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COMPARING CB-SEM AND PLS-SEM: A CASE SHOWING MANAGEMENT ACCOUNTING IMPACT ON PERFORMANCE

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Abstract: The objective of this article is to contrast two broad approaches to structural equation modelling (SEM): covariance-based (CB-SEM) and variance-based partial least square (PLS-SEM). Each approach was applied to estimate parameters of the same case model. Even though the results reveal some numerical differences, these differences do not seem to be of a great practical importance and less restrictive assumptions speak in favour of PLS-SEM. This study is one of the first attempts to apply and compare both approaches to SEM on actual (and not simulated) data, in this case data on management accounting (MA) obtained from 101 Czech and Slovak companies. From managerial viewpoint, the final model demonstrates that adoption of strategic MA techniques themselves without increase in organizational capabilities is insufficient for achieving higher return-on-assets (ROA).

Key words: SEM, partial least squares, covariance based SEM, strategic management accounting, performance

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Introduction

Statistical analysis has been used by social science researchers for at least a century. It was Fornell (1982) who distinguished two generation of statistical methods. The first generation dominated the research until the 1980s. These techniques encompass typical statistical methods such as multiple regression, analysis of variance, logistic regression, but also techniques focusing on dimension reduction such as exploratory factor analysis, cluster analysis, or multidimensional scaling.

Since the early 1990s, the actual second generation of statistical methods accounting for measurement error has emerged. Nowadays, these methods represent almost 50% of the statistical tools applied in some disciplines according to Hair et al. (2014). Structural equation modelling (SEM) is a typical example of these second-generation statistical methods. SEM enables researchers to investigate relationships between unobservable (latent, construct) variables measured indirectly by observed (manifest, indicator) variables. Contrary to the first-generation methods, SEM accounts for measurement errors. Measurement errors are those parts of the observed (manifest) variables that are measuring something other than what the latent variables are hypothesized to measure.

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Measurement errors arise due to a choice of inappropriate set of indicators, errors in data entry, different interpretation of questions by researcher and by respondent etc. Therefore, SEM analysis consists of two stages: firstly, the reliability and validity of the measurement (outer) model must be assessed to exclude the risk of excessive measurement errors. After that, the second stage continues with structural (inner) model estimation.

There are two types of SEM: covariance-based SEM (CB-SEM), which is the most widely known approach to SEM applied initially in psychological research, and variance-based SEM. Among variance-based SEM methods, partial least square SEM (PLS-SEM) is the most fully developed (Henseler et al., 2016). Because of its flexible nature, PLS-SEM has been called a “silver bullet” for estimating causal models in many theoretical and empirical data situations (Hair et al., 2011). On the contrary, Antonakis et al. (2010) conclude "there is no use for PLS whatsoever". Rönkkö et al. (2015) even warn "PLS should not be adopted as a tool for psychological research".

The outlined controversy raises the central research question (RQ) of this article whether PLS-SEM or CB-SEM should be applied in management accounting (MA) research. The article does not aspire to give an arbitrary answer. Rather, it follows more pragmatic view what consequences the choice of CB-SEM or PLS-SEM has in a real-life research. More particularly, to answer the (RQ), both approaches to SEM are applied on data from my own empirical survey among 101 profit seeking companies domiciled in the Czech and Slovak Republics. To the best of my knowledge, this study is the first attempt to apply and compare both approaches to SEM on actual data from Czech and Slovak companies.

Objectives and Methodology

The objective of this article is to contrast CB-SEM and PLS-SEM estimated parameters of the same studied case model, which captures relationships between adoption of strategic MA techniques and their consequences such as organizational capabilities, non-financial performance and eventually higher return-on-assets (ROA) reported in financial statements of the analysed companies. The need for such objective stems from the current hot debate about applicability of PLS-SEM and the claims of supremacy of one or the other SEM approach (Antonakis et al., 2010; Richter et al., 2016; Rigdon, 2016; Rönkkö et al., 2015; Rönkkö et al., 2016; Sarstedt et al., 2016).

For the study of differences in CB-SEM and PLS-SEM estimates, the model depicted in Figure 1 was selected.

Figure 1. The theoretical relationships in the studied case model

Figure 1 is a schematic representation of the general theory (Franco-Santos et al., 2012) suggesting that higher adoption of specific strategic MA techniques leads to a higher performance, which is measured non-financially or financially (through ROA). At the same time, the label of the arrow is insinuating that the hypothesized relation might not be direct, but indirectly mediated by organizational stakeholder management capabilities.

For the simplicity reasons, Figure 1 does not depict all potentially possible relationships among constructs, just the common direction of the expected causes and effects. That is why there could be e.g. direct relationships between strategic MA techniques and ROA, or even between non-financial performance and ROA etc. To investigate the model, SEM was selected since it allows modelling of more relationships simultaneously and captures relatively abstract constructs through the sets of directly observed indicators.

The constructs named in Figure 1 were measured in the following manner.

The construct *Customer strategic MA* drew on the classification of strategic MA tools by Cadez and Guilding (2008). Construct was derived from answers to the question “To what extent are the following techniques/methods applied in your company for the purposes of strategic management?” Respondents had the possibility of choosing on the scale from “0=not at all” to “10=dominant technique”. Specifically, they commented on these strategic MA techniques:

– (q27i) "Customer profitability analysis"
– (q27j) "Long-range value of customers and their portfolios (Customer equity)"

The construct *Stakeholder capabilities* was inspired by Koufteros et al. (2014). The respondents were asked to rate on the scale “0=not at all …10=totally" whether the strategic MA tools of their company:

– (q28f) "Improve the overall company's leadership in the market."
– (q28g) "Improve relationship with suppliers."
– (q28h) "Improve relationship with customers/clients."
– (q28i) "Increase motivation and commitment of our employees"

The construct *Non-financial Performance* was measured by question developed by Cadez and Guilding (2008) "Indicate your company’s performance relative to its competitors in the following criteria". The respondents were offered the scale 0=our company totally lacks behind its competitors to 10=our company is the best of all its competitors:

– (q30j) "Customer satisfaction"
– (q30l) "Quality of products/services."
– (q30n) "Employee satisfaction."

Finally, the construct *ROA* was measured based on the data published in the financial statements of the responding companies for the fiscal years ending 2012, 2013 and 2014. It would be better to use less archival data but these were not available in the BizNode database used at the time of the study. ROA was calculated as earnings before interest and tax (EBIT) divided by the closing balance of the total assets in each of the analyzed years.

A web-based questionnaire using GoogleDocs technology served as the tool for data collection. Each questionnaire started with a covering letter explaining the purpose of the study and a glossary of terms used. The questionnaire was distributed to profit seeking companies. The target group consisted of companies with more than 10 employees, because microenterprises are not supposed to apply sophisticated strategic MA techniques. The preferred recipients were top managers, especially financial managers.

A total of 101 answers was gathered during the period from December 2015 to February 2016. The count of top managers or owners amounted to 45, middle managers to 45 and 11 respondents were without managerial rank. Subsequent Kruskal-Wallis test did not identify statistically significant differences among answers of top, middle and non-managers.

From the territorial point of view, the respondents were from companies domiciled in the Czechia (the majority of 77 %) and Slovakia. The number of standalone companies was 53 and the remainder reported to be part of a group of companies.

From the sectoral point of view, industrial production was the main activity for 53 responding companies and 48 were involved in trade and services. The breakdown in the official EU size categories as defined in the EU recommendation 2003/361/EC based on staff headcount (European Commission, 2006) was: 26 small and medium-sized entities (SMEs) with 10 to 249 full-time employees (FTEs) and 75 large entities (more than 250 FTEs).

The statistical packages IBM SPSS Statistics version 23, IBM SPSS AMOS 23.0.0 (Build 1607) and SmartPLS ver. 3.2.6 were used for data processing. In all statistical procedures, the mean replacement of missing values was selected to preserve the sample size. The consequent pairwise deletion did not reveal different results partly as a consequence of the fact that missing data did not exceed 2 per cent. Finally, FIML was applied as default setting for missings treatment in CB-SEM software AMOS.

Skewness and kurtosis measures deviated from the interval [-1, 1] by indicators q27i, q29h, q29i, q30n. This deviation signals more severe violation of the normality assumption (Mareš et al., 2015). The strict Kolmogorov-Smirnov test indicated non-normality of all variables.

As far as the quality of measurement of constructs is concerned, the Composite Reliability indices for all constructs ranged from 0.85 to 0.90, which correspondents to Hair et al. (2014) recommendation "values between 0.70 and 0.90 (0.95) can be regarded as satisfactory." Convergent validity was tested by two criteria: factor loadings greater than 0.7 (Lee et al., 2011) and Average Variance Explained (AVE) values greater than 0.5 which indicates that the construct explaines more than half of the variance of its indicators. Both criteria were met with the only exception of indicator "q30n" (see Figures 2 and 3 below). Because this indicator was found statistically significant and theoretically important in all models, I did not exclude it. The discrimination validity of the constructs was confirmed through Fornell-Larcker criterion and the indicators' loadings on the construct greater than all its cross loadings with other constructs.

Results

The resulting model of statistically significant ($p < 0.05$) relationships among the studied constructs and their indicators is shown in Figure 2, where the CB-SEM approach was applied, and in Figure 3, where PLS-SEM approach was applied. In both cases, the depiction is similar. Latent constructs are depicted in ovals or circles, the indicators in rectangles. The numbers by the arrows are either standardized regression coefficients when connecting constructs or factor loadings when connecting construct with its indicators.

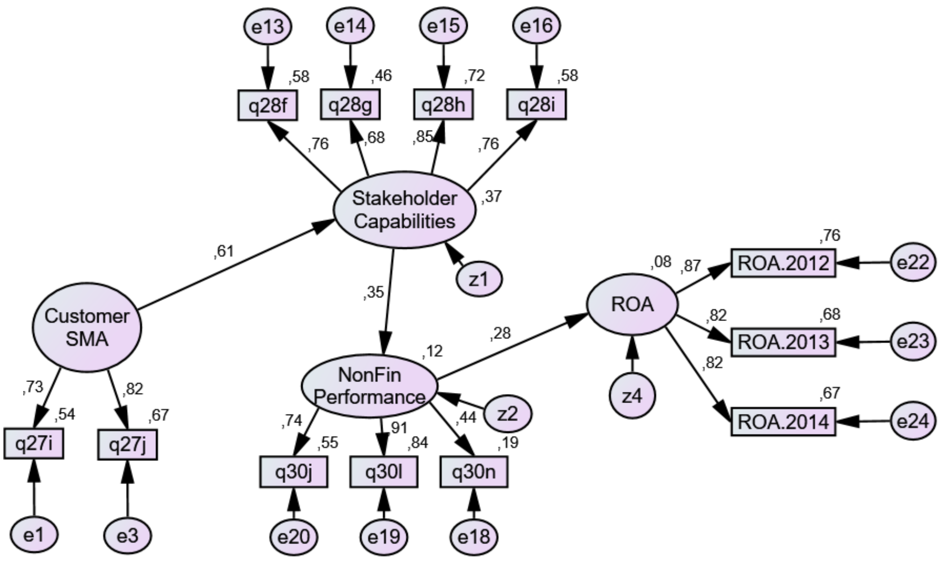

Figure 2. The studied model under CB-SEM approach

For full understanding of the AMOS output in Figure 2, the numbers near upper right-hand-side corners of indicators/constructs are R^2 (coefficients of determination) and the variables with names starting with letters "e" and "z" are error terms. The CB-SEM approach uses goodness of fit indices to assess the correspondence between model and data. The Chi-square statistics achieved 72.54 (df=51, p=0.025), RMSEA 0.065, CFI 0.95, TLI 0.92 and AIC 150.54. For the studied situation with less than 250 observations and the model with 12 observed indicators, these are the border-line values for acceptable fit of the studied model to the empirical data (Hair et al., 2014). However, due to violation of the multidimensional normality, there is a risk that resulting maximum likelihood estimates might be biased, even though there are studies that CB-SEM is relatively robust against this violation (especially with large samples).

Let us move our attention to the PLS-SEM approach. PLS-SEM algorithm applied in SmartPLS software produced parameter estimates of the same studied model, which are shown in Figure 3. The numbers in grey circles of the constructs are R^2 (coefficients of determination) for endogenous constructs. Numbers overlapping arrows are standardized regression coefficients and factor loadings.

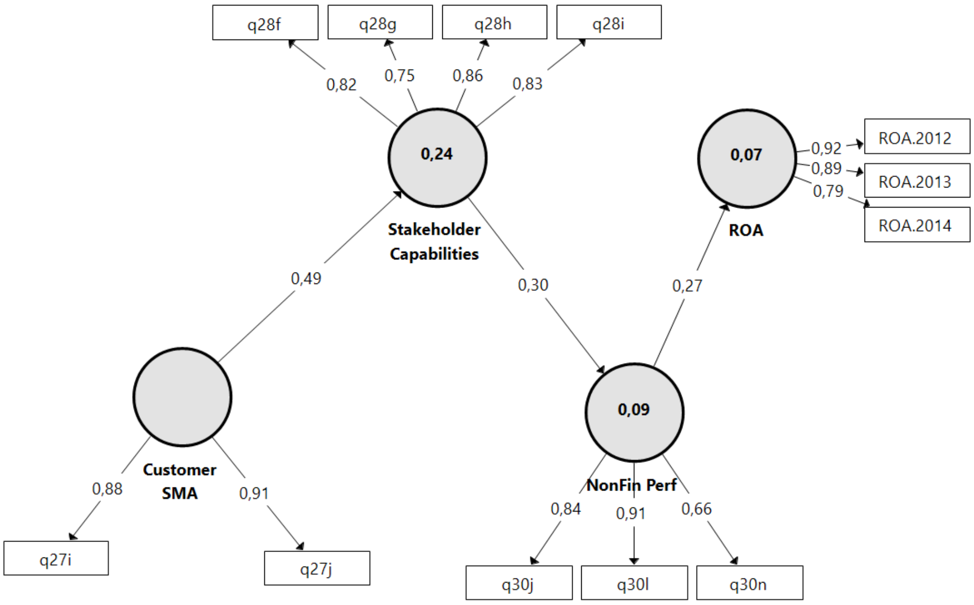

Figure 3. The studied model under PLS-SEM approach

Rigdon (2012) reminds that PLS-SEM does not allow for testing the overall goodness of the model fit in a CB-SEM sense. Therefore, the key criteria for assessing the structural model in PLS-SEM are the significance of the path coefficients and the level of the coefficients of determination (R^2 values). To calculate significance of the path coefficients, Bias-Corrected and Accelerated Bootstrapping with 5000 subsamples was applied. There are just statistically significant ($p < 0.05$) path coefficients/loadings in Figure 3. For the R^2, which represent the proportion of explained variance of each endogenous construct, Lee et al. (2011) offer as rule of thumb values of 0.10 and higher. Hair et al. (2014) tabulate the minimum sample size requirements necessary to detect predetermined minimum R^2 values of any endogenous constructs in the structural model for significance levels, assuming the commonly used level of statistical power of 80% and a specific level of complexity (i.e., the maximum number of arrows pointing at a construct in the PLS path model). I followed the same logic in G*Power 3.1 software (Faul et al., 2009) to compute the significance level assuming the statistical power of 80%, just one arrow pointing at a construct and the lowest R^2 value of 0.074 for ROA construct. The outlined procedure showed the significance level of 4.87%, thus verifying the statistical significance of the results presented in Figure 3.

Discussion

At the first sight, the comparison of Figures 2 and 3 shows models, which look very much alike. Even the same relationships were identified as statistically significant in both SEM-approaches. The strength of links in the outlined chains can be classified at most as "medium" according to suggestions for interpreting the strength of relationships coefficients (De Vaus, 2002).

If a closer look is taken, the detailed findings and differences correspond to the observation made by Rigdon (2016), who regarding PLS-SEM compared to CB-SEM states "estimates of factor model loadings will tend to be biased upwards (away from 0), while estimates of paths between factors will tend to be biased downwards (toward 0)." In other words, the relationships in PLS-SEM model (Figure 3) are a little bit weaker compared with CB-SEM model (Figure 2), while the opposite is true about loadings and therefore the variance captured trough constructs. The latter is consistent with the principle, how the constructs are generated in both SEM approaches. While PLS-SEM (similarly to principal component analysis) endeavours to capture the total variance in indicators, CB-SEM captures just the common part of it and that is why the loadings must be lower in comparison to their PLS-SEM counterparts.

The less experienced users of SEM-software would probably appreciate, that PLS-SEM employs bootstrapping as the default algorithm for determination of statistical significance and that is why it can handle non-normally distributed data. That seems to be big issue in AMOS software using CB-SEM where application of FIML excludes the application of bootstrapping and makes handling non-normality relatively difficult although not impossible.

Eventually, comparing models in Figures 2 and 3 raises the question, which SEM approach is more appropriate. Even though this question was not the objective of this study and that is why it is unanswerable based on the finding of the presented analysis, the simulation study done by Sarstedt et al. (2016) may be of help. For small sample of 100 observations, the quoted authors found that PLS-SEM and CB-SEM reported similar bias measured by coefficient’s mean absolute error in the common factor model situations and lower bias for PLS-SEM approach in the composite model situations.

Managerial implications

Despite the methodological merit of this article, there are important managerial implications as well. Both SEM-approaches reported the same chain of relationships: starting from higher adoption of customer strategic MA techniques, going through more developed stakeholder management capabilities and higher perceived performance in non-financial sense up to the financial effects reflected in higher reported ROA indicators of a responding company. In other words, no direct connection between adoption of strategic MA technique and performance was found, just indirect connections mediated by other constructs. This sends clear message to each manager contemplating introduction of some strategic MA technique into his or her firm. The presented findings mean that the adoption of strategic MA techniques itself has no practical meaning if such adoption is not driven by the purpose to develop or improve the managerial and organizational capabilities and by the struggle to increase the satisfaction of primary stakeholders and other measures of non-financial performance. Only in the latter situation, the effects on the profitability of the whole company can be expected, as opposed to the isolated and purposeless application of fashionable techniques.

Conclusion

Rigdon (2016) starts his article with words "Perhaps there has always been controversy between different approaches to structural equation modeling (SEM), ever since Herman Wold unveiled a composite-based alternative to Karl Jöreskog's common factor-based innovation." That is why the objective of this article was to contrast CB-SEM and PLS-SEM estimated parameters of the same real-life model from the field of MA research. The findings reveal differences between both SEM approaches, but the numerical differences in parameter estimates do not seem to be diametrically distinctive and of practical importance. Thus, from viewpoint of pragmatically thinking researcher, the both SEM approaches exhibit very similar results.

The survey based nature of the quantitative MA research perhaps favours a little bit more PLS-SEM application over more demanding CB-SEM. As mentioned by Smith and Langfield-Smith (2004), the smaller sample sizes are not such a problem for relatively flexible PLS-SEM, as well as almost no limiting assumptions regarding the model (non-normality, identification problems etc.). Moreover, the current simulation studies (Sarstedt et al., 2016) report the same or lower bias in PLS-SEM compared to CB-SEM applications in small samples. In contrast to the enumerated advantages of PLS-SEM, there should be caution in generalization of the findings which were obtained in small-sample studies (Rigdon, 2016).

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References

Antonakis J., Bendahan S., Jacquart P., Lalive R., 2010, *On making causal claims: A review and recommendations*, "Leadership Quarterly", 21(6).

Cadez S., Guilding C., 2008, *An exploratory investigation of an integrated contingency model of strategic management accounting*, "Accounting, Organizations and Society", 33(7–8).

De Vaus D.A., 2002, *Surveys in social research*, 5. ed, Crows Nest, NSW, Allen & Unwin.

Faul F., Erdfelder E., Buchner A., Lang A.G., 2009, *Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses*, "Behavior Research Methods", 41(4).

Fornell C., (Ed.), 1982, *A Second Generation of Multivariate Analysis*, Volume 1: Methods, New York, N.Y, Praeger Publishers.

Franco-Santos M., Lucianetti L., Bourne M., 2012, *Contemporary performance measurement systems: A review of their consequences and a framework for research*, "Management Accounting Research", 23(2).

Hair J.F., Hult G.T.M., Ringle C.M., Sarsted M., 2014, *A primer on partial least squares structural equations modeling (PLS-SEM)*, Los Angeles, SAGE.

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

Henseler J., Hubona G., Ray P.A., 2016, *Using PLS path modeling in new technology research: updated guidelines*, "Industrial Management & Data Systems", 116(1).

Koufteros X., Verghese A.J., Lucianetti L., 2014, *The effect of performance measurement systems on firm performance: A cross-sectional and a longitudinal study*, "Journal of Operations Management", 32(6).

Lee L., Petter S., Fayard D., Robinson S., 2011, *On the use of partial least squares path modeling in accounting research*, "International Journal of Accounting Information Systems", 12(4).

Mareš P., Rabušic L., Soukup P., 2015, *Analýza sociálněvědních dat (nejen) v SPSS*, Brno, Masarykova univerzita.

Richter N.F., Cepeda G., Roldán J.L., Ringle C.M., 2016, *European management research using partial least squares structural equation modeling*, "European Management Journal", 34(6).

Rigdon E.E., 2012, *Rethinking Partial Least Squares Path Modeling: In Praise of Simple Methods*, "Long Range Planning", 45(5–6).

Rigdon E.E., 2016, *Choosing PLS path modeling as analytical method in European management research: A realist perspective*, "European Management Journal", 34(6).

Rönkkö M, McIntosh C.N., Antonakis J., Edwards J.R., 2016, *Partial least squares path modeling: Time for some serious second thoughts*, "Journal of Operations Management", 47-48.

Rönkkö M., McIntosh C.N., Antonakis J., 2015, *On the adoption of partial least squares in psychological research: Caveat emptor*, "Personality and Individual Differences", 87.

Sarstedt M., Hair J.F., Ringle C.M., Thiele K.O., Gudergan S.P., 2016, *Estimation issues with PLS and CBSEM: Where the bias lies!*, "Journal of Business Research", 69(10).

Smith D., Langfield-Smith K., 2004, *Structural Equation Modeling in Management Accounting Research: Critical Analysis and Opportunities*, "Journal of Accounting Literature", 23.

PORÓWNANIE CB-SEM I PLS-SEM: STUDIUM POKAZUJĄCE WPŁYW RACHUNKOWOŚCI ZARZĄDCZEJ NA WYNIKI

Streszczenie: Celem tego artykułu jest skontrastowanie dwóch szerokich podejść do modelowania równań strukturalnych (ang. structural equation model ling, SEM): opartego na kowariancji (ang. covariance-based structural equation modelling, CB-SEM) i na wariancie częściowego najmniejszego kwadratu (ang. partial least square, PLS-SEM). Każde podejście zastosowano do oszacowania parametrów tego samego modelowego przypadku. Mimo, że wyniki wykazują pewne różnice liczbowe, różnice te nie mają dużego znaczenia praktycznego, a mniej restrykcyjne założenia przemawiają za PLS-SEM. Badanie to jest jedną z pierwszych prób zastosowania i porównania obu podejść do SEM w odniesieniu do danych rzeczywistych (a nie symulowanych), w tym przypadku danych dotyczących rachunkowości zarządczej (ang. management accounting, MA) uzyskanych od 101 firm czeskich i słowackich. Z punktu widzenia zarządzania, ostateczny model pokazuje, że samodzielne wdrażanie strategii MA bez zwiększenia zdolności organizacyjnych nie wystarcza, aby osiągnąć wyższy zwrot z aktywów (ang. return-on-assets, ROA).
Słowa kluczowe: modelowanie równań strukturalnych, częściowo najmniejszego kwadratu, opartego na kowariancji modelowaniu równań strukturalnych, strategia rachunkowości zarządczej, wydajność

比較CB-SEM和PLS-SEM：表現管理會計對績效的影響

摘要：本文的目的是對比兩種結構方程模型（SEM）：協方差（CBSEM）和方差偏最小二乘法（PLSSEM）的廣泛方法。應用每種方法來估計相同病例模型的參數。儘管結果顯示出一些數值差異，但這些差異似乎並不具有很大的實際重要性，而較少限制性的假設則表示贊成PLSSEM。這項研究是首次嘗試將實際（而非模擬）數據的SEM應用和比較，在這種情況下從101個捷克和斯洛伐克公司獲得的管理會計（MA）數據。從管理的角度來看，最終的模型表明，在不增加組織能力的情況下採用戰略性MA技術本身不足以實現更高的資產回報率（ROA）。
關鍵詞：SEM，偏最小二乘法，協方差法，戰略管理會計，績效考核。