# Why do students fail social statistics?

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I thank Shelley Pacholok for keeping the careful and detailed gradebook on which this research is based.

# ABSTRACT

Social statistics is often the most failed course in the undergraduate sociology major. In this paper we consider three theories of sociology undergraduates' weak performance in statistics courses. The first theory ascribes students' difficulties to poor math and logic skills. The second theory implicates lack of effort. The third theory points to distractions such as heavy courseloads and full- or part-time jobs.

Using data from a course of 45 students, we regressed midterm and final exam scores on measures of skill, effort, and distraction. The results suggest that low exam scores were strongly related to weak math skills and to neglect of assignments; distractions were relatively weak predictors of exam scores. We recommend that statistics courses include appropriate prerequisites and review materials in mathematics. We also discourage policies that encourage reduced effort—e.g., the policy of dropping the lowest assignment grade.

## INTRODUCTION

Sociology is a largely quantitative discipline, yet this is rarely why undergraduates choose the sociology major. To the contrary, statistics is often the most feared course in the sociology curriculum (Bridges *et al*. 1998). In our department, introductory statistics is repeated more than any other course. Although many students succeed in statistics, at least 17% either drop it or fall short of the C- required for graduation.[1]

If we wish to do a better job equipping undergraduates with the quantitative tools of our discipline, we need a better understanding of their difficulties. In the interest of understanding the causes of high and low achievement in statistics courses, this study tests three theories with broad currency among instructors.

1. Some instructors attribute students' difficulties to *distraction*, such as heavy courseloads or full- and part-time jobs.[2] Research on national samples of college students has found little relationship between grades and paid work (Ehrenberg & Sherman 1987), but the effect of courseload seems relatively unexamined.
2. Some instructors attribute differences in student achievement to differences in *effort*, for example attendance and completion of assignments. This is consistent with psychological research suggesting that skill acquisition is closely linked to time spent in deliberate practice (Ericsson *et al*. 1993).
3. Some instructors attribute students' difficulties to poor *math and logic skills*. Compared to students in other industrialized countries, US high school seniors have low levels of math literacy, but a high probability of attending college (Barro

and Lee 2001, Mullis *et al.* 1998). It is predictable that students entering college with poor math skills would have difficulty in a statistics course.

Note that these theories may be related. For example, math and logic skills may be a result of prior effort, and present effort may be reduced by distractions. Although my analyses explore some of these causal paths, my goal is not to trace students' difficulties to their ultimate causes. Instead, I try to identify *proximate* causes that might be altered by classroom interventions.

To test these theories, I used measures of distraction, effort, and skill to predict midterm and final exam scores. To preview the results:

1. Measures of distraction had little predictive value. As in studies of high school students (Schoenhals *et al*. 1998), I found that paid work had a negligible effect on exam scores when course effort was taken into account. Similarly, I found that courseload had little effect on exam scores, though it may have affected effort in a few extreme cases.
2. Measures of effort did a better job of predicting exam scores. Although attendance seemed to make little difference, neglect of assignments caught up with students by the final exam. This makes sense since attendance can be a relatively passive activity, while homework assignments require the kind of "deliberate practice" (Ericsson *et al*. 1993) required to build cognitive skills.
3. The most useful predictors were measures of math and logic skills. The math pretest was an excellent predictor of both the midterm and final exam scores. The logic pretest did not predict midterm scores, but did predict scores on the final exam. This makes sense since the midterm consisted largely of calculating descriptive statistics, while the final also

emphasized logical arguments using statistical inference.

Although we were initially surprised by these results, they are consistent with prior research. In general, educational research often finds that the greatest influences on achievement have their impact outside the classroom and before the course begins (*e.g.*, West *et al*. 2000; Downey, von Hippel, and Broh 2004). In particular, previous studies of introductory sociology students implicate pretests and prior achievement, while finding little effect of attendance or paid work (Szafran 1986; Neuman 1989). Previous studies, however, have not extended these results to statistics courses, and have not considered the effects of courseload and assignment completion.

The findings have changed our department's understanding of students' difficulties, and have provoked changes not only in my personal teaching style, but in departmental discussions regarding advising and prerequisite courses. I will discuss these changes later, under the heading of "Recommendations."

## DATA AND MODEL

### *Variables*

In winter 2003, 45 students enrolled in my social statistics course—22 sociology majors, 16 criminology majors, 3 double majors, and 4 students visiting from other departments. Throughout the term, a variety of information was collected on these students, including the following variables pertinent to student success:

1. *Skill variables*. On the first day of the term, students were given brief pretests on MATH and LOGIC skills. The logic pretest consisted of 3 original questions

illustrating the types of reasoning required in inferential statistics. The math pretest consisted of 12 questions drawn from a longer pretest in a statistics textbook (Gravetter and Wallnau 2000, Appendix A).[3] To facilitate comparison, both pretests were scored on a 0-3 scale; each logic question was worth a full point, and each math question was worth a quarter-point. Both pretests are reproduced in the Appendix.

2. *Distraction variables*. On the first day of class, students were given a questionnaire that asked, among other things, about their COURSELOAD: "How many classes are you taking this quarter (including this one)?" The questionnaire also asked "How many hours a week do you work for pay? (Answer 0 if you don't have a job.)" Paid hours of work was divided by 8 to give the length, in days, of the student's WORKWEEK.
3. *Effort variables*. Throughout the quarter, a graduate teaching assistant collected assignments and kept attendance records. From these records we could tell how many ASSIGNMENTS students SKIPPED, and how many WEEKS they were ABSENT, both BEFORE and AFTER THE MIDTERM. Before the midterm there were 4 assignments in 5 weeks. After the midterm there were 2 assignments in 3.75 weeks. These figures omit days lost to snow or exams, and omit one last, short assignment that was not collected due to a snow emergency.
4. *Exam scores*. About sixty percent of the course grade was based on a MIDTERM and a FINAL EXAM. The midterm covered descriptive statistics, as well as confidence intervals for a single mean or proportion. The final reviewed these materials, and also covered confidence intervals and hypothesis tests for comparing two or more means or

proportions. Both exams were scored out of 100 points; the final included 6 points of extra credit. Although the exams were not assigned letter grades, they contributed to a course grade where scores in the 90s were *A*s, scores in the 80s were *B*s, and so on.

The distributions of these variables are summarized in Figure 1. The top row shows that final exam scores were generally lower than midterm scores. Subsequent rows suggest some reasons why. After the midterm, attendance slacked off and students were more likely to skip an assignment. The course moved from descriptive to inferential statistics, so that logic as well as math skills became important.

**←FIGURE 1 HERE→**

Although Figure 1 is suggestive, the suggested relationships do not necessarily explain why final scores were lower than midterm scores. It could simply be that the final exam was more difficult. A formal model is needed to test the proposed relationships.

### *Model*

The data were modeled using a system of two linear equations. In the first equation, MIDTERM scores were modeled using measures of skill (MATH and LOGIC pretests), measures of distraction (length of WORKWEEK and size of COURSELOAD), and effort (WEEKS ABSENT, ASSIGNMENTS SKIPPED) from *before* the midterm. In the second equation, FINAL scores were modeled using the same variables, as well as measures of effort from *after* the midterm. More formally,

$$\text{MIDTERM} = \beta_{0m} + X_1\beta_{1m} + e_m \quad (1)$$

$$\text{FINAL} = \beta_{0f} + X_1\beta_{1f} + X_2\beta_{2f} + e_f \quad (2)$$

where

$X_1$ = (MATH, LOGIC, WORKWEEK, COURSELOAD,

WEEKS ABSENT BEFORE MIDTERM, ASSIGNMENTS SKIPPED BEFORE MIDTERM)

$X_2$ = (WEEKS ABSENT AFTER MIDTERM, ASSIGNMENTS SKIPPED AFTER MIDTERM)

and where both error terms ($e_m$, $e_f$) are normally distributed.

I expected that students who scored unexpectedly high (or low) on the midterm might also score high (or low) on the final. To model this possibility, I allowed the errors in predicting the midterm ($e_m$) to be correlated with errors in predicting the final ($e_f$). The error correlation relates this pair of *seemingly unrelated regressions* (Wooldridge 2002).

### ***Missing values***

Since Figure 1 reports less than 45 cases for each variable, it is evident that our data have some missing values. There were diverse reasons for this. One student did not take the initial pretests and questionnaire, and so is missing values for MATH, LOGIC, COURSELOAD, and WORKWEEK. Another student did take the questionnaire, but neglected the question regarding COURSELOAD. One student dropped the course before the midterm, and so is missing both exam scores and all measures of effort. Another student dropped the course after the midterm, and so is missing the final exam scores and measures of effort after the midterm. One student, was given customized assignments and tests; these were not comparable to those of other students and so were treated as missing.

The major cause of missing values, however, was a university policy affecting the 5 graduating seniors. Students who have registered to graduate at the end of the term must be given an early “senior final,” after which they are not expected to attend class. Since the senior final was shorter and less comprehensive than the regular final, and since the students taking the senior final had less time to prepare, final exam scores were treated as missing from the records of graduating seniors. These students were also missing values for how much of the course's last week they would have attended, had they been expected to do so. One approach to the missing attendance records would be to treat these students post-midterm absences as missing. A more careful approach is to break post-midterm absences into two components, absences before and after the senior final. Only the second component is missing values for graduating seniors. In effect, this means that we are adding a third equation to our model.

$$\text{WEEKS ABSENT AFTER MIDTERM} = \text{WEEKS ABSENT BETWEEN MIDTERM AND SENIOR FINAL} + \text{WEEKS ABSENT AFTER EARLY FINAL} \quad (3)$$

Unlike the first two equations, however, the third equation is deterministic instead of random, and has no parameters to estimate.

I handled these missing values using *multiple imputation*, which replaces each missing value with a sample of plausible values or imputations (Allison 2002). My analyses used 10 imputations per missing value, which should be quite adequate given the small number of missing values (Rubin 1987). My imputation model assumed that the missing values are normally distributed[4]; however, I rounded and truncated the imputed values to be consistent with other values in the gradebook.

Results using multiple imputation were similar to results using two alternative approaches to missing values: (1) *listwise deletion*, which deletes any student with missing values; and (2) normal *maximum likelihood*, which maximizes the likelihood of all the values in both complete and incomplete student records, assuming a normal distribution of missing values (Allison 2002; Little and Rubin 1989). Listwise deletion is the most common method for handling missing values, though not the best. Maximum likelihood approach is most appropriate for larger samples, but it provides useful chi-square tests of model fit, which I report below.

## RESULTS

The overall fit of the model w as reasonably good ($\chi^2(4)=4.65$, $p=.33$). Table 1 gives point estimates and 95% confidence intervals for the model parameters.

**←TABLE 1 HERE→**

### *Skill variables*

The only significant predictor of midterm scores was the math pretest. On average, an extra point on the 3-point math pretest predicted 0.27 to 17.33 extra points on the 100-point midterm. In other words, the effect of math skills was almost surely positive, and may have improved midterm scores by more than 1½ letter grades.

The math pretest was also a significant predictor of final exam scores. On average, an extra point on the 3-point math pretest predicted 3.41-19.93 extra points—1/3 to 2 letter grades—on the final exam. That is, an extra point on the math pretest would, on average, change a final-exam C to something between a C+ and an A. The logic pretest affected the final nearly as much. An extra point on the 3-point logic pretest improved the final exam score by 2.22-15.86 points—suggesting that the final, more than the midterm, tested logical as well as computational skill. This makes sense, since the midterm focused on descriptive statistics, while the final concentrated on inferential statistics.

### *Distraction variables*

The effects of the distraction variables—COURSELOAD and WORKWEEK—were harder to interpret. Considered together, distractions evidently had some effect; that is, if we remove the effects of both distractors on both exams, the fit of the model gets significantly worse ($\Delta\chi^2(4)=10.66$, $p=.03$). The specific effects of individual distractions on individual exams, however, were harder to evaluate. None of the point estimates was significant, and the confidence intervals indicated that the effects could be substantial or negligible, and positive or negative. Although negative effects were expected, positive effects are plausible if these variables proxy for something other than distraction. WORKWEEK, for example, might proxy for drive or energy, and COURSELOAD might proxy for status as a full-time student.

### *Effort variables*

Skipping assignments had a substantial effect on the exam scores. Although we did not detect a significant effect on the midterm, an effect would be hard to detect since relatively few students skipped an assignment. After the midterm, skipping assignments grew more common, and predicted an average decline of 1.06-14.77 points on the final exam. After the midterm, that is, skipping an assignment was almost surely detrimental, and may have reduced the final exam score by as much as 1½ letter grades.

The effects of the attendance variables—WEEKS ABSENT BEFORE and AFTER THE

MIDTERM—were harder to interpret. None of the estimated slopes was individually significant, and one estimate was positive, rather than negative as expected. Moreover, when we remove the collective effect of attendance, the fit of the model does not get significantly worse ($\Delta\chi^2(3)=2.35$, $p=.50$). Yet the confidence intervals contained some substantially negative values, and it seems hard to believe that the effect of absence could be anything but negative.

### *Residual error*

Although the analyses are focused on prediction of exam grades, the strength of these predictions should not be exaggerated. In Table 1, each regression has a residual standard deviation of more than 10 points, suggesting that it is not unheard of for a student to exceed expectations by a grade or more on each exam. That is, although a low math pretest is a worrying sign, it is not necessarily a death sentence. One student who missed a third of the math pretest questions scored a 96 on the midterm and an 85 on the final, finishing with an A- in the course. (Unfortunately, little was learned from her example. She insisted that she did “nothing special.”)

### *Sensitivity analysis*

Residual plots suggested slight violations of several model assumptions. The residual distributions had shorter-than-normal tails. The effect of logic scores seemed to be nonlinear, with the difference between 1 and 2 points mattering more than the difference between 2 and 3. There were also a couple of mildly influential cases, for example a student with weak math skills who averaged 91 on the exams.

These problems were all fairly minor. When I redressed them by recoding variables and deleting cases, the residual plots looked much better, but the basic flavor of the results did not change.

I also tried respecifying the effect of paid work. Some research suggests that, while long hours of paid work are detrimental, a few hours of paid work may actually improve students' grades. Rather than a straight line, that is, the effect of work may fit an "inverted-U" shape with a peak near two 8-hour days (Stern & Briggs 2001). I coded this effect as the square of WORKWEEK, centered around two days. When this term was included, however, the effect of paid work remained insignificant, and the estimated effect of other variables changed very little. This corroborates research on younger students, which suggests that, net of student effort, paid work has little effect on classroom achievement (Schoenhals *et al*. 1998).

Finally, I tried an alternative model specification in which the MIDTERM score was included among the predictors of the FINAL exam score. This specification proved slippery because the effect of the MIDTERM on the FINAL is confounded with the residual correlation between $e_m$ and $e_f$. In principle, it is possible to estimate both the residual correlation and the effect of the MIDTERM on the FINAL; in practice, however, attempts to estimate these parameters simultaneously foundered because of empirical underidentification.

## ANALYZING THE RISK FACTORS

In sum, the initial analysis identified two major risk factors that predicted low scores on the midterm and final. One risk factor was weak math (and logic) skills; the other was neglect of assignments.

An obvious follow-up question is what predicts these risk factors. Are there variables within our control that would increase the math skills or diligence of incoming students?

### ***Neglect of assignments***

In the case of assignment neglect, I identified a couple of plausible causes. One was distraction. Initial logistic regressions suggested that courseload was a strong predictor of skipping assignments. Closer inspection, however, showed that this estimated effect was due entirely to four extreme cases. At one extreme, two students enrolled in only one course, and neither of them skipped an assignment. At the other extreme, two students took on five courses, and both of them skipped an assignment; in fact, one of them skipped two. Although this difference is suggestive, these courseloads are very unusual. Over 80% of the students enrolled in three or four courses, and there is no evidence that those enrolled in four were any more likely to skip assignments than those enrolled in three (see Table 2a). We might advise students not to enroll for five courses when they take statistics—but since few of them are doing so anyway, this would have little impact on exam averages.

There are other plausible causes for assignment neglect. A leading candidate is my policy of allowing students to drop their lowest assignment grade. Although well-intentioned and not unique to my course, this policy may unwittingly create an incentive for students to skip one of their assignments. Two patterns are consistent with this view. First, hardly any students skipped more than one assignment (Table 2a). Second, most of the skipping was concentrated in the two assignments after the midterm (Table 2b). These patterns suggest that students felt they had a right to skip one assignment, and did not want to exercise that right prematurely.

←TABLE 2 HERE→

Of course, there are other plausible explanations for these patterns of assignment neglect. Assignments late in the term may have conflicted with term papers in other courses, or may have seemed less urgent in view of students' high midterm scores. Without varying the policy for dropping assignments, it is impossible to know whether this policy is affecting students' behavior. Given the impact of assignments on the final exam, however, changing the policy seems a worthwhile experiment.

### *Math and logic skills*

An obvious predictor of math skills is performance in prior math courses. This turns out to be a very good predictor. Of the 11 students with the lowest scores on the math pretest, 6 had received grades of *D*+ or worse in remedial math courses.

A less tractable predictor of math scores is race. The median math score for the 6 black students was 2, compared to 2.75 for the white students, and 3 (perfect) for the Asian students. The variation by race is significant using a robust small-sample test (Kruskal-Wallis $\chi^2(2)=9.32$, exact $p=.004$). A similar gap was observed on the logic test, where the median score for black students was 2, compared to 3 for white students (and 2 for Asians). This difference was not significant, however, perhaps because the logic test was a coarser measure, with fewer questions.

These race gaps show that the very social problems we study (*e.g.*, Jencks and Phillips 1998; Massey, Charles, Lundy, and Fischer 2003) are having an impact in our own classrooms. Unfortunately, a college statistics course seems an unlikely place to solve the race gap.

## RECOMMENDATIONS AND CONCLUSIONS

The results suggest that scores on statistics might improve if we could raise incoming math and logic skills, and encourage students to do all of their homework assignments. Other factors, such as attendance, might also be improved, but it is not clear how much test scores would benefit.

### *Math skills*

Prerequisite math courses are an obvious way to redress math skills. As mentioned earlier, though, many students are already taking remedial math courses, but earning poor grades. If we want our students to have better math skills, perhaps we should require not only that they take a prerequisite course, but that they earn a grade that reflects competence, if not mastery. Although coursework in logic might also be helpful, our results suggest that logic skills impact only one of the two exams; a logic course, then, might be only half as helpful as a math course.

Some students report that they once had the needed math skills, but those skills have atrophied from disuse. This seems plausible, since most of the required math skills are taught by the end of middle school. To help students brush up their math skills, I have begun offering extra credit for completion of the lengthy math review from Appendix A of Gravetter and Wallnau (2000). Nearly every student has taken advantage of this opportunity, and the correlation between exam scores and math pretest scores has declined.

### *Neglect of assignments*

If students suffer from neglect of homework, we must question the policy of allowing students to drop an assignment grade. This policy is popular among our department's statistics instructors, and for good reasons. The right to drop an assignment stems student anxiety and unrest, and it reduces pressure on the grader to accept late assignments. But if it gives students the impression that they can skip an assignment without consequences, the costs may outweigh the benefits.

The most obvious remedy is to repeal the policy entirely, and count all assignments grades even if some are missing. This may be the best policy for learning, but it might be unpopular among students and graders. In my course, I have adopted a milder alternative: I continue to drop an assignment grade, but I also give a bonus for completing all of the assignments. To prevent students from turning in blank or slipshod papers, the bonus requires a minimum score of 50% on each assignment.

### *Course examples*

In addition to changing course policies, results from this study can be used as course examples. For example, a simplified illustration of how homework impacts exam scores may inspire students to greater diligence. More generally, this study demonstrates that, far from being an abstract exercise, statistics have an impact on students' everyday lives. Skeptical students may be won over by the knowledge that the very course they are taking has benefited from statistical analysis.

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# TABLES

*Table 1*. Predictors of midterm and final exam scores: Seemingly unrelated regressions.

| Dependent variable | Independent variable | Estimate | 95% confidence interval |
|---|---|---|---|
| Midterm | Intercept | 58.58*** | (28.43, 88.72) |
| | Math pretest | 8.80* | (0.27, 17.33) |
| | Logic pretest | 3.45 | (-3.55, 10.45) |
| | Days worked for pay each week | 1.28 | (-1.09, 3.66) |
| | Courses enrolled | -2.06 | (-6.91, 2.79) |
| | Assignments skipped before midterm | -3.70 | (-14.12, 6.71) |
| | Weeks skipped before midterm | -2.20 | (-8.47, 4.08) |
| | Residual standard deviation | 12.92 | |
| Final | Intercept | 18.80 | (-14.09, 51.68) |
| | Math pretest | 11.67** | (3.41, 19.93) |
| | Logic pretest | 9.04* | (2.22, 15.86) |
| | Days worked for pay each week | -1.09 | (-3.61, 1.43) |
| | Courses enrolled | 2.52 | (-2.81, 7.84) |
| | Assignments skipped before midterm | -0.55 | (-14.03, 12.92) |
| | Weeks absent before midterm | -6.27 | (-15.68, 3.14) |
| | Assignments skipped after midterm | -7.92* | (-14.77, -1.06) |
| | Weeks absent after midterm | 2.09 | (-3.82, 8.00) |
| | Residual standard deviation | 11.95 | |
| | Residual correlation | 0.53 | |

*$p$<.05, **$p$<.01, ***$p$<.001. All other *p*s>.10.

Overall model fit: $\chi^2(4)=4.65$, $p=.33$

*Table 2*. Neglect of assignments, by courseload and time in the term.

*2a.*

| Assignments skipped | Courses enrolled: 1 | 2 | 3 | 4 | 5 | Total |
|---|---|---|---|---|---|---|
| 0 | 2 | 1 | 9 | 10 | | 22 |
| 1 | | 2 | 6 | 6 | 1 | 15 |
| 2 | | | | 1 | | 1 |
| 3 | | | | | 1 | 1 |
| Total | 2 | 3 | 15 | 17 | 2 | 39 |

*2b.*

| | Before midterm | | | | After midterm | | |
|---|---|---|---|---|---|---|---|
| | Asst. 1 | Asst. 2 | Asst. 3 | Asst. 4 | Asst. 5 | Asst. 6 | Total |
| Turned in | 41 | 41 | 39 | 41 | 36 | 34 | 232 |
| Skipped | 2 | 2 | 4 | 2 | 6 | 8 | 24 |
| Total | 43 | 43 | 43 | 43 | 42 | 42 | 256 |

# APPENDIX

*The following assessments of math and logic skills were collected on the first day of class. Both assessments are scored on a 3-point scale: on the logic assessment, each question is worth 1 point; on the math assessment, each question is worth ¼ point.*

*The logic assessment is original; questions on the math assessment come from Gravetter and Wallnau (2000, Appendix A).*

*Student scores are summarized in Figure 1.*

## ***Logic assessment***

Here are some word problems that give a flavor for the kinds of reasoning required in statistics. These problems are actually toy versions of statistical concepts we will encounter later in the course.

Question 1 calls for something like a *confidence interval*

1. I weigh myself on a bad scale. The scale reads 177, but I know it could be off by up to 5 pounds in either direction. What is a range of possible values for my weight?

Questions 2 and 3 relate to *hypothesis tests*:

2. My Weight Watchers goal is 170 pounds. Is it possible I've reached my goal weight?
3. Suppose I *were* at my goal weight. What would be the range of possible readings on the scale?

### *Math assessment*

Here are some problems that give a flavor for the kinds of math required in statistics. If these cause you any trouble, please read the math-review materials suggested in the syllabus for today.

1. 3+2(7) =
2. (3+2) 7 =
3. 12 / 4 + 2 =
4. 12 / (4 + 2) =
5. $4^2 + 2^2$ =
6. $(4+2)^2$ =
7. 12 / $(4+2)^2$ =
8. 6 + (-1) –3 – (-2) =
9. –2(-6) / (-3) =
10. $\sqrt{25-9}$ =
11. If (*X*-5) / 3 = 2 then *X* =
12. If *a*=3 and *b*=-1 then $a^2b$=

# FIGURE CAPTIONS

*Figure 1*. Distributions of studied variables. Scores on the final exam were generally lower than scores on the midterm. To some degree this reflects an increase in risk factors. While both exams required the skills on the math pretest, the final exam, which emphasized statistical inference, also required the skills on the logic pretest. Also, after the midterm, students were more likely to skip assignments, which reduced their exam scores.

By contrast, attendance, paid jobs, and courseload appeared to have relatively little effect on the exams.

# FOOTNOTES

[1] This figure is based on transcripts from 2000-01. 17% may be a conservative estimate, because transcripts do not report a course withdrawal if it occurs in the first 3 weeks of the term.

[2] I also viewed parenting as a potential distraction, but only one of my students reported having a child.

[3] The textbook used in my course was not Gravetter and Wallnau (2002), but Frankfort-Nachmias and Leon-Guerrerro (2002).

[4] Specifically, I used the MI and MIANALYZE procedures in SAS 8.02, estimating degrees of freedom with a method appropriate to this small sample (Barnard and Rubin 1999)