seen by many as a large economic bubble.

In any case, the early experience with tulip trading laid the foundation for elaborate and advanced trading institutions and pricing mechanisms in the flower business, notably the Dutch flower auctions.

Recent history of the world market for cut flowers

As recently as 40–50 years ago, the demand for cut flowers and potted plants around the world was generally satisfied by local production. In Europe, growing per capita income caused increased demand for flowers for everyday use and as gifts for special occasions. As transportation systems improved, more flowers were shipped from southern to northern Europe and the size of the European trade grew considerably. This was the start of the commercial flower industry as we know it today (Wernett, 1998).

The energy crisis in 1973 strengthened the comparative advantage of flower producers in southern Europe because of the large energy costs of greenhouse flower production. Energy costs constitute approximately 30–40 percent of the total variable costs in cut flower production in northern Europe, and significantly less in southern Europe. Increasing amounts of flowers from the south of Europe were therefore moved to the Dutch flower exchanges to meet the demand after 1973.

Later, increasingly, flowers bought in Europe were produced by Israeli producers. In Israel, flowers may be grown outdoors or in plastic tunnels all year round, eliminating both the energy costs and the fixed greenhouse costs that the European producers face. The Israelis faced two other limiting factors, however: transportation costs to Europe and water supply. These limitations were reduced through transport subsidies and research into watering systems to reduce water consumption in agricultural production (Wernett, 1998).

Starting in the 1970s, big marketing campaigns financed by the Holland Flower Council started to influence consumption patterns outside of Europe, and cut flowers from the Dutch flower exchange entered the American market, mostly through New York. At the same time, Miami developed as a base for flower imports from Colombia, for onward distribution in the

USA. This led to strong competition for local American producers that the Europeans used to their advantage. South American producers bought plant varieties from Europe, and North American producers were persuaded to buy production systems from Europe in order to counter the competition from the south (Wernett, 1998).

During the 1990s, African countries, in particular Kenya, exported increasing quantities of cut flowers to the European market. Together with the Israeli flower industry, Kenya is now a major competitor to the European producers.

As African producers entered the European market, European flower traders started to expand into Asia, especially to Japan, exporting cut flowers as well as production systems and technology. This drive into Asia was helped by aggressive marketing campaigns. Commercial flower production in Asia started to develop because of increasing demand for low-priced flowers from the European market and European, mainly Dutch, producers started to produce in East Asian countries.

What makes flower production in Asia different to that in Africa and South America is that the latter produce flowers almost exclusively for export, whereas in Southeast Asia there is a growing market for local consumption because of growing incomes.

In the future, the largest potential for development and expansion of the flower industry is assumed to be in Asia, both for local consumption and for export[viii].

Flowers by numbers - International production and trade[ix]

In 2008, the total area used for cut flowers and potted plants in the world was approximately 532,000 ha, an increase of 33 percent from 2005. The biggest producers in terms of land use were China with 286,000 ha (2006) and India with 70,000 ha (data from 1999 only). China almost doubled its flower production acreage during the last three years of the study period; the same is probably true for India. Almost 75 percent of all flower production land was in Asia, a 12 percent increase during the last three years. South America had almost the same area as Europe, approximately 50,000 ha, both stable since 2005.

If we look at the value of production, the picture is somewhat different. The total value of the world's flower production was approximately €24 billion in 2008, a 33 percent increase from 2005. European production constitutes almost half that value; the value of Asian production is approximately €7 billion.

The total value of world imports of cut flowers and potted plants in 2007[x] was estimated at €10.3 billion, Germany being the single biggest importing country with €1.5 billion. By comparison, USA and Japan imported flowers for €893 million and €241 million, respectively[ix].

The total value of flower exports in 2007 was €10.9 billion, of which the Netherlands was responsible for almost half. European exports constituted approximately two-thirds of total exports. The Americans were the second biggest exporters with €1.8 billion, (with Colombia, Canada and Ecuador as the biggest exporting countries). Asia was exporting approximately €1 billion and Africa €820 million. Kenya was the biggest flower exporting country in Africa with €500 million, up approximately 100 percent from 2004.

Table 1. Value (€ 1000) of imported cut flowers from Africa, Latin America, Asia and the Middle East to the Netherlands and EU (total).

To: From:	The Netherlands		EU total	
	2004	2007	2004	2007
Africa, total	288,806	312,365	347,569	447,371
Kenya	144,226	205,029	235,378	312,703
Latin America, total	64,844	105,615	171,934	235,533
Colombia	18,268	27,274	84,297	115,586
Ecuador	42,648	72,158	79,167	110,421
Asia (Middle East excluded)	4,546	5,394	21,490	26,574
Middle East, total	65,574	46,961	101,225	91,015
Israel	60,713	40,942	85,510	73,989
Total	423,770	470,335	642,218	800,493

Table 1 shows the value of imports from the major non-European flower producers into the Netherlands and the EU. More than half of the imports in 2007 came from Africa, with Kenya as the dominant exporting country. Almost 40 percent of total EU imports came from Kenya and together with Israel, Colombia and Ecuador these countries supplied 77 percent of EU imports (€613 million out of approximately €800 million in 2007). Total imports to Europe from non-European countries increased by 25 percent from 2004 to 2007, and the imports from Kenya by 75 percent in the same period. More than half of Europe’s flower imports went through the Netherlands (in 2007). This amount increased by approximately 60 percent during the 10 years to 2007. In 2007, Great Britain and Germany imported flowers valued at approximately €170 million and €50 million, respectively, from non-European countries.

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 percent of Great Britain’s imports and roughly 40 percent of the flower imports to France, by value, come from the Netherlands.

Fewer than 10 species make up the bulk of the cut flower trade: roses, chrysanthemums, tulips, lilies, gerberas, cymbidium, freesias, anthurium and alstromeria. While the value of cut flower species traded at Dutch auctions increased by 25 percent during the period 1998-2008, the value of the rose trade in the same period increased by more than 70 percent.

Table 2. Per capita consumption (€) and market value of consumption (million €) of flowers, 2006

	Per capita consumption			Population	Estimated market value		
	Cut flowers €	Plants €	Flowers, total €	Million	Cut flowers € million	Plants € million	Flowers, total € million
Germany	36	48	84	83	2,988	3,984	6,972
Netherlands	54	32	86	16	864	512	1,376
Norway	62	62	124	5	310	310	620
Russia	5	1	6	143	715	143	423
Switzerland	82	43	125	7	574	301	875
Europe	23	16	38	680	15,755	10,740	26,060
Japan*	54		54	128	6,912		6,912
USA*	21		21	306	6,426		6,426

*Cut flowers only

Table 2 shows the consumption of flowers (cut flowers and total) per capita in 2006, as well as the value of consumption. When it comes to total demand for flowers, Switzerland and Norway had the highest per capita total consumption of flowers in the world. The average per capita consumption of cut flowers (in 2006) in Europe (€23), even including the relatively low consumption in Eastern Europe and Russia, is higher than the per capita consumption in the USA (€21), but considerably lower than in Japan (€54). When we take into account the population of the different countries, Germany is by far the biggest consumer in Europe with a total consumption of flowers and plants of almost €7 billion. Of this, the value of cut flower consumption is €3 billion, which is approximately half the value of cut flower consumption in the USA. Japan is the biggest cut-flower-consuming country in the world with a value of €6.9 billion.

The Dutch flower auctions

The history of today's Dutch flower auctions dates back to 1911–12, when flower producers in the city of Aalsmeer established two flower auctions: "Bloemenlust" on the east side and "Central Aalsmeer Auction" in the city center. The auctions were established because producers felt they were in the hands of agents who manipulated prices and that the agents were not always reliable payers (van Lier, 2005).

The concept of the cooperative auctions was adopted from the fruit and vegetable industry. The producers hoped they would collectively become stronger and, by offering their product exclusively at the auctions, they forced the buyers to trade through the so-called auction clock[xi]. Thus, the introduction of the auctions seemed to shift power from agents to growers.

The aim of the clock auction was to generate a fair price. It increased competition on the demand side, because the buyers could get information about the prices and quantities of their competitors. On the supply side, it led to higher quality of the flowers offered at the auctions.

In 1972, Bloemenveiling Aalsmeer was established through the merger of several smaller auctions; most recently, in 2007, Bloemenveiling Aalsmeer and FloraHolland, the two largest flower auctions in the world, merged. The merged company, called FloraHolland, started its operations in January 2008.

The main reason given for this merger was the threat from developments in the international flower market, especially the opening of a flower market in Mumbai, India, and another one in Dubai. As India has evolved to be a very big flower producer, as well as a substantial consumer, and as Dubai is closer to the African flower producers than the Netherlands, there was a fear in Aalsmeer that trade would shift toward Dubai.

The Dutch flower auctions have so far have managed to develop and sustain a leading position in traded volume as well as in research, production, marketing, standardization, information and education (Wernett, 1998). In 2008, the merged FloraHolland had a turnover of €4.07 billion (FloraHolland, undated).

The flower auction in Aalsmeer is today one of Floraholland's six auction sites in the Netherlands but, because of its history and size, Aalsmeer requires some special attention. In 2008, Aalsmeer had a clock turnover exceeding 11 billion cut flowers and 800 million plants, amounting to a turnover of some €2.4 billion, more than half of the total clock turnover of Floraholland (FloraHolland, undated). The auctions take place in a huge trade center covering approximately 1 million square meters, which is roughly comparable to 250 soccer fields. Within this trade center, very complex logistical processes and auctions take place, which in turn determine world prices for flowers.

In any given week, around 100 species of cut flowers are traded in Aalsmeer and for many of the species there are several varieties. As many as 30 to 40 different varieties of roses are traded, with each variety possibly 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[xii].

Approximately 9,000 individual producers market their flowers at the auctions of FloraHolland, of whom 5,000 are exchange members. Since 2007, producers from non-European countries can become members of the cooperative. The new members are mostly "off-shore" Dutch producers located in Kenya and Uganda as well as Israeli growers. Each member has to make a deposit to the cooperative equal to 1 percent of their sales. The cooperative pays interest to members and the deposit is fully returned after nine years. Members can also give interest-bearing loans to the cooperative. The general assembly meets twice a year and members' voting power is determined by their sales (deposit).

One important objective of the FloraHolland cooperative is to sustain and improve its market position by offering quantity, quality and variety. The declared objective of FloraHolland, a nonprofit service organization, is to offer their members the best sales possibilities at a low cost (FloraHolland, undated).

The auctions

The day starts early at the Dutch flower auctions. The night before each trading day (Monday–Friday), flowers are unloaded from numerous trucks at the auction halls. The cut flowers are stored in carts in cold rooms. At 4:30 a.m., the flowers are transported to the huge collection halls and sorted by species and quality.

Each unit is quality checked and given a unique number. Then the carts are connected to each other and dragged into the auction rooms on small electrical trains. The auctions start at exactly 6:30 a.m.

As mentioned above, the auction mechanism is the so-called Dutch auction. As opposed to an English auction, the starting price is high rather than low. The auctioneer announces the flowers to be sold, including batch size, minimum buying quantity, name of the producer and comments, if any, from the quality inspector.

The bidding is controlled by a huge clock-like screen indicating the unit price (e.g., €100, €10 or €1). 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.

When a buyer stops the clock, he or she must immediately communicate to the auctioneer the quantity purchased at the given price. Soon afterward, the clock moves to a slightly higher price before it again starts its downward move. This procedure is repeated until the whole batch is sold. The procedure then re-starts for the next batch of flowers to be auctioned.

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.

Thus, 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"[xiii] and is considered strategically equivalent to a "first-price sealed-bid auction"[xiv]. Usually, there are only data on winning bids, but van den Berg and van der Klauuw (2007) perform an interesting structural empirical analysis of the auctions of potted plants using data on losing bids.

The buyers at the auctions mostly represent large flower wholesalers, exporters and large retailers. Up to 90 percent of flowers sold reach their final destination within 24 hours. Transportation within Europe mostly takes place in cooled trucks. Flowers are sent to the USA by plane; they usually reach New York during the evening or night of the sales day, and wholesalers in the New York flower district receive them as early as 3:30 a.m.

The 39 auction clocks of Floraholland are at the heart of the auction system. Every sales day, roughly 1,000 buyers gather in front of the clocks to follow the prices of the different flowers for sale. Different products are offered at different clocks. Each transaction takes only a few seconds. The auctions are therefore carried out at a tremendous speed, which is important for a highly perishable product. The FloraHolland auctions have approximately 125,000 transactions per day, which amounts to more than 12 billion cut flowers and more than 800 million potted plants traded each year (Floraholland, undated).

More than 60 percent of the world flower trade goes through the Dutch auctions. It is also possible to trade at the auctions without being physically present, following the clock via the Internet. There is also a gradual transition toward the flowers being presented through pictures rather than live at the auction, so that the flowers do not have to leave the cooled storage until they are transported directly to the buyer.

Floraholland employs 4,500 people, 2,000 of whom are in Aalsmeer. A further 12,000 people (in Aalsmeer) are employed in supporting activities such as wholesaling and exporting. The flower sector in the Netherlands is a significant sector, economically and socially. The contribution of the Dutch flower trade to the balance of trade is 20 percent. The direct and indirect employment in the flower sector is approximately 250,000 full-time jobs (Floraholland, undated).

Prices, price volatility and turnover at the Dutch flower auctions 1993–2008

Prices and traded volumes at the Dutch flower auctions are published weekly in “Vaakblaad vor der bloemisterij”. Here, weekly data for the period January 1993 to June 2008 are analyzed.

Flower prices

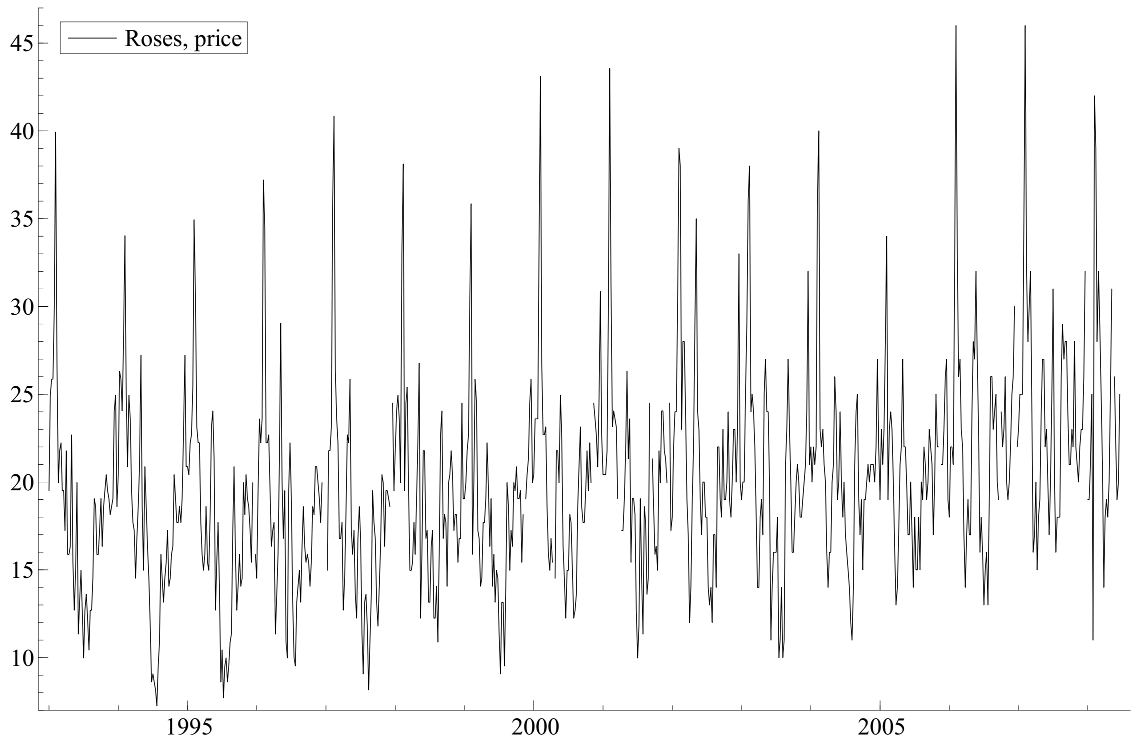

Figure 1. The nominal price of roses (Eurocent per stem) week 1, 1993 to week 25, 2008.

Figure 1 shows the weekly nominal rose prices, measured in Eurocent per stem, during the period 1993–2008. The rose price trended upward by 1.9 percent annually, as compared to the price of carnations, which increased by 1.2 percent annually. Chrysanthemums, however, saw stagnating prices during this period. The average inflation (CPI) in the Netherlands for this period was 2.3 percent annually, which means that the real price of cut flowers fell by 0.5–1 percent annually.

The demand for cut flowers is extremely seasonal, generating regular calendar patterns in prices. Therefore, to describe prices in a somewhat longer run, the series are smoothed (12-month moving average). Figure 2 visualizes what can be labeled the business cycles in the flower trade.

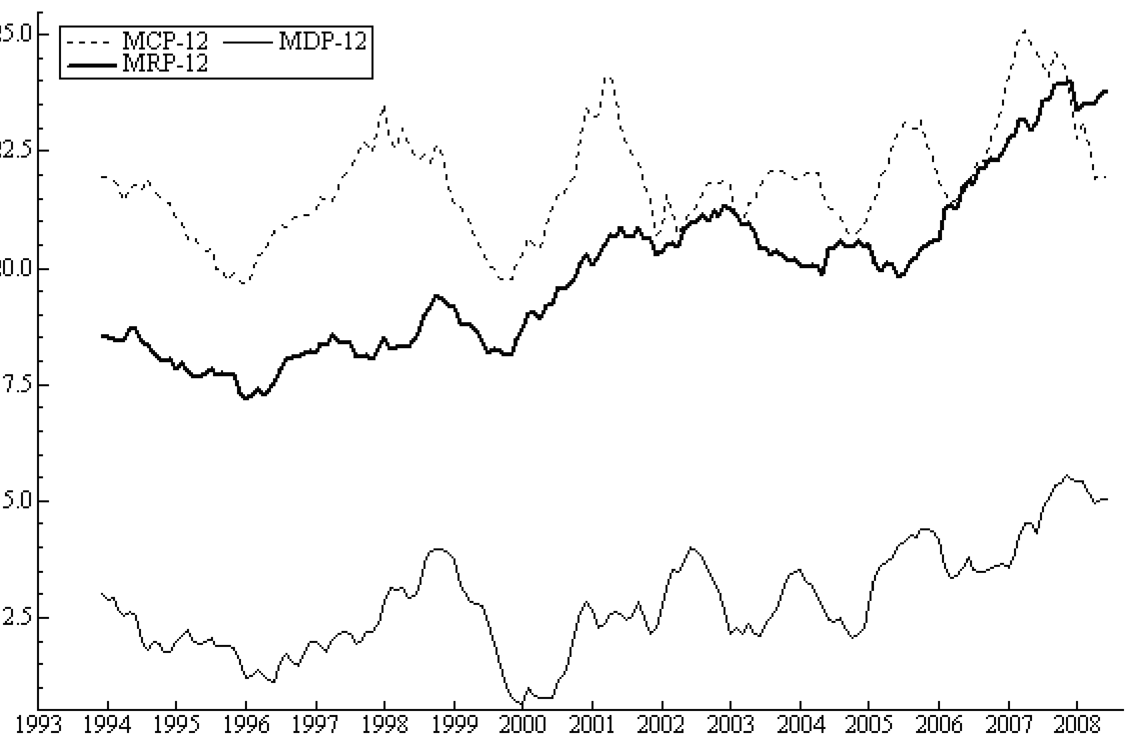

Figure 2. Smoothed prices (12-month moving average) for roses (MRP-12), chrysanthemums (MCP-12) and carnations (MDP-12); Eurocent/stem, 1994–2008

Disregarding the sharp seasonal price movements, rose prices trended quite steadily upward, particularly after 2005. Chrysanthemums, having had no long-term price increase, saw some large fluctuations with price peaks in 1998 and 2001. The long-term price growth for carnations is mainly a result of a price surge after 2000; at the end of the 1990s, carnation prices dropped dramatically.

Traded volumes

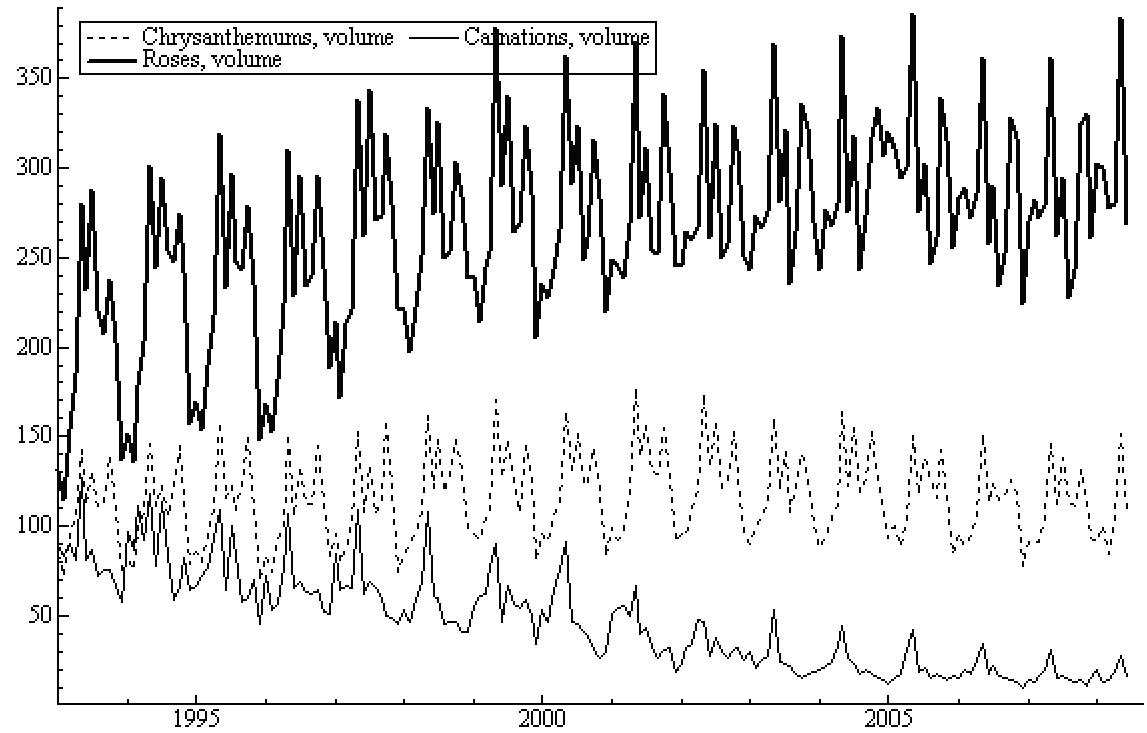

Figure 3. Traded volumes (million stems) of cut flowers per month in the period January 1993 – June 2008.

From Figure 3, we can see the cycles and trends in traded volumes during the study period. For the auction as a whole, there was a growth of 1.1 percent on an annual basis, mainly due to the increased demand for roses (+ 2.6 percent annually). For chrysanthemums, the traded volume during this period was stable; for carnations, there was a strong negative trend (12.4 percent on an annual basis).

The calendar patterns in prices are obviously reflected in volumes. Figure 4 shows the smoothed (12-month average) volumes.

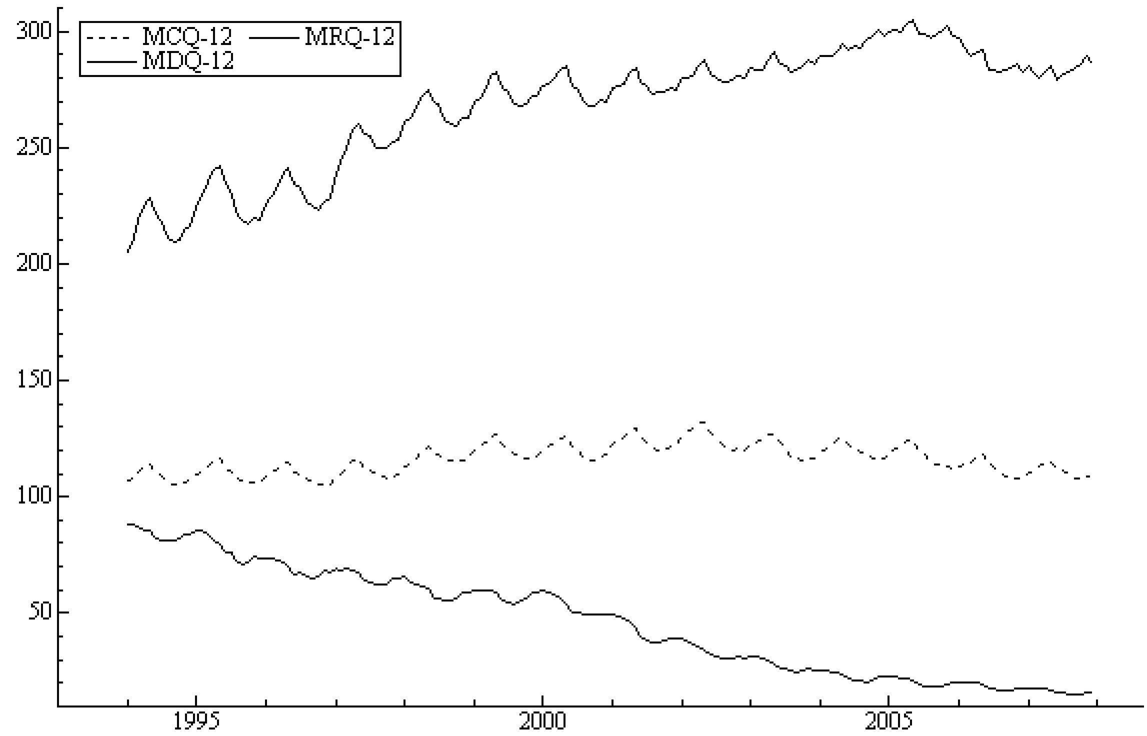

Figure 4. Smoothed volumes (12-month moving averages) for roses (MRQ-12), chrysanthemums (MCQ-12) and carnations (MDQ-12); million stems, 1994–2008

As can be seen, all three species have distinct calendar cycles up to 2000/2001. After that date, demand for roses and carnations appears to be smoother, while chrysanthemums maintain strong seasonalities throughout the period. Thus, the consumption pattern for roses and carnations seems to have changed over time, toward a more year-round, or “everyday” consumption, while the demand for chrysanthemums is still quite traditional, linked to the time of the year and to events occurring each year.

Seasonalities in prices and volumes

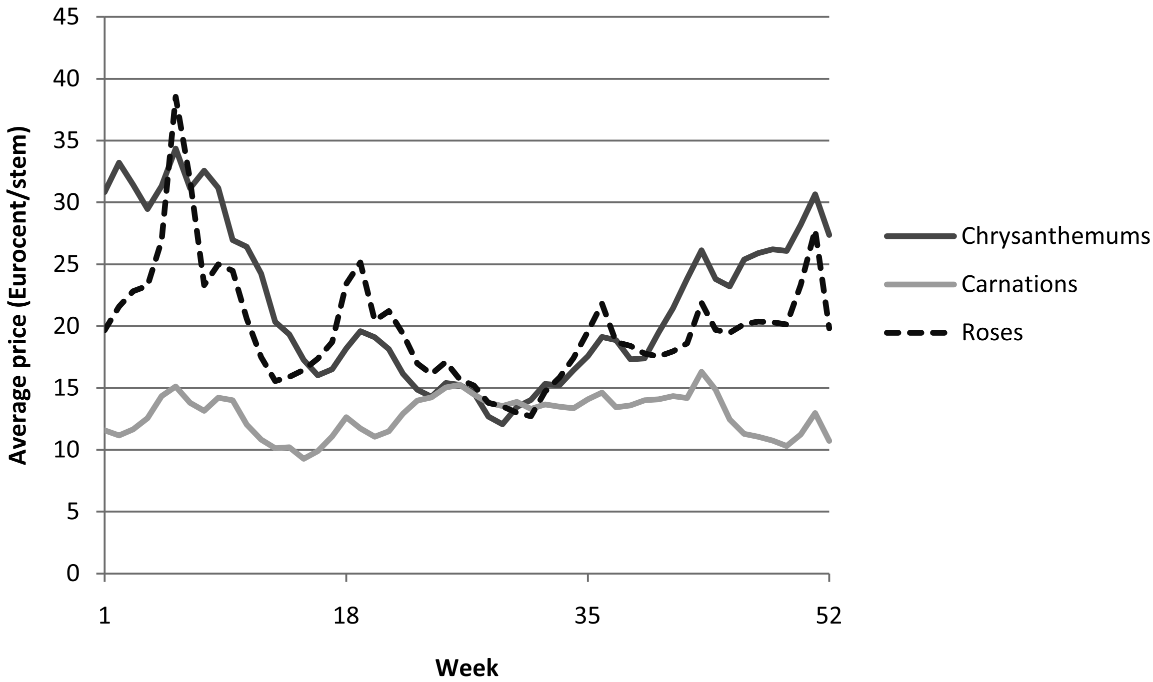

Figure 5. Average prices (Eurocent/stem) of cut flowers each week, weeks 1–52, 1993–2008

The seasonal patterns are further illustrated in Figure 5, displaying the mean prices for three main species of cut flowers over weeks 1–52. The overall mean prices of roses, chrysanthemums and carnations are approximately 20, 22 and 13 Eurocent/stem, respectively. Around these averages, the coefficients of variation (CV) are between 18 and 30 percent on a monthly basis, which makes flowers an extremely volatile commodity. The seasonal variation in prices is much higher for roses and chrysanthemums where the average price in the winter may be as high as 2–2.5 times the average price in the middle of the summer.

Figure 5 shows very strong seasonal cycles in the prices, but the cycles are not identical for the three groups of cut flowers shown. Roses are the most extreme, with a high of 39

Eurocent/stem before Valentine's Day down to 13 at the end of July. Again, chrysanthemums show a similar pattern to roses. Chrysanthemums usually have a lower price than roses in weeks 14–38 and higher prices the rest of the year (with the exception of Valentine's Day sales).

Carnations have different cycles to those of other cut flowers. Prices are relatively higher in February, June and October and lower in December and April. The differences between the high and low prices are smaller for carnations than for the other cut flowers.

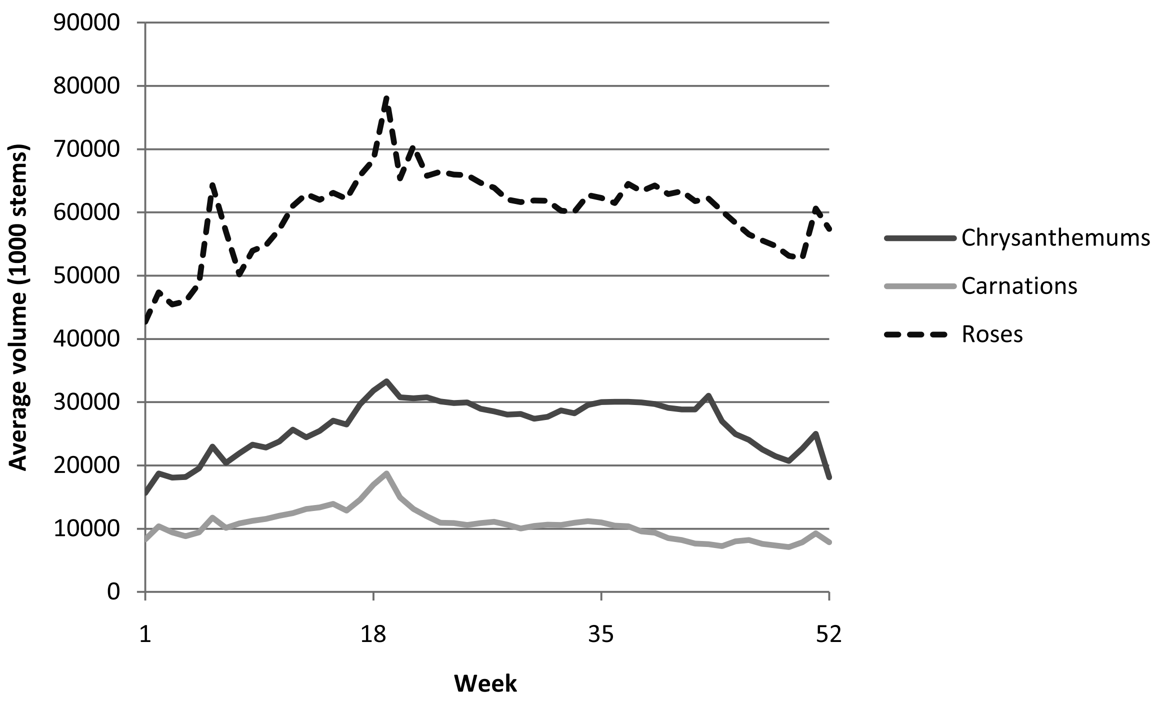

Figure 6. Average weekly volume of different groups of cut flowers, week 1, 1993 – week 25, 2008

Figure 6 shows the demand cycles over the year for roses, chrysanthemums and carnations.

For all species, traded volumes are relatively low during the winter period with the exception of sales around Christmas time. Thus, during the last couple of weeks of each year, traded volumes are up. For roses, January is a month with relatively low sales, but already in February, there is a distinct peak, particularly in week 6, coinciding with Valentine's Day and then Mother's Day. The traded volume of roses increases steadily until it reaches a maximum at the beginning of May. It then decreases slowly until July/August. After a slow increase in early fall, the sales decrease again until the beginning of December; finally, there is the Christmas sale.

Chrysanthemums follow roughly the same pattern as roses, but the peaks are less distinct. For cut flowers seen as a whole, the spring turnover is remarkably higher than the turnover during the rest of the year. This is mainly due to the demand for tulips and other bulbs in early spring.

Relative prices and consumer preferences

No big changes in relative production costs across different flower species have occurred during the past 15–20 years. Hence, changes in relative prices may be interpreted as changes in consumer preferences.

Figure 7 compares long-run changes in prices of different species using December 1993 as a common base. For most of the 1990s, prices tended to move together. Then, in 1998–99, a general reduction in prices took place, particularly for carnations. After that time, the rose price increased clearly more than the price of the two other species. While rose prices were up by almost 30 percent at the middle of 2008 compared with the 1993 level, carnations were up by only about 15 percent and chrysanthemums down by roughly 5 percent.

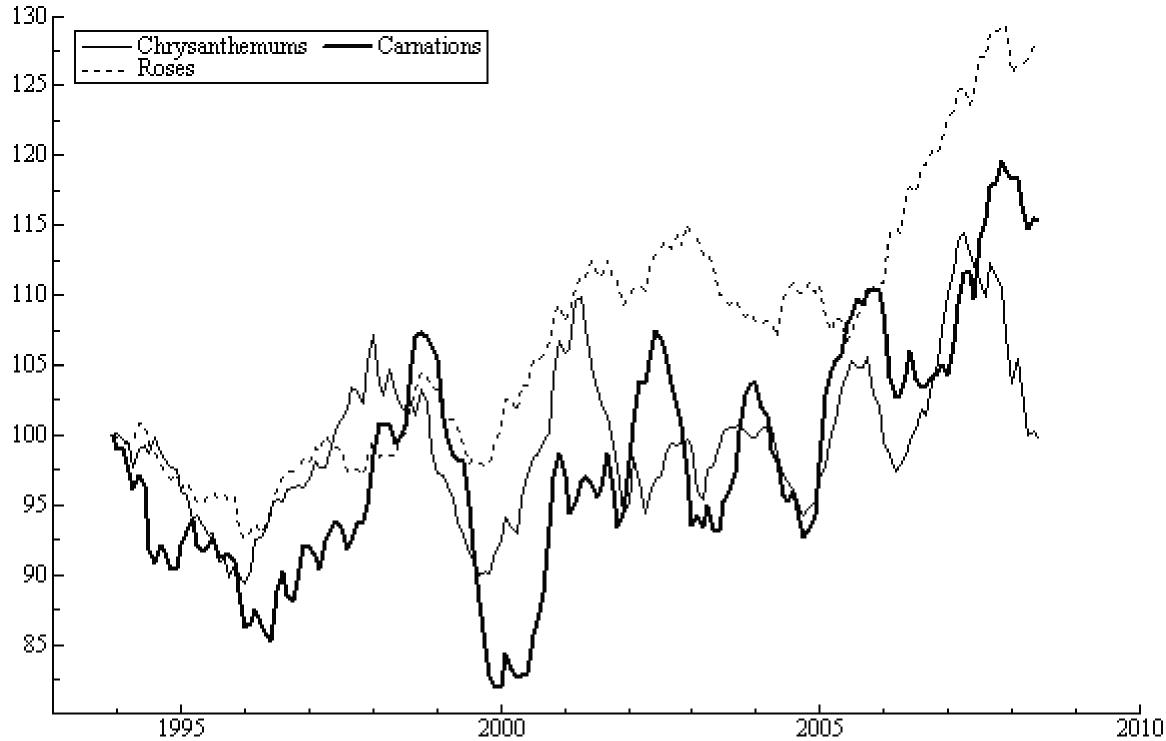

Figure 7. Price indices (smoothed) for roses, chrysanthemums and carnations 1993–2008 (December 1993 = 100).

Figure 8 illustrates this from a different angle, showing the scatter plot for the relative rose/chrysanthemum price together with a series for the smoothed average (exponentially weighted, alpha = 0.3) and the trend line. While a rose stem in the early 1990s was priced on average at 80–90 percent of a chrysanthemum stem, the rose stem attracted roughly the same price as a chrysanthemum after 2005. Thus, there seems to be a long-term trend in consumers' preferences toward roses relative to chrysanthemums. However, the huge and regular gyrations in the relative price clearly show that the two species have their separate high weeks when the relative price may move by as much as 30–40 percent over very short periods.

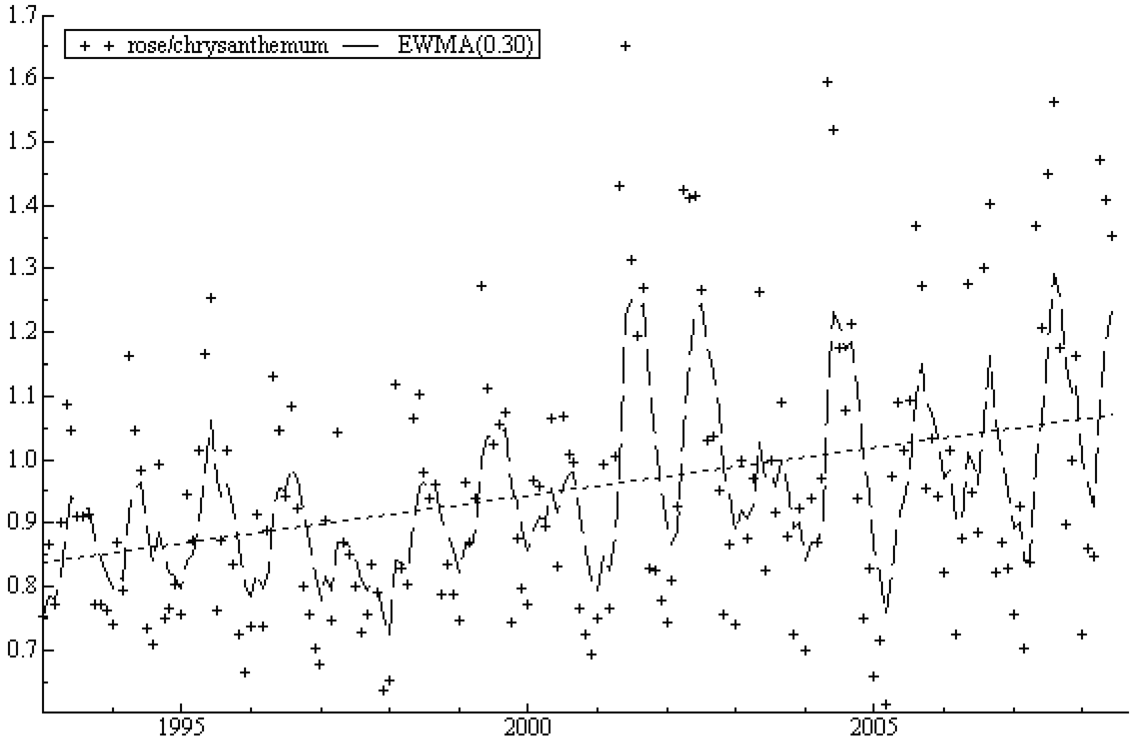

Figure 8. Relative prices roses/chrysanthemums, January 1993 to June 2008 (monthly data). Scatter plot; trend and smoothed (exponentially weighted moving average, alpha = 0.3).

Roses saw a price increase relative to chrysanthemums during the study period. Disregarding the seasonal price variations, roses became roughly 20 percent more expensive during the period. Carnations also became relatively more expensive than chrysanthemums in this period, by approximately 10 percent.

Changes in consumer preferences are also revealed through changes in realized demand. Figures 9 and 10 show the relative traded volumes of roses versus chrysanthemums and carnations, respectively.

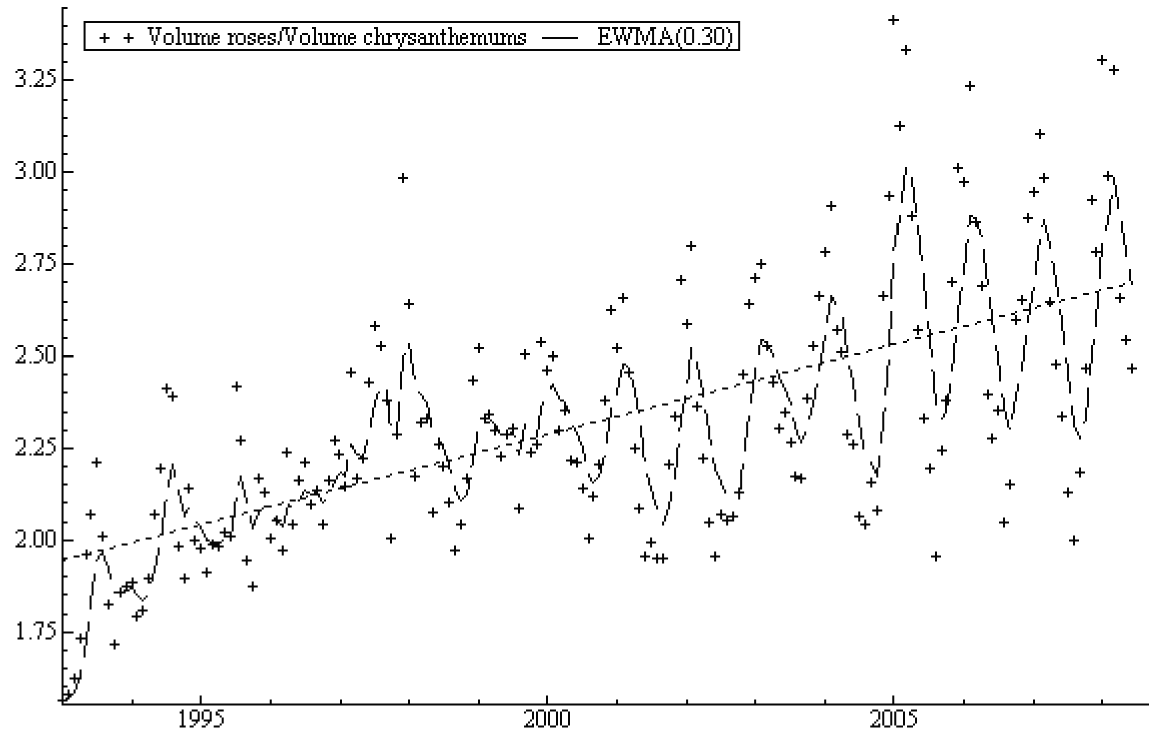

Figure 9. Relative traded volumes of roses/chrysanthemums from January 1993 to June 2008 (monthly data), scatter plot, trend and smoothed (exponentially weighted moving average, alpha = 0.3).

Disregarding seasonal variation in demand, the volume of roses traded in 1993 was about twice that of chrysanthemums. By the end of the period, in 2008, the volume of roses traded had increased to more than 2.5 times that of chrysanthemums.

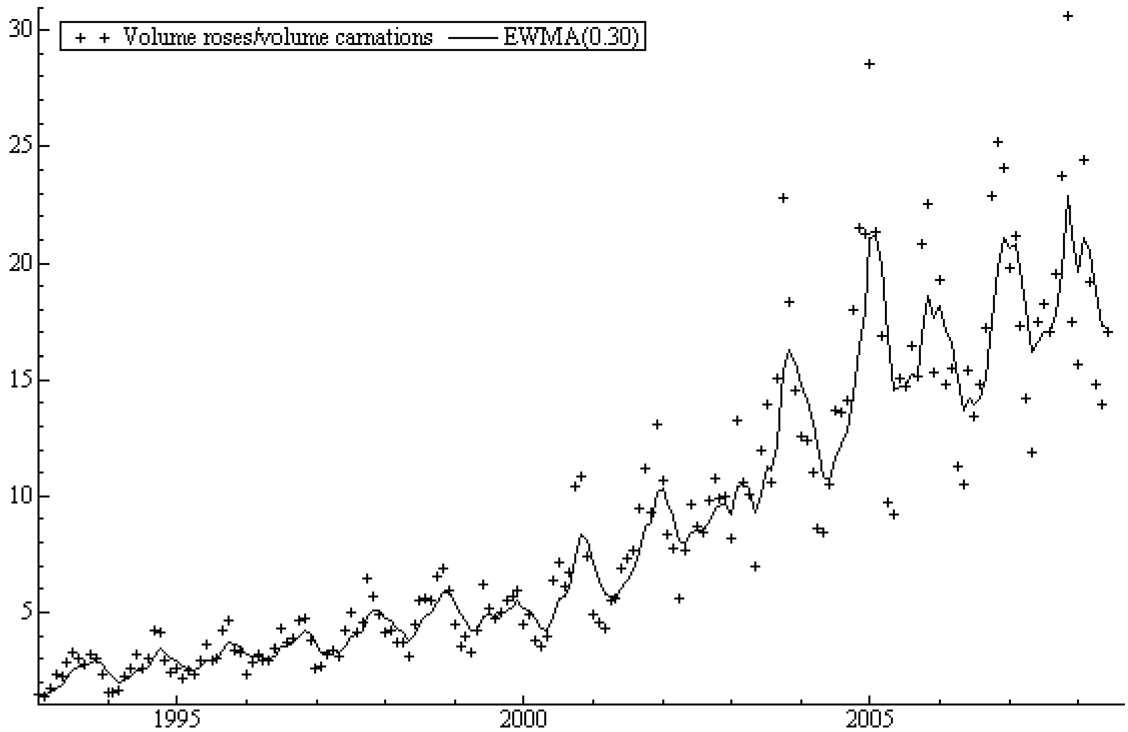

Figure 10. Relative traded volumes roses/carnations from January 1993 to June 2008 (monthly data), scatter plot, smoothed (exponentially weighted moving average, alpha = 0.3).

Roses clearly outpaced the other two species in terms of turnover and for carnations, even at an accelerating pace. For roses versus carnations, the change was extreme. At the beginning of the period, the volume of roses traded was about twice that of carnations, while at the end of the period (2008), the volume of roses traded was more than 20 times that of carnations. Therefore, rather than a linear trend as in roses versus chrysanthemums, we may talk about an exponential trend.

Flower prices, energy prices and the international flower trade

Cut flowers are beautified energy. During photosynthesis, carbon dioxide and water, in the presence of light and energy, are transformed into organic material and oxygen.

Energy costs form a large proportion of the variable costs of floriculture in Holland, as in other North European countries. The Dutch greenhouse industry accounts for 7 percent of the total energy use in the Netherlands, and approximately 4 percent of total CO_2 emissions (Lansink et al, 2001).

Energy costs can be reduced by investments in energy-saving technologies. The Dutch greenhouse sector has signed an agreement with the government aiming to reduce the energy use per unit of production by 65 percent between 1980 and 2010 (Stuurgroep Landbouw en Milieu, 2000). Energy use has been reduced since 1980 but, according to Stuurgroep Landbouw en Milieu (2000), it will be very difficult to achieve that target.

Net present value calculations evaluating the profitability of investments in energy-saving technologies in Dutch floriculture predict a much higher rate of adoption of such technologies than is actually observed (Diederen et al, 2003). One possible explanation for this is that the profitability of the investment is uncertain because of the stochastic nature of energy prices (Hasset and Metcalf, 1993). There is also uncertainty about the effects of increased production in other countries, viz. in Africa.

Another way to reduce energy use in the floriculture sector is to substitute solar power for oil, gas and electricity through imports from countries better endowed with sunlight.

If we observe large reductions in the long-term flower price/energy price ratio, this can be interpreted as the effect of changing production location, i.e., imports from countries in Africa, South America and Southeast Asia.

Figure 11 shows the ratio of monthly rose (Eurocent/stem) to crude oil (USD/bbl) prices.

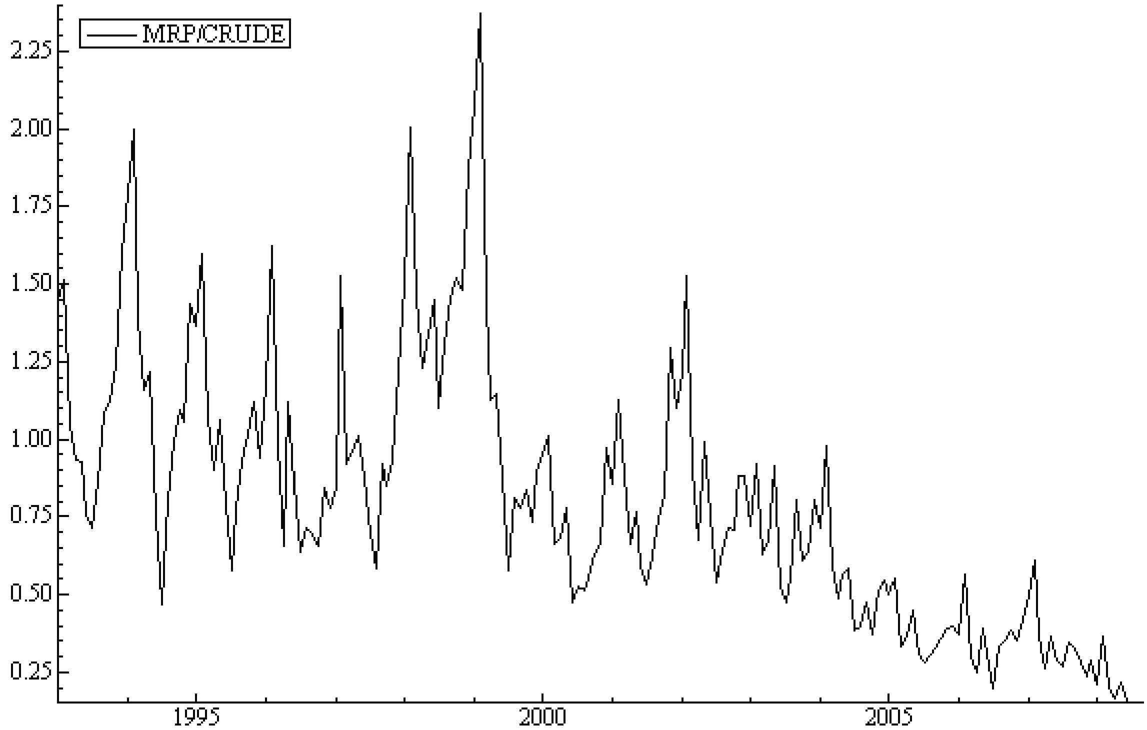

Figure 11. The ratio of monthly rose prices (MRP) measured in Eurocent/stem relative to the price of crude oil measured in USD/bbl, from January 1993 to June 2008.

The figure shows that until 1998 this ratio fluctuated around 1. From 2002 to 2003, this ratio decreased dramatically, and by 2008 it had fallen to approximately 0.25. Other cut flower prices show the same trend. We also observe less seasonal variation in the flower–oil price ratio. In other words, the price of cut flowers decreased dramatically relative to the price of energy (oil) after the 1990s. Because the introduction of more energy-efficient production in the Netherlands and northern Europe cannot explain the drastic cuts in energy use in flower production, the reason behind this development must be found elsewhere. The most obvious explanation is that there has been a change in energy sources in flower production. Through increased imports, solar power has been substituted for oil and gas.

As shown in Table 1, from 2004 to 2007 there was an increase of imports from non-European (African, Southeast Asian and South American) countries to Europe of 25 percent. Rose imports from these countries to the EU countries increased by 46 percent in the period 2004–2007. This clearly supports the hypothesis that changes in the output price/energy price ratio can be used to explain shifts in location of flower production. This is not the focus of this paper, but would be an interesting extension of this work.

Conclusions

Prices and traded volumes at the Dutch flower auctions during the 15 years from 1993 to 2008 reveal a number of distinct patterns and trends. For one, prices are highly volatile with persistent and strong seasonal patterns. The seasons are largely unique to each species of flowers. However, for some species the seasonality has gradually become less distinct. This is particularly the case for roses, which now seem to be year-round flower, while the demand for chrysanthemums continued to follow a more traditional cycle during the period of investigation. Flowers have become less expensive in real terms since the 1990s. Further, a relative increase in the price and demand for roses compared to other cut flowers indicates shifts in consumer preferences toward roses. Roses are clearly outpacing the two other major species in terms of turnover during the period of investigation, and for carnations, this is happening at an accelerating pace. While production in Europe is stable or declining, it is increasing rapidly in Africa, Asia and South America, and many Asian countries have experienced strong growth in consumption. This shift can also be traced as a decrease in cut flower prices relative to energy prices, especially during the last five years of the study period, due to strong growth in exports of flowers from Africa, notably Kenya, to Europe.

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[i] I would like to thank the referee for valuable comments on a previous version of the paper.

[ii] Performing arts differ in that such assets may be stored as audiovisual recordings.

[iii] Bolle (2001) discusses such signals in the light of cooperation and exploitation, in terms of transaction cost economics.

[iv] The history of the Dutch flower trade is discussed in, e.g., van Lier (2005).

[v] Why tulips only became the focus of a mania is hard to understand, as there were many flowers at the time that were considered more beautiful than the tulip.

[vi] The history of tulip virus diseases is discussed in, e.g., Lesnaw and Ghabrial (2000).

[vii] 1 aas = 1/564th of an ounce. The calculation of the index is explained in detail in Thompson (2007).

[viii] For an in-depth analysis of the history of flower markets and the potential of Asian commercial flower production, see Wernett, 1998.

[ix] The data on flower production, exports, imports and consumption are collected from International Statistics Flowers and Plants, 2005 and 2008.

[x] The EU data for 2007 include data for two new member countries, Bulgaria and Romania.

[xi] On a "one-armed clock", the clock arm moves counterclockwise, starting at a high price, which falls until the first buyer stops the clock at the price he or she is willing to pay.

[xii] Trip et al (2000) examined the price-predicting abilities of Dutch chrysanthemum farmers, finding evidence that predicting relative price positions (relative to other cultivars) was a skill. They also found that price differences among cultivars were nonrandom in time and that growers could adapt their production planning and cultivar choice to benefit from expected price variations.

[xiii] A more precise definition is "A sequential, private value auction of identical objects" (van den Berg et al, 1999).

[xiv] There is a huge body of literature on auction theory. A classical reference on auctions and bidding is McAfee and McMillan (1987). Van den Berg et al (1999) analyze the presence of declining prices at the auctioning of roses at the Dutch flower auctions. In addition, Kambil and van Heck (1995) perform an in-depth study of the features, strengths and weaknesses of the Dutch auctions and the effects of the introduction of new trading mechanisms based on information technology.

Essay 2

"When the night has been too lonely

and the road has been too long

and you think that love is only

for the lucky and the strong.

Just remember in the winter

far beneath the bitter snows

lies the seed that with the sun's love

in the spring becomes the rose".

Bette Midler, lyrics from "The Rose"

Forecasting Prices at the Dutch Flower Auctions[1]

Abstract

Prices at the Dutch flower auctions are extremely volatile. Price changes of +/-20 per cent one week to the next represent a normal event, and +/- 50 per cent is not uncommon. Since production planning in the flower business offers a complicated variation over the Newsboy Problem, good price forecasts would improve decision making on space allocation; what species to plant; the timing of harvesting, etc. The present paper analyses weekly prices for three major species, i.e. roses, chrysanthemums, and carnations, 1993-1996. We find that particularly for roses and chrysanthemums, there are strong calendar regularities. Establishing a model in which we combine information on seasonal regularities and autoregressive price patterns, we manage to explain a substantial part of the short-term price variability for all three species. The model is tested in an out-of-sample dynamic forecasting experiment during the first 35 weeks of 1997.

Introduction[2]

"The Dutch Tulip Mania" (1634-37) holds a prominent position in the Hall of Fame of "Extraordinary Popular Delusions and the Madness of Crowds" (Mackay, 1841). Outrageously speculative activities in the tulip market generated a gigantic price bubble, which subsequently burst[3].

The Dutch flower business, however, survived. Today's production in the Dutch ornamental plant industry is approximately USD 3 billion annually. This is twice as much as the German production and even more than that in the US[4]. A large part of the Dutch production is traded

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[1]Previously published: Steen, M. & Gjølberg, O. 1999. Forecasting Prices at the Dutch Flower Auctions. *Journal of Agricultural Economics,* 50**,** 258-268.

[2] We gratefully acknowledge some very useful comments from two anonymous referees on an earlier version of the paper.

[3] Garber (1990) presents interesting views on historic "bubbles", including the Tulip Mania.

[4] Detailed international production, value, trade and consumption statistics are published in the AIPH - Union Fleurs Statistical Yearbook. The data set used in this paper is collected from the weekly journal "Vakblad voor de Bloemisterij". The data are available on diskette from the authors on request.

at the flower auctions organised through the Association of Dutch Flower Auctions (VBN - Vereniging van Bloemenveilingen in Nederland). Furthermore, the Dutch auctions are market places for flowers produced elsewhere in the world, notably the increasing volume of imports from African producers.[5] Thus, the Dutch flower auctions serve as a place for price formation and information in domestic as well as international flower trade.

Although considerably less volatile than during the days of the tulip mania, short-term price changes in the Dutch flower market are still substantial. During recent years, major species have shown coefficients of variation based on *weekly* price observations from 22 per cent for carnations, 30 per cent for roses, and to 34 per cent for chrysanthemums (see table 1). The standard deviations of *weekly* per cent price changes are in the range of 17 - 20 per cent. Thus, on an annual basis[6], we have standard deviations of price changes from 120 to 140 per cent! This makes cut flowers probably *the* most volatile agricultural commodity. Cereals, potatoes etc. rarely show annual standard deviation of price changes beyond 20-30 per cent.

Some of this volatility is due to seasonal variations that are fairly regular in terms of the *direction* of the medium and long run[7]price changes. When making decisions as to whether one should cut the flowers today or wait another week, a long term upwards price trend may, however, be of little comfort. This is visualised in figure 1, showing the weekly per cent price changes for chrysanthemums and carnations 1993-96. While it is not uncommon that prices raise or drop 20-30 per cent from one week to the next, one has on several occasions during the last years witnessed weekly changes in the range of +/- 50-60 per cent! Cereals or other

[5] African horticultural exports have been expanding significantly during the last few years. In particular Kenya has a remarkable export performance, +20 per cent annually during the last five years. Kenya exported almost 36,000 tonnes of blooms to Europe in 1997, of which some estimated 24,000 tonnes were sold at the Dutch auctions. (Financial Times, April 23, 1998)

[6] 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 due to serial correlations in the changes.

[7] "Medium and long run" are relative entities. In the production and marketing of cut flowers, 3-6 months can be considered a long period.

agricultural commodities rarely exhibit short-term price changes in the neighbourhood of those reported from the Dutch flower market. Arriving one or two weeks too late or too early in the flower market, may represent significant opportunity losses. Obviously, the ideal situation would be the ability for a producer to predict such price changes at the start of a production cycle, 3 - 4 months ahead of harvesting. This would, however, be somewhat too optimistic. A more realistic goal would be to develop models that could improve forecasts 2 - 4 weeks ahead. Given the short-term volatility in these markets - and the possibility for producers to time marketing by regulating light and temperature, such short-term forecast could be of great economic value.

Table 1. Flower prices at the Dutch auctions; means and variability. Weekly observations 1993-96

	Cents per unit, Means	Std. Deviations	Weekly coefficients of variation
Chrysanthemums	46.37	15.87	34%
Carnations	26.59	5.89	22%
Roses	39.68	12.08	30%

Source: Weekly editions of "Vakblad voor de Blomisterij".

A major reason for the significant price volatility in the flower markets is, of course, the fact that cut flowers are rapidly perishable goods that not easily can be carried in inventory and sold in future periods. The inventory management has to be conducted prior to cutting, i.e. through decision-making on how much to plant, when to plant, and how much heat and light to be applied on standing stocks.

In the next section, we elaborate on the flower producer's decision problems as such. We then present empirical evidence in terms of price data from the Dutch flower auctions. The time series are decomposed in order to reveal seasonalities and autoregressive patterns. We also test for stationarity in order to establish models from which we can draw statistically sound conclusions. In the subsequent section we summarise the results from a specification search in a number of diagnostic tests of different time series models. The last section reports the results from applying a simple time series model with calendar effects in an out-of-sample forecasting experiment for the first 35 weeks of 1997.

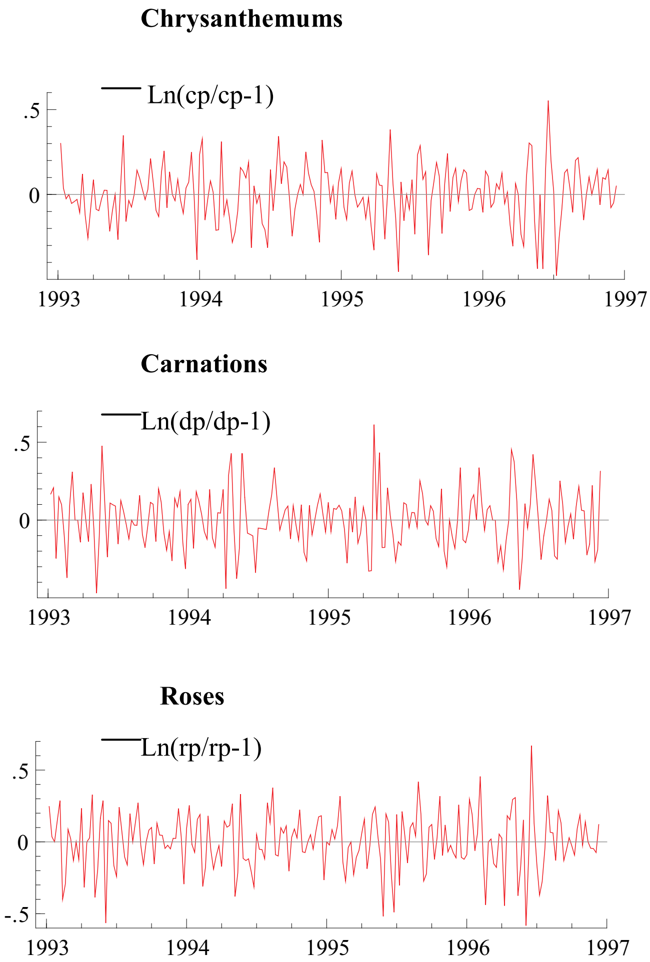

Figure 1. Weekly per cent price changes; chrysanthemums, carnations and roses, 1993-96

The flower producer’s problem

Decision-makers occupied with production planning and marketing in the cut flower business are faced with a number of rather challenging problems, one being similar to that of the newsboy. Orders have to be placed, i.e. flowers are rooted, several months prior to marketing. Once blossoming takes place, decay occurs rapidly. Just like yesterday’s newspaper, there is little demand for last week’s fresh flowers. True, cut flowers can be stored at reduced temperatures for a few days and blossoming can be delayed by regulating the amount of light exposure during the weeks prior to cutting. Beyond this, little can be done in terms of adjusting to stochastic demand once the plants are rooted.

Since stocks are limited by the size of the greenhouse, the "newsboy problem" for decision makers in this case is also a question of which product to order or which portfolio ("bouquet") of flowers to plant at a given space and time. The space for inventories is limited and represents a major cost in production. Therefore, the opportunity cost from having planted too many chrysanthemums given the demand subsequently observed is not simply the costs from producing an excess amount of this specific flower. The space allocated to chrysanthemums obviously could have been used for growing, say, carnations. Theoretically, the demand for the two may be negatively correlated. Thus, having planted what turns out to be a too large area of chrysanthemums means an even greater loss from not having planted more carnations. Consequently, decision-makers are confronted with both a decision problem related to portfolio composition and a "real option" problem related to flexibility and irreversibility. Planting X square meters of roses means that one forsakes the option of planting carnations on that very acreage for a given period of time. This is an irreversible decision for the subsequent production period, and to some extent also for production later on.

Different flower varieties have widely different growth cycles. Roses can be harvested several times a year, depending on temperature and the amount of light applied. Before the first generation is harvested, however, there is a rather long gestation period. Other varieties, like for instance chrysanthemums, enter very fast into the harvesting stage. However, once the first production phase is started, there are biological restrictions as to when the second, third etc. cohort can be harvested. To the extent that demand follows systematic calendar patterns during the year, the problem facing the decision-maker is that of phasing biological and business cycles together. Price peaks and throughs do, however, occur at different times for different species. Skimming the cream in the market by planning for systematic deliveries at the peaks is not easy since production periods very often differ widely from the business cycles. In addition, production costs vary during the year. In greenhouse production, energy is a major cost. The energy input for heating and light depends partly on fairly deterministic seasonal factors, but of course also of unpredictable temperature fluctuations. Stochastic energy prices add to the cost uncertainty.

Flower price characteristics: Time regularities and stationarity

Plotting median prices for week 1 - 52 for the years 1993-96 (figure 2) reveals seasonal regularities in the rose and chrysanthemum prices. As regards the roses, a very distinct price peak can be observed around week 6-7 every year. Then prices fall continuously until there again is a peak, or rather a number of peaks, in the early summer, normally around week 16-18. The general downward trend (disregarding the summer peaks) turns around week 30, when the price starts to climb gradually towards the winter season.

In the chrysanthemum market, there is a U-shaped price profile over the calendar year with a general upward trend from around week 27-30 until prices again drift downwards from around week 5-10. There are, however, local peaks within this "valley", notably a typical boom during the weeks 17-18 and some odd peaks around week 32-36.

For a third major species, i.e. carnations, the picture is less clear. Although one may glimpse some calendar regularities during parts of the year (like a general price reduction week 40 - 50), there are great variations in the timing of ups and downs from one year to another.

The differences in calendar regularities across species are revealed in the simple inter-year correlations in weekly prices. Thus, weekly rose prices show correlations across years from .66 (1994 vs. -96) to .85 (1993 vs. -94) and chrysanthemums .73 (1994 vs. -96) to .87 (1993 vs. -94). For carnations, on the other hand, the correlation across years is significantly different from zero (.43) only 1994 vs. -95. This is further illustrated in the autocorrelation plots in figure 3. For chrysanthemums, we see a significant annual cycle, with a peak in the plot around t-52. There is also a significant half-year cycle, with negative autocorrelation values outside the 5% significance line around t-26. A similar pattern is revealed in the rose plot. As regard the carnations, the autocorrelation plot is sinusoidal with peaks and throughs spaced some 5-10 weeks apart. These are, however, generally inside the 5% limits.

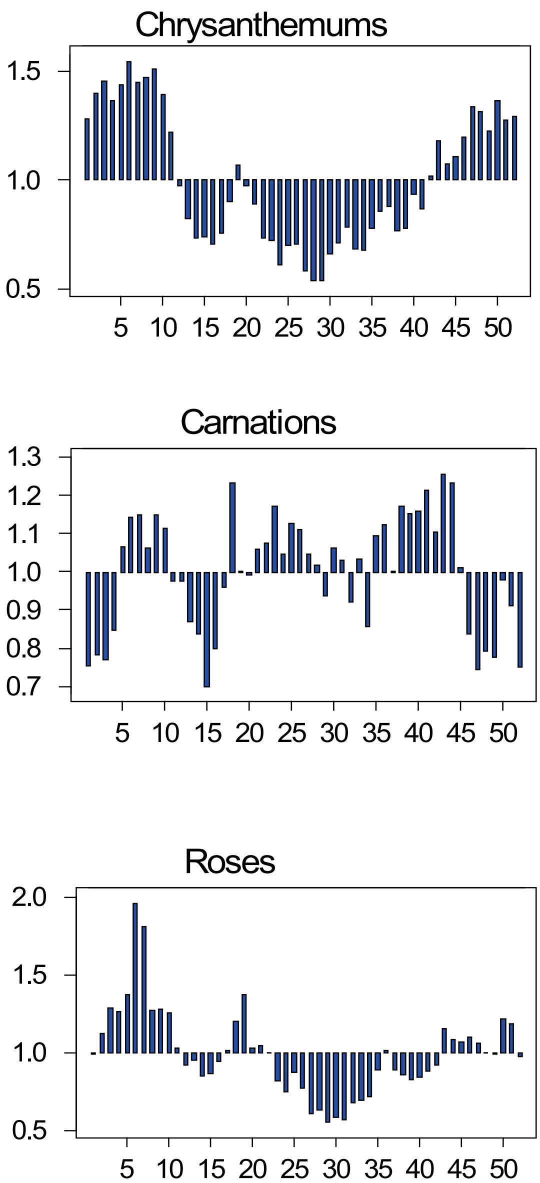

Figure 2. Seasonal indices; chrysanthemum, carnation and rose prices, week 1-52, 1993-96

The autocorrelations functions of the 52-week price differentials are plotted in figure 4. Together with the plots for the autocorrelations in levels (figure 3), these plots strongly indicate that the price series are stationary with an annual season. The autocorrelation functions in levels drop fairly rapidly towards zero, while those for the 52-week price differentials immediately move inside the 5%-lines. This visual impression is supported by more formal ADF-tests for unit roots. Thus, we have estimated

$$\Delta p_t = \alpha + \rho p_{t-1} + \sum_k \gamma_k \Delta p_{t-k} + \lambda p_{t-52} + \varepsilon_t \qquad (1)$$

for all three species. Δp_t is the price change from last week, while p_{t-i} is the price level in week t-i. An estimated ρ that does not differ significantly from zero indicates unit roots or non-stationary prices. The test statstics for ρ are reported in table 2 for k = 3, 5 and 8 lags for prices in levels (p_t) as well as for 52-week differences (p_t-p_{t-52}). The results are easily summarised. For all k, the null hypothesis (non-stationary in levels or differences) is rejected at 5% level.

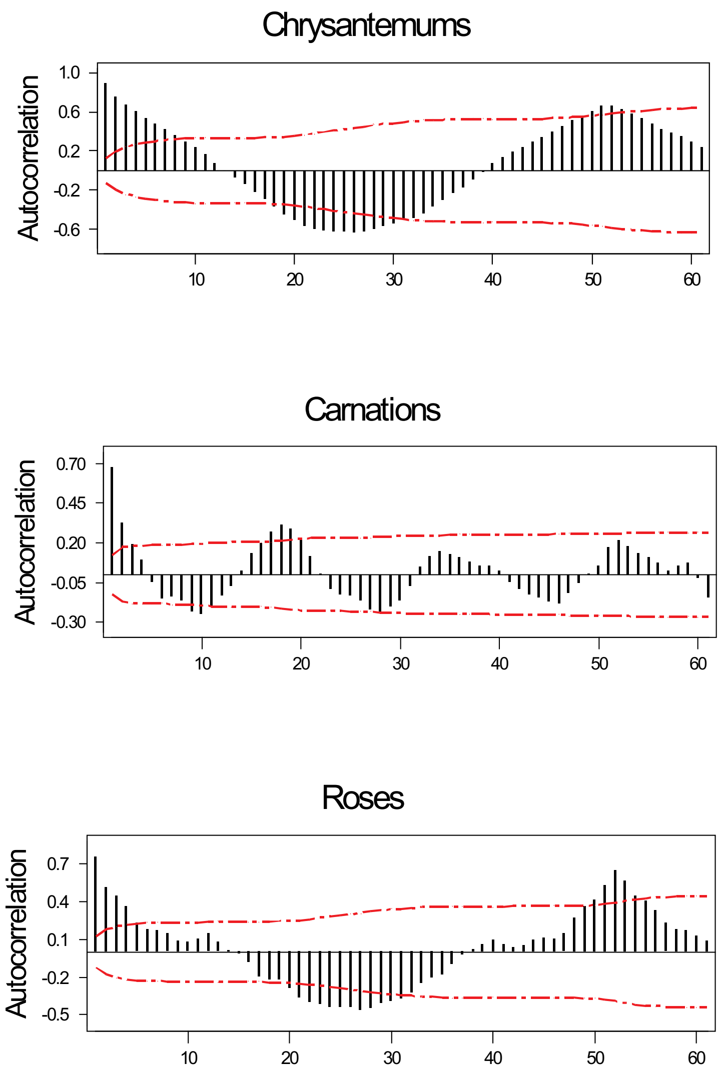

Figure 3. Autocorrelation functions; weekly chrysanthemum, carnation and rose prices 1993-96

Table 2. Augmented Dickey Fuller tests for stationarity

		k = 3 lags	k = 5 lags	k = 8 lags
Chrysanthemums	Price level	-5.621	-5.503	-5.454
Carnations	Price level	-5.332	-5.328	-5.772
Roses	Price level	-8.893	-8.353	-7.849
Chrysanthemums	52-week difference*	-5.816	-4.989	-3.197
Carnations	52-week difference*	-4.596	-5.327	-4.342
Roses	52-week difference*	-5.551	-4.198	-3.515

* = no season included
Critical values ADF test-statistics: 1% = -3.45; 5% = - 2.881; (MacKinnon, 1991)

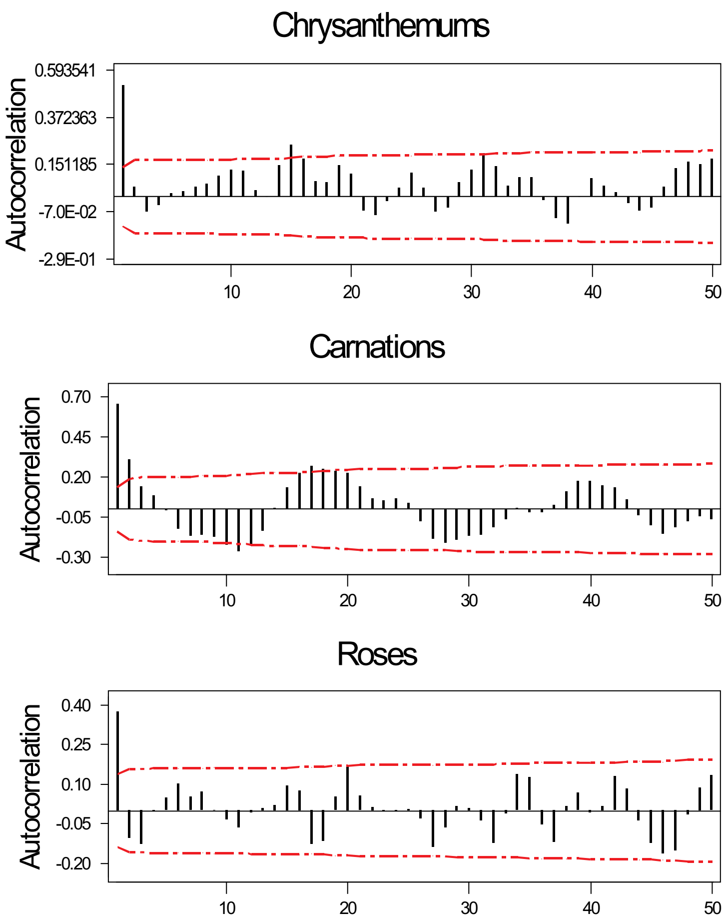

Figure 4. Autocorrelation functions; 52-week price differentials (p_t-$p_{t\ -52}$), weekly observations 1993-96.

Diagnostic testing

The autocorrelation plots above, together with plots for the partial autocorrelations (not reported), suggest that flower prices may be described as simple AR-processes adjusted for seasonality. In order to analyse this more systematically, we conducted a number of diagnostic tests on various ARIMA-type models. The aim of this search was to establish fairly simple models that can be applied in *ex ante* forecasting. Such diagnostic testing basically amounts to establishing models that explain a significant amount of the price variance while at the same time generating an error term that resembles white noise (Box et al, 1994, chap. 8).

Without going into details in the specification search, the results can be summarised as follows. A simple AR-specification (without seasonality included) did *not* produce white noise error terms for chrysanthemums as tested by a standard Lagrange-Multiplier (χ^2). For carnations and roses, on the other hand, the residuals in an AR(5) specification came out as uncorrelated. For chrysanthemums and roses, the explained variance increased when adding the price 52 weeks ago as an explanatory variable.

After having experimented with different specifications, we came to the conclusion that for chrysanthemums and roses a simple combination of an AR-process and seasonal regularities across species represents a good characterisation of short and medium term price movements in this market. The price of y (e.g. roses) in week t is as a function of y's price the five preceding weeks as well as its price 52 weeks ago *and* the price of the two other species 52 weeks ago. Defining chrysanthemums as 1, carnations as 2 and roses as 3, we have

$$p_{y,j} = \alpha + \sum_{i=1}^{5} \beta_i p_{y,t-i} + \sum_{j=1}^{3} \gamma_j p_{j,t-52} + \varepsilon_t \qquad (2)$$

where the γ's are the 52-week effects of chrysanthemums, carnations and roses respectively.

The estimation results are reported in table 3.

Table 3. Flower prices estimated as an A(R)-process with seasonal and cross-species effects (Eq. 2)

	α	β_1	β_2	β_3	β_4	β_5	γ_1	γ_2	γ_3	AdjR^2	χ^2(26 lags)
Chrysanthe-mum	12.33 (3.71)	0.80 (9.34)	-0.38 (-3.52)	0.17 (1.58)	-0.05 (-0.53)	-0.02 (-0.25)	0.25 (3.68)	-0.37 (-3.40)	0.18 (2.20)	0.84	29.49 [0.29]
Carnations	10.01 (3.27)	0.93 (11.09)	-0.43 (-3.73)	0.21 (1.76)	-0.03 (-0.33)	-0.10 (-1.12)	-0.02 (-0.61)	0.03 (0.46)	0.03 (0.58)	0.56	22.68 [0.65]
Roses	10.04 (3.05)	0.64 (8.23)	-0.43 (-4.54)	0.31 (3.19)	-0.19 (-2.02)	0.06 (0.84)	-0.02 (-0.46)	-0.26 (-2.63)	0.56 (6.50)	0.78	26.99 [0.41]

( ) = t-values
χ^2 = Lagrange-Multiplier (LM) test for serial correlation
[] = significance level χ^2 test

The residuals come out close to white noise (we have reported the χ^2 for 26 lags, the results are confirmed when testing for widely different lag lengths). For chrysanthemum and roses the model explains a substantial part of the variation in weekly prices (84% and 78%). For chrysanthemums, all the γ's are significant at a 5% level, i.e. the price 52 weeks ago for *all* three species contains information about today's chrysanthemum price. Last year's chrysanthemum price, on the other hand, does not seem to influence today's rose price. We also observe that carnation prices last year are *negatively* related to today's chrysanthemum and rose prices.

For carnations, none of the prices last year is significant, again indicating that in this case, the best model is simply an AR(3) model. Also, carnations appear to be more difficult to predict than the two other species. On the other hand, carnation prices are less volatile in general.

Out-of-sample forecasting results

The main purpose of the empirical analysis above was that of establishing forecasting models which may be applied in production and marketing of flowers. Given the extremely high short-term price volatility in this business, good timing may yield substantially higher returns. Consequently, good price forecasts 1-12 weeks ahead may be of great commercial interest.

In order to indicate what can be achieved by applying fairly simple time series model for the forecasting of flower prices, we conducted a small out-of-sample experiment. The forecasting performance of the autoregressive model with calendar regularities and cross species effects was studied by generating out-of-sample dynamic *ex ante* forecasts for the three cut-flower species during the first 35 weeks of 1997. *Ex ante* implies that the predicted values of RHS-variables for period t+i are used when forecasting values at t+i+1 etc. in an iterative process. The results were evaluated using a naïve forecast as a benchmark, i.e. defining the price in week t-52 as a forecast for the price in week t. For many practitioners, this is most likely a relevant benchmark when forming expectations.

Table 4 summarises the forecasting results of the time series model against the naive benchmark as measured by Root Mean Squared Error (RMSE) and Mean Absolute Deviation (MAD).

Table 4. RMSE and MAD, autoregressive model with calendar regularities versus naïve forecasting rule, 199701-199735

	Time series model with calendar regularities						Naïve forecasting rule	
	One week horizon		6 weeks horizon		12 weeks horizon			
	RMSE	MAD	RMSE	MAD	RMSE	MAD	RMSE	MAD
Chrysanthemums	4.425	3.644	4.734	3.736	4.732	3.871	8.875	7.057
Carnations	4.239	3.515	4.877	3.901	5.379	4.281	5.581	4.342
Roses	5.176	3.773	6.943	5.901	6.893	5.806	6.889	5.678

Time series model: $p_{y,t}^{F} = \alpha + \sum_{i=1}^{5} \beta_i p_{y,t-i} + \sum_{j=1}^{3} \gamma_j p_{j,t-52}$

Naïve forecasting rule: $p_t^F = p_{t-52}$

It is not easy to evaluate what this forecasting performance implies in economic terms. A rough translation can, however, be obtained by comparing the MADs with the means and standard deviations of the prices as reported in table 1 in the introduction. For chrysanthemums and roses, the standard deviations 1993-96 were 12.08 and 15.87 cents per unit, respectively. RMSEs and MADs of 5-8 cents for the naive forecasts and 3-4 cents for the time series model, suggest that a substantial amount of price risk can be eliminated through quite simple forecasting models.

The results show that the time series model at both 1, 6 and 12 weeks forecasting horizons outperforms the naïve model for chrysanthemums and carnations. The same result holds for the one-week forecast of the rose prices, while in this case the naïve model comes out slightly better than the 6 and 12 week forecasts of the time series model.

Accurate forecasts in terms of low RMSEs and MADs may, however, turn out to be less economically valuable than less exact forecasts. Sometimes, it may be of greater value to decision makers to have an idea about whether prices will raise or fall, rather than forecasting the future price with a high degree of precision. Table 5 reports on the qualitative performance in terms of predicting the correct direction of price changes using the *Ratio of Accurate Forecasts (RAF).* We evaluate the success ratio in a binomial test,

$$b(x; n, p) = \binom{n}{x} p^x (1-p)^{n-x} \tag{3}$$

where x is the number of correctly predicted (in terms of sign) price changes, n is the number of price changes in total for the forecasting period (zero price changes omitted) and p is the probability of success. The latter is estimated as follows. We have considered the same period of the year, that is week 1-35, during the three previous years. If there is a seasonal drift in prices either upwards or downwards, one cannot measure forecasting success against a benchmark of p = 0.5. Therefore, we use as our benchmark the proportion of price increases (or decreases) in the 3 previous years. If, for example, the proportion of positive overlapping 6-week price changes during these periods has been 0.7 we use p = 0.7 as our benchmark. Similarly, if the proportion of positive price changes has been 0.3, we evaluate the ratio of correct forecast direction against p = (1-0.3) = 0.7.

Table 5. Ratio of accurate forecasts (RAF), time series model versus naïve forecasting rule, 199701-199735

	Time series model			Naïve forecasting rule
	One week horizon	6 weeks horizon	12 weeks horizon	
Chrysanthemums	0.69*	0.88***	0.91***	0.72**
Carnations	0.68**	0.76**	0.91***	0.68*
Roses	0.82***	0.83***	0.91***	0.69**

Autoregressive model: $p_{y,t}^{F} = \alpha + \sum_{i=1}^{5} \beta_i p_{y,t-i} + \sum_{j=1}^{3} \gamma_j p_{j,t-52}$,

Naïve forecasting rule: $p_t^F = p_{t-52}$

Level of significance: *=10%, **=5%, ***=1%

The results reported in table 5 are rather impressive in terms of qualitative accuracy of the forecasts that are based on the time series model. Over a 12 weeks forecasting horizon, the time series model forecasts the correct direction for all three species in more than 90% of the weeks, while the naive model has a success ratio of 68-72%. Also, over the 6 weeks horizon, the time series model outperforms the naïve model for all species. In the extreme short run (one week), the time series model performs better than the naïve model for roses and chrysanthemums while the two forecasts have roughly equal success ratios as far as carnations are concerned.

Conclusions

Since flower auction prices fluctuate violently, successful forecasts and market timing may substantially increase profits. In the present paper, we have demonstrated that a rather simple time series model explains a substantial amount of the short-term price variability in this market. Furthermore, in our out-of-sample *ex ante* forecasting experiment, this time series model generated good forecasts, in terms of accuracy as well as direction of price changes.

Obviously, our 35 weeks out-of-sample experiment is too small for making strong conclusions. The continued success of the presented model will crucially depend on whether the observed pattern will remain stable. For the period in our study, recursive estimation as well as standard Chow-tests indicates that the parameters have been very stable. This may, of course, change. However, based on evidence from the last 3-4 years we conclude that agents operating at the Dutch flower auctions may obtain profitable forecasts by utilizing fairly simple time series models.

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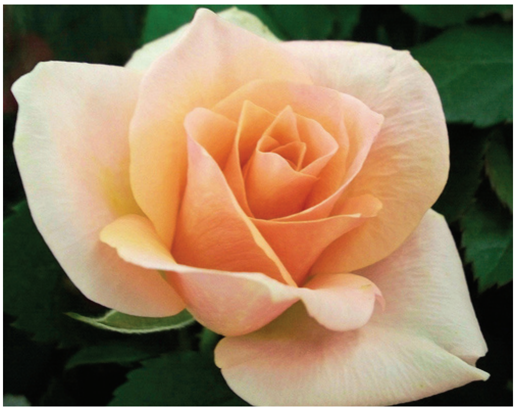
Essay 3



"On the third day he took me to the river
He showed me the roses and we kissed
And the last thing I heard was a muttered word
As he stood smiling above me with a rock in his fist

On the last day I took her where the wild roses grow
And she lay on the bank, the wind light as a thief
As I kissed her goodbye, I said, "All beauty must die"
And lent down and planted a rose between her teeth

They call me the wild rose
but my name was Elisa Day
Why they call me it I do not know
For my name was Elisa Day"

Nick Cave, lyrics from
"Wild rose"

Forecasting Prices at the Dutch Flower Auctions
- A Partial Least Squares (PLS) Regression Approach

Abstract

In this paper, Partial Least Squares (PLS) regression is applied to establish short- and medium-term price forecasts for cut flowers, using weekly price data from the Dutch flower auctions 1993-2008. The forecasting performance is studied generating h-step ahead, out-of-sample PLS forecasts for three major cut flower species. The PLS forecasts are compared with forecasts from univariate time series (AR) models, general time series models and a naïve model. The results show a very good overall performance for PLS. In general, PLS outperforms the second best method (simple AR models). This is especially clear in cases where significant information is contained in variables often omitted from simpler models.PLS can be recommended as a forecasting method compared to more standard forecasting models, measured both quantitatively (RMSE) and qualitatively (predicting the correct direction of price changes). In order to evaluate the economic results from applying PLS forecasts, alternative planting and harvesting decision rules are simulated. PLS turned out to yield clearly better results than a no-forecast strategy when applied in an out-of-sample experiment.

Introduction

The Dutch flower auctions are the main areas for trade, pricing, transmission of information in European floriculture and the major market places for flowers worldwide. A large volume of trade passes through the auctions, which to a large extent determine prices also outside the auctions. Floraholland (2009) reported a turnover of €16.7 mill per day in 2008. Both prices and traded volumes are highly volatile, and flower producers and traders could reduce risk substantially if they could base their planting, harvesting and marketing decisions upon good forecasts of prices and traded quantities.

Steen and Gjølberg (1999) have established a simple time-series model for short-term (1, 6 and 12 weeks) forecasting of the auction prices of three important cut flower species;

chrysanthemums, carnations and roses. They compared autoregressive models with calendar regularities to a naïve forecasting rule, i.e., that the price a certain week would be equal to the price the same week the year before. Their main conclusions were that the time series models, in terms of accurate forecasts, in general performed somewhat better than the naïve forecasting rule for chrysanthemums and carnations, but not for roses. In terms of predicting whether prices would go up or down, the time series models performed better than the naïve forecasting rule for 6 and 12 weeks forecasting horizon, but not for the one week horizon. The main result was that the time series models generated good forecasts, but that that their sample was too small (5 years of data in total) to make strong conclusions.

A common problem in forecasting is defining an appropriate model. The bigger and more complex the model the potentially more accurate the forecasts may become. On the other hand big and complex models often suffer from overfitting and multicollinearity, which reduces forecasting accuracy. Alternative measures are available to select forecasting models for classical time series models to take this into account, such as model selection based on out-of-sample forecasting performance. In parametric models this will involve some form of variable selection, omitting variables that do not add to out of sample forecasting accuracy. However, such model selection may cause a reduction in forecasting accuracy if relevant information is lost due to omittance of certain variables. The present paper offers an alternative to this approach. We establish forecasts based on Partial Least Squares (PLS) regressions, which has received some attention in the literature due to its robustness towards overfitting and multicollinearity (Esposito Vinzi et al., 2007). PLS bears some relation to principal components regression; it finds a linear regression model by projecting the predicted variables and the observable variables to a new space. Commonly, the estimated parameters from PLS are based on a few underlying factors in the independent variables, which best serve to predict the dependent variable. PLS will give biased parameter estimates, but when the focus is on forecasting and not understanding the underlying relationship between the variables, there are no practical reasons for requiring unbiased parameters. On the other hand, PLS may generate better results than more standard methods by limiting the number of factors included in the model, and avoiding overfitting and multicollinearity without explicitly excluding variables.

There are two main purposes of this paper. One is to establish forecasting models that can be applied in the production planning and marketing of cut flowers. The other to investigate whether the partial least squares (PLS) regression model can be recommended as a better forecasting method compared to alternative models when model definition is difficult. PLS is compared to more traditional forecasting models, like general time series models and autoregressive models, and as a benchmark we use the simple times series model that our best forecast is the observed value in the same week last year.

The wide fluctuations in prices and traded quantities should encourage flower producers and traders to invest resources in trying to forecast prices and/or quantities. This paper focuses on the short and medium run. Specifically, we establish price forecasts 1-2, and up till 8-14 weeks ahead. Forecasting in the short run is interesting because it is possible to shorten or delay the end of the production period by applying more or less heat or light (Larson, 1980). Forecasting the medium run is interesting in a production planning setting, e.g. when making decisions on whether or not to start a new cohort, and which varieties to plant.

The paper is organized as follows. First, the main features of the data are outlined. Then follows an overview of some of the general forecasting literature, as well as PLS forecasting literature. Then follows a short discussion of the models used and forecasting methods applied, followed by a section where the results from an out-of-sample ex-ante dynamic forecasting experiment based on the PLS model compared to general time series models, autoregressive (AR) models, and to a naïve model where the predicted price is equal to the price in the same week the previous year, are presented. The last section presents the results from a small practical experiment, where different production strategies using forecasts are compared to alternative strategies.

Data

Weekly price and quantity data from the Dutch flower auctions are published in "Vakblad voor de Blomisterij". We are using data from the first week of 1993 through week 25, 2008 for three major cut flower species; roses, chrysanthemums and carnations. The period 1993(1)-2007(25) is used to establish the models, while the forecasting period spans the weeks 2007(26) through 2008(25).

The basic statistics of the data are shown in table 1. During the period 1993 to 2008, the coefficients of variation range from 24 per cent (carnations) to 33 per cent (chrysanthemums).

Table 1. Correlations, Means, Standard Deviations and Coefficients of Variation (CV); Weekly Prices, 1993 to 2008

	Chrysanthemums	**Carnations**	**Roses**
Carnations	0.798		
Roses	0.655	0.260	
Mean (Eurocents)	21.89	12.82	19.94
Std. deviation (Eurocents)	7.31	3.06	5.77
CV (%)	33.4 (%)	23.9 (%)	29.4 (%)

Figure 1 shows the weekly prices of roses, chrysanthemums and carnations during our forecasting period (week 26,2007-week 25,2008). As we can see prices are highly volatile. Price changes of 30-40 per cent from one week to the next are not unusual.

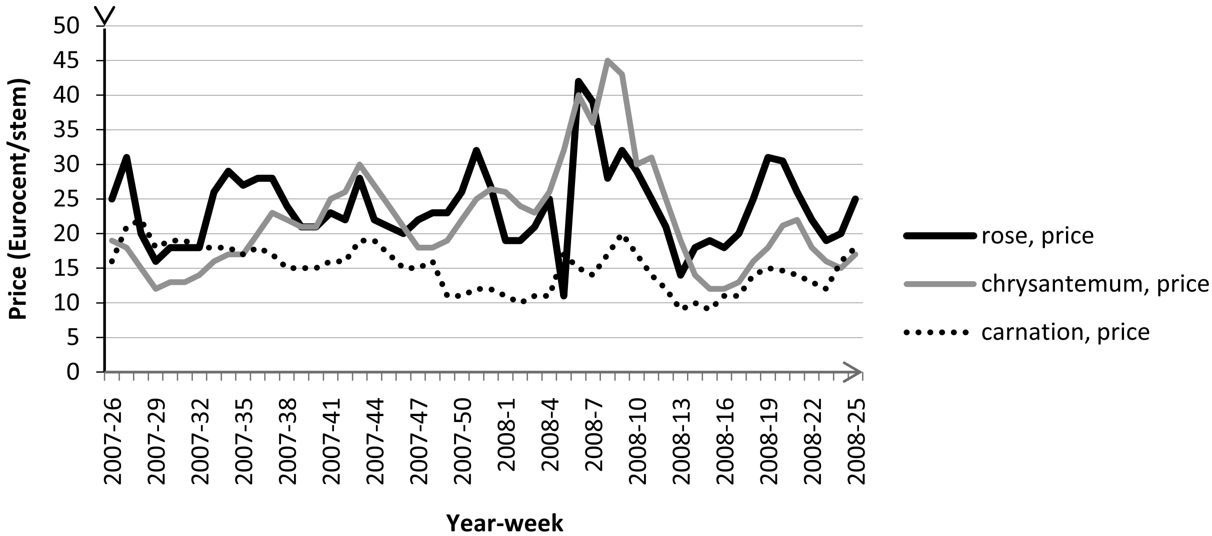


Figure 1. The nominal price of chrysanthemums, roses and carnations (Eurocent per stem) week 26, 2007 to week 25, 2008.

Chrysanthemums and roses follow similar patterns. We see high prices at the beginning of the year and low prices in early- to mid summer. For roses, there is an extreme price increase in week 6-2008, i.e., the week prior to Valentine's Day. For carnations the picture is a bit different. Here we see high relatively high prices in the late summer and fall, decreasing toward the end of the year, and increasing again until week 9. Common for all price series are that they are highly volatile.

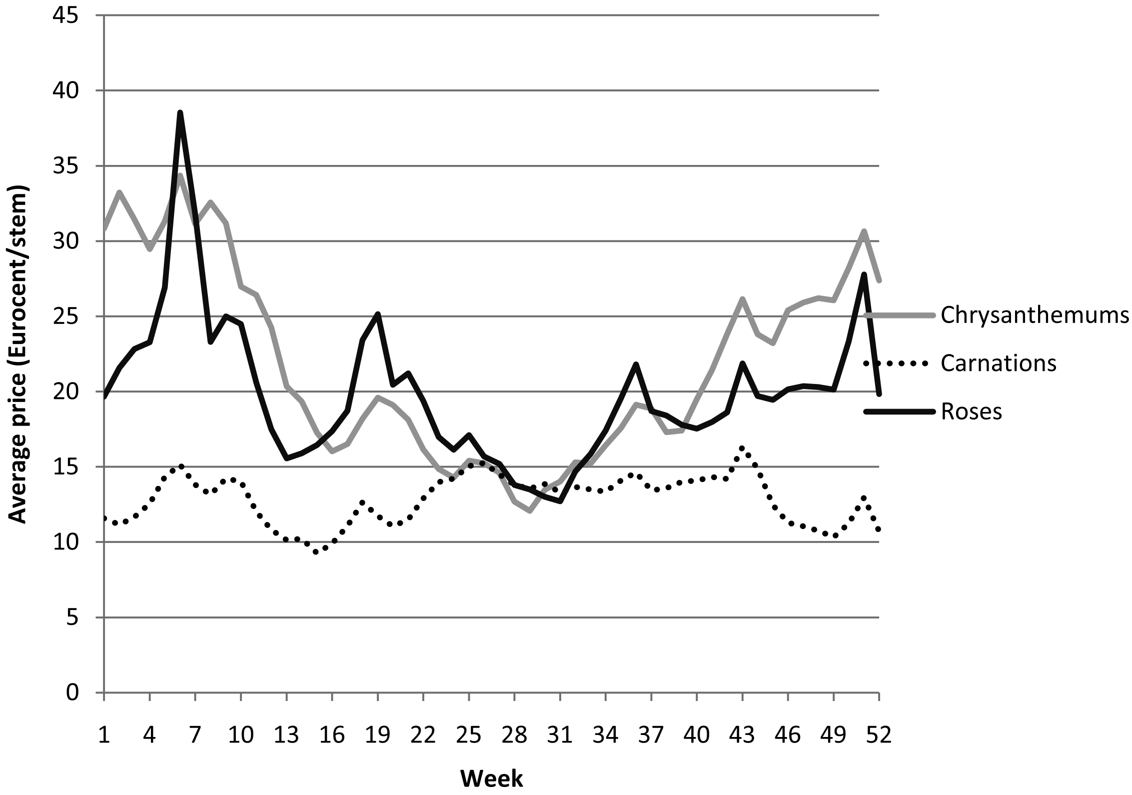


Figure 2. Average, weekly prices of chrysanthemums, roses and carnations (Eurocent per stem) week 1, 1993 to week 25, 2008.

The data show strong seasonal effects. This is illustrated in figure 2, showing the weekly average prices during 15 years.

Figure 3 shows the indices of traded volumes for the last 52 weeks of the data set, which also show high volatility. The rest of the data period of investigation gives the same general picture.

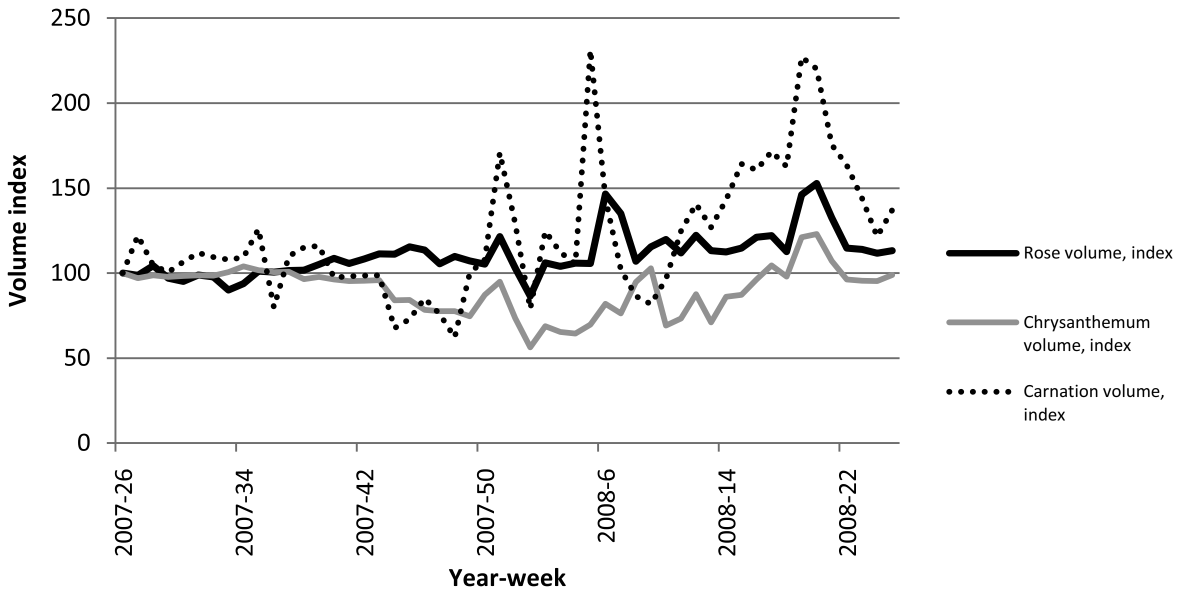


Figure 3. Traded volumes of chrysanthemums, roses and carnations week 26, 2007 to week 25, 2008. Week 26, 2007 = 100.

Literature on forecasting performance

There is a large body of literature on forecasting performance. The main classes of quantitative models used for forecasting in the field of economics are autoregressive models (AR, ARMA, ARIMA), general time series models and operational research based models.

Newbold and Granger (1974) represents an early study of the experience with forecasting univariate time series and combinations of forecasts. Reid (1975) and Schmidt (1979) compared Box-Jenkins models with structural econometric models and concluded that the former were more robust or at least as good as the latter. Narashimhan (1975) found that time series models tended to dominate the econometric models. Just and Rausser (1981) found that easily available information in the futures market generally were more accurate in terms of bias than the forecasts based on a number of well established large-scale econometric models (while the latter tended to be more accurate in terms of variance).

Numerous comparisons and evaluations of different forecasting techniques and models have been reported and several forecasting competitions have been held. In these competitions, a variety of forecasting methods applied to a large number of data series are compared. A number of competitions have been organized by Makridakis ("The M-Competitions") with results presented in various issues of the *International Journal of Forecasting*. Makridakis and Hibon (2000) provide such a survey. They sum up the results in four major conclusions. (1) Statistically sophisticated or complex methods do not necessarily produce more accurate forecasts than simple ones. (2) The rankings of the performance of the various methods vary according to the accuracy measure being used. (3) The accuracy of the combination of various methods outperforms, on average, the specific methods being combined and does well in comparisons with other methods. (4) The performance of the various methods depends upon the length of the forecasting horizon. Also, Hendry and Clements (2003) and Fildes (2002) describes recent advances and contributions to the understanding of economic forecasting.

During the last two decades there has been a rapid development in forecasting research using models like for instance ARIMA models, state-space models, Kalman filtering models and neural network models, applied to a broad range of topics (Fildes et al., 2008).

Partial Least Squares (PLS) regression is a relatively new method, commonly used for statistical prediction in fields outside economics, especially chemistry. It was originally proposed by Herman Wold (1966) as an econometric technique, but became popular first in chemometrics partly due to Herman's son Svante, (e.g., Wold et al, 2001). Until the last ten years there have been few applications in economics. The last decade though, the method has been applied to macroeconomic data, e.g. Stock and Watson (1999), Stock and Watson (2002), Bernanke and Boivin (2003), Marcellino, Stock et al. (2003), Groen and Pesenti (2009) and Franses and Legerstee (2010). Still, PLS regression is not recognized as a commonly used method in economics, as opposed to chemometrics, where PLS regression has emerged as the leading forecasting method (e.g. Geladi and Kowalski (1986), Martens et al. (2001) and Helland (2001)).

A brief description of PLS

Partial Least Squares regression is an extension of the multiple linear regression model. The multiple linear regression model has been extended in a number of ways and it serves as the basis for a number of multivariate methods such as discriminant analysis, principal components regression analysis (PCA), factor analysis and PLS regression. In essence PLS regression decomposes a dependent variable (or several variables) of interest into a predictable signal, based on some measured independent variables, and unpredictable error. Let **Y** be a matrix of dependent variables, **X** be a matrix of independent variables, **B** be a matrix of parameters and **U** be a matrix of error vectors. Then the model can be written as:

$$\mathbf{Y} = \mathbf{XB} + \mathbf{U} \tag{1}$$

This model is similar to a classical multiple regression model, deviating only in the way the parameter vector **B** is estimated. As with Principal Component regression and factor analysis the parameter estimates in PLS regression are based on a limited number of latent factors. However, since the main purpose of PLS is prediction the factors are extracted from the **Y'XX'Y** matrix as an attempt to identify the factors in **X** that best represent **Y**.

PLS regression is a flexible estimation technique for prediction models which can be used in situations where the use of traditional multivariate methods is limited, for instance when there are fewer observations than predictor variables, or it can be used to select suitable predictor variables and to identify outliers before classical linear regression. Its greatest strength with respect to forecasting using time series models is its robustness to overfitting and data problems such as multicollinearity. It may be quite difficult to identify the "best" lag structure to use. It may, therefore, be tempting to define a more complex model to improve forecasting ability, especially if large quantities of data are available. However, this may lead to coincidental correlations with error components that in essence cannot be predicted, which reduces forecasting accuracy. Further, lags of time series are typically highly correlated, leading to multicollinearity among the independent variables. This again causes an increase in forecasting variance. As demonstrated by e.g. Esposito Vinzi et al (2007) these problems can easily be avoided using a PLS regression model and choosing the number of underlying factors based on out of sample forecasting performance.

Benchmarking flower price forecasts

As regards forecasting prices and traded volumes in the flower business, not many articles have been published. Besides the paper by Steen and Gjølberg (1999), the only published study found on forecasting flower prices is a survey on price predicting skills of chrysanthemum prices among growers (Trip et al., 2000). The study, based on a survey among 26 participants, showed that growers who predict absolute prices well for one period did not have a higher chance of predicting well for other periods. With respect to predicting *relative* price positions (relative to other cultivars or other firms), they found evidence that this is a skill, especially for estimating the relative market position. Also, evidence was provided that price differences among cultivars are non-random in time. A conclusion from Trip et al was that growers could adapt their production planning and cultivar choice to benefit from expected price variations.

To see whether PLS regression is a model that can be recommended to forecast cut flower prices, we compare this model to general time series models, autoregressive models and a naive prediction rule, i.e. that the price forecast is equal to the price in the same week the previous year. Forecasting using PLS regression is in essence identical to forecasting using classical linear models, expect that the parameter vector is estimated by PLS regression. The predicted value is simply the independent variables times the estimated parameter vector, the non-random part of the statistical model. Franses and Legerstee (2010) were the first to address the use of PLS for multi-step forecasting.

One standard benchmark is the autoregressive model AR(m) defined as

$$p_{j,t} = \alpha_j + \sum_{i=1}^{m} \beta_{j,i} p_{j,t-i} + \varepsilon_{j,t} \qquad (2)$$

where j equals different cut flower varieties.

The traditional forecasting procedure, e.g. the use of short-horizon forecasts to compute longer-horizon forecasts, is used to produce multi-step ahead forecasts of the fitted AR(m) model. The main reason for this is that in an AR model the variables p_t and p_{t-i} are typically correlated, therefore the forecast p_{t+h} and p_{t+h-i} are also correlated for any i.

We use an AR (1) and an AR(5) model for all species in the empirical study. In order to capture calendar regularities, we include the t-52 lag in all models[1]. The general AR-model with calendar regularities then becomes:

$$p_{j,t} = \alpha_j + \sum_{i=1}^{m} \beta_{j,i} p_{j,t-i} + \gamma_j p_{j,t-52} + \varepsilon_{j,t} \qquad (3)$$

[1] This will capture fixed calendar regularities like Christmas and Valentines Day, but not floating holidays like Easter and Pentecost.

The parameters are estimated using OLS, which means that the sum of squared one-step-ahead forecast errors is minimized. Following the general setup of Franses and Legerstee (2010), for the AR(m) model the one-step-ahead forecast at time t is generated as

$$\hat{p}_{j,t+1} = \hat{\alpha}_j + \sum_{i=1}^{m} \hat{\beta}_{j,i} p_{j,t-i+1} + \hat{\gamma}_j p_{j,t-52+1} \tag{4}$$

The two-step-ahead forecast is created as

$$\hat{p}_{j,t+2} = \hat{\alpha}_j + \hat{\beta}_{j,1}\hat{p}_{j,t+1} + \sum_{i=2}^{m} \hat{\beta}_{j,i} p_{j,t-i+2} + \hat{\gamma}_j p_{j,t-52+2} \tag{5}$$

Finally, the h-step ahead forecast (when $h \leq m$) will then be

$$\hat{p}_{j,t+h} = \hat{\alpha}_j + \sum_{k=1}^{h-1} \hat{\beta}_{j,k}\hat{p}_{j,t-k+h} + \sum_{i=h}^{m} \hat{\beta}_{j,i} p_{j,t-i+h} + \hat{\gamma}_j p_{j,t-52+h} \tag{6}$$

Another way to address forecasting is that of including more relevant information, not just historic prices for the specific variety. Here, this is done by including the prices of all other species, traded volumes for all species, as well as prices for some major input factors, heating oil and fertilizer (ammonium). Since we use weekly data, we include 52 lags for all independent variables. The general model:

$$p_{t,j} = \alpha_j + \sum_{i=1}^{52}\sum_{l=1}^{3} \beta_{j,i,l} p_{l,t-i} + \sum_{i=1}^{52}\sum_{l=1}^{3} \gamma_{j,i,l} q_{l,t-i} + \sum_{i=1}^{52}\sum_{k=1}^{2} \phi_{j,i} r_{t-i,k} + \varepsilon_{j,t} \tag{7}$$

Where l represents the varieties chrysanthemum, carnations and roses, $k=1$ for fertilizer and 2 for heating oil. p denote flower prices, q flower quantities and r the other exogenous variables (in this case the prices of fertilizer and heating oil). This model is obviously subject to problems of overfitting and multicollinearity.

The forecasting procedure used here is what is called a direct multi-step method (see e.g. Kang, 2003). This means that a forecast for each multi-step horizon (1,2 and 8-14) is created from a regression where each time the parameters are estimated anew such that the squared multi-step-ahead errors are minimized, and not the squared one-step ahead errors.

The models estimated then become

$$p_{j,t+h} = \alpha_{j,h} + \sum_{i=1}^{52}\sum_{l=1}^{3}\beta_{j,i,l,h}p_{l,t+h-i} + \sum_{i=1}^{52}\sum_{j=1}^{3}\gamma_{j,i,l,h}q_{l,t+h-i} + \sum_{i=1}^{52}\sum_{k=1}^{2}\phi_{j,i,h}r_{k,t+h-i} + \varepsilon_{j,h,t} \tag{8}$$

The model is estimated using three procedures, PLS and OLS. In addition, we use Stepwise OLS, which represents another way of solving the problems of overfitting and multicollinearity. In stepwise OLS the number of independent variables is reduced according to the stepwise procedure in SAS®(2010). The number of factors included in the PLS estimations is based on out of sample prediction error.

$$\hat{p}_{j,t+h} = \hat{\alpha}_{j,h} + \sum_{i=1}^{52}\sum_{l=1}^{3}\hat{\beta}_{j,i,l,h}p_{l,t+h-i} + \sum_{i=1}^{52}\sum_{j=1}^{3}\hat{\gamma}_{j,i,l,h}q_{l,t+h-i} + \sum_{i=1}^{52}\sum_{k=1}^{2}\hat{\phi}_{j,i,h}r_{k,t+h-i} \tag{9}$$

Finally, we establish forecasts based on a naïve model, defined as

$$p_{j,t+h} = p_{j,t+h-52} + \varepsilon_{j,t} \tag{10}$$

i.e. the price in week t-52 is used as a forecast for the price in week t (the same week last year). To many practitioners, this *is* most likely close to what they expect prices to be.

The h-step forecast for this model is simply

$$\hat{p}_{j,t+h} = p_{j,t+h-52} \tag{11}$$

Forecasting results

The forecasting performance was studied generating out-of-sample, h-step ahead forecasts for the three cut flower species for the last 52 weeks of the data set (i.e. week 26,2007-week 25,2008), where h= 1, 2 (short term price forecasts), and 8, 10, 12 and 14 (medium term price forecasts) weeks. Table 2 summarizes the forecasting results of the OLS, PLS and AR models against the naïve model as a benchmark, measured by Root Mean Square Error (RMSE).

Table 2. Root mean square error (RMSE), PLS, general time series models (OLS and OLS-step), autoregressive models with calendar regularities (AR(1;52) and AR(5;52)) versus naïve forecasting rule, week 26,2007 – 25,2008

Species	Forecasting method	Forecasting horizon					
		1	2	8	10	12	14
Chrysanthemums	PLS	5,37	5,72	**5,85**	**5,75**	**5,66**	**5,62**
	OLS-full	5,43	8,18	10,19	10,36	9,48	9,09
	OLS-step	4,19	6,51	6,83	7,74	7,45	8,10
	AR(5;52)	**3,19**	**4,70**	6,09	6,05	6,04	6,04
	AR(1;52)	3,33	4,76	6,28	6,21	6,18	6,18
	Naïve	6,40					
Carnations	PLS	2,24	**2,36**	**2,47**	**2,46**	**2,45**	**2,46**
	OLS-full	3,74	5,03	5,18	5,35	4,66	4,99
	OLS-step	2,30	3,35	2,93	3,34	2,99	3,06
	AR(5;52)	**2,03**	2,76	3,48	3,49	3,49	3,49
	AR(1;52)	2,04	2,70	3,40	3,41	3,43	3,43
	Naïve	3,81					
Roses	PLS	**4,56**	4,81	4,88	4,84	4,78	4,74
	OLS-full	7,71	8,95	7,85	7,85	6,86	6,46
	OLS-step	4,90	5,42	5,73	5,75	5,29	4,69
	AR(5;52)	**4,56**	**4,66**	**4,70**	**4,70**	**4,70**	**4,69**
	AR(1;52)	4,57	4,76	4,71	4,71	4,71	4,71
	Naïve	5,59					

The lowest RMSE of each forecasting horizon are presented in bold font.

Table 2 summarizes the forecasting performance of the different models measured by root mean square error (RMSE). Forecasting the chrysanthemum and the carnations on a medium horizon (8-14 weeks ahead), PLS clearly outperforms the other forecasting methods. For carnations, PLS is the preferred method also for two-week-ahead forecasts, and performs fairly well also on the one-week forecast. For chrysanthemum, the AR(5;52) model has the best performance on the short run, with AR(1;52) as the second best. For roses, the picture looks quite different. Here AR(5;52) produces the best forecasts for all forecasting horizons. But PLS still performs much better than OLS-full and OLS-step, and the differences between the AR models and PLS are quite small.

In addition to evaluating at the performance in terms of RMSE's, it may be of interest to know whether future prices will rise or fall. Table 3 reports the qualitative performance in terms of Ratio of Accurate Forecasts (RAF). The success ratio is evaluated in a standard

binomial test, $b(x;n,p) = \binom{n}{x} p^x (1-p)^{n-x}$ (12)

where x is the number of correctly predicted (in terms of sign) price changes, n is the number of price changes in total for the forecasting period (zero price changes omitted) and p is the probability of success. As the benchmark of the probability of success we use the proportion of price increases (or decreases) the previous year.

Table 3. Ratio of accurate forecasts, PLS, structural econometric models (OLS and OLS-step), autoregressive models with calendar regularities (AR(1;52) and AR(5;52)) versus naïve forecasting rule, cut flower prices, week 26,2007 – 25,2008.

Species	Forecasting method	Forecasting horizon					
		1	2	8	10	12	14
Chrysanthemum	PLS	0,66*	0,73*	0,75*	**0,78***	**0,82***	**0,96***
	OLS-full	0,49	0,59*	0,63*	0,52	0,59	0,69*
	OLS-step	0,51	0,59*	**0,81***	0,70*	0,69*	0,76*
	AR(5;52)	0,72*	**0,76***	0,65*	0,74*	0,71*	0,82*
	AR(1;52)	0,72*	0,75*	0,67*	0,74*	0,71*	0,78*
	Naïve	**0,75***					
Carnation	PLS	**0,73***	**0,78***	0,82*	0,78*	0,78*	**0,85***
	OLS-full	0,60	0,60	0,69*	0,68*	0,72*	0,70*
	OLS-step	0,55	0,73*	**0,90***	**0,84***	**0,83***	0,83*
	AR(5;52)	0,55	0,69*	0,82*	0,76*	0,80*	0,77*
	AR(1;52)	0,60	0,67*	0,82*	0,78*	**0,83***	0,77*
	Naïve	0,61					
Rose	PLS	0,74*	0,84*	**0,80***	**0,84***	0,83*	0,74*
	OLS-full	0,57	0,71*	0,62*	0,58*	0,75*	0,79*
	OLS-step	0,74*	0,76*	0,78*	0,74*	0,83*	0,79*
	AR(5;52)	0,80*	0,86*	0,78*	0,82*	**0,88***	**0,83***
	AR(1;52)	**0,83***	**0,88***	0,78*	**0,84***	0,87*	**0,83***
	Naïve	0,78*					

*significant at 5% level

In terms of predicting the correct direction of the price change, PLS gave the best performance for 10, 12 and 14 week forecast for chrysanthemum (second best for the 8-

week forecast). Also for 1 and 2 week forecasts PLS performed much better than OLS-full and OLS step. For carnation, PLS was clearly best for short term forecasts, while the results on the medium run were more diverse, and also the differences between the different models were smaller. For roses, AR(1;52) performed best in the short run. PLS gave the best result for 8 and 10 week forecasts, while the AR-models were best for the 12 and 14 week forecasts.

A practical experiment

We have shown that PLS regression often outperforms other models and methods when it comes to forecasting in the short- and medium-term for various cut flowers.What are the practical implications of these results? For the producer, the proof of the pudding is the eating. Economic, rather than statistical significance is what interests the producer. Assume that a cut flower producer is supplied with (e.g.) 1-, 2- and 8-week price forecasts. How can these forecasts be applied in her decision making? What are the alternatives to making these forecasts? What are the decision rules when forecasts are available? One strategy could be to produce cut flowers on a routine basis without any consideration to forecasts. To make it simple, let us assume that only chrysanthemums are produced, and that identical size batches are marketed every week. Using data for the last 52 weeks, we would plant one new plot every week, and hence market identical batches every week. The expected sales price would be the average of the realized prices for that time period. Another strategy could be to use the short term chrysanthemum price forecasts. We initially plan to a new batch every week. If we assume that, at the end of the production period for a given batch, it is possible to postpone the sales by up to one week (postponing flower development by altering input factors like temperature, light and carbon dioxide), we use only the 1-week forecast $(\hat{p}_{t+1})$. The decision rule could then be to sell this week if the price today is equal to or higher than the price forecast for next week $(p_t \geq \hat{p}_{t+1})$, receiving p_t.If not, we postpone marketing by one week. In that case, for this batch we instead will receive next week's price (p_{t+1}). If we assume that it is possible to postpone the sales by up to two weeks we compare both the 1- and the 2-week price forecasts with the today's price. If either of the 1-week or 2-week price forecast is higher than today's price we postpone harvesting by one or two weeks. If the 2-week price forecast is higher than the 1-week forecast we postpone the sales by two weeks (and receive p_{t+2}). Otherwise we sell after one week and receive p_{t+1}. Table 4 below shows the results from this experiment in terms of obtained average prices and standard deviations. Comparing the use of short term forecasts to the routine-, no-forecasting production of 52 identical size batches, we see that both the PLS-1 and PLS-1 and 2 would have given a clearly higher average price (out-of-sample).

Table 4. Average price and standard deviation resulting from different marketing strategies for chrysanthemums, week 26, 2007 – 25, 2008

	Routine production, no forecasting	PLS 1-week forecast	PLS 1- and 2-week forecast combined	PLS 8-week forecast	Max26	Max13
Average price (Eurocent/stem)	21.86	22.30	22.99	23.99	26.75	29.73
Std.dev.	7.66	8.07	8.25	10.73	7.63	8.64

The 1-week PLS price forecasts would increase the average price by 2 percent and the risk in terms of standard deviation would be marginally increased compared to routine production. If we utilize the information from the 1- and 2-week forecasts combined we could increase the average price even more (5.2 percent) compared to routine production, but the risk would be slightly higher.

We can also use information from the medium term price forecasts in a practical setting. Again, we assume that we produce 52 batches in total during the year. These 52 batches, however, may be aggregated and marketed in "lumps" through the year. Here, the decision problem is whether or not to start a new batch in a given week. Assuming we have an 8 week production period for chrysanthemums, we look at the 8-week price forecast $(\hat{p}_{t+8})$. The decision rule could then be, in week t, to compare this price forecast with the average of the prices obtained in week t+8 the years prior to the forecasting period. This will take care of much of the price seasonality. From table 4, we see that utilizing the information from the PLS-8 forecasts would have increased the price by 16 %, which is substantial, but the price risk would be higher compared to routine production.

Whether this is economically significant may be a relevant question. A 2- 5 percent increase in the average price achieved (as we get using short term PLS forecasts) could accumulate to a significant number since the effect on costs from changing planting and harvesting decisions is marginal, and also the margins are small and the volumes are large.

Yet another strategy could be to look at the historical data and, for instance, pick the 26 weeks with the highest historical sales prices (since the data contain strong seasonal effects). Still, the total production in a year will be 52 batches, but now we chose to produce two batches per week in 26 weeks. The results from such a strategy is shown in table 4 as Max26, and we see that we get 22 percent higher price compared to routine production, and the lowest risk of all the alternatives. If we only picked the 13 weeks with the historically highest prices, we would get an even higher price (in this forecasting period). This is shown in table 4 as Max13. From the table we can see that this strategy will yield 29.73 Eurocent/stem, i.e. a price increase of 36 percent compared to routine production, but the risk would be higher than using short term PLs forecasts.

Finally let us assume that the producer is an extreme gambler, and that he chooses to produce one or two batches during this year (putting his eggs in the same basket). He would then look at the historic prices and pick the 1-2 weeks with the highest prices. For the time period of this study (1993-2007) this was week 6 (€C 33.97) and week 2 (€C 33.83). What would be the result of such a strategy? Historically, week 6 has had a standard deviation of €C 3.48. If we had applied such a strategy (selling everything in one week) through the experimental period (week 26, 2007-25, 2008) the producer would have sold the entire production in week 6 at €C 40. If he had sold half of his production in week 6 and the other half in week 2 he would have achieved €C 32.

Why don't producers follow such a strategy? The answer is that history does not necessarily repeat itself. Although week 6 historically has been "good", i.e., high price and relatively low variation, it may very well happen that a one-shot strategy in the future may turn out as a disaster.

Conclusions

In this article, we have evaluated various methods for forecasting flower prices 1-14 weeks into the future. For producers, traders and wholesalers, there is no doubt that obtaining <u>good</u> short term price forecasts are of great value. Flower prices fluctuate substantially from one week to the next, and there are potentially substantial gains from good forecasts of the future prices (or demand) in a market for (almost) non-storable products.

We established a set of short (1-2 week) and medium (8-14 week) price forecasts based on a PLS regression model. The forecasts are out-of-sample for the weeks 2007-26 to 2008-25. In order to benchmark the results, the PLS forecasts were compared to the results from univariate time series (AR(1) and AR(5)) models, structural economic models and a naïve model. The results show a very good overall performance of the PLS forecasts. It seems to outperform the second best methods, simple AR models, in cases where significant information is contained in the data omitted from the simpler models. This is especially true for chrysanthemum and carnations for longer time horizons. On the other hand simple AR models seem to be better at predicting prices for roses and at shorter run predictions.

The main conclusions from this paper are as follows. Firstly, cut flower producers should be able to benefit from applying forecasting models in the production planning and marketing of cut flowers. Secondly, a partial least squares (PLS) regression model can be recommended as a successful forecasting method compared to more standard forecasting models. Both measured in quantitative (RMSE) and qualitative (predicting the right direction of price changes) standards, PLS regression outperforms the other forecasting models. Simple PLS forecasts applied to harvesting and planting decisions in an applied experiment, turned out to yield clearly better economic results than routine production and no forecasts, when applied to an out-of-sample "real" experiment 2007-2008.

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Essay 4

"Ramblin' rose, rambling rose

Why I want you, heaven knows

Though I love you with a love true

Who can cling to a ramblin' rose".

Nat Cing Cole,
Lyrics from "Ramblin' rose"

Measuring price-quantity relationships in the Dutch flower market: Is there a potential for strategic behavior?

Abstract

International flower production and trade has grown into a multi-billion business with the Dutch flower auctions as its focal point of price and market information. Despite the size of the flower business relatively little market research has been published. This article is a contribution to bridge that gap, presenting econometric evidence on price-quantity relationships for major species of cut flowers at the Dutch flower auctions. We ask whether the producers can behave strategically by utilizing information on patterns in demand. An inverse linear approximate almost ideal demand model with seasonality is estimated. Based on the estimated values for price and scale flexibilities, a potential for strategic marketing or market timing seems to exist. The flexibility estimates vary across different species. While 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.

Introduction

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 and the highest in the world, which was more than twice the value of consumption in the USA. In the period 1995-2004 the value of imports of cut flowers to the European Union increased by approx. 40 percent, and from 2004-2007 the increase was 25 percent[1]. The total imports from non-European countries to the 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 came from Africa, with Kenya as the dominating country. In 1995,

[1] The data on flower imports are collected from "International Statistics Flowers and Plants", 1995, 2004, 2007 and 2008

turnover as measured at the wholesale level at the Dutch Flower Auctions was approximately 1.2 billion Euro. By 2008 the figure had reached some Euro 4.1 billion (FloraHolland, undated). The Dutch flower auctions represent the major market place in European and global flower trade. A substantial volume of trade passes through these auctions. More importantly, the auction prices to a large extent determine prices outside the auction premises. Hence, supply, demand, quantities and prices at the auctions are relevant to all European flower producers, importers and traders.

Despite its increasing size, the market for flowers has received little attention in the literature. Abdelmagid et. al. (1996) have 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 US, 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. Beyond these studies, little systematic analysis of the flower markets has been published in scientific journals.

Prices of cut flowers are very volatile. This is, of course, mainly due to the fact that cut flowers are highly perishable. The salvage value of yesterday's unsold cut flowers is close to zero. Based on information regarding the price and quantity data generating processes and the underlying demand/supply schedules, producers' risk management and strategic marketing behavior may generate less volatile prices (and higher producer utility). 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 because of the batch character of production and the problems connected to storing cut flowers. 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 market behavior should therefore involve systematic surveillance of variations in traded volumes.

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

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. In order 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 to that of using a standard dummy representation.

The paper proceeds as follows. First, the price and quantity data and some stylized facts from the Dutch flower auctions are presented. Then, the seasonally adjusted inverse almost ideal demand system is described and estimated. The results are summarized in the fourth section before some concluding remarks are offered regarding possible strategic behavior among producers.

Some stylized facts from the Dutch flower auctions[2]

Approximately 70 of the most important cut flower species, representing close to 100 per cent of the total value of cut flowers traded at the Dutch flower auctions are included in the data set. 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 summarizes the stylized facts regarding volume weighted prices and quantities. As can be seen, both prices and quantities vary substantially. The coefficients of variation, as regard weekly prices, range from approx. 21 per cent (roses) to 34 per cent (carnations), while the CV of quantities are between 9-18 per cent per week.

Table 1. Prices* and quantities major species, week 1, 1993 – week 21, 2005

	Prices, weekly observations			Weekly quantities (1000 stems)			Highest and lowest quantities observed (weekly)	
	Mean	**Std.dev.**	**Coeff. of variation**	**Mean**	**Std. Dev.**	**Coeff. of variation**	**Highest**	**Lowest**
Chrysant.	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

*Prices are measured in Eurocents per stem

On an annual basis we have standard deviations of price and quantity changes from approximately 60 to 140 per cent![3] This makes cut flowers probably *the* most volatile agricultural commodity. Cereals, potatoes etc. rarely show annual standard deviation of price changes beyond 20-30 per cent. For instance Pietola and Wang (2000) argue that the price of piglets are very volatile, reporting a CV of 11 % on an annual basis.

[2] Weekly price and quantity data for week 1, 1993 trough week 21, 2005 were obtained from weekly editions of the Dutch "Vakblad voor de Blomisterij".

[3] 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 due to serial correlations in the changes.

There are clear seasonal patterns in prices and quantities as shown in figure 1 below, but the patterns of the major cut flowers differ. For instance, the budget share of carnations is at its lowest in December-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 quarter. Chrysanthemums, on the other hand, show almost the opposite pattern as the carnations.

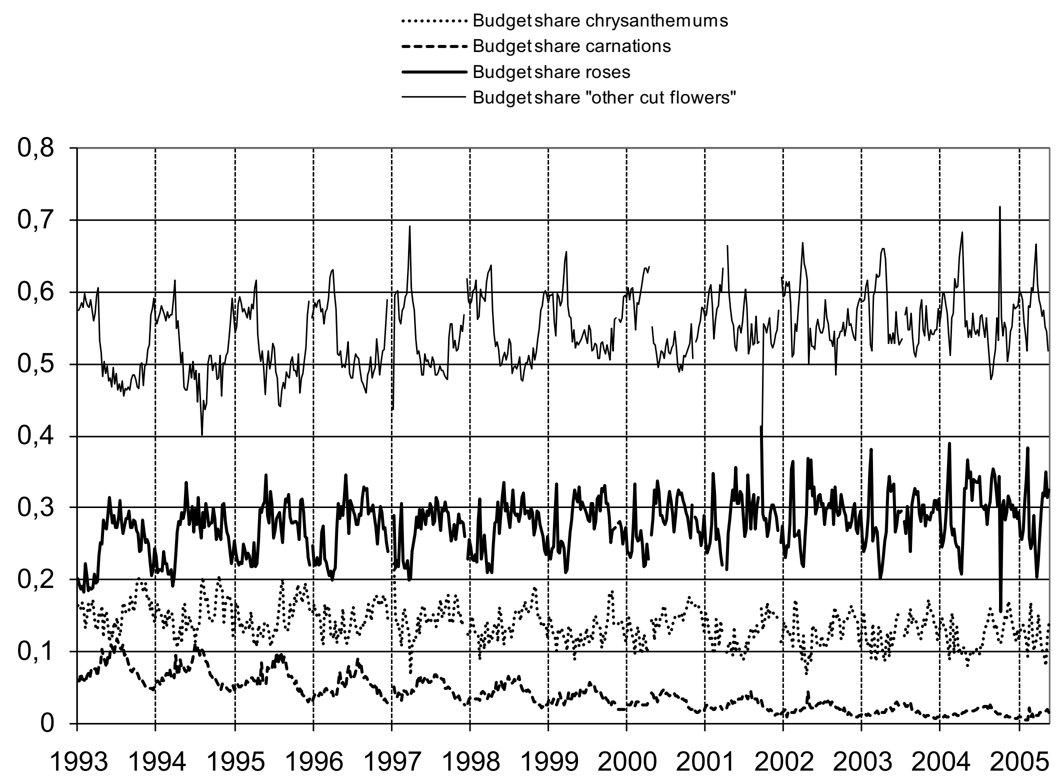

Figure 1. Budget shares of chrysanthemums, carnations, roses and other cut flowers out of the total expenditure of cut flowers from week 1-1993 to week 21-2005.

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 (e.g. Eales and Unnevehr, 1994), fish (Barten and Bettendorf, 1989) and vegetables (Rickertsen, 1997).

Weak separability of the utility function is assumed, which means that the demand for different types of flowers can be treated isolated from the demand for other goods. Only the prices and quantities of these flowers, and the total expenditure for this group, matter. Also it is assumed that collective consumer behavior in the flower market can be adequately described as that of the rational representative consumer.

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. Moschini and Vissa (1992), and Eales and Unnevehr (1994) followed this approach and developed an inverse almost ideal demand system where the uncompensated inverse almost ideal demand functions can be written in share form as

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

where w_i is the ith good's budget share, q_j is the quantity of cut flower j and $ln(Q)$ is a quantity index defined as

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

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

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

where

$$\ln(Q^*) = \sum_i w_i \ln(q_i) \tag{4}$$

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:

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

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

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

Deaton and Muellbauer (1980) suggested that other variables could be included in the AID model by allowing the constant terms in (2) and (3) to vary with them. Following this approach, seasonality is introduced into the model using seasonal dummy variables as shift variables where

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

where j=3, 12 and 51 for quarterly, 4-weekly and weekly seasons respectively. For the adding up condition to hold, $\Sigma a_{i0} = 1$ and $\Sigma \Theta_{ij} = 0$ 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:

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

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

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 52 variables per equation, one for each week, while the trigonometric approach only uses 2 variables per equation. This is especially important when estimating systems of equations.

Price and scale flexibilities are the natural concepts of uncompensated elasticitites 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.

The scale flexibilities are readily computed because $f_i = \sum_j f_{ij}$ (Moschini and Vissa, 1992).

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

$$f_{ij} = \frac{\gamma_{ij}}{w_i} - \beta_i \frac{w_j}{w_i} - \delta_{ij} \tag{10}$$

Here δ is the Kronecker delta ($\delta_{ij} = 1$ for $i = j$ and $\delta_{ij} = 0$ otherwise)

In the present case of four groups of cut flowers, weak separability is assumed. Only the quantities and prices of the different cut flower species and the total expenditure of cut flowers matter. Also, it is assumed that collective consumer behavior for cut flowers can be adequately described as that of the rational representative consumer.

The system consists of demand for chrysanthemums, carnations, roses and “others species”, respectively. The last equation was dropped in estimation due to singularity of the cross-equation covariance matrix. The system is estimated using seemingly unrelated regressions (SUR).

The system is tested for autocorrelation using a Breuch-Godfrey Score Test. The H_0 hypotheses were strongly rejected for all groups of cut flowers, and t-values were significant for the first 2 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 LA AIDS model in (3) is replaced by

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

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.

Since the score test indicates that the first two lags are the problem, two lags of the residuals are included in the corrected model.

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 autoregressive model was the tested for seasonality using an F-test, and the hypothesis of no seasonality was strongly rejected. Seasonality was included in the autoregressive model in 4 different ways; weekly, 4-weekly and quarterly dummy variables, as well as the trigonometric approach. The results of the different models were compared using the Baysian Information Criterion (BIC) (Greene 2000).

Econometric results

Table 2 displays the results from the estimation of the different seasonal models. We can see that the trigonometric model is producing the highest BIC value indicating that this is the preferred model. The trigonometric model is therefore used for the further estimations and to calculate the flexibilities.

Table 2. Baysian information criterion values for different seasonal models

Seasonal model	Number of parameters estimated	BIC
Sin/cos	36	-26.24625
4 seasons	39	-26.09681
13 seasons	66	-26.08487
52 seasons	183	-25.67211

The estimated coefficients and the summary statistics from (11) are presented in table 3.

Table 3. Coefficients and summary statistics of the LA/IAIDS system

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

(T-values in parentheses). β_i is the coeff. of the quantity index of equation i, and γ_{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

We can see from table 3 that all quantity coefficients as well as the coefficients of the quantity indices are highly significant. The seasonal cycles are different for the different groups of cut flowers. Beyond this, the demand seems to follow cosine waves for most of the species.

Table 4. Uncompensated price flexibilities (f_{ij}) and scale flexibilities (f_i) evaluated at mean shares of w_i, t-values in parentheses.

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

* = significant at 5 % level, ** = significant at 1 % level, *** = significant at 0.1 % level

Table 4 shows the price and scale flexibilities and the summary statistics. The price flexibilities show the percentage changes in the prices associated with a 1 per cent change in the supplied quantity of a group of cut flowers. 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. Taken at face value, the estimates indicate different effects from strategic marketing behavior across producers of different species. While 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 while the rest appear to be quantity-substitutes.

Furthermore, for chrysanthemums, roses and “others”, each of the cross-flexibilities has a lower numerical value than the corresponding own price elasticity, implying that the increased supply of a cut flower mostly affects the price of that cut flower itself. For carnations, however, it actually seems to be the case that increased supply affects the prices of chrysanthemums, roses and “others” more that it affects the price of carnations themselves. For instance, a 10 per cent increase in the supply of carnations will, according to the estimation results, reduce the price of roses by more than 5 per cent.

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 -.9 (roses) to -1.3 (carnations), indication that the hypothesis of homothetic preferences are rejected for all groups of flowers.

Conclusions

The aim of this paper was to provide information on price-quantity relationships for cut flowers traded at the Dutch flower auctions. 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 parsimony in use of regression variables is especially important when estimating systems of equations.

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. Further, given the results when it comes to cross flexibilities, chrysanthemum and carnations seem to be quantity complements, while the rest appear to be quantity substitutes. The hypothesis of homothetic preferences are rejected for all groups of cut flowers.

Based on the econometric results, a potential for strategic marketing or market timing seems to exist. Thus, if a producer is able to predict quantities supplied subsequent weeks he or she may be able to skim profits by adjusting lights and temperature in order to hit short-term price peaks (or also avoid weeks with excess supply and depressed prices). This means that utilizing the information in given weeks, on price-quantity relationships, even relatively small producers may be big enough to influence the prices. The differences in estimated flexibilitities across species suggest that there are different effects from strategic marketing behavior across different species. While 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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Essay 5

"Bread feeds the body, indeed,

but flowers feed also the soul".

From The Koran

"When you have only two pennies

left in the world,

buy a loaf of bread with one,

and a lily with the other".

Chinese Proverb

Risk Management in the flower business[1]

Abstract:

Flower producers face significant price risk, as do producers of other biological products. However, while producers of wheat, corn, hogs etc. may hedge price risk in well functioning futures markets, no such risk management instrument is readily available in the flower business. This paper suggests that flower producers take a portfolio approach to reduce risk. This means that individual producers diversify across different flower varieties. Since, however, such an individual multi-product approach may be costly, an alternative might be to achieve the diversification effect by pooling risk in a joint, multi-variety portfolio. The aim of the paper is to analyze the risk reduction potential from such diversification, individually or in a pool. Based on weekly price data 1993-2008 it is shown that price risk can be substantially reduced through establishing some quite simple portfolios.

Introduction

This paper analyzes price risk management in the flower business. Standard portfolio theory from finance is applied on price data from the Dutch flower auctions. The paper is in a similar vein as those by Sporleder (1988) and Buccola et al. (1989). However, while they focus on pool payment equity in agricultural marketing cooperatives, the present paper takes the pooling idea into the area of price risk management.

Some of the very first agricultural cooperatives were created with the sole purpose of risk management, for example, the mutual fire insurance organizations dating back at least to the nineteenth century. The idea was quite simple. While a fire could represent a disaster for an individual farmer, for one hundred or more fellow farmers in the neighborhood of the one who was struck, it was possible to lend a helping financial hand without depleting their own

[1] This is a substantially revised version of Gjølberg, O. & M. Steen (2000): "A Portfolio Approach to Cooperative Risk Management", Journal of Cooperatives, **14** (1):21-29.

resources. Actuarial intuition and group norms reducing the potential moral hazard turned many of these mutual fire insurance cooperatives into quite successful ventures.

Present day agriculture is confronted with highly volatile prices for many commodities. Most farmers are - for good reasons - risk-averters. While, on the average, a farmer's price expectations may be correct in the long run, this yields little comfort if in the meantime, deviations between expected and actual prices have been so large that the farmer is knocked out of business.

For some commodities it is possible to reduce price risk by using instruments offered by organized exchanges at which the trading of price risk is the name of the game. Thus, corn, wheat, soy, pork bellies, and other agricultural products are traded at futures exchanges where farmers may hedge against adverse price movements, although not against production risk. Price risk management through the futures market is, however, an option unavailable for most farmers. For several products no futures contract exists. Also, the correlation between the price changes of the contracts traded at the futures exchanges and the spot price changes of the commodity produced by a given farmer is often so low that the hedging efficiency of the futures contract is meager. Alternatively, farmers may try to reduce price risk through product diversification (see e.g. Helmberger and Chavas (1996), Johnson (1967), McFarquhar (1961)). Such product diversification can, however, be quite difficult and costly when carried out on an individual basis. In biological productions it is not easy to produce different products in a risk-reducing manner. Although it may technically be feasible, the gains, in terms of risk reduction, may be severely eroded by the costs of investing in equipment for producing a variety of products.

For flower producers, no futures market is presently available[2]. Hence, one way of reducing price risk for flower producers may be that of establishing risk-management cooperatives through which diversification is achieved without having to reduce individual gains from specializing in one or just a few varieties.

The goal of this paper is to demonstrate the possibilities of cooperative risk management in the flower business. First, we outline the basics of portfolio theory and try to point out how this theory can be applied in flower production. Second, we illustrate the portfolio approach by using market data from the Dutch flower markets, assuming that flower producers apply simple portfolio methods in a cooperative setting. Finally, we discuss some problems that have to be solved for establishing such risk management cooperatives.

A portfolio approach to risk management

Price risk management in a portfolio framework is based on the fact that a less-than-perfect (positive) correlation between two or more asset prices (or cash flow contributions or returns) makes the combined (portfolio) risk less than the individual asset risk. The expected return of *n* assets put together in a portfolio is simply the weighted sum of the expected return of the individual assets,

$$E(r_P) = \sum_{i=1}^{n} w_i E(r_i) \tag{1}$$

where r_p is the return of the portfolio and r_i is the return of asset *i*, while w_i is the weight of asset *i* and

$$\sum_{i=1}^{n} w_i = 1 \tag{2}$$

[2] Interestingly, the Dutch flower market historically represents one of the first futures markets ever. This market, however, died as a result of the so-called Tulip Mania 1636-37.

The variance of the portfolio return is given by

$$\sigma^2(r_p) = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j Cov(r_i, r_j) \tag{3}$$

For a given expected portfolio return, the goal is then to choose weights that minimize portfolio variance. This is known as the Markowitz portfolio selection model, and it is a trivial quadratic programming problem provided that we have estimates for the co-variances as well as expected returns for each product.

An alternative approach is the so-called single index model, assuming that the return of a given asset *j* (r_j) is determined by a single "driving" factor, like, for instance, the market index (r_m).

$$r_{j,t} = \alpha_j + \beta_j r_{m,t} + \varepsilon_{j,t} \tag{4}$$

where $r_{j,t}$ typically is calculated as

$$r_{j,t} = \ln(P_{j,t} / P_{j,t-1}) \tag{5}$$

In our setting $r_{j,t}$ is the return of flower *j* at time *t*, $r_{m,t}$ is the market return, and $\varepsilon_{j,t}$ is an unsystematic error term. The market return in this case may be a broad portfolio of flowers. The error term is assumed to have zero expectation and constant variance. It is, furthermore, assumed to be unsystematic over time and to have no covariance with the error terms of other varieties. β_j

measures the systematic risk of variety j, i.e., the risk that cannot be removed through diversifying. This implies that the expected portfolio return is

$$E(r_p) = \sum_{i=1}^{n} w_i \left[\alpha_i + \beta_i E(r_m)\right] \tag{6}$$

with variance

$$\sigma^2(r_P) = \left[\beta_P^2\right]\sigma^2(r_m) + \left[\sum_{i=1}^{n} w_i^2 \sigma^2(\varepsilon_i)\right] \tag{7}$$

where the portfolio beta $\beta_P = \sqrt{\sum_{i=1}^{n} w_i^2 \beta_i^2}$ is, i.e., the weighted beta of all assets in the portfolio. The portfolio beta measures the systematic risk of a portfolio given the w's. $\sigma^2(r_m)$ is the variance of the market index and $\sigma^2(\varepsilon)$ is the residual variance.

For a given required expected return the choice of portfolio weights is given by minimizing (7) subject to

$$\sum_i w_i = 1 \tag{8}$$

And (in our case) assuming that there is no short-selling, i.e.

$$w_i \geq 0, \forall i \tag{9}$$

In agricultural economics, the single index model has been applied in, inter alia, Collins and Barry (1986).

Portfolio management is typically focused on expected returns and the return variance. In agriculture the basis might be net return per acre. Alternatively, one may focus on price levels, bearing in mind that there is no simple relationship between price levels and returns. Thus, one will have to *scale* price levels one way or another when adding assets together in a portfolio and evaluating gains from diversification. This is more complicated when the portfolio is made up of products produced and owned by different farmers in cooperative risk management. One way of solving this problem is as follows. Let us assume that the cooperating farmers reach a consensus on price expectations (in practical terms, this may be handled within the cooperative's management). Assuming, then, that portfolios are established either through an optimization or simply by any sort of naïve or random weighting, the expected portfolio price and variance can be calculated (given the required inputs). Then *ex post,* the diversification gains can be shared according to deviations between expectations and realized prices. In the next section we shall try to illustrate how the gains from cooperative diversification in the flower business could be distributed in this way.

A slightly different approach could be that of focusing on price *changes* in the risk management. In that case, one would establish portfolios that reduce the overall price change from "today" until "tomorrow." As to expected price changes, a simple approach could then be to assume zero daily price changes, and then just build the portfolio to minimize variance.

In our empirical analysis, we will focus on two issues. For one, we will discuss the possibility of reducing return risk, i.e. establishing *ex post* portfolios that would have minimized the standard deviations of the weekly per cent *price changes*. Second, we establish portfolios with a minimum standard deviation around expected (or required) *price levels*.

For the former issue, we apply the single index model. For the latter, we take the Markowitz approach.

Portfolio optimization in the flower business

To our knowledge, very little research on risk management in the flower business has been published[3]. Our empirical illustration of portfolio risk management uses data from the Dutch flower auctions. Few, if any, commodities have price volatility near that of cut flowers. This is visualized in figure 1[4], describing weekly per-cent price changes for chrysanthemums from week 1, 1993 to week 25, 2008.

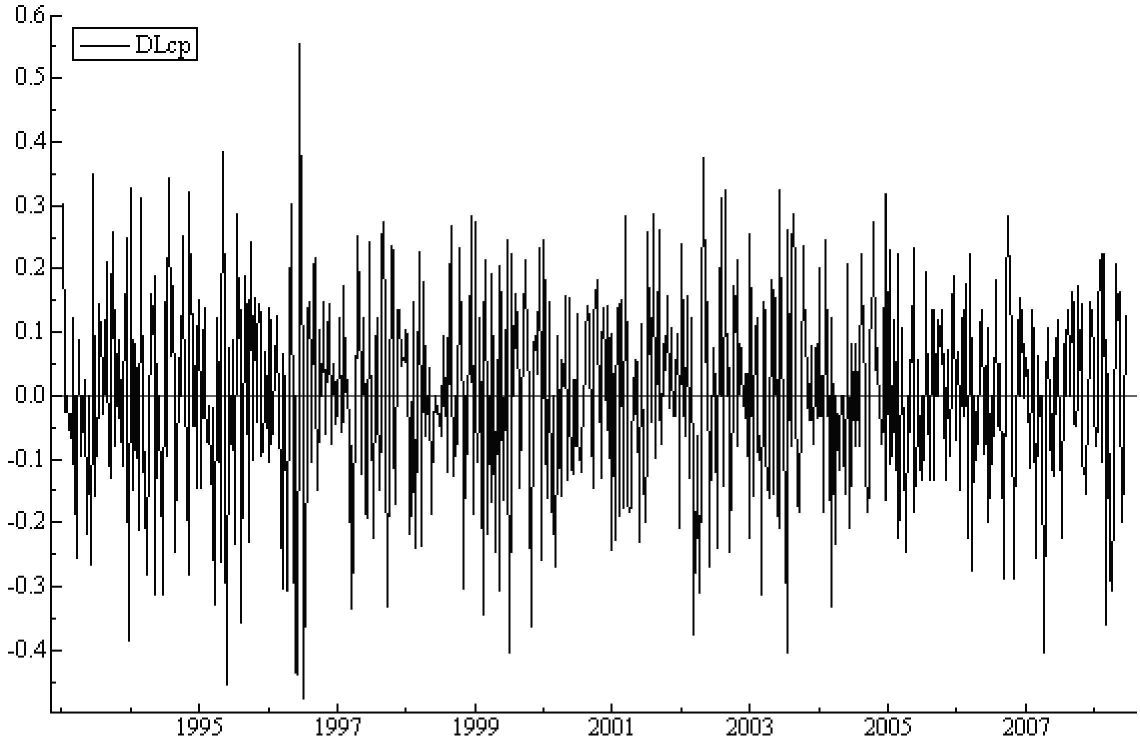

Figure 1. Weekly price changes (%) for chrysanthemum, 1993-2008. Data source: Weekly editions of *Vakblad voor de Blomisterij.*

As can be seen, chrysanthemum prices change typically +/- 15 to 20 percent on a *weekly* basis. However, it is not at all uncommon that prices raise or drop by 30 to 40 percent from one week to the next. Chrysanthemums are quite representative for other cut flowers as far as price volatility is concerned.

[3] Purcell et al. (1993) presented a portfolio approach to risk management in the horticultural industry. Their focus, however, was on space allocation.

[4] All price data are collected from weekly editions of *Vakblad voor de Blomisterij*, 1-1993 to 25-2008

Table 1. Means of prices, and correlations for prices and returns (in parentheses) monthly observations 1993 - 2008

	Chrysanthemums	Carnations	Roses	Others
Means (Eurocents)	21.88	12.85	19.98	19.59
Correlations				
Carnations	0.03 (0.29)			
Roses	0.74 (0.64)	0.18 (0.36)		
Others[5]	0.44 (0.41)	0.24 (0.33)	0.53 (0.62)	

The correlations between the monthly prices and returns for chrysanthemums, carnations, roses, and a bouquet[6] of the other cut flower varieties traded at the Dutch auctions are reported in table 1, together with the historic means of the prices. Carnations have had the lowest correlation with the other species, both in levels and returns. Roses and chrysanthemums are the two with the highest correlation. However, there are no really high correlations, implying a potential for risk reduction through portfolio management.

Table 2 shows the standard deviations of both the returns and the prices, together with the coefficients of variation for the prices. The return risk is quite stable over time. Chrysanthemums, carnations and roses seem to be equally risky, while the risk on return on “others” is lower, which is no surprise since “others” is a bouquet of a variety of cut flowers. The risk in prices tells a more diverse story. By looking at just the standard deviations it seems to have been an increase in risk for all the varieties. However, by taking the price increase into account and calculating the coefficients of variation by dividing by the means, we can see that the price risk for chrysanthemums and carnations has increased during this period, while the price risks on roses and “others” have actually decreased.

[5] Approximately 70 of the most important cut flower varieties, representing close to 100 per cent of the total value of cut flowers traded at the Dutch flower auctions are included in the data set. The cut flowers were aggregated into four groups, the three major species, chrysanthemums, carnations and roses, and a fourth aggrecated category, “other” cut flowers.

[6] The bouquet represents a value-weighted index of all other varieties traded.

Table 2. Standard Deviations and coefficients of variation (CV) of returns and prices; Monthly observations 1993 to 2008

	Chrysanthemums	Carnations	Roses	Others
Returns:				
1993-2008	0.24	0.22	0.24	0.16
1993-2000	0.23	0.22	0.23	0.16
2000-2008	0.25	0.21	0.25	0.17
Prices:				
1993-2008	6.76 (30.9)	2.51 (19.5)	4.66 (23.3)	3.61 (18.4)
1993-2000	6.18 (29.3)	2.17 (17.8)	4.36 (23.8)	3.07 (17.1)
2000-2008	7.19 (31.9)	2.65 (19.6)	4.42 (20.5)	3.40 (16.0)

(.) = Coefficients of variation (CV)

During the period 1993 to 2008, the coefficient of variation (CV) for the monthly chrysanthemum price was almost 31 percent and for roses and carnations some 20 percent. For the same period the annualized standard deviations on the monthly *returns*[7] for chrysanthemums, carnations and roses were 83 per cent, 76 per cent and 83 per cent respectively.

Minimizing return risk using a single-index model

Table 3 reports the results from OLS-estimations of equation 4, the "flower betas" based on a flower market index calculated as a value weighted index[8] using monthly returns.

Table 3. OLS-Estimations of the Simple Market Model

	β	σ_ε	$adjR^2$
Chrysanthemums	0.94 (0.08)	0.18	0.44
Carnations	0.53 (0.09)	0.20	0.17
Roses	1.26 (0.05)	0.12	0.76
Others	0.89 (0.03)	0.07	0.82

(.) = standard errors

σ_ε = residual standard error (unsystematic risk)

[7] Monthly standard deviation multiplied by the square root of 12.

[8] The weights are average values for the period 1993 - 2008.

Again, carnations appear to be different with a low β and also a low adjusted R^2, implying a high unsystematic (or unique) risk. Roses and "others" have the highest R^2, the former with a high systematic risk (β = 1.26). Disregarding this, the estimated betas strongly suggest that it is possible to compose portfolios with substantial risk reduction compared to putting all eggs in one basket. Roses have a "systematic risk" (beta of 1.26) well above the market average, while the opposite is the case for carnations (beta of 0.53).

Table 4. Portfolios minimizing risk in return, single index model, January 1993 – June, 2008

Time period	Weights					
	Chrysanthemums	Carnations	Roses	Others	β_p	Portfolio risk
1993-2008	0.19	0.23	0.18	0.40	0.48	0.10
1993-2000	0.20	0.21	0.19	0.40	0.50	0.10
2001-2008	0.18	0.25	0.18	0.39	0.45	0.11

Table 4 reports the results from minimizing return variance by means of the single-index model (Eq. 7 given eq. 8 and 9)) for the total period 1993-2008, and two sub-periods 1993-2000 and 2001-2008. The results are easily summarized. For one, the weights of the different varieties are very stable throughout the period. Second, by establishing portfolios in this way, one reduces return risk substantially. The minimum-risk portfolios typically consist of 20 per cent each of chrysanthemums, carnations and roses, and 40 per cent of other varieties. By composing such risk-minimizing portfolios one will have a "bouquet" with a beta (β) of roughly 0.45-0.50, i.e. a portfolio that has a clearly less volatile return. The standard deviation of this portfolio is 0.10-0.11, which is considerably less than the standard deviations of the individual flower variety returns (reported in table 2).

Minimizing portfolio variance using the Markowitz portfolio selection model

As described earlier, one may also be interested in focusing on minimizing a portfolio based on price levels of different varieties. Tables 5 and 6 report the standard deviations and portfolio weights of four portfolios on the efficient set (i.e. minimizing eq. 3 given eq. 1 and 2) for given portfolio price level expectations (the Markowitz portfolio selection model). When deriving the efficient set, we assume (for simplicity) that the expected price for each variety is equal to its historic average, that is, the prices reported in table 1 above[9]. Table 5 includes "others" in the possibility set. Since "others," per definition, represent a portfolio, we have excluded this bouquet from the efficient portfolios reported in table 6 where we have calculated efficient portfolios based on the three major cut flower varieties at the auctions.

Table 5. Mean-variance efficient portfolios, all varieties, month 1, 1993 – month 6, 2008

Weights					
Chrysanthemums	Carnations	Roses	Others	$E(P_p)$	$\sigma(P)$
3.0	71.0	4.4	21.7	14.89 (Eurocents)	2.24 (Eurocents)
3.8	40.4	20.0	43.4	17.00 (Eurocents)	2.52 (Eurocents)
61.5	0	0	38.5	19.00 (Eurocents)	3.17 (Eurocents)
83.3	0	0	16.7	21.50 (Eurocents)	5.92 (Eurocents)

Table 6. Mean-Variance Efficient Portfolios, "Others" Excluded, month 1, 1993 – month 6, 2008

Weights				
Chrysanthemums	Carnations	Roses	$E(P_p)$	$\sigma(P)$
5.1	83.1	11.8	14.20 (Eurocents)	2.34 (Eurocents)
11.2	44.8	44.0	17.00 (Eurocents)	3.04 (Eurocents)
15.5	17.9	66.6	19.00 (Eurocents)	4.04 (Eurocents)
79.9	0	20.1	21.50 (Eurocents)	6.13 (Eurocents)

The first portfolio expected price level (first row) in the column $E(P_p)$ is the price associated with the minimum variance, and the three next rows show arbitrarily chosen values on the efficient set. In table 5, including "others," we see that the efficient portfolios at low expected price levels mostly consist of carnations and "others." As the expectation level increases the share of chrysanthemums increases, while the share of carnations decreases. Roses enter with 20 per cent at the second expectation level, and at the two highest expectation levels we see a switch to chrysanthemums and others, while carnations and roses are no longer part of the optimal portfolios. Excluding "others," table 6 presents more variations in weights. Except

[9] Ideally, we should have adjusted prices for production costs, and in that way used net cash flow contribution. Not deducting costs means that we assume similar variable costs across all varieties.

from the highest expectation level, all varieties enter the efficient portfolios. At minimum variance the portfolio mostly consists of carnations, and as the expectation level increases the share of carnations decreases, and the share of roses increases up to the highest level, where we see a switch to chrysanthemums. The tables, furthermore, demonstrate the diversification effect on price risk. As an example, the portfolio in table 6, with 79.9 per cent chrysanthemums and 20.1 per cent roses, has an expected portfolio price of 21.5 Eurocents with a standard deviation of 6.13 Eurocents. This price risk is lower than that of chrysanthemums alone (6.76 Eurocents). The expected portfolio price, on the other hand, is just a little lower than that of chrysanthemums (21.88 Eurocents) while significantly higher than the expected rose price (19.98 Eurocents). In other words, there is no free lunch, as such. Producers may, however, sleep better if they pool their assets in portfolios.

Real life organization of risk management for flower producers

"Price averaging" is well known in agricultural marketing cooperatives. Various marketing boards have established rules so that members at different locations receive identical prices or so that the marketing board averages payoffs over time. The present paper is, however, considering risk management *without* the cooperative getting involved in the marketing. Similarly, the mutual fire insurance cooperative does not involve itself in constructing or rebuilding burned-down houses; the idea is to specialize in insurance or risk management. *Producers* handle the marketing.

How, then, could flower producers apply basic portfolio theory in a risk management cooperative in real life? A major obstacle to creating such a cooperative is related to the fact that, quite often, one will have to put "apples and bananas" into the portfolio. While financial assets can be evaluated in terms of expected (percent) returns, agricultural products yield cash flow contributions that cannot be easily compared, since costs may be quite different. Thus, cooperative price risk management would most likely have to focus on expected price levels and to establish portfolios with the aim of averaging prices over time.

One objective for the cooperative would then be to establish some consensus price forecasts among the participants, which could serve as benchmarks for calculating *ex ante* portfolio price-level (or return) expectations and risk for given portfolio combinations. Let us assume that the members of a price risk management cooperative are willing to commit themselves to the judgment made by a "market surveillance committee" that the cooperative has appointed. The member of the cooperative specializes in what he or she does the best, that is, flower production, leaving the market forecasts to those presumably in a better position to make such forecasts. For such a commitment to be sustainable, the market committee would have to present a good track record. The TV weather forecaster presents a good analogy: people will adjust behavior according to forecasts only if it seems that they are reasonably good, on the average as well as on a daily basis. If forecasts of a marketing committee are reliable, it would not be unrealistic to assume that flower producers would accept that their production (or parts of it) is put into a cooperative management pool.

This pool may be set up as follows. The market committee presents its price expectations for various products for given future dates. The members of the cooperative are then invited to announce given quantities of the relevant products or quantities for delivery in given time periods (weeks). The cooperative does not play any part in taking the physical products to the market. Thus, the cooperative acts simply as a bookkeeper. It keeps track of the members' positions, that is, the volumes registered for risk management by each member for a given week or month and the market prices for the period and product in question. Prices are, in this way, averaged on a continuous basis. The prices members receive may differ greatly from those they might have projected individually, independent of the cooperative. Spot prices would have to be a set of easily observable quotations from a source or a market place agreed upon by the members in advance. The cooperative then takes care of the redistribution of cash among its members.

Just as the clearing house at a futures exchange requires margin installments when hedgers buy futures contracts, the risk managing cooperative probably would charge its members a cash insurance premium. The redistribution of risk could then be calculated according to the deviations between the forecasts and the portfolio result *ex post*. In simple words, the members of the price risk management cooperative substitutes an "average" (portfolio) price for an individual product price. The idea is that the portfolio price is less volatile than the price of the member's specific product, or (alternatively) that the member can obtain a higher expected portfolio price by taking on some of his or her neighbors' risk. What such an arrangement simply achieves is the same as what the individual member would have done by diversifying his or her own production, for example, by growing more varieties or spreading harvesting or marketing over time. In a cooperative, the member can diversify without losing the benefits from specialization. In practical terms, cooperative members are simply credited or debited in the co-op's books according to whether actual prices (and portfolio average) turned out to be lower or higher than expected.

In financial portfolio management, it is generally quite easy to fine tune portfolio weights in order to establish portfolios on the efficient set. In the flower business, this is obviously not easy. Consequently, cooperative portfolio management cannot expect to end up with weights that represent minimum risk for a given expected portfolio price or return. The goal would have to be somewhat less ambitious. Portfolio weights, most likely, would have to be whatever the cooperative's members "announce" as their desired volumes to be put into the portfolio. This simply means that portfolio expected price and variance will have to be estimated *given* a set of weights. These estimates can then serve as benchmarks for the *ex post* redistribution of prices among the participants.

Assume that the cooperative's portfolio was weighted together so that the *expected* portfolio price was 18 Eurocents, based on three different assets put into the portfolio. These assets, we assume, had expected prices of 14 Eurocents, 17 Eurocents, and 21 Eurocents, respectively, and each asset made up a third of the portfolio. Reality then turns out to yield a portfolio price of, say, 16.2 Eurocents, that is, 10 % below expected price. A simple redistribution among the participants could then be to "pay out" a price that is a weighted adjustment of each asset's expected price. In this example, with each asset counting as a third, the prices to participants would be 12.6, 15.3, and 18.9 Eurocent respectively.

Concluding comments

There are, obviously, a number of problems related to cooperative price risk management in the flower business along the lines that we have suggested. One problem relates to specifying *qualities* when establishing a market reference price against which the cooperative accounting portfolio shall be evaluated. There also exists the issue of potential moral hazard or the possibility of individual large members cornering the market. Apparently, the cooperative would need rules regarding members' rights to take outright speculative positions in the pool. Thus, one would have to discuss whether a member should be allowed to register in the pool amounts significantly larger than his or her real production. There is also a problem related to the heterogeneity of different producers. In our example above, carnation growers seem to have a low systematic risk (a low β). Their partition in the cooperative portfolio would, therefore, require a willingness to take on additional risk and, as compensation, receive a higher expected return. In a way, this resembles the function of the speculator or investor, and it may be difficult to convince a sufficiently large number of producers to take such a role. Finally, the cooperative would have to establish rules in those cases where reality happens to be significantly different from expectations on the downside. Thus, if the marketing board is consistently wrong about future prices, the obvious result is that the cooperative represents no benefit to its members.

One could easily conceive different settings in which price risk (or return) management could be set up in a cooperative portfolio approach. One approach might be similar to the way hog producers confronted with wide price variations for both inputs and outputs could probably smooth net revenues by pooling their feed costs as well as their planned deliveries in the books of a cooperative accounting system[10]. Thus, flower producers could pool their price risk for their major inputs, i.e. energy and fertilizer. This could be done without involving the physical handling, storage etc. of heating oil or fertilizer. Instead the participants in the risk management pool could have the input costs tied to the output prices in a relatively simple accounting system in the pool. It is not unlikely that producers participating in this way could achieve the same amount of risk reduction as they would have been able to obtain through futures hedging. It may also turn out that simple cooperative risk management could be quite cost efficient.

[10] An interesting example of risk pooling in the hog industry is found in Finland (Pietola and Wang, 2000). Hog producers buy their piglets through the slaughter house. The price of the piglets is fixed as a function of the market price of pork at the time of slaughtering, that is, some ten to twelve weeks after the farmer received the piglets.

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Vakblad Voor De Bloemisterij 1993-2008. *Vaakblad voor de Bloemisterij.* Den Haag, Holland: Reed Business Information.

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Thesis number 2010:40
ISSN: 1503-1667
ISBN: 978-82-575-0950-7

Marie Steen was born in Kristiansund, Norway, in 1961. She holds a Cand. Agric Degree in Plant Sciences from the Norwegian University of Life Sciences, Norway (1986) and a MSc. Degree in Agricultural Economics from University of California, Davis, USA (1990).

The thesis consists of an introduction and five independent, but related essays. The unifying theme is the challenge of production and marketing of cut flowers under price uncertainty. Essay I gives an overview of international flower production, consumption and trade, with a special focus on the Dutch flower auctions. Essay II presents short-term price forecasting models that can be applied in the production and marketing of cut flowers. The results indicate that combining seasonal regularities and autoregressive price patterns, a substantial part of the short-term price variability can be explained. Essay III is a follow-up on essay II using an alternative methodological approach, i.e. partial least squares (PLS) regression. The results show that the PLS model can be recommended as a successful forecasting method compared to more standard forecasting methods. In essay IV price-quantity relationships and issues related to consumer behaviour are analyzed, estimating a demand system. The results suggest that a potential for strategic marketing or market timing exists. Finally, Essay V is addressing price risk, suggesting that flower producers take a portfolio approach to reduce risk. The results show that price risk can be substantially reduced through some quite simple diversification strategies.

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