DOCUMENT RESUME

ED 402 983 JC 970 053

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TITLE Using HLM To Investigate Instructor Grade Variability and Differences by Gender and Race-Ethnicity in Ethnically-Diverse Community College Math Courses.
PUB DATE 8 Apr 96
NOTE 23p.; Paper presented at the Annual Meeting of the American Educational Research Association (New York, NY, April 8-12, 1996).
PUB TYPE Reports - Research/Technical (143) -- Speeches/Conference Papers (150)

EDRS PRICE MF01/PC01 Plus Postage.
DESCRIPTORS *College Mathematics; Community Colleges; *Correlation; Females; *Grades (Scholastic); Males; Minority Groups; *Multivariate Analysis; *Student Characteristics; *Teacher Characteristics; Two Year Colleges; Two Year College Students
IDENTIFIERS *Hierarchical Linear Modeling

ABSTRACT

A study was undertaken at a large, ethnically diverse community college in California to identify instructor and course factors associated with grade variability and grade differences by gender and race/ethnicity in mathematics courses. The study used a statistical procedure called hierarchical linear models (HLM) to analyze the relationship between within-course variables (i.e., average grades awarded and average grade differences by gender and race/ethnicity) and between-course variables (i.e., instructor and class characteristics). The study sample included all 2,440 students in 68 pre-college and college-level mathematics courses in one term, while student-level data for the HLM analysis included gender, race/ethnicity, and final grades. Instructor- and course-level data were instructor gender, race/ethnicity, experience, and part-/full-time status and the level of the mathematics course. Study findings included the following: (1) a significant difference in average grades that was found between classes was determined to be related to instructor experience, with instructors having 10 or more years of experience assigning an average of .5 grade points lower than instructors with less than 10 years experience; (2) no differences were found for grades received by gender within classes, although there was substantial variation between classes; and (3) minority students averaged .2 grade points below white students within classes, while no significant variance was found between classes. While the HLM method can allow new questions to be asked about factors affecting grades, the focus on instructor characteristics may raise sensitive issues when used within individual colleges. Contains 30 references. (HAA)

Using HLM to Investigate Instructor Grade Variability and Differences by Gender and Race-ethnicity in Ethnically-Diverse Community College Math Courses

Session 3.22
Monday, April 8, 1996
2:15-3:45 pm

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Prepared for
the American Educational Research Association Annual Meeting
April 8-12, 1996
New York, New York

Background and Framework[1]

Students enrolled in community colleges reflect the increasing diversity of the general population in terms of race, ethnicity, and gender. (AACC, 1995, WICHE, 1993) For many traditionally disadvantaged racial-ethnic groups, new immigrants, and women returning to college, community colleges provide the major access to higher education (Nora and Rendon, 1988; Rendon, 1993; AACC, 1995). At the same time, the educators in technological fields have realized the importance of training more women and minorities in math and science in order to meet changing labor market needs (Burton and Celebuski, 1995; National Education Goals Panel, 1995). Community colleges offer an extensive math curriculum ranging from pre-college level basic skills math through calculus that can help meet the needs of women and people of color for the basic foundations of technological skills (California Community Colleges, 1995a).

A major concern of California Community Colleges is to insure that minority and female students succeed and persist to graduation and/or transfer at the same rate as that of white and male students (Academic Senate, 1993; Sheehan, 1995). The response of the California Community College system has been to develop programs to improve the success, retention, and persistence of all students, and to monitor differences in student progress by gender, race-ethnicity, and other factors (California Community Colleges, 1986; Seymour-Campbell Matriculation Act, 1986). These programs usually require the following components: 1) intensive orientation, counseling, and assessment programs designed to insure that new students start in courses appropriate to their skill levels; 2) consistent and effective instruction; and 3) monitoring of differences in course placement recommendations and outcomes by gender and race-ethnicity (California Community Colleges, 1995b). Research on course recommendations and results, however, is typically confounded by persistent variability in grades among instructors, within the same courses and over different courses (Boese and Birdsall, 1993; Rasor and Barr, 1993; Armstrong, 1995) . In addition, it is possible that variations in the ability of instructors to teach an increasingly culturally diverse student population may contribute to gender and race-ethnicity differences in academic performance. Information is needed to identify the factors that are associated with grade variability and grade differences by gender and race-ethnicity .

The study used a relatively new statistical procedure—hierarchical linear models (HLM)—to identify factors related to the variation in average grades and grade differences by gender and race-ethnicity among math courses (Arnold, 1992; Bryk and Raudenbush, 1992). HLM allows the

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association of instructor gender or race with grade differences by student gender or race within their classes.

Other college researchers have identified some relationships between grades and: student gender (Hughey and Harper, 1983), student and instructor gender (Pearson and Nelson, 1981), race-ethnicity of instructor and student (Carter and Schaefer, 1976), female students' interactions with faculty (Sax, 1993), students working with same-gender rather than opposite-gender tutors (House, 1988), and the interaction of teaching style and student gender (Thompson and O'Brien, 1991). Based on this research, factors hypothesized as associated with grade variability were instructor demographic characteristics such as gender and race-ethnicity. In addition, instructor factors such as years of experience, part-time status, and level of education as well as the level of the course were included as control variables.

Research on women and mathematics has documented many differences in mathematics achievement and differences in the ways females and males are treated in the classroom (Dossey, et al., 1988; Leder, 1990; Bridgeman and Wendler, 1991). Besides the continuation of "the monitoring of outcomes," these researchers also point to the need for research on "the characteristics of schools and classrooms where no gender differences in mathematics exist", and more research on successful classrooms, and the variation between classrooms in the same school (Leder and Fennema, 1990). Most statistical research shows that African American, Latino, and Native American students have lower academic performance in mathematics than white and Asian American students (Dossey, et al., 1988). African American researchers, however, caution that correlational studies do not adequately explain why black students do not achieve academically as well as white students, and suggest looking at other more political factors, such as racial stratification (Ogbu, 1988). Based on this research, the importance of instructors of the same gender and race-ethnicity was hypothesized. Instructor experience, education, part/full-time status and the course level were also included as control variables in the gender and race-ethnicity equations.

This paper has three major objectives:

1) to identify instructor and course factors associated with grade variability and grade differences by gender and race-ethnicity in math courses in an ethnically diverse community college.
2) to illustrate the use of hierarchical linear models (HLM) in investigating grade variability between courses and grade differences by gender and race-ethnicity within courses.
3) to discuss the implications of using these statistical models to study grade variability and grade differences by gender and race-ethnicity.

Methodology and Data Sources

This study posed a multilevel problem by analyzing the associations of class-level[2] variables with student-level outcomes and characteristics. The appropriate method for analyzing multilevel data is hierarchical linear models (HLM), which estimates the associations of factors at one level with outcomes of groups at the next lower level, while taking into account the variation at each level. In this study, HLM was used to analyze the association of the within-class outcomes of average grades and average grade differences by gender and race-ethnicity with the between-class factors of instructor and class characteristics. While this method has been used on large national datasets and on other educational and occupational data, this is one of the first times that HLM has been used to answer questions about community college research concerns (Arnold 1992; Arnold, 1993; Arnold, 1995). This study illustrates and raises questions about the usefulness of HLM for such community college research.

The sample for this study were students at a large urban community college in California. On this campus of 15,000, white students were in the minority as 45 percent of the student body, and African-American, Asian-American, Latino, and Filipino students each represented 10-15 percent of the students. All 2,440 students in 68 sections of pre-college and college-level math courses through beginning calculus during one term were selected. Student-level data were gender, race-ethnicity, and final grades. Instructor/class-level data were instructor gender, race-ethnicity, experience, and employment status (full-time/part-time) and the level of the math course. Table 1 presents the definitions, means, standard deviations, and ranges of the student-level and instructor/class-level variables.

[2]In this paper, "class" refers to each class taught by a different instructor at a different time, i.e., a course section. There were many course sections for each course and some instructors taught different sections of the same course. Each class has both course characteristics and instructor characteristics.

Table 1.—Definitions, means, standard deviations, and ranges for student-level and class-level variables

Variable Name	Variable Definition		Mean	(s.d.)	Range Min	Range Max
STUDENT-LEVEL VARIABLES						
Dependent Variable						
GRADE	0=W; 1=F, NC; 2=D; 3=C, CR; 4=B; 5=A		2.55	(1.81)	0	5
Independent Variables						
Gender						
FEMALE	0=Male;	1=Female	0.51	(.50)	0	1
Race-ethnicity						
MINORITY	0=White;	1=African-American, Asian-American, Filipino, Latino, Other	0.60	(.49)	0	1
AFRCAM	0=all others;	1=African American	0.11	(.31)	0	1
ASIANAM	0=all others;	1=Asian American	0.19	(.39)	0	1
FILIPINO	0=all others;	1=Filipino	0.12	(.32)	0	1
LATINO	0=all others;	1=Latino	0.17	(.38)	0	1
OTHERMIN	0=all others;	1=Other minority	0.03	(.17)	0	1
N of students		2440				
CLASS-LEVEL VARIABLES						
Instructor characteristics						
Gender						
INFEMALE	0=Male;	1=Female	0.22	(.42)	0	1
Race-ethnicity						
INMINORI	0=White;	1=African-American, Asian-American, Filipino, Latino, Other	0.26	(.44)	0	1
INASIAN	0=all others;	1=Asian American	0.12	(.32)	0	1
INLATINO	0=all others;	1=Latino	0.09	(.29)	0	1
INOTHMIN	0=all others;	1=Other minority	0.06	(.24)	0	1
Years of college teaching experience						
INEXPYRS	Number of years teaching		7.16	(8.97)	1	26
IN10PLUS	0=Less than 10 years;	1=10 or more years	0.25	(.44)	0	1
Educational attainment						
INEDUC	0=Master's degree;	1= Ph.D. degree	0.15	(.36)	0	1
Employment status						
INPART	0=full-time;	1=part-time	0.38	(.49)	0	1
Course characteristics						
Course level						
CRSLEVEL	1=Basic math 2=Elementary Algebra 3=Intermediate Algebra 4=College Algebra 5=Statistics 6=Trigonometry 7=Pre-calculus 8=Calculus		3.75	(2.02)	1	8
PRECOLL	0=College-level math	1=Pre-college math	0.56	(.50)	0	1
ADVMATH	0=All other course levels;	1=College math above statistics	0.19	(.40)	0	1
CALCULUS	0=All other course levels;	1=Calculus	0.07	(.26)	0	1
N of classes		68				

SOURCE: College Institutional Research Data Sets, 1993.

HLM Analysis

An HLM analysis was conducted on the final grade in these math classes. Each HLM analysis consists of the following steps.[3] In the first step, the within-class models are estimated using ordinary least squares (OLS) regression analysis. In this study, final grades were modeled at the student level within each class as a function of the student characteristics—gender and race-ethnicity. This resulted in an equation for each class that consisted of regression coefficients (called Betas in HLM) that estimated the association of the final grade with being female and with being a minority—sometimes called the "gender gap" and the "race-ethnicity gap." The equation also estimated an intercept, which represented the average grade in that class. Within each class, the equation took the form of the following OLS regression equation:

Within-class student-level equation[4]

$$y_i = B_{0i} + B_{1i}X_{1i} + B_{2i}X_{2i} + R_i \qquad (1.1)$$

where:

i represents the i^{th} class
y_i represents the final math grade of students in the i^{th} class
B_{0i} is the intercept, or the average grade in the i^{th} class
B_{1i} is the Beta coefficient for gender in the i^{th} class
B_{2i} is the Beta coefficient for race-ethnicity in the i^{th} class
X_{1i} represents the values of gender in the i^{th} class
X_{2i} represents the values of race-ethnicity in the i^{th} class
R_i is random error in the i^{th} class.

In the second step of the HLM analysis, the intercept and the regression coefficients from the first step in the analysis become the outcome measures in the second step. That is, each of these within-class parameters—the intercept and the Betas—is used as a dependent variable in a separate regression-like equation and the variation in these within-class parameters is modeled. When the class-level equations are estimated, the parameters from each class are weighted by the inverse of their variance. That is, the classes with the most variance (usually those from smaller samples) are given less weight in contributing to the final class-level equation.

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[3] These steps are actually simultaneous, but they can be understood most easily as sequential.

[4] The forms of these equations are taken from C.L. Arnold, An Introduction to Hierarchical Linear Models, *Measurement and Evaluation in Counseling and Development 25(2)* (July, 1992): 58-90.

At the within-class level, HLM requires researchers to specify which within-class variables will be modeled with random parameter variance and which will be specified with fixed parameter variance. In this study, the intercept, gender, and race-ethnicity parameters were allowed to vary randomly, and this variation was modeled as a function of the class-level characteristics across classes. These between-class equations produced regression-like coefficients (called Gammas in HLM) that estimated the effect of each class-level characteristic on either the average grade, the effect of gender on grades, or the effect of race-ethnicity on grades within the classes.

The following equations illustrate these models. First, the unconditional models are shown. These are the class-level models with only their intercept. They are called unconditional because they are not conditioned on any class characteristics. Following the unconditional models are the conditional models, which include the class characteristics as predictors for the random parameters.

Between-class class-level equations

a) Unconditional (before any class characteristics are added as predictors)

$B_0 = G_{00} + U_0$ (Intercept equation) (1.2)

$B_1 = G_{10} + U_1$ (Gender coefficient equation) (1.3)

$B_2 = G_{20} + U_2$ (Race-ethnicity coefficient equation) (1.4)

where:
B_0 represents the intercepts, or the average grades in all classes
B_1 represents the gender coefficients in all classes
B_2 represents the race-ethnicity coefficients in all classes
p is the number of within-class parameter equations (from 0 to 2 in this example)
G_{p0} is the intercept, or the average within-class parameter value in the p^{th} equation
U_p is random error in the p^{th} equation.

b) Conditional (with class characteristics added as predictors)

$$B_0 = G_{00} + G_{01}S_{01} + G_{02}S_{02} + \ldots + G_{0m}S_{0m} + U_0 \tag{1.5}$$

$$B_1 = G_{10} + G_{11}S_{11} + G_{12}S_{12} + \ldots + G_{1m}S_{1m} + U_1 \tag{1.6}$$

$$B_2 = G_{20} + G_{21}S_{21} + G_{22}S_{22} + \ldots + G_{2m}S_{2m} + U_2 \tag{1.7}$$

where: G_{p1} is the Gamma coefficient for the first class-level variable in the p^{th} equation
G_{p2} is the Gamma coefficient for the second class-level variable in the p^{th} equation
m is the number of class-level variables (from 0 to 2 in this example)
G_{pm} is the Gamma coefficient for the m^{th} class-level variable in the p^{th} equation
S_{p1} represents the values of the first class-level variable in the p^{th} equation
S_{p2} represents the values of the second class-level variable in the p^{th} equation
S_{pm} represents the values of the m^{th} class-level variable in the p^{th} equation

The coefficients, or Gammas, from these between-class equations are the major indicators of class correlates with grades and of class correlates with the association of gender and race-ethnicity with math grades. These three equations allow the following questions to be asked:

For the intercept equation:

- Is there variation in average grades between classes?
- What class variables are associated with that variation?

For the gender coefficient equation:

- On average, is there a difference in grades by gender within classes?
- Do these average differences vary by class?
- What class variables are associated with that variation?

For the race-ethnicity coefficient equation:

- On average, is there a difference in grades by race-ethnicity within classes?
- Do these average differences vary by class?
- What class variables are associated with that variation?

HLM Statistics and Software

Besides the Betas and Gammas, other statistics produced by the HLM analysis are helpful in interpreting the within-class parameters and the between-class models. For each of the three random within-class parameters—intercept, gender, and race-ethnicity—in each model, HLM provides the parameter variance, called Tau, a test of whether Tau is greater than zero, and the reliability, the percentage of the total variance around each parameter that is represented by parameter variance. The reliability does not change dramatically between models.

Parameter variance, or Tau, is the actual variation between classes around the parameters of the intercept and the gender and race-ethnicity coefficients in the within-class equations. The parameter variance usually changes between models. It is highest in the unconditional within-class models, where it indicates how much variance there is around each of the four parameters before any between-class variables are taken into account. The purpose of the between-class models is to explain, or reduce this parameter variance. A measure of how well each model explains the parameter variance is the R^{2*}. It is similar to a linear regression R^2, in that it represents the proportion of the original parameter variance that was explained by a particular between-class model. It is calculated by $[Tau_{conditional} - Tau_{unconditional}] / Tau_{unconditional}$

The HLM analyses in this study were produced using HLM/2L, a two-level HLM microcomputer program developed by Anthony Bryk, Stephen Raudenbush, and Richard Congden.[5]

[5]A.S. Bryk, S. W. Raudenbush, M. Seltzer, and R. Congdon, *An Introduction to HLM: Computer Program User's Guide* (Second Ed.) (Chicago, IL: University of Chicago, Department of Education, 1988) and *HLM/2L* (Chicago, IL: Statistical Software Incorporated, 1992). A preliminary version of the "C" version of HLM/2L was used for this analysis.

HLM Results

Unconditional equations: average differences within classes

Table 2 shows the results of the unconditional class-level estimates. The table includes the Gamma values with their standard error and t values as well as the reliability, parameter variance (Tau), degrees of freedom, and the chi-square test of Tau[6]. The significant intercept Tau value indicates that the average grade (2.55) varied significantly between classes. Therefore, there is variance to be explained. The average grade point gap between females and males (0.13) was not a significant difference. However, this gap varied significantly between classes, so there is variance to explain. In contrast, minorities averaged 0.17 grade points lower than whites, a somewhat significant difference. However, this difference did not significantly vary between classes, as indicated by a non significant Tau value, so it may not be possible to explain this difference.

Table 2.—Average within-class parameters of final math grades

WITHIN-CLASS PARAMETERS	Gamma Coefficient	Standard Error	t Value	
INTERCEPT (AVG. GRADES)	2.55**	0.07	35.15**	
FEMALE BETA COEFFICIENT	0.13	0.09	1.57	
MINORITY BETA COEFFICIENT	-0.17*	0.08	-2.08*	
Random within-class parameters	Reliability	Parameter Variance (Tau)	Degrees of Freedom	Chi-square test of Tau > 0
INTERCEPT (AVG. GRADES)	0.76	0.27**	67	293.93**
FEMALE BETA COEFFICIENT	0.28	0.14*	67	95.68*
MINORITY BETA COEFFICIENT	0.13	0.07	67	0.17

NOTE: ** probability ≤ .01; * probability ≤ .05.
SOURCE: College Institutional Research Data Sets, 1993.

[6]After tables 2 and 3, subsequent tables will include only the Gamma values and their significance and the parameter variances and their significance.

Conditional equations

1) Explaining grade variability between classes

Significant differences in average grades were found between classes, so all the class-level variables were tested to see which would explain this variation in the intercept equation. Table 3 shows the conditional equation for the full model. For each parameter equation, this table shows the Gamma coefficients and their tests of significance and Tau and its test of significance. Most instructor factors, such as gender, race-ethnicity, and employment status, and the level of the math course had no association with variations in average grades (table 3). However, controlling for all of these factors, this variation was related to one instructor-level variable—instructors with 10 or more years of full-time teaching experience assigned an average of 0.5 grade points lower to students in their classes than instructors with less than 10 years experience (table 3). More importantly, however, this equation explained only 3.7 percent of the parameter variance around average grades, so other variables are needed to explain the rest.

Table 3—Full model: Class-level predictors of student-level parameters of final math grades

WITHIN-CLASS PARAMETERS	Gamma Coefficient	Standard Error	t Value
INTERCEPT (AVG. GRADES)			
Intercept	2.68**	.23	11.49**
Instructor is female	-0.18	.18	-0.97
Instructor is a minority	-0.03	.19	-0.17
Instructor is part-time at this college	-0.01	.21	-0.04
Instructor has a Ph.D.	0.02	.22	0.80
Instructor has 10 or more years experience	-0.50*	.20	-2.46*
Course level	0.01	.04	0.28
FEMALE BETA COEFFICIENT			
Intercept	0.53	.29	1.87
Instructor is female	-0.10	.22	-0.47
Instructor is a minority	0.49	.22	2.01
Instructor is part-time at this college	-0.47	.25	-1.88
Instructor has a Ph.D.	-0.45	.27	-1.68
Instructor has 10 or more years experience	-0.26	.25	-1.01
Course level	-0.05	.05	-0.94
MINORITY BETA COEFFICIENT			
Intercept	-0.21	.28	-0.74
Instructor is female	0.31	.22	1.41
Instructor is a minority	0.10	.21	0.46
Instructor is part-time at this college	-0.21	.24	-0.90
Instructor has a Ph.D.	-0.004	.26	-0.02
Instructor has 10 or more years experience	0.25	.24	1.07
Course level	-0.01	.05	-0.18

Table 3—Full model: Class-level predictors of student-level parameters of final math grades (continued)

Random within-class parameters	Reliability	Parameter Variance (Tau)	Degrees of Freedom	Chi-square test of Tau > 0	R^2*
INTERCEPT (AVG. GRADES)	.88	.26**	61	255.08**	.037
FEMALE BETA COEFFICIENT	.43	.14*	61	86.67*	.00
MINORITY BETA COEFFICIENT	.13	.07	61	71.05	.00

NOTE: ** probability $\leq$ .01; * probability $\leq$ .05.
SOURCE: College Institutional Research Data Sets, 1993.

Examining three reduced models with several variations of the instructor race-ethnicity variable as the predictor revealed that Asian American instructors tended to assign lower average grades (0.5 grade points) than all other instructors (table 4). Table 4 shows the conditional equation only for the intercept equation[7] for three different models. The other instructor race-ethnicity variables were not related to average grades. Although Model 2 contains only one predictor variable, it explained more of the parameter variance (11%) than the full model.

Table 4—Instructor race-ethnicity predictors of average final math grades

WITHIN-CLASS PARAMETERS Between-class predictors	Gamma Coefficients Model 1	 Model 2	 Model 3
INTERCEPT (AVG. GRADES)			
Intercept	2.58**	2.60**	2.54**
Instructor is any minority vs. white	-0.12		
Instructor is Asian American vs. all others		-0.49*	
Instructor is Latino vs. all others			0.03

Random within-school parameters	Parameter Variance (Tau) Model 1	 Model 2	 Model 3
INTERCEPT (AVG. GRADES)			
Tau	.27**	.24**	.28**
R^2*	.00	.11	.00

NOTE: ** probability $\leq$ .01; * probability $\leq$ .05.
SOURCE: College Institutional Research Data Sets, 1993.

[7]Although HLM estimates all parameter equations simultaneously, for discussion purposes it is often easier to present these equations separately.

2) Explaining grade differences by gender within classes

While on average there were no grade differences by gender within these math classes, there was substantial variation between classes in these differences (table 2). That is, in some classes females received higher grades than males, and in other classes males received higher grades. However, none of the factors tested were related to these variations. Instructor gender had no association with grade differences by gender, controlling for instructor race-ethnicity, experience, and employment status and math course level (table 3). These results show that expected role-modeling theories may not apply in this setting for women or men. Other factors are needed to account for the variation in gender differences that still exists.

3) Explaining grade differences by race-ethnicity within classes

On average across these math classes, African American, Asian-American, Latino, Filipino, and other non-white groups together averaged 0.2 grade points below white students (table 2). This difference did not vary significantly between classes. However, when all class-level variables were controlled for, this difference disappeared (table 3). No instructor characteristics were associated with overall race-ethnicity differences in grades (table 3).

Examining course level specifically in several reduced models revealed that when only course level was controlled for, and specifically pre-college courses, there were also no average differences in grades between minority and white students (see table 5). This reflects the fact that most minority students were in the pre-college courses, and shows that within course type, there were no race-ethnicity differences in grades overall.

Table 5—Course level predictors of student-level parameters of final math grades

WITHIN-CLASS PARAMETERS Between-class predictors	Gamma Coefficients Model 1	 Model 2	 Model 3
INTERCEPT (AVG. GRADES)			
Intercept	2.56**	2.59**	2.55**
Course level	-0.00		
Math course is pre-college level		-0.80	
Math course is advanced math			-0.04
FEMALE BETA COEFFICIENT			
Intercept	0.22	0.05	0.09
Course level	-0.02		
Math course is pre-college level		0.14	
Math course is advanced math			0.29
MINORITY BETA COEFFICIENT			
Intercept	-0.23	-0.13	-0.17*
Course level	0.02		
Math course is pre-college level		-0.07	
Math course is advanced math			0.02

Random within-school parameters	Parameter Variance (Tau) Model 1	 Model 2	 Model 3
INTERCEPT (AVG. GRADES)	.28**	.28**	.28**
FEMALE BETA COEFFICIENT	.15*	.15*	.14*
MINORITY BETA COEFFICIENT	.07	.07	.07

NOTE: ** probability $\leq$ .01; * probability $\leq$ .05.
SOURCE: College Institutional Research Data Sets, 1993.

4) Explaining grade differences by race-ethnicity: within specific race-ethnicity groups

In order to examine grade differences by race more closely, the "minority" group of the student race-ethnicity variable was divided into five groups—African Americans, Asian Americans, Latinos, Filipinos, and other minorities, with white students as the reference group. Table 6 shows the unconditional model using these five dummy race-ethnicity variables in the within-class model. African-American and Latino students averaged significantly lower grades than white students at all levels (table 6), but the grades of Asian Americans, Filipinos, and other minorities were not significantly different from those of white students. Therefore, it was the grades of African-American and Latino students that produced the lower "minority" grades in table 2. Like the overall "minority gap," this "minority gap" for African-American and Latino students did not vary across classes.

Table 6.—Average within-class parameters of final math grades: expanded race-ethnicity variable

WITHIN-CLASS PARAMETERS	Gamma Coefficient	Parameter Variance (Tau)
INTERCEPT (AVG. GRADES)	2.55**	.27**
FEMALE BETA COEFFICIENT	0.14	.15**
AFRICAN AMERICAN BETA COEFFICIENT	-0.66**	.13
ASIAN AMERICAN BETA COEFFICIENT	0.17	.06
LATINO BETA COEFFICIENT	-0.32**	.06
FILIPINO BETA COEFFICIENT	0.01	.16
OTHER MINORITY BETA COEFFICIENT	-0.12	.04

NOTE: ** probability ≤ .01; * probability ≤ .05.
SOURCE: College Institutional Research Data Sets, 1993.

Although there was no parameter variance to explain in these race-ethnicity parameters, a reduced model was tested using just a few likely predictors for each parameter (table 7). Table 7 suggests that a) Asian American instructors average lower grades than all other instructors, controlling for years of experience, and b) minority instructors (almost half of whom were Asian American), give higher grades to Asian American students, controlling for course level. In addition, this model showed that African American and Latino students did not have lower grades than white students once course level was controlled for.

Table 7.—Reduced model predictors of within-class parameters of final math grades: expanded race-ethnicity variable

WITHIN-CLASS PARAMETERS	Gamma Coefficient	Parameter Variance (Tau)	R^2*
INTERCEPT (AVG. GRADES)		.23**	.15
Intercept	2.70**		
Instructor has 10 or more years experience	-0.38*		
Instructor is Asian-American	-0.45*		
FEMALE BETA COEFFICIENT		.15**	0
Intercept	0.13		
Instructor is female	0.05		
Instructor has 10 or more years experience	0.01		
AFRICAN AMERICAN BETA COEFFICIENT		.12	0
Intercept	-0.47		
Instructor is a minority	-0.32		
Course level is pre-college level	-0.15		
ASIAN AMERICAN BETA COEFFICIENT		.09	0
Intercept	0.05		
Instructor is a minority	0.63*		
Course level is pre-college level	0.002		
LATINO BETA COEFFICIENT		.08	0
Intercept	-0.12		
Instructor is a minority	-0.09		
Course level is pre-college level	-0.26		
FILIPINO BETA COEFFICIENT		.13	0
Intercept	0.01		
OTHER MINORITY BETA COEFFICIENT		.04	0
Intercept	-0.14		

NOTE: ** probability $\leq$ .01; * probability $\leq$ .05.
SOURCE: College Institutional Research Data Sets, 1993.

Table 8 provides a closer look at the instructor race-ethnicity variable as well as the student race-ethnicity variable, in order to determine the relationship between the instructor and the student race-ethnicity. Three reduced models included only one of the specific student race-ethnicity variables, and used only instructor race-ethnicity as a predictor. First, in the intercept equation in models 1 and 2, students in classes with Asian American instructors averaged lower grades. The results of the race-ethnicity equation in model 2 suggests that before controlling for other factors, Asian American students earned higher grades than all other students, and that Asian American students with Asian American instructors earned even higher grades than Asian American students with other instructors. According to model 1, African American students earned lower average grades than other students, but earned even lower grades if taught by an Asian American instructor than African American students with other instructors. There were no African American instructors in the sample to test the association of African American student grades with African American instructors. However, model 3 shows that Latino instructors neither increased or mitigated the lower average grade of Latino students. While these models did not explain the variance in average grades, model 1 reduced the variance for female and African American students by half.

Table 8—Instructor race-ethnicity predictors of student-level parameters of final math grades

WITHIN-CLASS PARAMETERS Between-class predictors	Gamma Coefficients African-American students Model 1	 Asian-American students Model 2	 Latino students Model 1
INTERCEPT (AVG. GRADES)			
Intercept	2.60**	2.60**	2.54**
Instructor is Asian-American	-0.49*	-0.49*	
Instructor is Latino			0.03
FEMALE BETA COEFFICIENT			
Intercept	0.10	0.09	0.13
Instructor is Asian-American	0.36	0.41	
Instructor is Latino			0.13
AFRICAN AMERICAN BETA COEFFICIENT			
Intercept	-0.53**		
Instructor is Asian-American	-0.67*		
ASIAN AMERICAN BETA COEFFICIENT			
Intercept		0.26*	
Instructor is Asian-American		0.70*	
LATINO BETA COEFFICIENT			
Intercept			-0.22*
Instructor is Latino			-0.32

Random within-school parameters	Parameter Variance (Tau) African-American students Model 1	 Asian-American students Model 2	 Latino students Model 1
INTERCEPT (AVG. GRADES)	.26**	.26**	.28**
FEMALE BETA COEFFICIENT	.06*	.14*	.17**
AFRICAN AMERICAN BETA COEFFICIENT	.07		
ASIAN AMERICAN BETA COEFFICIENT		.10	
LATINO BETA COEFFICIENT			.05

NOTE: ** probability ≤ .01; * probability ≤ .05.
SOURCE: College Institutional Research Data Sets, 1993.

Discussion of HLM results

The relationship between instructor and course factors and grade variability has only begun to be explored using HLM, so this study provided a first glimpse at both the related and unrelated factors contributing to grade variability. Various instructor factors sometimes assumed to cause grade variability—being female, being from most minority groups, working part-time, having more education— as well as the level of the course seemed to be unrelated to grading in these math classes. These results can lead to a de-emphasis of these factors and a search for the more relevant factors in these types of community colleges.

The association of instructor experience with lower grades may be related to the changing demographics of the student body. It is possible that more experienced instructors have higher grading standards than less experienced instructors. However, since students are advised into math courses based on test results, it is also possible that more experienced instructors cannot teach in the most effective way for the newer groups of students. This would need to be investigated further. Likewise, the tendency for Asian-American instructors to assign lower average grades could also be explained with the same reasons. Both of these factors raise the sensitive issue of the relationship between race-ethnicity (of students and instructors) and teaching standards, which the college would need to find a way to discuss before any further research could occur.

The lack of an average gender gap in grades is good news for the progress of women's achievement in mathematics. The lack of any predicting variables to explain why in some classes women have higher grades, and in other classes men have higher grades suggests that the expected positive effects of same-gender instructors may not apply in this setting for women or men. Since no variables tested here, including course level, made any difference in explaining this variation, other factors are needed to account for the variation in gender differences that still exists.

The gap between the average grades of African American and Latino students and white students is important to illuminate. However, the fact that it was reduced or eliminated by controlling for course levels showed that the differences were not occurring within courses. The suggestion that Asian American students earn higher average grades with Asian American instructors than with other instructors could simply be a correlation with a good explanation. Asian American students, who already have higher grades than all other students, may be choosing Asian American instructors. However, the finding that African American students earn lower average grades with Asian American instructors than with other instructors is a concern. The entire pattern of Asian American instructors giving lower grades to students overall, lower grades to African American students specifically, and higher grades to Asian American students needs to be examined, although it is a sensitive issue and faculty—or researchers—do not necessarily have productive ways to talk about it. The results could suggest the importance of hiring instructors who reflect the race-ethnicity of the students for optimum student success. However, more research would have to be conducted to confirm that this is the actual dynamic for Asian American students and for other racial-ethnic groups in this setting. For instance, this theory did not work for Latino students with Latino instructors.

Discussion of the HLM methodology

HLM analysis has the potential to allow new questions to be asked about the factors related to grade variations between classes and grade differences by gender and race-ethnicity within classes. HLM is a powerful analysis tool, and would seem to be perfect for investigating grade variability since it can explain student-level grade outcomes with instructor/class-level factors. This study illustrated the use of HLM on data from an ethnically-diverse community college campus and showed how the math curriculum can be monitored to insure equal outcomes by gender and race-ethnicity within classes. Showing that there were no gender or race differences within courses was a valuable contribution to this monitoring effort.

However, when gender or race-ethnicity differences appear, or when we try to explain any grade variability or differences by gender or race-ethnicity, we run into the sensitive issues of examining instructor characteristics that faculty—or researchers—may not yet have ways to discuss or act upon. Therefore, it is possible that this technique may be too powerful to use within individual colleges. It certainly cannot be used to evaluate individual instructors or individual classrooms, for HLM can only estimate overall theoretical relationships, since it "borrows" from all the classes for each class equation (Arnold, 1992). However, if ways to discuss these types of results can be found on college campuses, HLM may become a useful tool for both monitoring grade differences by gender or race-ethnicity on campuses, and investigating many of the possible factors that may be associated with these differences on a theoretical as well as practical level.

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