8-6-2011

A Dangerous Blind Spot in IS Research: False Positives Due to Multicollinearity Combined With Measurement Error

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ABSTRACT

Econometrics textbooks generally conclude that in regression, because the calculation of path estimate variances includes a variance inflation factor (VIF) that reflects correlations between "independent" constructs, multicollinearity should not cause false positives except in extreme cases. However, textbook treatments of multicollinearity assume perfect measurement – rare in behavioral research. VIF is based on apparent correlations between constructs -- always less than actual correlations when measurement error exists. A brief review of recent articles in the MIS Quarterly suggests that the conditions for excessive false positives are present in published research. In this paper we show (analytically and with a series of Monte Carlo simulations) that multicollinearity combined with measurement error presents greater than expected dangers from false positives in IS research when regression or PLS is used. Suggestions for how to address this situation are offered.

Keywords

Multicollinearity, measurement error, correlation, Type I error, false positive, VIF, variance inflation factor, regression, PLS, LISREL.

INTRODUCTION

Anyone who has studied regression analysis has probably read the section of a textbook dealing with multicollinearity. After discussing possible dangers, textbooks generally conclude that except under extreme circumstances, because the calculation of the standard error of the path estimates includes a Variance Inflation Factor (VIF) based on intercorrelations between independent constructs, the calculated standard errors will increase sufficiently to prevent false positives. Only when VIFs increase to near 10 (Neeter and Wasserman and Kutner, 1985, p. 392) is caution urged[1].

However, these regression textbooks assume constructs are measured without error. In this paper we start with the equations from regression textbooks for the standard error of regression path estimates, noting that they include a VIF that reflects any correlations between independent variables. However, when we add the recognition that in behavioral research there is generally measurement error, it is clear that what a regression analysis sees as the correlation between two independent variables measured with error is less than their actual correlation in the population. This is made clear in Nunnally and Bernstein's (1994) equation for the relationship between underlying correlation and apparent correlation, which they call a "correction for measurement error attenuation" (pp. 241, 257). When this attenuation for measurement error is factored into estimates of the correlations between independent constructs, it can be seen that when there is measurement error, the VIF is systematically underestimated, with the result that the standard error of path estimates is systematically underestimated.

[1] Some researchers suggest a smaller maximum value for VIFs, e.g. Craney and Surles (2002) who sluggest 3.33. The value of 10 is more commonly used, however.

Underestimated standard errors of course results in overestimated t statistics and the possibility of excessive false positives. The commonly accepted significance level of .05 in statistical testing means that the researcher is willing to risk a 5% chance of finding a false positive (Type I error). Our work suggests that under combinations of multicolinearity, measurement error and sample size actually found in published MIS research, the danger of false positives exceeds 10%. This can occur with VIFs as low as 2.0.

In this paper, we start by showing how the equation for the standard error of path estimates is affected by the combination of measurement error and multicolinearity. We then examine one particular paper from MIS Quarterly that well illustrates our concern, and we do a quick scan of high correlations in papers from that journal from 2007 to 2009 that might also have similar problems. This scan suggests that as many as a quarter of the path analysis papers have correlations high enough to cause real concern relative to this issue.

But theoretically showing that false positives are a possibility is quite different from showing that in practice false positives are likely. To address the question of how likely false positives are, we utilize Monte Carlo simulation to test the impact of multicolinearity on regression, LISREL and PLS. As the reader will see, we find that both regression and PLS are susceptible to excessive numbers of false positives under commonly occurring combinations of correlation, measurement error, and sample size.

MULTICOLLINEARITY: THE TEXTBOOK TREATMENT AND THE IMPACT OF MEASUREMENT ERROR

Without getting into details of the calculations of regression parameters, it is clear that econometrics textbooks all show that the calculation of the variance of the beta estimates is a function of the correlations between predictor variables, as embodied in the Variance Inflation Factor. As explained by Neter, Wasserman and Kutner 1985, p. 391, "the variance inflation factor for b_k' is:

$$(VIF)_k = 1/(1 - R_k^2) \qquad (1)$$

where R_k^2 is the coefficient of multiple determination when X is regressed on the p-2 other X variables in the model." When there are only two predictor variables that are correlated, VIF reduces to the following:

$$VIF = 1/(1 - r^2) \qquad (2)$$

where r is the simple correlation between the two correlated predictor variables.

We will use equations from Pindyck and Rubinfeld (1981 pp. 77-78) for the variance of the beta estimates, but we could have used equivalent equations from many textbooks (cf. Johnston 1983, p. 161; Neter, Wasserman, and Kutner 1985, p. 389, etc.) Pinkyck and Rubinfeld show that when there are only two predictor variables (X_2 and X_3), the variance of a beta path estimate for X_2 is:

$$var(\beta_2) = s^2 / [\Sigma x_{2\iota}^2 * (1-r^2)] \qquad (3)$$

or

$$var(\beta_2) = [s^2 / \Sigma x_{2\iota}^2] * VIF \qquad (4)$$

and similar for X_3. Here $1/(1-r^2)$ is the VIF and s^2 is an unbiased and consistent estimate of σ^2, the error variance of the regression equation[2].

As can be seen, the variance of the path estimate for either of the correlated predictors is a function of the VIF[3]. When there is no correlation between predictors, the VIF becomes one. When the two independent constructs are more correlated (as multicollinearity increases), r increases, the $(1-r^2)$ term will become smaller, and the variance inflation factor (and the variance of the path estimate) will become larger. In the limit when r = 1, the variance is infinite, and regression cannot be carried out. Thus multicollinearity is accounted for in the estimations of the variances (and standard deviations) of regression path estimates.

In general, to test the statistical significance of regression beta estimates, we take advantage of the fact that with normally distributed error terms, the following has a t distribution:

$$(\hat{\beta}_2 - \beta_2) / \hat{Var}(\hat{\beta}_2) \sim t_{N-K} \qquad (5)$$

[2] $s^2 = \Sigma\varepsilon^2_i / (N - K)$ where N is the sample size and K is the number of independent variables (including the constant).

[3] Since a standard deviation of a path estimate is the square root of the variance, standard deviation is also a function of VIF.

However, equations 1 through 5 above assume perfect measurement. When measurement is not perfect, there is no way for regression to determine the true correlation of the two independent constructs. Any estimate of the correlation (r) between constructs when there is measurement error that is based on averaged or summed indicator scores will be attenuated (reduced) by the measurement error, as expressed in the equation for the "correction for attenuation" (Nunnally and Bernstein, 1994, pp. 241, 257)

$$r_{23}^{corrected} = (r_{23}^{uncorrected}) \,/\, (\alpha_2 * \alpha_3)^{1/2} \quad (6)$$

Here α_2 and α_3 are the reliabilities of the two correlated predictors. It can be seen in equation (4) that if the correlation between two predictor variables (r) is underestimated because of the attenuation due to measurement error, then the variance of the path estimate will also be underestimated, and the t statistic will be overestimated. Our concern here is that if the t statistic is overestimated, then we should expect higher than acceptable numbers of false positives.

A Concrete Example of a Potential False Positive Situation

We reviewed all issues from the 2008 and 2009 volumes of MIS Quarterly. As we will discuss in more detail later in the paper, we found numerous examples of published articles where we believe that the conditions for potential false positives from multicolinearity problems hold. We have picked out one that illustrates the potential problem well. Note that we are not faulting these authors (or any others mentioned in this paper). Rather we wish to point out that although they followed established measurement validity practices in the field, in light of the additional insights offered by our work, it may be advisable for them (and others encountering high correlations) to review their results and re-consider their interpretations.

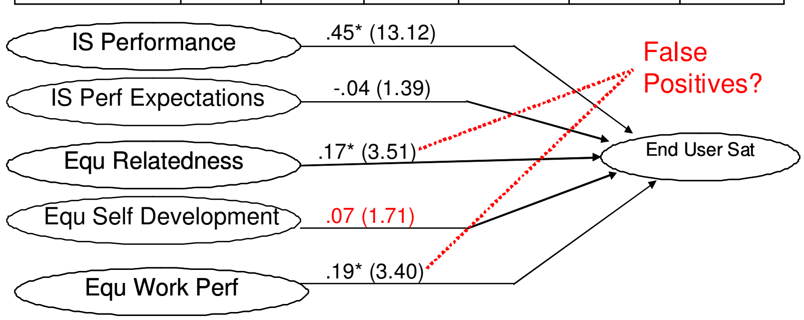
Au et al. (2008) used PLS to test a causal model explaining end user satisfaction for an information system. Among the independent variables were Equitable Relatedness Fulfillment, Equitable Self Development Fulfillment, and Equitable Work Performance Fulfillment. In this context, "equity" refers to the degree to which benefits in each of these three areas are commensurate with the effort needed to achieve the benefits. As shown on Au et al.'s page 52, these three independent variables have apparent inter-correlations of .73, .68, and .75, and reliabilities of .89, .90, and .87. Though not stated in the paper, our back of the envelope calculation suggests the VIF for the analysis would be approximately 2.8, far less than the standard danger signal of 10.

Partial results from Au et al.'s analysis are shown in Figure 1. As can be seen in the figure, these three independent constructs had roughly the same correlation with the dependent variable Satisfaction, .56, .57, and .60, respectively. However, as shown under the column for the betas, the beta for Equitable Self Development Fulfillment is small and not significant, while the betas for Equitable Relatedness Fulfillment and Equitable of Work Performance Fulfillment are moderately strong and statistically significant.

Figure 1. An Example: Understanding EUS Formation
Au et al., MISQ 2008

Correlation Matrix

	Sat	IS_Perf	IS_Exp	Equ_Rel	Equ_Dev	Equ_WP
Sat	1.000					
IS_Perf	0.664	1.000				
IS_Perf Exp	0.304	0.480	1.000			
Equitable_Rel	0.564	0.505	0.274	1.000		
Equitable_Dev	0.567	0.542	0.296	0.726	1.000	
Equitable_WP	0.604	0.583	0.328	0.679	0.745	1.000



One interpretation of Au et al.'s results is that because of measurement error combined with the high correlations between the three independent variables, the t statistics for the three paths might be overestimated. Because all three independent variables have almost the identical correlation with the dependent variable, we might expect that all have about the same impact on Satisfaction. However, that is not evident in the PLS path values -- for two variables the paths are much higher and more statistically significant than for the third. As Johnson (1972) notes, one of the characteristics of excessive multicolinearity is overestimation of one of a pair of correlated constructs, and underestimation of the other. More specifically, he says that a large correlation between independent variables

> "is thus likely to produce large and opposite errors in $\hat{\beta}_2$ and $\hat{\beta}_3$; if $\hat{\beta}_2$ underestimates β_2, then $\hat{\beta}_3$ is likely to overestimate β_3 and vice versa. It is thus very important that the standard errors should alert one to the presence of multicollinearity." (p. 162)

Thus one interpretation of the results is that because of multicollinearity, the path values for Equitable Relatedness Fulfillment and Equitable of Work Performance Fulfillment are overestimated, while Equitable Self Development Fulfillment is underestimated.

These results by themselves are not sufficient evidence that Au et al. have problems caused by multicollinearity. However, combined with the analytical evidence from the previous section, as well as the results of our Monte Carlo simulation that we will present, they are highly suggestive of a problem. Our interpretation of the Au et al. results is that because of the high correlations, the effects of these three variables cannot be disentangled. Trying to disentangle them (as Au et al. do), probably results in misinterpreting the results to mean that Equitable Self Development Fulfillment has no independent effect on Satisfaction.

In fact, they struggle with explaining the empirical results, since presumably Equitable Self Development Fulfillment was a factor that they thought would be important to satisfaction ratings. However, because the beta coefficient for the Equitable Self Development Fulfillment was not significantly significant, they presume that it has no impact, and suggest:

> "…..the absence of a direct significant impact of equitable self-development fulfillment on EUS (H5) could be explained in two ways. First, the application of IS in the service industry still mainly focuses on operational work. The scope of IS use is therefore likely to be routine-based. Hence, those employees who have the opportunity to seek greater challenges from the information system are likely to be in the minority. Second as information systems are mainly used for routine operational work, employees can get acquainted quickly with the required technical skills. To relate job security or career advancement to an individual's exceptionally poor or outstanding performance would difficult, and therefore equitable self-development fulfillment is not significantly linked to EUS [End User Satisfaction]. If this model is applied to higher level strategic information systems in other industries, it is likely that such an impact would be more significant. (page 53)"

It is clear that Au et al. still believe that Equitable Self Development Fulfillment is important, even though they assumed that they had disproven it for this environment:

> "Although it was found that equitable self-development has no direct impact on EUS, whether it has any indirect impact mediates through other variables is yet to be determined. (page 54)"

Given their level of intercorrelation, we would suggest it is quite possible that the other two predictors (Equitable Work Performance Fulfillment and Equitable Relatedness Fulfillment) are false positives, but is also possible that the path for Equitable Personal Development Fulfillment is a false negative. In fact with this level of correlation, it may be better not trying to disentangle the three effects, and instead (as Au et al. do at one point), treat the three as a single component, and test the impact of adding all three at once to the analysis. Doing this, they do suggest (without clear statistical evidence) that the group of three has an important effect.

Is This Issue Important for Information Systems Researchers?

Information System researchers often find themselves in a position where they have data that exhibit somewhat high correlations among predictor variables. Figure 2 shows that during the 2008 to 2009 period there were 34 paper in MISQ that used path analysis of some kind (typically PLS, regression, or LISREL/Other SEM approach). Of these, 8 had apparent correlations of .5 or above, and our assessment is that 6 of these have likely problems (either a false positive or a false negative). We reached this conclusion by looking at correlations between predictor and dependent variables (as well as the correlations among predictor variables), and comparing those with the size and sign of path estimates. Table 1 shows specific papers from MISQ during the years from 2007 through 2009, and the size of potentially problematic correlations.

Figure 2. MISQ 2008-2009
34 Papers with Path Analysis

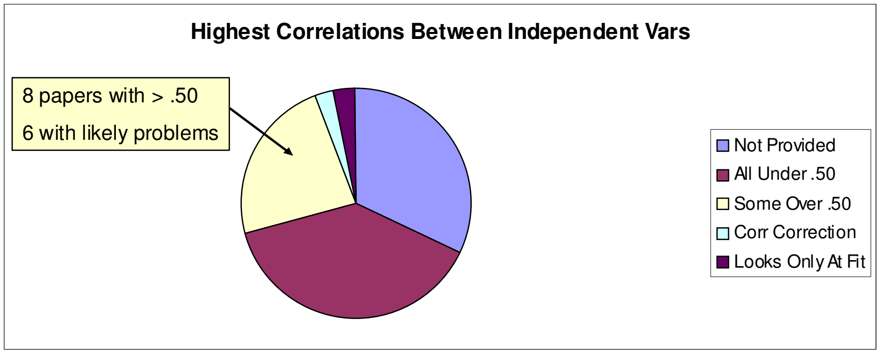


Table 1. High Correlations In MIS Quarterly 2007-2009

2009		Our Assessment	Stat Model	Rho
	Iacovou +	false neg?	PLS	.71, .51, .51
	Sia +	OK	PLS	0.68
	Hahn +	False Pos?	Regression	.95, .60
	Duan +	false neg?	Regression	0.68
	Kim +	false neg?	Lisrel	0.63
2008				
	Mithas +	False Neg?	Lisrel	0.74
	Au +	False Neg? False Pos?	PLS	0.75
	Hsieh +	OK	PLS	0.54
2007	Limayem +	OK	PLS	.75, .62
	Pavlou +	OK	PLS	0.63
	Ahuja +	False negative?	PLS	0.60
	Kanawattanachai +	OK	PLS	0.69
	McElroy +	False Positive?	Regression	0.52

About One Quarter of the Path Analysis Papers!

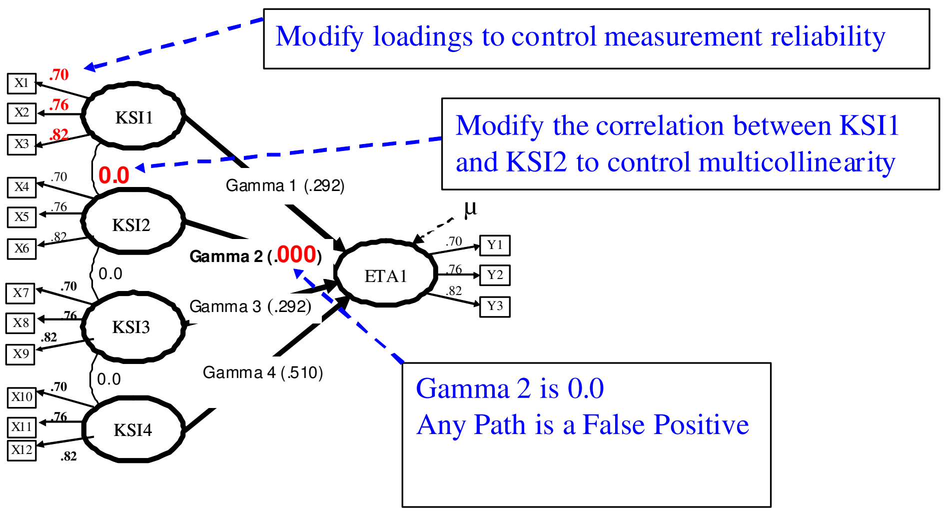
So the situation seen in the Au et al. paper is not unique. Even though a calculation of variance inflation factors in all these papers may suggest no concern (i.e., the VIFs are far less than 10), adding the variables one at a time might suggest many of the hallmarks of multicollinearity – path estimates that shift from positive to negative when a correlated construct is added, or greatly changing their value and significance (Neter, Wasserman, Kutner, 1985 p. 390).

Reference sources for guidance on determining whether or not excessive multicollinearity exists are inconsistent and not very helpful. Neter et al.'s informal methods for detecting multicollinearity might strongly suggest a problem, but at the same time the standard test (variance inflation factors) indicates no problem should exist. Our research suggests that correlations far less than required for high VIFs can generate unacceptably high proportions of false positives in regression. Since a reasonable protection against false positives is central to empirical research and the scientific method, we need more information about whether correlation and measurement error really do increase the risk of false positives, and if so, what level of correlations and measurement errors should be considered danger signs.

Using Monte Carlo Simulation to Discover If There Really Is a Problem

Monte Carlo simulation has been used extensively to investigate a variety of statistical analysis issues[4]. With Monte Carlo simulation, we start with a 'true' base model that has known properties because we define them in advance. The model we will use is shown in Figure 3. We then use random number generators to generate, in effect, questionnaire data drawn from a population where the model represents the true relationships between constructs and questions measuring them.

Figure 3. Baseline Model for Monte Carlo Simulation
(500 samples for each condition)



In Monte Carlo simulation in this context, the researcher generates numerous datasets that exhibit the desired properties, and uses any analysis technique of interest to analyze the data. The parameters of the base model can be used to generate specific characteristics in the data. In other words, Monte Carlo simulation can generate large numbers of samples in any desired condition, where what the true underlying distributions and paths are between constructs are precisely known. Because of the above, Monte Carlo simulation is very well suited to exploring the impact of multicollinearity and measurement error on statistical techniques.

For our Monte Carlo simulation work, we followed the general approach taken in Goodhue et al. (2007). We used different values for the correlation between Ksi1 and Ksi2 to create greater or lesser multicollinearity, and we changed the loadings on the construct indicators to create different levels of measurement reliability. (See Figure 3.) Because we generated many different random datasets (500 for each reliability / correlation condition), by looking across all the datasets in a particular condition we can get a fairly accurate understanding of the efficacy of the statistical techniques for that condition, and can also compare that efficacy across techniques, and across other conditions.

For our analyses here, we used a sample size (N) of 100, which is a common size for MIS research. Using Cohen's (1988) power tables and taking into account the baseline parameters and their measurement error, N = 100 should give us a

[4] For example Fornell and Larcker (1981) looked at the impact of different correlation structures on the chi-square goodness of fit tests for structural equation modeling. Goodhue, Lewis and Thompson (2007) looked at the efficacy of using PLS with product indicators for testing interaction effects.

sufficient sample size for 80% power for the Ksi1 and Ksi3 paths to Eta. As shown in Figure 3, each construct is measured by three indicators with initial loadings of .70, .76 and .82, which will give us a Cronbach's alpha of .80 for each of the constructs[5]. This alpha of .80 is equivalent to the usual recommended cut-off value for alpha in reasonably mature research streams (Carmines and Zeller 1979). Ksi1 and Ksi3 each have a moderate effect size[6] influence on Eta (due to a path value of .292); Ksi4 has a strong effect size influence on Eta (due to a path value of .51); Ksi2 has a zero effect on Eta. Therefore, any statistically significant value found for the Ksi2 to Eta path is a false positive.

As indicated in the square text boxes of Figure 3, we can manipulate the amount of correlation between Ksi1 and Ksi2 by changing the parameters of the underlying model. That is, we can change the correlation between KSI1 and KSI2 to reflect a correlation of .4 (or .6, etc.) instead of zero, generate a new set of 500 or so datasets, and see what kind of results we get from regression using this new data. We can also modify the measurement error by changing the loadings of the indicators.

For our initial analysis we tested 20 conditions: all combinations of four levels of reliability (1.00, .90, .80, and .70) and five levels of correlation between Ksi1 and Ksi2 (0.0, .4, .6, .8, and .9). For each condition that we tested, we generated 500 datasets of 100 questionnaires each and analyzed each of the 500 datasets separately using first regression and then LISREL. After that analysis, we then determined: (a) the average estimate value for each path, and (b) the number of paths (out of 500) with a statistically significant path. In the case of the Ksi2 to Eta path, every statistically significant value was a false positive. For each statistical technique and each condition, we calculated the proportion of false positives as the number of false positives divided by the number of datasets (500). Since this gives us a proportion, we can use a standard equation for the 95% confidence interval around our proportion of false positives[7].

Since we are using a statistical significance level of $p<.05$, we would expect about 5% of false positives. The confidence interval around a proportion of 5% with N=500 is 5% +/- 1.9, or from 3.1% to 6.9%. Any proportion higher than 6.9% is statistically significant evidence of excessive false positives.

Figure 4 shows our results using regression (on the top left) and LISREL (on the top right). The two dotted horizontal lines show the limits of the confidence interval around 5% false positives. As is easily seen, with an actual correlation of .6 and measurement validity of .80 or .70, the results show a statistically significant number of excessive false positives for regression (around 8%), but not for LISREL.

Our explanation for why regression has excessive false positives and why LISREL does not is the following. LISREL analysis is based on covariances between the indicators and thus its equations have access to information about reliability. Therefore it does not underestimate the correlations between Ksi1 and Ksi2, so it does not overestimate the t statistic for the Ksi2 to Eta path. Regression, on the other hand, has only the value of the constructs determined by summing or averaging the indicator values. Thus regression has no information about the measurement reliability, and cannot take that into account in its calculation of the standard deviation of the Ksi2 to Eta path.

Because with Monte Carlo simulation we know the true correlation between Ksi1 and Ksi2, we have a unique opportunity to ask what the results would be if Nunnally and Bernstein's equation for measurement attenuation were taken into account, and the standard deviation for the regression paths were corrected by the appropriate amount. Those results are shown in the bottom left of Figure 4. Two things are clear from the comparison of the top and bottom left hand graphs of Figure 4. First, when the correction for attenuation is used, the regression results no longer have excessive false positives, and secondly the corrected regression results mirror very closely those obtained by using LISREL.

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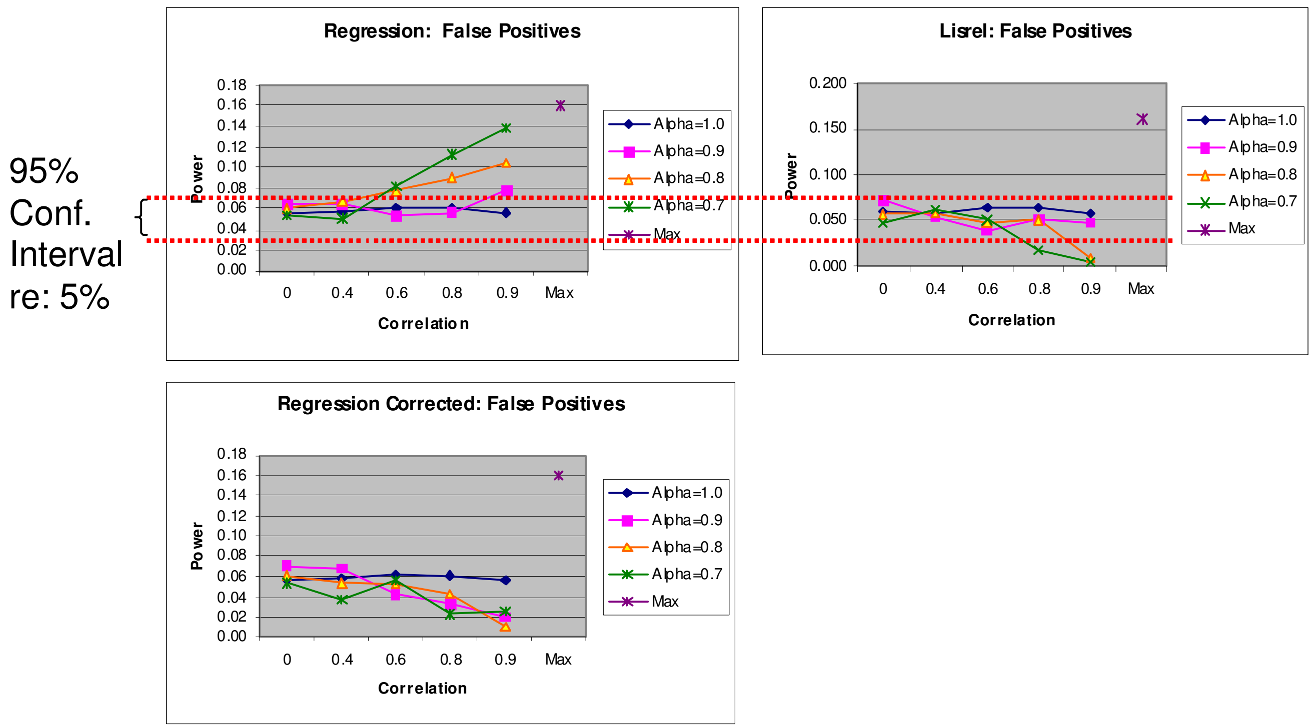
[5] Knowing the underlying loadings of the indicators, we can calculate their inter-item correlations and therefore their average correlation. With this we can use a standard equation for Cronbach's alpha: $\alpha = N*\rho_{avg} / [1+\rho_{avg}(N-1)]$ (Carmines and Zeller, 1979).

[6] If uncorrelated and measured without error, KSI1 through KSI3 would have an effect size of $.292^2/(1 - R^2)$ or .13,which is categorized as a moderate effect size according to Cohen 1988. Similarly, KSI4 would have a .39 effect size or a strong effect size. We note that with measurement error, the effect sizes of both are reduced – with alpha = .80, the two effect sizes are .08 and .25, again assuming no correlations.

[7] A standard equation for the 95% confidence interval around a proportion p with sample size n is: $p \pm 1.96\,[\,p(1-p) / n\,]^{.5}$

Figure 4. The Impact on False Positives of Correlation and Measurement Error (Plus a Correction for Regression)



Where Does PLS Fit Into the Picture?

Although our intial analysis was focused on regression and LISREL, in MIS research PLS is another frequently used statistical analysis technique. Though not as complete a picture at this time, we did conduct an analysis using 10 of the 20 conditions with PLS. (We have not yet included the alpha = 1.0 and alpha = .70 conditions.) Table 2 shows the results.

These results suggest that PLS suffers at least as much as regression does from problems with false positives. At least in this context, it appears that PLS is more like regression than it is like LISREL. However, a more thorough treatment using PLS is required before a more definitive conclusion can be reached.

Table 2. PLS Versus Regression Proportion of False Positives

(Bolded Numbers are outside
the 95% Confidence Interval Around .050 = +/- .019)
Based on 500 Datasets, each N = 100

	Alpha = .90			Alpha = .80	
Rho	Reg	PLS		Reg	PLS
0.0	0.064	0.062		0.060	0.068
0.4	0.064	**0.078**		0.068	0.060
0.6	0.054	0.054		**0.078**	**0.080**
0.8	0.056	0.068		**0.090**	**0.116**
0.9	**0.078**	**0.084**		**0.104**	**0.134**

CONCLUSION

While this research is still ongoing, we view this as very strong initial evidence of our ingoing assertion – multicollinearity combined with measurement error is a more dangerous condition than we might have been led to believe. What might be the danger signs? First it is important to recognize that in our Monte Carlo simulation, and in the correlations shown in Figure 4, the true value of the correlations are shown. However, regression analysis underestimates those correlations, as shown the equation for measurement attenuation. Therefore, if Ksi1 and Ksi2 are each measured with a reliability of .80, what level of apparent correlation be evident if the true correlation were .6. The math is shown below:

$$r_{23}^{corrected} = (r_{23}^{uncorrected}) \ / \ (\alpha_2 * \alpha_3)^1 \quad \text{From Equation (6)}$$

$$r_{23}^{uncorrected} = r_{23}^{corrected} * (\alpha_2 * \alpha_3)^{1/2} = .6 * (.80 * .80)^{1/2} = .48$$

This suggests that when constructs are measured with an alpha of .80, and appear to have a correlation of about .5, they really have a correlation of about .6, and paths from them may have about 8% false positives, a statistically significant increase above the allowable 5%. In a more extreme situation, with a reliability of .70 and an apparent correlation of .56, the actual correlation is close to .8, and the occurrence of false positives might be about 11%. We should note, however, that our results are specific to this study, in that if the measurement error were different in amount or form from what we used in the simulation, our results might have been slightly different. This could be the subject of a future study.

In addition, please note that not all high correlations will result in false positives or false negatives. Our initial rule of thumb is to be very cautious when apparent correlations are above about .50, with reliability at about .80 or below. Another danger sign is path estimates that are disproportional to the correlations between independent and dependent constructs. Under these circumstances, false positives (and false negatives) appear to be more frequent than current scientific method standards would allow, and hence more scrutiny would be suggested.

The obvious question is: What should one do under these circumstances? Our suggestion would be to use the following approach. First, as a way of more specifically exploring the degree of multicollinearity, you can add the individual correlated variables, each one by itself, to the analysis with all the non-correlated variables, to see what each variable's independent impact is. Then gradually add the additional correlated variables into the analysis, watching the changes each new correlated variable makes in the old correlated variable path values and significances. If values or significances don't change much as you add new correlated variables, you probably don't have multicollinearity problems. If the individual impacts do change when additional correlated variables are added, you have a strong case for multicollinearity.

One solution that may be tempting at this point would be to choose one of the variables with a high individual impact and drop the rest. This however would be misleading to readers, since you really don't have a way of separating out the impact of this one variable from that of the others.

Instead, difficult though it may seem if your hypotheses suggest different and separable impacts, if a set of predictor variables is highly correlated, it may be the reality that you will not be able to separate out the individual causal effects of each. Once this is accepted, you may be able to salvage some real value by considering the correlated variables as a group, and asking what the impact of the group is on the dependent variable. You can easily determine the increase in R^2 of the group, and an F test will allow you to determine whether the impact of the group is statistically significant. Future work may be able to better measure the different constructs to get separable impacts on the dependent variable. Or you may have determined that the several correlated predictor constructs are really so closely linked that they should be considered a single construct.

We suggest that bringing this perspective into our MIS research analysis and interpretation will sharpen our ability to develop accurate and useful causal models of the MIS environment.

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