APPENDIX

STATISTICAL ADJUSTMENT FOR EMPTY CELLS IN ANALYZING PROPORTIONS

Averaged over the four experiments, the signal detection analyses reported in this manuscript required dealing with 88% of subjects having one or more empty cells in the 2^4 classification of responses as signal (famous name) vs. noise (nonfamous name), male vs. female, old vs. new, and judgment of name (famous vs. nonfamous). The most frequently empty cells were ones for false alarms (nonfamous names judged famous). Also occasionally empty were cells for misses (famous names judged nonfamous). The presence of a single empty cell in a subject's data yielded a computationally obstructive infinity when the observed proportion of 0 was interpreted as an area to be converted to a standard normal deviate for computation of d' of log β.[1]

This appendix describes a method that was developed, in the course of the present research, to deal with the computational problem caused by empty cells, and compares this procedure to other existing fixup methods for dealing with empty cells. Although the new method is likely to be useful in other situations in which empty cells disrupt proportion- or ratio-based computations, no attempt is made here to establish its value in a general fashion.

Existing fixup methods. Four existing methods are (a) to drop subjects whose data have any empty cells, (b) to add the constant 0.5 to all cells in a design, guaranteeing no empty cells (Agresti, 1990), (c) to replace zeros with a very small constant such as 10^{-8} (Agresti, 1990), or (d) to set minimum and maximum values for proportions that might be computed from observed data, such as 0.005 and 0.995 (Ahroon & Pastore, 1977). Although no solution to the problem of empty cells is perfect, applications to simulated data resembling those of the present research made it apparent that each of the standard fixup methods is capable of producing noticeable distortions.

Simulation. The upper left panel of Figure A1 compares the four fixup procedures just listed, each applied to simulated data that might have been obtained in the present research. For these simulations, z values in the range from 0 to 3.5 were converted to probabilities (areas of the normal distribution to the right of the z-value). Then, each such probability was interpreted as a population proportion of yes responses, and 1000 samples of 18 yes-no responses — corresponding to the number of responses in each cell of the present experimental designs — were randomly generated from that proportion. After converting the resulting cell proportions to z-values for each of the resulting samples (first applying the fixup method for any zero values), the 1000 resulting estimates of each z were

[1] Each empty cell is paired with a full cell. For example, when no nonfamous names are judged famous, all nonfamous names are judged nonfamous. Full cells are computationally obstructive for the same reason that empty cells are. Because empty and full cells also prevent computation of ratios, ratio-based nonparametric forms of signal detection analysis do not escape the computational problem.

averaged. The simulation results shown in the upper left panel of Figure A1 make it obvious that each of the four existing fixup methods has substantial potential to produce biased estimates.

The lower left panel of Figure A1 shows standard deviations of the simulated estimates for each of the four existing fixup methods. The standard deviations associated with the method of replacing zero with 10^{-8} were severely inflated. For the methods of dropping subjects and adding 0.5 to all cells, it appeared that variability of larger absolute values of z were desirably low. However, that appearance is a consequence of the truncated range of possible values that the observed proportion could assume in each case, a factor that also causes these methods to be insensitive to variations in input value of z greater than about 1.5.

INSERT FIGURE A1 ABOUT HERE

Model-sensitive correction. Evidence for weakness of the standard fixup methods in the left-hand panels of Figure A1 led the authors to seek a more effective method for the severe empty cell problem that characterized the present data. A common feature of the four standard fixup methods is their *model insensitivity* — no matter what the theoretical model is for the condition in which an empty cell is found, a fixed replacement value is used. By contrast, the method developed for the present research is *model sensitive*. To appreciate the intuition that favors model-sensitive replacements for empty cells, consider that if an empty cell arises in an experiment in which the population proportion being estimated in the cell is small (say, 0.001), it would seem reasonable to use a method that replaces the empty cell with a numerically smaller value than should be used for an empty cell in an experiment with a higher population proportion (say, 0.1 or 0.25).

In the case of the present simulation, the best estimate of the expected proportion of yes responses is the observed proportion of yesses, averaged across subjects (p). The simplest model-sensitive fixup method for this situation is based on the assumption that, if another trial were to be conducted for a subject who has produced zero yes responses in k opportunities, the best estimate of a yes response for this additional trial is p. A possible fixup method, then, is to add a single hypothetical trial to the subject's data, distributing that trial proportionally to the yes and no categories. In the present simulation, the proportion of yes responses is changed from zero ($= 0/18$) to $p/(19)$ and the proportion of no responses is changed from 1.0 ($= 18/18$) to $(18+p)/(19)$. The estimates and standard deviations for this model-sensititve fixup method, computed for the simulation data, are plotted in the right panels of Figures A1. This model-sensitive fixup method resulted in noticeable distortions for higher input values of z, but these errors were ones of being mildlly *over*sensitive to differences among these higher input values, opposite to the problem of the methods in the left panels.

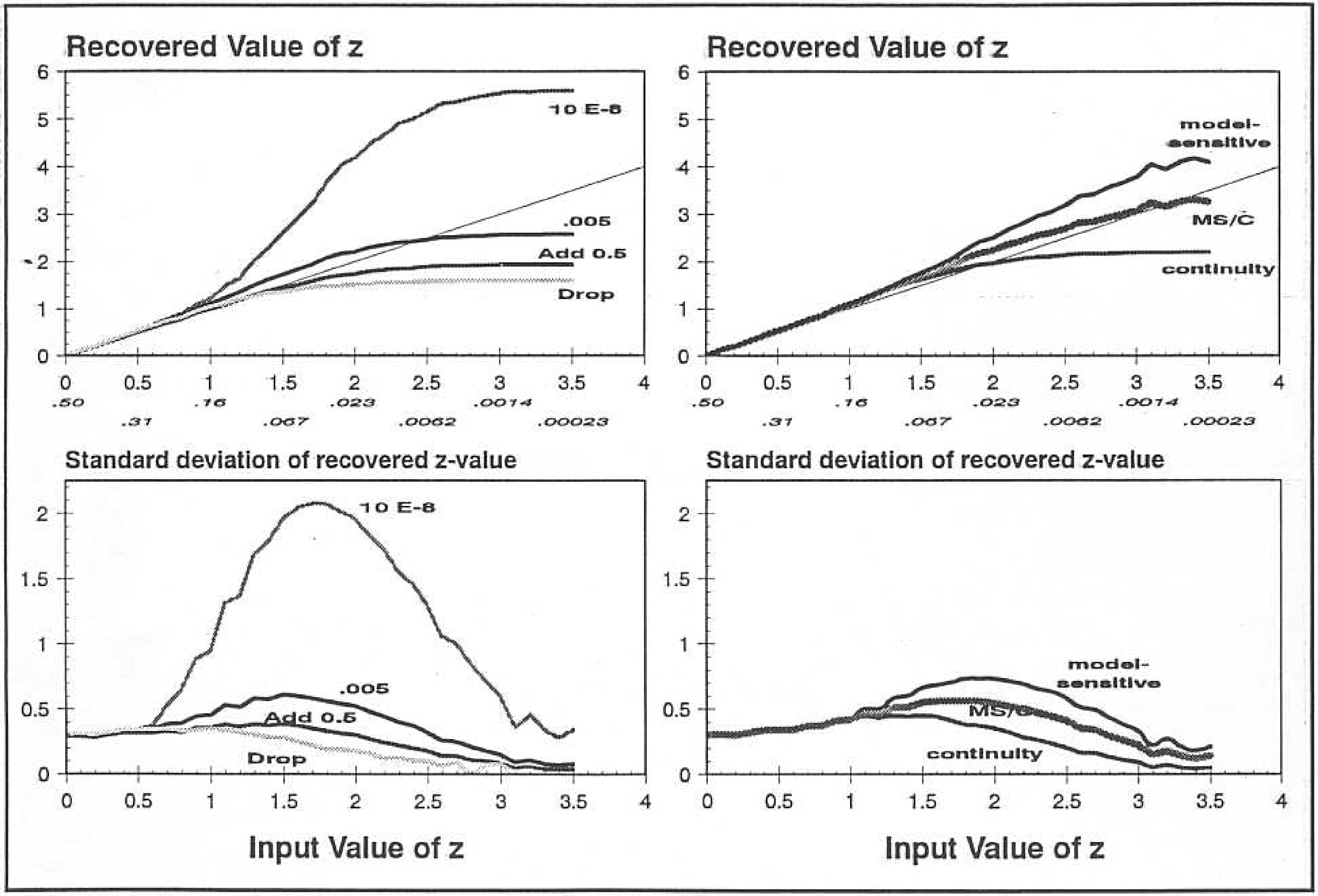
Continuity correction. With k observations aggregated in cell i, any observation x_i that has a value in the range $(1, k-1)$, inclusive, can be considered as representing the center of a range, $(x_i-.5,\ x_i+.5)$, along a hypothetical underlying continuum. By contrast, the extreme values of 0 or k for x_i represent just a single pole of their hypothetical underlying ranges of (0, .5) and (k–.5, k). To make these extreme values correspond to the center of their constituent ranges, they should be replaced, respectively, by .25 and k–.25. Simulated data for this continuity correction are shown in the right panels of Figure A1. It can be seen that this method was similar to the methods of dropping subjects and adding 0.5 to all observations, in both underestimating and being insensitive to variations among higher input values of z.

Combined method. The right panels of Figure A1 show one more method, which combines the model-sensitive and continuity corrections. This correction method is based on the assumption that the rationales for both the model-sensitive and continuity corrections are valid. That is, extreme values merit a correction to reflect the center of their underlying range on the continuum, but also one that is sensitive to the generating population proportion. The combined correction that was used takes the geometric mean of the two corrections, in order to preserve sensitivity to extreme values of the generating proportion. This fixup, labeled "MS/C" in the figures, performed better than all others in the present simulation context.

Application to the false fame experiments. Using just one sample-estimated parameter, the model-sensitive and MS/C methods shown in Figure A1 are the simplest of a potentially large class of model-sensitive methods. More complex model-sensitive methods can be constructed by using more parameters to model the expected proportion in an empty or full cell. For example, models for the experiments reported in the present article might use parameters for each of (a) the name fame condition (famous vs. nonfamous), (b) the name gender condition, (c) the familiarization (prior exposure) condition, (d) subject individual differences, and (e) interactions among these. All of these model parameters could be estimated within each experiment. However, in the context of testing substantive theoretical hypotheses, it is strategically inappropriate to base empty-cell replacements on estimates of model effects that are the target of statistical tests of theory-relevant null hypotheses. Model-sensitive corrections should be limited to theory-irrelevant design parameters. The major theory-irrelevant effects of the model for the present experiments were (a) subject individual differences, (b) overall effects of famous versus nonfamous names, and (c) the interaction of those two factors. In applying the MS/C method to the data of the present false fame experiments, replacements for empty cells were made sensitive to these effects by using individual subject hit and false alarm rates (i.e., averaged across name gender and familiarization experimental treatments separately for each subject) as the proportions combined with the continuity correction in replacing empty or full cells in the subject's data for hits or false alarms, respectively.

INSERT TABLES A1, A2, AND A3 ABOUT HERE

Tables 1-3 show statistical significance tests for the main effect of name gender, the main effect of prior exposure to name, and the interaction effect of those two factors on log β for each experiment, using the four existing empty-cell fixup methods along with the MS/C method. In these comparisons, it can be seen that the MS/C found the same significant and nonsignificant effects as the methods of adding 0.5 to all observations and replacing 0/1 with .005/.995. All of these methods appeared superior in sensitivity to the method of replacing with 10^{-8} and the method of dropping subjects, which was extremely inadequate for the present experiments because of the large amount of lost data. The observations of superior accuracy in Figure A1, together with the evidence from Tables A1-A3 that the MS/C suffers no loss of power, justified its use in analyzing the data of the present research.


Recovered Value of z
10 E-8
.005
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Standard deviation of recovered z-value
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Standard deviation of recovered z-value
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Figure A1