Open Journal of Modelling and Simulation, 2022, 10, 152-164
https://www.scirp.org/journal/ojmsi
ISSN Online: 2327-4026
ISSN Print: 2327-4018

Dynamics of the Austrian Food Market: Application of Lotka-Volterra Differential Equations

Romana Bauer, Florian Schwarzmayr, Norbert Brunner, Manfred Kühleitner

Department of Integrative Biology and Biodiversity Research, Institute of Mathematics, University of Natural Resources and Life Sciences, Vienna (BOKU), Vienna, Austria
Email: bauer_romana@gmx.at, florian.schwarzmayr@hotmail.com, norbert.brunner@boku.ac.at, manfred.kuehleitner@boku.ac.at

How to cite this paper: Bauer, R., Schwarzmayr, F., Brunner, N. and Kühleitner, M. (2022) Dynamics of the Austrian Food Market: Application of Lotka-Volterra Differential Equations. *Open Journal of Modelling and Simulation*, **10**, 152-164.
https://doi.org/10.4236/ojmsi.2022.102009

Received: February 18, 2022
Accepted: April 22, 2022
Published: April 25, 2022

Abstract

The organic food market has become an important part of food industry. We analyze sales data from Austria for 2014 to 2020 of 124 products from 25 product groups in six categories, each in conventional and organic form. We fitted their market shares by means of a modified Lotka-Volterra model with constant coefficients. When only organic and conventional products were compared, a significant increase in market shares was observed for 15 of 25 organic product groups, indicating a continuing growth of the organic food market. The typical Lotka-Volterra dynamics was a predator-prey dynamics with an organic product (group) predating on conventional products that were in symbiosis.

Keywords

Conventional and Organic Products, Market Shares, Market Dynamics, Lotka-Volterra Models, Agrarmarkt Austria GmbH (AMA)

1. Introduction

Organic production aims at sustainable and environmentally friendly production, where no pesticides, mineral fertilizers or genetically modified seeds or feed are used [1]. Since the 1990s, there has been a steady increase of organic farming area in Europe, whereby in Austria, organic farming area exceeds one-fourth of agricultural land [2]. The European Union common agricultural policy, in particular the Council Regulation on organic production and labelling of organic products [3], has been a major driver: The goal of this policy is a modern, resource-efficient, competitive, and sustainable organic agriculture that secures the supply of high-quality food at a fair income for the farmers. It aims at contributing towards mitigation of climate change, the preservation of the cultural landscape and biodiversity, and the strengthening of the economic development of rural areas. The most common organic labels used in Austria are EU-Bio Logo, Bio-Austria, AMA, or Demeter. The origin of the labelled products can be traced back electronically to the organic farmer.

Organic production no longer serves a niche market but owing to the willingness of consumers to pay a higher price for labelled products, in Europe, there is a mass market for organic products [4]. Our goal was to investigate the market shares of conventional and organic products and investigate the market dynamics: Is there still a trend towards more sales of organic products? We model the food market and its dynamics by means of a variant of the Lotka-Volterra system of differential equations. We have chosen this variant, as it has analytical solutions.

2. Method

2.1. Data

The data for this paper were provided by [5] from the Roll-AMA survey. AMA (Agrarmarkt Austria) is an institution that is responsible for quality control and assurance of farms and products in Austria. A search for other sources using Google, Google Scholar, MetaGer, ScienceDirect, Web of Science, and PubMed indicated that these data were insofar exceptional, as they informed in detail about sales of organic and conventional food in Austria over a time span of seven years. The other available data highlighted selected years, only, they compared highly aggregated data (e.g., all organic and all conventional products), or they did not differentiate between organic and conventional food.

The data covered the seven consecutive years 2014 to 2020 and informed about the annual sales (in tons) of 124 food products in Austria. (The data are provided in a supporting information.) The products were classified by six categories comprised of in total 25 groups of similar products. The definition of groups followed the conventions in the retail food sector. For each product (group, category) data came in pairs, one time series for the conventional version of the product and one for the organic version.

- For dairy products the groups were distinguished by the typical colors of the products: white (e.g., milk, cream, yoghurt), colored (e.g., yoghurt with fruits), yellow (e.g., hard and soft cheese), and fats (e.g., butter, margarine, clarified butter, but not lard).
- For butchery products, only two groups were distinguished: meat and poultry, and products from them (e.g., sausages, ham). Eggs formed a category of their own. Fish and fishery products were not considered.
- For fruits (6 groups), exotics mean certain tropical and subtropical fruits, soft fruits are berries, and other fruits are mainly nuts.

- For fresh vegetables (11 groups), stems (stem vegetables) are, e.g., asparagus, celery, or salsify. Preprocessed food means, e.g., ready to use salad, but not canned vegetables. Potatoes form a category of their own. Grains and products from them (e.g., bread, pastries, cereals) were not considered.

This paper defined the market shares of these products as ratio of the sold mass over the total mass of the considered market. We considered minimal markets (for each product, its conventional and organic version) and selected larger markets to identify the competitive roles and derived trends. Thereby we analyzed the trends for product groups within a given category.

The data were obtained from surveys of 2800 households and extrapolated to all 3,757,600 households of Austria. The surveys asked about sales at food retailers including discounters, specialist retailers, and direct marketers. In average, in each surveyed household there lived 2.15 persons at age 50.25 years with monthly net income of 2510 € per household.

2.2. Model

Marketing research applies multiple methods to analyze and forecast the time series of market shares [6]; examples include deterministic multiple regression models (linear or nonlinear) and stochastic single-equation time-series models (e.g., ARMA = autoregressive moving averages). To avoid overfitting, the more complex methods require longer time-series as input data. Therefore, for rather short time-series also linear trend methods were used. However, as by its definition the market share is bounded between 0 and 1, ordinary linear regression is not suitable, as in the long run it may forecast market shares beyond these bounds.

To overcome this difficulty, marketing literature [7] suggested logistic regression. Equation (1) models the logit (left-hand side) of the market share of good (index i) by a linear function of time. Equation (2) solves this equation for the market share. As for an example, [4] used this model to analyze the Swiss organic food market. Technical details about logistic regression and other generalized linear models can be found in [8].

$$\ln\left(\frac{s_i(t)}{1-s_i(t)}\right) = d_i + k_i \cdot t \qquad \begin{array}{r} s_i = \text{market share} \\ t = \text{time} \end{array} \tag{1}$$

$$s_i(t) = \frac{\exp(d_i + k_i \cdot t)}{1+\exp(d_i + k_i \cdot t)} \qquad \exp = \text{exponential function} \tag{2}$$

In this paper, we used an alternative approach: A variant of Lotka-Volterra differential equations with analytic solutions allows to identify trends for market shares and to analyze the dynamics of competition. Following [9], this approach starts with the definition of an outside good, typically the one with lowest market share (good $i = 0$ with market share s_0). For the other products ($i > 0$) it proposes a modification of Equation (1): It assumes that the left-hand side of Equation (3) is a linear function of time (right-hand side).

$$\ln\left(\frac{s_i(t)}{s_0(t)}\right) = d_i + k_i \cdot t \quad \text{for } i > 0 \tag{3}$$

This assumption was suggested in [10] for a different market, where it was explained that the left-hand side of Equation (3) may be interpreted as consumer utility. In the case of a market with only two products (market shares s_1 and $s_0 = 1 - s_1$), Equation (3) coincides with Equation (1). The solution of Equation (3) for the market share is given by Equation (4). Thereby, the market share of the outside good is the remainder of the other market shares to 1 (=100%).

$$s_i(t) = \frac{\exp(d_i + k_i \cdot t)}{1 + \sum_{i>0} \exp(d_i + k_i \cdot t)} \quad \text{for } i > 0 \tag{4}$$

When compared to the logistic trend model (1), the Lotka-Volterra model (3) has an additional benefit, as the market shares (for goods $i > 0$) are analytical solutions of the system (5) of autonomous differential equations of Lotka-Volterra type with constant coefficients. Further explanations can be found in [11].

$$\frac{s_t'(t)}{s_i(t)} = k_i - \sum_{j>0} k_j \cdot s_j(t) \quad \text{for } i > 0 \tag{5}$$

This system of differential equations characterizes the interaction of the market shares. One may classify the market dynamics as in **Table 1** in analogy to ecology, using only the coefficients k_i of Equation (5). In the following, we refer to them as growth coefficients (while k_i, d_i are the regression coefficients). Given two goods, if both of their growth coefficients are positive, then in view of Equation (5) the corresponding goods are in a state of competition, meaning that a higher market share for one good inhibits the growth of the other one. If both growth coefficients are negative, then the goods are in a state of mutualism (symbiosis), meaning that a higher market share for one good promotes the growth of the other one. If one growth coefficient is positive and the other is negative, then the good with the positive coefficient is the predator and the other good is the prey, whereby a high market share of the prey accelerates the growth of the predator, but a high market share of the predator inhibits the growth of the prey.

As the coefficients were estimated from data, in **Table 1** we use this characterization of the market dynamics for statistically significant signs of the

Table 1. Market dynamics[a].

Product No. j	Product No. i		
	Significantly $k_i > 0$	Significantly $k_i < 0$	Other
Significantly $k_j > 0$	Competition	Predator-prey	Dynamics indeterminate
Significantly $k_j < 0$	Predator-prey	Mutualism (Symbiosis)	
Other	Dynamics indeterminate		

[a]Table adopted from [9], but with a different meaning of "other".

coefficients, only. For, a statistically insignificant sign of a coefficient might not reflect the true market dynamics but rather a peculiarity of the sample occurring by chance, whence both dynamics with a positive and a negative parameter are conceivable.

To estimate the regression coefficients (d_i, k_i) from given sales data, literature uses different approaches, such as maximum likelihood based on a logistic distribution for model (1). Following [10], we used ordinary linear regression to fit models (1) and (3) to given data. As ordinary linear regression uses the assumption of normally distributed fit residuals, we first tested this assumption at the level of 95% significance, using the Anderson-Darling test [12] (If its p-value, $p < 0.05$, then the Lotka-Volterra model with the given outside good was not applied. As a remedy, we chose a different outside good). Linear regression theory provided the asymptotic multinormal distribution of the regression coefficients. (Its parameters are the expected values of the regression coefficients, d_i and k_i, and a 2 × 2 covariance matrix.) We used it for further analysis: Thus, we identified the 95% confidence interval for the regression coefficients in Equation (5): Given a growth coefficient, if 0 was outside its confidence interval, then the sign of the coefficient was significant. We further used this distribution to simulate markets, whereby **Table 2** explains the used scheme. Based on 1000 simulations, we identified the most common patterns of the dynamics of the simulated markets. Mathematica [13] was used for the computations.

3. Results

We first aggregated the sales data of the 124 products into groups of similar

Table 2. Scheme for fitting model (3) to data and using this model for simulations[a].

1: Market	Product No. 1	No. 2	...	No. n
2: Market shares	s_1	s_2	...	s_n
3: Outside good				Select[b]
4: Transformation	$\ln(s_1/s_0)$ = lshares1			
5: Regression model	Mod1 = Linear Model Fit [lshares 1, t, t]			
6: Regression line	$d_1 + k_1 \cdot t$ = Normal [Mod1]			
7: Residuals normally distributed?	Anderson Darling Test [Mod 1 ["Fit Residuals"]] < 0.05? If not: select different outside good	Do the same as for product 1	...	
8: Asymptotic parameter distribution	Dist1 = Multinormal Distribution[Mod 1 ["Best Fit Parameters"], Mod 1 ["Covariance Matrix"]]			
9: Random coefficients	$\{d_{1r}, k_{1r}\}$ = Random Variate [Dist 1, 1]			
10: Intermediate step	$\mathrm{Exp}_{1r} = \mathrm{Exp}[d_{1r} + k_{1r} \cdot t]$			$\mathrm{Sum}_r = \mathrm{Exp}_{1r} + \mathrm{Exp}_{2r} + \ldots$
11: Simulated share	$s_{1r} = \mathrm{Exp}_{1r}/(1 + \mathrm{Sum}_r)$			$s_{0r} = 1 - s_{1r} - s_{2r} \ldots$

[a]The table uses Mathematica notation. [b]Product n is defined as outside good; its index is changed to 0.

products to smoothen out random influences on the data: We identified 25 product groups. For them, we compared the sales of the conventional and the organic product groups (**Table 3**: for each group, the market consists of two elements, organic and conventional).

Table 3. Significant trends for conventional vs. organic product groups[a].

Group	Category	Confidence limits[b]				AD-test[c]	Significant trend[d]	MS 2020[e]
		d_{low}	d_{high}	k_{low}	k_{high}	p-value		
White	Dairy	1.89	2.07	−0.068	−0.028	0.29	Yes: −1	84%
Colored	Dairy	2.45	2.86	−0.058	0.034	0.59	No	92%
Yellow	Dairy	2.78	2.99	−0.088	−0.039	0.88	Yes: −1	92%
Fats	Dairy	2.75	3.17	−0.095	−0.002	0.99	Yes: −1	94%
Meat, Poultry	Butchery	3.65	3.92	−0.082	−0.02	0.68	Yes: −1	97%
Processed	Butchery	4.14	4.35	−0.075	−0.026	0.72	Yes: −1	98%
Citrus	Fruits	2.31	2.43	−0.101	−0.074	0.12	Yes: −1	85%
Pome fruits	Fruits	2.9	3.38	−0.079	0.029	0.64	No	95%
Stone fruits	Fruits	3.36	3.88	−0.017	0.1	0.87	No	98%
Soft fruits	Fruits	3.18	3.45	−0.043	0.018	0.32	No	96%
Exotics	Fruits	2.03	2.2	−0.05	−0.012	0.77	Yes: −1	87%
Other fruits	Fruits	2.56	2.93	−0.078	0.003	0.29	No	92%
Leaf-bearing	Fresh vegetables	3.48	4.15	−0.13	0.02	0.31	No	96%
Fruiting	Fresh vegetables	2.73	2.9	−0.08	−0.041	0.5	Yes: −1	92%
Roots	Fresh vegetables	1.74	2.01	−0.115	−0.053	0.98	Yes: −1	79%
Bulbs	Fresh vegetables	2.6	2.95	−0.186	−0.108	0.42	Yes: −1	85%
Cabbages	Fresh vegetables	2.85	3.41	−0.302	−0.176	0.28	Yes: −1	82%
Legumes	Fresh vegetables	2.75	3.69	−0.197	0.014	0.31	No	92%
Stems	Fresh vegetables	0.94	1.82	−0.122	0.075	0.59	No	79%
Herbs	Fresh vegetables	0.27	1.4	−0.251	0.001	0.27	No	42%
Mushrooms	Fresh vegetables	2.92	3.55	−0.306	−0.165	0.13	Yes: −1	83%
Other fresh	Fresh vegetables	0.87	3.86	−0.383	0.285	0.56	No	91%
Preprocessed	Fresh vegetables	2.24	2.43	−0.138	−0.094	0.7	Yes: −1	82%
Potatoes	Other categories	2.45	2.75	−0.148	−0.081	0.14	Yes: −1	86%
Eggs	Other categories	2.13	2.29	−0.08	−0.045	0.8	Yes: −1	86%

[a]Based on models (1) and (3): Each product defines a market consisting of the conventional and the organic versions of the product. [b]The intercept d was computed for the time series of years 1, 2, 3, … [c]AD-test: Anderson Darling test for normality of the fit residuals. [d]+1/−1 = significant growth/decrease of a conventional products in comparison to its organic version. [e]MS 2020 = market share in 2020 of conventional version (remainder to 100% = share of organic version).

As follows from Table 3, all fit residuals were normally distributed (Anderson-Darling p-values between 0.12 and 0.99). For 15 product groups there was a significant trend towards more sales of organic products, indicated by the significantly negative growth coefficients for conventional. The lowest shares were for fruits (two of six groups were significant) and vegetables (six of eleven groups were significant), the highest shares for products from butcheries and dairies.

The same outcome was obtained for the categories (aggregating to dairy, butchery, fruits, vegetables, potatoes, and eggs). When compared to organic categories, then for the conventional categories the growth coefficients were significantly negative. However, butchery products were an exception, as the Anderson-Darling test refuted the hypothesis of a normal distribution of fit residuals (p-value = 0.027).

For the single products, random influences blurred this picture. We analyzed, for each of the 124 products, the market consisting of its conventional and organic versions, only. For nine products some data for the organic version were missing, for seven products, the fit residuals for Equations (1) and (3), respectively, were not normally distributed (Anderson-Darling test: $p < 0.05$), and for 62 products there was no significant trend. There remained 46 products with a significant trend, whereby for 12 products, the market share of the conventional product was significantly increasing (meaning: growth coefficients were significantly positive) and for 34 products it was significantly decreasing, when compared to the organic counterpart. Details of these results are provided in a supporting information. As we could expect at most nine spurious significance tests (p-value = 0.044 for ten or more false reports of "95% significant", assuming a binomial distribution with 108 trials and a chance of 5% for errors), for both types of significant outcomes (increasing, decreasing) several were not spurious. Thereby, amongst 19 dairy products there were nine (47%) with a significantly increasing market share for the organic version and there was no dairy product with a significantly decreasing market share for the organic version. By comparison, amongst 53 vegetables the organic version outperformed the conventional one for 13 products (meaning: significant decrease of conventional) and the conventional version outperformed the organic one for 7 products.

Next, we used Lotka-Volterra models (3) to assess the market dynamics from the interaction of products. First, we considered the categories of products (Table 4). We defined the outside good as "organic butchery products and organic eggs", because these two groups of products had the lowest market shares, even when taken together. (The third smallest group was organic potatoes with less than 1% market share.) Considering the Lotka-Volterra equation, the growth coefficients of all conventional categories were significantly negative. For one organic category (organic potatoes with 1% market share in 2020), the growth coefficient was significantly positive and for another category (organic vegetables) it was significantly negative. For the remaining categories no sign was significant. Thus (Table 1), organic potatoes predated on the conventional categories

Table 4. Lotka-Volterra parameters for conventional and organic product categories[a].

Product group	Confidence limits of the model parameters[b]				AD-test[c]	Significant[d]	MS
	d_{low}	d_{high}	k_{low}	k_{high}	p-value		2020[e]
Conventional dairy	4.25	4.32	−0.0764	−0.0612	0.69	Yes: −1	35%
Conventional butchery	3.33	3.41	−0.0775	−0.0596	0.71	Yes: −1	14%
Conventional fruits	3.57	3.69	−0.0817	−0.0553	0.22	Yes: −1	18%
Conventional vegetables	3.19	3.31	−0.0654	−0.0383	0.91	Yes: −1	14%
Conventional potatoes	2.35	2.48	−0.0943	−0.0654	0.49	Yes: −1	5%
Conventional eggs	1.39	1.50	−0.0574	−0.0313	0.81	Yes: −1	2%
Organic dairy	1.97	2.19	−0.0496	0.0007	0.86	No	5%
Organic fruits	−0.71	−0.55	−0.0356	0.0001	0.39	No	2%
Organic vegetables	1.01	1.08	−0.0254	−0.0097	0.59	Yes: −1	2%
Organic potatoes	0.51	0.65	0.0376	0.0699	0.66	Yes: +1	1%

[a]Model (3) applied to the categories, using organic butchery plus organic eggs as outside good. [b]The intercept d was computed for the time series of years 1, 2, 3, … [c]AD-test: Anderson Darling test for normality of the fit residuals. [d]95% significance of the sign of parameter k_j. [e]MS 2020 = market share in 2020 (remainder to 100%: outside good).

and these in turn evolved in a symbiosis. Supplementing this outcome by simulations, then for 99% of the simulations, "organic potatoes" was the sole predator, and the other categories were prey. (Recall that the simulations used the multinormal distributions for the regression coefficients.)

A similar pattern was observed for the market dynamics of the classes within given product categories. For the following choices of outside goods, Anderson-Darling test did not refute any of the fit residuals as not normally distributed.

- For the market of dairy products (with organic fats as outside good), the growth coefficients were significantly negative for all conventional groups, except yellow (insignificant sign). For all organic groups, the sign the growth coefficients were insignificant, except for organic yellow with a significantly positive coefficient. For 93% of the simulations, one of two patterns emerged.

For 46% of simulations, organic yellow (with 1% market share in 2020) was the sole predator and the other groups were prey (outside goods were not classified). For 47% of simulations, organic white (10% market share in 2020) and organic yellow were (competing) predators and the other groups their prey.

- For the butchery market (with organic processed products as outside good), the growth coefficients of the conventional groups (meat & poultry, processed products) were significantly negative, and for organic meat & poultry the sign was insignificant. The simulations of the butchery market displayed two outcomes: For 55% of simulations, organic meat (below 2% market share in 2020) predated on the other groups. For 45% of simulations, all products were in symbiosis.
- For the market of fruits (with organic other fruits as outside good), for conventional fruits the growth coefficients were significantly negative for citrus, pome, soft and stone fruits, and exotics, while the signs were insignificant for other fruits. For organic fruits, the growth coefficients were significantly negative for pome and stone fruits and the sign was insignificant for all other organic fruits. For 91% of the simulations, one of two patterns emerged. For 54% of simulations, all groups were in a symbiosis. For 37% of simulations, "organic citrus fruits" (3% market share in 2020) was the sole predator and the other groups were prey.
- For the market of fresh vegetables (with conventional and organic herbs, organic legumes and organic other fresh vegetables as outside good), the signs of all growth coefficients were insignificant, except a significantly negative growth coefficient for conventional legumes and a significantly positive coefficients for organic bulb vegetables, organic cabbage vegetables, and organic preprocessed vegetables. The simulations showed no dominant pattern: Of more than two hundred patterns that were realized, none was supported by more than 7% of the simulations. However, for 57% of simulations, for seven or eight of the eight organic groups the growth coefficients were positive and for at least eight of the ten conventional groups the growth coefficients were negative.

To explore the accuracy of the model, **Figure 1** plots the market shares, model curves and prediction limits at the 95% level of confidence for the dairy market (defined above). A similar outcome could have been obtained by ordinary linear regression for the market shares. (Basically, the accuracy depends on the number of data points.) However, the long-term perspectives differ: A linear regression would predict indefinite growth of conventional yellow (green dots). For the Lotka-Volterra model, the growth coefficient of conventional yellow is negative, and the model predicts that the market shares will finally decay. (However, for the present growth function this will occur in 25 years.) Thus, in a market with three or more products, a negative growth coefficient does not necessarily mean an immediate decay if the predator is still small (a flea rather than a lion).

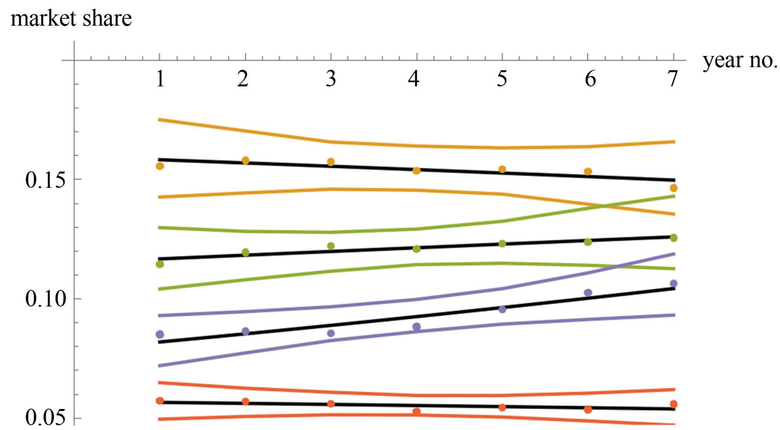

Figure 1. Plot of the market shares of four groups from the dairy market (dots)[a], 95% prediction limits (lines in the same colors)[b], and the model curves (black) for the Lotka-Volterra model. [a]Product groups are (from above): Conventional colored, conventional yellow, organic white and conventional fats. Plot using Mathematica 13. [b]The lower and upper prediction limits are the 2.5% and 97.5% quantiles of 1000 simulated LV-model functions.

4. Discussion

Our results have shown that the trend for the consumption of more organic food continued from 2014 to 2020. For, when compared to their conventional counterparts (using logistic regression), a significant increase of the market shares was observed for 34 of 124 organic products, for 15 of 25 product groups, and for five of six product categories. This outcome is comparable to [4] for Switzerland. Further, there is a large body of literature about the organic food market that ascertained its potential for further growth. For instance, [14] confirmed for Polish consumers their willingness-to-pay more for organic food.

More refined information was expected from a study of the market dynamics by means of Lotka Volterra models. This paper is the first one, which has applied this model to the organic food market, using an approach from [10] with linear utilities. [9] has applied a similar approach to the beer market in Japan and to the telecommunication market in Greece, [15] to tourism in Italy, [16] to competition between ports, [11] to the green cars market in Austria, Germany, and Switzerland, and [17] to the dynamics of internet searches. However, owing to the larger data sets, the latter papers used more complex nonlinear utility functions and non-autonomous Lotka-Volterra differential equations.

In the simulations of the Lotka-Volterra dynamics, in general, most conventional product groups or categories had a negative growth coefficient, while several organic product groups or categories had a positive coefficient. Thus, there was a symbiosis of certain conventional products (negative growth coefficients). If several products are in symbiosis this may indicate that these products share a common trait that makes them attractive for a certain group of consumers (even if overall a predator may dominate the market in the long run). We, therefore, conclude that for a large group of consumers the generally lower price lets them prefer conventional products over organic ones. This result supports by previous findings that price-sensitive consumers may purchase conventional food, even if they would prefer organic one [18].

Further, we repeatedly observed predator-prey dynamics, where the growth coefficients of certain organic products with comparatively small market shares were positive. These products behave like innovative products starting as predators on outdated products (the prey). In the present context, this may indicate an emerging awareness of consumers about the specific benefits of organic production for these foods. For instance, organic yellow as predator in the dairy market may indicate a higher valuation of consumers for more expensive cheese varieties. For, as was noted in [19], consumers increasingly prefer artisan cheese varieties. Similarly, in the fruits market, consumers may prefer organic citrus fruits over conventional ones, as they use their peel (for cakes, or for using fruit slices as decorations for drinks), while for other fruits the benefits of organic production may be less obvious to them. Thus, there was a significantly negative trend for organic cherries in comparison to conventional ones. Perhaps, consumers were satisfied with regional production (in Austria and neighboring countries), while they apparently did not perceive organic production as an added value for stone fruits.

A competitive market (several competing products) was observed for the simulations of vegetables, only. The reason for the low level of competition in the other markets may be due to the definitions of the groups. Thus, the dairy market did not consider the emerging demand for milk substitutes (e.g., oat milk, soy milk), which is driven by eating trends (veganism) and food intolerances.

The main limitation of our study was the relatively short time span of observations. We therefore could not discern long-term changes in consumer behavior. Further, the COVID-19 pandemic may have had a disruptive effect on the 2020 data, as stay-at-home rules imposed during 2020 may have changed the pattern of consumption. For instance, during school closures, there was no demand for milk from the school milk scheme. For this reason, data from 2020 to 2022 cannot be used for the verification of the model. Conversely, in view of the broad prediction bands (**Figure 1**), we do not expect that a significant difference to the pre-COVID trends could be discerned.

Further, a perhaps surprising feature of our data was the definition of the market share relative to the mass of purchased products rather than to their economic value. This addressed price uncertainties caused, e.g., by promotions.

Supporting Information

The authors provide a spreadsheet, MS Excel file SupportingInformation.xlsx, with the data and certain computations. The first two rows explain the data. Column 1 lists 150 names and column 2 informs if this name denotes a product, class, or category. Thereby, a class is in the first-mentioned category above it and a product in the first-mentioned class above it. Columns 3 to 7 list the annual sales of the conventional versions of each product (class, category), and columns

8 to 14 inform about the sales of the organic versions; sales are in tons. Column 15 informs whether data were missing. If so, the market for this product was not modeled. Columns 16 to 22 inform about the market shares of the conventional version of a product; thereby the minimal market consisting of the conventional and organic product was considered (The remainder to 100% is the organic market share).

The subsequent columns summarize the results for model (1). Columns 23 to 29 compute the logits of the market shares. Columns 30 and 31 inform about the model parameters (d and k), which were computed from the logits in years 1 (=2014) to 7 (=2020) by an ordinary linear regression. The following four columns identify the 95% confidence intervals for these parameters. Columns 36 and 37 inform about the Anderson-Darling test for the fit-residuals (p-value and conclusion if the residuals were normally distributed). The final two columns inform, if model (1) detected a significant increasing or decreasing trend for the (logits of the) conventional market shares.

Acknowledgements

The authors are grateful to AMA [5] for providing them access to their data and permission for their publication. The authors thank Bernhard Wurzer for facilitating the contact with AMA. This paper resulted from the master thesis of R.B. and F.S. at the University of Natural Resources and Life Sciences, Vienna. R.B. and F.S. thank N.B. and M.K. for their support and supervision.

It is my (N.B.) sad duty to inform the reader that our coauthor, Manfred Kühleitner, deceased on 15. 04. 2022.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Eyhorn, F., Muller, A., Reganold, J.P., Frison, E., Herren, H.R., Luttikholt, L., Mueller, A., Sanders, J., El-Hage Scialabba, N., Seufert, V. and Smith P. (2019) Sustainability in Global Agriculture Driven by Organic Farming. *Nature Sustainability*, **2**, 253-255. https://doi.org/10.1038/s41893-019-0266-6

[2] Willer, H., Travnicek, J., Meier, C. and Schlatter, B. (2021) The World of Organic Agriculture—Statistics and Emerging Trends 2021. Research Institute of Organic Agriculture, Frick. https://www.fibl.org/en/shop-en/1150-organic-world-2021

[3] European Union (2007) Council Regulation 834/2007 on Organic Production and Labelling of Organic Products. European Union, Brussels.

[4] Götze, F., Mann, S., Ferjani, A., Kohler, A. and Heckelei, T. (2016) Explaining Market Shares of Organic Food: Evidence from Swiss Household Data. *British Food Journal*, **118**, 931-945. https://doi.org/10.1108/BFJ-09-2015-0318

[5] AMA (2020) Roll AMA Haushaltspanel. Agrarmarkt Austria Marketing GmbH, Vienna.

[6] Wang, W. and Yildirim, G. (2022) Applied Time-Series Analysis in Marketing. In:

Homburg, C., Klarmann, M. and Vomberg A., Eds., *Handbook of Market Research*, Springer, Cham, 469-513.

[7] Papke, L.E. and Wooldridge, J.M. (1996) Econometric Methods for Fractional Response Variables with an Application to 401(k) Plan Participation Rates. *Journal of Applied Econometrics*, **11**, 619-632.

[8] Agresti, A. (2013) Categorical Data Analysis. 3rd Edition, John Wiley & Sons, Hoboken, NJ.

[9] Marasco, A., Picucci, A. and Romano, A. (2016) Market Share Dynamics Using Lotka-Volterra Models. *Technological Forecasting and Social Change*, **105**, 49-62. https://doi.org/10.1016/j.techfore.2016.01.017

[10] Marasco, A., Picucci, A. and Romano, A. (2016) Determining Firms' Utility Functions and Competitive Roles from Data on Market Shares Using Lotka-Volterra Models. *Data in Brief*, **7**, 709-713. https://doi.org/10.1016/j.dib.2016.03.020

[11] Ziegler, A.M., Brunner, N. and Kühleitner, M. (2020) The Markets of Green Cars of Three Countries: Analysis Using Lotka-Volterra and Bertalanffy-Pütter Models. *Journal of Open Innovation*: *Technology*, *Market and Complexity*, **6**, Article No. 67. https://doi.org/10.3390/joitmc6030067

[12] Anderson, T.W. and Darling, D.A. (1952) Asymptotic Theory of Certain "Goodness-of-Fit" Criteria Based on Stochastic Processes. *Annals of Mathematical Statistics*, **23**, 193-212. https://doi.org/10.1214/aoms/1177729437

[13] Wolfram Research (2021) Mathematica, Version 13.0. Wolfram Research Inc., Champaign, IL. https://www.wolfram.com/mathematica/

[14] Bryła, P. (2018) Organic Food Online Shopping in Poland. *British Food Journal*, **120**, 1015-1027. https://doi.org/10.1108/BFJ-09-2017-0517

[15] Romano, A. (2016) A Study of Tourism Dynamics in Three Italian Regions Using a Nonautonomous Integrable Lotka-Volterra Model. *PLoS ONE*, **11**, e0162559. https://doi.org/10.1371/journal.pone.0162559

[16] Marasco, A. and Romano, A. (2018) Inter-Port Interactions in the Le Havre-Hamburg Range: A Scenario Analysis Using a Nonautonomous Lotka Volterra Model. *Journal of Transport Geography*, **69**, 207-220. https://doi.org/10.1016/j.jtrangeo.2018.04.018

[17] Sotis, C. (2021) How Do Google Searches for Symptoms, News and Unemployment Interact during COVID-19? A Lotka-Volterra Analysis of Google Trends Data. *Quality and Quantity*, **55**, 2001-2016. https://doi.org/10.1007/s11135-020-01089-0

[18] Stolz, H., Stolze, M., Hamm, U., Janssen, M. and Ruto, E. (2011) Consumer Attitudes towards Organic versus Conventional Food with Specific Quality Attributes. *Wageningen Journal of Life Sciences*, **58**, 67-72.

[19] Velčovská, Š. and Sadílek, T. (2015) Certification of Cheeses and Cheese Products Origin by EU Countries. *British Food Journal*, **117**, 1843-1858. https://doi.org/10.1108/BFJ-10-2014-0350