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A SYNTHETIC EVALUATION OF THE INNOVATIVENESS OF FOOD INDUSTRY BRANCHES IN POLAND

Maria Magdalena Grzelak
Department of Economic and Social Statistics, University of Lodz
e-mail: mgrzel@wp.pl

Abstract: The aim of the presented study is the assessment of the innovativeness of particular food industry classes in Poland conducted on the basis of statistical methods for linear objects grouping. In the study there were used unpublished statistical data characterising the innovativeness of enterprises conducting economic activity in particular branches of the food industry.

Keywords: innovativeness, competitiveness, food industry, statistical methods for linear objects grouping

INTRODUCTION

Poland's integration with the European Union and globalisation processes that make the country increasingly open to contacts with the world economy increase competition among companies in both domestic and international markets. To maintain their market positions, companies must constantly develop and be innovative. This means that the expansion of the food industry in Poland depends on its innovativeness which, quite naturally, implies the need to analyse the aspects of the process.

This research assesses the level of innovativeness of the food industry branches in Poland with a linear ordering of objects used in statistics. It is based on the unpublished GUS (Polish Central Statistical Office) statistics on the innovativeness of companies operating in particular branches of the food industry in the years 2005-2011.

THE LINEAR ORDERING PROCEDURE

A linear ordering of objects generally follows a pattern made of six successive steps[1], i.e.:

1. Defining the purpose of the analysis and the preliminary hypotheses.
2. Specifying the substantive (objects, indicators) and temporal scope of research.
3. Setting up a database containing the values of acceptable diagnostic indicators.
4. Preliminary data analysis:
   - Descriptive analysis of the diagnostic indicators (measures of location, range and variance).
   - Analysis of correlation, reduction and selection of diagnostic indicators.
   - Determination of the character of the diagnostic indicators and applying a stimulation procedure if necessary.
   - Assigning weights to the diagnostic indicators.
5. Linear ordering of objects:
   - Normalization of the diagnostic indicators.
   - Selecting an aggregation formula for the diagnostic indicators (a model-based method, a non-model-based method, the orthogonal projection of objects onto a line).
   - Evaluation of the quality of the results and selection of the optimal solution.
6. Interpretation of the completed linear ordering of objects.

EVALUATION OF THE INNOVATIVENESS OF THE MANUFACTURING SECTOR' DIVISIONS – AN ATTEMPT AT CONSTRUCTING ITS SYNTHETIC MEASURE AND CARRYING OUT AN EMPIRICAL VERIFICATION

This part of the article describes the process of developing a synthetic measure of innovativeness of food industry branches based on the aforementioned linear ordering procedure.

Indicators of innovativeness in manufacturing companies

The set of diagnostic indicators that could show the innovativeness of food companies in Poland was compiled with the unpublished data from a GUS survey based on the PNT-02 form *„Sprawozdanie o innowacjach w przemyśle"*(Statement of Innovations in the Industry), which was carried out as part of the *CIS* programme. The means of the indicators were calculated for the years 2005-2011

[1] Developed by the author based on [Grabiński et al. 1989, pp. 87-89] and [Kolenda 2006, pp. 139-140].

and then were used as a starting point for analysing innovativeness in this sector of industry. The indicators were the following:

1. innovative companies as a share of all companies,
2. companies that introduced new or significantly improved products as a share of all companies,
3. companies that introduced products that are new to the market, or significantly improved, as a share of all companies,
4. companies that introduced new or significantly improved processes as a share of all companies,
5. companies involved in innovative activity that made outlays to innovate as a % of all companies,
6. total outlays on innovative activities (R+D, the purchase of technologies, software, investment outlays on capital assets, personnel training, marketing, other outlays) per company,
7. total R&D outlays as a share of total innovation outlays,
8. outlays on company's own R&D activity as a share of total innovation outlays,
9. purchase of ready-made technologies as a share of total innovation outlays,
10. software outlays as a share of total innovation outlays,
11. outlays on buildings, structures and land as a share of total innovation outlays,
12. outlays on machinery and technical equipment as a share of total innovation outlays,
13. outlays on imported machinery and technical equipment as a share of total innovation outlays,
14. outlays on personnel training as a share of total innovation outlays,
15. marketing outlays as a share of total innovation outlays,
16. sales of innovative products as a share of total sales,
17. sales of innovative products that are new to the market as a share of total sales,
18. sales of innovative products that are new only to the company as a share of total sales,
19. manufacturing companies with cooperation agreements on innovation activity concluded with other entities as a share of all companies,
20. manufacturing companies with cooperation agreements on innovation activity concluded with other entities as a share of all actively innovative companies,
21. the number of automated production lines per company,
22. new or significantly improved products sold as a share of the total sales of products.

Preliminary data analysis–selecting the diagnostic indicators

In selecting the diagnostic indicators, the following informational criteria should be applied [Ostasiewicz 1999, p. 110]: universality, variation, significance, correlation.

The variation of the potential diagnostic indicators was assessed with the classical coefficient of variation (V_j). Indicators with $V_j < 0.1$ were removed from the set.

Another measure of variation used in course of the analysis was the coefficient of the relative amplitude of fluctuations $A(X_j)$ [Kukuła 2000]:

$$A(X_j) = \frac{\max_i x_{ij}}{\min_i x_{ij}}, \ (i = 1,...,n; j = 1,...,m), \tag{1}$$

where $\min_i x_{ij} \neq 0$. Taking an additional condition $A(X_j) \geq c$, where $c = 1{,}2$ allows variables with a low amplitude of fluctuations to be eliminated.

In the first step of the preliminary analysis, variables 16, 17, 18 with data gaps caused mainly by changes in the PNT-02 methodology were taken out from the set of the potential diagnostic indicators which were selected to evaluate the innovativeness of food industry branches in Poland.

The remaining 19 indicators were found satisfactory regarding variation and amplitudes of fluctuations.

In the next step, in order to carry out the reduction procedure and to select the final set of indicators, the potential indicators were assessed for correlation. Diagnostic indicators (j rows) with the greatest sum of the absolute values of correlation coefficients in the row of the correlation matrix R were rejected. In adding up the coefficients in the j row of the correlation matrix R only the strongly correlated variables were taken into account $(r_{j\bullet} > 0{,}5)$, thereby diagnostic indicators showing the strongest (total) correlation with other indicators were eliminated.

Summing up, as a result of the correlation analysis indicators 2, 5, 19, 3, 8, 4, 12, 15, 20, 21, 22 and 14 were excluded from further processing. These indicators were removed because they had a small informative capacity; the high correlation with other indicators means a transfer of the same information about compared objects. The final set of diagnostic indicators that was used to rank Polish food companies by their innovativeness consisted of 7 indicators (Table 1) that in the evaluation of innovativeness were treated as stimulants.

Table 1. The diagnostic indicators of manufacturing companies' innovativeness

No.	Symbol [a]	Preferences [b]	SPECIFICATION
1	Z1	S	Innovative companies as a % of all companies
2	Z6	S	Innovation outlays per enterprise carrying on innovative activity (PLN thousands)
3	Z7	S	R&D outlays as a % of innovation outlays
4	Z9	S	Outlays on the purchase of ready-made technologies as % of innovation outlays
5	Z10	S	Software outlays as a % of innovation outlays
6	Z11	S	Investment outlays on buildings, structures and land as a % of innovation outlays
7	Z13	S	Investment outlays on imported machinery and technical equipment as a % of innovation outlays

[a] Corresponds to the indicator's number in section **Indicators of innovativeness …** ;
[b] S – stimulant

Source: developed by the author

In this research, individual variables were assumed to be equally important for the lack of non-trivial ways enabling the determination of their weights with additional information; hence:

$$\alpha_j = 1/m, (j = 1,...,m). \tag{2}$$

Linear ordering of objects

The most important requirement that a normalisation procedure is expected to meet is that the transformation does not affect the correlation between the characteristics as well as the basic indicators determining the shape of their distribution (skewness, kurtosis). This requirement is satisfied by transformations based on standardisation (3) and unitarisation (4) [Zeliaś 2000, p. 792]:

$$z_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j}, (j = 1,...,m), \tag{3}$$

$$z_{ij} = \frac{x_{ij} - \bar{x}_j}{\max\limits_i x_{ij} - \min\limits_i x_{ij}}, \ (j = 1,...,m). \tag{4}$$

Because the literature of the subject offers a range of normalisation methods[2], the theoretical properties of particular approaches [Kukuła 2000, pp. 77-

[2]As far as normalisation procedures are concerned, [Grabiński et al. 1989, pp. 27-28] indicate 3 transformations that are used the most frequently; [Domański et al. 1998, pp. 49-

100] must be assessed to establish their usefulness before a transformation with the best characteristics is selected and applied to perform a linear ordering of objects.

In this research two variants of calculations are presented; one is based on the unitarisation of diagnostic indicators (variant I) and the other uses the classical standardisation of diagnostic indicators (variant II) – see Table 2.

The synthetic measure M with values μ_i for the $i-$th object $(i=1,...,n)$ computed on the basis of normalised variables z_{ij} and weights α_j $(j=1,...,m)$ assigned to variables $\alpha_j \in (0;m)$, particularly those weights for which $\sum_{j=1}^{m} \alpha_j = 1$, can be expressed as the arithmetic, harmonic and geometric means of the diagnostic indicators. The comparative studies typically use a formula based on the mean of normalised diagnostic indicators [Gatnar, Walesiak 2004, p. 355]:

$$\mu_i = \frac{1}{m}\sum_{j=1}^{m}\left(z_{ij}\alpha_j\right), \tag{5}$$

the formula can be applied if all variables were originally measured on an interval scale or a quotient scale and the normalisation procedure was based on standardisation, unitarisation or zero unitarisation.

In the calculations, the diagnostic indicators were aggregated by adding up their normalised values. This approach yields exactly the same linear order of objects as aggregation making use of the arithmetic mean of the normalized values of the diagnostic indicators (see formula 5).

It was only recently, in 2006, that the need to evaluate ranking quality and to choose the optimal solution started to emerge in the literature as a precaution against inference based on rankings constructed with „*ad hoc*" selected partial procedures.

The statistical quality of the rankings can be assessed with the directional variance of the synthetic variable M^* given by the formula [Kolenda 2006, pp. 137-140]:

$$s^2\left(M^*\right) = \frac{\sum_{i=1}^{n}\left(\mu_i^* - \overline{\mu}^*\right)^2}{n}, \ (i=1,...,n), \tag{6}$$

48] present 5 standardisation and 10 quotient transformations; [Kukuła 2000, pp. 106-110] takes a different division with 10 normalisation transformations; [Zeliaś 2002, pp. 792-794] discusses 2 standardisation methods, 4 unitarisation methods and 6 quotient transformations; [Walesiak 2006, pp. 16-22] analyses a total of 11 transformations; [Młodak 2006, pp. 39-42] presents 4 standardisation methods, 7 unitarisation methods and 8 quotient methods, including author's own proposals based on location statistics.

where μ^* stands for the values of the synthetic variable M^*, n is the number of objects, and $\overline{\mu}^*$ denotes the arithmetic mean μ_i^* of the synthetic variable M^* $\left(\overline{\mu}^* = 0\right)$ determined from:

$$\mu_i^* = \sum_{j=1}^{m} \left(z_{ij} w_j\right), \ \left(i = 1, \ldots, n\right), \tag{7}$$

$$\sum_{j=1}^{m} w_j^2 = 1, \ w_j > 0, \tag{8}$$

where w_j are weights being the coordinates of the unit vector.

It is so, because any other result of the ordering of objects obtained with the values of, for instance, the synthetic measure M with any weights α_j adding up to one, is transformable into the result of the ordering of objects according to the values of M^* (orthogonal projection) with weights w_j meeting condition (8) derived from formula (9):

$$w_j = \frac{\alpha_j}{\sqrt{\sum_{j=1}^{m} \alpha_j^2}}, \tag{9}$$

If the sum of the values of μ_i^* calculated with the normalised values of individual variables z_{ij} tends to a maximum, then the mean sum of squares $s^2\left(M^*\right)$, i.e. the directional variance of the synthetic measure given by formula (6), also tends, under $\overline{\mu}^* = 0$, to a maximum and provides an unambiguous criterion for selecting the best ordering of objects[3].

The results of the linear ordering of food industry branches generated by variants I and II are presented in Table 2.

[3] The directional variance method applied to evaluate the correctness of the ordering of objects can be found in Kolenda 2006, pp. 137-140; Mikulec 2008, pp. 35.

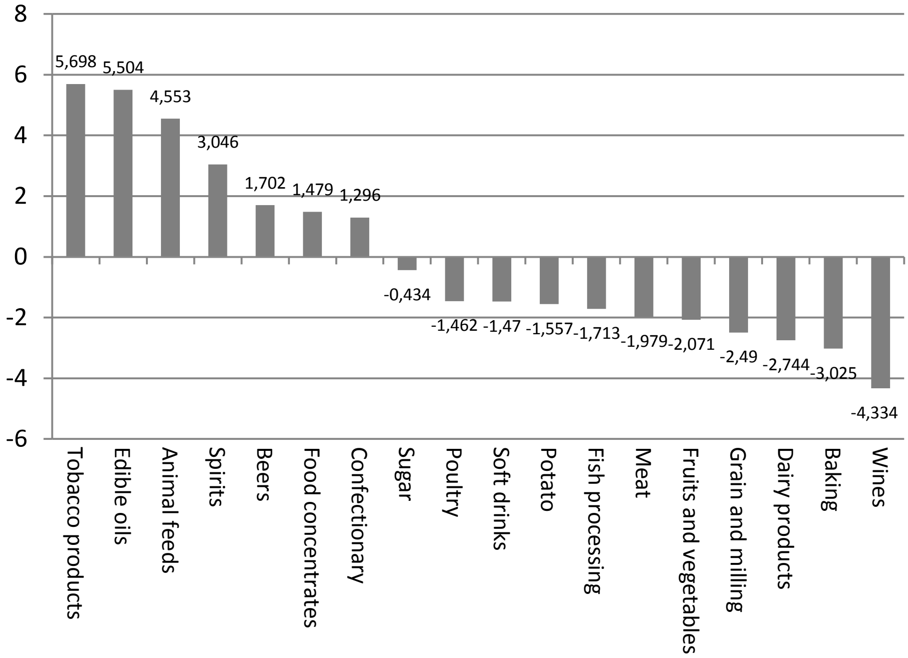
Table 2. The numerical characteristics of the linear ordering of food companies and the evaluation of ordering quality by variant: I – unitarisation of the diagnostic indicators, and II – classical standardization of the diagnostic indicators

Industry (branch)	Synthetic measure M 2005-2011		Values of $\left(\mu_i^* - \bar{\mu}^*\right)^2$ 2005-2011	
	Variant I - unitarisation	Variant II - standardisation	Variant I – unitarisation	Variant II - standardisation
Meat	1.323	-1.979	0.0008	0.0014
Poultry	1.437	-1.462	0.0005	0.0062
Fish processing	1.374	-1.713	0.0006	0.0086
Dairy products	1.142	-2.744	0.0014	0.0220
Potato	1.433	-1.557	0.0005	0.0071
Fruits and vegetables	1.288	-2.071	0.0009	0.0125
Edible oils	3.337	5.504	0.0065	0.0883
Grain and milling	1.224	-2.490	0.0011	0.0181
Sugar	1.731	-0.434	0	0.0006
Animal feeds	2.875	4.553	0.0031	0.0604
Baking	1.051	-3.025	0.0018	0.0267
Confectionary	2.152	1.296	0.0003	0.0049
Food concentrates	2.227	1.479	0.0004	0.0064
Soft drinks	1.460	-1.470	0.0004	0.0063
Spirits	2.670	3.046	0.0020	0.0271
Wines	0.737	-4.334	0.0035	0.0548
Beers	2.288	1.702	0.0006	0.0084
Tobacco products	3.334	5.698	0.0066	0.0947
$s^2\left(M^*\right)$	X	X	0.0017	0.0258

Source: developed by the author

Following the application of the criterion of maximising the directional variance of the synthetic measure that in this case called for transforming the values of the synthetic measure M into the outcome of the orthogonal projection of objects onto line M^* it turned out that variant II generated “better” rankings of food industry companies with respect to their innovativeness – see Table 2.

Figure 1. Food industry branches in Poland ranked by innovativeness, years 2005-2011



Source: developed by the author

The analysis of the correlation between the diagnostic indicators and the values of the synthetic measure showed that the direction of the correlation (positive) and the strength of the indicators' impact on the value of the synthetic measure were consistent, thus confirming that the set of variables was correctly selected for analysis.

SUMMARY AND CONCLUSIONS

The level of innovativeness in the food industry is specific to its branches, as proven by the results of the presented attempt at constructing and making an empirical verification of a synthetic measure of innovativeness.

The diagnostic indicators used in the analysis show that in the years 2005-2011the most innovative were tobacco companies (5,698), which were followed in the ranking by the producers of edible oils (5,504) and animal feeds(4,553). The spirits companies also showed a relatively high level of innovativeness (3,046). The other branches of the food industry were markedly less innovative. Wine-making companies took the last place in the ranking (- 4,334). The leaders were branches with large shares of direct foreign investments.

For the time being, however, the level of innovativeness of Polish food companies, and thereby their long-term growth, are still lower than in countries that are better developed. Among the biggest weaknesses troubling the domestic system of innovation there are low allocations to R&D activity, their inefficient structure, and a very limited transfer of knowledge between R&D institutions and industry.

The results of this research may serve as an indication as to the future policy of support for innovation activities among Polish food companies.

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