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ABSTRACT

An investigation of the effects of randomly missing data in two-predictor regression analyses is described. The differences in the effectiveness of five common treatments of missing data on estimates of R-squared values and each of the two standardized regression weights is also investigated. Bootstrap sample sizes of 50, 100, and 200 were drawn from three sets of actual field data. Randomly missing data were created within each sample, and the parameter estimates were compared with those obtained from the same samples with no missing data. The results indicate that three imputation procedures (mean substitution, simple, and multiple regression imputation) produced biased estimates of R-squared values and both regression weights. Two deletion procedures (listwise and pairwise) provided accurate parameter estimates with up to 60% of the data missing. Twelve data tables, 9 figures, and a 20-item list of references are included. (Author/TJH)

Randomly Missing Data in Multiple Regression: An Empirical Comparison of Common Missing Data Treatments

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Abstract

This research is an investigation of the effects of randomly missing data in two-predictor regression analyses and the differences in the effectiveness of five common treatments of missing data on estimates of R^2 and each of the two standardized regression weights. Bootstrap samples of size 50, 100, and 200 were drawn from three sets of actual field data. Randomly missing data were created within each sample and the parameter estimates were compared with those obtained from the same samples with no missing data. The results indicated that three imputation procedures (mean substitution, s..mple and multiple regression imputation) produced biased estimates of R^2 and both regression weights. Two deletion procedures (listwise and pairwise) provided accurate parameter estimates with up to 60% of the data missing.

Empirical research in any field is frequently hampered by missing data, but in no field is the problem more pervasive than in the social sciences. Research subjects may fail to respond to every item on a survey, students may be absent from classes during testing, questionnaires may be lost or inadvertently discarded by either the respondent or the researcher. To this list, one must add the considerations of equipment failures, illegible handwriting, and miscoded data fields.

Each time a set of data with missing fields is encountered, some type of missing data treatment is mandated. Summary statements in research reports such as "the missing data were ignored" or "only complete cases were used in the analysis", suggest that the explicit treatment of data absences is optional in statistical analyses. Such statements are misleading, however, because they describe (although implicitly) two types of missing data treatments, namely the pairwise and listwise deletion procedures. The researcher may be unaware that any missing data treatment has taken place, and consequently may be unconcerned about the effects of such treatment on any subsequent analyses, interpretations, and conclusions.

Although discourse on methods for dealing with missing data is not uncommon in the social science literature, and although packaged computer software for applied data analysis typically is programmed to treat missing data without explicit user directions, little is presented either in research literature or in software users' manuals to guide the applied researcher in grappling with the problem in any practical manner. The issues surrounding the problem of missing data and its treatment are presented in surprisingly vague and imprecise terms. Typically, the researcher is advised that if data are randomly missing and if the amount of missing data is not excessive, then any treatment is as good as any other.

The purpose of this research is to provide practicing researchers with practical advice on three missing data issues: (a) the extent to which data may be missing before statistics are seriously affected, (b) the best treatment to apply to missing data matrices, and (c) the effects of missing data and their treatment on the statistics interpreted in applied research.

Classifications of Missing Data

Little and Rubin (1987) distinguished two conceptually different types of missing data on a global level. The first type constitutes situations in which the underlying value of a variable would have been observed had the data collection been improved in some way. Nonresponse to surveys, equipment failures and lost records are examples of this type of missing data. This is contrasted with the second type, situations in which a missing data point represents unique information which is different from any observed values of the variable. For example, a respondent who is unable to indicate a preference between products or political candidates represents a new response category (i.e., No Preference), not an underlying preference which was masked by the occurrence of nonresponse.

In another broad categorization of missingness, Anderson, Basilevsky, and Hum (1983) distinguished situations in which data are missing by design, and those in which data are inadvertently missing. Of the former type, experimental designs such as the Latin-square design are examples. In such designs, combinations of independent variables are purposely omitted under the explicit assumption that interaction effects are negligible. An additional example of data missing by design, encountered in survey research, is partial matrix sampling (Shoemaker, 1973). The distinguishing feature of data missing by design is that the occurrence of missing data is under the control of the researcher. The occurrence of inadvertently missing data, in contrast, is not under the direct control of the researcher. Malfunctioning equipment, non-readable survey responses, and student absenses on the day of data collection are examples of data that are missing inadvertently.

An additional categorization of types of missing data distinguishes missing fields from missing entire records. The latter is the problem of nonresponse in sample surveys, while the former is the problem of a single variable (or several variables) being unobserved in an otherwise complete case. The treatment of missing records is typically different from the treatment of missing fields within records.

Finally, the intent of the analysis of data has been used to distinguish among types (Frane, 1976). Analyses intended to provide estimates of parameters and tests of hypotheses regarding the magnitudes of parameters may be subject to different missing data treatments than analyses intended to estimate derived scores for individual subjects, such as factor scores.

The nature of randomness in missing data has received much attention in the consideration of types of missing data. Little and Rubin (1987) distinguish between the assumptions of data being "Missing at Random" and data being "Observed at Random" (see also Rubin, 1976). The first type consists of situations in which the observed units are a random subsample of the sampled units. The observance of a variable (or conversely, the occurrence of a missing data point for a variable) does not depend on the value of the variable itself. Data are "Observed at Random" if the observed units are a random subsample only within classes of some other variable. Thus, missing data on X_1 is correlated with some other variable, X_2. Given knowledge of X_2, however, the missingness on X_1 can be made conditionally independent.

An Overview of Treatments of Missing Data

Although the specific methods of treating missing data that have been detailed in the literature are numerous, two fundamental approaches are evident. In the first general approach, missing data are not included in the statistical calculations. Entire data records evidencing missing data may be deleted (the listwise deletion approach) or observations are deleted only if the missing data occur on variables needed for a particular calculation (the pairwise deletion approach). In the second general approach to missing data treatment, an estimate of each missing datum is calculated and the estimated value is used in statistical computations. The estimated value may be the mean of the variable for the total set of data (the mean substitution approach), the mean of a subgroup of the data (subgroup mean substitution), the value of the variable occuring on a similar data record (the hot-deck approach), or a predicted value based upon the relationships among variables in the data. This latter prediction of missing data may be based upon the regression of the variable with missing data on the single variable most highly correlated with it (the simple regression estimation approach) or the regression may be computed on all variables (the multiple regression approach). Frane (1976) provided a lucid critique of the many forms of regression approaches to missing data treatment.

In contrast to the deletion techniques and the imputation techniques, the maximum likelihood approach to missing data treatment uses the characteristics of an assumed population distribution to provide estimates of the values of parameters (typically, a vector of population means and matrix of population variances and covariances). The values are selected which maximize the likelihood of the observed data, given the population distribution.

Most published considerations of the maximum likelihood procedures for treating missing data are found in the technical statistics journals (Kariya, Krishnaiah, & Rao, 1983; Dempster, Laird, & Rubin, 1977) and are not encountered in the journals of applied research. The technical treatments of the procedures, although appropriate for the target journals, may reduce their appeal to practitioners. The practical utility of maximum likelihood estimation procedures may be further reduced because the procedures are not available as options in packaged statistical analysis programs (a notable exception being the BMDP package, Dixon, 1983).

Comparisons of Missing Data Treatments

With the breadth of missing data treatments available, ranging from default methods on statistical packages to those requiring iterative estimations, applied researchers are likely to be confused about which methods work best with particular data structures and with particular levels of missing data. The extant literature on the comparison of missing data treatments may leave the researcher with few clear guidelines.

Research on missing data treatments that will be useful to researchers facing a missing data problem should address three practical concerns evident in applied data analysis:

1. The impact of missing data and the effectiveness of their treatment must be examined in terms of the effects on the parameter estimates that are to be interpreted.

2. The effects should be examined in the context of the sampling variation of the parameter estimates.

3. The data matrices investigated should reflect realistic data encountered in actual field research.

Comparisons Using Computer Generated Data

Haitovsky (1968) compared listwise and pairwise treatments with eight sets of data generated from either multivariate normal or uniform distributions. Haitovsky examined the bias and variance of each regression weight as criteria of the effectiveness of the missing data treatments. The listwise approach was found to be superior to the pairwise method in both bias and efficiency, although no test of the significance of differences was conducted.

Timm (1970) compared the use of four missing data techniques in the computation of correlation matrices and variance-covariance matrices. Using samples generated from multivariate normal distributions, Timm randomly deleted 1%, 10%, or 20% of the data. The samples were generated in accord with correlation matrices obtained from field research, to represent patterns of high, moderate, and low levels of variable intercorrelations. The number of variables comprising the matrices was controlled at two, five, or 10 variables. The missing data treatments were evaluated on the basis of the difference between the known population matrix and the matrix computed from the treated data. No uniformly best technique was observed in the study, although the regression estimation technique showed the highest average congruence with the population matrices. The design included only three samples from each combination of sample size, number of variables, proportion missing, and extent of variable intercorrelation. Additionally, Timm presented the results as relative efficiencies (ratios of the effectiveness of one treatment to the effectiveness of another). Such a presentation allows comparisons between pairs of methods, but mitigates any attempt at discerning the degree to which any of the techniques reproduced the original population matrices.

Gleason and Staelin (1975) compared the effectiveness of five missing data treatments in reproducing known population correlation matrices, using the same measure of differences between matrices as Timm (1970). The researchers manipulated sample size, number of variables, average magnitude of intercorrelation between variables and the proportion of missing data. The study provided no replications within cells, i.e., only one sample was drawn from each combination of sample size, number of variables, average intercorrelation, and proportion missing. Additionally, some missing data treatments were applied in situations that normally would be inappropriate in actual data analysis. The number of variables (three levels: 10, 15, and 30) was large relative to the number of observations (three levels: 50, 100, and 200). The construction of a regression equation to predict a missing value using 29 predictors when the number of cases prior to missing data deletions is only 50 must be viewed as a questionable practice at best (Frane, 1976).

Beale and Little (1975) compared six missing data treatments in treating samples from computer-generated multivariate distributions, produced according to seven patterns of correlation. Samples of sizes 50, 100, and 200 were selected and random deletions of 5%, 10%, 20%, or 40% of the observations on each variable were produced. The criterion of the effectiveness of missing data treatments was the percent increase in the residual sums of squares (over the complete data case), when the complete data were fitted to the obtained regression equation.

Beale and Little's results support the use of an iterated regression estimation, especially with 40% of the data missing. In this situation, only the results for samples of 200 were reported. The iterated regression approach resulted in increases of SS_{resid} ranging from 1.9% to 24.4%, while the multiple regression estimation approach resulted in increases ranging from 3.3% to 33.4%. Both approaches performed least well in two four-predictor situations in which the population value of R^2 was greater than 0.98. Both procedures performed best on a two predictor model with $R^2 = 0.95$. The methods diverged in models of moderate values of R^2 (values from 0.44 to 0.72), with the iterative approach showing marked improvement over the multiple regression approach.

Donner and Rosner (1982) compared listwise deletion, pairwise deletion, regression estimation, and maximum likelihood estimation in the simple case of two predictors, one of which has missing values. Data were randomly generated to conform to several correlation patterns and all were drawn from the multivariate normal distribution. Following sample generation, the values of one predictor were randomly deleted, yielding three levels of missing data (10%, 25%, and 50%). All comparisons were made relative to the maximum likelihood estimator. The absolute value of the deviation of the maximum likelihood estimator from the known regression coefficient was compared to the deviation of the other estimators from the known. The results were reported as the proportion of such comparisons in which the ML procedure deviated more (the magnitudes of the deviations were ignored). These comparisons were conducted for estimates of the regression coefficients for the variable with missing data and the coefficients for the variable without missing data.

Only partial results were reported by the authors. For the variable without missing data, 72 comparisons were reported (three comparisons between estimators, eight patterns of correlation, and three degrees of missing data). Although most of the proportions reported favor the maximum likelihood method (most were less than 0.5), and the authors interpreted the results as supporting the superiority of maximum likelihood techniques, only 16 of the 72 comparisons were significantly different from a null proportion of 0.5 (constructing 95% confidence intervals around the reported proportions). Of these, 10 comparisons were between the pairwise deletion approach and the maximum likelihood approach. In the estimation of the regression parameter of the variable with missing values, only the comparisons between the listwise procedure and the ML procedure were reported. Of these 72 comparisons, none was significantly different from the null proportion.

Kim and Curry (1977) generated 10 data sets of five variables, randomly deleted 10% of the observations on each variable, and compared pairwise and listwise deletion approaches. The index of effectiveness of the missing data procedures was the deviation of the zero-order correlation coefficient from the total sample value. This deviation was averaged over the entire matrix. These researchers, in contrast to Haitovsky, found that pairwise deletions were superior to listwise. Moreover, the differences between estimated correlations and "true" correlations were only slightly greater than the sampling variation in the coefficients obtained from the complete samples.

The contradictory results obtained by Kim and Curry (1977) and Haitovsky (1968) on the relative effectiveness of listwise deletion and pairwise deletion may have little consequence in practical applications. Kim and Curry examined data generated from a single multivariate distribution and drew only 10 samples for their computations, and in neither study were the magnitudes of the effects tested for statistical significance. The later research by Basilevsky, Sabourin, Hum and Anderson (1985) and Donner and Rosner (1982) suggest that the differences between these methods are small and nonsignificant even with much greater proportions of data missing.

Comparisons Using Actual Field Data

Guertin (1968) compared listwise deletion, mean substitution, and regression estimation in computing zero-order correlations between student grade point average and each of 10 achievement tests. The listwise deletion method yielded the highest correlation coefficients on 28 of the 50 computed, and the regression estimate produced higher correlations than the mean substitution method on 34 of the 50 correlations. However, lacking criterion values for the correlations, decisions about which treatment yielded the most accurate correlation estimates cannot be made.

Raymond (1987) analyzed field data in which missing values occurred. He compared listwise deletion, pairwise deletion, and regression imputation of missing data on the resulting regression equation built from the data matrix. The data consisted of 230 cases with 12 variables for each case. One hundred seventy-four of the cases presented no missing data (76% of the cases complete).

The magnitudes of the value of R^2 obtained from pairwise deletion and from regression estimation were similar (0.291 and 0.299, respectively), but both were notably less than that obtained from the listwise deletion R^2 (0.354). Using a stepwise method of equation building, the pairwise method yielded only a four variable equation, while the other two methods entered five predictors. Such a difference in the resulting equations makes comparison of the individual regression weights across the methods misleading. Further, the comparison of the missing data treatment methods is inhibited because a criterion value of R^2 is not available. Raymond did not provide a cross-validation of the three regression equations within his research design, so an evaluation of the stability of the resulting equations was also not possible.

<u>Comparisons Incorporating Sampling Variability</u>

Raymond and Roberts (1987) compared four common missing data procedures: listwise deletion, mean substitution, simple regression estimation, and iterated regression estimation. Using computer generated multivariate normal datasets for three predictors and one criterion variable, the researchers compared the four techniques while manipulating sample size (with sizes of 50, 100, and 200), and the percentage of missing data (2%, 6%, and 10%). Additionally, the characteristics of the matrix of correlations among the four generated variables were manipulated to conform to matrices encountered in selection research. The efficacy of missing data treatments was indexed by two regression criteria, the deviation of R^2 from that of the complete sample and the sum of regression weight deviations from those of the complete sample.

The data were analyzed using analysis of variance. The experimental design crossed sample size, percent missing, and missing value treatment. The data matrix provided 30 replications per cell. The datasets generated from each of the four correlation matrices were analyzed separately. Significant main effects for sample size and proportion missing were obtained, as expected (as sample size increases and as the proportion of missing data decreases, the effectiveness of any missing data treatment is improved). Additionally, as expected, the researchers found that the four missing data procedures converged as the sample size increased and as the proportion of missing data decreased. This corresponds to the textbook prescription that if little data are missing, all methods are about equally effective.

In general, the two regression estimation procedures (simple regression and iterated regression) were superior to the others and the mean substitution procedure was superior to the case deletion method. In addition to the accuracy of the estimates, the obtained variability of the estimates followed the same pattern, i.e., the regression estimates were the most consistent and the case deletion method was the least consistent. Because case deletion is the typical default missing data treatment in multivariate software, the results of the Raymond and Roberts' study suggest that "ignoring the missing data" is not only not the best approach, it may be the worst approach. While the obtained effect was evident on either criterion measure of effectiveness, the differences between missing data treatments were more pronounced on the regression weight criterion than on the overall magnitude of R^2.

Basilevsky, Sabourin, Hum, and Anderson (1985) compared nine missing data treatments using computer generated multivariate normal data. In addition to several deletion and imputation methods, these authors included several estimation techniques based on a principal components analysis (originally derived by Dear, 1959). The latter techniques derive the largest principal components from the complete data matrix and use these components to estimate individual missing data elements.

The researchers controlled sample size (two levels: n=60 and n=600), degree of collinearity among five predictors (three levels: .10, .50, and .90), predictability of the dependent measure (three levels: R^2=.20, .50, and .90), and extent of missing data (three levels: 10%, 30%, and 50% missing). The fifth factor (the missing data treatment) was designed as a within-subjects factor giving a five-dimensional completely-crossed design. Ten replications (different computer generated samples) were produced for each cell. Three dependent measures were used to evaluate the effectiveness of the missing data treatments: deviation of obtained value of R^2 from actual R^2, average regression weight deviation from the actual values, and difference in mean square error from that of the population.

Unfortunately, the results of the study are difficult to assess because of the way in which they were reported. The authors asserted that no significant interactions were obtained in the study but no ANOVA table was provided in their report. It is surprising that the convergence of methods when applied to larger samples and samples with greater degrees of completeness reported by Raymond and Roberts (1987) was not replicated on these data. Additionally, the results were reported in the form of Fisher LSD comparisons of each treatment with the treatment that gave the least degree of deviation from the complete sample values. The significance of the deviation of any missing data treatment method from the results obtained for the complete sample was not evaluated. Further, the results were reported as common logarithms, having been transformed from the original values for the analysis of variance.

While this simulation suggests that the commonly used missing data treatments may be superior to more complex treatments and are certainly no worse, the artificial nature of the simulated data limits its generality (the multivariate normal distribution used to generate the data had all pairwise zero-order correlations among the predictors equal to each other). Further, the lack of clarity in the reported results limits the degree of confidence in the outcome. The research also failed to indicate how poorly any estimate was, so conclusions about how much missing data is too much cannot be reached.

Summary

The empirical comparisons of missing data treatments are of limited utility to the applied researcher, not because the results are contradictory (although such contradictions are evident in the research summarized here), but because the critical concerns of the applied researcher have been inadequately addressed.

First, the effectiveness of a missing data treatment must be evaluated against a criterion. The early report of Guertin (1968) and the more recent work of Raymond (1987) showed that different missing data treatments lead to different values for computed statistics but allow no method of determining which value of the statistic is closest to the truth (either the parameter being estimated or the sample value of the statistic which would have been obtained if no data were missing). The work of Timm (1970), Donner and Rosner (1982), and Raymond and Roberts (1987) evaluated effectiveness in terms of deviation from a criterion. When such results are presented as ratios, the relative effectiveness of treatments can be addressed but an index of the absolute effectiveness of any treatment is lost. Beale and Little (1975) reported results as direct deviations from a criterion without creating ratios, a presentation which allows the reader to judge the absolute effectiveness of a treatment for a given missing data situation.

The choice of a criterion is a closely related issue. Timm

(1970) and Gleason and Staelin (1975) used an index of agreement between correlation matrices as the criterion of effectiveness. In much applied research, the correlation matrix is only a preliminary step in the analysis. The use of regression coefficients and associated statistics as criteria more closely address the effects of treatments on statistics which are likely to be critical to a research project. Beale and Little's (1975) criterion of the percent increase in SS_{resid} provides an index of the overall quality of a regression equation. Most applied research, however, involves the interpretation of regression weights and magnitudes of R^2. The effects of missing data treatments on these statistics may not be proportional to those observed on sums of squares, as suggested by the research of Basilevsky et al. (1985).

Second, the manifest differences among outcomes must be compared with differences likely to arise due to chance. Although some researchers have reported tests of hypotheses regarding differences among treatments (Basilevsky et al., 1985; Raymond and Roberts, 1987), no test of the significance of the difference between a treated matrix and the complete sample matrix has been reported. Kim and Curry (1977) reported that the estimated values obtained from their treated matrices were not notably discrepant from the variation in complete data statistics resulting from sampling.

Finally, the treatments must be applied to realistic situations. Comparisons based on actual field data (Guertin, 1968; Raymond, 1987) or on simulations based upon matrices obtained from field data (Timm, 1970; Raymond & Roberts, 1987) provide a better index of effectiveness than simulations based upon matrices not encountered in the real world (Basilevsky et al., 1985).

In general, simulation studies have dealt with idealized data produced by random number generators following an exact mathematical model (typically the multivariate normal distribution). Any actual field data naturally violates distributional assumptions to some extent. Further, the studies have failed to provide answers to the critical questions facing applied researchers concerning the selection of treatments and the amount of missing data. An examination of the effects of missing data treatments with actual field data rather than with computer generated data provides a useful extension and test of the real-world applicability of the simulations. Attention to the significance of differences in results obtained from the incomplete samples from those obtained in the complete samples will potentially yield insights not suggested from the previous research.

Method

Bootstrap samples were drawn from three large sets of actual field data, representing three types of data commonly encountered in social research: achievement test data, opinion rating scales (Likert rating data), and factor score scales (psychological trait data). Each sample was analyzed as a two-predictor regression model. Descriptive statistics on the variables comprising the three sets of data are presented in Table 1, and the regression models computed on these pseudo-populations are presented in Table 2.

From each data set 100 samples of size 50, 100, and 200 were drawn with replacement. Within each of the samples of each size, a proportion of the observations were randomly selected and assigned missing values in lieu of the existing values of one predictor variable. One hundred samples were examined at each of six levels of missing data: 10%, 20%, 30%, 40%, 50%, and 60% missing. Finally, the 100 samples of each size were examined with no missing data.

Treatments of the missing value data sets based upon listwise deletion, pairwise deletion, mean imputation, simple regression imputation, and multiple regression imputation were computed and the resulting regression parameters were compared with those of the 100 samples with no missing data. The details of these MDTs have been extensively described elsewhere (e.g., Kim & Curry, 1977), and will not be repeated here.

Data Analysis

This experimental study represents a 3 X 3 X 6 X 5 design, with two between-subjects factors (parent population and sample size) and two within-subjects factors (proportion of data missing and missing data treatment method). The dependent variables analyzed were the sample estimates of R^2 and each of the two standardized regression coefficients. The data were analyzed by computing the effect sizes obtained from the missing data treatment conditions relative to the complete sample condition.[1]

Results

The cell means and standard deviations of the obtained values of R^2, the regression weight of the variable with missing data and the regression weight of the variable without missing data are presented in Tables 3, 4, and 5, respectively.

Effects of Missing Data on R^2

The cell means for values of R^2 are presented in Figures 1, 2, and 3. Three trends in these data are evident in the figures. First, the differences among the MDTs increase as the proportion of missing data increases, an effect which is anticipated based upon previous empirical research on randomly missing data (e.g., Gleason & Staelin, 1975; Raymond & Roberts, 1987). Second, the use of larger sample sizes does not substantively ameliorate the effect of missing data on the estimates of R^2. The effects of the missing data and their treatment are relatively stable

[1] Analyses of variance were computed on these data. Because of the large sample size, all effects and interactions were statistically significant. To conserve space, the details of these analyses are not presented here, but are available upon request from the authors.

across the sample sizes examined. Finally, differences in the effectiveness of the MDTs are evident.

The use of multiple regression imputation consistently yields overestimates of R^2. Conversely, the use of mean imputation consistently yields underestimates of R^2. The simple regression imputation procedures overestimates R^2 only in the psychological trait data, where the overestimation is consistent. In the other two sets of data, the simple regression imputation procedure underestimates R^2, with the exception of the samples of size 50 in achievement data, where a slight overestimation is evident. The use of listwise deletion typically overestimates R^2 (in some exceptions, the listwise procedure underestimates the value of R^2, but the effect is very small). The pairwise deletion procedure shows a similar overestimation of R^2, with instances of underestimation. Although no MDT yields consistently best estimates of R^2 across the data sets, sample sizes, and levels of missing data examined, the listwise and pairwise deletion procedures perform better in most situations than the use of mean imputation and the two regression imputation techniques.

Effects on Beta for the Variable with Missing Data

The cell means obtained for the values of the regression weight of the variable with missing data are plotted in Figures 4, 5, and 6. The divergence in the resulting values attributed to the MDTs that was evident in the values of R^2 is also evident in the values of these regression weights. The use of multiple regression imputation consistently overestimates this regression weight, and the use of mean imputation consistently underestimates it. Simple regression yields an overestimate in the psychological trait data, an underestimate in the achievement data, and virtually no effect in the Likert rating data. The pairwise deletion procedure yields inconsistent, and small overestimates or underestimates. The listwise deletion procedure yields a small, consistent underestimate of this regression coefficient in the achievement data, and a small but inconsistent effect in the psychological trait data and Likert rating data.

Effects on Beta for the Variable without Missing Data

The cell means obtained for the values of the regression weight of the variable without missing data are presented in Figures 7, 8, and 9. The divergence of values evident with increases in the amount of missing data is also apparent in these figures. However, the direction of effects obtained from the missing data procedures are the opposite of those obtained for the other regression weight. The use of multiple regression imputation underestimates this regression weight, and the use of mean imputation overestimates it. Simple regression yields an underestimate in the psychological trait data, and small, inconsistent effects in the achievement data and Likert rating data. The pairwise deletion yields a small underestimate in the Likert rating data, but the direction of the effect is inconsistent in the achievement data and in the psychological trait data. The listwise deletion procedure yields small effects (inconsistent in direction) in all three types of data.

Discussion

As an aid to interpretation of these data, the cell means were transformed to effect sizes, according to the formula:

$$E_{hijk} = \frac{(\hat{\mu}_{hijk} - \hat{\mu}_{h00k})}{\hat{\sigma}_{h00k}}$$

where E_{hijk} = the effect size in data set h, for missing data treatment i, with proportion of missing data j and sample size k.

$\hat{\mu}_{hijk}$ = the obtained mean in data set h, for missing data treatment i, with proportion of missing data j and sample size k.

$\hat{\mu}_{h00k}$ = the obtained mean in data set h, for the 100 samples of size k with no missing data.

$\hat{\sigma}_{h00k}$ = the obtained standard deviation in data set h, for the 100 samples of size k with no missing data.

The effect sizes for the values of R^2, and each regression weight are presented in Tables 6, 7, and 8. To summarize the results obtained for the three sets of data, the obtained effect sizes were classified as significant or non-significant, from a practical perspective, on the basis of their magnitude. Effect sizes with absolute values less than 0.3 were considered to present no practical problem for the researcher, and those with effect sizes greater than or equal to 0.3 (in absolute value) were considered large enough to distort the interpretation of the regression. The criterion of 0.3 is somewhat more conservative than the 0.5 value recommended by Light and Pillmer (1984) in their consideration of "noticeable" effects. The more conservative criterion is recommended because, in contrast to the context in which Light and Pillmer were working, the regression parameters are likely to be subject to both a substantive interpretation and a test of statistical significance. A summary of this analysis of effect sizes is presented in Table 9.

In this table, the differences in performance of the missing data treatments is particularly evident. Specifically, the use of the mean substitution provided effect sizes greater than 0.3 in 61% of the situations examined in the estimation of R^2, in 93% of the situations in the estimation of the regression weight for the missing data variable, and in 78% of the situations in the estimation of the regression weight for the variable with no missing data.

A more detailed examination of the performance of the mean substitution technique shows substantial variations according to the data set analyzed. In the achievement data, only 17% of the estimates of R^2 exceeded the 0.3 effect size limit, but 94% of the estimates of each regression weight exceeded this limit. In the psychological trait data, 72% of the R^2 estimates exceeded the limit, as did 83% of the estimates of the regression weight for the variable with missing data. However, only 39% of the estimates of the regression weight for the variable without missing data exceeded the limit. Finally, in the Likert rating data, 94% of the R^2 estimates exceeded the effect size limit, as did all of the regression weight estimates (for both the variable with missing data and the variable without missing data).

Similarly, most of the effect sizes obtained with the use of the multiple regression imputation technique exceeded the 0.3 criterion. Thirty-nine percent of the effect sizes for R^2 exceeded 0.3 in the achievement data, 61% percent in the Likert rating data, and 83% in the psychological trait data. More than two-thirds of the regression weight effect sizes exceeded 0.3.

The simple regression procedure performed inconsistently in this analysis. None of the estimates of R^2 exceeded the effect size limit of 0.3 in the achievement data, but 28% exceeded this limit in the Likert rating data, and 78% exceeded the limit in the psychological trait data. In estimating the regression weight for the predictor with missing data, none of the estimates for the Likert data and only 11% of the estimates for the achievement data exceeded the effect size limit. However, 83% of the estimates for the psychological trait data exceeded this limit. The performance of the simple regression imputation procedure was better for estimation of the regression weight of the variable without missing data. For this regression weight, 28% of the estimates exceeded the effect size limit in the psychological trait data and none of the estimates exceeded the limit for the other two types of data.

The two deletion procedures yielded more accurate estimates of R^2 and both regression parameters than any of the imputation procedures. In the estimation of R^2, both the pairwise deletion approach and the listwise deletion approach yielded estimates beyond the 0.3 effect size limit in only 4% of the situations examined. In the estimation of regression weights the listwise procedure performed slightly better than the pairwise deletion procedure. None of the estimates of the regression weights exceeded the 0.3 effect size limit with the listwise deletion approach, and only 4% of the estimates exceeded this limit with the pairwise approach. However, the missing data situations in which estimates of R^2 and regression weights exceeded these limits were those in which at least 50% of the data were missing. For missing data conditions less severe than 50% missing, neither deletion procedure yielded effect sizes greater than 0.3.

Although of less concern than bias in the estimates resulting from missing data and their treatment, differential increases in the sampling variability of the parameter estimates are also evident in these data. To assist in the interpretation of these effects, ratios of the standard deviations of each regression statistic, relative to the standard deviation obtained from the complete data samples were computed.

$$\text{SD Ratio}_{hijk} = \frac{\hat{\sigma}_{hijk}}{\hat{\sigma}_{h00k}}$$

where SD Ratio_{hijk} = the standard deviation ratio in data set h, for missing data treatment i, with proportion of missing data j and sample size k.

$\hat{\sigma}_{hijk}$ = the obtained standard deviation in data set h, for missing data treatment i, with proportion of missing data j and sample size k.

$\hat{\sigma}_{h00k}$ = the obtained standard deviation in data set h, for the 100 samples of size k with no missing data.

The standard deviation ratios for the estimates of R^2, the regression for the variable with missing data, and the regression for the variable without missing data are presented in Tables 10, 11, and 12, respectively. The largest increases in the variability of R^2 are evident with the listwise deletion procedure and the two regression imputation techniques. As anticipated, the variability increases with the proportion of missing data. At the most extreme (simple regression imputation with samples of psychological trait data), the standard deviation of R^2 is twice as large as that obtained with complete data samples.

The increases in variability of the regression weights (Tables 11 and 12) are larger in magnitude than those associated with R^2 (Table 10), in some instances (i.e., multiple regression imputation in the samples of achievement data) becoming three times as large as the variability in the complete data samples. The only missing data treatment that is not associated with increases in variability is the mean imputation technique. However, the extent of bias evident with the mean imputation procedure renders its resistance to variability inflation of secondary importance.

In conclusion, the three imputation techniques examined in this study (multiple regression imputation, simple regression imputation, and mean imputation) did not perform well when applied to situations of actual field data presenting randomly missing values. Even with as little as 10% data missing, the imputation procedures can yield biased estimates with effect sizes greater than 0.3. An exception may be evident for the simple regression imputation procedure when the correlation between the predictors is very high, and the focus is on the magnitude of regression weights rather than on R^2. However, caution should be taken in using this technique. In situations where the simple regression imputation procedure was ineffective, the resulting values were extremely biased.

In contrast, the deletion procedures appear to yield results that are not appreciably different from those obtained in sets of data without missing data. Furthermore, the effectiveness of the deletion procedures are maintained throughout the range of missing data examined in this study. Even when more than half of the data are missing, the deletion procedures typically yield accurate estimates of R^2 and regression weights. The increase in the variability of the statistics evidenced in the missing data analyses implies that the researcher should make an adjustment to standard errors when testing hypotheses and constructing confidence intervals. When the level of missing data reaches 30%, an increase in the standard error of approximately 50% should provide a conservative adjustment for this increase in variability.

Without suggesting that applied researchers become complacent about missing data problems, this research provides empirical support for the use of certain MDTs and for the avoidance of other MDTs. The differences in the effectiveness of the treatments across the three types of data examined in this study highlight the need for further research to identify the types of data matrices that may be amenable to analysis by these MDTs. Equally important to the generalizability of the results are the consideration of regression models with more predictor variables, and matrices in which missing data occur on more than one predictor. Finally, additional research on variations in the nature of the missing data mechanism (i.e., nonrandomly missing data, Kromrey & Hines, 1990), will provide empirical support for the use of MDTs in situations for which the critical assumption of randomness is untenable.

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Table 1

Summary Descriptive Statistics for the Pseudo-Populations.

Achievement Data (N=1000)

Scale	Mean	SD	Skewness	Kurtosis	Reliability[a]
Mathematics	710.17	25.88	-0.01	2.02	0.96
Reading	725.09	57.27	-0.41	0.50	0.96
Language	707.77	42.18	-0.50	1.86	0.94

Correlations

	Mathematics	Reading
Reading	0.69	
Language	0.75	0.80

Likert Rating Data (N=618)

Scale	Mean	SD	Skewness	Kurtosis	Reliability[a]
Job-Relatedness	3.75	0.74	-0.50	0.17	0.84
Importance for Certification	3.75	0.76	-0.53	0.15	0.89
Frequency of Use	3.64	0.73	-0.47	0.09	0.83

Correlations

	Job-Relatedness	Importance for Certification
Importance for Certification	0.83	
Frequency of Use	0.90	0.79

Psychological Trait Data (N=908)

Scale	Mean	SD	Skewness	Kurtosis	Reliability[a]
Self-Anxiety	50.00	10.00	-1.26	0.82	0.81
Parental Anxiety	50.00	10.00	-0.04	-0.12	0.80
Parent-Child Anxiety	50.00	10.00	-0.42	0.11	0.72

Correlations

	Self-Anxiety	Parental Anxiety
Parental Anxiety	0.22	
Parent-Child Anxiety	0.44	0.38

[a]The reported reliability is the KR-20 coefficient.

Table 2

Regression Models Evaluated in the Study as Computed on the Pseudo-populations from which Samples were Drawn

Data Set	Dependent Variable	Predictors	Beta	R^2
Achievement Data	Math Score	* Reading Score	0.2338	0.5891
		Language Score	0.5673	
Psychological Trait Data	Parent-Child Anxiety	* Self-Anxiety	0.3353	0.2515
		Parental Anxiety	0.3060	
Likert Rating Data	Importance for Certification	* Job-Relatedness	0.6263	0.6990
		Frequency of Use	0.2258	

Note. The predictor with missing values is coded with an asterisk.

Table 3

Cell Means and Standard Deviations of R^2 in Three Types of Field Data.

Sample Size	Missing Data Treatment		Achievement Data							Psychological Trait Data							Likert Rating Data						
			Percent of Data Missing							Percent of Data Missing							Percent of Data Missing						
			0%	10%	20%	30%	40%	50%	60%	0%	10%	20%	30%	40%	50%	60%	0%	10%	20%	30%	40%	50%	60%
50	Mean	MN	0.605	0.602	0.601	0.598	0.595	0.597	0.595	0.257	0.243	0.241	0.222	0.212	0.208	0.200	0.708	0.689	0.672	0.662	0.657	0.651	0.650
	Sub	SD	0.100	0.101	0.103	0.100	0.104	0.102	0.103	0.094	0.097	0.094	0.096	0.096	0.103	0.094	0.098	0.101	0.103	0.108	0.105	0.107	0.109
50	Simple	MN	0.605	0.604	0.605	0.605	0.610	0.613	0.615	0.257	0.263	0.285	0.294	0.304	0.351	0.385	0.708	0.707	0.697	0.699	0.705	0.702	0.700
	Reg	SD	0.100	0.103	0.103	0.104	0.116	0.119	0.124	0.094	0.099	0.103	0.120	0.129	0.160	0.177	0.098	0.105	0.106	0.113	0.124	0.130	0.141
50	Multiple	MN	0.605	0.609	0.613	0.622	0.633	0.641	0.659	0.257	0.263	0.286	0.296	0.312	0.354	0.413	0.708	0.718	0.720	0.735	0.748	0.759	0.783
	Reg	SD	0.100	0.101	0.100	0.100	0.101	0.109	0.123	0.094	0.099	0.103	0.119	0.129	0.155	0.174	0.098	0.102	0.099	0.104	0.110	0.122	0.118
50	Listwise	MN	0.605	0.606	0.609	0.614	0.609	0.629	0.618	0.257	0.261	0.266	0.257	0.271	0.282	0.315	0.708	0.713	0.710	0.708	0.716	0.703	0.717
	Deletion	SD	0.100	0.110	0.104	0.115	0.127	0.136	0.150	0.094	0.100	0.104	0.113	0.124	0.144	0.156	0.098	0.105	0.105	0.124	0.132	0.158	0.148
50	Pairwise	MN	0.605	0.606	0.609	0.614	0.619	0.622	0.623	0.257	0.253	0.264	0.259	0.258	0.274	0.286	0.708	0.715	0.715	0.716	0.724	0.730	0.747
	Deletion	SD	0.100	0.101	0.100	0.100	0.099	0.101	0.104	0.094	0.098	0.098	0.107	0.107	0.126	0.117	0.098	0.103	0.101	0.113	0.113	0.129	0.125
100	Mean	MN	0.591	0.588	0.585	0.581	0.581	0.580	0.578	0.256	0.243	0.235	0.223	0.205	0.200	0.191	0.707	0.680	0.668	0.659	0.651	0.648	0.645
	Sub	SD	0.065	0.066	0.065	0.065	0.065	0.065	0.067	0.074	0.071	0.069	0.070	0.069	0.074	0.066	0.075	0.075	0.077	0.079	0.079	0.080	0.078
100	Simple	MN	0.591	0.588	0.586	0.586	0.587	0.590	0.601	0.256	0.267	0.286	0.301	0.306	0.345	0.377	0.707	0.703	0.696	0.690	0.688	0.696	0.680
	Reg	SD	0.065	0.065	0.065	0.068	0.071	0.078	0.091	0.074	0.078	0.080	0.084	0.095	0.127	0.148	0.075	0.076	0.083	0.079	0.095	0.106	0.101
100	Multiple	MN	0.591	0.593	0.595	0.602	0.605	0.617	0.631	0.256	0.266	0.283	0.298	0.300	0.341	0.385	0.707	0.713	0.724	0.732	0.744	0.766	0.770
	Reg	SD	0.065	0.065	0.067	0.070	0.070	0.078	0.086	0.074	0.077	0.081	0.085	0.093	0.126	0.141	0.075	0.075	0.077	0.077	0.081	0.083	0.085
100	Listwise	MN	0.591	0.594	0.596	0.599	0.604	0.614	0.601	0.256	0.256	0.261	0.261	0.252	0.270	0.276	0.707	0.706	0.714	0.707	0.712	0.718	0.714
	Deletion	SD	0.065	0.068	0.079	0.080	0.090	0.093	0.108	0.074	0.076	0.078	0.085	0.095	0.119	0.123	0.075	0.078	0.082	0.093	0.096	0.106	0.105
100	Pairwise	MN	0.591	0.592	0.592	0.595	0.596	0.601	0.603	0.256	0.256	0.259	0.259	0.248	0.260	0.267	0.707	0.706	0.714	0.712	0.715	0.725	0.726
	Deletion	SD	0.065	0.065	0.067	0.067	0.067	0.070	0.071	0.074	0.074	0.075	0.076	0.081	0.096	0.093	0.075	0.076	0.080	0.083	0.083	0.098	0.097
200	Mean	MN	0.587	0.583	0.580	0.575	0.573	0.572	0.571	0.262	0.249	0.239	0.229	0.214	0.204	0.196	0.696	0.669	0.655	0.647	0.638	0.636	0.631
	Sub	SD	0.043	0.042	0.043	0.041	0.042	0.041	0.042	0.055	0.055	0.054	0.054	0.053	0.055	0.056	0.056	0.055	0.058	0.061	0.062	0.062	0.064
200	Simple	MN	0.587	0.586	0.583	0.581	0.578	0.577	0.577	0.262	0.272	0.288	0.307	0.329	0.356	0.410	0.696	0.689	0.681	0.677	0.671	0.669	0.668
	Reg	SD	0.043	0.042	0.043	0.044	0.043	0.043	0.045	0.055	0.057	0.062	0.067	0.072	0.088	0.103	0.056	0.056	0.057	0.059	0.065	0.073	0.083
200	Multiple	MN	0.587	0.590	0.592	0.598	0.602	0.609	0.618	0.262	0.271	0.286	0.304	0.324	0.350	0.401	0.696	0.704	0.711	0.720	0.732	0.755	0.767
	Reg	SD	0.043	0.043	0.045	0.044	0.051	0.055	0.058	0.055	0.058	0.063	0.068	0.072	0.090	0.107	0.056	0.055	0.054	0.058	0.063	0.069	0.070
200	Listwise	MN	0.587	0.589	0.586	0.589	0.593	0.579	0.586	0.262	0.260	0.262	0.266	0.264	0.265	0.274	0.696	0.697	0.698	0.698	0.695	0.702	0.699
	Deletion	SD	0.043	0.045	0.050	0.053	0.059	0.066	0.073	0.055	0.057	0.060	0.065	0.068	0.078	0.082	0.056	0.056	0.058	0.069	0.071	0.079	0.082
200	Pairwise	MN	0.587	0.588	0.587	0.589	0.589	0.588	0.589	0.262	0.261	0.262	0.265	0.263	0.264	0.275	0.696	0.697	0.699	0.698	0.698	0.706	0.704
	Deletion	SD	0.043	0.043	0.044	0.043	0.046	0.046	0.045	0.055	0.056	0.058	0.060	0.061	0.070	0.076	0.056	0.055	0.057	0.064	0.065	0.069	0.073

Table 4

Cell Means and Standard Deviations of Beta for the Variable With Missing Data in Three Types of Field Data.

Sample Size	Missing Data Treatment		Achievement Data: Percent of Data Missing 0%	10%	20%	30%	40%	50%	60%	Psychological Trait Data: Percent of Data Missing 0%	10%	20%	30%	40%	50%	60%	Likert Rating Data: Percent of Data Missing 0%	10%	20%	30%	40%	50%	60%
50	Mean Sub	MN	0.211	0.165	0.141	0.113	0.087	0.085	0.074	0.324	0.298	0.296	0.258	0.241	0.225	0.204	0.616	0.416	0.295	0.223	0.165	0.119	0.112
		SD	0.163	0.155	0.147	0.144	0.124	0.133	0.117	0.111	0.113	0.105	0.112	0.104	0.112	0.119	0.240	0.237	0.173	0.152	0.144	0.123	0.114
50	Simple Reg	MN	0.211	0.213	0.207	0.200	0.209	0.212	0.205	0.324	0.330	0.360	0.363	0.375	0.424	0.440	0.616	0.612	0.609	0.610	0.603	0.607	0.646
		SD	0.163	0.169	0.178	0.211	0.233	0.270	0.288	0.111	0.123	0.132	0.161	0.169	0.197	0.253	0.240	0.262	0.259	0.293	0.320	0.338	0.408
50	Multiple Reg	MN	0.211	0.234	0.248	0.272	0.317	0.323	0.358	0.324	0.331	0.365	0.374	0.398	0.447	0.485	0.616	0.666	0.721	0.778	0.857	0.968	1.106
		SD	0.163	0.184	0.207	0.285	0.326	0.412	0.556	0.111	0.121	0.127	0.153	0.161	0.180	0.287	0.240	0.279	0.289	0.336	0.385	0.451	0.656
50	Listwise Deletion	MN	0.211	0.213	0.210	0.207	0.209	0.204	0.189	0.324	0.313	0.331	0.318	0.314	0.325	0.323	0.616	0.613	0.614	0.620	0.599	0.610	0.647
		SD	0.163	0.167	0.175	0.214	0.211	0.254	0.273	0.111	0.119	0.118	0.136	0.138	0.150	0.190	0.240	0.260	0.256	0.290	0.321	0.344	0.391
50	Pairwise Deletion	MN	0.211	0.214	0.213	0.221	0.209	0.233	0.193	0.324	0.317	0.333	0.317	0.320	0.334	0.345	0.616	0.635	0.645	0.623	0.626	0.620	0.765
		SD	0.163	0.169	0.192	0.248	0.269	0.294	0.307	0.111	0.116	0.118	0.137	0.135	0.160	0.190	0.240	0.305	0.348	0.371	0.408	0.605	0.719
100	Mean Sub	MN	0.215	0.179	0.141	0.112	0.097	0.090	0.064	0.335	0.315	0.299	0.276	0.239	0.226	0.205	0.620	0.405	0.299	0.225	0.167	0.142	0.108
		SD	0.117	0.114	0.106	0.095	0.099	0.090	0.092	0.080	0.073	0.080	0.080	0.078	0.086	0.082	0.193	0.144	0.124	0.110	0.101	0.080	0.079
100	Simple Reg	MN	0.215	0.209	0.197	0.198	0.189	0.204	0.211	0.335	0.353	0.377	0.395	0.400	0.438	0.464	0.620	0.614	0.621	0.605	0.615	0.637	0.587
		SD	0.117	0.121	0.122	0.143	0.160	0.187	0.237	0.080	0.081	0.093	0.106	0.116	0.154	0.189	0.193	0.197	0.204	0.204	0.226	0.246	0.295
100	Multiple Reg	MN	0.215	0.232	0.246	0.281	0.301	0.361	0.375	0.335	0.352	0.375	0.395	0.399	0.447	0.494	0.620	0.662	0.747	0.799	0.900	1.020	1.102
		SD	0.117	0.135	0.149	0.194	0.221	0.280	0.374	0.080	0.082	0.093	0.103	0.107	0.142	0.164	0.193	0.201	0.229	0.246	0.274	0.279	0.438
100	Listwise Deletion	MN	0.215	0.212	0.204	0.210	0.196	0.208	0.204	0.335	0.334	0.337	0.336	0.313	0.325	0.333	0.620	0.619	0.630	0.616	0.627	0.648	0.598
		SD	0.117	0.123	0.124	0.147	0.153	0.166	0.206	0.080	0.078	0.087	0.095	0.096	0.117	0.129	0.193	0.198	0.206	0.205	0.223	0.239	0.292
100	Pairwise Deletion	MN	0.215	0.220	0.213	0.223	0.218	0.243	0.214	0.335	0.335	0.339	0.337	0.319	0.331	0.339	0.620	0.611	0.659	0.628	0.640	0.687	0.676
		SD	0.117	0.132	0.135	0.156	0.170	0.184	0.224	0.080	0.078	0.087	0.092	0.095	0.119	0.131	0.193	0.191	0.241	0.264	0.277	0.346	0.487
200	Mean Sub	MN	0.237	0.191	0.160	0.120	0.096	0.085	0.065	0.341	0.319	0.303	0.283	0.256	0.232	0.213	0.628	0.408	0.294	0.232	0.170	0.140	0.108
		SD	0.094	0.090	0.089	0.079	0.070	0.071	0.068	0.058	0.058	0.056	0.061	0.053	0.057	0.060	0.129	0.115	0.095	0.077	0.066	0.072	0.052
200	Simple Reg	MN	0.237	0.235	0.226	0.222	0.206	0.216	0.207	0.341	0.357	0.379	0.402	0.431	0.461	0.520	0.628	0.623	0.610	0.612	0.615	0.633	0.608
		SD	0.094	0.101	0.104	0.108	0.121	0.130	0.150	0.058	0.061	0.065	0.080	0.080	0.096	0.108	0.129	0.137	0.140	0.157	0.159	0.185	0.181
200	Multiple Reg	MN	0.237	0.260	0.275	0.314	0.339	0.394	0.441	0.341	0.355	0.376	0.401	0.428	0.459	0.519	0.628	0.682	0.737	0.802	0.909	1.041	1.151
		SD	0.094	0.108	0.119	0.141	0.192	0.219	0.277	0.058	0.063	0.067	0.079	0.081	0.092	0.105	0.129	0.143	0.160	0.168	0.188	0.221	0.236
200	Listwise Deletion	MN	0.237	0.239	0.233	0.235	0.223	0.236	0.226	0.341	0.339	0.341	0.342	0.339	0.338	0.352	0.628	0.630	0.622	0.628	0.636	0.660	0.632
		SD	0.094	0.101	0.105	0.110	0.130	0.141	0.154	0.058	0.061	0.063	0.071	0.069	0.079	0.091	0.129	0.138	0.141	0.159	0.158	0.186	0.174
200	Pairwise Deletion	MN	0.237	0.241	0.232	0.238	0.235	0.221	0.219	0.341	0.339	0.341	0.343	0.340	0.340	0.355	0.628	0.632	0.635	0.631	0.637	0.653	0.644
		SD	0.094	0.101	0.108	0.121	0.134	0.145	0.156	0.058	0.061	0.062	0.071	0.069	0.077	0.088	0.129	0.147	0.172	0.165	0.202	0.236	0.248

Table 5

Cell Means and Standard Deviations of Beta for the Variable Without Missing Data in Three Types of Field Data.

			Achievement Data							Psychological Trait Data							Likert Rating Data						
	Missing		Percent of Data Missing							Percent of Data Missing							Percent of Data Missing						
Sample Size	Data Treatment		0%	10%	20%	30%	40%	50%	60%	0%	10%	20%	30%	40%	50%	60%	0%	10%	20%	30%	40%	50%	60%
50	Mean	MN	0.589	0.634	0.659	0.683	0.706	0.711	0.726	0.289	0.295	0.303	0.314	0.317	0.325	0.329	0.234	0.433	0.552	0.623	0.677	0.718	0.728
	Sub	SD	0.159	0.146	0.137	0.121	0.105	0.109	0.090	0.146	0.145	0.148	0.143	0.149	0.149	0.153	0.243	0.239	0.178	0.150	0.143	0.111	0.109
50	Simple	MN	0.589	0.584	0.588	0.592	0.584	0.577	0.584	0.289	0.285	0.281	0.276	0.271	0.260	0.250	0.234	0.235	0.231	0.230	0.239	0.231	0.188
	Reg	SD	0.159	0.164	0.169	0.196	0.213	0.245	0.257	0.146	0.145	0.148	0.141	0.146	0.145	0.163	0.243	0.262	0.258	0.290	0.307	0.317	0.393
50	Multiple	MN	0.589	0.566	0.553	0.531	0.489	0.475	0.439	0.289	0.283	0.276	0.269	0.256	0.249	0.238	0.234	0.185	0.128	0.074	-0.005	-0.116	-0.252
	Reg	SD	0.159	0.177	0.194	0.261	0.307	0.380	0.518	0.146	0.146	0.153	0.149	0.167	0.175	0.245	0.243	0.278	0.292	0.334	0.376	0.433	0.651
50	Listwise	MN	0.589	0.586	0.592	0.595	0.590	0.600	0.604	0.289	0.299	0.285	0.275	0.299	0.289	0.307	0.234	0.239	0.236	0.227	0.250	0.224	0.197
	Deletion	SD	0.159	0.167	0.165	0.200	0.196	0.246	0.260	0.146	0.154	0.167	0.178	0.182	0.200	0.231	0.243	0.260	0.261	0.291	0.329	0.346	0.397
50	Pairwise	MN	0.589	0.586	0.588	0.581	0.592	0.568	0.603	0.289	0.288	0.290	0.295	0.289	0.292	0.285	0.234	0.216	0.205	0.227	0.224	0.225	0.086
	Deletion	SD	0.159	0.161	0.182	0.226	0.244	0.259	0.267	0.146	0.145	0.150	0.145	0.158	0.163	0.181	0.243	0.302	0.347	0.358	0.389	0.568	0.706
100	Mean	MN	0.582	0.616	0.653	0.678	0.694	0.703	0.721	0.298	0.305	0.313	0.321	0.330	0.335	0.343	0.233	0.446	0.551	0.624	0.676	0.703	0.733
	Sub	SD	0.102	0.097	0.088	0.078	0.072	0.069	0.057	0.090	0.089	0.093	0.091	0.092	0.090	0.096	0.196	0.150	0.127	0.103	0.098	0.081	0.078
100	Simple	MN	0.582	0.583	0.590	0.586	0.592	0.577	0.574	0.298	0.292	0.286	0.281	0.278	0.262	0.255	0.233	0.234	0.221	0.233	0.219	0.200	0.239
	Reg	SD	0.102	0.109	0.111	0.128	0.138	0.161	0.193	0.090	0.088	0.092	0.091	0.092	0.091	0.106	0.196	0.200	0.206	0.204	0.220	0.238	0.291
100	Multiple	MN	0.582	0.564	0.550	0.517	0.494	0.438	0.423	0.298	0.291	0.282	0.274	0.268	0.249	0.233	0.233	0.192	0.106	0.055	-0.046	-0.162	-0.250
	Reg	SD	0.102	0.121	0.130	0.169	0.195	0.248	0.327	0.090	0.090	0.095	0.095	0.100	0.111	0.139	0.196	0.205	0.232	0.245	0.273	0.281	0.436
100	Listwise	MN	0.582	0.586	0.594	0.589	0.603	0.599	0.590	0.298	0.297	0.299	0.298	0.303	0.303	0.297	0.233	0.232	0.225	0.236	0.225	0.206	0.254
	Deletion	SD	0.102	0.108	0.113	0.134	0.143	0.152	0.186	0.090	0.094	0.102	0.106	0.122	0.139	0.160	0.196	0.205	0.211	0.208	0.228	0.251	0.300
100	Pairwise	MN	0.582	0.577	0.583	0.574	0.578	0.557	0.582	0.298	0.297	0.297	0.299	0.303	0.299	0.301	0.233	0.242	0.194	0.224	0.212	0.169	0.176
	Deletion	SD	0.102	0.117	0.115	0.132	0.143	0.153	0.180	0.090	0.089	0.094	0.093	0.095	0.095	0.110	0.196	0.194	0.240	0.254	0.268	0.334	0.477
200	Mean	MN	0.560	0.604	0.636	0.670	0.691	0.703	0.718	0.306	0.314	0.322	0.328	0.338	0.346	0.352	0.220	0.438	0.551	0.611	0.668	0.698	0.726
	Sub	SD	0.083	0.078	0.071	0.063	0.051	0.049	0.045	0.068	0.068	0.068	0.071	0.068	0.069	0.069	0.134	0.124	0.101	0.081	0.074	0.071	0.058
200	Simple	MN	0.560	0.558	0.562	0.563	0.571	0.558	0.564	0.306	0.301	0.295	0.288	0.280	0.269	0.246	0.220	0.219	0.225	0.220	0.211	0.190	0.213
	Reg	SD	0.083	0.090	0.092	0.096	0.111	0.119	0.139	0.068	0.067	0.066	0.070	0.066	0.066	0.065	0.134	0.143	0.148	0.161	0.161	0.180	0.170
200	Multiple	MN	0.560	0.538	0.522	0.485	0.457	0.403	0.355	0.306	0.300	0.291	0.282	0.271	0.258	0.230	0.220	0.166	0.111	0.047	-0.061	-0.189	-0.300
	Reg	SD	0.083	0.095	0.103	0.125	0.169	0.194	0.249	0.068	0.067	0.068	0.074	0.073	0.077	0.089	0.134	0.147	0.166	0.171	0.190	0.220	0.237
200	Listwise	MN	0.560	0.559	0.563	0.562	0.574	0.552	0.564	0.306	0.305	0.304	0.307	0.307	0.309	0.301	0.220	0.218	0.227	0.220	0.209	0.188	0.216
	Deletion	SD	0.083	0.091	0.092	0.098	0.117	0.128	0.151	0.068	0.069	0.075	0.080	0.085	0.091	0.098	0.134	0.144	0.146	0.172	0.166	0.191	0.178
200	Pairwise	MN	0.560	0.556	0.564	0.559	0.561	0.572	0.574	0.306	0.307	0.307	0.306	0.309	0.311	0.308	0.220	0.216	0.214	0.217	0.209	0.197	0.205
	Deletion	SD	0.083	0.089	0.091	0.105	0.112	0.120	0.130	0.068	0.068	0.068	0.073	0.069	0.071	0.075	0.134	0.151	0.175	0.160	0.198	0.226	0.237

Table 6

Effect Sizes of Mean Value of R^2 Obtained Under Missing Data Treatments Relative to the Distribution Under Complete Data Conditions.

		Achievement Data						Psychological Trait Data						Likert Rating Data					
		Percent of Data Missing						Percent of Data Missing						Percent of Data Missing					
Sample Size	Missing Data Treatment	10%	20%	30%	40%	50%	60%	10%	20%	30%	40%	50%	60%	10%	20%	30%	40%	50%	60%
50	Mean Sub	-0.030	-0.040	-0.070	-0.100	-0.080	-0.100	-0.149	-0.170	-0.372	-0.479	-0.521	-0.606	-0.194	-0.367	-0.469	-0.520	-0.582	-0.592
50	Simple Reg	-0.010	0.000	0.000	0.050	0.080	0.100	0.064	0.298	0.394	0.500	1.000	1.362	-0.010	-0.112	-0.092	-0.031	-0.061	-0.082
50	Multiple Reg	0.040	0.080	0.170	0.280	0.360	0.540	0.064	0.309	0.415	0.585	1.032	1.660	0.102	0.122	0.276	0.408	0.520	0.765
50	Listwise Del	0.010	0.040	0.090	0.040	0.240	0.130	0.043	0.096	0.000	0.149	0.266	0.617	0.051	0.020	0.000	0.082	-0.051	0.092
50	Pairwise Del	0.010	0.040	0.090	0.140	0.170	0.180	-0.043	0.074	0.021	0.011	0.181	0.309	0.071	0.071	0.082	0.163	0.224	0.398
100	Mean Sub	-0.046	-0.092	-0.154	-0.154	-0.169	-0.200	-0.176	-0.284	-0.446	-0.689	-0.757	-0.878	-0.360	-0.520	-0.640	-0.747	-0.787	-0.827
100	Simple Reg	-0.046	-0.077	-0.077	-0.062	-0.015	0.154	0.149	0.405	0.608	0.676	1.203	1.635	-0.053	-0.147	-0.227	-0.253	-0.147	-0.360
100	Multiple Reg	0.031	0.062	0.169	0.215	0.400	0.615	0.135	0.365	0.568	0.595	1.149	1.743	0.080	0.227	0.333	0.493	0.787	0.840
100	Listwise Del	0.046	0.077	0.123	0.200	0.354	0.154	0.000	0.068	0.068	-0.054	0.189	0.270	-0.013	0.093	0.000	0.067	0.147	0.093
100	Pairwise Del	0.015	0.015	0.062	0.077	0.154	0.185	0.000	0.041	0.041	-0.108	0.054	0.149	-0.013	0.093	0.067	0.107	0.240	0.253
200	Mean Sub	-0.093	-0.163	-0.279	-0.326	-0.349	-0.372	-0.236	-0.418	-0.600	-0.873	-1.055	-1.200	-0.482	-0.732	-0.875	-1.036	-1.071	-1.161
200	Simple Reg	-0.023	-0.093	-0.140	-0.209	-0.233	-0.233	0.182	0.473	0.818	1.218	1.709	2.691	-0.125	-0.268	-0.339	-0.446	-0.482	-0.500
200	Multiple Reg	0.070	0.116	0.256	0.349	0.512	0.721	0.164	0.436	0.764	1.127	1.600	2.527	0.143	0.268	0.429	0.643	1.054	1.268
200	Listwise Del	0.047	-0.023	0.047	0.140	-0.186	-0.023	-0.036	0.000	0.073	0.036	0.055	0.218	0.018	0.036	0.036	-0.018	0.107	0.054
200	Pairwise Del	0.023	0.000	0.047	0.047	0.023	0.047	-0.018	0.000	0.055	0.018	0.036	0.236	0.018	0.054	0.036	0.036	0.179	0.143

Table 7

Effect Sizes of Mean Value of Beta for the Variable With Missing Data Obtained Under Missing Data Treatments Relative to the Distribution Under Complete Data Conditions.

		Achievement Data						Psychological Trait Data						Likert Rating Data					
		Percent of Data Missing						Percent of Data Missing						Percent of Data Missing					
Sample Size	Missing Data Treatment	10%	20%	30%	40%	50%	60%	10%	20%	30%	40%	50%	60%	10%	20%	30%	40%	50%	60%
50	Mean Sub	-0.282	-0.429	-0.601	-0.761	-0.773	-0.840	-0.234	-0.252	-0.595	-0.748	-0.892	-1.081	-0.833	-1.338	-1.638	-1.879	-2.071	-2.100
50	Simple Reg	0.012	-0.025	-0.067	-0.012	0.006	-0.037	0.054	0.324	0.351	0.459	0.901	1.045	-0.017	-0.029	-0.025	-0.054	-0.038	0.125
50	Multiple Reg	0.141	0.227	0.374	0.650	0.687	0.902	0.063	0.369	0.450	0.667	1.108	1.450	0.208	0.438	0.675	1.004	1.467	2.042
50	Listwise Del	0.012	-0.006	-0.025	-0.012	-0.043	-0.135	-0.099	0.063	-0.054	-0.090	0.009	-0.009	-0.013	-0.008	0.017	-0.071	-0.025	0.129
50	Pairwise Del	0.018	0.012	0.061	-0.012	0.135	-0.110	-0.063	0.081	-0.063	-0.036	0.090	0.189	0.079	0.121	0.029	0.042	0.017	0.621
100	Mean Sub	-0.308	-0.632	-0.880	-1.009	-1.068	-1.291	-0.250	-0.450	-0.738	-1.200	-1.363	-1.625	-1.114	-1.663	-2.047	-2.347	-2.477	-2.653
100	Simple Reg	-0.051	-0.154	-0.145	-0.222	-0.094	-0.034	0.225	0.525	0.750	0.813	1.288	1.613	-0.031	0.005	-0.078	-0.026	0.088	-0.171
100	Multiple Reg	0.145	0.265	0.564	0.735	1.248	1.368	0.213	0.500	0.750	0.800	1.400	1.988	0.218	0.658	0.927	1.451	2.073	2.497
100	Listwise Del	-0.026	-0.094	-0.043	-0.162	-0.060	-0.094	-0.013	0.025	0.013	-0.275	-0.125	-0.025	-0.005	0.052	-0.021	0.036	0.145	-0.114
100	Pairwise Del	0.043	-0.017	0.068	0.026	0.239	-0.009	0.000	0.050	0.025	-0.200	-0.250	0.050	-0.047	0.202	0.041	0.104	0.347	0.290
200	Mean Sub	-0.489	-0.819	-1.245	-1.500	-1.617	-1.830	-0.379	-0.655	-1.000	-1.466	-1.879	-2.207	-1.705	-2.589	-3.070	-3.550	-3.783	-4.031
200	Simple Reg	-0.021	-0.117	-0.160	-0.330	-0.223	-0.319	0.276	0.655	1.052	1.552	2.069	3.086	-0.039	-0.140	-0.124	-0.101	0.039	-0.155
200	Multiple Reg	0.245	0.404	0.819	1.085	1.670	2.170	0.241	0.603	1.034	1.500	2.034	3.069	0.419	0.845	1.349	2.178	3.202	4.054
200	Listwise Del	0.021	-0.043	-0.021	-0.149	-0.011	-0.117	-0.034	0.000	0.017	-0.034	-0.052	0.190	0.016	-0.047	0.000	0.062	0.248	0.031
200	Pairwise Del	0.043	-0.053	0.011	-0.021	-0.170	-0.191	-0.034	0.000	0.034	-0.017	-0.017	0.241	0.031	0.054	0.023	0.070	0.194	0.124

Table 8

Effect Sizes of Mean Value of Beta for the Variable Without Missing Data Obtained Under Missing Data Treatments Relative to the Distribution Under Complete Data Conditions.

		Achievement Data						Psychological Trait Data						Likert Rating Data					
		Percent of Data Missing						Percent of Data Missing						Percent of Data Missing					
Sample Size	Missing Data Treatment	10%	20%	30%	40%	50%	60%	10%	20%	30%	40%	50%	60%	10%	20%	30%	40%	50%	60%
50	Mean Sub	0.283	0.440	0.591	0.736	0.767	0.862	0.041	0.096	0.171	0.192	0.247	0.274	0.819	1.309	1.601	1.823	1.992	2.033
50	Simple Reg	-0.031	-0.006	0.019	-0.031	-0.075	-0.031	-0.027	-0.055	-0.089	-0.123	-0.199	-0.267	0.004	-0.012	-0.016	0.021	-0.012	-0.189
50	Multiple Reg	-0.145	-0.226	-0.365	-0.629	-0.717	-0.943	-0.041	-0.089	-0.137	-0.226	-0.274	-0.349	-0.202	-0.436	-0.658	-0.984	-1.440	-2.000
50	Listwise Del	-0.019	0.019	0.038	0.006	0.069	0.094	0.068	-0.027	-0.096	0.068	0.000	0.123	0.021	0.008	-0.029	0.066	-0.041	-0.152
50	Pairwise Del	-0.019	-0.006	-0.050	0.019	-0.132	0.088	-0.007	0.007	0.041	0.000	0.021	-0.027	-0.074	-0.119	-0.029	-0.041	-0.037	-0.609
100	Mean Sub	0.333	0.696	0.941	1.098	1.186	1.363	0.078	0.167	0.256	0.356	0.411	0.500	1.087	1.622	1.995	2.260	2.398	2.551
100	Simple Reg	0.010	0.078	0.039	0.098	-0.049	-0.078	-0.067	-0.133	-0.189	-0.222	-0.400	-0.478	0.005	-0.061	0.000	-0.071	-0.168	0.031
100	Multiple Reg	-0.176	-0.314	-0.637	-0.863	-1.412	-1.559	-0.078	-0.178	-0.267	-0.333	-0.544	-0.722	-0.209	-0.648	-0.908	-1.423	-2.015	-2.464
100	Listwise Del	0.039	0.118	0.069	0.206	0.167	0.078	-0.011	0.011	0.000	0.056	0.056	-0.011	-0.005	-0.041	0.015	-0.041	-0.138	0.107
100	Pairwise Del	-0.049	0.010	-0.078	-0.039	-0.245	0.000	-0.011	-0.011	0.011	0.056	0.011	0.033	0.046	-0.199	-0.046	-0.107	-0.327	-0.291
200	Mean Sub	0.530	0.916	1.325	1.578	1.723	1.904	0.118	0.235	0.324	0.471	0.588	0.676	1.627	2.470	2.918	3.343	3.567	3.776
200	Simple Reg	-0.024	0.024	0.036	0.133	-0.024	0.048	-0.074	-0.162	-0.265	-0.382	-0.544	-0.882	-0.007	0.037	0.000	-0.067	-0.224	-0.052
200	Multiple Reg	-0.265	-0.458	-0.904	-1.241	-1.892	-2.470	-0.088	-0.221	-0.353	-0.515	-0.706	-1.118	-0.403	-0.813	-1.291	-2.097	-3.052	-3.881
200	Listwise Del	-0.012	0.036	0.024	0.169	-0.096	0.048	-0.015	-0.029	0.015	0.015	0.044	-0.074	-0.015	0.052	0.000	-0.082	-0.239	-0.030
200	Pairwise Del	-0.048	0.048	0.012	0.012	0.145	0.169	0.015	0.015	0.000	0.000	0.074	0.029	-0.030	-0.045	-0.022	-0.082	-0.172	-0.112

Table 9

Number and percent of cells yielding effect sizes greater than or equal to 0.3.

Estimation of R-Square

Missing Data Treatment	Achievement Data	Psychological Trait Data	Likert Rating Data	Overall
Mean Substitution	3 (17%)	13 (72%)	17 (94%)	33 (61%)
Multiple Regression	7 (39%)	15 (83%)	11 (61%)	33 (61%)
Simple Regression	0 (0%)	14 (78%)	5 (28%)	19 (35%)
Listwise Deletion	1 (6%)	1 (6%)	0 (0%)	2 (4%)
Pairwise Deletion	0 (0%)	1 (6%)	1 (6%)	2 (4%)

Estimation of the Regression Weight for the Variable With Missing Data

Missing Data Treatment	Achievement Data	Psychological Trait Data	Likert Rating Data	Overall
Mean Substitution	17 (94%)	15 (83%)	18 (100%)	50 (93%)
Multiple Regression	13 (72%)	15 (83%)	16 (89%)	44 (81%)
Simple Regression	2 (11%)	15 (83%)	0 (0%)	17 (31%)
Listwise Deletion	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Pairwise Deletion	0 (0%)	0 (0%)	2 (11%)	2 (4%)

Estimation of the Regression Weight for the Variable Without Missing Data

Missing Data Treatment	Achievement Data	Psychological Trait Data	Likert Rating Data	Overall
Mean Substitution	17 (94%)	7 (39%)	18 (100%)	42 (78%)
Multiple Regression	14 (78%)	8 (44%)	16 (89%)	38 (70%)
Simple Regression	0 (0%)	5 (28%)	0 (0%)	5 (9%)
Listwise Deletion	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Pairwise Deletion	0 (0%)	0 (0%)	2 (11%)	2 (4%)

Table 10

Ratios of Within-cell Standard Deviation of R^2 Under Missing Data Treatments to the Within-cell Standard Deviation Under Complete Data Conditions.

Sample Size	Missing Data Treatment	Achievement Data						Psychological Trait Data						Likert Rating Data					
		Percent Mising						Percent Mising						Percent Mising					
		10%	20%	30%	40%	50%	60%	10%	20%	30%	40%	50%	60%	10%	20%	30%	40%	50%	60%
50	Mean Sub	1.010	1.030	1.000	1.040	1.020	1.030	1.032	1.000	1.021	1.021	1.096	1.000	1.031	1.051	1.102	1.071	1.092	1.112
50	Simple Reg	1.030	1.030	1.040	1.160	1.190	1.240	1.053	1.096	1.277	1.372	1.702	1.883	1.071	1.082	1.153	1.265	1.327	1.439
50	Multiple Reg	1.010	1.000	1.000	1.010	1.090	1.230	1.053	1.096	1.266	1.372	1.649	1.851	1.041	1.010	1.061	1.122	1.245	1.204
50	Listwise Del	1.100	1.040	1.150	1.270	1.360	1.500	1.064	1.106	1.202	1.319	1.532	1.660	1.071	1.071	1.265	1.347	1.612	1.510
50	Pairwise Del	1.010	1.000	1.000	0.990	1.010	1.040	1.043	1.043	1.138	1.138	1.340	1.245	1.051	1.031	1.153	1.153	1.316	1.276
100	Mean Sub	1.015	1.000	1.000	1.000	1.000	1.031	0.959	0.932	0.946	0.932	1.000	0.892	1.000	1.027	1.053	1.053	1.067	1.040
100	Simple Reg	1.000	1.000	1.046	1.092	1.200	1.400	1.054	1.081	1.135	1.284	1.716	2.000	1.013	1.107	1.053	1.267	1.413	1.347
100	Multiple Reg	1.000	1.031	1.077	1.077	1.200	1.323	1.041	1.095	1.149	1.257	1.703	1.905	1.000	1.027	1.027	1.080	1.107	1.133
100	Listwise Del	1.046	1.215	1.231	1.385	1.431	1.662	1.027	1.054	1.149	1.284	1.608	1.662	1.040	1.093	1.240	1.280	1.413	1.400
100	Pairwise Del	1.000	1.031	1.031	1.031	1.077	1.092	1.000	1.014	1.027	1.095	1.297	1.257	1.013	1.067	1.107	1.107	1.307	1.293
200	Mean Sub	0.977	1.000	0.953	0.977	0.953	0.977	1.000	0.982	0.982	0.964	1.000	1.018	0.982	1.036	1.089	1.107	1.107	1.143
200	Simple Reg	0.977	1.000	1.023	1.000	1.000	1.047	1.036	1.127	1.218	1.309	1.600	1.873	1.000	1.018	1.054	1.161	1.304	1.482
200	Multiple Reg	1.000	1.047	1.023	1.186	1.279	1.349	1.055	1.145	1.236	1.309	1.636	1.945	0.982	0.964	1.036	1.125	1.232	1.250
200	Listwise Del	1.047	1.163	1.233	1.372	1.535	1.698	1.036	1.091	1.182	1.236	1.418	1.491	1.000	1.036	1.232	1.268	1.411	1.464
200	Pairwise Del	1.000	1.023	1.000	1.070	1.070	1.047	1.018	1.055	1.091	1.109	1.273	1.382	0.982	1.018	1.143	1.161	1.232	1.304

Table 11

Ratios of Within-cell Standard Deviation of the Regression Weight for the Variable With Missing Data Under Missing Data Treatments to the Within-cell Standard Deviation Under Complete Data Conditions.

		Achievement Data						Psychological Trait Data						Likert Rating Data					
		Percent Mising						Percent Mising						Percent Mising					
Sample Size	Missing Data Treatment	10%	20%	30%	40%	50%	60%	10%	20%	30%	40%	50%	60%	10%	20%	30%	40%	50%	60%
50	Mean Sub	0.951	0.902	0.883	0.761	0.816	0.718	1.018	0.946	1.009	0.937	1.009	1.072	0.988	0.721	0.633	0.600	0.513	0.475
50	Simple Reg	1.037	1.092	1.294	1.429	1.656	1.767	1.108	1.189	1.450	1.523	1.775	2.279	1.092	1.079	1.221	1.333	1.408	1.700
50	Multiple Reg	1.129	1.270	1.748	2.000	2.528	3.411	1.090	1.144	1.378	1.450	1.622	2.586	1.163	1.204	1.400	1.604	1.879	2.733
50	Listwise Del	1.025	1.074	1.313	1.294	1.558	1.675	1.072	1.063	1.225	1.243	1.351	1.712	1.083	1.067	1.208	1.338	1.433	1.629
50	Pairwise Del	1.037	1.178	1.521	1.650	1.804	1.883	1.045	1.063	1.234	1.216	1.441	1.712	1.271	1.450	1.546	1.700	2.521	2.996
100	Mean Sub	0.974	0.906	0.812	0.846	0.769	0.786	0.913	1.000	1.000	0.975	1.075	1.025	0.746	0.642	0.570	0.523	0.415	0.409
100	Simple Reg	1.034	1.043	1.222	1.368	1.598	2.026	1.013	1.163	1.325	1.450	1.925	2.363	1.021	1.057	1.057	1.171	1.275	1.528
100	Multiple Reg	1.154	1.274	1.658	1.889	2.393	3.197	1.025	1.163	1.288	1.338	1.775	2.050	1.041	1.187	1.275	1.420	1.446	2.269
100	Listwise Del	1.051	1.060	1.256	1.308	1.419	1.761	0.975	1.088	1.188	1.200	1.463	1.613	1.026	1.067	1.062	1.155	1.238	1.513
100	Pairwise Del	1.128	1.154	1.333	1.453	1.573	1.915	0.975	1.088	1.150	1.188	1.488	1.638	0.990	1.249	1.368	1.435	1.793	2.523
200	Mean Sub	0.957	0.947	0.840	0.745	0.755	0.723	1.000	0.966	1.052	0.914	0.983	1.034	0.891	0.736	0.597	0.512	0.558	0.403
200	Simple Reg	1.074	1.106	1.149	1.287	1.383	1.596	1.052	1.121	1.379	1.379	1.655	1.862	1.062	1.085	1.217	1.233	1.434	1.403
200	Multiple Reg	1.149	1.266	1.500	2.043	2.330	2.947	1.086	1.155	1.362	1.397	1.586	1.810	1.109	1.240	1.302	1.457	1.713	1.829
200	Listwise Del	1.074	1.117	1.170	1.383	1.500	1.638	1.052	1.086	1.224	1.190	1.362	1.569	1.070	1.093	1.233	1.225	1.442	1.349
200	Pairwise Del	1.074	1.149	1.287	1.426	1.543	1.660	1.052	1.069	1.224	1.190	1.328	1.517	1.140	1.333	1.279	1.566	1.829	1.922

Table 12

Ratios of Within-cell Standard Deviation of the Regression Weight for the Variable Without Missing Data Under Missing Data Treatments to the Within-cell Standard Deviation under Complete Data Conditions.

Sample Size	Missing Data Treatment	Achievement Data						Psychological Trait Data						Likert Rating Data					
		Percent Mising						Percent Mising						Percent Mising					
		10%	20%	30%	40%	50%	60%	10%	20%	30%	40%	50%	60%	10%	20%	30%	40%	50%	60%
50	Mean Sub	0.918	0.862	0.761	0.660	0.686	0.566	0.993	1.014	0.979	1.021	1.021	1.048	0.984	0.733	0.617	0.588	0.457	0.449
50	Simple Reg	1.031	1.063	1.233	1.340	1.541	1.616	0.993	1.014	0.966	1.000	0.993	1.116	1.078	1.062	1.193	1.263	1.305	1.617
50	Multiple Reg	1.113	1.220	1.642	1.931	2.390	3.258	1.000	1.048	1.021	1.144	1.199	1.678	1.144	1.202	1.374	1.547	1.782	2.679
50	Listwise Del	1.050	1.038	1.258	1.233	1.547	1.635	1.055	1.144	1.219	1.247	1.370	1.582	1.070	1.074	1.198	1.354	1.424	1.634
50	Pairwise Del	1.013	1.145	1.421	1.535	1.629	1.679	0.993	1.027	0.993	1.082	1.116	1.240	1.243	1.428	1.473	1.601	2.337	2.905
100	Mean Sub	0.951	0.863	0.765	0.706	0.676	0.559	0.989	1.033	1.011	1.022	1.000	1.067	0.765	0.648	0.526	0.500	0.413	0.398
100	Simple Reg	1.069	1.088	1.255	1.353	1.578	1.892	0.978	1.022	1.011	1.022	1.011	1.178	1.020	1.051	1.041	1.122	1.214	1.485
100	Multiple Reg	1.186	1.275	1.657	1.912	2.431	3.206	1.000	1.056	1.056	1.111	1.233	1.544	1.046	1.184	1.250	1.373	1.434	2.224
100	Listwise Del	1.059	1.108	1.314	1.402	1.490	1.824	1.044	1.133	1.178	1.356	1.544	1.778	1.046	1.077	1.061	1.163	1.281	1.531
100	Pairwise Del	1.147	1.127	1.294	1.402	1.500	1.765	0.989	1.044	1.033	1.056	1.056	1.222	0.990	1.224	1.296	1.367	1.704	2.434
200	Mean Sub	0.940	0.855	0.759	0.614	0.590	0.542	1.000	1.000	1.044	1.000	1.015	1.015	0.925	0.754	0.604	0.552	0.530	0.433
200	Simple Reg	1.084	1.108	1.157	1.337	1.434	1.675	0.985	0.971	1.029	0.971	0.971	0.956	1.067	1.104	1.201	1.201	1.343	1.269
200	Multiple Reg	1.145	1.241	1.506	2.036	2.337	3.000	0.985	1.000	1.088	1.074	1.132	1.309	1.097	1.239	1.276	1.418	1.642	1.769
200	Listwise Del	1.096	1.108	1.181	1.410	1.542	1.819	1.015	1.103	1.176	1.250	1.338	1.441	1.075	1.090	1.284	1.239	1.425	1.328
200	Pairwise Del	1.072	1.096	1.265	1.349	1.446	1.566	1.000	1.000	1.074	1.015	1.044	1.103	1.127	1.306	1.194	1.478	1.687	1.769

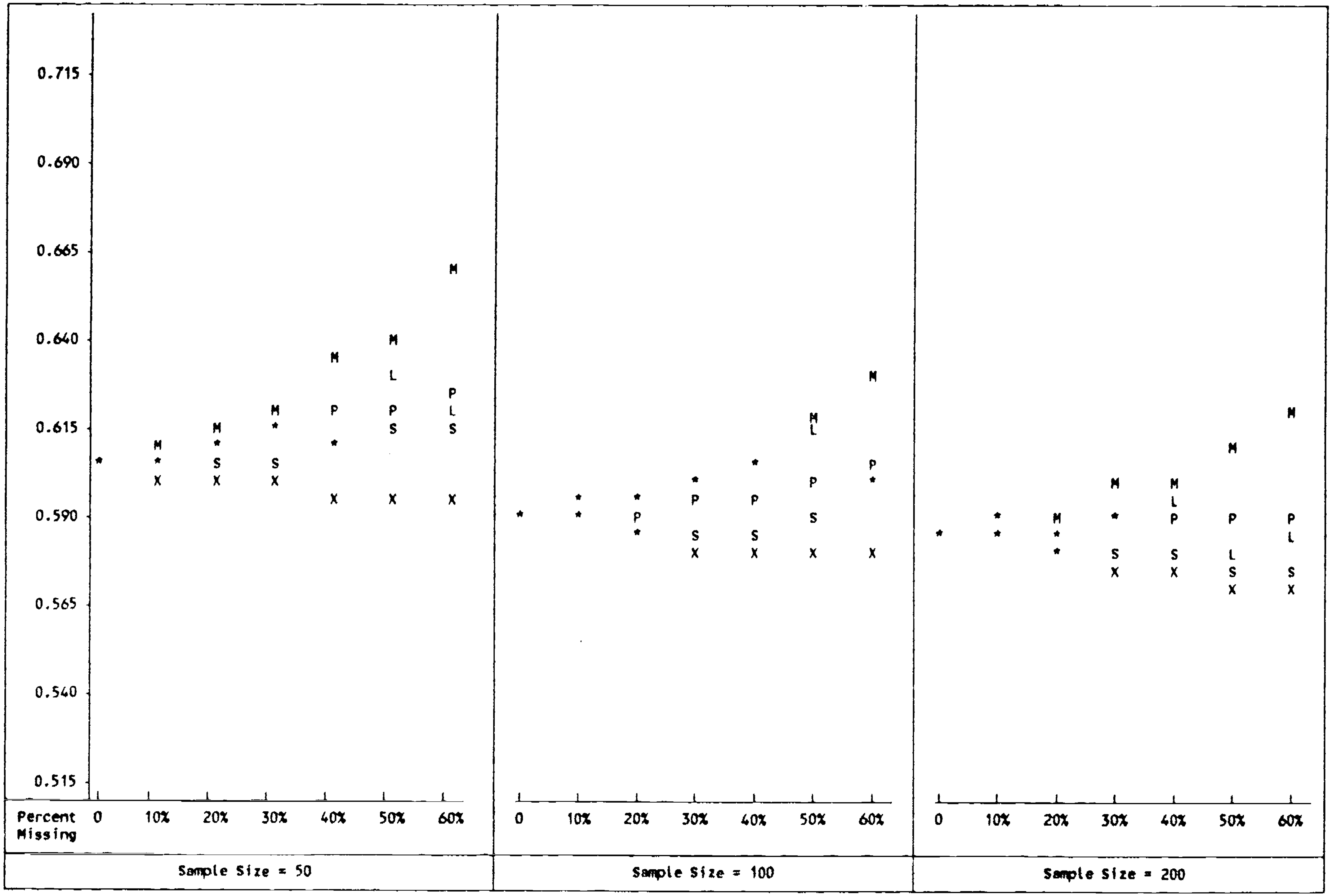

Figure 1
Cell Means of R^2 in Achievement Data Samples.

Key:

M: Multiple Regression Imputation
S: Simple Regression Imputation
X: Mean Imputation
L: Listwise Deletion
P: Pairwise Deletion
*: Mulitple Cell Means

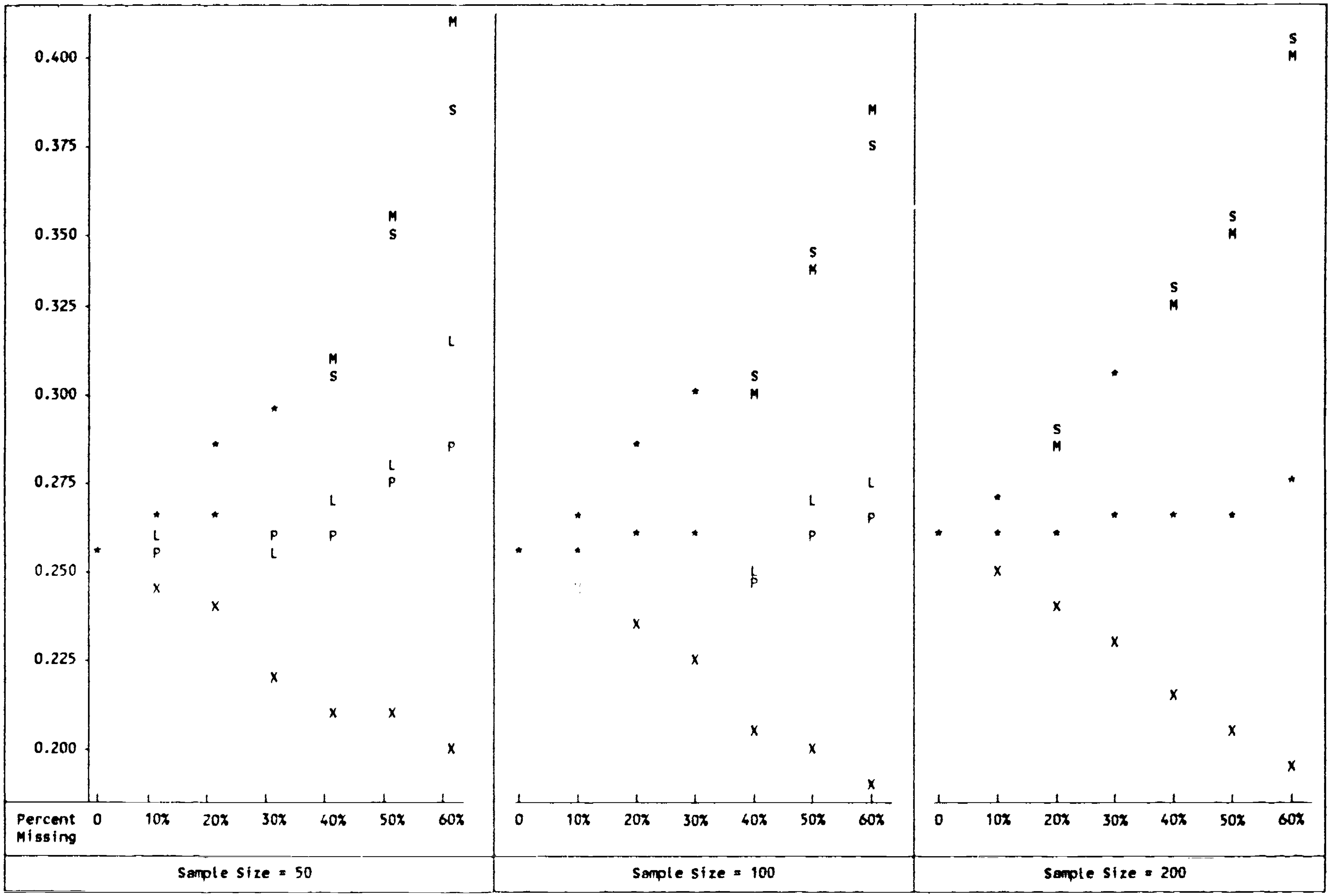

Figure 2
Cell Means of R^2 in Psychological Trait Data Samples.

Key:

M: Multiple Regression Imputation
S: Simple Regression Imputation
X: Mean Imputation
L: Listwise Deletion
P: Pairwise Deletion
*: Mulitple Cell Means

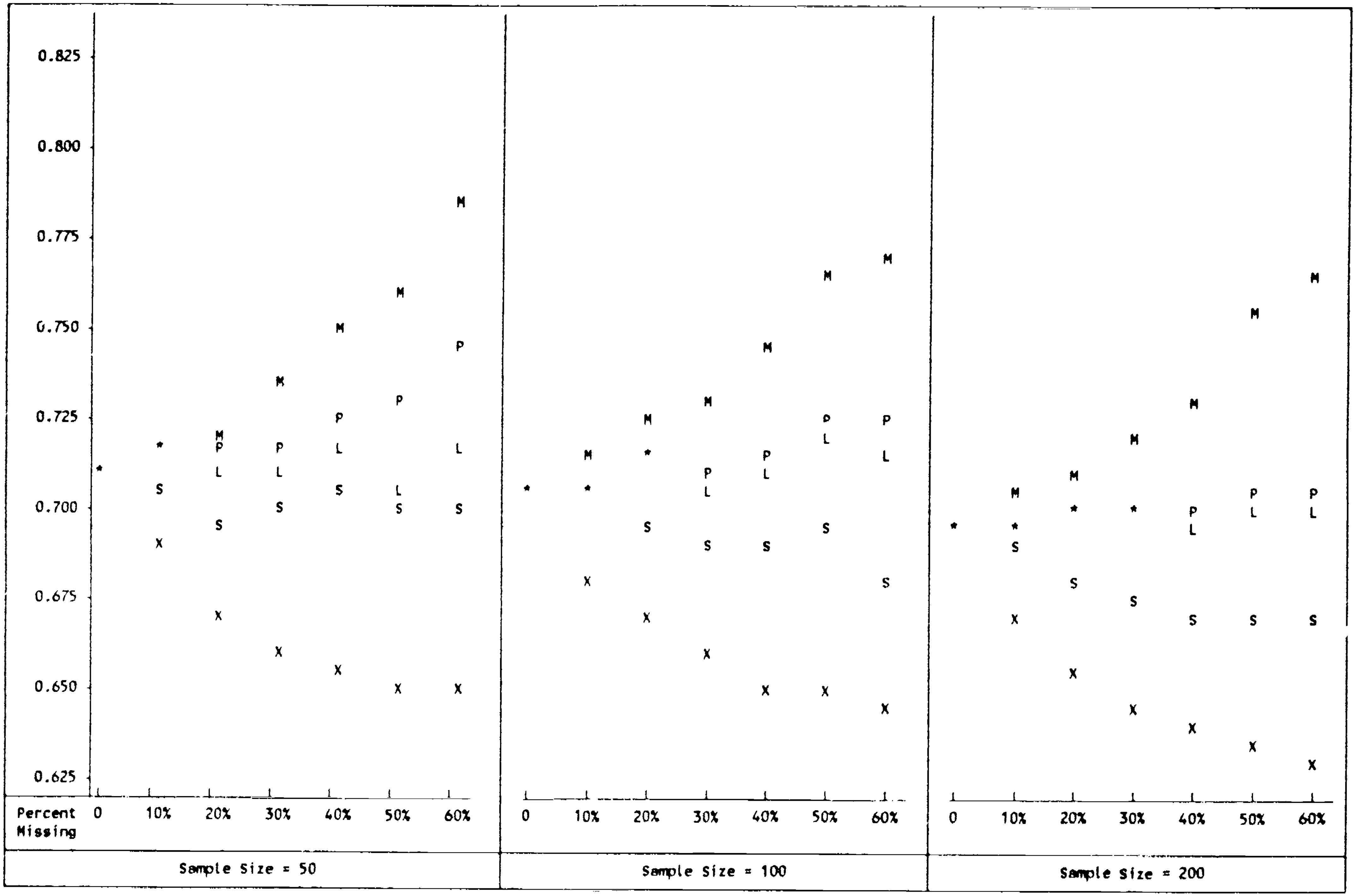

Figure 3
Cell Means of R^2 in Likert Rating Data Samples.

Key:

M: Multiple Regression Imputation
S: Simple Regression Imputation
X: Mean Imputation
L: Listwise Deletion
P: Pairwise Deletion
*: Mulitple Cell Means

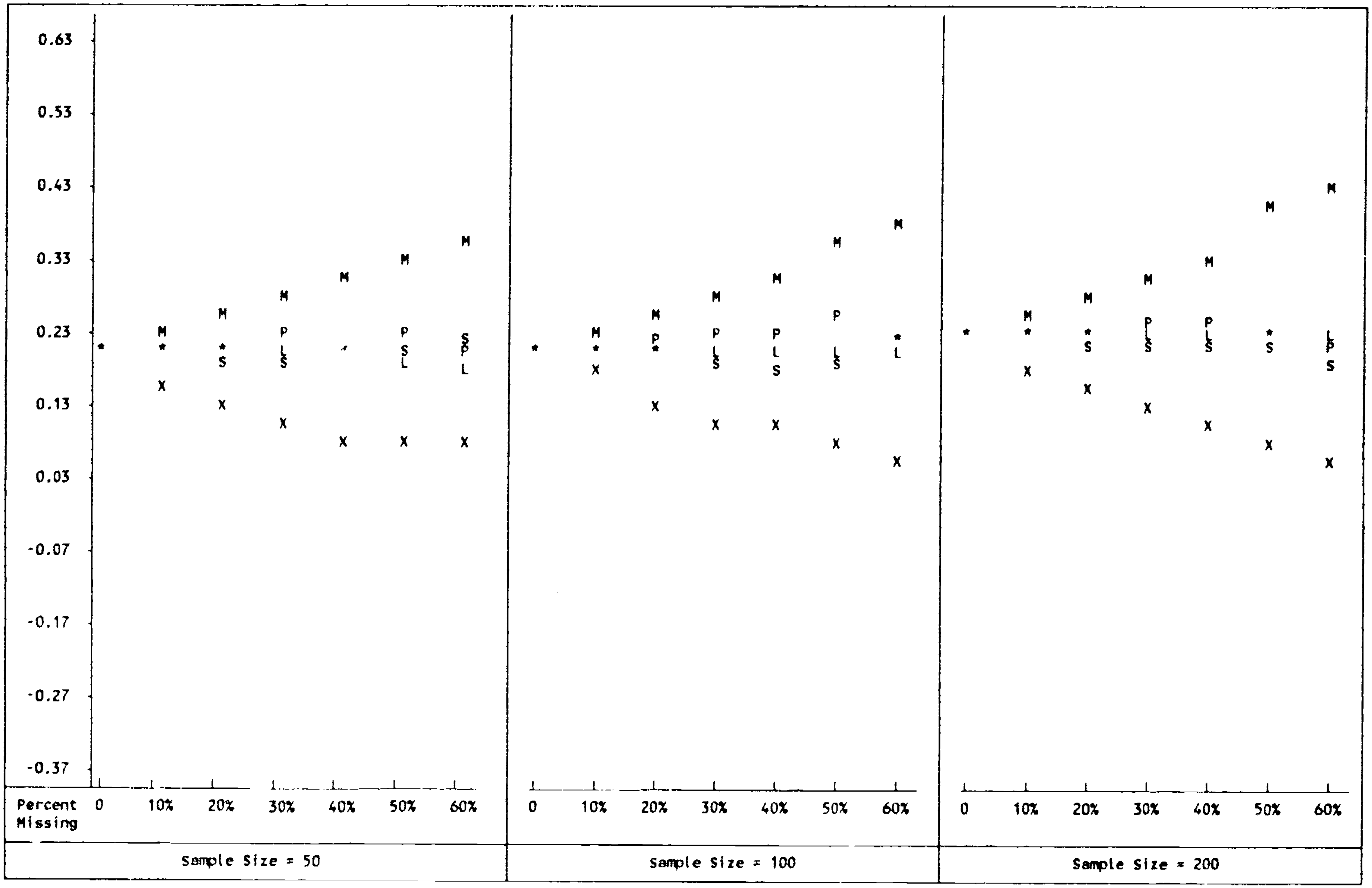

Figure 4
Cell Means of Regression Weight for the Variable with Missing Values in Achievement Data Samples.

Key:

M: Multiple Regression Imputation
S: Simple Regression Imputation
X: Mean Imputation
L: Listwise Deletion
P: Pairwise Deletion
*: Mulitple Cell Means

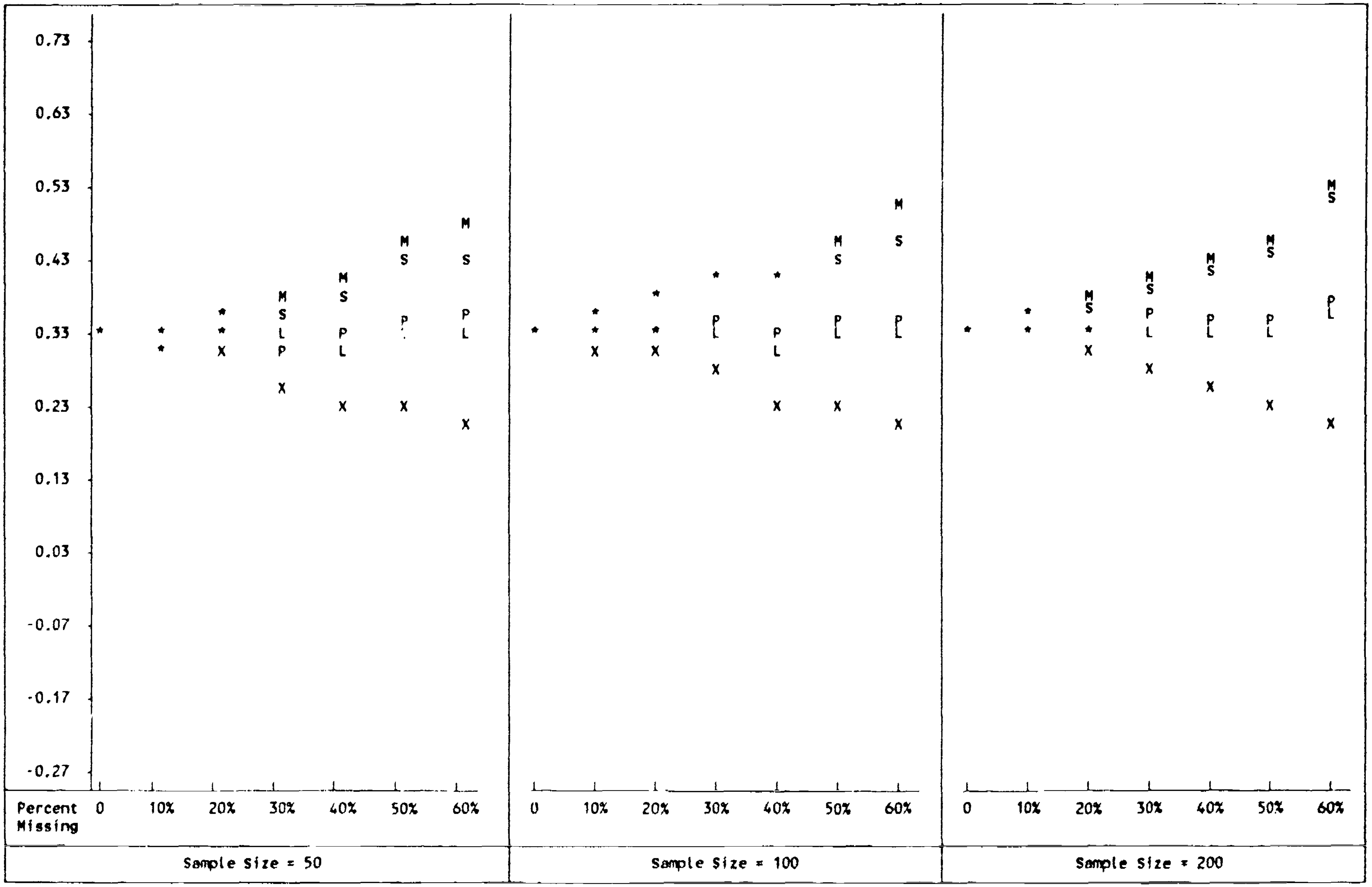

Figure 5
Cell Means of Regression Weight for the Variable with Missing Values in Psychological Trait Data Samples.

Key:

M: Multiple Regression Imputation
S: Simple Regression Imputation
X: Mean Imputation
L: Listwise Deletion
P: Pairwise Deletion
*: Mulitple Cell Means

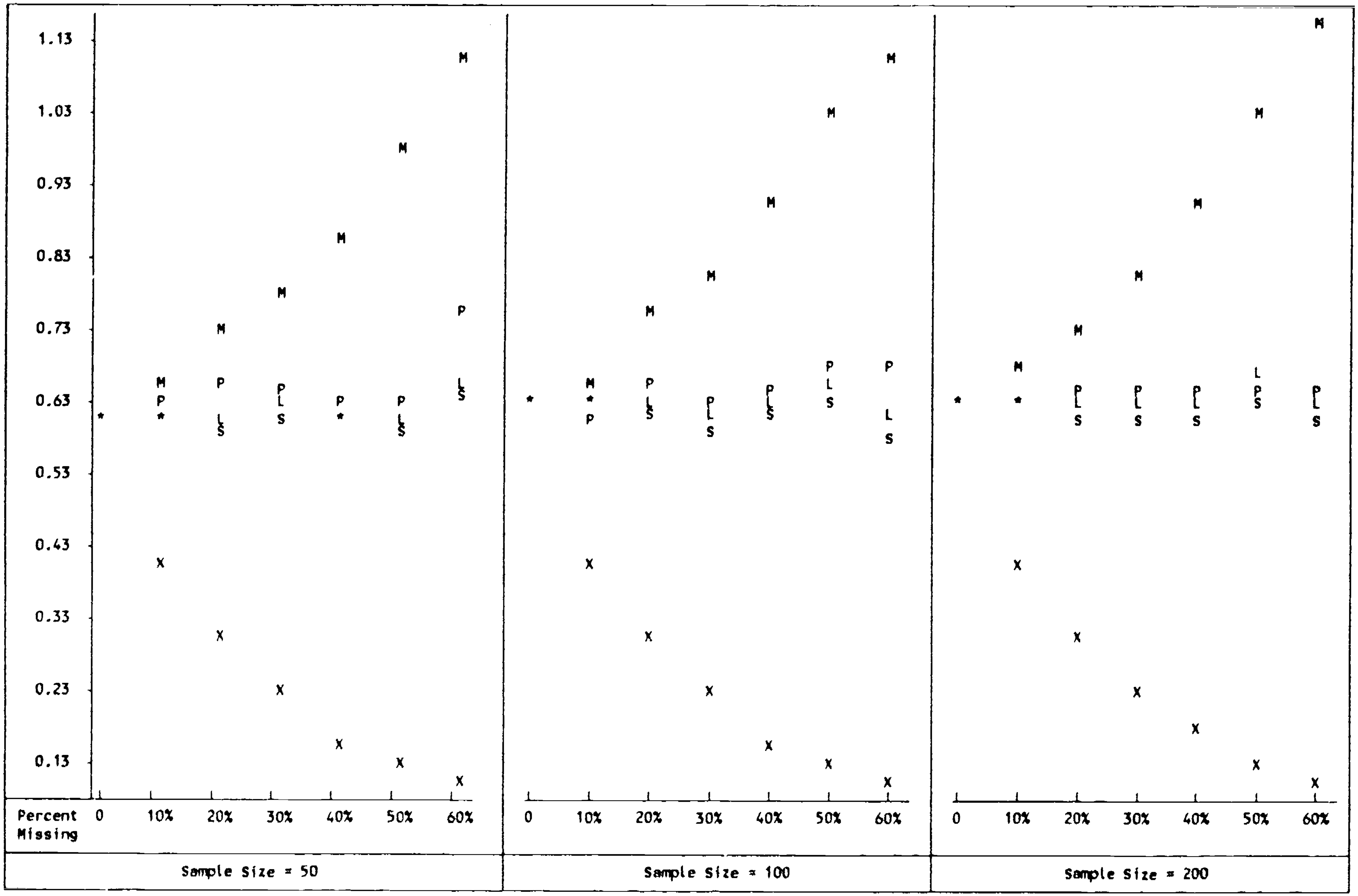

Figure 6
Cell Means of Regression Weight for the Variable with Missing Values in Likert Rating Data Samples.

Key:

M: Multiple Regression Imputation
S: Simple Regression Imputation
X: Mean Imputation
L: Listwise Deletion
P: Pairwise Deletion
*: Mulitple Cell Means

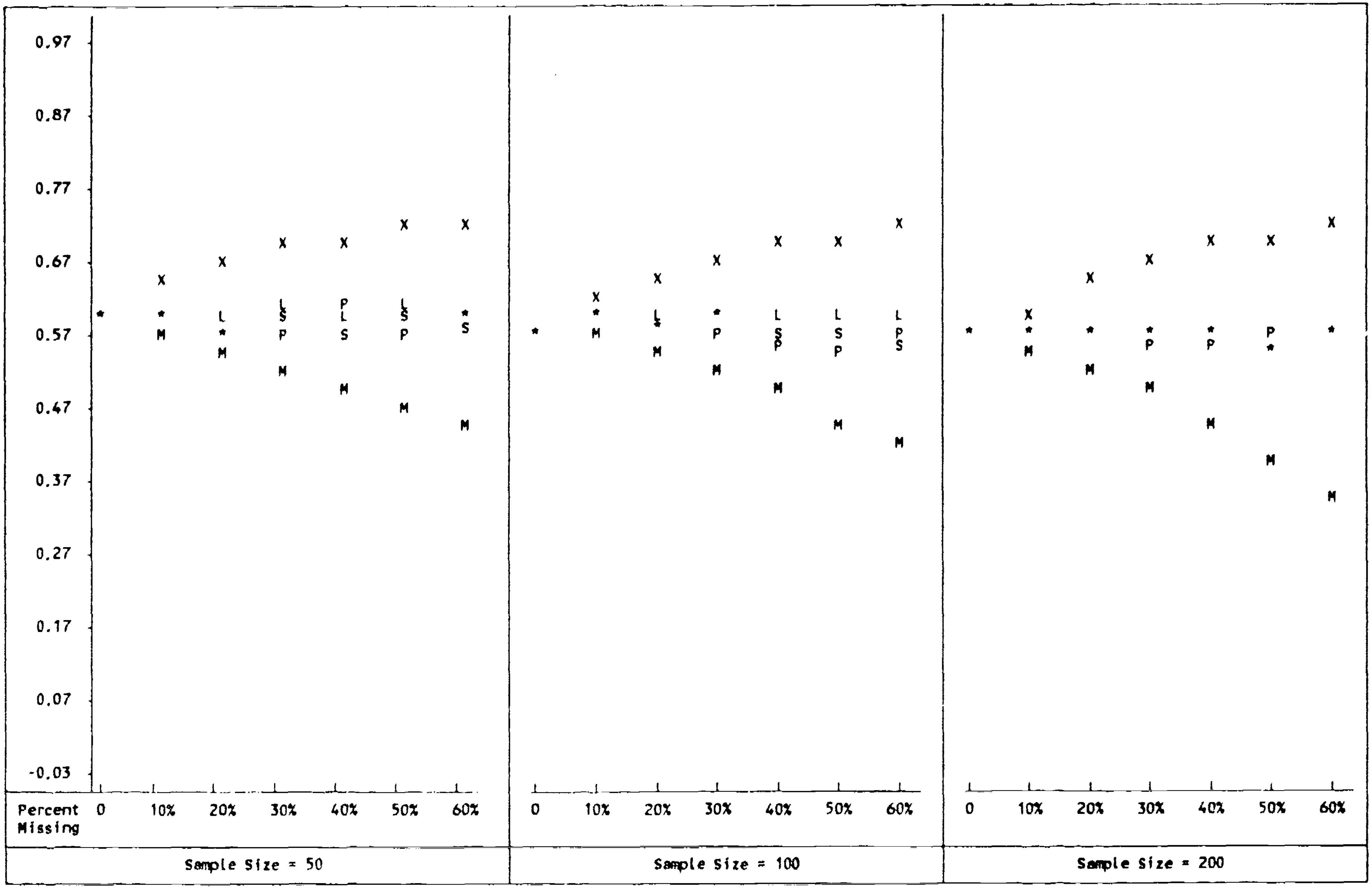

Figure 7
Cell Means of Regression Weight for the Variable Without Missing Values in Achievement Data Samples.

Key:

M: Multiple Regression Imputation
S: Simple Regression Imputation
X: Mean Imputation
L: Listwise Deletion
P: Pairwise Deletion
*: Mulitple Cell Means

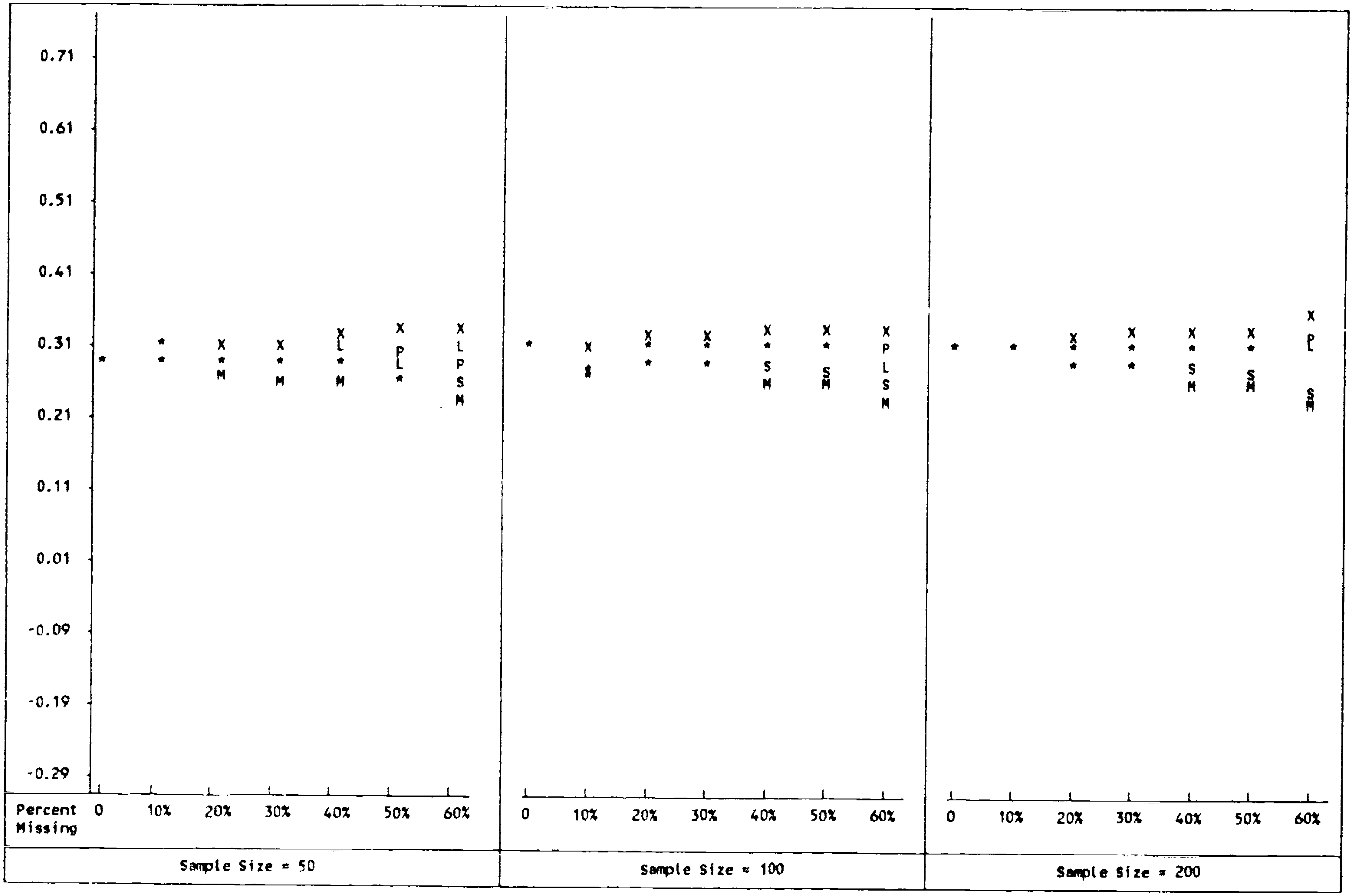

Figure 8
Cell Means of Regression Weight for the Variable Without Missing Values in Psychological Trait Data Samples.

Key:

M: Multiple Regression Imputation
S: Simple Regression Imputation
X: Mean Imputation
L: Listwise Deletion
P: Pairwise Deletion
*: Mulitple Cell Means

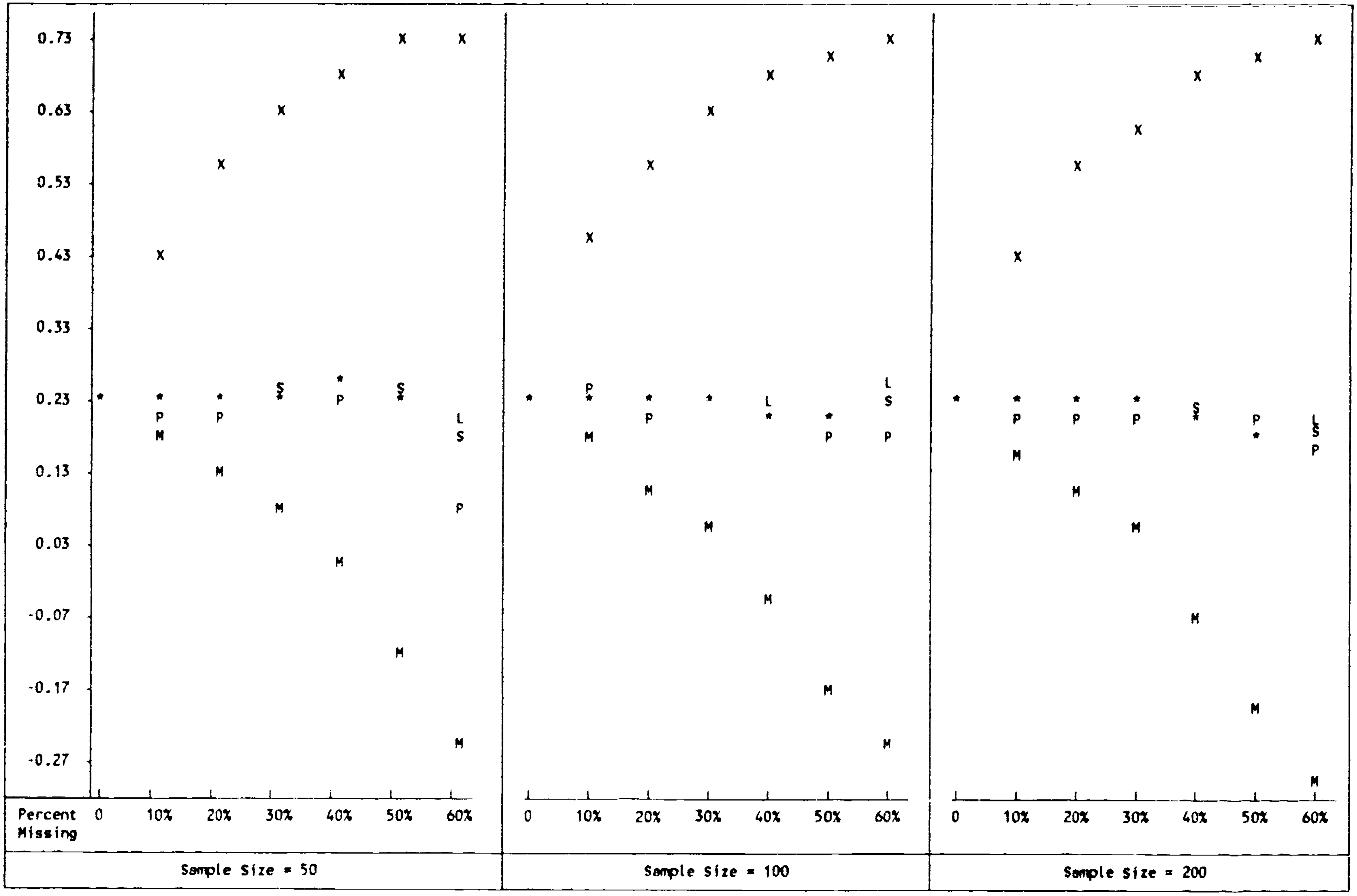

Figure 9
Cell Means of Regression Weight for the Variable Without Missing Values in Likert Rating Data Samples.

Key:

M: Multiple Regression Imputation
S: Simple Regression Imputation
X: Mean Imputation
L: Listwise Deletion
P: Pairwise Deletion
*: Mulitple Cell Means