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EVALUATING THE DOWNSTREAM EFFECTS OF THE TWO-STEP TRANSFORMATION TOWARD NORMALITY: IMPLICATIONS FOR MIS RESEARCH

Research-in-Progress

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Abstract: This paper empirically evaluates the usefulness of the Two-Step approach for transforming continuous variables toward normality. The study uses 27 corporate financial performance (CFP) variables on 39,216 US corporations to compare three variable sets: 1) random-normal, 2) original, and 3) transformed toward normality using the Two-Step. The results of several statistical procedures relevant to formative index (construct) construction are used to compare the three variable forms. The results provide strong evidence that the Two-Step approach is useful for 1) achieving normality improvements in continuous variables, 2) improve sampling adequacy for factor analysis, 3) dramatically increase intercorrelations, and 4) dramatically increase main effects tests involving the CFP variables. The findings have tremendous implications for MIS research and practice, as the Two-Step technique is shown here to change effects tests significantly and consequently has profound implications for the advancement of the MIS discipline and practical applications (e.g., data mining).

Keywords: Two-step transformation, normality, index construction, construct development

Introduction

The Two-Step approach for transforming arbitrarily distributed variables toward normality has been proposed as one important solution to the *Productivity Paradox* (authors hidden to maintain anonymity). The technique has been found to empirically enhance normality across a diverse set of continuous variables with very few constraints (authors hidden to maintain anonymity). Unfortunately, no empirical research has been done to explore the efficacy of the Two-Step in its enhancement of empirical results in studies. Specifically, this research addresses the following question: Does employing the Two-Step approach influence the outcomes of statistical procedures pertinent to MIS researchers? To answer this question, each of three alternative distributions (normal random, original, and transformed toward normality) available to users of the technique must be evaluated and compared using a variety of statistical procedures. This paper compares the results of procedures commonly used in formative construct development, which is of growing significance in the field. In particular, we compare each distribution using techniques for investigating univariate normality, intecorrelation, sample quality, and main effects testing.

This paper is significant in at least three ways. First, it provides empirical guidance regarding the efficacy of the Two-Step approach when using a variety of statistical procedures. Second, it shows how the structures of formative indices depend on the extent of successful normality transformation. Third, no previous research has compared distributional forms for their downstream effects in tests of association. We anticipate that this research will advance any problem domain (e.g., IT business value) using and relying on formative measures. As such, we believe it will encourage research and improve the ability of researchers to replicate studies involving formative indicators.

We begin with a background on distributional effects on formative construct development, then provide the methodology, a progression of the study, findings, discussion, and conclusions.

Background

Three generic distributional forms are conveniently available when most continuous variables are used in research. The forms include the original variable and two distributions produced by the 'Two-Step' transformation approach articulated by (hidden to preserve anonymity). The first step involves transforming the original variable to uniform using a fractional rank transformation applied to the original variable. The second step applies the inverse normal function to the results of the first step. Variables with a low number of levels (e.g., Likert's scales) and highly influential inflated frequencies may not be as amenable to the approach as those with a high number of levels and no inflated frequencies. Without such delimiters, the result of the Two-Step will be a normally distributed form of the original variable that retains the original order of values.

Formative construct development is an important problem domain in MIS research for at least two reasons. First, information stored in digitized form has become progressively more abundant, especially in an environment of proliferating remote sensors. Second, formative construct development is important due to published evidence of a widespread problem of misspecification in MIS studies (Petter, Straub and Rai, 2007). Unfortunately, very little has been written or established in the area of achieving reliability in formative construct development. Formative construct development has been described as a multiple staged process with the earlier stages containing downstream effects on construct reliability (Hair, Black, Babin, and Anderson, 2010). This paper investigates the effects of one of the earliest decisions available to researchers: distributional form. We anticipate that as information systems are applied to more problem domains across disciplines, researchers developing formative constructs will be faced with non-normal indicators. In those situations, our findings regarding the merits of three general distributions will be informative (Diamantopoulos and Winklhofer, 2001).

Prior to formative construct development, researchers are availed a number of strictly formative indicators (Petter et al., 2007), which are unique and independent representations of meaning. Developing a series of formative indicators toward a valid and reliable formative construct involves two goals: 1) retaining representativeness of meaning and 2) maximizing parsimony. To achieve representativeness, a formative indicator (which is known to be unique and independent) should generally not be removed from the analysis during formative construct development. However, for the sake of parsimony, indicators containing redundant information should be considered for removal. Therefore, data reduction for achieving the representativeness and parsimoniousness is an important step in formative construct development.

Data reduction toward formative constructs is best accomplished through factor analysis (Hair et al., 2010). Because of the representativeness goal, factor analysis for reducing formative indicators involves a single iteration since non-loading items should be retained in the analysis. Because of the use of a single iteration in factor analysis, a special opportunity exists that is yet to be explored in the formative construct development literature. That is, we develop and apply several meta-analytic criteria that are generalizable across single-iteration factor analyses toward data reduction to compare the relative merits of three general distributional alternatives. The objective of this comparison is to evaluate the effects of distributional choices on downstream effects on formative construct reliability.

Non-normality has been cited as a problem that has limited statistical conclusions across the sciences. However, investigations into the relative advantages of transforming variables toward normality has received no attention. Consequently, nothing is understood about the relative merits of using the three generic distributions in research, aside from simulation studies using random variates. We selected a staged formative construct development methodology to explore whether the distributions will impact some of the early decisions that significantly influence the structure and performance of a given formative construct. This study uses 28 corporate financial performance (CFP) ratios deriving from accounting research (Ou and Penman, 1989ab) and relied upon heavily in IT Business Value research. CFP variables are renowned for having poor distributional properties (Deakin, 1976) and consequently, all three generic distributions are relevant to the entire dataset. We will investigate the influence of distributional differences on two important steps influencing construct reliability during formative construct development: 1) data reduction based on factor analysis, and 2) reliability testing.

Research Questions

The research questions are organized to progress along the suggested developmental path of formative index construction (Hair et al., 2010). As with any developmental method, the earlier stages have downstream effects on later stages, and the set of questions influence later reliability in subsequent studies. The questions also have implications outside index construction, which will be described in the Discussion section.

One basic assumption among parametric multivariate statistical procedures is the existence of normally distributed indicators. In multiple regression, non-normality in the dependent variable causes heteroscedasticity, which means that regression coefficients are "no longer minimum variance unbiased estimators" (Neter, Wasserman, and Kutner, 1990, p. 423). Thus, non-normality may impair interpretations of multiple regression results in MIS studies that do not address the problem. The long history of research on CFP confirms that such indicators severely depart from normality. Therefore, comparing versions of CFP that are observed and transformed using the Two-Step approach is needed:

Research Question 1: How do the distributional forms differ in terms of normality diagnostics tests?

The Two-Step approach has not yet been studied for its efficacy in influencing the findings of association tests. Studies on the influence of normality on association tests has traditionally used simulated data (Hindelang, 1971; Edgell and Noon, 1984). Because original CFP variables are known to have extensive normality problems, they offer an excellent opportunity for such a test. A basic question regarding the Two-Step is regarding its influence on intercorrelations among CFP variables compared to original versions:

Research Question 2: How do the distributional forms differ in terms of intercorrelation?

Factor analysis is a common way in which researchers engage in "data reduction," or the prioritization of data sets such that a subset of independently related variables are later used to represent an overall construct. For example, any variable in the set of CFP variables may be used to represent the overall construct. Factor analysis is a common approach for exploring the dimensions of CFP that should be represented in the construct, as well as the items that would be useful as surrogate representatives for each dimension. There are two basic tests for determining whether a sample is adequate before factor analysis may apply. First, the Kaiser-Meyer Olkin test, which ranges from 0 (the sample is not adequate) to 1 (the sample is adequate). Second, the Bartlett test, which ranges from 0 to 1, tests the hypothesis that all of the variables are uncorrelated.

Research Question 3: How do the distributional forms differ in terms of the Kaiser-Meyer-Olkin test?

Research Question 4: How do the distributional forms differ in terms of the Bartlett test?

After formative indices are constructed, a subset of surrogate measures are used in subsequent studies for prediction testing. The utility of the indicators in subsequent testing is its value to the research community and should it underperform, modifications will be considered. Therefore, it is important to assess the usefulness of the three variable versions (random, original and transformed) in the testing of main effects, or the extent to which they may predict theoretically important endogenous variables. Therefore, an important question is:

Research Question 5: How do the distributional forms differ in terms of exogenous effects?

Methodology

The input variables needed to calculate the set of 28 CFP indicators were extracted from Compustat™. The resulting CFP indicators were transformed according to the Two-Step procedures. This resulted in three representations for each CFP indicator: 1) random normal, 2) original (arbitrary), and 3) transformed toward normality using the Two-Step. The original versions of variables may be described as homogenous, as each are in monetary units and are ratios. Each was found to severely depart from normality, as is consistent with the long tradition of CFP research. An observation of distributional properties also revealed that all variables were continuous and few had observable influential inflated frequencies. We used the outcome variables provided in a meta-analysis on CFP studies (Capon, Farley and Hoenig, 1990) and these variables had similar characteristics.

To address the research questions, meta-analytic descriptive statistics regarding the three sample distributions were calculated for four analytic perspectives: 1) indicator normality (of the CFP variables), 2) intercorrelation, 3) sample quality, and 4) main effects testing.

Findings

Pursuant to RQ1 (How do the distributional forms differ in terms of normality diagnostics tests?), Table 1 shows a stark contrast in statistical normality between the original variables and their associated transformed versions. Among original variables, all were significantly skewed. Seven were negatively ($p<.05$) skewed while twenty were skewed positively (p>.95). Furthermore, all original variables were found to have significant positive kurtosis (p>.95), and deviated from normality according to the K-S statistic (p<.05). The Two-Step procedure successfully transformed 26 of 27 (96%) variables to remove all significant skewness. Only one variable, ratio66, was found to have significant skewness (p>.95). Application of the Two-Step resulted in 25 of 27 (92%) variables having insignificant Kurtosis at the .10 level of significance and 26 of 27 (96%) at the .05 level: ratio33 (p<.10) and Ratio66 (p<.99). Consistent with the other two tests, 26 of 27 (96%) of all CFP variables were found to be normal using the K-S test for normality. Only ratio 66 (p<.05) was not found to be statistically normal.

Due to these results, further investigation into ratio33 and ratio 66 was warranted. While these variables were found to be questionable based on the normality tests, it should also be mentioned that the Two-Step approach improved the skewness of ratio33 from -91.84 to -0.01 and the Kurtosis from 10313.57 to -0.04. In ratio66, the procedure improved the skewness from 71.16 to 1.05 and reduced the Kurtosis from 5869.99 to 0.114. This shows that even though the abnormally high standard of 'statistical normality' was applied, two 'failed' variables faired very well due to the application of the Two-Step. The remainder of this section reports the findings of tests commonly used for formative index construction.

Table 1: Normality Diagnostics of Study Versions of Corporate Financial Performance Variables

Variable	N	Original			Two-Step		
	Valid	Skewness p	Kurtosis p	K-S p	Skewness p	Kurtosis p	K-S p
ratio2	16307	1.000	1.000	.000	0.500	0.361	1.000
ratio4	16342	1.000	1.000	.000	0.500	0.361	1.000
ratio8	13633	1.000	1.000	.000	0.500	0.355	1.000
ratio9	21050	1.000	1.000	.000	0.502	0.351	1.000
ratio10	14194	1.000	1.000	.000	0.500	0.356	1.000
ratio11	14194	1.000	1.000	.000	0.500	0.356	1.000
ratio12	19213	1.000	1.000	.000	0.500	0.366	1.000
ratio13	18594	1.000	1.000	.000	0.669	0.126	.802
ratio16	18264	1.000	1.000	.000	0.500	0.364	1.000
ratio17	19983	0.000	1.000	.000	0.500	0.367	1.000
ratio18	18705	1.000	1.000	.000	0.500	0.365	1.000
ratio19	16347	1.000	1.000	.000	0.500	0.361	1.000
ratio20	17099	1.000	1.000	.000	0.500	0.362	1.000
ratio21	21308	1.000	1.000	.000	0.500	0.364	1.000
ratio22	16566	1.000	1.000	.000	0.500	0.361	1.000
ratio30	19191	1.000	1.000	.000	0.500	0.366	1.000
ratio31	20033	0.000	1.000	.000	0.500	0.367	1.000
ratio32	21306	0.000	1.000	.000	0.500	0.369	1.000
ratio33	20625	0.000	1.000	.000	0.283	0.098	.998
ratio38	13661	0.000	1.000	.000	0.500	0.355	1.000
ratio41	20448	1.000	1.000	.000	0.500	0.367	1.000
ratio53	20025	1.000	1.000	.000	0.500	0.367	1.000
ratio54	17504	1.000	1.000	.000	0.500	0.363	1.000
ratio55	17592	0.000	1.000	.000	0.500	0.332	1.000
ratio57	21295	0.000	1.000	.000	0.500	0.369	1.000
ratio61	14731	1.000	1.000	.000	0.501	0.353	1.000
ratio66	19562	1.000	1.000	.000	1.000	0.999	.000

Tests to explore RQ2 (How do the distributional forms differ in terms of intercorrelation?) indicated a distinct difference between the three variable forms. Table 2 shows that that only 8 (2.1%) of all correlation tests involving random normal variates were found to be significant at the .01 level. The original CFP variables produced 55 (15.7%) of such tests, while the Two-Step transformation produced 286 (81.5%). Using a significance of .10, the results were similarly dramatic: 92 (24.3%) for random normal, 81 (23.1%) for original, and 309 (88.0%) for the transformed version. Futher, mean values for absolute correlation and significance showed favorable results for the transformed version.

Table 2: Effects of Distributional Differences on Formative Construct Development					
Aspect	*Relevant RQ*	*Effect*	*Random Normal*	*CFP Data*	
				Original	*Two-Step*
Indicator Normality	*1*	*Mean Kolmogorov-Smirnov Significance (normality)*	*.118*	*.000*	*.956*
		Mean Skewness Significance	*.421*	*.741*	*.517*
		Mean Absolute Skewness	*.023*	*75.95*	*.04*
		Mean Kurtosis Significance	*.340*	*1.000*	*.366*
		Mean Absolute Kurtosis	*.060*	*7719.27*	*.02*
Intercorrelation	*2*	*Number of correlation tests (among 27 CFP indicators)*	*351*		
		Tests <.01	*8*	*55*	*286*
		% of Tests Significant at .01	*2.1*	*15.7*	*81.5*
		Tests <.10	*92*	*81*	*309*
		% of Tests Significant at .10	*24.3*	*23.1*	*88.0*
		Mean Absolute Correlation	*.000*	*.025*	*.144*
		Mean Correlation Significance	*.249*	*.579*	*.057*
Sample Quality	*NA*	*Sample Size (Listwise)*	*5552*		
	3	*Kaiser-Meyer-Olkin*	*.500*	*.479*	*.687*
	4	*Bartlett's Test Significance*	*.122*	*.000*	*.000*
Main Effects Testing	*5*	*Number of correlation tests (between 27 CFP and 10 outcome variables)*	*270*		
		Tests <.01	*2*	*60*	*204*
		% of Tests Significant at .01	*0.7*	*22.2*	*75.6*
		Tests <.10	*35*	*76*	*229*
		% of Tests Significant at .10	*13.0*	*28.1*	*84.8*
		Average Absolute Correlation (between Antecedents and Response Variables)	*.000*	*.014*	*.052*
		Average Correlation Significance (between Antecedents and Response Variables)	*.470*	*.475*	*.079*

DNC = Factor analysis did not converge

Table 2 also shows differing results for addressing RQ3: Do the distributional forms differ in terms of the Kaiser-Meyer-Olkin test? The Kaiser-Meyer-Olkin test produced values of .500 for random normal, .479 for original, and .687 for transformed versions. According to Kaiser (1974), these values are categorized as "miserable", "don't factor", and "mediocre", respectively. Pursuant to RQ4 (How do the distributional forms differ in terms of the Bartlett test?), Table 2 shows that the Bartlett's test produced values of .122 for random normal and .000 for both original and transformed versions. This indicated that the test was not significant for random variables and that the original and transformed versions did have enough intercorrelation to justify conducting factor analysis.

Table 2 provides several indicators pursuant to RQ5, which is concerned with the extent to which the distributional forms differ in terms of exogenous effects. Of 270 tests with each category, a distinct difference in terms of correlation effects is shown. Using a significance level of .01, 2 (0.7%) of the tests involving random normal variates were significant compared to 60 (22.2%) among original and 204 (75.6%) among transformed versions. At a significance level of .10, 35 (13.0%) of random normal, 76 (28.1%) of original, and 229 (84.8%) of transformed versions were found to be correlated. Regarding average absolute value of correlations, the random normal (.000) and observed variables (.014) were similar to each other and differed from transformed versions (.052). Accordingly, the average correlation significance was .470 for random variates, .475 for original, and .079 for transformed versions.

Discussion

These findings have important implications for both index and construct development in IS research. We see at least four important impacts of the Two-Step that researchers should consider when developing indices. First, the Two-Step can improve the sample quality as shown by the Kaiser-Meyer-Olkin test results. Surprisingly, the original variables were considered less amenable to factor analysis than random variables according to the KMO. Yet, both versions would not be appropriate for factor analysis according to the recommendations provided by the creator of the test (Kaiser, 1974). By contrast, the transformed versions were found to be amenable to factor analysis. Thus, the factor analysis procedure that is so central to index construction would not be practical without the transformed versions.

Second, the findings indicate that the Two-Step transformation is unprecedented in its capacity for transforming variables toward normality. In the above analysis, only two variables were questionable regarding their achievement of 'statistical normality.' In both cases, the kurtosis and skewness were improved dramatically. Thus, in all 27 CFP variables used in this analysis, normality was improved dramatically. The subsequent analyses showed that the technique can have a tremendous impact on the results of index construction efforts.

Third, the findings indicate strong evidence that the Two-Step dramatically improves intercorrelation among the CFP variable set. The number of significant intercorrelation effects at the .01 level increased 520% (from 55 to 286) when the original variables were transformed to normal. At the .10 level, the significant intercorrelations increased 381% (from 81 to 309). The mean absolute correlation and the average correlation significance values also showed the relative power of using the Two-Step over the original CFP values. Clearly, intercorrelations were increased significantly and these effects influenced other statistical procedures (i.e., factor analysis) involved in index construction.

Fourth, the findings show that the CFP indicators were far more correlated with theoretical consequences after being transformed using the Two-Step. Of the sample of main effects, the number of correlation tests at .01 increased by 340% (204/60) and the number of tests at .10 increased 301% (229/76). This shows that the Two-Step procedure dramatically improves main effects in the CFP theoretical domain. The mean absolute correlation and the average correlation significance values also indicated that the transformed versions were more effective than the original CFP variables at predicting theoretical outcomes.

These findings have powerful implications for 'construct development', which we differentiate from index construction. By contrast, we view construct development as generally the vast amount of perceptual research using a low number of levels (e.g., 5- and 7-item Likert scales) while index construction generally uses secondary data (e.g., CFP and remotely sensed weather). While the Two-Step is not as powerful in situations where a low-number of levels is used (author's identity withheld to retain anonymity), our findings provide powerful support for changes to be made in behavioral research to take advantage of the Two-Step. We recommend that scholars engaged in perceptual research begin developing and adapting existing scales to have up to 100 levels. The findings of this study indicate that such changes will be well worthwhile. Resulting data sets may be transformed using the Two-Step to achieve greater effect sizes and more reliable results in theory testing. Such advancements may improve scale quality, as our findings show much greater intercorrelational explanation in variables transformed using the technique.

Our findings also have implications for multivariate research in general. The study findings suggest to us that researchers should use caution when generating random variables for simulation studies. Table 2 shows that simple random normal variables are not comparable to observed normal variables in many statistical procedures. As examples, intercorrelations and main effects using random normal variables are much lower than using observed variables transformed using the Two-Step approach.

Conclusions

Due to the increasing diffusion of remote sensing in a variety of fields, massive amounts of data will continue to make itself available to researchers in MIS and other disciplines. For example, electroencephalography (EEG) is an IT innovation that provides neurological researchers with extensive data on brain activity. The EEG data is continuous and its departure from normality has been cited as a serious problem in neurological sciences (van Albada and Robinson, 2007). As such, formative construct development (Hair, et al, 2010) methods for fully formative, homogenous, continuous, and non-normal data will grow in prominence. Appropriate analyses for data similar to CFP will become more common in practice and formative construct development represents a ripe problem domain for MIS research. It was shown here that the Two-Step transformation toward normality can be an invaluable tool for improving datasets that are subject to formative index construction.

Our findings suggest that the full Two-Step transformation toward normality optimizes the normality of indicators, greatly increases intercorrelation among theoretically related variables (which is typical in index construction situations), improves sample adequacy for factor analysis, and dramatically improves main effects testing. Distributional form should be an important topic in the discussion of the content validity of constructs, as it influences criterion-related validity. The findings shed light on a possible solution to the productivity paradox – distributional selection. Specifically, we address the kinds of effects each distributional form has on different stages of formative construct development. Our findings inform future research aimed at improving our understanding of how CFP variables behave across industrial, geographic, and temporal sections.

The criteria chosen to compare the three distributions available to MIS researchers were chosen based on their applicability to formative construct development. However, the generalizability of these criteria to other research settings makes the findings useful far beyond the formative construct development literature. When conducting MIS studies, researchers can use the findings to guide their justifications for using the Two-Step. The results are applicable in the many practical situations where all indicators are formative (independent and homogenous) and includes ordinal, interval, and ratio data.[1]

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[1] We anticipate that the number of fully formative constructs available to IS researchers is high, especially the econometric measures used in IT business value research.

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