Research and Development Activity Matrix – New Conception in the Performance Evaluation of Research and Development

LÁSZLÓ MOLNÁR, Ph.D. Assistant Professor

e-mail: laszlo.molnar@uni-miskolc.hu

SUMMARY

In the first part of the paper, we examine the different measurement methods of research and development activity within a corporation with particular attention to the composite indicators widespread in practice and to the multivariate statistical methods applied to create complex indices. In the second part, the research and development activity matrix is introduced in detail. The newly developed analysing method is a portfolio technique that describes the input and output activity of the research and development units in respect of quantity (performance) and quality (efficiency) and enables the categorisation of the observation units into four groups: stars, those lagging behind, quantity-oriented units and quality-oriented units.

Keywords: Research and development; performance measurement

Journal of Economic Literature (JEL) code: O32

INTRODUCTION

Increasing interest is being shown from both political decision-makers and public opinion regarding the complex indices that compare the performance of countries. The indices that allow us to compare nations in an easy way are suitable for demonstrating very complex and elusive fields, such as technological development, innovation, and research and development. It is easier to inform the public opinion with these indicators than finding a common trend from a number of single indices and they have proved to be useful in benchmarking international performance. At the same time, complex indices can send a misleading political message if they were created in a wrong way or misunderstood. The image shown by the indices often forces the users especially the political decision-makers - to make simplistic analytical or political conclusions, instead of utilising the composite indicators as keynotes and for arousing interest in the publicity. Their suitability can only be evaluated by the fields affected (Nardo et al. 2005).

The main goal of our research activity is to create a new measurement method in the performance evaluation of research and development that will it make possible to measure corporate R&D activity on the basis of a sophisticated methodology. We made an attempt to set up the measurement sub-models of the R&D activity in two aspects:

- The first module of the measurement model of the R&D activity contains only objective and quantitative data which are expressed as allowances in kind (million HUF, person and piece). This is the so-called Quantitative Measurement Model (QN-MM).
- In the second module qualitative features dominate. The base of the structure of this module – the so-called Qualitative Measurement Model (QL-MM) – is relative numbers.

The largest difference between the measurement models is the variables used. We distinguish quantitative data and qualitative features. The most important similarity between these models is the source of information, because both modules contain variables that can only come from business surveys.

The objective requires us to use a methodology that fits the norms of international and domestic economics. Thus we put constant emphasis on choosing the relevant research methods, qualitative and quantitative techniques and mathematical and statistical analyses.

➤ We did not rely on only the theoretical and secondary results to set up the integrated research and development model. We carried out in-depth interviews in order not to leave out any relevant factor or internal relation from our own created theoretical conception. Five of the experts were from the central governmental sector and the other five were from the large business sector. ➤ Finally we finished our work with the business survey. It was introduced by the trial testing of the questionnaire among those research and development experts who had helped us in the model set-up phase. During the quantitative primary research 67 large (more than 250 employees) businesses located in Hungary were surveyed with the help of the final questionnaires and telephone interviews as well. The accuracy level of the total sample is ±8.8 percentage point on a 95 per cent confidence level. The data analysis was carried out by Excel and SPSS software packages.

In the following sections we present the research results: first the research and development composite indicators and measurement methods used in international comparisons as well, then we summarize the theoretical and practical information of the R&D Performance Index and R&D Efficiency Index that we created. Finally we introduce the R&D Activity Matrix, which uses the recently developed complex indicators as axes.

THE COMPOSITE INDICATORS OF RESEARCH AND DEVELOPMENT

Organizations such as the International Institute for Management and Development (IMD), the National Scientific Board, RAND, and the United Nations Development Programme (UNDP) have tried to measure the research and development and innovation performance of countries with composite indicators. However, each of these attempts was only for one year and did not go on (IMD 2009; Wagner et al. 2001a, 2001b; NSB 2008; (UNDP 2008). We would like to mention the attempts which were made to measure especially the R&D activity of the industrial and service sectors (Hollanders and Kanerva 2009), the creativity which serves as a basis for research and development activity (Hollanders and van Cruysen 2008a; Hui et al. 2005) and economic globalization (OECD 2005).

Beside the composite indicators used in international comparisons it is worth mentioning those mathematical and statistical methods that have been used in the performance evaluation of research and development in recent years. Borsi and Telcs (2004) tried to get an answer as to whether a composite indicator can be constructed for the understandable groups of R&D statistics that adequately explains a large part from the standard deviation of the indices. They answered the question with Principal Component Analysis (PCA) (Niwa and Tomizawa 1995). According to their findings, the set up composite ranks that consider several indices can be interpreted well with the help of this method.

Borsi and Telcs (2004) tried to find whether an not arbitrary weighting between research and development indices can be created with which a statistically consistent rank can be determined. They gained an answer with one of the popular heuristic optimum searching solutions, Genetic Algorithm (GA), and they stated that a concrete position can be defined onto the countries analysed with the help of the method.

The Fuzzy Set Theory (FST) that is often applied in the fields of management sciences (Tran et al. 2002; Tsaur et al. 2002; Moon and Kang 1999; Sohn et al. 2001) was first used by Moon and Lee (2005) to make composite science and technology indices. The science and technological indices analysed were assigned according to secondary and primary research, and then they asked experts of different fields (academic sector, civil sector, industry, natural sciences and social sciences) to give their opinion on the relative significance of the indicators with the help of attributes. From the indicators - weighting the experts' answers with the particular value with the help of the Fuzzy Set Theory – they created three composite indicators: "R&D input" (R&D personnel, R&D expenditure, and R&D stock), "R&D output" (patents, papers, technology trade) and "economic output" which were applied for cross section and longitudinal analysis.

Borsi (Borsi 2005; Török 2005) used the Data Envelopment Analysis (DEA) in the Hungarian professional literature (Bunkóczi and Pitlik 1999; Fülöp and Temesi 2001; Koty 1997; Tibenszkyné 2007; Tóth 1999) for the first time for analysing R&D efficiency based on Färe et al. (1994). However in the international professional literature (e.g., Nardo et al. 2005) this field of application is not new. In the data envelopment analysis they use R&D expenditures and the number of R&D workers as inputs and the numbers of publications and patents as an output. The data envelopment analysis calculates those points in the multidimensional space that represent the countries performing the best. The points determine the curve of the efficiency potentials. The countries below the curve are not effective; at the same time, from the efficiency indices of those countries that can be found near them the position of the ineffective countries can be assigned.

In summary, the quantitative and qualitative measuring methods of the separate indices can be observed as facts. With their help the relative position of the countries can be determined in a specific area and the spatial or temporal direction of change can be assigned. Furthermore the indicators are useful in order to determine trends, to arouse attention in connection with a topic, to set up political priorities, and for the benchmarking or monitoring of performance. We talk about composite indicators when separate indices create a single index on the basis of a mathematic or calculation model. The composite indicator is able to measure multidimensional concepts that separate indices cannot catch (Nardo et al. 2005).

Table 1. contains the indicators used in international comparisons of research and development.

	Developer of the index	Factors	Methodology	Source
Summary Innovation Index (SII)	European Commission	Thirty EIS indicators	Unweighted mean of transformed values of thirty EIS indicators	Hollanders and van Cruysen (2008b) EC (2009)
Global Innovation Scoreboard Index (GIS Index)	European Commission	GIS indicators	Dimension Composite Innovation Index (DCII) is the simple mean of indicators that create it, Weighted mean of three Dimension Composite Innovation Indices	Archibugi et al. (2009)
Revealed Regional Summary Innovation Index (RRSII)	European Commission	RIS indicators	Weighted mean of transformed values of Regional National Summary Innovation Index (RNSII) and Regional European Summary Innovation Index (REUSII)	Hollanders (2007)
Technological- Advance Index (Tech- Adv)	United Nations Industrial Development Organisation (UNIDO)	Medium- and high-tech added value of industry on the total added value, the total of manufacturing exports	Mean of the indicators	UNIDO (2005)
Technological Activity Index (TAI)	United Nations Conference on Trade and Development (UNCTAD)	Labour force employed in R&D related activities, the amount of patents and scientific publications	-	UNCTAD (2005)
ArCo Technology Index (ArCoTI)	Archibugi and Coco	Numbers of patents and the scientific articles, old and new technologies (Internet penetration, telephone penetration, electricity consumption) development of human skills	Mean of three indicators, which are also means of variables that create them	Archibugi and Coco (2004)
Twelfth pillar of the Global Competitiveness Index (GCI)	World Economic Forum (WEF)	Capacity of innovation, quality of scientific research institutions, company spending on R&D, university-industry research collaboration, government procurement of advanced technology products, availability of scientists and engineers, utility patents	-	WEF (2009)
Third pillar of the Knowledge Economy Index (KEI) and the Knowledge Index (KI)	World Bank (WB)	Royalty and license fee payments and receipts, patent applications granted by the USPTO, scientific and technical journal articles	-	WB (2009)

Table 1. Composite indicators of the research and development activity on an international, macroeconomic and regional level

Source: Compiled by the author

THE R&D PERFORMANCE INDEX AND THE R&D EFFICIENCY INDEX

In the next section we introduce and verify the quantitative and qualitative measurement sub-models.

Quantitative measurement sub-model

The structure of the quantitative measurement model is built up of four principal component analyses: "R&D performance", "input performance", "process performance" and "output performance".

The first hidden variable in the principal component analysis of R&D performance is "input performance," which includes the usage intensity of financial and human resources based on objective and quantitative data that appear on the input side of research and development activity. The second latent variable in the principal component analysis is "process performance," meaning activity based on objective and quantitative data coming to the surface during the research and development process carried out by entrepreneurial R&D units. Their typical appearances are the usage of information sources and co-operation with other R&D units. The third hidden variable of the analysis is "output performance," which contains the quantitative data of down-to-earth results like publications and patents that emerge on the output side of R&D activity done by companies. Figure 1 contains the quantitative measurement sub-model that allows measurement based on quantitative and objective data of R&D performance. It links with the principal component analysis already mentioned above.



Source: Compiled by the author

Figure 1. Quantitative measurement sub-model

The adequacy¹ of the principal component analysis of R&D performance is mediocre (KMO=0.695), the significance value of the Bartlett test² is 0.000. It follows from the values that principal component analysis is a suitable method on the latent components and the variables are not correlated pairwise. The eigenvalue of the first component is 2.097, therefore two-thirds (69.9%) of the information quantity carried by the original variables could be aggregated into the component. On the basis of the variance proportion explained one component can be created. The factor weight of the "input performance" is 0.802, that of the "process performance" is 0.849, while "output performance" has 0.856. The high factor weights clearly show a significant, positive, strong relationship between the composite indicators of R&D performance and the original variables. The variance proportion explained by latent components is 64.4% in the case of "input performance", 72.1% for "process performance" and 73.3% for "output performance"; therefore, the composite indicator created by principal component analysis contains the majority of the whole information quantity. We can state that, according to the results of principal component analyses concerning the quantitative measurement sub-model, the verification of the sub-model yielded the results required: it was successful in giving parameters to the measurement method explaining R&D performance. We can call this composite indicator the R&D Performance Index (R&D-PERFIND). Its calculation process is contained in Appendix 1.

Qualitative measurement sub-model

The structure of the qualitative measurement model – like the quantitative measurement sub-model – is built up of four principal component analyses: "R&D efficiency", "input efficiency", "process efficiency" and "output efficiency".

The first hidden variable in the principal component analysis of R&D efficiency is "input efficiency" that includes the usage intensity of financial and human resources based on objective and qualitative data that appear on the input side of research and development activity. The second latent variable in the principal component analysis is "process efficiency" that means activity based on objective and qualitative data coming onto the surface during the research and development process carried out by the entrepreneurial R&D units. Their typical appearances are the usage of information sources and co-operation with other R&D units. The third hidden variable of the analysis is "output efficiency" that contains the qualitative data of down-to-earth results like publications and patents that emerge on the output side of R&D activity done by companies. Figure 2 contains the qualitative measurement sub-model that allows the measurement based on qualitative and objective data of R&D efficiency. It links the principal component analysis already demonstrated above.



Source: Compiled by the author

Figure 2. Qualitative measurement sub-model

¹ "It is an indicator measuring the adequacy of the factor analysis. Its high values (0.5-1.0) show that the factor analysis is appropriate. The factor analysis cannot be applied if its values are less than 0.5" (Malhotra 2002, p. 674).

² "Test statistics with the help of which we examine the hypothesis that says the variables do not correlate pairwise in the population. In other words the correlation matrix in the population is an identity matrix where each variable perfectly correlates with itself (r=1) but does not correlate pairwise with the other variables (r=0)" (Malhotra 2002, p. 674)

Principal component analysis is quite poor according to the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO=0.585), but the Bartlett test (Sig.=0.001) met the expectations. The eigenvalue of the first component is 1.818, meaning that 60.6% of the information quantity of the original variable could be reduced into one variable. As the eigenvalues of the other two components were less than 1.000, it is clear that we have to keep only the first one. The factor weight of "input efficiency" is 0.62, therefor this variable has less weight in creating the principal component. The factor weight of "process efficiency" is 0.83 and the factor weight of "output efficiency" is 0.87. These variables are dominant in the composite indicator of the R&D efficiency. If we examine the extraction communalities of the original variables, it can be stated that the common factor namely, the composite indicator of the R&D efficiency explains the determining majority of variance of the "process efficiency" (0.69) and "output efficiency" (0.75), apart from the "input efficiency" (0.38). According to the results of the principal component analysis concerning the qualitative measurement submodel, we can declare that it was successful in giving parameters to the measurement method explaining R&D efficiency of the companies: the verification of the submodel brought the results required. We can call this composite indicator the R&D Efficiency Index (R&D-EFFIND). Its calculation process is contained in Appendix 2.

THE R&D ACTIVITY MATRIX

We examine the quantitative and qualitative aspects of R&D activity, because if we contrast the aggregated dimensions of the performance and efficiency then we can arrive at a portfolio technique that helps with the demonstration and easy visualisation of both R&D performance and R&D efficiency of research and development institutes (academic, higher educational and entrepreneurial) at the same time. We can call this portfolio technique the R&D Activity Matrix. Figure 3 shows the research and development activity of the Hungarian large businesses that are included in the sample.



Source: Compiled by the author

Figure 3. R&D Activity matrix

Hungarian large businesses can be categorized into four groups according to their performance and efficiency of research and development activity.

- "Stars": Companies having performance and efficiency above the mean. Firms in this category recognise that research and development has a key role in their success. They have decisions considering this. Their rate in the sample is 21.2%.
- ➤ "Quantity orientated": The companies in this group have a performance above the mean but operate with efficiency below the mean. Their activity can be described with high quantitative data but low qualitative features. Their rate in the sample is 7.5%.
- "Laggers": More than half of the companies (51.5%) fall into this category. They are significant neither in the area of R&D performance or in R&D efficiency, at least in the comparison with the other Hungarian large enterprises sampled.
- "Quality orientated": This is the smallest group (12.1%). It is created by quality-orientated business organisations that lag behind the average in performance but carry out research and development activity above the mean in terms of efficiency in comparison with the other Hungarian companies with over 250 employees.

CONCLUSION

The significance of performance evaluation is becoming larger in every economic branch, and especially in the research and development sector, as a possible way out of the economic crisis. Therefore the aim of our research was to develop a new measurement method with the help of which we can achieve sophisticated monitoring and controlling in the area of corporate R&D activity. In order to establish the new conception we carried out indepth interviews with ten Hungarian experts and tested the sub-models developed theoretically in the form of a business-to-business survey with a small sample. The following research results were obtained:

➤ The quantitative measurement sub-model (QN-MM) created to measure the R&D activity makes a composite indicator on the basis of the relationship among quantitative data. This composite indicator is called the R&D performance index (R&D-PERFIND). The qualitative measurement sub-model (QL-MM) developed to measure the R&D activity creates a composite indicator on the basis of the relationship among qualitative features, and is called the R&D efficiency index (R&D-EFFIND). The R&D performance index and the R&D efficiency index and the R&D efficiency index the relation about the research

and development activity input, process and output performance and efficiency, but they also carry important information themselves. The newly developed complex indices make it possible to monitor and control R&D activity on a micro level. If the indices are aggregated they can also serve as a basis for macroeconomic and international competitiveness analyses. These activities serve as a fundamental part of the job of decision makers and managers. In this area the strict monitoring techniques based on a complex method can be very useful.

➤ The R&D Activity Matrix is a simple but also complex analysis technique in the area of research and development activity whose axes are created by the above-mentioned R&D performance index and R&D efficiency index. The method is appropriate for carrying out both cross-sectional and longitudinal comparisons. The names representing the plain quadrants were chosen in a way to refer clearly to the quantitative and qualitative features of the research and development activity of the companies in the given category. With the help of the R&D Activity Matrix we can not only evaluate corporate or project activity but also can highlight the growth-orientated development directions of the activity after deeper analysis and explanation.

Acknowledgements

The author is grateful to the interviewed experts for their valuable opinions: dr. Zsuzsanna Szunyogh, Hungarian Central Statistical Office; dr. Attila Nyíry, NORRIA North Hungarian Regional Innovation Agency; dr. Ádám Török, Budapest University of Technology and Economics, dr. Tivadar Lippényi, National Innovation Office, dr. András Bakács, Ministry of National Economy; dr. Károly Tihanyi, Richter Gedeon Nyrt.; Nagyézsda Major, Borsodchem Zrt.; dr. Gábor Nagy, TVK Nyrt.; Péter Kinczel, Chinoin Zrt.; Gyula Gondos, Robert Bosch Power Tool Kft.

This research was carried out as part of the TAMOP-4.2.1.B-10/2/KONV-2010-0001 project with support by the European Union, co-financed by the European Social Fund

REFERENCES

ARCHIBUGI, D. – COCO, A. (2004): A New Indicator of Technological Capabilities for Developed and Developing Countries (ArCo). World Development. 32. évf. 4. sz. 629–654. old.

ARCHIBUGI, D. – DENNI, M. – FILIPPETTI, A. (2009): Global Innovation Scoreboard 2008. Pro Inno Europe/Inno Metrics. Brussels.

BORSI B. (2005): Tudás, technológia és a magyar versenyképesség. PhD-értekezés. Budapest.

BORSI B. – TELCS A. (2004): A K+F-tevékenység nemzetközi összehasonlítása ország-statisztikák alapján. Közgazdasági Szemle. 51. évf. 2. sz. 153–172. old.

BUNKÓCZI L. – PITLIK L. (1999): A DEA (Data Envelopment Analysis) módszer falhasználási lehetőségei üzemhatékonyságok méréséhez. Agrárinformatika. Debrecen.

EC (European Commission) [2009]: European Innovation Scoreboard. Brussels.

FÄRE, R. – GROSSKOPF, S. – KNOX LOVELL, C. A. (1994): Production Frontiers. Cambridge University Press. Cambridge.

FÜLÖP J. – TEMESI J. (2001): A Data Envelopment Analysis (DEA) alkalmazása ipari parkok hatékonyságának vizsgálatára. Szigma. 32. évf. 3–4. sz. 85–109. old.

HOLLANDERS, H. (2007): Regional Innovation Scoreboard 2006. Pro Inno Europe/Inno Metrics, Brussels.

HOLLANDERS, H. – KANERVA, M. (2009): Service Sector Innovation – Measuring Innovation Performance for 2004 and 2006 Using Sector Specific Innovation Indexes. Pro Inno Europe/Inno Metrics. Brussels.

HOLLANDERS, H. – VAN CRUYSEN, A. (2008a): Design, Creativity and Innovation – A Scoreboard Approach. Pro Inno Europe/Inno Metrics. Brussels.

HOLLANDERS, H. – VAN CRUYSEN, A. (2008b): Rethinking the European Innovation Scoreboard – A New Methodology for 2008–2010. Pro Inno Europe/Inno Metrics. Brussels.

HUI, D.– NG, C.– MOK, P. – FONG, N. – CHIN, W. – YUEN, C. (2005): A Study on Creativity Index. Hong Kong Home Affairs Bureau. The Hong Kong Special Administrative Region Government. Hong Kong.

IMD (International Institute for Management and Development) (2009): World Competitiveness Yearbook 2009. Lausanne.

KOTY, L. (1997): A gazdasági hatékonyság számítása DEA lineáris programmal. Statisztikai Szemle. 75. évf. 6. sz. 515–524. old.

http://www.ksh.hu/statszemle_archive/1997/1997_06/1997_06_515.pdf

MALHOTRA, N. K. (2002): Marketingkutatás. KJK-KERSZÖV Jogi és Üzleti Kiadó. Budapest.

MOON, H. S. – LEE, J. D. (2005): A Fuzzy Set Theory Approach to National Composite S&T Indices. Scientometrics. 64. évf. 1. sz. 67–83. old.

MOON, J. H. – KANG, C. S. (1999): Use of Fuzzy Set Theory in the Aggregation of Expert Judgments. Annals of Nuclear Energy. 26. évf. 1. sz. 461–469. old.

NARDO, M. – SAISANA, M. – SALTELLI, A. – TARANTOLA, S. – HOFFMAN, A. – GIOVANNINI, E. (2005): Handbook on Constructing Composite Indicators – Methodology and User Guide. Organisation for Economic Co-operation and Development. Paris.

NSB (National Science Board) (2008): Science and Engineering Indicators 2008. Arlington.

NIWA, F. – TOMIZAWA, H. (1995): Composite Indicators – International Comparison of Overall Strengths in Science and Technology. National Institute of Science and Technology Policy. Tokyo.

OECD (Organisation for Economic Co-operation and Development) (2005): Measuring Globalization – OECD Handbook on Economic Globalisation Indicators 2005. Paris.

SOHN, K. Y. – YANG, J. W. – KANG, C. S. (2001): Assimilation of Public Opinions in Nuclear Decision-making Using Risk Perception. Annals of Nuclear Energy. 28. évf. 6. sz. 553–563. old.

TIBENSZKYNÉ F. K. (2007): Az oktatás hatékonyságának mérése a ZMNE 2006-ban végzett hallgatóin Data Envelopment Analysis (DEA) módszer használatával. Hadmérnök. 2. évf. 2. sz. 149–165. old.

TÓTH, Á. (1999): Kísérlet a hatékonyság empirikus elemzésére. Magyar Nemzeti Bank. Budapest.

TÖRÖK Á. (2005): Competitiveness in Research and Development – Comparisons and Performance. Edward Elgar Publishing. Cheltenham.

TRAN, L. T. – KNIGHT, C. G. – O'NEILL, R. V. – SMITH, E. R. – RIITTERS, K. H. – WICKHAM, J. (2002): Fuzzy Decision Analysis for Integrated Environmental Vulnerability Assessment of the Mid-Atlantic Region. Environmental Management. 29. évf. 6. sz. 845–859. old.

TSAUR, S. H. – CHANG, T. Y. – YEN, C. H. (2002): The Evaluation of Airline Service Quality by Fuzzy MCDM. Tourism Management. 23. évf. 2. sz. 107–115. old.

UNCTAD (United Nations Conference on Trade and Development) (2005): World Investment Report 2005. New York. UNDP (United Nations Development Programme) (2008): Human Development Report 2007/2008. New York.

UNIDO (United Nations Industrial Development Organization) (2005): Industrial Development Report 2005. Vienna. WAGNER C. S. – HORLINGS, E. – DUTTA, A. (2001a): Science and Technology Collaboration – Building Capacity

in Developing Countries. RAND. Santa Monica.

WAGNER C. S. – HORLINGS, E. – DUTTA, A. (2001b): Can Science and Technology Capacity be Measured? RAND. Santa Monica.

WB (World Bank) (2009): World Development Indicators 2009. Washington.

WEF (World Economic Forum) (2008): The Global Competitiveness Report 2008–2009. Geneva.

APPENDICES

Appendix 1: Calculation process of the R&D-PERFIND

The first step of calculation of the R&D-PERFIND is standardisation of the quantitative indicators before using them, e.g.:



In the second step we define the input, process and output performance indicators, which are the sum of standardized quantitative indicators, weighted by factor score coefficients.

$$\begin{split} \text{IN_ACT_OBJ_QN_i} &= W_{\text{EXP_OBJ_QN}} \cdot \overline{\text{EXP_OBJ_QN}} + W_{\text{RES_OBJ_QN}} \cdot \overline{\text{RES_OBJ_QN}} \\ \text{PROC_ACT_OBJ_QN_i} &= W_{\text{SOURC_OBJ_QN}} \cdot \overline{\text{SOURC_OBJ_QN_i}} + W_{\text{COOP_OBJ_QN_i}} \cdot \overline{\text{COOP_OBJ_QN_i}} \\ \text{OUT_ACT_OBJ_QN_i} &= W_{\text{PUBL_OBJ_QN}} \cdot \overline{\text{PUBL_OBJ_QN_i}} + W_{\text{PAT_OBJ_QN}} \cdot \overline{\text{PAT_OBJ_QN_i}} \end{split}$$

In case of Hungarian large businesses the standardized quantitative indicators should be weighted by the following factor score coefficients.

W_{EXP_OBJ_QN}=0.54; W_{RES_OBJ_QN}=0.54 W_{SOURC_OBJ_QN}=0.60; W_{COOP_OBJ_QN}=0.60 W_{PUBL_OBJ_QN}=0.70; W_{PAT_OBJ_QN}=0.70

R&D-PERFIND is the sum of input, process and output performance indicators weighted by factor score coefficients.

 $\mathsf{R} \And \mathsf{D} - \mathsf{PERFIND}_i = \mathsf{W}_{\mathsf{IN_ACT_OBJ_QN}} \cdot \mathsf{IN_ACT_OBJ_QN}_i + \mathsf{W}_{\mathsf{PROC_ACT_OBJ_QN}} \cdot \mathsf{PROC_ACT_OBJ_QN}_i + \mathsf{W}_{\mathsf{OUT_ACT_OBJ_QN}} \cdot \mathsf{OUT_ACT_OBJ_QN}_i + \mathsf{W}_{\mathsf{OUT_ACT_OBJ_QN}} \cdot \mathsf{W}_{\mathsf{OUT_ACT_OBJ_QN}} = \mathsf{W}_{\mathsf{OUT_ACT_OBJ_QN}} \cdot \mathsf{W}_{\mathsf{OUT_ACT_OBJ_QN}} = \mathsf{W}_{\mathsf{OUD$

According to the business survey the following weights should be used in case of input, process and output performance indicators.

WIN_ACT_OBJ_QN=0.38; WPROC_ACT_OBJ_QN=0.41; WOUT_ACT_OBJ_QN=0.41

Appendix 2: Calculation process of the R&D-EFFIND

The first step of calculation of the R&D-EFFIND is standardisation of the qualitative indicators before using them, e.g.:



In the second step we define the input, process and output efficiency indicators, which are the sum of standardized qualitative indicators weighted by factor score coefficients.

$$\begin{split} \text{IN_ACT_OBJ_QL}_i &= W_{\text{EXP_OBJ_QL}} \cdot \overline{\text{EXP_OBJ_QL}_i} + W_{\text{RES_OBJ_QL}} \cdot \overline{\text{RES_OBJ_QL}_i} \\ \text{PROC_ACT_OBJ_QL}_i &= W_{\text{SOURC_OBJQL}} \cdot \overline{\text{SOURC_OBJQL}_i} + W_{\text{COOP_OBJ_Q}} \cdot \overline{\text{COOP_OBJ_QL}_i} \\ \text{OUT_ACT_OBJ_QL}_i &= W_{\text{PUBL_OBJ_QL}} \cdot \overline{\text{PUBL_OBJ_QL}_i} + W_{\text{PAT_OBJ_QL}} \cdot \overline{\text{PAT_OBJ_QL}_i} \end{split}$$

In case of Hungarian large businesses the standardized qualitative indicators should be weighted by the following factor score coefficients.

W_{EXP_OBJ_QL}=0.59; W_{RES_OBJ_QL}=0.59 W_{SOURC_OBJ_QL}=0.58; W_{COOP_OBJ_QL}=0.58 W_{PUBL_OBJ_QL}=0.60; W_{PAT_OBJ_QL}=0.60

R&D-EFFIND is the sum of input, process and output efficiency indicators weighted by factor score coefficients.

According to the business survey the following weights should be used in case of input, process and output efficiency indicators.