VALUE GENERATORS FOR BUSINESSES IN AGRICULTURE

Veronika Machová – Jaromír Vrbka

Abstract

The field of agriculture is very important for the national economy. Agriculture is a source of food of both animal and plant origin and is a producer of many raw materials for other industries. Agriculture meets basic human needs. A balanced and sustainable development of agriculture is therefore a must. That is why it is necessary to know which items have the greatest impact on the value of the farm. The aim of this paper is to identify generators of the value of businesses in agriculture in the Czech Republic, provided that we measure the value of an enterprise using an EVA equity indicator. The comprehensive data set contains the complete annual accounts of agricultural holdings in the Czech Republic for 2016. For each enterprise, EVA equity is calculated, using Statistica software with the automated artificial neural network tool for analysis. A total of 1,000 artificial neural networks – multi-layer perceptron neural networks (MLP) and radial basic function neural networks (RBF) – have been generated. The five best-performing structures are preserved. Based on the sensitivity analysis, the most important items of financial statements that are most involved in the value of businesses in agriculture are identified.

Key words: value generators, agriculture, EVA equity, artificial neural networks, value management

JEL Codes: C45, G32, M21

Introduction

One of the most important aspects to be considered in relation to the performance measurement process is that performance measures qualitatively provide useful information about the products, processes and services that are produced in the enterprise. Implementing performance measures is therefore a great way to understand and manage and improve what a business organization does. If an enterprise wants to succeed, it must monitor not only the development of the external and internal environments, but it is also important to measure the performance of the business (Ferraz and Gallaro-Vázquez, 2016).

The ultimate purpose of the business process is to promote business values. Therefore, any process that can not improve or promote business value, should be upgraded or modified so that business values can be achieved. In order to cope with changes in the business environment, an enterprise should be able to define the necessary measures based on the measurement of business values (Frajtová-Michalíková, Klieštik and Musa, 2015). As far as the commercial value is concerned, it is an informal term in the field of management, which includes all forms of value that determine the health and wellbeing of the company in the long term. The business value includes the purely economic (financial) value, but also the value of the employee, customer, supplier, business partner, managerial values and social values. Many of these formulas are not directly measured in monetary terms (Wang and Vaughan, 2014).

Since the business values pursued by today's businesses are an abstract concept, measuring these values and achieving them is not straightforward. For example, Kang et al. (2012) propose a framework for measuring and managing value achievements that recursively decomposes business values to create a hierarchy of values, and then links them to the business process hierarchy. The framework allows you to measure the achievement of trace value, processes, and take the necessary measures in response to measured progress in achieving value. Specifically, this paper will address the determination of the economic value of the enterprise or generators of this value globally for agricultural enterprises. Like every branch of the national economy, however, agriculture has its own specificities. These consist mainly in satisfying basic human needs. Agriculture is a source of food of both animal and plant origin, which is necessary for human nutrition. It produces many raw materials for other industries. According to Waheed et al. (2018), agriculture is primarily characterized by its maximum dependence on natural conditions, weather. Agricultural land is therefore the main production means for agricultural production.

Agricultural production systems use sophisticated techniques to correlate human, natural, industrial and economic resources. This is done to meet the demand for food in today's highly competitive and demanding market for environmental and social sustainability (Bronnmann and Asche, 2015). In this context, performance rating systems must be used to generate useful information for managers. Such systems enable managers to anticipate the consequences of possible decisions on aspects they consider to be critical to business success. Over the years, a great deal of scientific effort has been devoted to ensuring a balanced and sustainable development of the agricultural sector. In the field of management, science offers performance assessment systems that, although largely based on mathematical calculations, do not meet the needs of managers in the field. Researchers such as Dantsis et al. (2010) and Scott et al. (2015) found that the decision-making environment in fast-growing areas such as the agricultural sector in recent years has found a competitive advantage in the singularities of their physical context and the values and preferences of managers. Now, however, the question arises as to how to determine generators of enterprise value, that is, specific items that affect the value of a business. In addition to well-known methods for analyzing and evaluating businesses, artificial neural networks also exist. They have relatively considerable benefits in applying to business practice. One of the benefits is, for example, the ability of a high-quality prediction. According to Vochozka and Machová (2017), artificial neural networks are widely used, they can be used in many areas, and they are gaining popularity due to the increasing volume of collected data. Neural networks are able to analyze complex patterns quickly and with high precision and are flexible in their own use (Vochozka, 2017). The disadvantage of these networks is their demand for large sample data, because a lot of test observations are needed to create such data, which is very uncomfortable for users. The second major drawback is the process of optimizing topology of hidden layers, which is time consuming and complicates the computation process (Hossain et al., 2017).

The value of agricultural holdings can be determined using the EVA method, namely EVA Equity. According to Vochozka and Machová (2017) EVA Equity deals with an alternative calculation according to the methodology of the Ministry of Industry and Trade of the Czech Republic, which makes it unnecessary to transfer the current financial statements, as outputs from accounting, to economic ones. This type of calculation only considers equity, ie, that the return of the available capital can not include the yield of the foreign capital providers, ie the interest paid. Their requirements can also not be taken into account and only costs of equity are considered.

The aim of the paper is to identify generators of agricultural holdings in the Czech Republic, provided that we measure the value of an enterprise using the EVA equity indicator.

1 Methodology

The data for the analysis will come from the Albertina database of Bisnode Czech Republic, a. s. (public limited company). It will deal specifically with farms operating on the Czech market in 2016. These companies were active (not in liquidation) and reported profit in the year. The data set will therefore include enterprises classified in the CZ NACE classification of economic activities in section A: Agriculture, forestry, fisheries, division 01 – Plant and animal production, hunting and related service activities, division 02 – Forestry and logging, division 03 – Fisheries and aquaculture. In total, the dataset will contain records of exactly 3100 businesses. Businesses included in the analysis will be selected at random. The dataset will contain their complete financial statements (except attachments). Therefore, data from balance sheets, profit and loss statements and cash flow statements will be used. The data will then be arranged in an Excel spreadsheet table, which will be sorted by company by alphabet. The columns will then be the individual information from the financial statements. In the next step, EVA will be calculated for the shareholders (owners) of each enterprise in the year in which they operate on the market, ie EVA equity.

The assumption is first to calculate the weighted average cost of capital (Neumaierová and Neumaier, 2008):

$$WACC = r_f + r_{LA} + r_{entrepreneurial} + r_{FinStab} \tag{1}$$

where: $WACC$ = Weighted Average Cost of Capital, r_f = risk-free yield (risc free), r_{LA} = function of indicators characterizing enterprise size, $r_{entrepreneurial}$ = function of indicators characterizing the production power generation, $r_{FinStab}$ = function of indicators characterizing the relationship between the property of the enterprise and the source of its coverage.

Subsequently, the value of the alternative cost of equity will be determined (Neumaierová and Neumaier, 2008):

$$r_e = \frac{WACC * \frac{UZ}{A} - (1-d) * \frac{U}{BU+O} * (\frac{UZ}{A} * \frac{VK}{A})}{\frac{VK}{A}} \tag{2}$$

where: r_e = equity costs (rate of equity), $WACC$ = Weighted Average Cost of capital, UZ = money resources (equity and interest-bearing foreign capital), A = assets, VK = equity, BU = bank loans, O = bonds, $\frac{U}{BU+O}$ = interest rate, may also be marked as i, d = income tax rate (may also be marked as t – tax).

The economic value added for shareholders will be derived from the relationship (Neumaierová and Neumaier, 2008):

$$EVA\ Equity = (ROE - r_e) * VK \tag{3}$$

where: ROE = Return on Equity.

The file will then be limited by eliminating businesses that are not able to calculate EVA equity - due to unknown or zero core values for the calculation. The resulting table will be further imported into Statistica Version 12, which will look at the extent to which EVA equity is dependent on individual items in the financial statements.

Initially, the basic data statistics will be performed, a correlation matrix will be created. If a correlation is found between the two variables, it is highly probable that they will depend on each other, so only the items of the financial statements that are related to each other are selected. In addition, automated neural network tools will be used, regression will be used. EVA equity will be determined as the dependent variable, the selection of variables will be made with respect to the business management theory of production factors. The data set will then be divided into three sets. The training set of data will be 70% of the input data, in the test and validation set it will be 15% of the input data. The training set serves to generate neural structures, the test and validation sets serve to verify the reliability of the found neural structure. A total of 1,000 neural networks will be generated, of which 5 that have the best results1, will be retained. Two types of neural networks, namely multi-layer perceptron neural networks (MLP) and radial basic function neural networks (RBFs), will be used. The following distribution functions will be considered in the hidden and output layer: linear, logistic, atanh (hyperbolic tangent), exponential, sinus.

The result will be neural structures that will predict EVA equity based on input data from which we will be able to derive the probable EVA equity value. The model will take into account only those variables that will be of real significance to the resulting EVA equity value. A neural network that can describe the relationship as accurately as possible (ie with the best performance in the training, test and validation data set, the minimum error in each set of data and with a clear economic interpretation) will be selected. A sensitivity analysis will also be performed to help determine which variables enter the calculation and which significantly affect the result. The result will be generators of farm value.

2 Results

After adjusting for businesses that failed to calculate EVA equity, there are exactly 3003 farms in the Czech Republic left to calculate the data. On the basis of the methodology, the independent variables that were entered into the calculation (based on the correlation and the economic interpretation) were determined. These include: long-term financial assets, long-term receivables, short-term receivables, trade receivables, short-term financial assets, consumption of material and energy, consumption, margins, performance, value added,

[1] Orientation will be done using the smallest squares and entropy method. Network generation will be terminated if there is no improvement, ie a decrease in the sum of squares, or to reduce disorder.

personnel costs, depreciation of intangible and tangible fixed assets income, interest income, financial result, profit or loss for ordinary activities. Table 1 shows the five best generated and preserved neural networks.

Tab. 1: Retained Neural Networks

	Network name	Training perform.	Testing Perform.	Valid. perform.	Training error	Testing error	Valid. error	Training algorithm	Error function	Activation of hidden layer	Output activ. funct.
1	MLP 16-21-1	0.999351	0.738359	0.753034	9018932	16804812	9120657	BFGS (Quasi-Newton) 64	Sum of sq.	Exponential	Tanh
2	MLP 16-26-1	0.999334	0.750791	0.735904	9245022	16272409	9606443	BFGS (Quasi-Newton) 41	Sum of sq.	Exponential	Tanh
3	MLP 16-8-1	0.998788	0.738791	0.740694	16846971	28594877	13987543	BFGS (Quasi-Newton) 1026	Sum of sq.	Logistic	Sinus
4	MLP 16-12-1	0.999342	0.772104	0.769764	9193858	16038226	8834873	BFGS (Quasi-Newton) 105	Sum of sq.	Tanh	Tanh
5	MLP 16-6-1	0.999327	0.766123	0.750292	9343687	16481214	9089074	BFGS (Quasi-Newton) 72	Sum of sq.	Logistics	Sinus

Source: Authors.

It is clear from the table that all retained networks are multi-layer perceptron networks. They therefore have the best characteristics. In all cases, quasi-newton was used as a training algorithm, but always in a different variant. The least squares method was determined as an error function for each of the preserved networks. The hidden layer of neurons is activated in two cases by an exponential function, in the other two cases a logistic function and one by the hyperbolic tangent function. The output activation functions are two, in three cases the hyperbolic tangent function and in two cases the sinus function. Interestingly enough, the number of neurons in the first layer is in all cases 16 neurons. If all of them are represented by the same variables, we can boldly identify, with fairly high precision, generators of the value of businesses in transport companies.

The relevance of the generated networks is shown in Table 2.

Tab. 1: Performance of generated networks

Neural Network	Training	Testing	Validation
MLP 16-21-1	0.999351	0.738359	0.753034
MLP 16-26-1	0.999334	0.750791	0.735904
MLP 16-8-1	0.998788	0.738791	0.740694
MLP 16-12-1	0.999342	0.772104	0.769764
MLP 16-6-1	0.999327	0.766123	0.750292

Source: Authors.

In the table, we monitor the performance of individual networks, always in all three sets of data - ie, training, testing and validation. In the optimal case, we look for the highest value of the performance (correlation coefficient) and, at the same time, the same value for all data sets. At first glance, we can see that the highest performance in the training and test data sets is achieved by the first retained MLP 16-12-1 network. All networks are very similar, though. The training value is almost 100% ideal, the testing and validation performance values are not bad, but the problem is that the values in all three sets of data should be the best. Testing and validation performance is, of course, lower than in the training group of data.

For better estimation of the correct result, table 3 provides predictive parameters for individual networks.

Tab. 3: Prediction Parameters

Prediction parameter	1.MLP 16-21-1	2.MLP 16-26-1	3.MLP 16-8-1	4.MLP 16-12-1	5.MLP 16-6-1
Minimum prediction (Training)	-58524	-56451	-57574	-45499	-44136
Maximum prediction (Training)	5389826	5388705	5370923	5376853	5391753
Minimum prediction (Testing)	-34486	-33728	-69347	-37983	-33102
Maximum prediction (Testing)	86871	96509	150293	112221	112764
Minimum prediction (Validation)	-57498	-51038	-56021	-73579	-50900
Maximum prediction (Validation)	28998	30417	55128	29695	31356
Minimum residues (Training)	-40010	-40987	-83216	-40263	-37269
Maximum residues (Training)	27266	29774	25287	30262	29909
Minimum residues (Testing)	-34315	-34691	-53205	-35016	-33777
Maximum residues (Test)	49184	48779	78931	51770	48152
Minimum residues (Validation)	-29639	-30872	-32856	-30955	-26865
Maximum residues (Validation)	39469	37630	39040	35239	33098
Minimum standard residues (Training)	-13	-13	-20	-13	-12
Maximum standard residues (Training)	9	10	6	10	10
Minimum standard residues (Testing)	-8	-9	-10	-9	-8
Maximum standard residues (Testing)	12	12	15	13	12
Minimum standard residues (Validation)	-10	-10	-9	-10	-9
Maximum standard residues (Validation)	13	12	10	12	11

Source: Authors.

It is clear from the table that the differences in the prediction are quite different. This is evidenced by the extreme predictive values but also the extreme residue values.

Additionally, the sensitivity analysis was reported, the results of which are shown in Table 4.

Tab. 4: Sensitivity analysis

Indicator	1.MLP 12-15-1	2.MLP 12-16-1	3.MLP 12-27-1	4.MLP 12-29-1	5.MLP 12-12-1	Average
Profit or loss for ordinary activities	5.1076	6.4888	310.8789	4.8144	3.8575	66.2294
Value added	2.232096	1.470144	1.080830	1.886440	2.383702	1.810642
Depreciation of intangible and tangible fixed assets	1.805575	1.842941	1.674565	1.582534	1.803577	1.741838
Performance consumption	1.227688	1.632098	2.009700	1.081095	1.52283	1.494573
Performances	1.369748	2.455272	0.998876	1.132130	1.451711	1.481548
Personal expenses	1.462663	1.298241	1.057123	1.190487	1.572832	1.316269
Long-term receivables	1.161140	1.180884	1.080421	1.563773	1.471636	1.291571
Consumption of material and energy	1.015000	1.081607	1.441746	1.093046	1.059132	1.138106
Short-term receivables	1.001415	1.022315	1.420005	1.090457	1.090150	1.124868
Other operating income	1.044033	1.044393	1.060735	1.076642	1.113567	1.067874
Financial results	1.062129	1.067227	1.060941	1.040569	1.100700	1.066313
Trade receivables	1.002246	1.009375	1.078894	1.103095	1.087835	1.056289
Short-term financial assets	1.019496	1.028804	1.063074	1.102671	1.033412	1.049491
Long-term financial assets	1.043809	1.045544	1.050069	1.015286	1.027693	1.036480
Trade margin	1.022186	1.017009	0.999963	1.007936	1.008011	1.011021
Interest income	0.996753	0.996950	0.998643	1.047544	1.013342	1.010646

Source: Authors.

The table shows that the same variables have always been included in the calculation. Although the order of significance varies from one network to another, the difference is not very significant (up to the value of the profit or loss for ordinary activities, especially MLP 12-27-1). In the first place comes the result of ordinary activities and below that there is added value, depreciation of intangible and tangible fixed assets, performance consumption or performance. Further down we have personnel costs, long-term receivables, material and energy consumption, short-term receivables, other operating income, financial result, trade receivables, short-term financial assets, long-term financial assets, trading margins and interest income. Although these variables have an impact on the value of the transport company, their value is not very large. As the main value generator, all retained networks selected the profit or loss for ordinary activities. The first retained MLP 12-15-1 network further selected value added and depreciation of long-term intangible and tangible assets as generators of value. The second retained MLP 12-16-1 network, on the other hand, selected performance and depreciation of intangible and tangible fixed assets. The third network MLP 12-27-1 puts performance consumption in the second place and the aforementioned depreciation in the third. The fourth retained network MLP 12-29-1 and the fifth retained network MLP 12-12-1 copy the overall results, placing value added in the second place, and depreciation in the third place.

Conclusion

The aim of the paper was to identify generators of the value of agricultural holdings operating in the Czech Republic in 2016. An adequate methodology was developed and value generators were identified. A total of 16 variables were selected, which mainly enter the value-creation process we measure with the EVA equity indicator. The following variables were identified as the most significant items: the profit or loss for ordinary activities, value added and depreciation of intangible and tangible fixed assets. An agricultural enterprise operating in the Czech Republic should focus primarily on these three items of financial statements, not forgetting other selected items that are also involved in creating the value of the business. The aim of the paper was therefore fulfilled.

The potential of the results is important, and can be followed by further research. It is now appropriate to identify the impact of individual variables on EVA equity and, at the same time, the relationship of these variables to EVA equity. In the next step, the appropriate indicators will be decomposed and integrated into the tactical and operational objectives of the company. The strategic goal is known - it is value growth for shareholders.

References

Bronnmann, J., & Asche, F. (2015). The Value of Product Attributes, Brands and Private Labels: An Analysis of Frozen Seafood in Germany. *Journal of Agricultural Economics, 67*(1), 231-244.

Dantsis, T., Douma, C., Giourga, C., Loumou, A., & Polychronaki, E. A. (2010). A methodological approach to assess and compare the sustainability level of agricultural plant production systems. *Ecological Indicators, 10*(2), 256-263.

Ferraz, F. A., & Gallardo-Vázquez, D. (2016). Measurement tool to assess the relationship between corporate social responsibility, training practices and business performance. *Journal of Cleaner Production, 129*, 659-672.

Frajtová-Michalíková, K., Klieštik, T., & Musa, H. (2015). Comparison of Nonparametric Methods for Estimating the Level of Risk in Finance. *Procedia Economics and Finance, 24*, 228-236.

Hossain, M. S., Ong, Z. C., Ismail, Z., Noroozi, S., & Khoo, S. Y. (2017). Artificial neural networks for vibration based inverse parametric identifications: A review. *Applied Soft Computing, 52*, 203-219.

Kang, S., Lee, J., Lee, D., & Baik, J. (2012). A Framework for Measuring and Managing Value Achievement in Business Processes. *IEICE Transactions on Information and Systems, E95.D*(10), 2456-2468.

Neumaierová, I., & Neumaier, I. (2008). Finanční analýza průmyslu a stavebnictví za rok 2007. *Analýzy MPO*, (1), 1-187.

Scott, J., Ho, W., Dey, P. K., & Talluri, S. (2015). A decision support system for supplier selection and order allocation in stochastic, multi-stakeholder and multi-criteria environments. *International Journal of Production Economics, 166*, 226-237.

Vochozka, M. (2017). Inventory management using artificial neural networks in a concrete case. *Proceedings of the 5th International Conference Innovation Management, Entrepreneurship and Sustainability, Prague, Czech Republic*, 1084-1094.

Vochozka, M., & Machová, V. (2017). Enterprise Value Generators in the Building Industry. *SHS Web of Conferences – Innovative Economic Symposium 2017, České Budějovice, Czech Republic, 39*, 01029.

Wang, F., & Vaughan, L. (2014). Firm web visibility and its business value. *Internet Research*, *24*(3), 292-312.

Waheed, R., Chang, D., Sarwar, S., & Chen, W. (2018). Forest, agriculture, renewable energy, and CO 2 emission. *Journal of Cleaner Production*, *172*, 4231-4238.

Contact

Veronika Machová
University of Economics
Nám. W. Churchilla 4, 130 67 Praha 3 – Žižkov, Czech Republic
machova@mail.vstecb.cz

Jaromír Vrbka
Institute of Technology and Business in České Budějovice
Okružní 517/10, 370 01 České Budějovice, Czech Republic
vrbka@mail.vstecb.cz