Beyond Sectionality and into Sizeness or How Course Size Effects Grades: An Exploration of the MultipleInstitution Database for Investigating Engineering Longitudinal Development through Hierarchal Linear Models

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How Course Size Effects Grades: *Sizeness* and the Exploration of the Multiple-Institution Database for Investigating Engineering Longitudinal Development through Hierarchal Linear Models

Introduction

In a recent study, an effect entitled *sectionality* was probed to determine the effect of different course sections at various schools had on students' grades.[1] A caveat of that study brought up numerous times in lectures and via private correspondence – one left out of the original paper – was the effect of *class size* (or *sizeness*) for the same introductory courses. While anecdotally, faculty from all over the country had discussed with the researchers in the past few years that course size either does or does not affect course grades, the researchers left this question unanswered in the literature. In order to address this question, we opened the question to present the answers to the community at large.

While the topic of engineering grades remains an important one to our community,[2-9] it could be easily argued that the subject of the effect of *class size* on grades is even more universally debated – both outside [10-13] and within the sphere of higher education.[14, 15] Some studies actually shirk the question of the effect of class size on grades altogether and opt to probe class size's effect on teacher evaluations![16] More general and historically-minded reviews of the subject in higher education are beyond the scope of this paper, but are easily accessible.[17] The debate of many state legislatures, programs such as No Child Left Behind (NCLB), and even more recent ones such as the Common Core (CC) have all focused on average class size at one point or another.

Multi-Level Models (MLM) or Hierarchical Linear Models (HLM) offer a solution to probing the question of grade disparity with respect to course size. We decided to use a simple null model due to its powerful and direct results in order to express the differences between variances of course grades as a result of being enrolled in the course itself and course grades as a result of being present in a particular course of one particular size. The null model provides the basics for what statisticians call the intraclass correlation coefficient (ICC). [18, 19] The ICC is a simple measurement of the intra- versus inter-group variance in a given quantity. If the ICC is 1, that means that all of the variance in a quantity – in this case, grades – lies within the domain of *course size*. If the ICC is 0, that means that the *course* itself is the sole arbiter of grade variance. In a perfect world, our null model would tell us that course size is indeterminate of course grade variance – that students could perform equally well in a given course at any given time based solely on their work and the potential distractions of pitfalls of course size do not affect their grades.

Why Choose HLM?

The use of HLMs in our field and elsewhere, a brief history, and more have been discussed at length in a previous work.[1] For those interested, the world of hierarchical linear models (HLMs) is an expansive space, and fundamental texts in the discipline describe it in a detail beyond this paper.[8, 20-31] If one is interested in starting a project in using HLM, two major pieces of advice can be offered. First, it would behoove the researcher to learn how to program them from scratch as much as possible using an environment such as R or even a higher functioning one such as SAS. Specialized programs abound that offer easily-accessible results, but blind the researcher to important computational steps (and potential follies) along the way. Second, avoid the distraction of different *names* for HLMs. They can be called multi-level models, split plot models, null models (confusingly as this is a type of expression of a HLM), mixed models, mixed effects models, etc.

HLMs have a few features and assumptions that differ them from standard methods of analysis. First, that all data is organized into nested levels or sets. Second, the variance of the model itself is not endemic to one such level, but can lie in both. Third that the establishment of cross-parameterization links different levels together. This may be the most important feature of HLMs. We do not want to simply know the change in a second order variable, we want to know the change in a second order variable with respect to unit change of a first order variable. Fourth, empty data in one particular nested regime does not invalidate the analysis; and predictors at one level can be aggregated upwards. Essentially, this means that unlike linear regression techniques, HLM does not require complete data sets at all levels. Data can be missing.

Do Changes in Course Size Affect Grades or Not?

Within our field, no papers have substantially probed a connection between course size and grade distribution, and there has been a lack of HLM papers in our field over the past few years, a few here are of note.[32] While Egan's sample size appears large (N ~ 110,000), he only analyzed 349 response surveys. Furthermore, Egan makes a critical mistake in the fact his ratio of employees to supervisors is roughly 6:1. To the casual observer, this may seem acceptable, but to a statistician or one familiar with the limits of dimensional reduction, it is nearly impossible to dimensionally reduce with less than an 8:1 ratio. Similarly in HLM work, the community usually agrees on an 8:1 ratio given certain caveats that are explored in depth by the more mathematically inclined.[21] Strict tests of convergence must be performed when a data set for HLM analysis is so small, as canned methods cannot be relied upon under such circumstances. Finally, subsetting from 110,000 samples to 349 presents a stochastic concern in that the 349 individuals probed are within the counting error for a data set of 110,000 when presented without a control group.

Another of the early papers within our field that described the use of a HLM to analyze a multi-tiered arrangement of students, but is critically flawed because it did not actually analyze data.[33] Harper et al. performed a study of co-curricular activities, and the results indicated that faculty and institutional programs tend to outweigh the effects of gender and SAT on student participation in co-curricular events.[34] The 2005 paper by Padilla et al. elaborates the importance of careful data aggregation and delimitation in HLM.[35] They make proper use of one of the best features of HLM – that variables have a representation at each level – while making use of first level variables and aggregates of them in a subsequent one. Padilla's most important result is that 19% of the variance in student grades can be directly related to differences in a student's home institution. This runs analogously to Astin's famous quote of the most important data point is the student's institution.

There are several key studies of the effect of course size on student *performance,* some of them analyzing grades and others analyzing standardized test scores. The various studies at both the pre-college and college levels are not without significant caveats – for instance, the work of Chingos,[12] while obviously a lightning rod for criticism, must be properly situated. Simply stating that smaller class sizes have no effect on achievement scores means nothing without specifics. Chingos, being aware of this minefield, even states in the title of his paper that this is a study of the net contention of *public policy* in Floridian schools, more specifically in this case, a universal mandate. While some may not agree, the Van der Hulsts[36] of the world understand that class size mandates are *curricular* changes. In the case of Floridian schools, the universal mandate is the largest-scale type of curricular change possible, one with many drawbacks, namely, the flexibility of individual school systems to customize them to their needs. Some school districts simply did not take funding that required them to abide by the mandate. Other schools already had the mandated level of students per classroom; therefore did not receive additional funding and their relative change in achievement per student remained (unsurprisingly) the same.

At the college level (and specifically within our field), the literature is practically nonexistent for the effect of class size on grades, although decent analogues exist, especially in the field of economics.[37] For instance, there are papers such as Raimondo's that study the variances in grades at the college level for specialized introductory courses.[14] In fact, one defining factor of Raimondo's study is that it is one of few papers at the college level to specifically focus on college *grades* and differentiate itself from research focused on *college achievement scores*.[38] His work found that other than a somewhat different drop in grades between the introductory courses and intermediate courses in micro- to macro-economics, course size had a measureable effect on course grades if the students introductory course had fewer students. In other words, if students took a large introductory course at first, then their overall performance in later, more specialized courses, would be slightly lower than students taking smaller introductory courses. Of course, the pitfalls of even such a well-designed study lies in the details, and with Raimondo's N of 146 over two sequences (micro- and macro-economics), his delimitations, in his own words, *are preliminary*.

As an aside, many studies exist that study effects similar to class size, but indirectly measure outcomes related to size. For instance, while Vogt's 2008 study used a metric of faculty *distance* or the degree to which faculty directly interact with students due to course size,[7] no scaled correlation between course size and individual course grades was made.

Methodology

At the time of this data set being released, the MIDFIELD schools were all public institutions and mostly located in the southeastern United States, yet their size and diversity helped make the results generalizable. All of these partner institutions have larger overall enrollment and engineering programs than average compared to the more than 300 colleges with engineering programs. The partners include six of the fifty largest U.S. engineering programs in terms of undergraduate enrollment, resulting in a population that includes more than 1/10 of all engineering graduates of U.S. engineering programs. MIDFIELD's female population comprises 22.1 percent of students, which aligns with national averages of 20 percent from 1999-2003[39] and 22 percent in 2005.[40]

A Note on Our Data Set and MIDFIELD in General

In this iteration of MIDFIELD, we kept the number of students the same to keep the results as complimentary to the original study. Here, the MIDFIELD database contains records for 701,190 first-time-in-college students matriculating in any major at participating institutions.[41, 42] The first cut of data began with 137,071 first-time-in-college (FTIC) students who ever matriculated in engineering at one of nine of our MIDFIELD institutions in 1988 and later. The data for these students is *complete*, in other words we have everything that the registrar has for these students. The students were further delimited to a set of students who repeated a particular course (receiving zero credits at their home institution). We finally, we had 161,456 grades for instances of where students who sometime in their careers declared an engineering major took one of three introductory courses.

The students' sections for each course are counted, and they are divided into different groups by the section they are in under the specific individual course for every term in a year. The courses chosen once again are equivalent courses – a fact we did not originally adequately define. *Equivalent* here means that for a course of *Calculus I,* this means that at a given institution, a student who is an engineer and wishes to graduate can take that particular *Calculus I* course and graduate. These equivalencies were tallied by examining each course number and what would count as a *Calculus I* requirement for a graduating engineer.

The Basic Form of a Hierarchical Linear Model

A Hierarchical Linear Model (HLM) can begin with the construction of a linear regression formulae, such as that of a line,

$$Y_i = \beta_0 + \beta_1 X_i, + e_i$$

Where Y_i is the dependent variable (or criterion), β_0 is the intercept, β_1 is the slope, X_i is the predictor variable, and e_i is the residual (or sometimes as it is colloquially called, the *error*).

In HLM, a standard model equation looks like,

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_i, + e_{ij}$$

The unit notation *j* here denotes our clustered unit factor that allows us to subset our data with this linear regression equation. Why this is important is that for every set of *j*, there is a subset of including an outcome (dependent variable), an intercept, a residual, and a slope.

When looking at course size, what this means is that for a given overall course, there are different course sizes with their own outcomes, intercepts, residuals, and slopes.

For our results presented within this paper, we utilized the simplest form of HLM, which is called the *null model* or the *intercept only model*,

$$Y_{ij} = \beta_{0j} + e_{ij}$$

The intercept only model is also called the *null model* or the *empty model* or the *fully unconditional model*.[23]

The intra-class correlation (ICC) function must next be calculated. As previously discussed, the ICC is a direct measure of where variance is distributed. The ICC is given by,

$$ICC = \rho = \frac{\tau_{00}}{\tau_{00} + \sigma^2} = \frac{UN(1,1)}{UN(1,1) + e_{ij}}$$

The factor τ_{00} is the variability between levels and σ^2 is the variability within levels. At the zeroth or null model level for HLM, σ^2 is actually the residual of the fit of our model. Another way of looking at this is that it is *all of the remaining variability* left after calculating τ_{00}. So a value of 0.10 means that 10% of the variability in a course's grades lies within the realm of the size of the course chosen.

Results

We present the following results from an analysis of course sizes in calculus 1 (Table 1), chemistry 1 (Table 2) and Physics I (Table 3). The same random number that was chosen to mix institutions is used again for comparison of the same intercept (average course grade) to previous results. In SAS and many HLM notation systems, UN(1,1) is the standard notation for τ_{00}, in this case, the variability between course size. The residual value here is e_{ij} or σ^2, which is the variability within course sizes. The ρ value for all results was less than 0.005 – the threshold for statistical significance here. The highest value of the ICC for each table are highlighted in green and the lowest values in yellow.

Institution	UN(1,1)	SE	Residual	SE	ICC	Intercept	SE
ALL	0.06619	0.00806	1.2416	0.00786	0.05061	2.3047	0.009864
1	0.1064	0.02979	1.6443	0.02502	0.06077	2.5309	0.01841
2	0.09529	0.03632	1.9132	0.05258	0.04744	1.9803	0.02991
3	0.01587	0.01008	1.7758	0.04644	0.00886	2.1321	0.02369
4	0.01279	0.00556	1.5109	0.02181	0.00839	2.4528	0.02274
5	0.1068	0.03210	2.0088	0.04829	0.05048	2.5186	0.02334
6	0.02384	0.00851	1.5395	0.02550	0.01525	2.3323	0.04033
7	0.03363	0.00831	1.3098	0.01910	0.02503	2.3486	0.02294
8	0.06339	0.02279	1.6661	0.02388	0.03665	2.0184	0.04819
9	0.05872	0.02420	1.7281	0.04470	0.03286	1.8378	0.03316

Table 1. Table of results from the first core calculus course

Institution	UN(1,1)	SE	Residual	SE	ICC	Intercept	SE
ALL	0.07077	0.00961	1.4505	0.00881	0.04652	2.3047	0.00986
1	0.2316	0.05447	1.0834	0.01507	0.17612	2.5309	0.01841
2	0.01725	0.01252	1.5906	0.03574	0.01072	1.9803	0.02991
3	0.1407	0.04098	1.7679	0.04350	0.07371	2.1321	0.02369
4	0.04289	0.01538	1.2470	0.02909	0.03325	2.4528	0.02274
5	0.1821	0.03159	1.3997	0.01917	0.11512	2.5186	0.02334
6	0.1407	0.04098	1.7679	0.04350	0.07371	2.3323	0.04033
7	0.06082	0.01610	0.9528	0.01807	0.06000	2.3486	0.02294
8	0.1163	0.04377	1.9506	0.06525	0.05626	2.0184	0.04819
9	0.04634	0.01555	1.6135	0.03875	0.02791	1.8378	0.03316

Table 2. Table of results from the first core chemistry course

Institution	UN(1,1)	SE	Residual	SE	ICC	Intercept	SE
ALL	0.06629	0.00806	1.2416	0.007857	0.05068	2.4221	0.01405
1	0.07935	0.02679	1.0642	0.02030	0.06938	2.6287	0.02693
2	0.01425	0.0087	1.2524	0.03768	0.01125	2.3403	0.02883
3	0.1066	0.02	1.3811	0.0207	0.07165	2.1877	0.03016
4	0.07838	0.01634	1.2413	0.01989	0.05939	2.3778	0.0327
5	0.07410	0.01815	1.3186	0.01972	0.05320	2.3858	0.02867
6	0.1491	0.04401	1.6741	0.04909	0.08177	2.5402	0.05799
7	0.01501	0.00366	0.8358	0.01107	0.01764	2.7459	0.01902
8	0.2972	0.07042	1.3501	0.04031	0.18041	1.8588	0.07346
9	0.1800	0.08124	1.0337	0.08193	0.14830	2.5246	0.1132

Table 3. Table of results from the first core physics course

Discussion and Conclusion

Before directly discussing the results of this work, it is important to discuss some of the main points to critique at this juncture in any HLM analysis. The work of Coleman, Hoffer, and Kilgore significantly influenced the author and many other researchers in the world of HLM.[43, 44] Two questions they would ask, and the researcher must also ask after a zeroth-order analysis of variance are: first, to what degree are the variances endemic to one group or another; and second, what are the limitations of this method of analysis. The second question is rarely discussed in many HLM papers, so we will address it here. The theoretical treatment of HLM teaches that below either the counting threshold for data and/or for a combination of other factors endemic to the system analyzed, that an extremely low or high ICC value can be indicative of a poor model choice.[21] In a system that is complete such as this one, where all data is available to the researchers, the N value is high, and the number of groups relative to subgroups is also high (aka more than two orders of magnitude relative to each other), the counting threshold error is not the issue at hand.

The issue, though, of an ICC well below 3% of above 97% is a debated topic among researchers, and often means that another treatment may be more appropriate for isolating the variance parameters. Typically, the next method of choice for analysis is the structural equation model (SEM) technique. One reason SEMs are a natural second choice is because in a dataset with high enough N values and group/subgroups, the first stage in the SEM process – a factorial analysis - has a good chance of being dimensionally reduced to a suitable point. Second, when performing a cluster analysis on HLM-formatted data, one can glean a good idea of the representative delimitating factors for a SEM construction. Third, and a little more subtle, is that when constructing and analyzing a robust HLM of first, second, or even third order, one will be able to determine whether or not the cross parameters and variances are more indicative of a power law distribution analysis – a rare but important observation to make. The net contention of this analysis process for a complete data set for the researcher means he can, with mathematical rigour, determine the most appropriate technique.

Beyond the low ICC values in the results that merit further study, a few striking conclusions can be made from the three tables presented. First, variability differs remarkably from school to school and from course to course. There are values as low as 0.83% in the case of calculus 1 for school 4 and as high as 18.0% for physics I at institution 8. Here, we find few relationships across the schools to indicate a systemic problem of grade variability in relation to course size – in itself a positive result. Schools such as 3 and 4 demonstrated extremely low variability in grades with respect to class size in calculus, maintained a low variability, but not as far below the average in physics and chemistry as they were for calculus.

Second, we find that calculus has a consistently low variability in course grade variability with respect to course size, although chemistry is fairly similar if we throw out schools 5 and 1. There are a number of reasons for this that would lead to further study. First, the relative consistency of varying course sizes for calculus may lead to a more consistent distribution of variances across course sizes. Second, as noted in previous work, there are schools that appear to have a curve instituted in across some courses.[1] An artificial curve across course sections would dramatically affect the variability of grades with respect to varying course size.

Third, there are a few notable comparisons between variability of grades between course sections and grades between course sizes. Schools 8 and 9 had high rates of course section grade variability and also high size grade variability for physics. Institution 1 had a relatively high course section grade variability for chemistry and course size variability for chemistry. Schools 2, 4, 5, and 7 maintained their relatively low variability for both course section and course size grades in physics. Schools 2 and 9 also maintained a relatively low variability for grade variability in chemistry for sections and sizes.

Unlike the first study, it is much more difficult to determine if one course type that has a consistently high or low variability, although physics does appear to be more consistently higher than the others - the inverse of the results when probing course section variance. Previously for the effects of section size, we found that chemistry to have the greatest potential for a large variability of a course grade being determined by section. Here, we find that physics has a larger percentage of grade variability contained in course size than the other two courses. The relative stability of intra-course grade variability could be offset by great variability contained in the factor of course size. Also, unlike the previous study, assigning one institution as a *problem* institution for having consistently high variability is not possible for course size variation, which is another positive development.

The results here are useful to the greater engineering education community, especially when paired with knowledge of variance between course sections. It appears that the effect of course size on the variability of grades presents difficulties in isolating, and is not as great as the variability of course sections on grades. Furthermore, unlike course section variance, there is the potential argument with some of the low ICC values within this study that a structural equation model (SEM) treatment would potentially be as effective in investigating these differences.[21, 22] Expansion of the minutia of class size grade variance in MIDFIELD coupled with targeted qualitative analysis can potentially yield further novel results.

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