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Forecasting Prices at the Dutch Flower Auctions: Calendar Patterns and Other Time Regularities

By

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Abstract

Flower prices at the Dutch flower auctions are extremely volatile. An increase or decline of 20 per cent one week to the next represents 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 at the Dutch flower auctions 1993 through 1996. We conclude that for roses and chrysanthemums, calendar regularities provide fair long-term (12 months) forecasts. For carnations no such calendar regularity can be identified. For all three species, combining information on calendar regularities, cross-species correlation and auto regressive patterns, results in very good short-term forecasts.

Key words: Flower prices. Greenhouse production planning. Forecasting

Introduction

"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.[1]

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.[2] A large part of the Dutch production is traded at the flower auctions organised through the Association of Dutch Flower Auctions (VBN - Vereniging van Bloemenveilingen in Nederland). Although

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[1] Garber (1990) in his article on "Famous First Bubbles" argues that neither the "Tulip Mania" nor the "Mississippi and South Sea Bubbles" qualify as true bubbles. We'll not get involved in a discussion on how to define a bubble. In any case, the price movements in the 17th century were significant.

[2] 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 available on diskette from the authors on request.

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 to 34 per cent for chrysanthemums (see table I). The standard deviations of *weekly* per cent price changes are in the range of 17 - 20 per cent. Thus, annualising we have standard deviations of price changes from 120 to 140 per cent! To some extent, this volatility reflects seasonal variations that are fairly regular in terms of the *direction* of price changes. Still, cut flowers are among *the* most volatile commodities. 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 agricultural commodities rarely exhibit short-term price changes in the neighbourhood of those reported from the Dutch flower market.

Table 1. Flower prices at Dutch auctions; weekly observations 1993-96

	Cents per unit, Means	**Std. Deviations**	**Coefficients of variation**	**Std.deviations weekly per cent changes, annualised**
Chrysanthemums	46.37	15.87	0.34	121.1
Carnations	26.59	5.89	0.22	134.1
Roses	39.68	12.08	0.30	142.0

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, before we present empirical evidence in terms of price data from the Dutch flower auctions and the econometric results from estimating some simple time series models. Our goal is to establish a set of simple rules that can be used as input in more complex production planning models. We start out by analysing calendar patterns in the price data before we estimate AR(n)-models in which the calendar regularities are included. The last section summarises our main findings.

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 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 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 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 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. The problem is illustrated in figure 1, which graphs weekly prices for chrysanthemum, carnations, and roses 1993-97. One can easily see fairly regular peaks and throughs. These, 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.

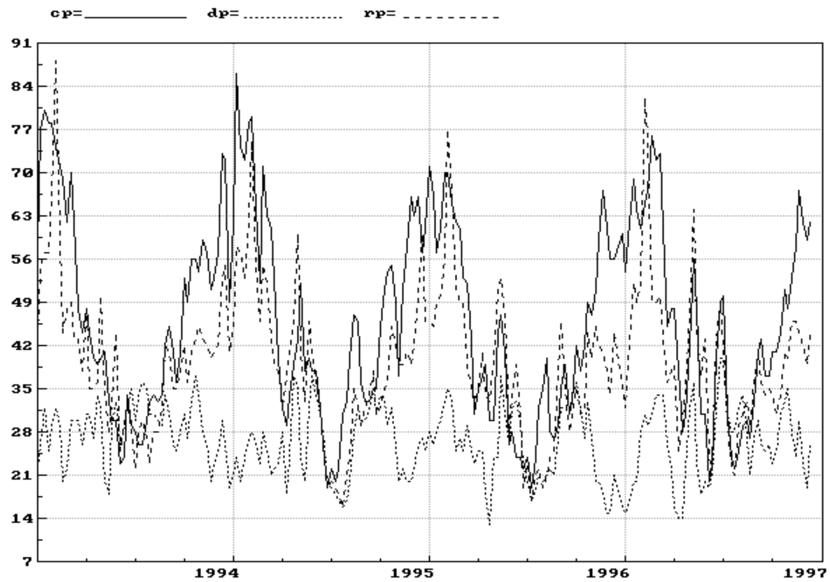


Figure 1. Dutch flower prices (NLG cents per unit), 1993-97 (weekly observations).
Legend. cp = chrysanthemums; dp = carnations; rp = roses

Calendar regularities in flower prices

To some extent, flower prices exhibit calendar patterns.

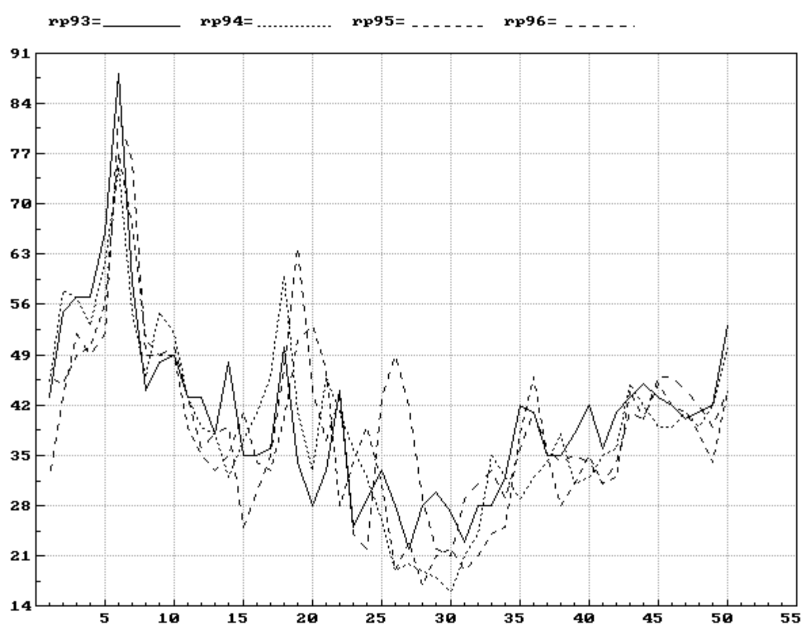


Figure 2. Rose prices (cents per unit), week 1-50; 1993, -94, -95, and -96

This is illustrated in the graphs below, where prices for roses (figure 2) and chrysanthemums (figure 3) from week 1 through 50 for the years 1993, -94, -95, and -96 are graphed together.[3]

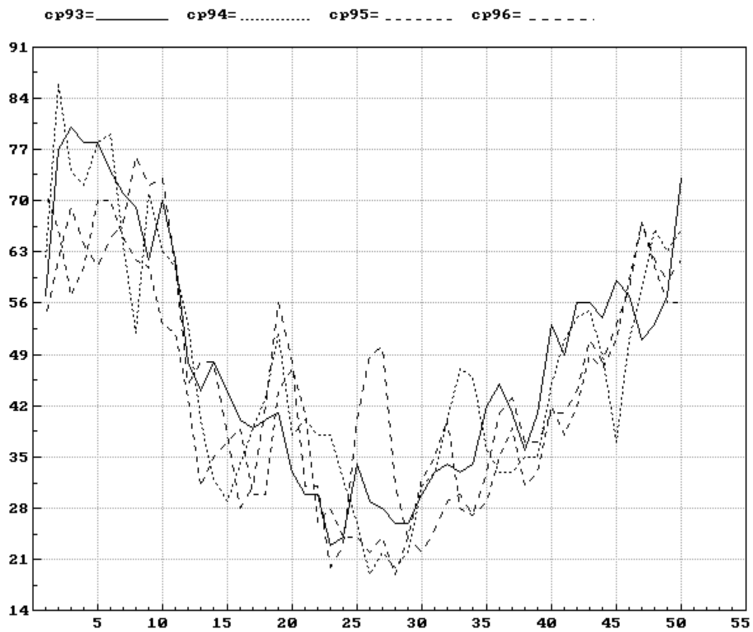


Figure 3. Chrysanthemum prices (cents per unit), week 1 - 50; 1993, -94, -95, and –96

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

[3] All price and volume data in this paper are gathered from the weekly journal "Vakblad voor de Bloemisterij".

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, as illustrated in figure 4. 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.

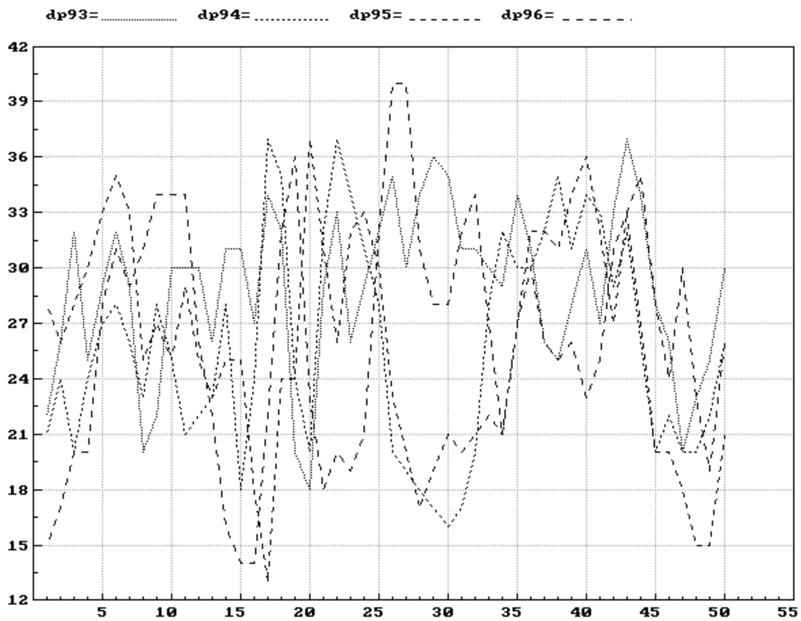


Figure 4. Carnation prices (cents per unit), week 1 - 50; 1993, -94, 95, and –96

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.

Assuming a naïve forecasting rule, i.e. the price this week equals the price 52 weeks ago, we get a mean error over the period 199401 - 199650 (154 weeks) ranging from 0.22 cents (roses) to 0.87 cents (carnations), none differing significantly from zero (table 2). Compared to the price levels (27 - 46 cents) and standard deviations (6 - 16 cents), these errors must indeed be considered minor.

Table 2. Naive one-year forecasts. The price in week t as a forecast for the price in week (t+52), 199401-199650

	Mean naïve forecast error (cents per unit)	**Std. Deviation**	**t-value**	**Mean forecast error in per cent of mean price**
Chrysanthemums	0.51	9.15	0.69	1.1%
Carnations	0.87	7.58	1.42	3.3%
Roses	0.22	7.75	0.35	0.5%

More systematically, table 3 reports the OLS-estimation results from estimating

(1) $$p_{y,t} = \alpha + \beta_1 p_{y,t-52} + \varepsilon_{y,t}$$

(2) $$p_{y,t} = \alpha + \beta_1 p_{y,t-52} + \beta_2 p_{x,t-52} + \beta_3 p_{q,t-52} + \varepsilon_{y,t}$$

(3) $$p_{y,t} = \alpha + \beta_1 p_{y,t-52} + \beta_2 p_{x,t-52} + \beta_3 p_{q,t-52} + \lambda_1 E + \lambda_2 W + \varepsilon_{y,t}$$

using weekly observations 1993 through 1996. Subscripts y, x and q represent different species whereas E and W are dummies for Easter and Whitsun, respectively.

Relation (1) is the standard test of whether the price in week t-52 is an unbiased forecast of the price this week, i.e. whether β differs significantly from unity. In eqn. (2), we include the prices for two additional species in order to test whether today's price of, say, roses is some weighted average of the price of roses, carnations and chrysanthemum

52 weeks ago. The idea is to capture possible interrelationship between species that to some extent are close substitutes. Finally, in relation (3) we include two holidays, i.e. Easter and Whitsun, for many people occasions for giving flowers to friends and lovers or decorating one's house. Since these two holidays are moving on the calendar from one year to another, they unlike the other holidays are not immediately reflected in last year's prices.

Table 3. Calendar patterns in flower prices. OLS-estimations of Eqs. (1) - (3)

	α	β_1	β_2	β_3	λ_1	λ_2	**DW**	**Adj R^2**	
Eqn. (1) **Chrysanthemums**	8.24 (3.85)	0.81 (18.75)					0.94	0.69	
Carnations	21.25 (8.90)	0.17 (1.98)					0.61	0.03	
Roses	8.05 (3.98)	0.79 (16.18)					1.16	0.63	
Eqn. (2) **Chrysanthemums**	20.56 (5.45)	0.57 (7.46)	-0.59 (-.51)	0.37 (3.63)			0.92	0.72	β_2=carnations β_3= roses
Carnations	21.66 (7.64)	0.12 (1.22)	-0.06 (-1.06)	0.10 (1.28)			0.60	0.04	
Roses	18.10 (5.44)	0.90 (10.04)	-0.06 (-0.90)	-0.44 (-3.77)			1.17	0.65	β_3 = carnations
Eqn. (3) **Chrysanthemums**	19.36 (5.14)	0.60 (7.92)	-0.57 (-4.35)	0.35 (3.47)	3.71 (1.08)	-7.36 (-1.55)	0.87	0.74	β_2=carnations β_3= roses
Carnations	22.98 (8.26)	-0.10 (-1.78)	0.10 (1.02)	0.13 (1.72)	-4.37 (-1.73)	-5.78 (-1.64)	0.62	0.07	β_3= roses
Roses	17.59 (5.34)	0.90 (10.04)	-0.05 (-0.79)	-0.43 (-3.68)	0.56 (0.18)	-5.61 (-1.35)	1.11	0.67	β_3= carnations

( ) = t-values

The OLS-estimations[4] reported in table 3 show that for roses and chrysanthemums, the price 52 weeks ago is significantly different from zero in all three models. In the simplest specification (Eqn. (1)), the parameter's numeric value is not very far from unity. It is,

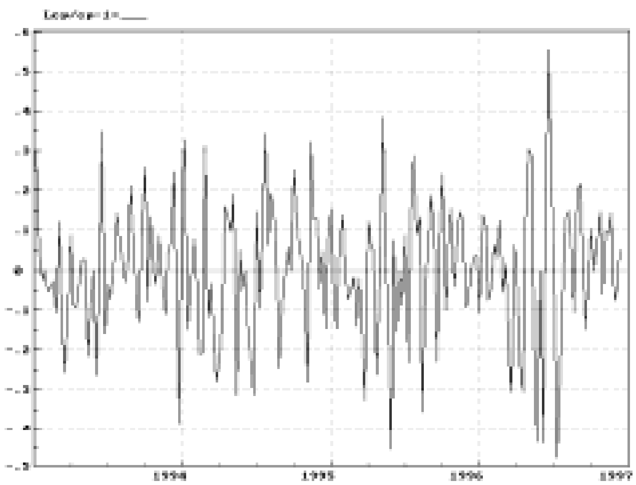
[4] OLS-estimation of (1) - (3) requires stationary variables. The price series have been tested for unit roots by standard Dickey-Fuller procedures (ADF) applying widely different number of lags. The unit root hypothesis is persistently rejected, i.e. the price series appear to be stationary.

however, statistically less than one, which may suggest that there is a long-term *mean reversion* in flower prices. A very high price in week X is followed by a lower price in the same week next year, and *vice versa.* The simple model yields an explained variance as high as .63 for roses and .69 for chrysanthemums. For the latter, last year's carnations and rose prices are also significant, whereas last year's carnations price comes out as statistically significant (negative) for this week's rose price, increasing the explained variance a few points. For carnations, on the other hand, last year's price although weakly significant, has far less explanatory power. The two moving holidays do not add significantly to the explanation for any species.

Despite the obvious presence of serial correlation (Durbin-Watson statistics from .6 to 1.17), which is something that must be expected when using overlapping observations, there is little doubt that price observations for roses and chrysanthemum in a given week entail significant information for the prices 52 weeks ahead. The unity-hypothesis, however, is rejected in favour of a mean-reverting process.

Calendar regularities and auto regressive patterns: Short term forecasts

The importance of good production planning and the need for good price forecasts is illustrated in figure 5, visualising weekly *per cent* price changes for chrysanthemum and carnations 1993-97.



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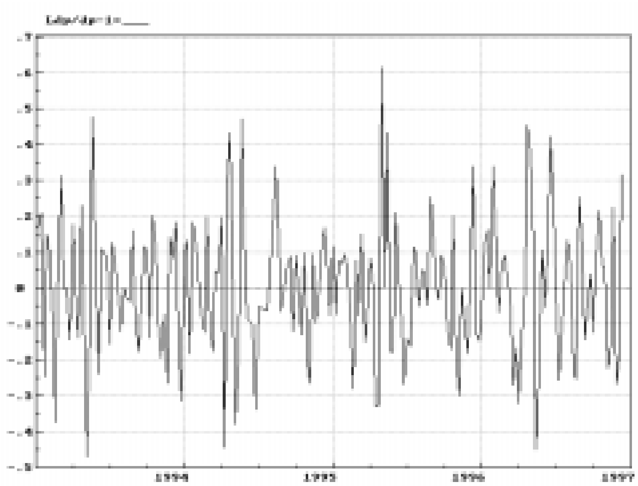


(b)

Figure 5. Weekly per cent price changes, chrysanthemum (a) and carnations (b), 1993-96

As can be seen, arriving one or two weeks too late or too early in the flower market, may represent significant opportunity losses. It is not uncommon that prices jump or fall by 20 - 40 per cent from one week to the next. 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.

As an exploratory introduction, we estimated the forecast errors using the calendar regularities discussed above as a simple AR(4) process,

$$(4) \qquad (p_t - p_{t-52})_t = \alpha_0 + \sum_{i=1}^{4} \alpha_i (p_t - p_{t-52})_{t-i} + \varepsilon_t$$

The results are reported in table 4. As can be seen, in all three cases the forecast errors come out significantly as AR(2).

Table 4. Estimating 52-weeks forecast errors as AR(4) (Eqn. (4)).

	α_0	α_1	α_2	α_3	α_4	**DW**	**AdjR^2**
Chrysanthemums	0.32 (0.52)	0.69 (8.31)	-0.38 (-3.81)	0.01 (0.98)	-0.03 (-0.42)	2.00	0.33
Carnations	0.28 (0.62)	0.85 (10.37)	-0.33 (-3.08)	0.12 (1.13)	-0.02 (-0.20)	1.98	0.49
Roses	0.16 (0.28)	0.52 (6.25)	-0.32 (-3.45)	0.08 (0.84)	0.03 (0.39)	2.00	0.23

Further tests revealed a strong autoregressive pattern in weekly prices. Combining this with the calendar regularities reported above, *and* the indications that there is a long-term correlation across the major species, a very simple prediction model emerges, i.e.

$$(5) \qquad p_{y,t} = \alpha + \sum_{i01}^{5} \beta_i \, p_{y,t-i} + \sum_{j=y,q,w} \gamma_j \, p_{j,t-52} + \varepsilon_t$$

In other words, this week's price for y is assumed to be a function of its own price 1-5 and 52 weeks ago, as well as the price for q and w 52 weeks ago. The OLS-results reported in table 5 again confirm the strong calendar regularities for chrysanthemums and roses (γ_1).

Table 5. Flower prices estimated as an auto regressive process with calendar regularities (Eqn. (5))

	α	β_1	β_2	β_3	β_4	β_5	γ_1	γ_2	γ_3	**DW**	**AdjR^2**	
Chrysanth.	12.34 (3.71)	0.80 (9.34)	-0.38 (-3.52)	0.17 (1.58)	-0.05 (-0.53)	-0.01 (-0.25)	0.26 (3.68)	-0.37 (-3.40)	0.19 (2.20)	1.86	0.84	γ_2=carn. γ_3 = roses
Carnations	10.01 (3.28)	0.93 (11.09)	-0.43 (-3.71)	0.21 (1.76)	-0.04 (-0.33)	-0.09 (-1.12)	0.03 (0.58)	0.03 (0.46)	-0.02 (-0.61)	2.00	0.56	
Roses	10.05 (3.05)	0.64 (8.23)	-0.43 (-4.54)	0.31 (3.19)	-0.19 (-2.02)	0.05 (0.84)	0.56 (6.50)	-0.02 (-0.46)	-0.26 (-2.63)	1.94	0.76	γ_3=carn.

We also again observe the long-term cross-species relationship from the price last year to this week's price. Thus, both the carnation and the rose price week t-52 are significantly related to this week's chrysanthemum price (γ_2 and γ_3). The "effect" from last year's carnation price on the chrysanthemum price is negative, while that of the roses is positive. Rose prices, on the other hand, are negatively related to last year's carnation price, while there is no long-term calendar pattern in the carnation price series. The over all conclusion is that this combination of calendar regularities, long-term cross species correlations and a short-term autoregressive patterns explain a very high proportion of the considerable price variations for the chrysanthemums (.84) and the roses (.76). As regards the carnations, there are no significant long-term patterns. The autoregressive (short-term) movement, however, explain some .56 of the variation.

As to the short-term price changes, the spectrum plots[5] in figure 6 reveal a pattern different from the "typical spectral shape" (Granger (1966)) for all three species. Thus,

[5] The spectrum consists of a smoothed function of autocorrelations, symmetric between $-\pi$ and π.

none has a pronounced peak at the low frequency. Instead, there is a peak at around .3 - .5π. The graphs suggest that there is an auto regressive pattern in price *changes* as well as price levels. The spectrum is a smoothed function of autocorrelations. The results from estimating the weekly per cent price changes (log (p_t / p_{t-1}) as an AR(6) process (not reported) gives a significant (at .01 level) parameter of approximately -.3 for lag 2. for all three species. This is a rather remarkable result when analysing relative price changes. Thus, there seems to exist a mean-reverting process in price changes, not only in levels. The reason may be due to the fact the problems of storing cut flowers. Another reason may simply be that flower market participants do not analyse price changes with the same intensity as agents in other commodity markets (where persistent patterns like this seldom are found). In any case, today these patterns can be used for forecasting purposes in the flower business.

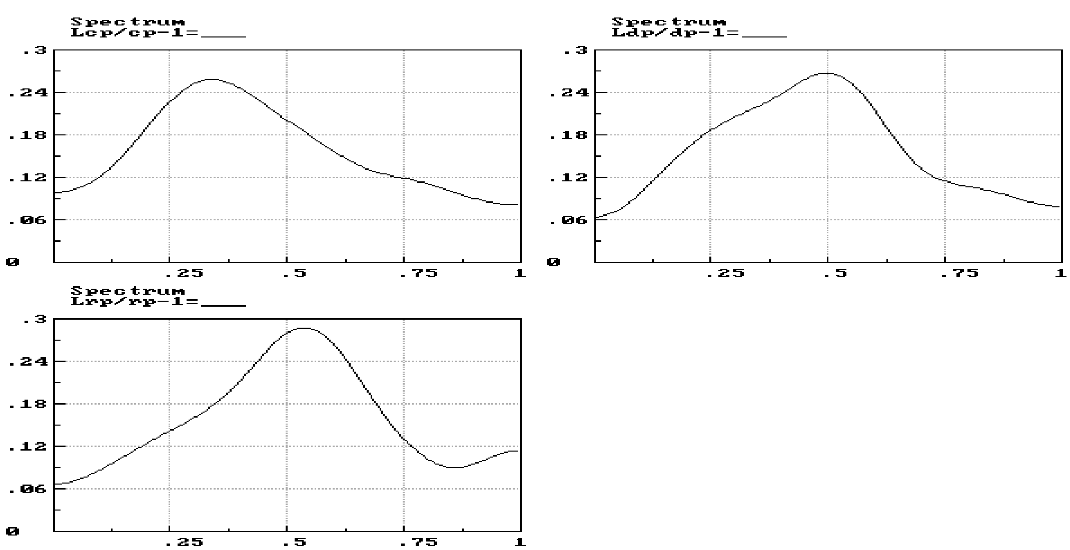
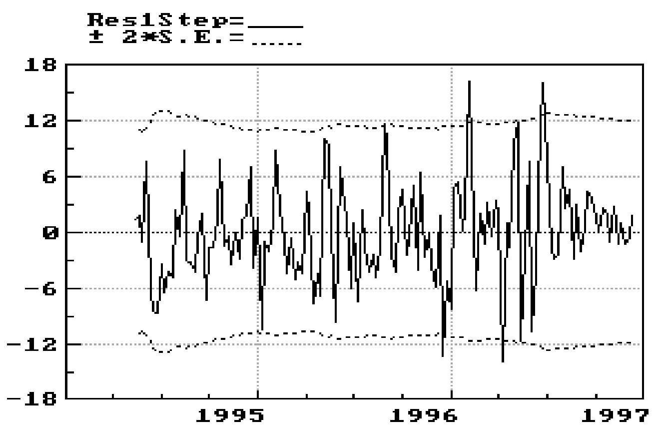


Figure 6. Relative price changes, spectrum (upper left chrysanthemums; upper right carnations; bottom roses)

The practical value of these simple prediction models will, of course, depend crucially on whether the observed patterns remain stable. For the period being analysed in this study, recursive estimation indicates that the parameters have been quite stable. Furthermore, the forecast Chi^2's for chrysanthemums and roses come out as not significantly different from zero over various forecast periods. Likewise, the 1-step ahead forecast errors also tend to move within an approximate 95% confidence interval (see figure 7).



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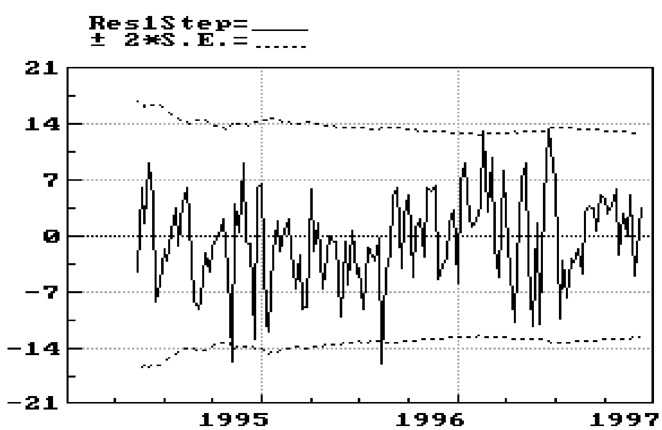

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Figure 7. One-step ahead forecast errors, roses (a) and chrysanthemums (b)

Concluding comments

For two major species, i.e. roses and chrysanthemums, prices follow a calendar pattern that yields good long-term (52 weeks) forecasts. A tendency towards “mean reversion” suggests that an adaptive expectations model gives better long-term forecasts than simple naïve forecasts. Thus, the 52-weeks naive forecast error follows an AR(2) process. Furthermore, the analysis reveals that there are long-term cross-species price correlations. Thus, there are statistically significant relationships between today’s price of chrysanthemums, last year’s chrysanthemum price and also last year’s rose and carnation prices. Utilising these calendar regularities could be of significant economic value used as input in a larger model for long-term (defined as 12 months) green house production planning. Combining the information inherent in the long-term calendar regularities and cross-species correlations with short-term autoregressive price movements results in a model which explains between .56 (carnations) and .84 (chrysanthemums) of the very volatile short-term (i.e. weekly) price movements. Although producers’ leeway is limited in terms of hastening or delaying marketing, regulation of light and temperature opens up possibilities for utilising such short-term forecasts.

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