View metadata, citation and similar papers at core.ac.uk
brought to you by CORE
provided by Digital Commons@Wayne State University

DigitalCommons @WayneState

Journal of Modern Applied Statistical Methods

Volume 6 | Issue 2 Article 18

11-1-2007

From Information Lost to Knowledge Gained: The Benefits of Analyzing all the Research Evidence

Joseph L. Balloun
Mercer University, balloun_jl@mercer.edu

Hilton Barrett
Elizabeth City State University

Follow this and additional works at: http://digitalcommons.wayne.edu/jmasm

Part of the Applied Statistics Commons, Social and Behavioral Sciences Commons, and the Statistical Theory Commons

Recommended Citation

Balloun, Joseph L. and Barrett, Hilton (2007) "From Information Lost to Knowledge Gained: The Benefits of Analyzing all the Research Evidence," *Journal of Modern Applied Statistical Methods*: Vol. 6: Iss. 2, Article 18.
Available at: http://digitalcommons.wayne.edu/jmasm/vol6/iss2/18

This Regular Article is brought to you for free and open access by the Open Access Journals at DigitalCommons@WayneState. It has been accepted for inclusion in Journal of Modern Applied Statistical Methods by an authorized administrator of DigitalCommons@WayneState.

Journal of Modern Applied Statistical Methods
November, 2007, Vol. 6, No. 2, 537-543
Copyright © 2007 JMASM, Inc.
1538 – 9472/07/$95.00

From Information Lost to Knowledge Gained: The Benefits of Analyzing All the Research Evidence

Joseph L. Balloun
Mercer University

Hilton Barrett
Elizabeth City State University

Data analyses should reveal truths about data. To the extent possible analyses should tell a complete picture. Data analyses should not inadvertently ignore phenomena that might be discovered in sample data sets. However, common univariate or multivariate data analysis methods tend to be based on only the means, standard deviations, and Pearson correlations. The result is that many important truths are discovered, but not the whole truth. This article illustrates in a sample data set that (a) data analyses of other properties of variables and groups are feasible and practical, and (b) such analyses may reveal important information not otherwise detectable. These extensions of common statistical methods are applicable to data analysis and interpretation issues in the social and behavioral sciences.

Key words: Data analysis strategy, skewness, kurtosis, survey

Introduction

Research findings depend on what is analyzed and on what is not. In this sense, data do not speak for themselves. The data analyst chooses what methods will be used, and this choice shapes what interpretations can be made of the data. The purpose of this article is to show how conventional data analysis strategies may ignore important information, and to demonstrate a somewhat more comprehensive data analysis approach.

Outside of the methodological or statistical literature, many researchers describe univariate data primarily by variables' means, and secondarily by the variables' standard deviations or variances. Relationships among variables tend to be analyzed by a variety of calculations derived from linear correlations. The univariate means and standard deviations often are used to appropriately scale such relationships, as in multiple regression analyses.

Strengths of Classical Statistical Methods

There are important strengths in current data analysis strategies that tend to assume univariate and multivariate normality. Their greatest advantage is that researchers in many different fields have made very impressive discoveries and practical improvements by using such statistical methods. Most academic researchers have been educated in the appropriate use of the traditional statistical methods. Widely distributed and inexpensive statistical packages such as SPSS (2007) and NCSS (Number Cruncher Statistical System, 2007) have made these methods easily accessible and usable for seasoned besides new researchers.

The classical methods have strong technical virtues. Their simplifying assumptions make them parsimonious, easily understood, and analytically or computationally tractable. When

Joseph L. Balloun, Ph.D., is Professor of Education at Mercer University. He has published extensively on social science research methods, statistical techniques, and developing information systems. Hilton Barrett, Hilton Barrett, D.B.A., is Associate Professor of Business at Elizabeth City State University. He has published in *Journal of Marketing Theory and Practice*, *Entrepreneurial Theory and Practice*, and *Marketing News*.

their assumptions are met (e.g., no outliers or unduly influential observations, minimal missing data, univariate and/or multivariate normality, homoscedasticity, uncorrelated residual errors, sampling from a single identifiable population), they are fully informative.

Extensions of Common Statistical Data Analysis Methods

For many data sets, there are individual observations within two or more subgroups. Most researchers typically report or analyze subgroup statistics such as the sample size, mean, standard deviation and within group covariances or correlations where applicable. Yet, there is substantial evidence that many population distributions are not Gaussian (Micceri, 1989; Rousseau & Leroy, 1987).

Subgroup differences in variances or covariances, or non-normality might provide useful information. There is some evidence that researchers do not typically analyze subgroup departures from normality. For instance, we searched article abstracts for "skewness" or "kurtosis" in the *Journal of Marketing Research*, the *Academy of Management Journal*, and the *Psychological Bulletin* during calendar years 2004 - 2006. However, in these three journals for these calendar years, the words "skewness", or "kurtosis" never appeared in the abstracts. This suggests that researchers seldom consider skewness or kurtosis of primary importance when summarizing data analyses.

A possible alternative data analysis strategy is to consider these other characteristics of subgroup data as possibly informative. The analyst should analyze more than subgroup means and pooled group statistics. Possibly subgroup differences in standard deviations, skewness or kurtosis may also be informative. Moreover, with current computer power, it is practical to analyze more than subgroup means and statistics pooled over groups.

Methodology

An Illustrative Example Using a Real World Data Set

Barrett, Balloun & Weinstein (2004) gathered data on marketing and management factors related to performance of profit and non-profit organizations. The resulting snowball sample consisted of 696 usable individual responses within 60 organizations. Barrett, et al. evaluated how organizations' implementations of market orientation (MKT), learning orientation (LRN), entrepreneurial orientation (ENT), and organizational flexibility (ORG) were related to perceived organizational performance (PERF) in for-profit and nonprofit settings. Further details about the purposes, methods and conclusions of the study are reported in Barrett, et al. (2004).

One of their intriguing results was that variability within organizations was greater than the variability among organizations for most of the variables used in their study. This finding points to the possibility that besides the mean levels of postulated success factors for each organization, levels of within-organization variability might be related to organizational performance. But the standard deviation and the mean do not necessarily describe all the information about univariate distributions. Possibly the skewness or kurtosis of the distributions of variable scores within an organization also might be related to organizational performance.

There are analogous ideas that come from the social or behavioral sciences. For example, Yerkes & Dodson (1908) described how arousal levels could be curvilinearly related in an inverse U-shaped way to the rapidity of habit formation. Katz & Kahn (1966) discussed how variety of internal subdivisions in an organization should be adapted to the variety of organizational inputs. Groupthink ideas also seem to imply that some variety of viewpoints should be important in creating better organizational decisions. Newell & Hancock (1984) discussed how skewness and kurtosis could influence inferences in studies of motor tasks. There was sufficient prior knowledge to warrant an exploration of the possible relations of within-organization variability, skewness, or kurtosis of variables to organizational performance.

Calculations of Statistics

The calculations were done with SPSS 14.0 (SPSS, 2004). Several subgroup statistics were computed for each of the scales ENT, ORG, MKT, LRN and PERF for each of the 60 organizations included in the study (Barrett, et al., 2004). The means of each scale were computed in the usual way within each organization. The large sample formulas were used to estimate the sampling errors of the standard deviation, skewness or kurtosis.

The Standard Deviation (SD) was computed as the square root of the unbiased variance. The Skewness (SK) and the Kurtosis (KU) were computed by Fisher's g1 and g2 formulas respectively. Within each organization, the sampling distribution was treated as normally distributed for each statistic. The means of the standard deviation, skewness or kurtosis were supplied for each organization. The distributions of the sample statistics within each organization were assumed normal in the population. The standard deviations of simulated sample statistic observations within each organization were calculated so that they would yield the large sample standard error of the statistic if the simulated sample observations were raw data and the standard error of interest were that of the sample mean. With those sampling assumptions, sample data observations were simulated within each organization for each statistic.

Results

Do Organizations Differ in the Central Tendency of the Statistics?

Four statistical attributes were used to describe the distributions of each of the five scales included in this study. Each attribute of each scale differed among the sixty organizations. Table 1 summarizes the distribution of each attribute for each scale over the sixty organizations.

For each of the five scales, the organizations were compared to see whether they differed significantly in the central tendency of the several distribution attributes. Eta Squared from the analysis of variance (ANOVA) was used to index the magnitude of differences among organizations. The comparisons of the distribution attributes were repeated for each of the five scales. Table 2 summarizes the results of these analyses.

For each of the five scales, a critical question is whether the additional distribution attributes improve modeling of PERF. Researchers tend to model the expected or conditional mean of a dependent variable. However, there may be additional aspects of a dependent variable to be modeled. These might include its spread or shape. In the following analyses, the organizational PERF means, standard deviations, skewnesses and kurtoses were modeled from attributes of the other scales in the study.

Maintaining Parsimonious Models

A version of hierarchical multiple regression was used in this study. The subgroup scale attributes are somewhat correlated with each other. The first step of the hierarchical regression involved forcing the lower order moments as applicable into the regression equation first. Within each hierarchical step, the significant independent variables were chosen stepwise. On subsequent regression steps, the simpler attributes of each independent variable were entered into the equation first, followed by progressively more complex independent variable attributes. The purpose of this hierarchical or sequential procedure was to ensure that the developed regression models remain as parsimonious as possible (Cohen, et al., 2003, Pp. 186-187). At each of these steps, the information gain from the addition of the more complex independent scale attributes was assessed by the significance test for the increase in the ordinary least squares sample R^2. Hierarchical regression models were developed for each of the dependent variable attributes. The results are summarized in Table 3.

Table 1
Basic Description of Differences among Organizations

Scale	Attribute	Differences among Organizations					
		Minimum	Maximum	Mean	SD[a]	SK[b]	KU[c]
	N Per Organization	4.00	31.00	11.60	5.05	.93	2.42
ENT	MEAN	2.74	5.83	4.04	.68	.18	-.13
	SD	.32	1.70	.88	.27	.44	.34
	SK	-1.44	1.25	-.05	.63	.07	-.54
	KU	-2.92	2.05	-.09	1.09	-.02	-.13
ORG	MEAN	2.90	5.68	4.04	.56	.43	.67
	SD	.34	1.64	.91	.25	.41	.85
	SK	-1.87	2.02	-.08	.77	.17	.24
	KU	-4.32	5.44	.36	1.62	.49	1.79
MKT	MEAN	3.19	5.99	4.60	.67	-.25	-.66
	SD	.23	1.35	.83	.21	-.15	1.23
	SK	-1.78	1.52	-.18	.64	.00	.14
	KU	-2.82	3.82	-.02	1.35	.65	.22
LRN	MEAN	3.20	5.31	4.40	.49	-.43	-.26
	SD	.50	2.21	1.04	.31	1.14	2.74
	SK	-1.82	2.01	-.27	.73	.40	.64
	KU	-5.00	4.29	.09	1.60	-.04	1.89
PERF	MEAN	3.50	6.75	5.06	.73	-.01	-.55
	SD	.27	1.45	1.01	.26	-.63	.39
	SK	-1.94	1.49	-.21	.79	.03	-.31
	KU	-3.03	3.19	.06	1.53	.41	-.31

Table 2
Univariate Scale Attribute Differences among Organizations[a]

Scale	Scale Distribution Attribute			
	MEAN	SD	SK	KU
ENT	.38***	.19***	.12*	.16***
MKT	.25***	.14***	.18***	.17***
ORG	.38***	.18***	.14***	.14***
LRN	.19***	.18***	.14***	.16***
PERF	.32***	.56***	.18***	.16***

Table 3
Hierarchical Multiple Regression to Detect Significant Effects

Independent Scales' Subgroup Attributes	PERF (Dependent Scale) Subgroup Attributes			
	MEAN	SD	SK	KU
Means	.34***[b]	.04*	.00	.00
Squares of Means	.08***[c]	.00	.00	.00
SDs	.00[d]	.27***	.03*	.08**
SKs	.00[e]	.00	.00	.00
KUs	.05**[f]	.00	.00	.00
Total PRESS R^2	.47***[g]	.31***	.03*	.08**

Conclusion

Do the Scale Attributes Differ Among Organizations?

Table 1 reveals substantial differences in scale attributes among organizations. The results shown in Table 2 reveal that all the statistical attributes for the five scales are significantly different among organizations at or beyond the .05 level by the one-way ANOVA. Among the subgroup means, the Eta Squareds are sizeable for social science studies, and vary from .19 to .38 with a median of about .32. Eta Squareds for the standard deviations varied from .14 to .56 with a median of .18. The skewnesses varied from .12 to .18 with a median of .14. Moreover, kurtoses had Eta Squareds in the range from .14 to .17 with a median of about .16. These results support the conclusion that the scale attributes differ importantly among organizations.

Do the Additional Scale Attributes Add Useful Information?

Table 3 shows the effects of using distribution attributes beyond the mean for each organization. There are statistically significant effects for each of the attributes of PERF. Table 3 shows that aspects of the independent scales beyond the mean scores of each subgroup may contribute importantly to improving regression models. For example, the kurtosis of the ORG scale accounts for a PRESS R^2 increment of 5% in the variance in PERF. When considered in the context of the prior PRESS R^2 of .42, this is a 12% improvement in variance accounted for.

Such incremental improvements in the forecasting accuracy of prediction models can produce large economic gains. For example, where there are many job applicants for a single job and there is high variance among people in their predicted job performance, then a small increment in R^2 can result in large financial gains for an employer. Similarly, in choosing which products to bring to market, a small improvement in demand forecasting accuracy can create large financial gains when spread over several hundred thousand potential customers.

The obtained increments in the sample or PRESS R^2s were expected to decline as more abstract attributes of the distribution of the dependent variable were modeled. For every organization's PERF attribute the stringent reproducibility requirement, that the PRESS R^2 be statistically significant at or beyond the .05 level, was met. This suggests that many more such effects may be found when one looks for them. And the example data set has shown with a substantial sample size and a carefully collected (albeit necessarily "snowball") data base that it is certainly possible to explore such phenomena.

Do these effects matter?

At present such possible effects as predictability of variability seem to be ignored. But ignoring phenomena observable in data does a disservice to researchers and to the general progress of our sciences and allied disciplines. For example, in the social sciences moderators remain a popular topic. But most discussions of moderation assume that moderators only are interaction effects in the analysis of variance sense. Yet, moderation may connote at least two different things. First, it may be that the slope of the regression of a dependent variable on two or more independent scales depends on the levels of one or more other independent scales (IVs). This is equivalent to interaction effects in the analysis of variance sense

But there is another sense in which the term moderator has been used. Second, correlations, or the absolute size of model errors, among IVs and the dependent variable (DV) may differ depending on the levels of other IVs. This also implies that the multiple correlations among a subset of IVs and the DV may differ depending on the level of other IVs. This is not the same phenomenon as possible interaction effects. It is theoretically similar to suggestions that the absolute size of errors in a model may be a replicable function of one or more independent scales of predictability (Ghiselli, 1956). Ghiselli discussed several applications of his moderator idea in personnel selection. Modeling the conditional spread (standard error of prediction) is quite similar to this old idea of moderation. In an econometric context, such effects are called conditional variance, or are discussed under the topic of heteroscedasticity (e.g., Vytlacil, 2005). In econometrics researchers have also successfully modeled the conditional SK or conditional KU besides the conditional SD (e.g., Ahgiray, Booth, Hatem & Mustafa, 1991; Perez-Quiros & Timmermann, 2001).

The methods suggested here for modeling the spread of the dependent variable pose another strategy for dealing with this possible phenomenon. Moreover, by also modeling the conditional SK and KU of the DV, the methods suggested can lead to further extensions of moderation ideas. See also Sharma, et al. (1981) and Baron & Kenny (1986) for related ideas.

Some Cautions

In this article, it has been argued that data analysts should use more of the information available in a data set. The information gain made possible by expanding the data analyses has been demonstrated in this example data set. Yet reasonable caution should be exercised. Data analysts should tell the truth and the whole truth. But one should ensure that the data analysis tells only the truth. In statistical folklore the cautionary saying is "Torture the data and it will confess." In any practical application one should be cautious to not create artificial results or misleading interpretations from overly elaborate data analyses. There is a danger that using the methods suggested in this article might lead to unnecessarily complex models for a given purpose. Research is constrained by time and cost factors and expected payoffs from more complex analyses. That is certainly a valid point, and Ghiselli (1956) and others were aware of this some time ago (cf. Zikmund, 2003, p. 12).

What are the Implications of this Study?

If researchers do not look for distribution differences among subgroups other than central tendency then they are bound to not find them. The demonstration data set was chosen because the authors of the prior study made it available. The data set was not chosen because it was expected to reveal SD, SK or KU differences among organizations. Instead it was matter of strong suspicion that most data sets involve differences in spread and shape besides differences in central tendencies. Upon analysis, some of the suspected effects with higher order moments were revealed.

It is not known how large or important such effects from higher order subgroup moments may be. But in this study, when the subgroup variances or shapes of the independent variables were included, replicable gains in variance accounted for in attributes of the dependent variable were common. Other researchers should routinely examine their data to see whether subgroup SDs, SKs or KUs, as in this study, produce large and important information gains.

References

Ahgiray, V., Booth, G. G., Hatem, J. J., & Mustafa, C. (1991). Conditional dependence in precious metal prices. *The Financial Review*, *26*, 367-386.

Baron, R. & Kenny, D. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *31*, 1173-1182.

Barrett, H., Balloun, J. L. & Weinstein, A. (2004). Success factors for 21st century organizations: A multi-sector, multiple respondents approach. *The International Journal of Business, 15 (2),* 79-88.

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). . *Applied multiple regression/ correlation analysis for the behavioral sciences*. Mahwah, NJ: Lawrence Erlbaum.

Ghiselli, E. E. (1956). Differentiation of individuals in terms of their predictability. *Journal of Applied Psychology*, *40*, 374-377.

Katz, D. & Kahn, R. (1966). *The social psychology of organizations*. New York: Wiley.

Micceri, T. (1989). The unicorn, the normal curve, and other improbable creatures. *Psychological Bulletin*, *105*, 156-166.

Number Cruncher Statistical System. (2007). *NCSS 2007 for Windows*. Released March 16, 2007. Kaysville, Utah: NCSS, Inc.

Newell, K. M., & Hancock, P. A. (1984). Forgotten moments: A note on skewness and kurtosis as influential factors in inferences extrapolated from response distributions. *Journal of Motor Behavior*, *16*, 320-335.

Perez-Quiros, G. & Timmermann, A. G. (2001). Business cycle asymmetries in stock returns: evidence from higher order moments and conditional densities. ECB Working Paper No. 58. Retrieved May 2, 2005 from http://ssrn.com/abstract=356061

Rousseeuw, P. J. & Leroy, A. M. (1987). *Robust regression and outlier detection*. Hoboken, New Jersey: Wiley.

Sharma, S., Durand, R. M., & Gur-Arie, O. (1981). Identification and analysis of moderator scales. *Journal of Marketing Research*, *18* , 291-300.

SPSS. (2007). SPSS 16 for Windows. Released 2007. Chicago: SPSS, Inc.

Vytlacil, E. (2005). 102B: Introduction to econometrics Stanford University, Winter 2005. Retrieved April 26, 2005 from Stanford University Website: http://www.stanford.edu/~vytlacil/_teaching/syllabus_102B_winter_2005.pdf.

Yerkes, R. M. & Dodson, J. D. (1908). The relation of strength of stimulus to rapidity of habit-formation. *Journal of Comparative Neurology and Psychology*, *18*, 459-482.

Zikmund, W. G. (2003). *Business research methods*. (7th edition). Mason, OH:South-Western.