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METHODOLOGY USED IN ANALYSING ABSORPTION CAPACITY OF EU FUNDS IN ALBANIA

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ABSTRACT

Uncontrolled credit rises have the capacity to cause serious banking crises. Global banking crises have led to discussions on credit-to-GDP gaps and new credit modelling structures. In this study, both developed and emerging economies are analyzed regarding increased credit, non-performing loans, and credit-to-GDP gaps. Panel logit models are used, as well as z-score and capital adequacy variables. The results indicate that increasing bank credit is an integral factor in banking crises. Furthermore, increases of non-performing loans also pose major systemic risks. The financial strength of banks is essential to preventing financial crises. This is not valid for capital adequacy regulations. Instead of minimizing banking system risk, on the contrary, high and firm capital adequacy ratio regulations cause a system to be more fragile.

JEL Classification: G01; G21; C23.

Keywords: Absorption capacity, EU Funds, Methodology.

1. INTRODUCTION

The utilization of EU funds in Albania has been of high importance by both the Government and EU on their use, transparency and accountability and impact these funds have in supporting Government reforms in its way to EU. This paper intends to provide an overview on the methodological approach used in analyzing the absorption capacity of EU funds in Albania as part of dissertation PhD thesis of the Author. Firstly, we describe the information that was obtained through the questionnaire used on the importance of factors affecting the effective and efficient absorption of EU funds in Albania. And secondly, we represent the statistical models uses in analyzing the data obtained by the questionnaire respondents. The results of the findings are not subject of this paper as they are integral part of my PHD dissertation however it can be summarized that according to the tested model, we verified that administrative capacity factor is the most important factor, affecting the abosrption capacity of EU funds in Albania, macroeconomic capacity ranks second and last affective is financial capacity factor. Results also showed that there is no relation between the three factors affecting absorption capacity of EU funds in Albania

2. PART I: QUESTIONNAIRE

2.1 Designing the questionnaire

The main objective of the questionnaire used, is identifying the main factors of absorption capacity of EU funds and highlighting the importance of these factors in improving absorption capacity to absorb as much funds into different sectors of the economy.
In designing the questionnaire and alternatives response, we have considered the three factors affecting absorption capacity of EU funds such as macroeconomic, financial and administrative through careful examination. This methodology and type of questionnaire has not been used before in similar analyzes by other authors while analysing EU absorption capacity for the countries of the region, member countries such as Romania, Bulgaria and Croatia or candidate countries such as Montenegro, FYROM and Serbia.
During the analysis of the respondents, indicators have been analysed as determinants of the absorption capacity of EU funds, and some techniques and statistical tests were used to see the correlation of variables as the main core of this section. The process of designing the questionnaire as well as the data collection is described in more details in the following sections
Testing the Questionnaire

In designin the questionaire we based our knowledge in the litearture review. The questionnaire consists of the data collection section, composed of the three key factors affecting the absorption capacity according to specific determinants; open and closed questions section and the section on demographic data collection with a total of 41 attributes for which the information is required.

While designing the questionnaire, we used the Likert scale with 7 units, and for the open questions the scale with 10 units. Everyone is asked to evaluate the importance of the attributes by selecting points of scale that can better represent his/her opinion. An incremental rate for units is used, where number 1 indicates a trivial factor, 3 and 4 show an average significant rating and 7 indicates the highest importance factor. Instructions on completing the questionnaire were given to individuals via email and phone clearly before filling in the questionnaire, ensuring equal treatment of data and maintaining anonymity. With reference to the questions about the organization in which the respondent participates, it was left open based on the principles of protecting the anonymity.
The time needed to complete this questionnaire is between 10-15 minutes, considering that respondents are and have been experts in this field and do not need much time for in-depth thoughts. The following is a discussion of the content of the questionnaire.

2.2 Contents of the Questionnaire Sections

The questionnaire is composed of 11 questions on the demographic data of the respondents to obtain demographic information of the respondents. This includes residence, current job position, previous experience with EU funds management, years of experience in the EU funded projects and sector, name of the institution of respondents, the sector in which the organization is oriented, type of organization, level of organization activity, gender, age group, and level of education of the respondents.
Collection of these factors enabled us to test the hypothesis of diffrent demographic and profesional factors and it can affect during the evaluation and importance given to diffrent factors.
With the questionnaire, we gather information on the importance of defining macro-economic absorption capacity, financial capacity and administrative capacity to absorb EU funds. A total of 39 attributes are organized according to the three main factors of absorption capacity of EU funds, respectively 18 attributes are analyzed for macroeconomic capacity, 3 attributes for financial capacity and 18 attributes for administrative factor. The questionnaire is attched as evidence in Annex A of this study.
Menawhile in the open question section, respondents can give their opinion on other factors that they think are important and affect the absorption of EU funds in Albania which are not listed in the questionnaire.

2.3 Population and selection

The population is defined as the entire interest group from which information can be obtained to achieve the main objective of the study. In the case of this study, the surveyed population includes all public administration persons who have previously worked and work in the central institutions, in special departments, sectors or agencies and with clear mandates in managing EU funds in the Albanian Administration. Also, accurate identification of persons to be involved in the questionnaire was carried out. Initially, we have analysed all the structures of central government that are given the responsibility and competences derived by the obligation from the Framework Agreement between the European Commission and the Council of Ministers of the Republic of Albania for the managment of EU funds. Furthermore, we have identified the respective staff working in each units/structures involved following the stages from programing at the policy level in the Prime Minister‘s Office - Department of Development and Foreign Assistance Management, Ministry for Europe and Foreign Affairs - EU Fund Management Directorate at the level of national coordinator; The Ministry of Finance and Economy as the central body for implementing and controling the EU funds (deputy Minister of Finance in the role of National Authorizing Officer, his support office NAO Office, National fund, Central Financing and Contracting Unit); all the staff in directorates that covers European Union Integration and management of EU funds in the Line Ministries, the staff of European Integration and projects units in the High State Control, Bank of Albania, Competition Authority,Parliament, IPARD Managging Authority in the Ministry of Agriculture and Rural Develomennt, IPARD Agency staff and the Audit Authority staff.

2.4 Validity and Reliability of Data

In our case and with reference to the guarantee on the validity of the questionnaire, and effectivity of measure, we have used several evaluation criterias to validate wether the questionnaire measures respectivley the objective for which it has been created, and if yes, how much correct is the performed measure.
Some of the criterias used to ensure validity are: to analyze whether questions are properly formulated in the context of the study and whether the questionnaire as a whole measures the main factors of absorbtion capacity of EU funds in Albania; use of performance measurement and comparison with standard measures; the internal validity criterion which relates to conclusions based on actual results and not in opinions influencing the bias of research; the external validity criterion, which shows us the criterion of the level of application of the survey findings to the population as a whole.

In this study, the above criteria were analyzed to evaluate the reliability of the questionnaire, based on the same and consistent results in similar measurements.Therefore, possible questions about the credibility and validity of the questionnaire designed for this study can be answered on the basis of the results we have achieved. The designed questionnaire measures the criteria of the absorption capacity of EU funds according to the determining factors and based on this information, we can answer the research questions raised to confirm the hypothesis of the study. However, being unique of this type, the credibility of this questionnaire can be improved and / or enriched by performing exploratory literature studies in other dimensions.
While analysing the collected data from the questionnaire, and in order to measure the importance of the factors affecting the absorption capacity of EU funds, some quantitative analysis was used, the methodology which is explained in part two of this paper.

3. PART II
STATISTICAL MODEL USED IN CALCULATING THE ABSORPTION CAPACITY OF EU FUNDS IN ALBANIA

3.1 Bivariate Analyses
3.1.1 Contingency Tables and Hi-Squares Test

The term Hi-square refers to a statistical distribution and hypothesis testing procedure that computes a statistic, which is approximately distributed as a hi-square distribution otherwise called Hi-square Pearson (Pearson‘s chi-square) statistics. This test serves as a measure of the appropriateness of a good model where data is categorized according to a dimension and as a common test of contingency tables, where the categorization takes place in two or more dimensions. Hi-square standard statistics are calculated as:

H0 Hypothesis assumes that there is no relation between the variables. The variation of one of the variables is not associated with the variation of the other variable. The alternative hypothesis is formulated on the basis of the existence of a link between the two variables, but does not specify the type of connection, which is done by examining the data.
In double entry tables, the expected value for each table cell is the total output ratio according to the total by column, with the total number of observations. The distribution of this statistic is (Hi-square) with (r-1) (c-1) degree of freedom, where r represents the number of rows of the two-entry table and c represents the number of columns. This kind of distribution only takes positive values.

Hi-square tests are only valid when the sample size is sufficient. But there are also some conditions that need to be considered for the test to be valid. For tables with more than 40 observations, it can be used if no more than 20% of the table cells have printed frequencies smaller than 5 and none of them receives less than 1. In this study, the Hi-square test will be used to test whether attribution estimates depend on the characteristics of respondents such as. gender, age group, experience of the relevant organization regarding the management of EU funds etc.

3.1.2 Comparison of Averages: T-test for independent samples

The t test allows us to compare the means of the two groups. This test raises the question of whether the difference between the means of the two groups may have been due to a random chance in the sample selection. The difference is more likely to be meaningful and real if; a) the difference between the means is high; b) the size of the sample is high and; c) the responses are generally around average values and not widely distributed around them (standard deviation is low). The statistical significance of the test and the effect are two main test results. The statistical significance shows if the difference between the sample means is likely to represent a current difference between populations and the effect shows whether the difference is sufficiently large to be virtually meaningful.

3.1.3 ANOVA: The model, statistical hypothesis and testing

The objective for carrying out ANOVA is to see if there is any difference between certain groups on the given estimates or the measurements of a variable. The data can be parametric (results) and non-parametric (sorting). We have several types of ANOVA. For the purpose of this paper, ANOVA will be used with an input between the groups, which tests the differences between the groups and is the simplest version of ANOVA being determined by a variable.

An ANOVA analysis looks at the changes within the group and compares them to the differences between the groups. ANOVA calculates the mean for each group, the total mean of all combined groups and then within each group, calculates the total deviation of each individual's score from the group's average. This is also a variation within the group. Further, calculate the deviation of the average of each group from the general average. Finally, ANOVA calculates the F statistic that is the ratio between the Variation between the Groups with the Variance within the Group. If the Variation Between Groups Is Higher than the Variation Within the Group, then there is likely to be a statistically significant difference between the groups.

3.2 Structural Equation Model (SEM)

The Modeling of Structural Equations (SEM) displayed over the last three decades, has created a new level of sophistication in quantitative modeling through uses in addressing numerous fundamental and methodological issues. SEM enables simultaneous modeling between multiple dependent and independent variables. In many areas of research, latent factors are widespread and modeling by structural systems dominates the analysis when the sample is independent (Jöreskog, 1971). Modeling by structural equations enables the analysis of multiple levels of variables and seen from this point of view has created an unexplored potential earlier (Preacher et al., 2016; Preacher et al., 2010).

The SEM model has the backing support for covariate analysis. The model of structural equations based on covariance is a well-known statistical methodology that enables the description of the hidden structure that lies beneath a community of observed variables and the evaluation and modeling of links between hidden variables (Jöreskog, 1969, Kline, 2011)

Advantage: The covariance analysis uses the ML function to minimize the difference between sample covariances and those predicted by the model. In this way, the obtained covariance matrix is assumed to be based on independent observations. Independence comes from the fact that the correlation between the predicted parameters is zero and at the same time it is assumed the normal distribution of model parameter values, ie multinomial distribution.

Limitation: In addition to the advantage of using covariance analysis, it is worth mentioning that this model as other models has limitations related to distribution specifications (parameter normality), metering level, sample size (problem in sample cases (Chin, 1998; 2010; Hair et al., 2011; Hulland et al., 2010). SEM is mainly used in social sciences, especially in testing hypotheses of causal influences.

3.2.1 Literature review of the SEM Model

There are many authors who have supported model estimation by SEM and some authors supporting this method are as follows:

Characteristics that make SEM a technique not only very valuable but also unique are as; a) Estimates multiple relationships of dependent variables b) Include hidden, latent variables that can not be directly measured. Latent variables are constructs that can not be directly observed , but should be evaluated based on a number of observed variables (Brown, 2015); c) Defines a specific model; d) SEM allows the estimation of hidden constructs, taking into account the measurement error that accompanies each variable instead of the mean; e) SEM enables the

modeling of more complex patterns than OLS regression (can be included in multiple medial models and not just a dependent variable); ė) SEM offers advanced ways to handle missing data; f) SEM provides accurate indicators (hi-square χ^2 statistic) and approximate eligibility (CFI, RMSEA).
Adaptation indicators show how well the model fits with data compared to alternative models; g) SEM enables the disclosure of measurement invariance (MI) to determine whether measurement operations have generated indicators with similar specifications. MI testing is important when data is collected by individuals belonging to different clusters, countries, or cultures.

According to Shook (2004) modeling of structural equations is a robust but very complex analytical technique. It is part of statistical models that aim to explain the relationship between multiple variables and analyze the structure of mutual relationships expressed in a series of equations, similar to a series of multiple regression equations; can be considered a unique combination of both interdependence and dependence techniques (Hair et al., 2006: 711).
This technique is particularly useful when in a subsequent relationship of dependence is achieved to turn a dependent variable in an independent variable (ibid: 718)
According to Byrne (2000: 54), compared to multivariate procedures, Modeling Structural Equations is a more powerful alternative considering interconnected independence, error measurement, and multiple latent independence. SEM could include latent variables in the analysis and provides the model of measurement which specifies the correlation rules between measured and latent variables.
Other authors highlight that SEM estimates a series of separate but interdependent variables (Hair et al., 2006). Normally, the researchers will base the proposed relationship of a model on the previous theory and experience and then turn these variables into a series of structural equations for each dependent variable. What is thought to make SEM unique is that it only allows a single relationship between dependent and independent variables. Also, this statistical method can improve the statistical evaluation, present the theoretical framework, and identify the measurement error.
Although statistical models can evaluate the importance of variables and models, an econometric model generally needs to be developed based on some fundamental theories closely related to the relevant field.
Starting from this point, this method that is widely used in empirical studies consists of Measurement Models as well as Structural Models. This model includes the specification of structural relationships between latent constructs that can be associated with variables measured by a relationship of dependence (Lee, 2007).
There are two types of potential relationships during the construction of these models:
First, it is a relationship of dependence, which is always described by a right arrow and is used between an exogenous construct and an endogenous construct and the second is a correlation relationship, which is described by a double-link arrow, which can to be divided only between exogenous constructs.

3.2.2 Differences between SEM models based on component and covariance models

Two complementary schools have emerged in the field of modeling the structural equation (SEM): SEM based on covariance and SEM with component are shown in table number 1:

Criteria	**SEM based on component**	**SEM based on the covariance**
Objective	Oriented through prediction	Oriented by parameter
Approach	Based on variance	Based on covariance
Assumptions	Nonparametric	Parametric
Parameter Estimaation	Almost consistent	Consistent
Number of latent variables	Every number	Limited number (max. 8)
Number of observed variables	At least one	At least two
Results from latent variabale	Estimated in excplicit method	Anspecified
Min number of champion	20 – 100	200 – 800
The Complexity of the model	Very Complex	Law Complexity

The first school was developed by Karl Jöreskog. It can be considered as a generalization of core component analysis models and factor analysis in the case of some of the data tables related to causal links. Different

evaluation methods used for SEMs, based in covariance like Various Luarelihood (ML) or Unesched Weight Squares (ULS) are complete information methods.
The second school was developed by Herman Wold under the name "PLS" (partially less squares). This is a partial information method. This is a two-step method: (1) latent variables results are calculated using the PLS algorithm and (2) OLS regression is performed on the LV results for the estimation of structural equations.
Recently, Hwang and Takane (2004) have proposed a new comprehensive information method, optimizing a global criterion and called the General Structured Components Analysis (GSCA).
The basic model of structural equations can be expanded in several ways, two of the most used are multivariate analysis and means involvement. These extensions are particularly robust when they are used simultaneously, as they offer an alternative to (co) variance analysis to test multiple multicenter groups.
Statistical analysis, which includes several traditional multivariate procedures, is provided by the models of structural equations. Are included factor analysis, regression analysis, discriminatory analysis, and as a special case canonical correlation. The model of structural equations can be considered as a combination of factor analysis and regression or path analysis. The structural equation itself has its roots from the path analysis.
The connecting path diagram consists of a box with several arrow-linked circles. The latent (unobtrusive) factors are represented by circles or eclipses, while the observed variables are presented in square or rectangular boxes.
Mutual relations in the model are determined by one-way arrows (representing regression coefficients), whereas covariances or correlations without causal interpretations are provided by two-way arrows (covariances).
Before the analysis starts, the model should be specified according to the combination of theory and the empirical results that result from previous research. Following the specification of the model, the load factor and the covariance are estimated

It is a statistical analysis that determines the number of fundamental factors and assesses the load factor. Factorial analysis proceeds assuming that there is no hypothesis about the number of hidden factors and the links between hidden factors and observed variables. In this analysis the model is arbitrary, while if there is a clear hypothesis about the factor structure, a confirmatory factorial analysis is used which is double; The Varimax rotation method is used to improve the interpretation of the results.

The two main purposes of the confirmative factorial analysis are:

1. Aims to provide estimates for model parameters such as factors load, variance and covariance of the factor, as well as variance of the residual error of the observed variables
2. The second purpose relates to whether the model fits well with the data. Usually some load factors are limited to zero.

According to (Bollen, 1989), for statistically significant reasons, SEM is usually analyzed for the covariance matrix rather than the matrix of correlation, while standardized estimates are used for interpretations. The hi-square test ascertains whether the hypothetical model matches the data. If the hi-square test is very important then the hypothetical model is rejected, and a better model must be found.
In SEM it is assumed that all information is provided by the means and covariance matrices, so the sample data has normal multivariate distribution. The basic model of statistical modeling is: data = model + error. The most likelihood ML method mentioned above assumes normal multivariate data and a reasonable sample size of about 200 observations (Boomsma, 1997).

The indicators to be considered in the model analysis are those of validity and reliability. (Henseler et al., 2009; Hair et al., 2010):

- Examination of standardized direct weights related to reflective indicators (expected value> 0.7) and explained variance (expected value> 0.5).
- Examination of validity of composure of the hiden concept (expected value >0.7)
- Examining the average variance obtained from the hidden variable (expected value> 0.5)
- Examination of discriminatory validation with differential analysis between AVE and CR

If we have a great champion, the statistical tests for the adaptability of the model have a problem because their power depends on the size of the sample. So in the conditions of big champions, we will always reject the model, even when the model currently describes the data very well.

Given this problem with the adaptability variables, some other variables of adaptibility have been suggested.

Variables of adaptability	**Recommended value**	**Variables of adaptability**	**Recommended value**
v²/d.f.	<5,00	NFI	>0,90
GFI	>0,90	NNFI	>0,90
AGFI	>0,80	CFI	>0,90
RMSEA	< 0,06	IFI	>0,90
SRMR	< 0,08		

Source: Based on literature (Hooper et al., 2008; Byrne, 2010; Hair et al., 2010)

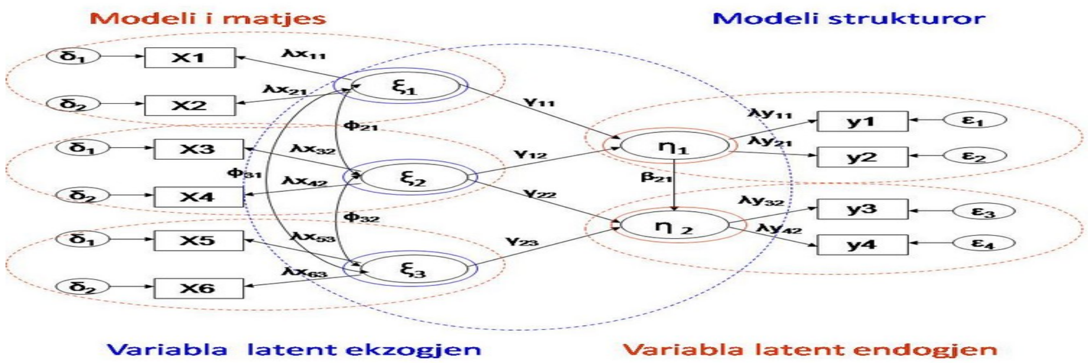
The strongest point of SEM is the ability to produce meaningful identification of the correlations between the factors.

3.2.3 Structural Equations Modeling Steps

1. Developing of Hypothesis/Theory

Given the fact that SEM is a confirmatory technique, the researcher should be based on the theory of potential variables relationships. The model should be based on theory and for its construction we can ask the following questions: How many variables are observed? What are the observed variables? What are latent variables? How many latent variables are there? What is the link between latent variables? What is the link between latent variables and observed variables? Are there errors related to measurement?

2. Diagram of relationpath (path diagram)



3. Model Specification:

The model can be specified by various methods such as Bentler-Weeks or LISREL. The parameters to be evaluated are the regression coefficients and variances and covariances of independent variables in the model (Bentler, 1995). A hypothetical model needs to be created in order to explain the relationships between multiple variables, as well as to convert the model into multiple equations. Make a process by who is determined which effects are zero, which are constant, and which differ. The effects of the variables correspond to the arrows in the diagram, while the zero effects correspond to the absence of arrows.

4. Identification model:

The relation between the latent variables given by the structural model is based on the formula:

$$\eta = B\eta + \Gamma\xi + \zeta$$

η = vector of hidden endogenous variables / ξ = vector of hidden exogenous variables / ζ = disturbances vector / B = coefficient matrix for η for effects η / Γ = coefficient matrix for ξ against η effects

The relation between endogenous and exogenous constructs is called gamma (γ) and the relation between two endogenous constructs is called beta (β). The structural model assumes that the average of the disturbances is zero [E (ζ) = 0] and that the disturbances are not correlated with the exogenous hidden variables [COV (i ζ, i ξ) = 0].

Model of measurement represents the relation between latent variables and observed variables and is given by the formula:
x = indicators of ξ / Λx = factor load ξ for x / y = indicators of η / Λy = factor load η against y / δ = measurement error for x / ε = measurement error for y
The part of the model that links the indicators to the hidden factors, the model of measurement is the analytical part of the factor and the respective regression coefficients are called lambda (l) / load. The measurement model assumes that the mean of the disturbances (single factors) [E (ε), E (δi)] are zero and that the different disturbances are not correlated with each other and neither with the exogenous hidden variables [COV ε, ξ), COV (δi, ξ), COV (ε, ζ), COV (δi, ζ) are all zero.

5. Parameter estimation:

The expected covariance structure is tested against the covariance matrix of observed data:
H0: Σ = Σ (θ)
The technique used to calculate parameters and test how well the model fits with the data.
Model evaluation:

The indexes that evaluate the conformability of the structural model are RMSEA, Tucker-Lewis index (TLI), relative suitability index (CHI) and so on.

$$RMSEA = \sqrt{\frac{T_m - df_m}{(N-1)df_m}} \qquad NFI = \frac{T_b - T_m}{T_b} \qquad IFI = \frac{T_b - T_m}{T_b - df_m}$$

Tb = Hi-square test statistic for the basic model
Tm = Hi-square test statistic for the assumed model
dfb = degrees of freedom for the basic model
dfm = degrees of freedom for the hypothetical model
The average variance is removed, and the stability of the construct is etimated through the composite stability. The square coefficient of multiple correlation (SMCC) is used to identify the proportion of construction variance explained by previous constructs.

6. Model modification:
According to Anderson & Gerbing (1988) SEM analysis can be realised in two phases.
First, the validity of the construct is confirmed by the analysis of the main components (CFA) in order to measure the pattern for each construct.
Secondly, the structural equation model is evaluated for the conceptual model. After evaluating the conceptual model, a modified conceptual model is developed for subsequent analysis. The conceptualized model is evaluated in terms of eligibility indicators, statistical significance of coefficients and interpretation.

Conclusions and Recommendations:

The objective of this paper was to give an overview on the methodology used to measure and analyze the three factors affecting absorption capacity of EU funds in Albania. Based on the literature review and analyses perfomred as the scope my phd disertation thesis, the results are not part of this paper.
However we can summarise that from the analyses of data and according to the tested model, we verified that administrative capacity factor is the most important factor, affecting the abosrption capacity of EU funds in Albania, macroeconomic capacity ranks second and last affective is financial capacity factor. Results also showed that there is no relation between the three factors affecting absorption capacity of EU funds in Albania

REFERENCES

Jöreskog, K. G. (1971). Simultaneous Factor Analysis in Several Populations. *Psychometrika*, 36(4), 409–426.

Preacher, K. J., Zyphur, M. J., & Zhang, Z. (2010). "A General Multilevel SEM Framework for Assessing Multilevel Mediation", *Psychological Methods,* Vol.15 (3), page 209.

Kline, R. B. (2011). "Principles and Practice of Structural Equation Modeling", *Guilford Press,* New York.

Jöreskog, K. G. (1969). "A General Approach to Confirmatory Maximum Likelihood Factor Analysis", *Psychometrika*, 34(2), 183–202.

Kline, R. B. (2011). "Principles and Practice of Structural Equation Modeling", *Guilford Press,* New York.

Chin, W.W. (1998). "The Partial Least Squares Approach for Structural Equation Modeling", *Modern Methods for Business Research*, George A. Marcoulides, ed., Mahwah, NJ: Lawrence Erlbaum, 295–336.

Chin, W. W. (2010). "How to write up and report PLS analyses, in Handbook of Partial Least Squares", *Concepts, Methods and Application. Esposito Vinzi, V.; Chin, W.W.; Henseler, J.; Wang, H. (Eds.*), Springer, Germany, 645-689.

Hair, J., Ringle, C.M & Sarstedt, M. (2011). PLS-SEM, "Indeed a Silver Bullet", *Journal of Marketing Theory and Practice*, Vol.19 (2), Page139–151.

Hulland, J. Ryan, M.J. and Rayner, R.K. (2010). "Modeling customer satisfaction", a comparative performance evaluation of covariance structure analysis versus partial least squares; Handbook of Partial Least Squares: Concepts, *Methods and Application. Esposito Vinzi,* V.; Chin, W.W.; Henseler, J.; Wang, H. (Eds.), Springer, Germany, pp.307-325.

Brown, T. A. (2015). "Confirmatory Factor Analysis for Applied Research", *the Guilford Press*, New York.

Hair J. F., Black W. C., Babin B. J., Anderson R. E. & Tatham R. L. (2006). "Multivariate Data Analysis" *6th edition. Pearson Prentice Hall,* New Jersey.

Byrne, B. M. (2000). "Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming", Lawrence Erlbaum Associates, Mahwah, NJ: Lawrence Erlbaum Associate

Lee, C. W. (2007). "The success of biotech new ventures when combined with strategic alliance", International Journal of Management & Enterprise Development, Vol.4 (3), pp. 293-315.

Bollen, K.A. (1989). "Structural Equations with Latent Variables", John Wiley & Sons, New York.

Boomsma, A. (1997). "On the Robustness of LISREL (Maximum Likelihood Estimation) against Small Sample Size and Nonnormality", Sociometric Research Foundation Amsterdam.

Henseler, J., Ringle, Ch. M. & Sinkovics, R. R. (2009). "The Use of Partial Least Squares Path Modeling in International Marketing", in: Advances in International Marketing, Vol.20, pp. 277–320.

Anderson, J. C. & Gerbing, D. W. (1988). "Structural equation modelling in practice", a review and recommended two-step approach', Psychological Bulletin, Vol.103 (3), pp. 411-423

Framework agreement between European Commission and Albania on the arrangements for implementation of union financial assistance to the Republic of Albania under the instrument for pre-accession assistance (IPA II)