The Effect of Class Size on Student Performance and Retention at Binghamton University

by

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Abstract

New York, like many other states, has had a call to increase faculty productivity. One proposed way to do this is to increase class sizes. Many oppose this measure, arguing that class size is a quantitative measure of productivity that does not include qualitative factors. Research on the effects of class size has been conducted, primarily, at the elementary and secondary levels. We analyze the effects of class size at Binghamton University in two important areas: student performance and student retention. The results of the study suggest that greater attention needs to be paid to the trade-off between faculty productivity and student success.

Executive Summary

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New York, like many other states, has had a call to increase faculty productivity. One proposed way to do this is to increase class sizes. Many oppose this measure, arguing that class size is a quantitative measure of productivity that does not include qualitative factors. We analyze the effect of class size at Binghamton University in two important areas: student performance and student retention.

First, we find that increasing class size has a negative effect on student achievement. The model predicts that a student in a class of 5 has a probability of receiving an A of .52. This is 2.4 times higher than a student in a class of 290 students, where the predicted probability of receiving an A is .22. Furthermore, we find that increasing class size lowers student achievement at a *decreasing* rate. This means that adding 10 students to a class of 10 has a larger negative impact on grades than adding 10 students to a class of 200.

Second, we find that increasing average class size decreases the likelihood of a student returning to Binghamton. The model predicts that a student with an average class size of 20 has a .97 probability of returning to the University, whereas a student with an average class size of 240 has a probability of returning of only .80. However, unlike student achievement, increasing class size lowers student retention at an *increasing* rate. This means that adding 10 students to an individual's average class size of 200 has a greater negative effect than adding 10 students to an average class size of 10.

The analysis of student achievement produces a puzzling result regarding the effects of discussion/lab sections. As expected, discussion/lab sections are beneficial to grades in science and mathematics courses, though this effect dissipates with larger classes. However, in other courses, discussion/lab sections are detrimental to grades. More research is needed to explain this finding.

Large classes adversely affect both student performance and retention at Binghamton University. Substantially increasing class sizes would likely have a greater negative effect on retention rates than on student performance.

Introduction: The Call For Accountability

There have been numerous studies examining the relationship between class size and academic performance in elementary and secondary education. Few, however, have examined this relationship in higher education. Generally, studies that have been conducted support the view that small classes are preferable to large ones because they result in a higher level of student academic performance (Hou 1994; Franklin et. al. 1991; Goldfinch 1996; Scheck 1994; Knight 1991; Raimondo et. al. 1990; Gary and Rosevear 1986). Recent studies have broadened the positive effects of smaller class sizes beyond academics to such important areas as student retention (Lopus and Maxwell 1995; Ashar and Skenes 1993), instructor evaluation (e.g., Mateo and Fernandez 1996; Gunter and Gunter 1994), alumni satisfaction (Davis 1988), and institutional reputation (Ramaswamy 1992).[1]

The research on the effect of class size takes on new importance in an era when institutions of higher education are being asked to do more with less. In New York, the Board of Trustees of the State University of New York (SUNY) system has recommended that its faculty should be at least as productive as their national counterparts (see *Rethinking SUNY*). In addition, a June 1997 preliminary audit by the New York State Comptroller's Office recommends that SUNY schools increase their mean class size in an effort to make their faculty more "productive." However, the audit ignores almost all of the qualitative benefits of small classes discussed in the literature. Instead, the audit focuses on one quantitative measure of productivity - the number of students each faculty member has in class (student contact/credit hours). To investigate the impact that implementing the auditors' recommendation would have on our institution, Binghamton University, we explore the influence of class size in two important areas: academic performance and student retention.

Institutional Setting

Binghamton University is a public university, part of the State University of New York system. Undergraduate enrollment is just under 9,300. The university is academically oriented, and its students are well above the national average in quality measures such as SAT scores and high school rank. Other measures, such as retention and graduation rates, are also very high. Binghamton University is separated into five schools: Decker School of Nursing, Harpur College of Arts & Sciences, the School of Education and Human Development, the School of Management, and Watson School of Engineering and Applied Science. Harpur College is by far the largest of the five schools, enrolling 78% of all full-time, matriculated freshmen. The School of Education and Human Development did not accept freshmen until 1997, so it is not included in our analysis.

Hypotheses

In this study, we test the following two hypotheses on the student body at Binghamton University.

<u>*Hypothesis 1*</u> – *There is an inverse relationship between class size and student achievement.*

<u>*Hypothesis 2*</u> – *There is an inverse relationship between the probability that a student will be retained and the average size of that student's classes.*

Methodology

Two samples of data are used in this study. The first is used to test our hypothesis on student achievement and it contains data summarized at the student-course level. In other words, the data sample contains one data record for each course in which a student is enrolled. The second data set, used to test our hypothesis on retention, is slightly different. Because a student's retention status does not vary from one course to another, it is not appropriate to use the student-course level data. Instead, we use one record per student with variables measuring the student's classroom experience in the aggregate.

For both of these samples we select the student records from the Fall 1996 and Spring 1997 semesters for all first-time, full-time, degree-seeking freshmen enrolled at Binghamton University in the Fall of 1996.

Student Achievement

The hypothesis on student achievement requires that we measure, for each of a student's classes, both the student's achievement and the size of the class. We use a student's end-of-term course grade as the measure of achievement. We obtain this information from the University's student record file. Binghamton University distributes grades in the following fashion, A, A-, B+, B, B-, C+, C, C-, D, F. For methodological considerations described below, we collapse these grades into a five-category scale: A, B, C, D, and F. These letter grades are assigned numeric values of 4, 3, 2, 1, and 0, respectively. A's account for 33% of the grades in the sample, B's represent 39%, C's 20%, D's 4%, and F's make up the remaining 4%.

Class size is measured using the same student record file. For each course, we count the number of students enrolled. These enrollments reflect end-of-semester class sizes. To insure that our class size indicator accurately reflects each student's classroom experience, we use the

University's course system to account for cross-listed sections. Two students registering for a cross-listed course could have different course names on their records. If we did not use the course system to decipher which courses of different names were in fact meeting together, we would over count the number of courses and undercount, perhaps significantly, the number of students in each class.

In addition to this linear specification of the relationship between class size and student achievement, we also test whether the relationship is non-linear. Specifically, we check to see if the natural logarithm of class size is a better predictor of student achievement than class size itself. We do so for two reasons. The first is methodological. Acton (1959: 223) points out that data that are counts of populations are almost always improved by taking logs (cited in Tufte 1974: 108). This is because logging produces a "nice" distribution so that values that were originally clustered are spread out, and values that were originally outliers are pulled toward the middle of the distribution. More importantly, aside from the methodological conveniences of logging class size, there is a persuasive *theoretical* justification for logging the class size measure. That is, we posit (as have Glass *et al*. (1982)) that the relationship between class size and student achievement is likely to be shaped like a negative log function. A negative log function slopes down from left to right at a diminishing rate, meaning that there are large negative consequences for student achievement in adding additional students to a *small* class. However, the negative consequences for adding each additional student to a *large* class are not as great. In other words, beyond some number of students in a class, adding more students to that class has very little negative impact.

To control for possible confounding influences on grades we use many other variables in our regression.[2] These include dichotomous variables for race/ethnicity: Black, Hispanic, Asian, Non-Resident Alien, and Unknown Ethnicity/Not Given. Whites make up the comparison category. Other demographic variables used as controls are age, gender, and admission under New York's Educational Opportunity Program (EOP). To roughly capture each student's abilities, we use rank in high-school class and SAT verbal and math scores. We also include a dummy variable for whether the student took the TOEFL (Test of English as a Foreign Language) exam. Binghamton University has four schools to which freshmen are admitted. We use dichotomous variables to indicate each student's school of enrollment – the School of Management, the Decker School of Nursing, or the Watson School of Engineering (the fourth school, Harpur College of Arts & Sciences is the comparison group). It is possible that some courses are more difficult, and thus have lower grades independent of class size. To capture this effect, we include a dummy variable denoting whether each course is a science or mathematics course.[3] Finally, we control for the presence of non-credit bearing discussion and activity sections that are attached to some courses. Typically, graduate student teaching assistants run these subsections. We use a dichotomous variable to control for subsections attached to science and mathematics courses, and a second for subsections attached to other, non-science-and-mathematics courses. We also create two interaction terms by multiplying each of these dummy variables by class size.[4]

Descriptive statistics for all of the variables included in the analysis of achievement are shown in Table 1 (see Table 1 at the end of this paper).

Student Achievement Results

Because the grades assigned to students represent discrete categories rather than a continuous measure, Ordinary Least Squares (OLS) is inappropriate. In addition, since there are more than two categories of the dependent variable, the oft-used binary logit and probit models are also inappropriate. Instead, we use Ordered Logistic Regression, which is appropriate when the dependent variable has more than two possible values, and is a categorical variable ranked ordinally along some underlying dimension. In this analysis, the dependent variable is made up of five categories, grades of F, D, C, B, and A, ranked ordinally along the dimension of achievement.[5]

Output from ordered logit regression includes a constant term and coefficients analogous to those produced in OLS models. Unlike OLS models, however, ordered logit regression estimates threshold parameters that separate adjacent categories of the dependent variable (Liao 1994: 38; Greene 1993; King 1989: 116; McKelvey and Zavoina 1975). These threshold parameters, along with the regression coefficients, allow the substantive interpretation of the ordered logit results. In the five-category case we have here, there are three such threshold parameters, μ_2, μ_3 and μ_4. Given these μs and the regression coefficients, we can interpret the effect of each independent variable in determining the category of the dependent variable in which any particular observation is likely to fall. In other words, based on the results of the regression, we can estimate the predicted probability of a given student receiving a particular grade, based on their values for the variables we have included in the model, e.g. class size, SAT scores, course subject matter, etc. For a complete description of ordered logistic regression, see McKelvey and Zavoina (1975) and Greene (1993).

The results from our first analysis, in which we investigate the influence of class size on students' grades, are reported in Table 2. Four models are presented in this table. Models I and II include the linear specification of class size while models III and IV include the logged class size variable. In addition, Models II and IV include interaction variables created by multiplying the subsection dummy variables by the respective class size measures.

In all four models, the class size indicator is negative and significant well beyond standard thresholds. The chi-squared[6] values for the logged class size models are higher than the respective statistics for the linear models, meaning that the logged specification of class size has superior predictive power.[7] These results are similar to those reported by Glass *et al*. (1982), who in their meta-analysis of the literature on class size effects find a negative log relationship between class size and achievement.

(see Table 2)

Most of the control variables in the four models perform as we expected, in particular, the variables measuring students' ability levels. SAT scores and rank in high school class exhibit strong positive influences on grades. However, the results pertaining to the presence of subsections are surprising.

First, in Models I and III, which do not contain the subsection-class size interaction variables, the two subsection variables are both significant and negative. Thus, regardless of class type, i.e., science/math or other, the presence of a subsection actually decreases student grades, but these effects change somewhat when the interaction variables are introduced. In Model II, the linear specification that tests for interaction effects between the presence of subsections and class size, there are no significant interaction effects for either science/math or other types of subsections.

However, the logged specification, Model IV, shows significant interaction effects in both types of classes, yet the nature of the relationship differs with regard to class type. In non-science/math courses, we see that there is a negative subsection effect, and a positive interaction effect between this variable and class size. In other words, the detrimental effect of subsections on grades in these courses is lessened as the size of the main section of the course increases.

Although we did not develop an explicit hypothesis about the subsection indicators and the possible interaction effects, we expected the presence of a subsection to counter any detrimental class size effects. Our expectation on this point mirrors the conventional wisdom. Discussion/lab sections provide students the opportunity to ask clarifying questions and to perform exercises aimed at re-enforcing course material in a much smaller and more intimate setting than the larger, main section of the course.

In Model IV, in which we added interaction variables to the logged specification, the conventional wisdom is supported for subsections tied to science/math courses, but not others. Here the science/math subsection indicator is significant and positive meaning that subsections in these courses help students achieve higher grades. These subsections counter the negative effects of class size. The significant and negative interaction term means that as the size of the main science/math section increases, the positive effect of these subsections is diminished, suggesting that subsections are better at helping students in small courses than they are in large courses. As was the case with Model II, however, the presence of subsections tied to non-science/math courses runs counter to the conventional wisdom – they decrease, rather than increase grades.

In their study of student attitudes towards large and small classes, Cammarosano and Santopolo (1958: 340) reported that “The employment of graduate assistants even in so small a role as attendance-taking diluted the intimacy of faculty-student contact.” The result was that professors experienced, “Greater difficulty in uncovering students’ individual academic difficulties and in stimulating the complacent members of their classes.” Our findings do not support their conclusion. While we do not have a concrete explanation for our findings, we can say that in science/math courses offered at our institution, the presence of a graduate assistant leading a discussion section has a positive effect on students' grades.

What we have found, however, suggests a slightly more complicated relationship between discussion sections and student performance; one that depends on the nature of the subject matter being taught. One plausible explanation for our findings on subsections is that there is something inherent in science/math courses, perhaps the need for repetition, that is well-served through a discussion/lab subsection. In other types of courses, different subject matter is discussed, perhaps largely theoretical concepts, for which discussion subsections are less helpful. We have not provided any test of this hypothesis and so we cannot say whether this is correct; we simply offer this as one of many possible explanations.

Returning now to our results on class size. You will recall that Table 2 shows that the model with the best predictive capacity is Model IV, which contains a logged measure of class size. One of the nice features of the ordered logit analysis conducted here is that it allows us to predict the likelihood that a student will receive a particular grade given various class sizes. To show the effects of class size on student achievement, as predicted by the model, we present Figure 1, which shows the predicted probability that a student will receive a given grade in classes of varying size.[8] For any given class size, these probabilities sum to 1.0. Notice the strong, negative effect of class size on the predicted probability of a student receiving an A. The model predicts that a student in a class of 5 students has a .52 probability of receiving an A, 2.4 times higher than a student in a class of 290 students, where the predicted probability of receiving an A is .22.

(see Figure 1)

Figure 1 also shows that as the likelihood of an A grade decreases, the likelihood of each of the other grades increases. If we compare the low to high ends of the class size axis we see that up to a class size of around 20, the most likely grade is an A, followed by B, C, D, and F, respectively. For classes between 20 and 260 students, the most likely grade is a B, followed by A, C, D, and F, respectively. For classes with more than 260 students, the most likely grade is still a B, however, the second most likely grade is now a C, followed by A, D, and F, respectively. Figure 1 reinforces the results shown in Table 2 and depicts graphically the relationship between class size and student performance.

Freshman Retention

While much of the literature on class size focuses on its effect on student achievement, it seems plausible that class size affects other important aspects of a student's college experience. Therefore, when analyzing the costs associated with small classes, one must consider their benefits across a broad range of areas. In this section, we test for a class-size influence in one of these other important areas: student retention.

Student retention is an important measure for many institutions of higher education. Each student that is not retained is an example of the university failing to complete its mission. Such attrition is costly, as new students must be recruited and oriented to replace those who have left. Poor retention of students can be costly to an institution's reputation as well, since retention rates are commonly used by guidebooks and the media to assess the quality of various institutions. Thus, understanding the factors that contribute to student retention can be very beneficial to universities.

Our hypothesis on retention requires a different research design from what was needed to test our hypothesis on student achievement. For student achievement, we operated at the level of the student-class. To test our retention hypothesis, we moved to a less detailed unit of analysis, the student. We created a binary dependent variable that indicated whether each first-time, full-time, degree-seeking freshman from the Fall 1996 semester returned for the Fall 1997 semester. This is consistent with the University's official method of measuring first-year retention rates.

Our independent variable of interest, class size, was created by averaging the enrollment of all of each student's course sections over the Fall 1996 and Spring 1997 semesters. This average thus accounts for all of each student's classroom experiences for these two semesters, including all discussion and activity sections (which we referred to in the previous section as subsections). Again, we tested for the presence of a non-linear relationship by running a second model, which included the natural log of this class size variable.

As in the previous analysis, we controlled for possible confounding influences on retention. For the most part, the control variables in the retention analysis are identical to those in the achievement analysis. The two main differences are that instead of a dummy variable indicating a science or math course, at the student level of analysis, we modify this variable to account for the *percentage* of each student's credit hours devoted to science and math courses. (Thus, we also drop the interaction variables between the various types of subsections and class size.) The second difference in control variables between the two analyses is that we include each student's first-year college grade point average in our analysis of retention. We suspect that a student's academic performance in the previous year will be an important determinant in that student's decision to return to school the following year.[9] Table 3 gives descriptive statistics for the variables included in our analysis of retention.

(see Table 3)

Student Retention Results

Due to the binary nature of the retention dependent variable, we use logistic regression analysis to gauge the effects of class size on the likelihood that a student returns for a second year at Binghamton University. Table 4 presents our results.

(see Table 4)

As you can see, the results in Table 4 show there to be a significant and negative relationship between class size and student retention. As a student's average class size increases, he or she becomes less likely to return to the University. This effect is present despite the numerous control variables included in the models. However, unlike the student achievement analysis, the relationship between class size and retention does not appear to be log-shaped. Though the logged class size variable is negative and statistically significant, the model is inferior to the linear model as shown by the linear model's higher chi-squared statistic.

Aside from the class size and grade point average variables, none of the other variables in the retention model are statistically significant. Recall this was not the case in the student achievement analysis. We suspected that this might be caused by collinearity among some of the independent variables measuring student ability. Although Pearson's r values among these variables were low, we tried dropping these variables one at a time. None of these changes led to different conclusions. It appears different factors influence retention and achievement at Binghamton University.

Figure 2 is a plot of the predicted relationship between average class size and student retention. It shows the predicted probability that a student will be retained as that student's average class size increases. The model predicts that a student with an average class size of 20 has a .97 probability of returning to the University, whereas a student with an average class size of 240 has a probability of returning of only .80. The former student is 1.2 times more likely to return to the University than the latter.

Summary and Conclusions

This study is novel for two reasons. First, it is one of the few that examine the relationship between class size and student achievement at the post-secondary level. Much of the research up to now has been conducted on elementary and secondary school students. Second, it explores the effects of class size in an area other than student performance: retention.

Please bear in mind as we summarize our findings that these results apply to only Binghamton University. We cannot say whether these relationships apply to other institutions of higher education. Our results certainly suggest avenues for further research and it would be desirable to examine these relationships using data from more than one institution.

Nonetheless, we have found class size to be a significant factor influencing both of these aspects of a student's college experience at Binghamton University. Our analysis of student achievement found a strong negative relationship between class size and the likelihood of receiving a course grade of A. As class size increases, the probability of receiving an A is lowered, but at a decreasing rate.

Similarly, we found a negative relationship between class size and retention. Students with smaller average class sizes are more likely to return for a second year at Binghamton.

However, unlike the relationship between class size and achievement, the relationship between class size and retention decreases at an *increasing* rate. In sum, our results suggest that adding 50 students to a class of 150 may not significantly lower student grades, but it would likely lead to a large decrease in retention.

Notes

[1] The latter two, alumni satisfaction and academic reputation, although not analyzed here, are of increasing importance given the high profile rankings provided by a number of college guides. For example, U.S. News and World Report's Best College's relies heavily on these two measures, with 25% of a school's rank based on its academic reputation and 5% based on its alumni giving rate.

[2] Since our primary variable of interest is class size and how it affects student achievement and retention, we make no effort to develop directional hypotheses about any of these control variables.

[3] We define science and mathematics courses as those offered in the following subject areas: Biology, Biochemistry, Chemistry, Geology, Mathematics, Psychology, and Physics.

[4] In the models in which the logged class size variable is included, these interaction terms are created by multiplying the subsection dummies by the logged class size measure.

[5] Recall that these five categories result from collapsing A- and A into one category, B+, B, and B- into another category, etc. This was done because of software limitations. We used LIMDEP 5.1 to estimate the ordered logit regressions. This version of LIMDEP did not produce reliable results when the original, 9 category, grade scale was used. The regression estimated correctly when the number of dependent variable categories was reduced. For lack of a better method of grouping the grades, we chose to group all A's together, all B's together, and all C's together. Along with the D's and F's, this method produced the five-category variable used in the analyses.

[6] The chi-squared values are used to evaluate the significance of the overall model as compared to a null model in which the all of the independent variables are assumed to equal zero. Thus,

the chi-squared statistic in maximum likelihood estimation is analogous to the f-statistic in Ordinary Least Squares regression.

[7] We tested two additional specifications of the class size variable: class size weighted by the number of hours the class meets per week (weighted) and class size squared (curvilinear). The results of these two specifications were similar to those presented, although neither was as strong as the logged specification.

[8] As is standard practice when analyzing the results of maximum likelihood models, we hold all other independent variables at their mean values while analyzing the effect of class size (Liao 1994).

[9] We were forced to drop the dummy variable indicating that a student took the TOEFL exam because all such students (for whom we had complete data) were retained.

TABLE 1
DESCRIPTIVE STATISTICS OF VARIABLES IN STUDENT ACHIEVEMENT ANALYSIS

Variable	Mean	Standard Deviation
Class Size	142.66	121.41
EOP Student	0.08	0.27
Management Student	0.10	0.31
Nursing Student	0.03	0.17
Engineering/Computer Science Student	0.09	0.29
Age of Student	17.86	0.53
Female Student	0.58	0.49
Unknown Ethnicity	0.04	0.19
Black	0.05	0.21
Hispanic	0.06	0.23
Asian	0.15	0.36
Non-Resident Alien	0.01	0.08
TOEFL Test	0.02	0.15
High School Rank	87.59	10.69
SAT Verbal	581.13	85.94
SAT Math	601.59	78.79
Science or Math Course	0.37	0.48
Subsection	0.30	0.46
Subsection*Class Size	43.89	78.10
Subsection (Science/Math)	0.16	0.37
Sci./Math Subsection*Class Size	40.63	101.37
n = 9345		

TABLE 2

Ordered LOGIT Regression models of Students' course grades

	Model I		**Model II**		**Model III**		**Model IV**	
n	9,345		9,345		9,345		9,345	
LL Full Model	-11,141		-11,136		-11,098		-11,086	
LL Null Model	-12,151		-12,151		-12,151		-12,151	
Chi-squared	2,020		2,030		2,106		2,129	
Significance	.0000		.0000		.0000		.0000	
Variable	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
Constant	-2.9875***	.7306	-2.9800***	.7311	-1.8650**	.7382	-1.8019**	.7401
Class Size	-.0021***	.0002	-.0019***	.0002	-----	-----	-----	-----
Class Size (Natural Log)	-----	-----	-----	-----	-.3181***	.0221	-.3221***	.0246
EOP Student	.0833	.0982	.0887	.0982	.0167	.0988	.0168	.0988
Management Student	-.0352	.0674	-.0452	.0675	-.0254	.0676	-.0411	.0679
Nursing Student	-.0849	.1225	-.1414	.1249	-.0764	.1223	-.1539	.1258
Engineering/Computer Science Student	-.5271***	.0691	-.5369***	.0693	-.5253***	.0689	-.5249***	.0689
Age of Student	.1311***	.0371	.1296***	.0371	.1268***	.0371	.1232***	.0372
Female Student	.1904***	.0436	.1890***	.0436	.1833***	.0437	.1792***	.0437
Unknown Ethnicity	-.1449	.1055	-.1412	.1058	-.1481	.1058	-.1431	.1061
Black	-.3775***	.1003	-.3686***	.1004	-.3950***	.1005	-.3882***	.1006
Hispanic	-.3084***	.0914	-.3057***	.0914	-.3201***	.0918	-.3164***	.0917
Asian	-.3128***	.0577	-.3048***	.0577	-.3212***	.0577	-.3115***	.0577
Non-Resident Alien	-.4221	.2756	-.4084	.2758	-.4361	.2767	-.4071	.2770
TOEFL Test	1.1583***	.1414	1.1593***	.1415	1.1765***	.1414	1.1770***	.1416
High School Rank	.0205***	.0019	.0206***	.0019	.0205***	.0019	.0207***	.0019
SAT Verbal	.0022***	.0003	.0022***	.0003	.0022***	.0003	.0022***	.0003
SAT Math	.0037***	.0003	.0037***	.0003	.0037***	.0003	.0037***	.0003
Science or Math Course	-1.1297***	.0569	-1.1525***	.0576	-1.0802***	.0567	-1.0771***	.0570
Subsection	-.6760***	.0532	-.7556***	.0905	-.4772***	.0560	-1.3707***	.2997
Subsection*Class Size	-----	-----	.0004	.0006	-----	-----	-----	-----
Subsection*Class Size(Natural Log)	-----	-----	-----	-----	-----	-----	.1842***	.0634
Subsection (Science/Math)	-.4803***	.0676	-.1224	.1428	-.3784***	.0686	1.2803**	.5097
Sci./Math Subsection*Class Size	-----	-----	-.0014***	.0005	-----	-----	-----	-----
Sci./Math Subsection*Class Size(Natural Log)	-----	-----	-----	-----	-----	-----	-.3058***	.0950
Mu(2)	.7670***	.0411	.7670***	.0411	.7685***	.0412	.7689***	.0412
Mu(3)	2.5007***	.0549	2.5047***	.0549	2.5063***	.0550	2.5125***	.0550
Mu(4)	4.4747***	.0600	4.4801***	.0600	4.4925***	.0601	4.5023***	.0601

Notes: One-tailed probability levels reported for class size indicator. Two-tailed probability levels reported for all other variables.
Significance levels indicated by: ** < .05, *** < .01

TABLE 3

DESCRIPTIVE STATISTICS OF VARIABLES IN STUDENT RETENTION ANALYSIS

Variable	**Mean**	**Standard Deviation**
Retained	0.91	0.28
Class Size	99.11	32.52
EOP Student	0.08	0.27
Management Student	0.10	0.30
Nursing Student	0.03	0.17
Engineering/Computer Science Student	0.09	0.29
Age of Student	17.86	0.54
Female Student	0.57	0.50
Unknown Ethnicity	0.04	0.20
Black	0.05	0.21
Hispanic	0.06	0.24
Asian	0.16	0.36
Non-Resident Alien	0.01	0.08
First-Year GPA	2.87	0.63
High School Rank	87.33	11.04
SAT Verbal	579.65	86.14
SAT Math	600.38	78.86
% Science and Math Credits	0.36	0.20

n = 1221

TABLE 4
LOGIT REGRESSION MODELS OF FIRST-YEAR RETENTION

Linear Model

n	1221
LL Full Model	623.25
LL Null Model	711.19
Chi-squared	87.94
Significance	.0001

Variable	**Coefficient**	**Std. Error**	**Prob. Level**
Constant	2.8268	4.2926	.5102
Class Size	-.0093	.0043	.0153
EOP Student	-.0053	.6430	.9935
Management Student	.6430	.4613	.1634
Nursing Student	1.1079	1.0504	.2916
Engineering/Computer Science Student	-.2090	.3960	.5976
Age of Student	.1053	.2139	.6226
Female Student	-.3736	.2449	.1271
Unknown Ethnicity	.2817	.5953	.6361
Black	.9981	.8296	.2289
Hispanic	-.5455	.4631	.2388
Asian	.0035	.3080	.9911
Non-Resident Alien	-.7111	1.1261	.5278
First-Year GPA (Natural Log)	2.8506	.3720	.0001
High School Rank	-.0150	.0128	.2431
SAT Verbal	-.0018	.0017	.2713
SAT Math	-.0031	.0020	.1186
% Science and Math Credits	.8580	.6784	.2060

Log Model

n	1221
LL Full Model	624.09
LL Null Model	711.19
Chi-squared	87.10
Significance	.0001

Variable	**Coefficient**	**Std. Error**	**Prob. Level**
Constant	5.6162	4.7592	.2380
Class Size (Natural Log)	-.8214	.4267	.0271
EOP Student	-.0342	.6480	.9580
Management Student	.6546	.4613	.1559
Nursing Student	1.1767	1.0476	.2613
Engineering/Computer Science Student	-.1674	.3937	.6706
Age of Student	.1102	.2135	.6057
Female Student	-.3866	.2445	.1139
Unknown Ethnicity	.2700	.5903	.6474
Black	.9738	.8201	.2351
Hispanic	-.5554	.4626	.2299
Asian	-.0050	.3077	.9869
Non-Resident Alien	-.7029	1.1250	.5321
First-Year GPA (Natural Log)	2.8609	.3720	.0001
High School Rank	-.0151	.0128	.2393
SAT Verbal	-.0019	.0017	.2609
SAT Math	-.0031	.0020	.1190
% Science and Math Credits	.7248	.6607	.2727

Note: One-tailed probability levels reported for class size indicator. Two-tailed probability levels reported for all other variables.

Figure 1

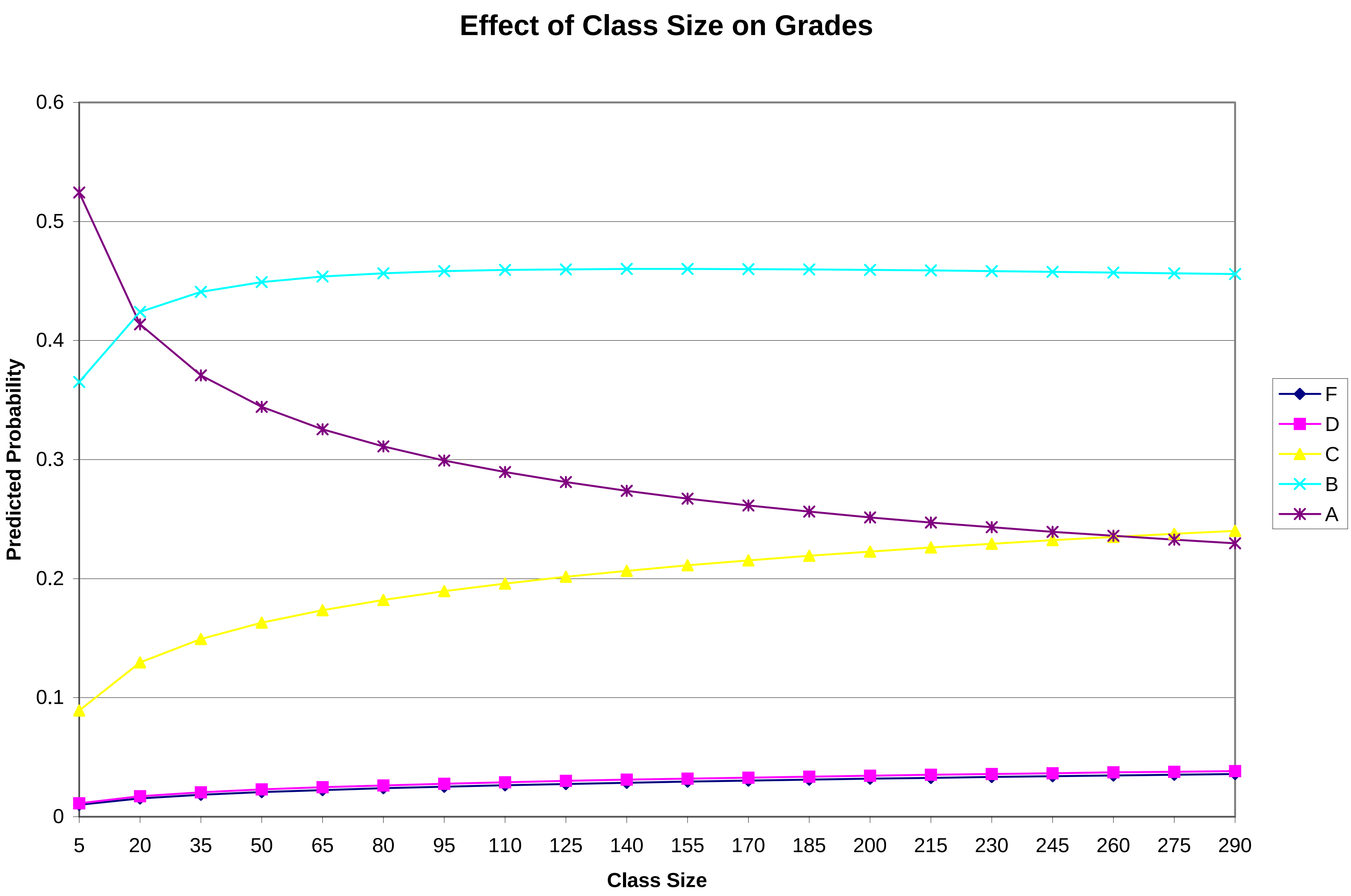
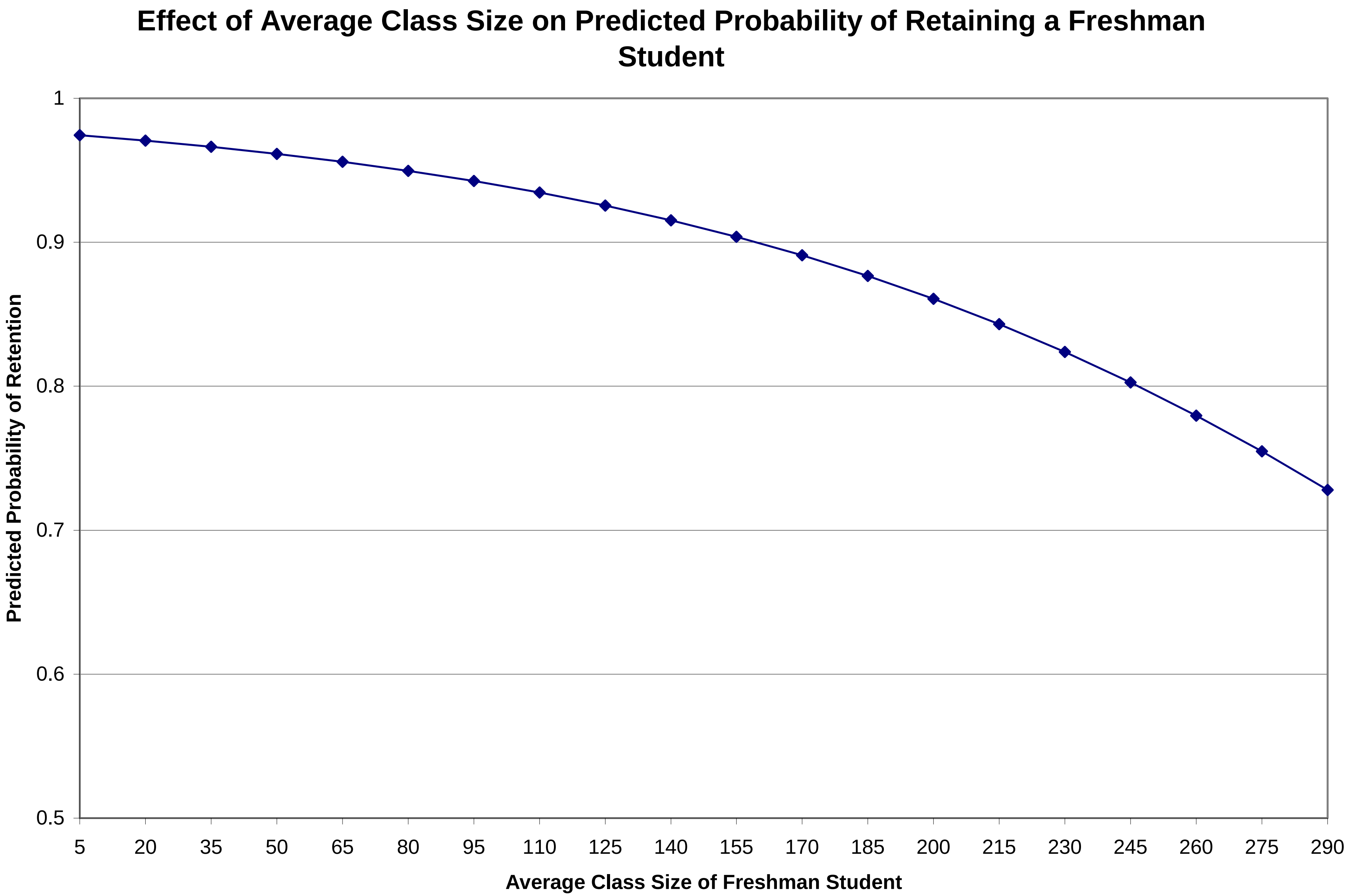

Effect of Class Size on Grades
Predicted Probability
0.6
0.5
0.4
0.3
0.2
0.1
0
5
20
35
50
65
80
95
110
125
140
155
170
185
200
215
230
245
260
275
290
Class Size
F
D
C
B
A

Figure 2


Effect of Average Class Size on Predicted Probability of Retaining a Freshman Student
Predicted Probability of Retention
1
0.9
0.8
0.7
0.6
0.5
5
20
35
50
65
80
95
110
125
140
155
170
185
200
215
230
245
260
275
290
Average Class Size of Freshman Student