https://doi.org/10.17221/196/2022-AGRICECON

Scheduling vegetable sales to supermarkets in Europe: The tomato case

Juan Carlos Pérez-Mesa[1], *Francisco Javier Pérez-Mesa*[2], *Juan José Tapia-León*[1]*, *Diego Luis Valera*[2]

[1]*Department of Economics and Business, Agrifood Campus of International Excellence, ceia3, Mediterranean Research Centre on Economics and Sustainable Development, CIMEDES, University of Almería, Almería, Spain*

[2]*Department of Engineering, Agrifood Campus of International Excellence, ceia3, CIAMBITAL Research Centre, University of Almería, Almería, Spain*

**Corresponding author: tlj354@ual.es*

Citation: Pérez-Mesa J.C., Pérez-Mesa F.J., Tapia-León J.J., Valera D.L. (2022): Scheduling vegetable sales to supermarkets in Europe: The tomato case. Agric. Econ. – Czech., 68: 403–412.

Abstract: This article analyzes the temporal programming of sales for a horticultural marketing company, e.g. a cooperative. The empirical study references the European tomato market, where most of the production is sold through the retail channel dominated by large distribution chains. We study the marketing schedule for an individual company, or even a prominent farmer, using a modified Markowitz model, assuming that his decisions do not affect the balance of market prices. As a result, this model can manage risk and improve decision-making. The data also provide information on the risk borne by marketers depending on their sales calendar, which often depends on their geographic location.

Keywords: cooperative; optimization; coordination mathematical programming; marketing

Production planning involves making decisions about what type of crops to use and the timing of harvests over time. Such scheduling aims to avoid drops in income in the agricultural market, with traditionally rigid demand. In other words, the demand cannot absorb increases in supply, and this absorption capacity is even lower in short periods and with perishable products. For this reason, declines in prices and revenues are often disproportionate. This situation has been pervasive in recent years in the fruit and vegetable sector in Europe (Pérez-Mesa et al. 2019). In this context, this article raises the possibility of programming the tomato sales of an individual operator, for example, a cooperative, according to historical prices at the point of sale (supermarkets). This mechanism would imply improving internal coordination to establish plantations in line with the best price.

Climatic factors have a relevant influence on unexpected variations in supply and demand in the horticultural sector (Solaymani 2018; Akbari et al. 2020); therefore, not all variations can be attributed to a lack of programming. However, a heterogeneous production system of farms of different sizes fosters supply organization and coordination difficulty. Another aspect that makes the level of organization low is the duality of marketing systems: *i*) cooperatives, closely related to farmer scheduling, and *ii*) auctions, which complicate crop scheduling.

Supported by the Project SmartRed No. UAL2020-SEJ-D026 (UAL/CTE-ICU/FEDER), 'Adapting intermodal transport of perishables within an intelligent supply chain'.

https://doi.org/10.17221/196/2022-AGRICECON

The European tomato supply chain starts with a farmer who sells his product through cooperatives or auctions (Figure 1). Through the retail channel, dominated by large distribution chains, 70% of the production is sold (Hernández-Rubio et al. 2018). In short, the customers are usually the same regardless of where production starts.

The present study concentrates on harvest programming and attempts to provide several management systems to improve farmers' and cooperative decisions. To this end, we bear in mind some challenges and considerations. It is necessary to determine the optimum production for this system to correct the deficiencies in programming; in other words, the quantity supplied to the market to maximize profits and revenues.

When only one reference variable exists, such as price, obtaining the optimum is usually a complex task. As a consequence, production scheduling depends on price sampling, which generally has a large variability due to: *i*) the existence of complementary supplies unrelated to those we are trying to plan, *ii*) climatic factors such as seasonal changes in demand, or *iii*) structural changes such as variations in consumption habits.

Furthermore, we must include operator's capacity, which controls a substantial percentage of the sector, to alter the market in maximizing margins and revenues. In this sense, the European tomato market is quite atomized: at the destination, one can find products from different origins (the Netherlands, Southeast Spain, Morocco, Belgium, France, Turkey). The highest percentage of imports corresponds to the Netherlands (28%) and Spain (21%). Moroccan tomatoes represent 19% of total imports of the EU and the United Kingdom (Eurostat 2021).

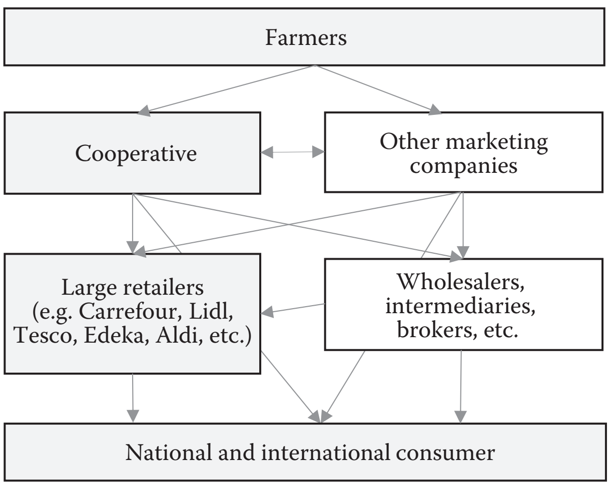

Figure 1. European tomato supply chain

Priority channel is marked in grey
Source: Own elaboration

Several studies have dived into these questions by implementing different scheduling methodologies that apply mainly to the selection between crops, not to the temporal distribution of sales. We used the classic method for production programming, the mean-variance quadratic equation (M-V) developed by Markowitz (1952). Some studies have applied this formula in order to find efficient crop planning (Gómez-Limón et al. 2003; Živkov et al. 2022). Other programming models utilized in the farming sector are minimization of total absolute deviation (MOTAD) and target MOTAD (Tauer 1983). These methods seek to minimize absolute deviations for a sector of activities using a subjective risk aversion parameter for each decision-maker (Romero and Rehman 2003; Langemeier et al. 2020; Akbari et al. 2022). At the same time, the mean-semi-absolute deviation (SAD) model uses SAD as a risk estimator of study variable values concerning a fixed goal (Zhang et al. 2015). We must also mention the advances in nonlinear programming techniques. Those, which stand out, are direct expected utility maximizing nonlinear programming (DEMP) (Lambert and McCarl 1985; Pannell and Nordblom 1998), recently implemented and enhanced by Aljanabi et al. (2018) or Li et al. (2020) using utility efficient programming (UEP) and the combination of both (DEMP-UEP). The modified Markowitz model was chosen for its easy fitting to an optimal time distribution, despite the need to implement nonlinear programming.

The present study has several aims. On the one hand, it aims to develop a harvest/marketing programming model, which can easily be applied by grower-marketing entities, i.e. cooperatives, and utilized for the temporal distribution sales throughout the growing season. On the other hand, the study highlights the improvements that could be achieved due to coordination among members of a cooperative enterprise.

The European tomato trade calendar. The European market is very competitive. European product dominates over extra-European product. The Netherlands is the leading supplier (28% of the total), which uses its re-export capacity to market tomatoes from other areas, something that France is also taking advantage of (with tomatoes from Morocco) and even Germany (with tomatoes from Spain). The Netherlands has a calendar centered on the summer months (April–September), although it gradually extends into the autumn and winter months thanks to artificial light and heating in its greenhouses (Hernández et al. 2016;

https://doi.org/10.17221/196/2022-AGRICECON

Table 1. EU and United Kingdom trade calendar for the year 2021

Partner	Jan	Feb	Mar	Apr	May	June	July	Aug	Sept	Oct	Nov	Dec	Total
	(%)												(tons per month)
Netherlands	6	5	6	**10**	**12**	**12**	**11**	**9**	**9**	7	6	6	871 339
Spain	**12**	**15**	**15**	**9**	6	4	3	3	4	5	**9**	**13**	662 459
Morocco	**13**	**11**	**14**	**10**	5	3	2	2	4	9	**14**	**14**	584 549
France	**11**	**10**	**11**	9	6	4	4	3	4	**14**	**12**	**13**	217 271
Belgium	4	4	4	**8**	**11**	**15**	**12**	**11**	**11**	7	5	6	184 101
Turkey	**11**	**10**	**12**	**10**	**8**	7	3	6	8	5	6	**16**	175 659
Germany	**12**	**12**	**12**	**11**	**8**	6	5	3	4	5	8	**13**	86 210
Italy	**9**	**10**	**15**	**13**	**8**	8	7	5	5	6	7	**8**	60 669
Portugal	1	0	0	0	2	**9**	**10**	**13**	**31**	**23**	**6**	3	60 529
Others	5	3	6	9	**12**	**11**	**12**	**10**	**11**	**10**	3	**7**	91 634
Intra-EU 27	8	**8**	**9**	**9**	**9**	**9**	8	7	8	8	7	**9**	2 272 480
Extra-EU 27	**12**	**11**	**13**	**10**	6	4	3	3	5	8	**11**	**14**	815 155
Total	**9**	**9**	**10**	**10**	8	8	7	6	7	8	**8**	**10**	3 087 635

Numbers in bold are the centered calendar of every country

Source: Own elaboration with Eurostat (2021) data and UK Trade Info (2021)

Kubota et al. 2018). Spain is the second supplier (21%): its calendar is centered on the autumn-winter-spring months (November–April), practically the same calendar as Morocco, the third European supplier (18% of the total). In general, the European import calendar follows a stable pattern, with a predominance of the months between November and April, which correspond to the export periods of important export areas: Southeast Spain, Morocco, Turkey, and Italy (Table 1).

On the demand side, Germany (27% of the total) is the primary buyer, followed by France (17%), the United Kingdom (13%), and the Netherlands (6%), highlighting its capacity for re-export (Eurostat 2021; UK Trade Info 2021). The three main customers, Germany, France, and the United Kingdom, account for almost 60% of sales, so we will focus on their supermarket prices for further analysis.

MATERIAL AND METHODS

Time scheduling model. Variability in prices and both technical and climatic factors mean that decisions in the horticultural sector are made under uncertainty. It is interesting in this work to distinguish between situations of uncertainty and risk. When we cannot predict or quantify the future, we are in a context of uncertainty. If there is the possibility of knowing the probabilities associated with those relevant events, we are in a context of risk. In the present analysis, we consider that decisions will be made in the context of risk. Several studies point to a process of risk aversion within the decision-making process in the agricultural sector (Pannell and Nordblom 1998). In this situation, farmers often try to diversify by introducing new crops or modifying their production schedules (Komarek et al. 2020).

In this paper, it is assumed that farmers are profit maximizers and that, in a risky situation, they behave following the postulates of the expected utility theory (EUT) according to Von Neumann and Morgenstern (1947). However, this theory has been criticized for using functions with a single measurable, i.e. only in monetary units (profit). At the same time, several authors have highlighted the complexity of farmers' decision-making through studies evaluating different criteria (Solano et al. 2001; Gómez-Limón et al. 2003, 2004; Sulewski and Kłoczko-Gajewska 2014; Duong et al. 2019). The above studies conclude that when making production decisions, farmers have in mind the hope of profit and several considerations related to the social, economic, environmental, and cultural environment. They will therefore try to satisfy all these objectives simultaneously. Despite this series of drawbacks, the overall approach followed is considered adequate because it is reasonable given the highly competitive system that characterizes horticultural agriculture in Europe. If any grower deviated from this profit-maximizing behavior, he would be quickly driven out of the market.

In the case of an individual company, we propose the Markowitz model for its simplicity and easy iterative resolution. This model also facilitates its application by farmers. This work improves the general formulation

https://doi.org/10.17221/196/2022-AGRICECON

of the model to schedule weekly periods (Sidhoum and Serra 2016) and to introduce, as a novelty, commercial criteria when deciding on a production-marketing plan:

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

where: σ_{ij}^{sc} – covariances of gross margins obtained during different years between crop c and crop s for the weeks i and j, or between crops s and c for the week i; X_i^s – production that will be marketed of crop s for the week i; X_j^c – production that will be marketed of crop c for the week j.

Subject to constraints:

$$\sum_{c}^{p}\sum_{i}^{n} M_i^c X_i^c = M_0 \tag{2}$$

$$\sum_{c}^{p}\sum_{i}^{j} X_i^c = N \tag{3}$$

$$X_i^c N \geq 0 \text{ with } c = 1, ..., p;\ i = 1, ..., n \tag{4}$$

where: X_i^c – production that will be marketed of crop c for the week i; M_0 – target margin; N – total production by farmer [$N = 1$ is usually utilized (this will allow us to deal with percentages)]; M_i^c – mean gross unit margin of crop c for the week i [meaning, the arithmetic mean, for the years considered in the series, of the difference between variable prices and costs (which are fixed for a given week) expressed in EUR/kg]:

$$M_i^c = P_i^c - C^c \tag{5}$$

where: P_i^c – price of crop c for the week i; C^c– cost of crop c.

Equation (1) is the variance of the marketing plan that measures the risk taken, which is the sum of the variances and covariances of the gross margins weighted by the production-marketing devoted to each crop in a given month. Equation (2) shows the expectations of the production-marketing plan as the sum of the average gross margins multiplied by the amount. This constraint is parameterized. By varying M_0, the model obtains the specific plans that satisfy the economic expectations. Ultimately, the computed plans will minimize the variance risk [Equation (1)] for the value of expectations [Equation (2)].

The proposed model will allow the company to decide what to market and on what dates. However, the production capacity may be such that changing one crop for another is impossible. For example, suppose that only two agricultural machines are available, one for peppers and one for tomatoes, and switching products is impossible. In this case, two models can be calculated for each crop. If we decided to include it in a single model, we would introduce the following constraint by substituting [Equation (3)]:

$$\sum_{i}^{n} X_i^c = \frac{h^c}{N} \text{ with } \sum_{c}^{p} h^c = N \tag{6}$$

where: h^c – production of crop c that the production capacity can manage, for example, suppose a company has only two farm machines (specialized in the crop and with equal working capacity), one for tomatoes and one for peppers; consequently, it will devote half of the marketing 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 there are programmed commitments with customers by the farmer, a new restriction will be introduced that will imply the existence of a designated production n for a specific product and a fixed date:

$$X_i^c \geq n_i^c \tag{7}$$

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

$$X_i^c \leq m_i^c \tag{8}$$

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

$$X_i^c M_i^c \geq CF_i \tag{9}$$

If we are interested in the relationship between risk (variance) and profitability (margin), we could reformulate the classic M-V problem using the commitment programming approach (Duval and Featherstone 2002):

$$\begin{aligned} \text{Min } L(x) &= \omega_M \frac{M^+ - M(x)}{M^+ - M^-} + \omega_V \frac{V^+ - V(x)}{V^+ - V^-} = \\ &= M(x) - \frac{\omega_V \left(M^+ - M^-\right)}{\omega_M \left(V^+ - V^-\right)} V(x) + C \end{aligned} \tag{10}$$

subject to restrictions [Equations (3–9)] and $\omega_V + \omega_M = 1$

https://doi.org/10.17221/196/2022-AGRICECON

where: C – constant; M^+ – maximum portfolio margin possible; M^- – minimum margin possible; V^- – minimum portfolio variance possible; V^+ – maximum variance possible; ω_M, ω_V – weights (or coefficients) on the margin and the risk, respectively; and

$$M(x)=\sum_{c}^{p}\sum_{i}^{n}M_i^c X_i^c .$$

Solutions to Equation (10) satisfy the following first-order condition:

$$M(x)=\theta V(x);\quad \theta=\frac{\omega_V\left(M^+-M^-\right)}{\omega_M\left(V^+-V^-\right)} \tag{11}$$

where: θ – proportional risk-margin ratio.

As can be seen in Equation (11), by varying the weights, ω_M and ω_V, we can outline the M-V efficient set, as occurs in the original problem defined by Equations (1–9), since, according to Duval and Featherstone (2002), the compromise programming approach is a generalization of the traditional M-V models. Taking Equation (11) as the starting point and knowing the values of θ calculated previously, we can ascertain the values of ω_M and ω_V. This approach provides an intuitive view for the decision maker, who can quickly check the weighting of risk and profitability assumed in each case without understanding the concept of utility.

RESULTS AND DISCUSSION

Case 1: Sales all year round. In the first example, we assume that there is a farmer or cooperative that produces and markets tomatoes to the EU and the United Kingdom throughout the year (weeks 1–52). The model proposed above could include several products simultaneously. We carry out the practical application exclusively on tomato, as it is the most traded horticultural product.

For our analysis, we use the following data: average selling prices of loose tomatoes, in all formats, lose, bag, and net for six seasons (2016–2021), an average of supermarkets in the United Kingdom, France, Germany, and Spain. The data source was the Spanish Federation of Fruit and Vegetable Exporters (FEPEX 2022). The model described uses margins; in our case, only sales prices are considered, not to consider a specific commercial origin. In any case, if we consider the export of tomatoes by a cooperative from Southeast Spain, the marketing cost would be EUR 0.87/kg to France and EUR 0.93/kg to Germany. Figure 2 shows the average costs and standard deviations (SD) calculated. Note the significant margin of the remaining intermediaries and supermarket chains: the average selling price is EUR 3.12/kg, and the margin of intermediaries and distribution chains is more than EUR 2.00/kg.

Table 2 and Figure 3 show the results of the applied model. It can be seen that the target that minimizes the risk is EUR 3.10/kg, which practically coincides with the average price of the series. From the calculated weights, risk (ω_V) and profitability (ω_M), it follows that at all the points on the efficient frontier M-V, the risk weighting is much lower than that of the price. The decision maker can easily see that excessive risks are not being taken, even in the case of programs with higher variances. Moreover, the weights for natural, more efficient distribution (M_0 = 3.1) show that the risk taken is bearable: the decision-maker weights the price twice as much as the risk taken (variance). In general, the

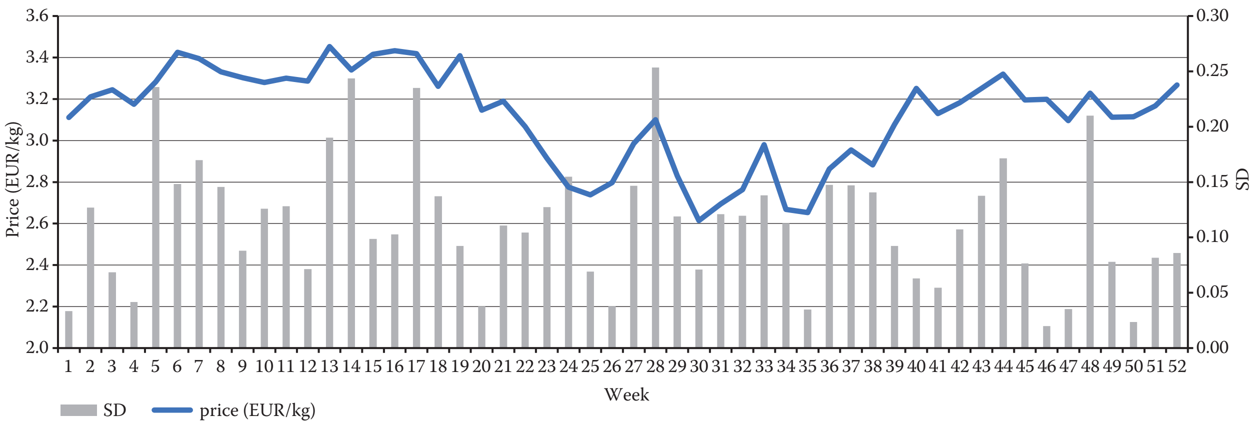

Figure 2. Weekly tomato prices in European supermarkets

Source: Own elaboration

https://doi.org/10.17221/196/2022-AGRICECON

Table 2. Results of the model: Marketing all year round (weeks 1–52)

Price objective (M_0)	Variance (V)	Coefficient of variation	Weight (coefficient) on the risk (ω_V) (%)	Weight (coefficient) on the margin (ω_M) (%)
2.90	0.0028	0.0010	21	79
3.00	0.0018	0.0006	29	71
3.10	0.0015	0.0005	34	66
3.20	0.0019	0.0006	30	70
3.30	0.0038	0.0012	18	82
3.40	0.0131	0.0039	6	94

Source: Own elaboration

market appears to be a market where the risk taken by traders is acceptable.

From the point of view of the temporal distribution, some relevant results are obtained (Figure 4):

– In the sales period between February and mid-May (weeks 5–20), which corresponds M_0 ≤ EUR 3.0/kg, the target price does not compensate the risk.
– The optimal plan (M_0 = EUR 3.1/kg) shows stability in sales. There is no predominant period: autumn--winter-spring (typical of supply from Southeast Spain and Morocco) or summer period (typical of sales from the Netherlands).
– For high target values with moderate risks (EUR 3.2/kg ≤ M_0 ≤ EUR 3.3/kg), marketing tends to the autumn--winter-spring period, which corresponds to the Spanish and Moroccan sales period.
– These months, which correspond to the Dutch sales period, but where there is a national offer in each country, would undoubtedly be the worst sales scenario from a profitability-risk point of view. Note that this period is the one with the highest demand but also the one where the most varied supply is concentrated.

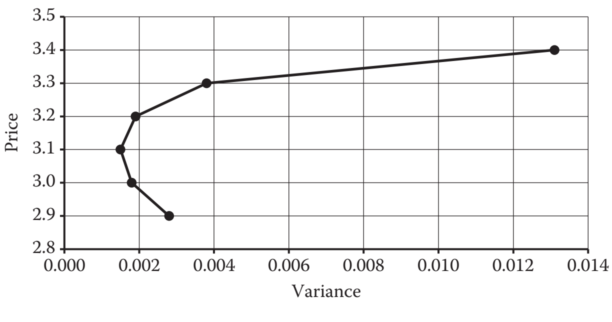

Figure 3. Model solutions mean-variance quadratic equation (M-V): Mean (price)-variance; marketing all year round (weeks 1–52)

Source: Own elaboration

Note that the above results would only be applicable when the company, due to its sales volume, would not be able to disrupt the market equilibrium. The current EU tomato market shows significant diversity in terms of origins. However, supply and demand for agricultural products are known to be very rigid, which could mean that minor variations in supply could alter prices more than proportionally. Taking Spain as a reference, the largest tomato marketing company [Cooperativa Agrícola San Isidro (CASI) cooperative] has a production volume of around 200 000 tons, 50% of which is destined for the export market, i.e. 100 000 tons, which barely represents from 7% to 9% of the European market.

On the other hand, the implementation of a calendar in a cooperative would require a great deal of internal organization, where the management would have the ability to impose sowing dates on farmers according to the expected risk-income ratio. This scenario is not always possible in social economy enterprises (cooperatives), where it is difficult to reach an agreement among many members (Bijman et al. 2014). Therefore, a reorientation of the cooperative system toward markets is needed (Bijman 2016).

Case 2: Autumn to spring season. In the second example, we assume that there is a farmer or cooperative that produces and markets tomatoes to the EU during the 40th week of year x to the 20th week of year x + 1, which is equivalent to a typical greenhouse cycle in Southeast Spain. In this case, the value M_0 = 3.22 minimizes the coefficient of variation (variance = 0.0022). This value implies the following weights: ω_V = 31%, ω_M = 69%. Again, it can be seen (Figure 5) that the risk levels assumed are moderate. Note that the calendar, in this case, is centered on week 46 of year x to week 4 of year x + 1, coinciding fully with the Christmas sales campaign: although it is not the period with

https://doi.org/10.17221/196/2022-AGRICECON

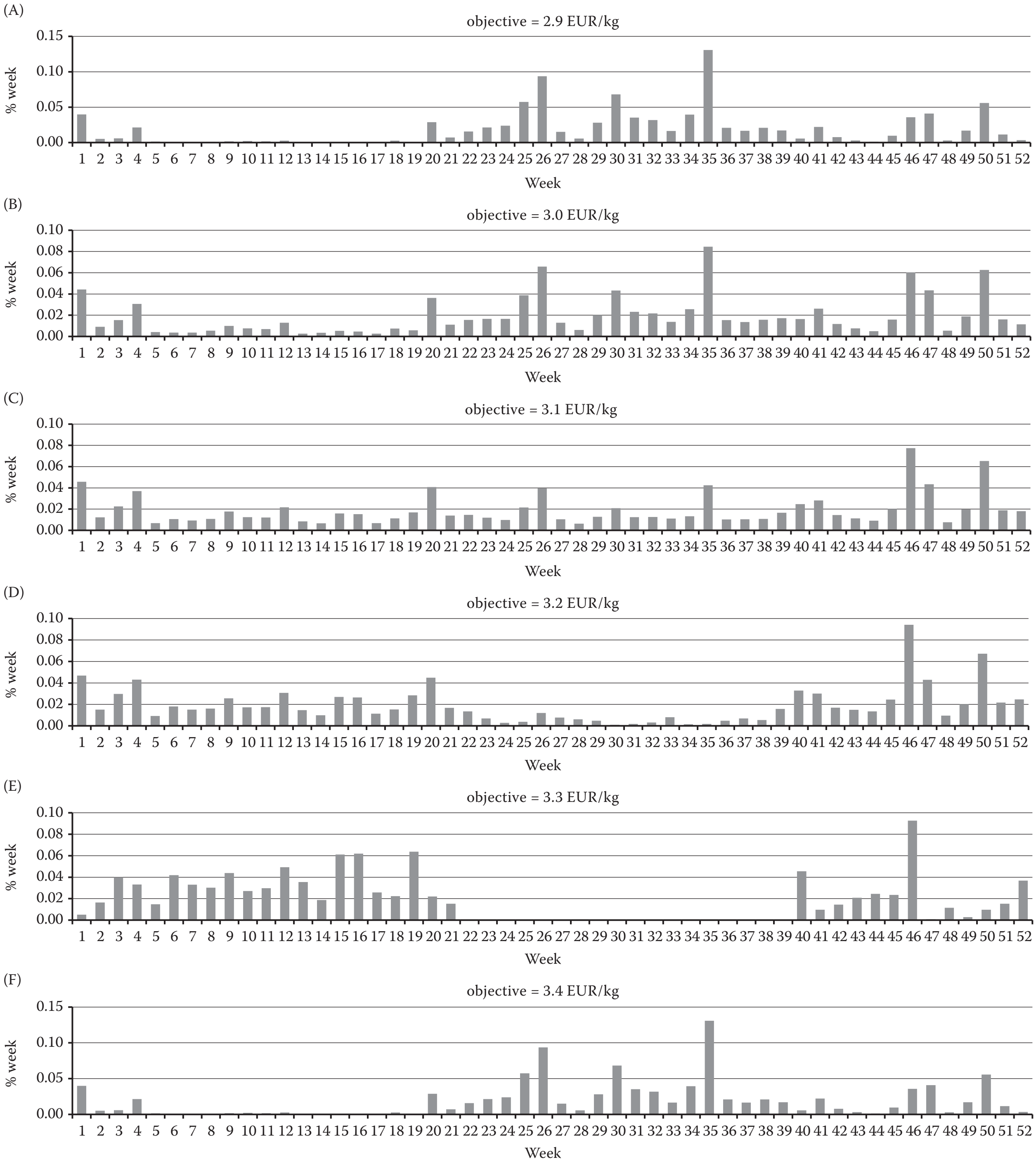

Figure 4. Weekly sales distribution: (A) objective = 2.9 EUR/kg, (B) objective = 3.0 EUR/kg, (C) objective = 3.1 EUR/kg, (D) objective = 3.2 EUR/kg, (E) objective = 3.3 EUR/kg, and (F) objective = 3.4 EUR/kg

Source: Own elaboration

the best average prices, it is the most stable concerning risk (weekly variance).

Case 3: Spring to summer season. In the third example, we assume that there is a farmer or cooperative that produces and markets tomatoes to the EU during weeks 14–44, which is equivalent to a standard greenhouse commercial cycle in the Netherland. In this case, the value M_0 = 3.00 minimizes the coefficient of variation (variance = 0.0030). This value implies the following weights: ω_V = 33%, ω_M = 67%. It can be seen (Figure 6) that the risk taken to achieve a lower price, than in the previous case, is higher. Note that although

https://doi.org/10.17221/196/2022-AGRICECON

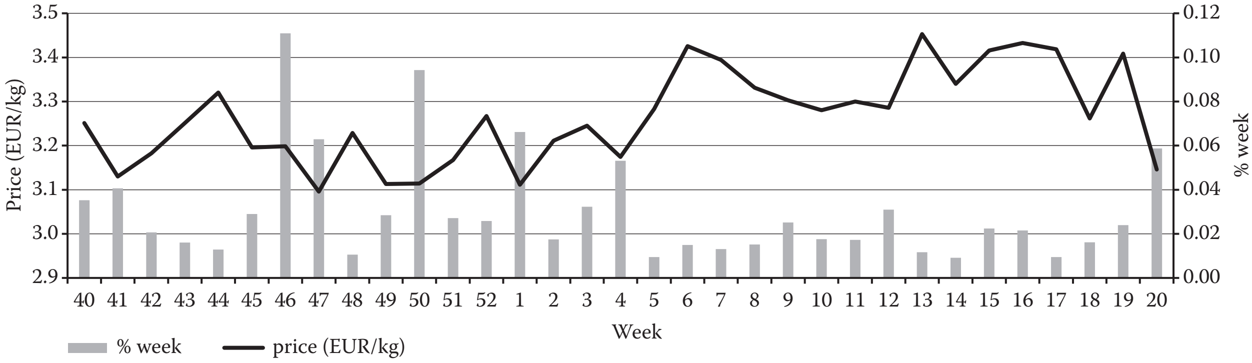

Figure 5. Weekly sales distribution and prices for weeks 40–20

Source: Own elaboration

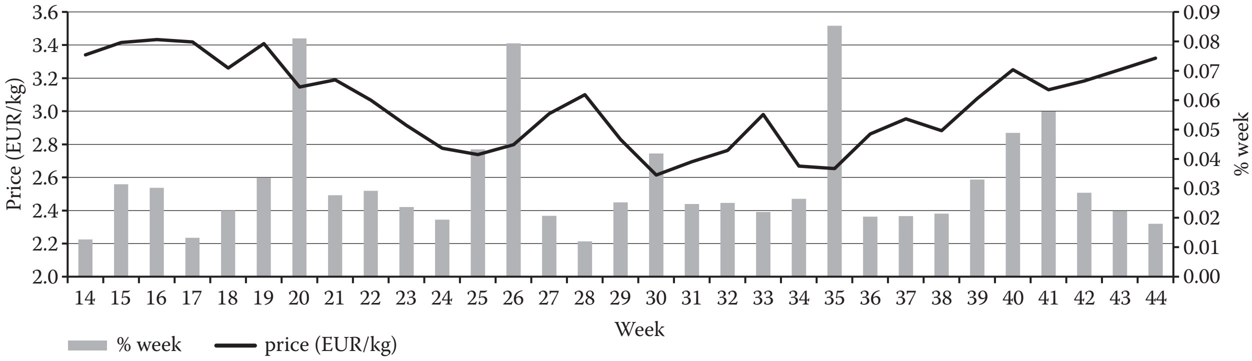

Figure 6. Weekly sales distribution and prices for weeks 14–44

Source: Own elaboration

prices appear to be (on average) more stable, the weekly variance makes the entire schedule riskier than in the previous case.

CONCLUSION

This article provides an analytical framework for scheduling marketing calendars in horticultural production. The empirical analysis is based on the case of tomato marketing in Europe. The results show that the proposed improved Markowitz model can be effectively used for the weekly production scheduling of an individual farmer or a cooperative. However, considering static prices, it is supposed that decisions made by the farmer or the cooperative will not influence the overall equilibrium of the system. In other words, the firm's weight in the market should not be significant. This assumption is a relevant limitation of the model for its possible use. In any case, this model allows different revenue or margin targets to be set: firms can have different targets in this respect, which would vary the schedule, avoiding collusion of sales.

The article also raises some policy implications. For example, the current distribution of tomato sales allows producing and marketing companies from different geographical areas to reach agreements to increase their bargaining power. It is the task of the European Administration to determine whether this is negative or on the contrary, favors market balance because the demand (supermarket chains) is increasingly concentrated.

The model results also provide information on the risks of the different companies that sell tomatoes in Europe, depending on the location and production calendar. For example, sales calendars oriented towards autumn-winter-spring (i.e. those located in Spain or Morocco) run a lower risk than companies that produce in the summer months (i.e. the Netherlands). As can be seen, the current trend toward year-round marketing (Kubota et al. 2018) may be a strategy to protect against price risk.

This model can generally improve decision-making by trying to schedule production, which is impossible without enhancing the coordination mechanisms

https://doi.org/10.17221/196/2022-AGRICECON

between production and marketing. This task is not easy in the case of cooperatives. In addition to the above, if the cooperatives could 'fine-tune' the time scheduling process, coordination between the chain members, in this case, the cooperative-retailer, would be improved (Pérez-Mesa and Galdeano-Gómez 2015). Analyzes like this would improve other processes, such as transport, which would be optimized according to demand. The sales planning process generally becomes a key point for generating synergies within and outside the company.

Finally, this article aims to stimulate the debate about the most appropriate methodology to search for seasonal programming methods for agricultural production. Studies have focused narrowly on selecting different crops than seasonal marketing distribution over time.

REFERENCES

Akbari M., Alamdarlo H.N., Mosavi S.H. (2020): The effects of climate change and groundwater salinity on farmers' income risk. Ecological Indicators, 110: 105893.

Akbari M., Alamdarlo H.N., Mosavi S.H. (2022): Economic effects of changing the quality and quantity of water in drought conditions, case study: Qazvin, Iran. International Journal of Environmental Science and Technology, 19: 2951–2960.

Aljanabi A.A., Mays L.W., Fox P. (2018): Optimization model for agricultural reclaimed water allocation using mixed-integer nonlinear programming. Water, 10: 1291.

Bijman J., Hanisch M., van der Sangen G. (2014): Shifting control? The changes of internal governance in agricultural cooperatives in the EU. Annals of Public and Cooperative Economics, 85: 641–661.

Bijman J. (2016): Agricultural cooperatives and market orientation: A challenging combination? In: Martin H., Paul C., Adam L. (eds): Market Orientation. Transforming Food and Agribusiness around the Customer. London, United Kingdom, Routledge: 151–168.

Duong T.T., Brewer T., Luck J., Zander K. (2019): A global review of farmers' perceptions of agricultural risks and risk management strategies. Agriculture, 9: 10.

Duval Y., Featherstone A.M. (2002): Interactivity and soft computing in portfolio management: Should farmers own food and agribusiness stocks? American Journal of Agricultural Economics, 84: 120–133.

Eurostat (2021): Exportation Data. [Dataset]. Eurostat. Available at https://ec.europa.eu/eurostat/web/international-trade-in-goods/data/database (accessed June 15, 2022).

FEPEX (2022): Tomato Prices in European Supermarkets (Precios de Tomate en Supermercados Europeos). [Dataset]. FEPEX (Spanish Federation of Associations of Producers and Exporters of Fruits, Vegetables, Flowers and Live Plants). Available at https://servicios.fepex.es/login (accessed May 3, 2022). (in Spanish)

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

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

Hernández R., Eguchi T., Deveci M., Kubota C. (2016): Tomato seedling physiological responses under different percentages of blue and red photon flux ratios using LEDs and cool white fluorescent lamps. Scientia Horticulturae, 213: 270–280.

Hernández-Rubio J., Pérez-Mesa J.C., Piedra-Muñoz L., Galdeano-Gómez E. (2018): Determinants of food safety level in fruit and vegetable wholesalers' supply chain: Evidence from Spain and France. International Journal of Environmental Research and Public Health, 15: 2246.

Komarek A.M., De Pinto A., Smith V.H. (2020): A review of types of risks in agriculture: What we know and what we need to know. Agricultural Systems, 178: 102738.

Kubota C., de Gelder A., Peet M.M. (2018): Greenhouse tomato production. In: Heuvelink E. (ed.): Tomatoes. Wallingford, United Kingdom, CABI Publishing: 276–313.

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

Langemeier M.R., Fang X., O'Donnell M. (2020): Comparison of long-run net returns of conventional and organic crop rotations. Sustainability, 12: 7891.

Li M., Fu Q., Singh V.P., Liu D., Li T., Zhou Y. (2020): Managing agricultural water and land resources with tradeoff between economic, environmental, and social considerations: A multi-objective non-linear optimization model under uncertainty. Agricultural Systems, 178: 102685.

Markowitz H. (1952): Portfolio selection. Journal of Finance, 7: 77–91.

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

Pérez-Mesa J.C., del Mar Serrano-Arcos M., Sánchez-Fernández R. (2019): Measuring the impact of crises in the horticultural sector: The case of Spain. British Food Journal, 121: 1050–1063.

Pérez-Mesa J.C., Galdeano-Gómez E. (2015): Collaborative firms managing perishable products in a complex supply network: An empirical analysis of performance. Supply Chain Management: An International Journal, 20: 128–138.

https://doi.org/10.17221/196/2022-AGRICECON

Romero C., Rehman T. (2003): Multiple Criteria Analysis for Agricultural Decisions. 2nd Ed. Amsterdam, the Netherlands, Elsevier: 186.

Sidhoum A.A., Serra T. (2016): Volatility spillovers in the Spanish food marketing chain: The case of tomato. Agribusiness: An International Journal, 32: 45–63.

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

Solaymani R. (2018): Impacts of climate change on food security and agriculture sector in Malaysia. Environment Development and Sustainability, 20: 1576–1596.

Sulewski P., Kłoczko-Gajewska A. (2014): Farmers' risk perception, risk aversion and strategies to cope with production risk: An empirical study from Poland. Studies in Agricultural Economics, 116: 140–147.

Tauer L.W. (1983): Target MOTAD. American Journal of Agricultural Economics, 65: 606–610.

UK Trade Info (2021): Exportation of Commodities. UK Trade Info. Available at https://www.uktradeinfo.com/trade-data/ots-custom-table (accessed May 20, 2022).

Von Neumann J., Morgensten O. (1947): Theory of Games and Economic Behaviour. Princeton, US, University Press: 641.

Zhang B., Peng J., Li S. (2015): Uncertain programming models for portfolio selection with uncertain returns. International Journal of Systems Science, 46: 2510–2519.

Živkov D., Balaban S., Joksimović M. (2022): Making Markowitz portfolio with agricultural commodity futures. Agricultural Economics – Czech, 68: 219–229.

Received: July 1, 2022
Accepted: October 5, 2022
Published online: November 7, 2022