International Food and Agribusiness Management Review
Volume 14, Issue 4, 2011

Management System for Harvest Scheduling: The Case of Horticultural Production in Southeast Spain

Juan C. Pérez-Mesa[ᶲa], Emilio Galdeano-Gómez[b] and
José A. Aznar-Sánchez[c]

[a] *Professor, Department of Business Administration and Management, Universidad de Almería, Campus de Excelencia Internacional Agroalimentario (ceiA3), La Cañada de San Urbano 04120 Almería, Spain*

[b] *Professor, Department of Applied Economy, Universidad de Almería, Campus de Excelencia Internacional Agroalimentario (ceiA3), La Cañada de San Urban 04120 Almería, Spain*

[c] *Professor, Department of Applied Economy, Universidad de Almería, Campus de Excelencia Internacional Agroalimentario (ceiA3) La Cañada de San Urbano 04120 Almería, Spain*

Abstract

This article analyzes the programming of farm production, understood not only as the choice among several crops, but also as their temporal distribution. The empirical study takes as a reference the horticultural sector in southeast Spain, since this area constitutes the highest concentration of small-scale farm production in Europe, where the climatic conditions allow the possibility of several harvests in year-round production, as well as several alternative crops. Firstly, we study the production programming for an individual farmer, under the assumption that their decisions do not affect the balance of market prices. In this case a modified Markowitz model is used for the scheduling of crop marketing. Secondly, we study the sales arrangements for a farming-marketing cooperative, under the assumption that their sales volume is such that the entity is capable of altering the market balance. A model of monthly revenues and margins is proposed, and the results show a clear improvement in both margins and revenues if the harvest is programmed in this way.

Keywords: horticultural farmer, optimization, planning, mathematical programming, marketing, cooperative

[ᶲ]Corresponding author: Tel: +34 950 015166
Email: juancarl@ual.es

E. Galdeano-Gómez: galdeano@ual.es
J. A. Aznar-Sánchez: jaznar@ual.es

Introduction

Production planning, seen from an operational point of view, implies making decisions about the choice of crops and programming harvests over time. Doing this properly will avoid decreases in prices (revenues) as the demand in the agricultural market is usually rigid. In other words, it does not absorb unexpected increases in supply, particularly over short periods of time and with perishable products. For this reason prices and revenues experience disproportionate decreases. This has been a very common situation in recent years for the Spanish fruit and vegetables sector (De Pablo and Pérez-Mesa 2004) in which price fluctuation is very high (Galdeano-Gómez 2007). For example, during the 2008/09 growing season there was a 10% production increase which led to price drops of over 19% among key products such as cucumber, pepper and tomato (AFAC 2010).

The traditional agricultural systems in Spain are located mainly in the Mediterranean areas, and southeast Spain currently represents the main horticultural concentration of the country. Production is based on greenhouses (over 26,000 hectares[1]) and over 13,500 small family farms with an average of 2 hectares of land (Galdeano-Gómez et al. 2011). The climatic conditions and technology allow harvesting during most of the year, and farmers can alternate different horticultural crops; mainly pepper, tomato, cucumber, zucchini, eggplant, melon, watermelon, green bean, and lettuce. Over 95% of total production is marketed within the European Union, and exports represent about 65% of total sales.

In this horticultural sector not all variations can be attributed to programming deficiencies alone, as climatic factors are also involved. The lack of organization related to supply is due to a production system comprised of small-scale farms, which makes coordination very difficult. The low level of organization is also a result of the duality of the marketing systems: cooperatives market 60% of total produce and are also closely related to farmers' programming; the remaining 40% of produce is wholesale auctioned, which complicates crop scheduling (Pérez-Mesa 2007).[2]

The present study focuses on harvest programming and aim to put forward several management systems to improve the decision making of both individual farmers and cooperatives. To this end, certain challenges and considerations must be taken into account. In particular, in order to correct the deficiencies in programming, the optimum production for a given system must be determined, i.e. the quantity that should be supplied to the market so that profits and revenues are maximized. This proves difficult to calculate, since there is essentially only one reference variable: the price. As a result, production programming will ultimately depend on a sampling of prices which are subject to high variability for the following reasons: the existence of complementary supplies unrelated to those which we intend to plan, climatic factors (either seasonal changes in demand, when planning production for periods of under one year) or structural changes (considering variations in consumption habits). Furthermore, when programming for operators that

[1] This represents the highest concentration of greenhouses in the world (UNEP 2005).

[2] We are analyzing a sector with many types of small-scale farm traditionally using two kinds of marketing. In the first, the farmers themselves auction their goods and also follow their own individual programming system. In the second, farmers are members of a cooperative which markets goods collectively. In addition, the presence of high sales margins has often made it difficult to impose any strict scheduling on growers, even in the case of cooperatives. In fact, many cooperatives merely go as far as suggesting scheduling, without ever imposing it. Altogether, these factors cause a relative lack of supply planning.

control a substantial percentage of the sector and are therefore capable of altering the market balance, this fact must also be included in order to maximize their margins and revenues.

Several studies have tackled these questions by implementing different methodologies. The classic method for production programming is the mean-variance quadratic equation (M-V) developed by Markowitz (1952), applied by several researchers to schedule crops efficiently (e.g. Alejos and Cañas 1992; Gómez-Limón and Arriaza 2003). Other programming models utilized in the farming sector include MOTAD (Minimization of Total Absolute Deviation) and Target MOTAD. The objective of these methods is to minimize absolute deviations for a sector of activities using a risk aversion parameter which is subjective for each decision-maker (Romero and Rehman 2003). Another model is Mean-SAD, which uses Semi-Absolute Deviation as a risk estimator to study variable values, with respect to a fixed goal (see e.g. Berbel 1988, 1989).

Advances in non-linear programming techniques should also be mentioned. The following are particularly noteworthy (Ahumada and Villalobos 2009): Direct Expected utility Maximizing non-linear Programming (DEMP) developed by Lambert and McCarl (1985), Utility Efficient Programming (UEP) by Patten et al. (1988) and the combination of both (DEMP-UEP) proposed by Pannell and Nordblom (1998).[3]

The present study has several objectives. The first is to develop a harvest programming model which can easily be applied by grower-marketing entities, i.e., cooperatives, and utilized for both the selection of crops and their distribution throughout the growing season. The second, proposes the creation of a programming optimization method that can be employed by large-scale operators with the capacity to alter the price balance. In order to achieve the first objective it is proposed that the M-V model be modified so as to adapt it to the requirements of programming over time, as well as to include commercial aspects in its formulation. To attain the second objective we develop a multi-equation model for revenue and margin maximization using a monthly system of simultaneous equations.

The rest of the paper is structured as follows. Section 2 outlines the management system of programming production for an individual farmer (M-V model) and shows an empirical application. Section 3 presents a model of management decision considering a monthly program. Section 4 shows the application to a large-scale producer or cooperative. Section 5 outlines the discussion of the results. Finally, conclusions are drawn in Section 6.

Programming Production for an Individual Farmer

Framework and Markovitz Model

Decisions in the horticultural sector are rarely based on certainty due to price variation alone and usually include technical and climatic factors. When we are incapable of predicting or quantifying the future, we find ourselves in a context of uncertainty. When it is possible to calculate the probabilities of those events relevant to our decision, we are in a context of risk. In the present analysis, we consider that decisions will be made in a context of risk. Indeed, several studies

[3] It is important to point out that all the models, including M-V, have the same drawback, which is the 'subjective' selection of the mathematical expression of the utility function.

suggest that the decision making process in the agricultural sector is subject to risk aversion (e.g. Pannell and Nordblom 1998; Hardaker et al. 1991, 1997). When faced with this type of situation, farmers will normally try to diversify, either by introducing new crops or by modifying their production calendars (Pannell and Nordblom 1998).

The present study implicitly assumes that individual farmers are profit maximizers, and that in a situation of risk they behave following the postulates of the Expected Utility Theory (EUT) according to Von Neumann and Morgenstern (1947). At the same time, through empirical studies evaluating different criteria, various authors have revealed the complexity of decision making for farmers (Willock et al. 1999; Costa and Rehman 1999; Solano et al. 2001; Gómez-Limón et al. 2003, 2004). These studies share the same conclusion, namely that when the time comes to make decisions on production, in the farmer's mind, besides the hope of profit, there are a series of considerations related to their economic, social, cultural and environmental surroundings. As a result, they will try, insofar as it is possible, to satisfy all of these objectives simultaneously. Despite this series of drawbacks, the overall approach followed is considered adequate because it is a plausible correct approximation given the highly competitive system which characterizes intensive farming in southeast Spain. In fact, if there were any growers who deviated from this type of behavior which seeks maximum profit, they would be quickly expelled from the market.

In the case of an individual farmer, we propose the Markowitz model (1952) for its simplicity and easy iterative resolution[4]. Furthermore, this model offers an intuitive analysis system that is easy to understand with respect to other programming methods insofar as it does not require prior knowledge about how to apply the expected utility theory (Duval and Featherstone 2002). This also makes it that much easier for farmers to implement. The general formulation of the model has been improved in order to program on a monthly basis and to select among a wide variety of products. Moreover, this makes it possible to introduce commercial criteria when deciding on a production-marketing plan:

$$(1) \qquad \text{Min } V(x) = \sum_{s}^{p}\sum_{c}^{p}\sum_{i}^{n}\sum_{j}^{n}\sigma_{ij}^{sc} X_i^s X_j^c$$

Subject to constraints:

$$(2) \qquad \sum_{c}^{p}\sum_{i}^{n} M_i^c X_i^c = M_0$$

$$(3) \qquad \sum_{c}^{p}\sum_{i}^{j} X_i^c = N$$

$$(4) \qquad X_i^c \geq 0 \text{ with c = 1...p; i=1...n}$$

where:

[4] For example using an Excel spread sheet by means of the option 'solver'. Although some authors criticize that a quadratic utility function is rarely observed in reality (Meyer and Rasche 1992), Kroll et al. (1984) demonstrated that the E-V analysis is a good approximation to reality even when these conditions are not met.

X_i^c = Production that will be marketed of crop *c* for month *I*, which is, therefore, the decision variable.

M_i^c = mean gross unit margin of crop *c* for month *i*; meaning, the arithmetic mean, for the years considered in the series, of the difference between variable prices and costs (which are considered fixed for a given month) expressed in euros/kg:

$$M_i^c = Px_i^c - Cx^c \tag{5}$$

N = Total production by farmer. N = 1 is normally utilized (this will allow us to deal with percentages).

σ_{ii}^{cc} = Variance of gross margins obtained during different years for crop *c* for month *i*.

σ_{ij}^{sc} = Covariances of gross margins obtained during different years between crop *c* and crop *s* for months *i* and *j*; or between crops *s* and *c* for month *i*.

Expression (1) will be the variance for the marketing plan, which will measure the risk assumed, which is nothing more than the sum of the variances and covariances of the gross margins weighed by production-marketing dedicated to each crop in a given month. Equation (2) shows the expectations of the production-marketing plan as the sum of the mean gross margins multiplied by the amount. This restriction is parameterized. By varying M_o, specific plans will be attained which satisfy the economic expectations. In short, the calculated plans will minimize the variance-risk (1) for the value of the expectations (2).

The proposed model will make it possible for a company to decide what to market and at what time of year. Nevertheless, reality tends to be more complicated:

It is possible that the production capacity is such that it does not permit substituting one crop for another; for example, only two types of farming machinery are owned, one used for peppers and the other for tomatoes, meaning the products cannot be switched. In this case two models can be calculated, one for each crop. If we decided to include this in only one model, we would introduce the following restriction substituting (3):

$$\sum_i^n X_i^c = \frac{h^c}{N} \quad \text{with} \quad \sum_c^p h^c = N \tag{6}$$

where h^c is the production of crop *c* which can be managed by the production capacity. For example, let us suppose that a company has only two pieces of farming machinery at its disposal (crop specialized and with equal working capacity), one for tomatoes and the other for peppers. As a result, half of all commercialization will necessarily be dedicated to peppers and the other half to tomatoes, meaning, (with N=1) $h^{Tomato} = 0.5$ and $h^{Pepper} = 0.5$.

On the other hand, if a farmer has programmed commitments with customers, a new restriction will be introduced that will imply the existence of a production *n* designated for a specific product and fixed date:

$$(7) \qquad X_i^c \geq n_i^c$$

If the farmer has a maximum monthly capacity *m* available per crop, we will add the restriction:

$$(8) \qquad X_i^c \leq m_i^c$$

If we consider that a farmer must cover fixed monthly costs *CF*, we will introduce the restriction:

$$(9) \qquad X_i^c \cdot M_i^c \geq CF_i$$

Should we be interested in studying in greater depth the relationship between risk (variance) and profitability (margin), the starting point would be to reformulate the classic M-V problem using the compromise-programming approach[5] (Duval and Featherstone, 2002):

$$(10) \quad \text{Min } L(x) = w_M \frac{M^+ - M(x)}{M^+ - M^-} + w_V \frac{V^+ - V(x)}{V^+ - V^-} = M(x) - \frac{w_V (M^+ - M^-)}{w_M (V^+ - V^-)} \cdot V(x) + C$$

subject to restrictions (3) to (9) and $w_M + w_V = 1$

Where $M(x) = \sum_{c}^{p} \sum_{i}^{n} M_i^c X_i^c$; C = a constant; M^+ = the maximum portfolio margin possible, M^- = the minimum margin possible, V^- = the minimum portfolio variance possible, V^+= the maximum variance possible, and w_M and w_V are weights (or coefficients) on the margin and the risk, respectively. Solutions to (10) satisfy the following first order condition (11) which means that for any result there is a stable relationship between the program variance and its expected margin, which depends on the weights attributed to the margin and risk (i.e., the value of ϕ):

$$(11) \qquad M(x) = \phi V(x); \quad \phi = \frac{w_V (M^+ - M^-)}{w_M (V^+ - V^-)}$$

As can be seen in (11), varying the weights, w_M and w_V, we can trace out the EV efficient set, as occurs in the original problem defined by (1) to (9), since, according to Duval and Featherstone (2002), the compromise programming approach is a generalization of the traditional M-V models. Taking (11) as the starting point and knowing the values of ϕ calculated, we can ascertain the values of w_V and w_M. This approach provides an intuitive view for the decision maker,

[5]For an introduction to compromise programming in agricultural economics literature see Romero and Rehman (2003) and Ballestero (1997).

who can easily check the weighting of risk and profitability that is being assumed in each case without understanding the concept of utility. In order to interpret the weights it must be taken into consideration that w_M, according to (10), ponders the degree of drift from the desired margin in relation to the maximum margin; and that w_V is the degree of drift from the desired variance in relation to the maximum variance. Therefore, an elevated value for w_M and a low value for w_V will provoke a "high risk" position.

Example of Application

In the example, for the sake of simplicity in estimations, we assume that there is a farmer who produces and markets two products via a cooperative: tomatoes and peppers. These two products were chosen because in the study area (southeast Spain) tomatoes and peppers represent nearly 50% of all production and marketing (Figure 1).

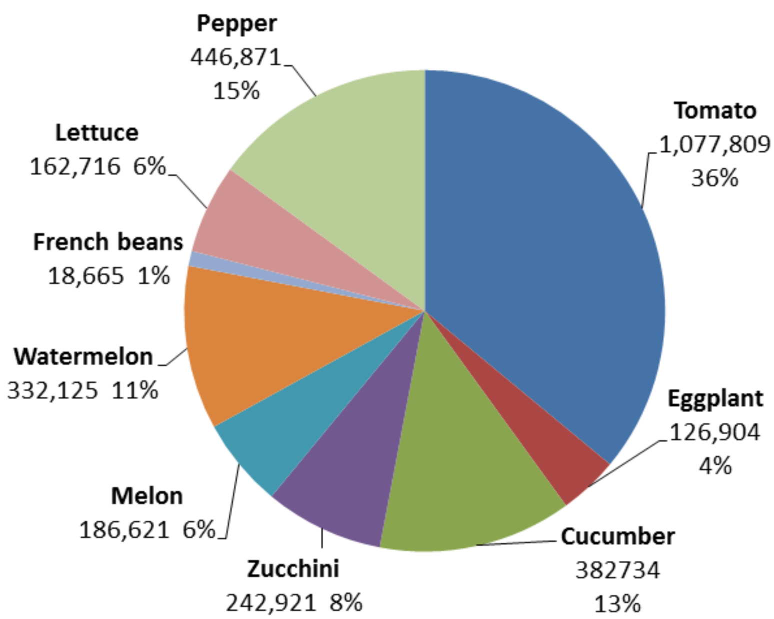

Figure 1. The most important crops produced and marketed in southeast Spain.
Tons. 2007/2008 Season.
Source: Pérez-Mesa, Galdeano-Gómez and Aznar-Sánchez. Created using data from the Agricultural Ministry of Andalusia

For our analysis we use the following data:

1. Spanish export prices to the European Union (FOB) expressed in euros/kg were collected from Eurostat.[6] Bear in mind that southeast Spain represents 71% of Spain's annual pep-

[6] The FOB prices maintain a relationship with the payment price given to the farmer in a cooperative. At the same time, a relationship exists between these prices and the exchange prices as the cooperatives have to follow auction prices to establish their payment price (as these are the only references available on site); otherwise they could lose their members. For a detailed description of the relationship between Cooperatives and Exchanges see e.g. De Pablo and Pérez-Mesa (2004).

per exports (De Pablo and Pérez-Mesa 2004). We have a seven-year series of data for the months that comprise the typical growing season in southeast Spain:[7] September-May. The prices have been deflated and expressed in 2007 monetary terms.

2. In order to calculate the monthly commercial margins, we deduct from the prices per kg the sum of the variable production and marketing costs[8]: 0.51 euros/kg for tomatoes and 0.64 euros/kg for peppers.

The description of the calculated margins can be seen in Table 1. It should be remembered that this margin must include a hypothetical profit attributed to the member-farmer[9] and the company, as well as the fixed costs of both.

Table 1. Monthly and total margin for tomato and pepper crops. Jan 1999 to Dec 2005. Data used for the Markowitz model.

	Tomato			**Pepper**		
Month	Average €/kg	Standard Dev.	Var. Coef.	Average €/kg	Standard Dev.	Var. Coef.
September	0.19	0.13	0.70	0.26	0.08	0.28
October	0.37	0.19	0.51	0.34	0.09	0.25
November	0.37	0.14	0.38	0.46	0.21	0.44
December	0.48	0.12	0.25	0.64	0.21	0.31
January	0.47	0.15	0.32	0.68	0.19	0.26
February	0.52	0.21	0.40	0.70	0.23	0.31
March	0.59	0.30	0.51	0.77	0.19	0.24
April	0.57	0.25	0.44	0.70	0.22	0.30
May	0.19	0.13	0.70	0.64	0.22	0.33

Source: Pérez-Mesa, Galdeano-Gómez and Aznar-Sánchez.

As this is an example, an unrestricted model is applied (Table 2, See Appendix), which means no kind of restriction is imposed. This model chooses between the two crops; for example, for the most conservative distribution (expectation of 0.38 euros/kg) 49% tomatoes would be produced (with peaks in the months of October, December and April) and 51% peppers (concentrated in the months of September and October); for the distribution with the highest risk (expectation of 0.77 euros/kg), only peppers would be produced in the month of March[10]. The scenario which offers the lowest risk per margin unit (expectation of 0.50 euros/kg), in other words, with the smallest variation coefficient, would be that which produces 62% tomatoes (with peaks in December and April) and 38% peppers (with peaks in February and April).

[7] For peppers, there is a sampling that extends from January 1995 to December 2005 (11 years). In this section we will use the shorter sampling for both peppers and tomatoes (7 years).
[8] The updated costs have been calculated based on Salinas and Palao (2002). They include the variable production costs assumed by the farmer-member: manual labor and maintenance. Marketing costs are: packing, handling (including manual labor), overheads and transport costs. Fixed monthly costs are established (per year) as a great deal of costs only receive annual survey (e.g. manual labor of the farmer that affects production costs; and manual labor for packing and handling that influences marketing costs). This hypothesis is used to simplify modeling.
[9] The payment price of the product weight the farmer brings to the cooperative could have been considered a cost, later adding the marketing costs of the company.
[10] In this item it is worth pointing out that the optimum solution chosen for each farmer and company will depend on their 'absolute' and 'relative' aversion to defined risks respectively, by Pratt (1964) and Arrow (1965).

Subsequently, we assume that there exists a fixed production capacity which permits management of 65% tomatoes and 35% peppers (Table 3, See Appendix). This system is equivalent to applying the model independently to later distribute marketing in the proportion deemed appropriate: the results show a conservative distribution (0.41 euros/kg margin) concentrated in the months of October, December and April for tomatoes; and in September for peppers. The highest risk model (0.64 euros/kg) would mean marketing tomatoes in April and December and peppers in March. The scenario which offers the lowest risk per margin unit (expectation of 0.50 euros/kg) would mean marketing mainly tomatoes in the months of October, December and April, and selling the majority of peppers in October, February and April.

Figure 2 shows the actual distribution and those programs with the lowest variation coefficient, that is, those with a lower risk-margin ratio. The actual distribution is softer than the rest and it underlines the difficulty in achieving efficient programs, even in those cases which include restrictions which are in agreement with the observed distribution of production (pepper = 35% of production; tomato = 65%). It can be seen that the actual distribution is no more than a program that is severely restricted by external and internal factors (for instance, demand, production capacity, climate, etc).

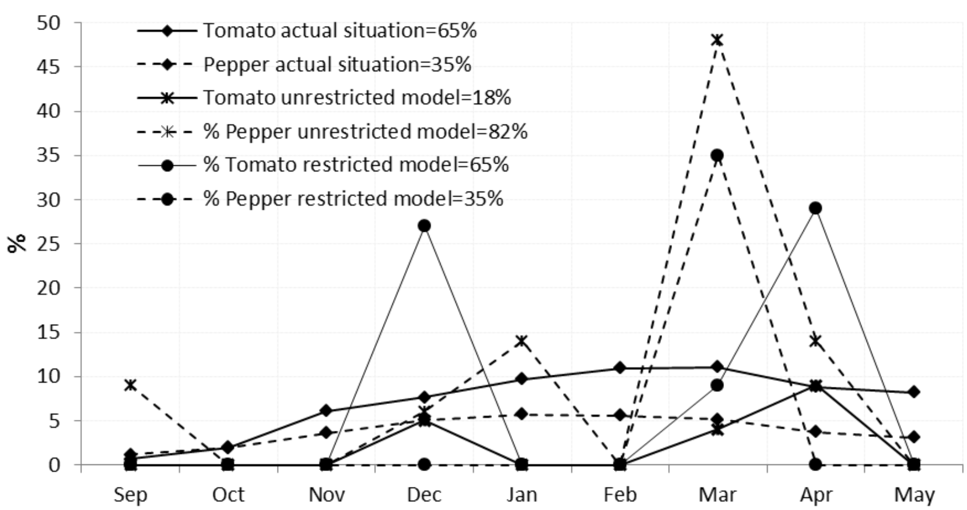

Figure 2. Distribution of pepper and tomato production-exports. Sampling average (actual situation) and calculated closest optimal distributions.
Source: Pérez-Mesa, Galdeano-Gómez and Aznar-Sánchez

From the calculated weights[11] (Tables 2 and 3), w_V and w_M, it follows that at all the points on the efficient frontier M-V the weighting of the risk is very much lower than that of the margin. Using these weights, the decision maker can easily see that even in the case of programs with higher variances, excessive risks are not being taken. Moreover, the weights for actual distribu-

[11] The value of ϕ will be equal to the ratio between margin and variance calculated in Tables 2 and 3. The maximums and minimums of the margin and the variance (M^+, M^-, V^+ *and* V^-) will be the same as those in Tables 2 and 3. Moreover, knowing that $W_M + W_V = 1$ we can clarify the value of W_V and W_M.

tion of the production show that the average horticultural farmer in southeast Spain is not conservative but nor do they assume excessive risk when temporarily programming their farming production. Nonetheless, farmers may not want to implement the optimal plans (although they imply lower risk) as they mean reducing the possibility of obtaining the highest revenues.

Production Programming for a Large-Scale Producer: Cooperative

Monthly Model

The problem now at hand is how to program the production of a cooperative which has the capacity to alter market balance as a result of its marketing volume. European Union regulations allow a group of companies (Associations of Fresh Fruit and Vegetables Producer Organizations) to collaborate in programming harvesting, that is, adapt their supply to the demand. Let us suppose there is a company or group of companies (Associations of Fresh Fruit and Vegetables Producer Organizations) with a high percentage of marketed production and we apply the Markowitz model described above. As expected, although its function is optimal, prices suffer because the crop is concentrated into a few months[12] since the distribution of production will alter the market balance prices which will be static as occurred in the Markowitz model.

An alternative approach to the programming model, which tries to resolve the above-mentioned problem set, would consist of estimating a function for demand per crop[13]

$$(12)\quad X = f(Px)$$

which would relate the monthly marketed amounts with their corresponding prices (Px) for the total sampling of years available[14]. Multiplying (12) by Px, we would obtain the revenue $IT(Px) = Px \cdot f(Px)$, calculating with respect to the price and equaling it to zero

$$(13)\quad IT' = f(Px) \cdot \left[1 + f'(Px) \cdot \frac{Px}{f(Px)} \right] = 0$$

we would attain a value of an optimum price (Px_{opt}) that would maximize revenue and entail an optimum quantity of monthly commercialization. Bear in mind that the second part of the brackets in (11) corresponds to the price elasticity of the estimated function (which requires that ε_{Px} = -1 so that the derivative is equal to zero). Also, taking into consideration that the total margin $MT(Px) = (Px - Cx) \cdot f(Px)$ could have been maximized; obtaining the optimum price by means of: $MT' = f(Px) + (Px - Cx)\, f'(Px) = 0$; and later finding X_{opt} of (12).

Example of Application

---

[12] We find ourselves before a spider's web effect, but with additional complications as we analyze not only the total annual variation of the production but also its distribution throughout the year.

[13] The superscript *c* is omitted in the notation. Also, it is assumed no relationship exists between different crops.

[14] This analysis could have been complicated by introducing other explanatory variables along with price; on the other hand, when using periods of data of less than one year price plays a more important role against other variables (e.g., income).

In this section we will utilize the monthly series of prices and export amounts for Spanish peppers in the EU (between January 1995 and December 2005) to obtain a marketing distribution which maximizes monthly revenue and margin. A summary of the data utilized can be seen in Table 4.

Table 4. Prices and export amounts for Spanish peppers to the EU. Jan 1995 to Dec 2005. Data used for the revenues and margins maximization model.

Month	Average Prices (€/kg)	Average Exports (tons)	Standard Dev. Prices	Standard Dev. Exports
September	0.95	9,927	0.09	1,974
October	1.00	16,174	0.12	3,242
November	1.08	30,469	0.22	3,961
December	1.26	43,354	0.21	6,167
January	1.35	48,715	0.20	4,814
February	1.33	47,673	0.23	5,759
March	1.10	43,948	0.18	3,212
April	1.36	31,394	0.25	3,857
May	1.25	26,020	0.23	2,979

Source: Pérez-Mesa, Galdeano-Gómez and Aznar-Sánchez.

We will concern ourselves only with the typical growing season in southeast Spain from September to May (n=8), for which we will use the following model. The estimation made is:

$$(14) \qquad X_{it} = \alpha + \beta \; Px_t + \sum_{i}^{n-1} \theta_i D_{it} + \varepsilon_{it}$$

where D_{it} will be a dummy variable that will take a value of 1 for the corresponding month (n) and zero for all other cases. The original remainders ε_{it} will be modeled using:

$$(15) \qquad \varepsilon_{it} = \delta\varepsilon_{it-1} + \mu_{it}$$

Therefore, model (13) would equate to the estimation of n-1 equations[15], one per month (i) which would take the following structure:

$$(16) \qquad X_{it} = (\alpha + \theta_i)(1-\delta) + \beta Px_{it} - \delta\beta Px_{it-1} + \delta X_{it-1} + \mu_{it} \quad \text{with i=1…n-1}$$

Where μ_{it} are the remainders of the final model. Modelling (15) would serve to test the possibility that amounts marketed are influenced by the results of previous years, as can be seen in equation (16). We should bear in mind that the model assumes no production capacity restrictions and no substitution in production among commodities.

[15] Note that we use n-1 dummies to avoid multi-collinearity.

The results of the model (14) including the modelling of the residues (15) can be seen in Table 5. The estimations are carried out following linear and logarithmic models, obtaining similar results[16]. The calculated models show a high significance. The logarithmic estimation considers the existence of a single price elasticity (value of β) irrespective of the month in question. In this particular case $\beta < 1$, and so the short-term price variations will produce changes that are less than proportional to the amount sold. Nevertheless, it is considered that a single elasticity (logarithmic model) may lead to results that are unrealistic, and so price elasticities are calculated monthly using the linear model (Table 6).

Table 5. Estimation of models

Variable	X_t	$\ln(X_t)$
α	58,581.730 (0.000)	12.452 (0.000)
β	-140.980 (0.000)	-0.554 (0.000)
D_{Jan}	4,724.302 (0.000)	0.107 (0.001)
D_{Feb}	4,163.992 (0.011)	0.097 (0,058)
D_{Mar}	2,569.409 (0.130)	0.074 (0.154)
D_{Apr}	-9,959.225 (0.000)	-0.230 (0.000)
D_{May}	-17,874.34 (0.000)	-0.481 (0.000)
D_{Sept}	-39,592.31 (0.000)	-1.634 (0.000)
D_{Oct}	-32,168.60 (0.000)	-1.098 (0.000)
D_{Nov}	-15,033.13 (0.000)	-0.390 (0.000)
δ	0.449 (0,000)	0.419 (0.000)
R^2	0.946	0.961
H-Durbin	1.808	1.821
F	165,34 (0,000)	234,668 (0,000)

Source: Pérez-Mesa, Galdeano-Gómez and Aznar-Sánchez.

Observing the results and speaking in terms of total levels (Table 6), there is currently a calculated 40% supply excess in respect of maximum revenue and 73% in respect of maximum margin. January to March is the period in which the most substantial excess can be seen (Figure 3). These months coincide with the period of greatest production and the highest prices of the whole season. What the marketer cannot know is that prices could increase even more if the amount produced were reduced. At the start of the campaign (September-October), the potential for price increase by regulating production is moderate due to the existence of other areas of

[16] Estimations have also been made including dummy variables on slope (β) of equation [13], but without significant results.

production (e.g. Holland). Generally speaking, it seems that companies in southeast Spain are only interested in sales, and they neglect the temporal programming of their production.

Table 6. Optimum quantity distribution using the Linear Model.

	Sept	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Total
Actual Situation										
Average X (t)	9,927	16,174	30,469	43,354	48,715	47,673	43,948	31,394	26,020	**297,674**
Average Px (€/100 kg)	95	100	108	124	130	133	140	136	125	***119**
Total Revenue (Mill. €)	9.4	16.2	32.9	54.8	65.9	63.4	48.3	42.7	32.5	**366.1**
Total margin (Mill. €)	3.1	5.8	13.4	27.0	34.7	32.9	20.2	22.6	15.9	**175.6**
ε_{Px} Short-term	-1.349	-0.872	-0.500	-0.411	-0.392	-0.393	-0.353	-0.611	-0.677	
ε_{Px} Balance	-0.743	-0.480	-0.275	-0.226	-0.216	-0.217	-0.194	-0.337	-0.373	
Max Revenue										
Px (€/100 kg)	67	94	154	208	225	223	217	172	144	***167**
Quantity (t)	9,495	13,207	21,774	29,291	31,653	31,373	30,576	24,311	20,354	**212,033**
Total Revenue (Mill. €)	6.4	12.4	33.5	60.9	71.2	70.0	66.3	41.8	29.3	**391.9**
Total margin (Mill. €)	0.3	4.0	19.6	42.2	51.0	49.9	46.8	26.3	16.3	**256.2**
Max Margin										
Px (€/100 kg)	99	126	186	240	257	255	249	204	176	***199**
Quantity (t)	4,983	8,695	17,263	24,780	27,142	26,862	26,064	19,800	15,842	**171,431**
Total Revenue (Mill. €)	4.9	11.0	32.1	59.5	69.8	68.5	64.9	40.4	27.9	**378.9**
Total margin (Mill. €)	1.7	5.4	21.1	43.6	52.4	51.3	48.2	27.7	17.7	**269.2**

(*) Average.
Source: Pérez-Mesa, Galdeano-Gómez and Aznar-Sánchez

Equation (16) shows that there exists a lagged price in one period which means we must identify two types of elasticity: one is short-term[17] (all, except September, are inferior to the unit, which demonstrates that price is losing importance in favor of quality and service issues); and the other is balance elasticity, which we calculated for equation (17) utilizing:

$$(17) \qquad \varepsilon_{Px-Balance} = f'(Px) \cdot \frac{Px}{f(Px)} = \beta(1-\delta) \cdot \frac{Px}{f(Px)}$$

with price and amounts being the averages of the sampling[18].

[17] Calculating as: $\varepsilon_{Px-Short} = f'(Px) \cdot \frac{Px}{f(Px)} = \beta \cdot \frac{Px}{f(Px)}$, using the average values per month of amounts and prices. For example, for September $\varepsilon_{Px-Short} = -140.580 \cdot \frac{95}{9{,}927} = -1.349$

[18] For September, $\varepsilon_{Px-Balance} = -1.349 \cdot (1-0.449) = -0.743$

The balance elasticity is composed of a short-term elasticity and a long-term one. Therefore, the price elasticity will depend on two circumstances: i) pricing strategy, in the short-term, which is something that will indeed be controllable and with which we can influence demand; ii) whether products are marketed in function of the prices and amounts of the previous season (which is equivalent to $\delta \neq 0$). The estimation of δ (Table 5) shows that the decision maker takes into account the prices and amounts marketed during the previous cycle when scheduling crops. This may prove hazardous, as it may result in major fluctuations in prices and amounts marketed from one season to the next.

From our perspective, our mission should be to influence the system so $\delta = 0$, in other words, provoke a structural change (something that logically cannot be achieved in the short or medium-term). Consequently we focus our interest on the short-term elasticities, which we will utilize to maximize revenue and margin. In this case $\delta \neq 0$ and the equilibrium price elasticity is lower than that in the short-term, which indicates that when growers plan their marketing they place more importance on the volumes from past years than on price.

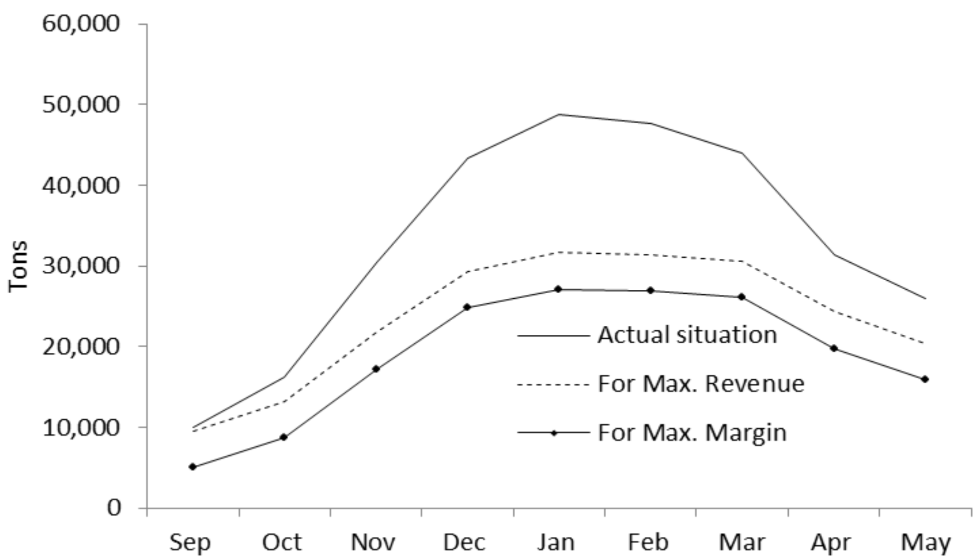

Figure 3. Distribution of pepper production-exports
Source: Pérez-Mesa, Galdeano-Gómez and Aznar-Sánchez

In accordance with Table 6, the average price obtained as a result of revenue maximization would be 1.67 €/kg, meaning there is a price increase upward of 40% with respect to the actual price. The average price obtained as a result of margin maximization would be 1.99 €/kg; a 67% price increase in relation to the actual price. Maximizing the total revenues would obtain 391.1 million euros; a 7% increase with respect to the actual revenue. The maximum margin calculated would be 269.2 million euros (a 53% increase with respect to the actual margin).

Discussion

In general, there is a significant improvement observed in the results, which is a consequence of reducing the amounts of the produce marketed; primarily in the months with the highest sales.

This problem would be easy to solve for an individual company programming its dates for planting . In southeast Spain there are more than 110 cooperatives (Galdeano et al. 2011) that market fruit and vegetables. As individual entities they have no bargaining power with their customers (large distribution chains), but if they sold together (for example through an Association of Producer Organizations) they would have a substantial market share that would boost their market power. Figure 4 displays southeast Spain's market share in relation to all the tomatoes and peppers marketed in the EU.

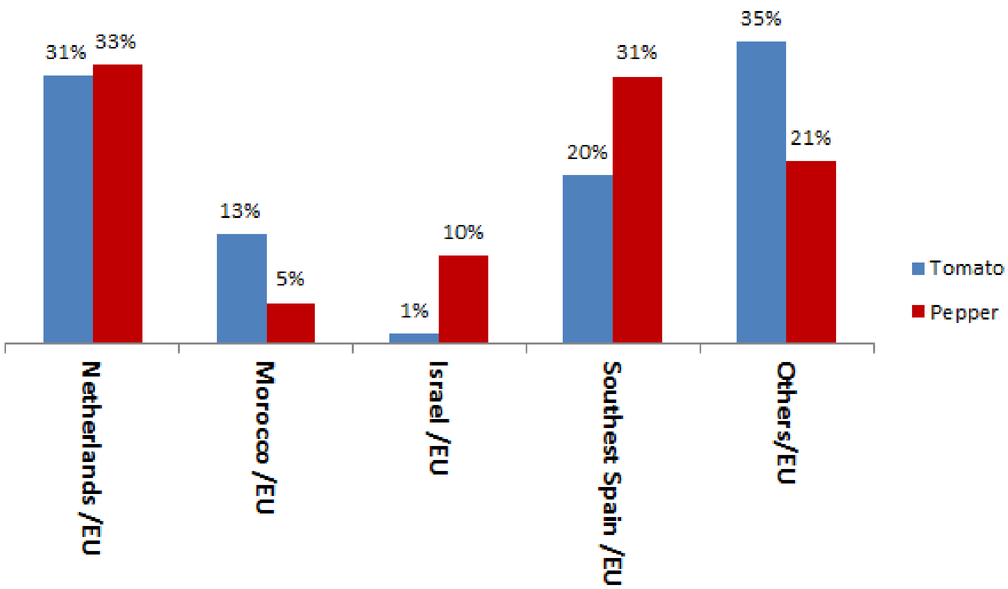

Figure 4. Market Share of each exporting region over the amount purchased by the 27 members of the EU. Tons.
Source: Pérez-Mesa, Galdeano-Gómez and Aznar-Sánchez. From Euostat, 2010.

In addition, by way of example, we would like to highlight that the approach of the monthly demand model could be compatible with the Markowitz model if we supposed that the monthly variance between years would remain constant. Then, by transferring the data to a spreadsheet, which in this case is the distribution in terms of percentages which maximizes margin, we could automatically get an idea of the risk involved, which would be the same as the variance of the proposed program (according to equation 1). Therefore, in the case of peppers, applying the Markowitz model to the distribution calculated according to (13) which maximizes revenues, we would obtain a margin of 0.67€/kg and a variation coefficient of 0.22. If we apply the same process to the distribution of marketing that maximizes the margin, we would obtain a variation coefficient of 0.21 and a unitary margin of 0.68€/kg. In short, this would mean making decisions with more information in different scenarios.

These results also demonstrate that a maximization strategy for revenues and margins need not be optimal from the point of view of risk minimization. Caution should be taken, however, when making any comparison of the M-V model and the optimization model calculated by regression, as they are based on different assumptions.

Conclusions

This paper provides an analytical framework on harvesting programs for horticultural production. The empirical analysis takes as a reference the case of farmers and cooperatives in Southeast Spain.

The results show that the Markowitz model (improved to facilitate provisional planning for harvest and also to include commercial aspects) can be easily utilized for the monthly production programming of an individual farmer. However, by assuming static prices, it is assumed that the decisions made by the farmer will not affect the general balance of the system. In order to avoid this drawback, we have developed a model for maximum monthly revenue (or margin), which helps to program production for a cooperative which has a significant presence in the sector and can therefore alter the market balance.

Through empirical applications we obtained different results when considering a M-V model and a monthly model. Nevertheless, an improved Markovitz model and the monthly model are compatible under the assumption of constant variance. Aside from concrete numbers, a clear improvement is observed due to the process of trying to program production: something which is impossible to do without improving the coordination mechanisms between production and marketing within companies.

For southeast Spain, crop scheduling with the objective of maximizing prices and margins is complicated; given the current situation of multiple and small businesses. It would imply coordinating a very large number of companies. However, if the scheduling was coordinated, profits could increase substantially, as shown in the model estimations.

Finally, this article hopes to serve as an incentive to promote a debate concerning the most appropriate methodology to utilize in the search for a method for seasonal programming of agricultural production. To date, books and studies have focused more on the selection of different crops than on the seasonal distribution of marketing over time.

Acknowledgments

This research was partially funded by Spanish MCINN and FEDER aid (project ECO2008-02258, ECO2008-03445 and ECO2011-24930) and from Junta de Andalucía (project SEJ-5827, Consejería de Economía, Innovación y Ciencia). The authors would like to thank the Peter Goldsmith, the IFAMR Executive Editor, and the anonymous reviewers for their recommendations to improve this manuscript.

References

Ahumada, O. and J. R. Villalobos. 2009. Application of planning models in the agri-food supply chain: A review. *European Journal of Operational Research* 195: 1-20.

Alejos, A. and J. Cañas. 1992. Obtención de planes de cultivo eficientes en el sentido de Markowitz en la provincia de Córboba. *Investigaciones Económicas* 16(2): 281-297.

AFAC (Andalusian Federation of Agricultural Cooperatives). 2010: Statistical data. http://www.faeca.es (assessed 3/2/2010).

Arrow, K.J. 1965. *Aspects of the theory of risk-bearing*. Academic Publishers, Helsinki.

Ballestero, E. 1997. Utility functions: A compromise approach to specification and optimization. *Journal of Multi-Criteria Decision Analysis* 6:11–16.

Berbel, J. 1988. Target returns within Risk programming Models: a multi-objective approach. *American Journal of Agricultural Economics* 39: 263-270.

Berbel, J. 1989. Analysis of protected cropping: an application of multi-objective programming techniques to Spanish horticulture. *European Review of Agricultural Economics* 16: 203-216.

Costa, F. and T. Rehman. 1999. Exploring the link between farmers' objectives and the phenomenon of pasture degradation in the beef production systems of Central Brazil. *Agricultural Systems* 61: 135-146.

De Pablo, J. and J.C. Pérez-Mesa. 2004. The group of Almerian (Spain) social economy companies working in the field of agrarian commercialization: description, general problems and their prospects with regard to competiveness. *Estudios Agrosociales y Pesqueros* 202: 71-100.

Duval, Y. and A. M. Featherstone. 2002. Interactivity and Soft Computing in Portfolio Management: Should Farmers Own Food and Agribusiness Stocks?. *American Journal of Agricultural Economics* 84(1): 120–133.

Engle, R.F. and C.W.J. Granger 1987. Cointegration and error correction: representation, estimation and testing. *Econometrica* 55: 251–276.

Galdeano-Gómez, E. 2007. Composite price expectations: An empirical analysis for the Spanish horticultural sector. *Agribusiness* 23(1): 57-83.

Galdeano-Gómez, E., J.A. Aznar-Sánchez and J.C. Pérez-Mesa. 2011. The complexity of theories on rural development in Europe: An analysis of the paradigmatic case of Almería (Spain). *Sociologia Ruralis* 51(1): 54-78.

Gómez-Limón, J.A. and M. Arriaza. 2003. "Modeling farmers' response to a decoupled subsidy via Multi-Attribute Utility Theory and E-V analysis". 25th International Conference of Agricultural Economists, August 16-22, Durban, South Africa.

Gómez-Limón, J.A., M. Arriaza and L. Riesgo. 2003. An MCDM analysis of agricultural risk aversion. *European Journal of Operational Research* 151(3): 569-585.

Gómez-Limón, J. A., L. Riesgo and M. Arriaza. 2004. Multi-Criteria analysis of input use in agriculture. *Journal of Agricultural Economics* 55(3): 541-564.

Hardaker, J. B., R. B. Huirne and J. R. Anderson. 1997. *Coping with risk in agriculture*. CAB International, Wallingford (UK).

Hardaker, J. B, and S. Pandey. 1991. Farm planning under uncertainty: A review of alternative programming models. *Review of Marketing and Agricultural Economics* 59: 9-22.

Kroll, Y., H. Levy and H. M. Markowitz.. 1984. Mean-variance versus direct utility maximization. *The Journal of Finance* 39 (1): 47-61.

Lambert, D.K. and B. A. McCarl, 1985. Risk modeling using direct solution of non-linear approximations of the utility function. *American Journal of Agricultural Economics* 67(4): 846-852.

Markowitz, H. M. 1952. Portfolio Selection. *Journal of Finance* 7 (1): 77-91.

Meyer, J. and R. H. Rasche. 1992. Sufficient conditions for expected utility to imply mean-standard deviation rankings: empirical evidence concerning the location and scale condition. *The Economic Journal* 102: 91-106.

Pannell, D.J. and T. C. Nordblom. 1998. Impact of risk aversion on whole-farm management in Syria. *Australian Journal of Agricultural and Resources Economics* 42: 227-247.

Patten, L. H., J. B. Hardaker and D. J. Pannell. 1988. Utility-efficient programming for whole-farm planning. *Australian Journal of Agricultural Economics* 32 (2-3): 88-97.

Pérez-Mesa, J.C. 2007. Should Almería (Spain) have to be worried, thinking that their tomato export is currently affected by international competition? *Agricultural Economics Review* 8(2): 42-54.

Pratt, J.W. 1964. Risk aversion in the small and in the large. *Econometrica* 32: 122-136.

Romero, C. and T. Rehman. 2003. *Multiple Criteria Analysis for Agricultural Decisions*. Second edition, Elsevier, Amsterdam, Netherlands.

Salinas, J.A. and F. Palao. 2002. *Potential traffic of fruit and vegetables through the ports of Almeria and Motril*. Universidad de Almería, Spain.

Solano, C., H. León, E. Pérez. and M. Herrero. 2001. Characterising objective profiles of Costa Rican dairy farmers. *Agricultural Systems* 67:153-179.

UNEP, United Nations Environment Programme. 2005. *One Planet, Many People: Atlas of Our Changing Environment*. UNEP.

Von Neumann, J. and O. Morgensten. 1947. *Theory of Games and Economic Behaviour*. University Press, Princeton.

Willock, J., I. J Deary, G. Edwards-Jones, G. J. Gibson, M.J. McGregor, A. Sutherland, J. B. Dent, O. Morgan and R. Grieve. 1999. The role of attitudes and objectives in farmer decision making: business and environmentally-oriented behavior in Scotland. *Journal of Agricultural Economics* 50(2): 286-303.

Appendix 1.

Table 2. Results of unrestricted model

					% Tomato									% Pepper										
Mean Euros/kg	Variance	Var. Coef.	w_M	w_V	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	% Tomato	% Pepper
0.38	0.0029	0.14	0.92	0.08		0.13	0.07	0.17				0.12		0.31	0.16						0.03		50	50
0.41	0.0030	0.13	0.92	0.08		0.14	0.05	0.20				0.12		0.22	0.19				0.03		0.04		51	49
0.45	0.0032	0.13	0.92	0.08		0.16	0.03	0.24				0.13		0.08	0.24				0.07		0.05		56	44
0.50	0.0039	0.12	0.92	0.08		0.17		0.30				0.15			0.17		0.01	0.03	0.08	0.02	0.08		62	39
0.60	0.0075	0.14	0.87	0.13		0.08		0.27				0.15					0.07	0.10	0.04	0.16	0.13		50	50
0.70	0.0189	0.20	0.76	0.24				0.05			0.04	0.09					0.06	0.14		0.48	0.14		18	82
0.77	0.0370	0.25	0.65	0.35																1.00			0	100
*0.55	0.0105	0.18	0.82	0.18	0.01	0.02	0.06	0.08	0.10	0.11	0.11	0.09	0.08	0.01	0.02	0.04	0.05	0.06	0.06	0.05	0.04	0.03	65	35

Table 3. Results of restricted capacity model (35% pepper, 65% tomato)

					% Tomato									% Pepper								
Mean Euros/kg	Variance	Var. Coef.	w_M	w_V	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0.41	0.0031	0.14	0.92	0.08	0.05	0.16	0.08	0.21				0.15		0.23	0.11						0.01	
0.45	0.0032	0.13	0.92	0.08		0.18	0.07	0.25				0.15		0.14	0.15				0.03		0.03	
0.50	0.0036	0.12	0.92	0.08		0.18	0.02	0.30				0.15			0.20			0.02	0.07		0.07	
0.60	0.0067	0.14	0.89	0.11		0.11		0.35				0.19					0.02	0.04		0.25	0.04	
0.62	0.0090	0.15	0.86	0.14		0.04		0.39				0.22								0.35		
0.64	0.0146	0.19	0.79	0.21				0.27			0.09	0.29								0.35		
*0.55	0.0105	0.18	0.82	0.18	0.01	0.02	0.06	0.08	0.10	0.11	0.11	0.09	0.08	0.01	0.02	0.04	0.05	0.06	0.06	0.05	0.04	0.03

(*) Actual distribution of production.