Contingent Instructors and Student Outcomes: An Artifact or a Fact?

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ABSTRACT

This study addresses methodological problems surrounding existing research on exposure to contingent instructors and student outcomes. By applying non-aggregated and aggregated measures of exposure to contingent instructors to the same data, this analysis demonstrates that effects of commonly used measures of exposure to contingent instructors have little to do with actual contingent instructor effects on student outcomes. Two multi-level approaches—cross-classified and multiple membership models—are applied in the single-institution analysis of faculty status effect on student outcomes—grades and one-year retention. The analysis showed no variability in student retention and a significant variability in grades by faculty characteristics. Compared to their tenured and tenure-track peers, contingent instructors are likely to assign higher grades, which may lead to lowered levels of academic challenge and student motivation to do their best work.

KEY WORDS: contingent instructors; retention; college grade performance; multilevel models; cross-classified models; multiple membership models.

INTRODUCTION

In the view of some prominent commentators, American research universities “have too often failed … their undergraduate populations” (Boyer Commission 1998, p.5). This concern arises in part from the growing reliance of research universities on so-called contingent instructors—part-time, non-tenure-track faculty, and graduate teaching assistants—and its presumed impact on the quality of instruction. Wellman, Desrochers, and Colleen (2008) report that, since 1998, the percentage of spending for the direct cost of instruction—faculty salaries and benefits—has declined. This decline reflects a continuing growth in the share of part-time and non-tenure track faculty in U.S. postsecondary institutions.

The most important reason for hiring contingent instructors is budgetary constraints. Colleges “can hire up to two dozen part-time faculty for roughly the same amount it costs to hire a full-time faculty member" (Stephens & Wright, 1999). Another important advantage is providing institutional flexibility. When enrollment drops or changes are introduced in the general education curriculum, “the number of part-time faculty is easily adjusted by not renewing contracts” (Banachowski, 1997). Departments with a professional orientation also seek to hire contingent instructors who possess practical experience and expertise in the area (Banachowski, 1997, Haeger, 1998). Finally, sometimes part-time faculty themselves are “grateful for being able to teach part-time because of the prestige and fulfillment it adds to their life” (Reed, 1985, cited in Banachowski, 1997).

Contingent instructors typically lack job stability and may also lack adequate support services, office space, benefits, professional development opportunities, and equal pay for equal work. Their lower earnings and lack of benefits are “likely to interfere with their work” (Benjamin, 2002), and their employment conditions can lead to dissatisfaction (Gappa, Leslie, 1997). Another important concern surrounding reliance on contingent faculty is related to the academic quality of instruction and the overall academic experience of students. “It’s conceivable that face-to-face exchanges between students and faculty outside the classroom will decline because part-time faculty spend less time on campus and often do not have a designated space to meet with students after class” (Kuh, Laird, Umbach, 2004). Thus, employing contingent instructors provides financial benefits and flexibility for institutions but may limit student-faculty interaction and further affect student outcomes.

The debate over the relative effectiveness of contingent instructors has led to a growing number of studies that explore the effect of exposure to contingent instructors on student outcomes. Kehrberg and Turpin (2002) studied the relationship between exposure to part-time faculty and first-year retention. The overall negative association between such exposure and retention disappeared after controlling for student academic preparation. Ronco and Cahill (2004) studied the effect of exposure to contingent instructors and graduate teaching assistants on retention, academic achievement and student ratings of instruction. They reported that there is “little evidence that instructor type has a widespread impact on student outcomes” (p.17). Counter to these hopeful results, Schibik and Harrington (2004) indicate that “holding academic preparation constant, exposure to part-time faculty at levels above 50% during their first semester on campus has a direct and significant negative impact on student retention into the second semester” (p.5). Jaeger and Hinz (2008) found that as exposure to instruction by part-time faculty increases, the odds of being retained decrease. Eagan and Jaeger (2009) studied the effects of exposure to part-time faculty in a community college system and later transfer to a four-year institution. They concluded that students are less likely to transfer within five years of enrolling in the system of community colleges as the proportion of credits a student took with part-time faculty increases. Based on the association between graduation rates and the use of non-tenure-track faculty (whether part-time or full-time) and, Ehrenberg and Zhang (2004) concluded that increase in the shares of either part-time or full-time non-tenure-track faculty leads to the reduction of graduation rates.

The problem with these studies of the effectiveness of contingent instructors is that they essentially study the correlation between student outcomes and unspecified student characteristics that happen to be correlated with the number and percentage of courses students take that are taught by contingent instructors. Findings reported by these studies are likely to be a mere statistical artifact. As demonstrated by Bettinger and Long (2005), students who take courses from adjuncts differ systematically from students who take courses from tenure-track faculty. Student-level aggregation of faculty characteristics may reflect nothing more than systematic differences between students who take courses from contingent instructors and students who take courses from tenure-track faculty. Similarly, institutions with higher shares of contingent instructors are likely to be systematically different from institutions with lower shares of such instructors. Hoffmann and Oreopoulos (2006) suggest that a negative relationship between student persistence and adjunct usage in institution-level studies could be driven by the tendency for schools with higher proportion of adjuncts to have students on the margin of dropping out.

The studies of exposure to contingent instructors continue to emerge, and the methodological problems associated with these studies persist. The study presented here applies non-aggregated and aggregated measures of exposure to contingent instructors to the same data and demonstrates that, when aggregated to the student level, a measure of exposure to contingent instructors, or percentage of courses taken from contingent instructors, has little to do with the instructor's effect on student outcomes. Two multi-level approaches—cross-classified and multiple membership models— are discussed for the analysis of how faculty status affects class grades, one-year cumulative GPA, and one-year retention. Advantages and limitations of these multi-level approaches are pointed out.

CONCEPTUAL ISSUES

"Perhaps the most commonly applied theory used today to understand contingent workers is social exchange theory" (Connelly and Gallagher, 2004, p.977). In contrast to economic exchange, social exchange (Blau, 1964) involves unspecified obligations and requires trust. By treating employees fairly, an organization initiates social exchange and encourages employees to reciprocate to the organization. However, contingent work relationships are based on an "asymmetrical" power balance that favors employers (Beard and Edwards, 1995; see also Gallagher, 2002). Contingent workers hold insecure positions with little control and predictability and are, therefore, less willing to reciprocate by effort. Umbach's (2007) findings were consistent with this reasoning. Based on data from the Faculty Survey of Student Engagement (FSSE), Umbach concludes that contingent faculty interact with students less frequently, use active and collaborative techniques less often, spend less time preparing for class, and have lower academic expectations for student performance than do their tenured and tenure-track peers. These characteristics of contingent faculty conceivably have different and complex effects on different student outcomes of interest.

First, if contingent instructors have lower academic expectations, they are also likely to give higher grades. Further, professors frequently believe that grades influence student evaluations. Adjunct and part-time faculty are "especially vulnerable to student evaluation pressures" (Kamber 2008b, p.57) and might be expected to give higher grades. If the share of classes from contingent instructors measured the effect of contingent instructors, higher shares of classes from contingent instructors would lead to higher grade point averages.

Yet grades are not the only student outcome variable of interest. The quality of faculty-student interaction is a central factor in student attrition (Tinto, 1993). If contingent faculty interact with students less frequently (Umbach, 2007), one would expect that students who take fewer classes from contingent faculty and more classes from tenure-track faculty would be more likely to persist, even though exposure to contingent faculty tends to raise students' grades.

Two control variables—discipline area and class size—are included at the faculty level in the models of class grades. Johnson (2010) indicates that class size has a negative effect on students' grades; and models with logarithmic representation of a class size show a superior fit thus indicating that the effect of class size diminishes as class size increases. A logarithmic representation of class size is incorporated in the models of class grades presented here; and this variable is hypothesized to have a negative effect on grade performance.

Prior studies (Benjamin, 2002; Bettinger and Long, 2005) show that the share of contingent instructors varies by discipline. Further, grades vary across disciplines. Therefore, discipline areas are included in the models of class grades. The discipline areas are categorized based on the Biglan (1973a, 1973b) classification scheme that involves three dimensions: hard versus soft, applied versus pure, and life versus non-life. The hard-soft dimension distinguishes fields that have attained a paradigmatic status (Kuhn 1962) from fields that have not attained a paradigmatic status, or fields that have achieved a high degree of consensus about their knowledge and methods and fields that have not achieved such consensus. The applied-pure dimension distinguishes between fields that concentrate on creating knowledge (pure) or applying knowledge from other fields (applied). The life-non-life dimension distinguishes disciplines by their objects of study: ‘‘lifesystems’’ (life) or non-living objects. (The fields associated with each Biglan area can be found in variable descriptions of Table 1.) It is expected that grades significantly vary by the faculty area of expertise with fewer high grades in hard disciplines.

At the student level, prior research on the effect of first-year student exposure to contingent instructors on student outcomes have typically controlled for gender, ethnicity, age, high school GPA, state residency, test scores, and course load (see, for example, Bettinger, 2005; Ronco, 2004; Schibik and Harrington, 2004). Because the new freshmen at the study institution are traditional students coming directly from high school, age is not included in the models here. On the other hand, membership in a fraternity or sorority is included in the models here, since about a third of new freshmen at the study institution are members of such social organizations. Fraternities and sororities “provide individuals with opportunities to establish repetitive contact with other members of the institution in circumstances which lead to the possibility of integration” (Tinto, 1988, p.446). Hence, Greek membership is expected to have a significant positive effect on retention. At the same time, the author remains agnostic about its effect on grade performance.

METHODOLOGICAL PROBLEMS

No matter what their results, previous studies of exposure to contingent instructors (e.g., Kehrberg and Turpin, 2002; Schibik and Harrington, 2004; Ronco, 2004) have measured exposure as the share of courses from contingent instructors divided by the overall number of courses a student took. The percentages of courses taught by contingent instructors were frequently grouped in ranges such as 0% to 24%, 25% to 49%, 50% to 74%, and 75% to 100%. Such an approach is likely to lead to a statistical artifact (Johnson, 2006). For example, a student taking only one class can have either 0-24% exposure or 75%-100% exposure, but not 25%-49% or 50%-74% exposure. A student taking two classes cannot have 25%-49% exposure. Table 2 provides an illustration of the association between the measure of exposure and the number of classes a student takes.

Even if the share of courses taught by contingent faculty is not grouped into faulty ranges, it is reasonable to expect a significant correlation between students' course load and their exposure to contingent instructors. To avoid the correlation between the exposure to contingent instructors and the number of classes a student takes, one can substitute these two predictors with the number of classes from tenure-track faculty and the number of classes from contingent instructors. If the hypothesis of equality of coefficients for classes from tenure-track faculty and classes from contingent faculty is rejected, one would conclude that there is a significant difference in student outcomes depending upon faculty status. However, whether one uses the share of courses from contingent instructors or the test of the null hypothesis of the equality of regression coefficients, the result will be prone to errors, because both approaches are based on the aggregation of student-faculty level to the student level.

The problems that arise with aggregation are frequently described in literature devoted to multi-level analysis. Snijders and Bosker (1999) point out potential errors resulting from aggregation: the "*shift of meaning*," the "*ecological fallacy*," and neglect of the original data structure. For example, exposure to contingent faculty is a student-level variable that does not necessarily reflect the faculty-student interaction (the shift of meaning). A significant positive correlation between exposure to contingent faculty and grade point average does not imply that a student's grade is likely to be lower in a class taught by tenure-track faculty or vice versa (the ecological fallacy). The ecological fallacy is also related to the issue of *confounding* (see, for example, Freedman, 1999): students who take more courses taught by contingent instructors may be different from students who take more courses taught by tenure-track faculty in many ways besides exposure to contingent instructors.

As illustrated by Aitkin and Longford (1986), aggregation and neglect of the original data structure can be "dangerous at best and disastrous at worst" (p.42). Fig.1 illustrates how disregard for the original data structure can be misleading in studies of exposure to contingent instructors. Based on the left-hand graph of the student-faculty data, student 1 received grades of "C" and "B" from tenure-track faculty members and an "A" from a contingent instructor. Student 2 received a grade of "C" from a tenure-track faculty member and a grade of "B" from a contingent instructor. Student 3 received a grade of "D" from a tenure-track faculty member and grades of "C" and "D" from contingent instructors. Overall, the graph on the left-hand side of Fig.1 clearly indicates that students are more likely to receive higher grades in courses taught by contingent instructors. But aggregation of these grades to the student level would result in a negative association between exposure to contingent instructors and grade point averages. Student 1 has the lowest exposure to contingent instructors (33%) and the highest grade point average (3.00). Student 3 has the highest exposure to contingent instructors (67%) and the lowest grade point average (1.33). Student 2 is in between with the 50% exposure to contingent instructors and the grade point average of 2.50.

One cannot model student-faculty data as independent observations, since it would lead to the "miraculous multiplication of units" (Snijders and Bosker, 1999, p.15). In the example presented in Fig. 1, treating student-faculty observations as independent would mean treating three students as eight. This would lead to a serious risk of committing type 1 errors (asserting that there is an association, whereas there is no such association in the population). Ideally, one would take into account the multi-level data structure of student exposure to contingent faculty. The problem is that, while the data structure in studies of student exposure to contingent instructors is multi-level, it is not strictly hierarchical. Two models suggested in the multi-level literature for non-hierarchical data structures are cross-classified and multiple membership.

Cross-Classified Model: Class Grade as Dependent Variable

In a cross-classified model of student exposure to contingent instructors, a grade Y_{ij} is nested within the cross-classification of a student *i* and faculty member *j* (see Fig. 2). On the one hand, students attending classes taught by the same faculty member share some common experiences and cannot be treated as independent observations. On the other hand, grades are affected by student characteristics; and several observations for one student cannot be treated as independent. A cross-classified model (Raudenbush, Bryk, Cheong, and Congdon, 2004; Raudenbush and Bryk, 2002) properly treats dependencies among multiple observations related to a single faculty member and multiple observations related to a single student and provides estimates of the variation introduced by different levels of the hierarchical structure, i.e. the extent to which grades of a typical student vary by faculty members and the extent to which grades given by a typical faculty member vary by students. The estimation of the cross-classified models in this study is carried out using HLM 6, one of the dominant and user-friendly multi-level software packages.

A drawback in using this software to analyze grade data is that the scale of measurement of class grades is ordinal, but at the time of writing HLM 6 did not estimate cross-classified models for ordinal dependent variables. Consequently, several models with binomial outcomes were specified instead. The three constructed models estimate separately log-odds of probabilities of getting a grade of "A," a grade of "B" or higher, and a grade of "C" or higher. The unconditional model (model without predictors) estimating the log-odds of the probability of getting an "A", a "B" or higher, or a "C" or higher is as follows:

$$\ln\left(\frac{P_{Y_{ij}=1}}{1-P_{Y_{ij}=1}}\right)=\beta_{0ij} \qquad \text{(Level 1)}$$

Where the grade Y_{ij} is within the cross-classification of student *i* and instructor *j*.

$$\beta_{0ij}=\gamma_{00}+u_{0i}+v_{0j} \qquad \text{(Level 2)}$$

Where γ_{00} is the intercept, u_{0i} is a residual (also called random effect) for students and v_{0j} is a residual for faculty members. It is assumed that $u_{0i} \sim N(0,\delta_u^2)$ and $v_{0j} \sim N(0,\delta_v^2)$. A variance component for students δ_u^2 estimates the extent to which the probability of getting a certain grade from a typical faculty member varies by student. A variance component for faculty members δ_v^2 estimates the extent to which the probability of getting a certain grade by a typical student varies by a faculty member.

Multiple Membership Linear Regression Model: Grade Point Average as Dependent Variable

While there can be multiple class grades per student, there is only one cumulative grade point average per student at a given time. This means that the lowest level for grade point averages is the student level and that a cross-classified model cannot be applied. Each student takes courses from several faculty members, and, therefore, the strictly hierarchical structure of students nested within faculty cannot be applied either. The model that accommodates the data structure where lower units belong to several classification units is a multiple membership model (Hill and Goldstein, 1998; Rasbash and Browne, 2001; Browne, Goldstein, and Rasbash, 2001). Fig. 3 illustrates the difference between data structures for cross-classified and multiple membership models. A single arrow represents a single membership classification or a grade belonging to one student and one faculty member. A pair of arrows represents multiple membership or one student exposure to multiple instructors.

The outcome variable is the second-semester cumulative grade point average, which is defined on the usual 0.00 to 4.00 scale and treated as a continuous variable. The multiple membership model of the grade point average can be represented as follows:

$$y_i = \beta_{0i} \qquad \text{(Level 1)}$$

$$\beta_{0i} = \beta_0 + \sum w_{ij} u_{0j} + e_{0i} \qquad \text{(Level 2)}$$

Where β_0 is the intercept, u_{0j} is a residual for instructors and e_{0i} is a residual for students with $u_{0j} \sim N(0, \delta_u^2)$ and $e_{0i} \sim N(0, \delta_e^2)$. A variance component for faculty members δ_u^2 estimates the extent to which grade point averages vary by faculty members. A variance component for students δ_e^2 estimates the extent to which grade point averages vary by students. Weight w_{ij} is attributed to a student-faculty combination and can be either equal for all faculty members a student has been exposed to or proportionate to the number of credit hours a student took from a given faculty members. The sum of weights should equal to one for each student.

Multiple Membership Logit Model: Retention as Dependent Variable

Because the lowest level for retention is the student level and a student is exposed to several faculty members, a multiple membership model also applies here. The dependent variable equals one if a student returned for the second year and zero if a student did not return. The multiple membership model with a binomial outcome can be represented as follows:

$$\ln\left(\frac{P_{Y_j=1}}{1-P_{Y_i=1}}\right)=\beta_{0i} \qquad \text{(Level 1)}$$

$$\beta_{0i}=\beta_0+\sum w_{ij}u_{0j} \qquad \text{(Level 2)}$$

Where β_0 is the intercept and u_{0j} is a residual for instructors with $u_j \sim N\left(0,\delta_u^2\right)$. A variance component for instructors δ_u^2 estimates the extent to which the probability of return by a typical student varies by faculty members.

Currently, only the software package MLwiN has special features for estimating multiple membership models with a detailed manual for implementing such models (Browne, 2009). MLwiN is an excellent choice for estimating a multiple membership variance decomposition model or an unconditional model. However, it does not provide a possibility of adding predictors at the faculty level and cannot resolve the issue of aggregation of exposure to contingent faculty to the student level. Thus, while being resolved in a cross-classified model, the problem associated with aggregation of independent variables to the student level persists in multiple membership models.

DATA AND DESCRIPTIVE STATISTICS

The institution studied is a Research University (high research activity) with about 4,000 first-time freshmen enrolled each fall. Data for 2008 new freshmen are included in the analysis. The course information was taken from the fall and spring semesters of the first year of studies. The variable descriptions as well as descriptive statistics are presented in Table 1.

The data for the study include 3,911 observations at the student level, 671 observations at the faculty level, and 31,199 student-faculty combinations. If a student took more than one class from the same faculty member, the grades from these classes are averaged. Each faculty member in the data set can teach more than one class to first-year freshmen. At the same time, one can expect that several classes taught to freshmen by the same faculty member are similar in class size. Taking into account that class level is not introduced here, an average class size for all classes a faculty member taught to new freshmen is included as a proxy of a class size.

Based on descriptive statistics in Table 1, first-year students take less than one third of their courses (2.87 out of 9.37) and credit hours (8.88 out of 27.49) from tenured or tenure-track faculty. At the same time, the share of tenured or tenure-track faculty in the data is about 44%. The distribution by discipline areas shows that most of the courses taken by first-year students come from hard-pure-non-life (22%) and soft-pure-non-life disciplines (38%), which is expected because of the prevalence of Science, Mathematics, and Humanities in the university's Core Curriculum. Grade distribution presented in Table 1 shows a substantial percentage of high grades: a grade of an "A" constitutes 33% of all grades given to new freshmen during the first year of their studies, a grade of "B" constitutes about 34%; and a grade of "C" constitutes about 18%. The rest of grades included grades of "D" and "F" as well as incompletes and withdrawals. A small number of pass-fail grades were excluded.

CROSS-CLASSIFIED MODELS OF CLASS GRADES

Unconditional Models

The unconditional models presented in Table 3 estimate the extent to which grades vary across faculty members and across students. Based on Model 1, the expected probability of getting an "A" for a typical student taught by a typical instructor is 0.35 or an "antilogit" of the intercept, $\gamma_{00}: \frac{e^{\gamma_{00}}}{1+e^{\gamma_{00}}} = \frac{e^{-0.61}}{1+e^{-0.61}}$. For a student one standard deviation below the average, the probability of getting an "A" is 0.09 or an "antilogit" of the intercept minus the square root of a variance component for students, $\gamma_{00} - \delta_u : \frac{e^{\gamma_{00}-\delta_u}}{1+e^{\gamma_{00}-\delta_u}} = \frac{e^{-0.61-\sqrt{2.83}}}{1+e^{-0.61-\sqrt{2.83}}}$ and for a student one standard deviation above the average, the probability of getting an "A" in a typical class is 0.75 or an "antilogit" of the intercept plus the square root of a variance component for students, $\gamma_{00} + \delta_u : \frac{e^{\gamma_{00}+\delta_u}}{1+e^{\gamma_{00}+\delta_u}} = \frac{e^{-0.61+\sqrt{2.83}}}{1+e^{-0.94+\sqrt{2.83}}}$. Based on "antilogits" for faculty, for a faculty member one standard deviation below the average, the probability of getting an "A" for a typical student is 0.13; and for a faculty member one standard deviation above the average, the probability of getting an "A" for a typical student is 0.66.

The expected probability of getting a "B" or higher is 0.80 or an "antilogit" of the intercept in Model 2 of Table 3. The probability of getting a "B" or higher is 0.43 for a student one standard deviation below the average and taught by a typical faculty. The probability of getting a "B" or higher is 0.96 for a student one standard deviation above the average and taught by a typical faculty. The probability of getting a "B" or higher for a typical student is 0.55 in a class taught by a faculty member one standard deviation below the average and 0.93 in a class taught by a faculty member one standard deviation above the average.

The expected probability of getting a “C” or higher is 0.93 (see Model 3 in Table 3). The probability of getting a “C” or higher is 0.74 for a student one standard deviation below the average and 0.98 for a student one standard deviation above the average. For a typical student the probability of getting a “C” or higher is 0.82 in a class taught by a faculty member one standard deviation below the average and 0.97 in a class taught by a faculty member one standard deviation above the average.

The average expected probabilities of getting an “A”, a “B” or higher, and a “C” or higher with a one standard deviation range for students and faculty are presented in Fig. 4. Differences in grades assigned by faculty members are substantial compared to differences in grades received by students. Based on the models in Table 3, differences between faculty members account for about 37% $\left(\frac{1.64}{1.64+2.83}\right)$ of the variance in the model of the log-odds of getting an “A”, 34% $\left(\frac{1.48}{1.48+2.84}\right)$ of the variance in the model of the log-odds of getting a “B” or higher, and 31% $\left(\frac{1.11}{1.11+2.60}\right)$ of the variance in the model of the log-odds of getting a “C” or higher. One should also note here that, taking into account that the population under study consists of first-time freshmen, the extent of variation among classes and faculty members is expected to be lower than if all undergraduate students were considered. This is due to the fact that freshmen are more likely to take similar courses, such as courses required by the university’s Core Curriculum, than are seniors who take courses in their respective majors.

Conditional Models

Consistently across models presented in Table 4, a faculty member's tenure-track status has a significant negative impact on the odds of getting higher grades. Based on the models without control for the discipline area and class size, the average expected probability of getting an "A", a "B" or higher, and a "C" or higher are 0.39, 0.85, and 0.95 if a grade is given by a contingent instructor and 0.26, 0.73, and 0.91, if a grade is given by a tenure-track faculty member. (These average expected probabilities are calculated based on Model 1.1, Model 2.1 and Model 3.1 in Table 4 and sample means in Table 1.)

After controlling for discipline area and class size, the effect of faculty status on grades becomes less substantial, but remains statistically significant. Based on model 1.2 in Table 4 and sample means in Table 1, the average expected probability of getting an "A" is 0.39 if a grade is given by a contingent instructor and .29 if a grade is given by a tenure-track instructor. The average expected probability of getting a "B" or higher is 0.85 if a grade is given by a contingent instructor and 0.77 if a grade is given by a tenure track faculty (Model 2.2 in Table 4 and sample means in Table 1). The probabilities of getting a grade of "C" or higher are 0.95 and 0.92 for contingent and tenure track instructors (Model 3.2 in Table 4 and sample means in Table 1). These results also indicate that the discrepancies in the probabilities depending upon a faculty status are more substantial for higher grades.

Models 1.2, 2.2, and 3.2 in Table 4 also show a significant variation in the probability of getting a higher grade depending upon class size. For example, a change in class size from 10 to 100 leads to a decrease in the expected probability of getting an "A" from 0.45 to 0.26 (see Table 5). A comparison of probabilities in Table 5 also suggests that the effect of class size varies depending upon which grade is examined. Class size has a bigger effect on the probability of getting an "A" than on the probability of getting a "B" or higher. And the effect of class size on the probability of getting a "B" or higher is more pronounced than the effect of class size on the probability of getting a "C" or higher. For instance, a typical student taught by a typical instructor is 1.74 $\left(\frac{0.45}{0.26}\right)$ times more likely to get an "A" in a class of 10 than in a class of 100; 1.17 $\left(\frac{0.87}{0.75}\right)$ times more likely to get a "B" or higher in a class of 10 than in a class of 100; and only 1.03 $\left(\frac{0.95}{0.93}\right)$ times more likely to get a "C" or higher in a class of 10 than in a class of 100. Overall, while the effect of class size on the probability of getting a "C" or higher is statistically significant, it is not substantial. This corresponds to prior research (see, for example, Johnson, 2010) suggesting that the impact of class size is greater on the likelihood of getting a grade of "A" than on a grade of "C" or higher.

The probabilities presented in Table 5 also show a substantial variation in grades depending upon a discipline, with lower probabilities of getting higher grades in hard-pure-life and hard-pure-non-life disciplines and higher probabilities of getting higher grades in soft-applied-life disciplines. Thus, a typical student is 4.13 $\left(\frac{0.86}{0.21}\right)$ times more likely to receive a grade of "A", 1.59 $\left(\frac{0.96}{0.61}\right)$ times more likely to get a grade of "B" or higher, and 1.14 $\left(\frac{0.98}{0.86}\right)$ times more likely to receive a grade of "C" or higher from an instructor in soft-applied-life than from an instructor in hard-pure-life discipline.

At the student level, the most interesting finding is related to the effect of Greek membership on grade performance. While being a member of a Greek organization does not have a significant effect on the odds of getting an “A,” it does have a significant effect on the odds of getting a “B” or higher and a “C” or higher. The probability of getting a “B” or higher for a typical student taught by a typical instructor is 0.82. This probability is 0.81 for a non-member and 0.83 for a member of a Greek organization. The probability of getting a “C” or higher for a typical student taught by a typical faculty member is 0.94. This probability is 0.94 for non-members and 0.95 for members of Greek organizations. A positive effect of Greek membership could be associated with minimum grade-point standards required for continued Greek membership.

The effects of other student-level characteristics do not hold surprises. Based on Models 1.2, 2.2, and 3.2 in Table 4, female students are significantly more likely to get higher grades. Thus, the expected probability of getting an “A” for a typical student taught by a typical faculty is 0.34. This probability is 0.40 for female students and 0.29 for male students. The probability of getting a “B” or higher is 0.85 for female students and 0.78 for male students. The probability of getting a “C” or higher is 0.95 for females, and 0.93 for males.

According to the expected probabilities by ACT scores in Table 5, students who come to the study university with the ACT score of 30 are, on average, 4.04 $\left(\frac{0.55}{0.14}\right)$ times more likely to receive an “A”, 1.51 $\left(\frac{0.91}{0.60}\right)$ times more likely to receive a “B” or higher, and 1.10 $\left(\frac{0.97}{0.88}\right)$ times more likely to receive a “C” or higher in their first-year courses than students who come with the ACT score of 20. Students with 4.00 high school GPA are 3.43 $\left(\frac{0.47}{0.14}\right)$ times more likely to receive an “A”, 1.59 $\left(\frac{0.89}{0.56}\right)$ times more likely to receive a “B” or higher, and 1.16 $\left(\frac{0.97}{0.83}\right)$ times more likely to receive a “C” or higher than students with 3.00 high school GPA.

The cross-classified conditional models presented here show that the instructor’s tenure-track faculty status has a significant negative effect on a student’s probability of getting higher grades; and this negative effect remains significant after control for discipline area and an average class size for an instructor. Such faculty-level characteristics as discipline area and an average class size also show a significant association with student grade performance.

MULTIPLE MEMBERSHIP MODELS OF PERSISTENCE AND GRADE POINT AVERAGE

Unconditional Models

The unconditional single-level and multiple membership models are presented in Table 6. As mentioned before, in multiple membership models we assign weights for each pairing of a faculty and a student. These weights sum to 1 for each student. In multiple membership models of exposure to contingent faculty, one can explore at least two ways to attribute weights to instructors. On the one hand, one can assign a weight that is proportional to the number of credit hours associated with a student-faculty combination. On the other hand, one can assign an equal weight to each faculty member. Based on the unconditional models presented in Table 6, one can, on the one hand, test the null hypothesis that the faculty-level random effect is zero, $H_0 : u_{0j} = 0$, and, on the other hand, define whether equal or proportional weights model better fits the data.

The null hypothesis of a zero faculty-level random effect can be tested using Deviance, or a measure of lack of fit between a model and data[1]. The larger the Deviance, the poorer the fit. The difference between the Deviance for a model without a faculty-level random effect and the Deviance for a model with faculty-level variance component has a χ^2 distribution with the degrees of freedom equal to the difference in the number of parameters estimated. Deviance Information Criterion (DIC) adjusts for the number of parameters in the model and can be compared directly, without taking into account the degrees of freedom. A smaller DIC suggests a better model (Browne 2009, 28-33).

A comparison of the unconditional models of retention in Table 6 shows that adding faculty-level variance component did not lead to significant changes in Deviance and Deviance Information Criterion. Proportional weights and equal weights models also show close to zero and insignificant faculty-level variance component. Based on ”antilogits” for a proportional weights model, for a faculty member one standard deviation below the average, the probability of return for a typical student is 0.87 (or, more precisely, 0.868); and for a faculty member one standard deviation above the average, the probability of return for a typical student is 0.87 (or, more precisely, 0.872). In other words, no variability in log-odds of retention is found depending upon faculty members students are exposed to. At the same time, important variability exists in student grade point averages depending upon faculty members teaching the courses they took.

Based on DIC comparison for models of spring 1 cumulative GPA in Table 6, an equal weights model has a superior fit. The following interpretations are based on the equal weights model. Based on intra-class correlation, the proportion of the total variance in grade point averages which can be attributed to between-faculty differences is substantial - about 0.76:

$$\rho = \frac{\delta_{u0}^2}{\left(\delta_{u0}^2 + \delta_{e0}^2\right)} = \frac{1.72}{\left(0.53 + 1.72\right)} \approx 0.76.$$

Fig. 5, a so-called caterpillar plot, provides a visual aid in assessing the statistical significance of differences in mean grade point averages by faculty members. There are 553 residuals plotted, each representing a single faculty member.[2] (Residuals represent departures from the overall mean for each faculty member, i.e. u_{0j}.) Faculty members are ranked based on the magnitude of the residual. Goldstein and Healy (1995) recommend this type of presentation to judge statistical significance based on non-overlapping confidence intervals. They indicate that, while "[i]t is a common statistical misconception to suppose that two quantities whose 95% confidence intervals fail to overlap are significantly different at the 5% level" (p.175), one can adjust the confidence level to be able to use the non-overlap criterion. The width of the intervals to achieve a 5% significance level should be $\pm 1.396 \times \delta$, and this width is used in Fig.5. While the proportion of the total variance in grade point average explained by between-faculty differences is substantial, it is clear from the graph that there is a considerable overlap of intervals, so that only relatively widely separated faculty members can be judged as having significantly different residuals.[3]

No significant variation in log-odds of retention was found depending upon which faculty members students are exposed to. At the same time, significant variability depending upon instructors was found in student grade point averages. A comparison between proportional weights and equal weights multiple membership models for GPA as an outcome showed a superior fit of the equal weights models. The next step is increasing the complexity of the model by adding predictors.

Conditional Models

The unconditional model of student retention shows that there is no significant amount of variability in the intercept across instructors. Taking this into account, the faculty-level random effect, u_{0j}, can be removed from the equation. Absence of significant variability across instructors also implies that in the study presented here, retention is sufficiently explained by student-level characteristics. (Testing the variability in the slope coefficients is beyond the scope of this study.) This leads to the conclusion that the effect of faculty status and other faculty characteristics on the log-odds of second-year return is not significant.

The unconditional model of grade point averages showed significant between-faculty variability. The next step is to explain this variability by faculty-level variables. Based on the results of the cross-classified models presented above, one can already ascertain that course grades are related to the faculty status of the instructor—tenure-track or non-tenure-track. The analysis presented below will demonstrate that the association between the student-level measure of exposure to contingent faculty and grade point average cannot be used to make inferences about a student grade being lower in a class taught by tenure-track faculty or vice versa.

Because the equal weights unconditional model showed a superior fit, the subsequent conditional models will be equal weights models with exposure to contingent instructors being measured by classes as opposed to credit hours. (While not presented here, the analysis based on credit hours was also carried out and showed results substantively similar to the results presented here, but a slightly inferior model fit.)

In view of a prior finding of a negative association between the tenure-track faculty status and the probability of getting higher grades, one would expect a positive association between the proportion of courses taught by contingent instructors and grade point average. Two approaches are used to measure the effect of contingent instructors on student GPA in Table 7. One of these approaches follows prior research on exposure to contingent instructors and uses the index of exposure or the number of classes taught by contingent instructors divided by the overall number of classes a student took. The other approach is based on estimating the regression coefficients of the number of classes taught by tenure-track instructors and the number of classes taught by contingent faculty and testing the null hypothesis that these regression coefficients are equal. The equality of these regression coefficients is tested using Wald test (Rasbash, Steele, Browne and Goldstein, 2009, pp.125-126) of the null hypothesis $H_0 : \beta_1 - \beta_2 = 0$ where β_1 and β_2 are the coefficients for the number of classes taught by tenure-track faculty and number of classes (taught by contingent instructors respectively.

Model 1.1 and Model 1.2 of Table 7 do not agree with findings of a cross-classified model. Based on Model 1.1, exposure to contingent instructors has a significant negative effect (-0.47) on cumulative GPA. The more classes are taught by contingent instructors, the lower the cumulative GPA is. Based on Model 1.2, the coefficient for the number of classes taught by tenure-track faculty (0.20) is greater than the coefficient for the number of classes taught by contingent instructors (0.14), and the null hypothesis on the equality of regression coefficients can be rejected based on the Wald test: $\chi^2(1) = 18.60$, significant at the 5% alpha level. Based on these results alone, one would conclude that the exposure to contingent instructors has a negative impact on student grades. Yet a comparison of findings based on the cross-classified model and multiple membership model with aggregated measure of exposure to contingent instructors reflects the worst-case-scenario provided in a hypothetical example of Fig. 1 and clearly demonstrates that aggregation in this case is misleading.

The explanation for higher grade point averages for students who are more exposed to tenure-track faculty can be related to correlation between the measures of exposure to contingent instructors and certain student characteristics. Bettinger and Long (2005) demonstrate that students with higher ACT scores are less likely to take classes taught by adjuncts during their first semester and provide plausible reasons for this. Thus, some universities allow students with high ACT scores to register for classes sooner than other students and these students choose classes taught by tenure-track instructors. Sometimes departments assign adjuncts to classes at times of the day that are less likely to attract typical high performing students. Tenure-track faculty members are more likely to teach Honors classes at the study institution, and the significant positive correlation between the number of courses taught by tenure track faculty and grades can be expected. A further exploration reveals that there are correlations, significant at the 1% alpha level, between students' high school GPA and the number of hours or courses taught by tenure-track faculty and by contingent faculty. For example, the correlation between the high school GPA and the number of courses taught by tenure-track faculty is positive (0.130) and significant at the 5% alpha level, while the correlation between the high school GPA and the number of courses taught by contingent faculty is negative (-0.124) and significant at the 5% alpha level. The correlation between ACT test scores and number of classes taught by tenure-track faculty is significant and positive (0.279), while the correlation between test scores and number of classes taught by contingent instructors is significant and negative (-0.284).

After controlling for high school GPA and ACT scores in Models 2.1 and 2.2 in Table 7, the effect of exposure to contingent instructors becomes insignificant at the 5% alpha level (Model 2.1), and the difference between the effects of number of classes or hours taught by tenure track faculty and number of hours taught by contingent faculty ceases to be significant at the 5% alpha level: $\chi^2(1) = 0.17$. Thus, the negative effect of exposure to contingent instructors in Models 1.1 and 1.2 of Table 7 was a mere reflection of class taking behaviors of high performing students.

While the effects of aggregated measures of exposure to contingent instructors on cumulative GPA in multiple membership models in Table 7 do not align with the effects of tenure-track status of faculty members on probability of getting higher grades in cross-classified models in Table 4, the effects of student-level characteristics, such as number of classes a student took, gender, ethnicity, state residency, high school GPA, ACT test, and Greek membership, have consistent signs and statistical significances. Based on the Equal Weights cumulative GPA Model 2 in Table 8, female students have higher grades; so do students who take more classes. The effects of ethnicity and state residency on cumulative GPA are not significant. The effects of high school GPA, ACT and Greek membership are positive and significant.

GPA Model 1 in Table 8 shows that, after control for other student-level characteristics (gender, ethnicity, state residency, high school GPA, ACT, and Greek membership), the effect of exposure to contingent instructors on cumulative GPA remains insignificant. The regression coefficients for the number of classes taught by contingent instructors and the number of classes taught by tenure-track faculty are practically identical. And, the null hypothesis on the equality of these regression coefficients cannot be rejected based on the Wald test: $\chi^2(1) = 0.14$, not significant at the 5% alpha level. Finally, the model that combines these two independent variables into one, the overall number of classes a student took, shows a superior fit based on Deviance and Deviance Information Criterion.

A comparison of the logistic regression coefficients for the number of classes taught by contingent instructors (0.58) and the number of classes taught by tenure-track faculty (0.57) in single-level model retention model in Table 8 shows that these coefficients are very similar. The null hypothesis on the equality of these regression coefficients cannot be rejected based on the Wald test: $\chi^2(1) = 0.10$, not significant at the 5% alpha level. And, the single-level retention Model 2 that combines these two independent variables into one—the overall number of classes a student took—shows a superior fit based on Deviance and Deviance Information Criterion.

The results of the retention model 2 in Table 8 indicate that the odds of return increase 1.79 ($e^{0.58}$) times with each additional class a student takes, which, on the one hand, could reflect the well documented association between part-time enrollment and retention. On the other hand, this association can be related to the fact that students who took more classes should have been enrolled both in fall and spring semesters, while those who took fewer classes could have been enrolled in fall only and dropped out before the spring semester. State residents have 2.12 ($e^{0.75}$) times higher odds of return compared to non-residents. The increase of high school GPA by 1 leads to 1.95 ($e^{0.67}$) increase in odds of return; and the increase of ACT score by 5 leads to 1.22 ($e^{5\times0.04}$) time increase in odds of return. Members of Greek organizations have 2.64 ($e^{0.97}$) times higher odds of return compared to non-Greeks. The effects of gender and ethnicity are not significant at the 5% alpha level.

LIMITATIONS

The study has several limitations. First, the analysis is based on data from a single moderately large research institution. Types of contingent instructors as well as the effect of contingent instructors on student outcomes may vary across institutions; and the findings presented here might not apply to other institutions and institution types.

Second, while a non-proportional or partial proportional odds model is a better alternative for student grades as outcomes, several models with binomial outcomes—a grade of “A”, a grade of “B” or higher, and a grade of “C” or higher—were analyzed instead. At the time of writing, non-proportional or partial proportional odds cross-classified models were not estimated in HLM.

A third limitation is that class size in the cross-classified model was aggregated to the faculty level. While instructors are likely to teach first-year courses or Core Curriculum courses of similar sizes, a more accurate model specification with grades nested within students and classes and classes nested within faculty members should be considered in future research.

IMPLICATIONS

The analysis presented here illustrates that the index of exposure to contingent instructors used in many prior studies of instructor effectiveness is liable to errors resulting from aggregation. Such errors are widely discussed in the literature devoted to multi-level analysis and include the shift of meaning, the ecological fallacy, and the neglect of the original data structure.

In the present study, a cross-classified model of student grades—a model with grades nested within student and faculty members—shows that students are more likely to have higher grades in courses taught by contingent instructors. At the same time, when faculty status (tenure-track versus contingent) is aggregated to the student level, the effect of exposure to contingent instructors on grade performance becomes negative. After controlling for high school academic performance, the effect of exposure to contingent instructors becomes insignificant. Thus, the absence of association between the aggregate measure of exposure to contingent instructors does not mean that there are no differences in grades given by tenure-track and contingent faculty.

Studies that suffer from errors of aggregation continue to emerge and sometimes lead to strong messages. For example, Glenn (2008) suggests that one should keep adjuncts away from introductory courses. This message was based on the study of Eagan and Jaeger (2008) who used the percentage of introductory courses with graduate students and the percentage of introductory courses with other part-time faculty as a student-level measure of exposure to different instructor types. A comparison of aggregated and non-aggregated results provided here warns researchers that the percentage of courses taught by contingent instructors should not be used to measure the effect of contingent instructors on student outcomes.

If a student grade is the dependent variable, it is methodologically appropriate to use a cross-classified model and incorporate faculty status—contingent or tenure-track—at the faculty level. However, the cross-classified model cannot be used when the dependent variable is at the student level and not at the cross-classification of student and faculty, which is the case with student retention and grade point average. A hierarchical two-level model would not be appropriate either, since each student can be exposed to more than one faculty member.

Effects on a student-level response variable, such as retention, with each student being exposed to multiple faculty members, can be conceptualized within the framework of multiple membership models. Multiple membership models are useful when the researcher is interested in variance decomposition. At the same time, adding predictors from the faculty level is problematic. Thus, while multiple membership models take into account the original data structure, these models do not provide means for testing the fixed effects from the level of multiple membership, such as faculty status.

The unconditional model of retention presented here showed no variability in log-odds of retention depending upon faculty members students are exposed to. Hence, no evidence suggests that faculty characteristics, including faculty rank or status, affect the probability of student return for the second year at the study institution. At the same time, the unconditional model of grade point averages suggests a significant variation by faculty members.

Overall, the models presented here indicate that at the study institution the contingent status of instructors does not affect student probability of return for the second year. At the same time, grades are affected by instructor type. Controlling for other faculty-level and student-level characteristics, contingent instructors give higher grades. Since professors who give easy grades are believed to have higher teaching evaluations, it is plausible that contingent instructors are more hesitant to give low grades to assure that they will continue to teach after the current contract expires.

Grade inflation can lead to lowered levels of academic challenge and student motivation to do their best work. Possible ways to deal with the disparity between grading practices by tenure-track faculty and contingent instructors should be discussed at the institutional level. Strategies that can be implemented include: adopting caps that limit the proportions of “A” grades that can be awarded; weighting student evaluations of instruction on the basis of grade distribution (Kamber, 2008a); or providing training and support to help adjunct faculty abide by grading standards used by tenure-track faculty (Sonner, 2000).

END NOTES

[1] A cross-classified model is estimated in HLM using restricted maximum likelihood method. One practical consequence is that the likelihood ratio test or Deviance is not available (Raudenbush, Bryk, Cheong, and Congdon, 2004, p.11). Multiple membership models, on the other hand, are estimated in MLwiN using Markov Chain Monte Carlo (MCMC) methods (Browne, 2009); and likelihood ratio tests are available.

[2] The data structure for multiple membership models has one observation per student. For each student in the data set there is an information for up to 12 instructors they were taught by in columns faculty 1, faculty 2, …, faculty 12. The corresponding information about weights is included in columns weight 1, weight 2, … , weight 12 for proportional weights and ew1, ew2, …, ew12 for equal weights. There are 671 instructors in the data set, but only 553 appeared in the first column. MLwiN plot is based on the instructors that appeared in the first column.

[3] Based on a similar plot with the width of intervals of 1.96, one can also gauge groups of faculty members at the lower and upper end of the plot where the confidence intervals for their residuals do not overlap zero, which would mean that these are the faculty members that differ from the average at the 5% alpha level.

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TABLE 1. Variable Description and Descriptive Statistics

Variable	Variable description	Mean (SD)
Level-1		
Course credit hours	Number of hours a student took from a faculty member	3.30 (0.83)
Grade "A"	1 for a grade of "A"; 0 otherwise	0.33 (0.47)
Grade "B" or higher	1 for a grade of "B" or higher; 0 otherwise	0.67 (0.47)
Grade "C" or higher	1 for a grade of "C" or higher; 0 otherwise	0.85 (0.36)
# of level-1 observations		*31,199*
Level-2: Student characteristics		
Female	1 if female; 0 otherwise	0.52 (0.50)
Non-Caucasian	1 if ethnicity is Caucasian; 0 otherwise	0.12 (0.32)
State resident	1 if state resident; 0 otherwise	0.59 (0.49)
High School GPA	High School GPA	3.69 (0.43)
ACT or SAT Equivalent	ACT or SAT Equivalent	25.87 (3.48)
Greek	1 if a member of a fraternity or sorority; 0 otherwise	0.34 (0.47)
Number of courses	Number of courses a student took during the fall and spring semester of the first year of studies	9.39 (1.45)
Number of hours	Number of hours a student took during the fall and spring semester of the first year of studies	27.49 (3.66)
Courses taught by tenure track faculty	Number of courses taught by tenure track faculty	2.87 (1.60)
Courses taught by contingent instructors	Number of courses taught by contingent instructors	6.52 (1.89)
Credit hours taught by tenure track faculty	Number of credit hours taught by tenure track faculty	8.88 (4.91)
Credit hours taught by contingent instructors	Number of credit hours taught by contingent instructors	18.61 (5.23)
Spring 1 Cumulative GPA	Cumulative GPA for fall and spring semester of the first year of studies	2.80 (0.85)
Retention	1 if returned; 0 otherwise	0.87 (0.34)
# of student-level observations		*3,911*
Level-2: Faculty characteristics		
Tenure-track	1 if tenure-track; 0 otherwise	0.44 (0.50)
Hard-pure-life	1 if Biological Sciences; 0 otherwise	0.03 (0.18)
Hard-pure-non-life	1 if Chemistry, Geology, Mathematics, Statistics, Physics, or General Sciences; 0 otherwise	0.22 (0.41)
Hard-applied-life	1 if Agriculture, Aquaculture, Forestry, Nutrition, Pharmacy, or Veterinary Medicine; 0 otherwise	0.04 (0.19)
Hard-applied-non-life	1 if Engineering or Computer Science; 0 otherwise	0.07 (0.25)
Soft-pure-life	1 if Social Sciences; 0 otherwise	0.08 (0.28)
Soft-pure-non-life	1 if Humanities; 0 otherwise	0.39 (0.49)
Soft-applied-life	1 if Education, Family Studies, Communication Disorders, or Nursing; 0 otherwise	0.08 (0.28)
Soft-applied-non-life	1 if Economics, Business, or Architecture; 0 otherwise	0.09 (0.29)
Log (class size)	Natural logarithm of average class size for a faculty member	3.46 (0.72)
# of faculty-level observations		*671*

TABLE 2. Student Course Load and Exposure to Contingent Instructors

Course Load	Exposure to Contingent Instructors			
	0%-24%	25%-49%	50%-74%	75%-100%
One course	+	–	–	+
Two courses	+	–	+	+
Three courses	+	+	+	+

TABLE 3. Cross-Classified Unconditional Models

	Model 1: Grade "A"	Model 2: Grade "B" or higher	Model 3: Grade "C" or higher
Intercept $\beta_0\,(SE(\beta_0))$	-0.61 (0.06)*	1.42 (0.06)*	2.60 (0.06)*
Student $\left(\delta_u^2\right)$	2.83	2.84	2.42
Faculty $\left(\delta_v^2\right)$	1.64	1.48	1.11

*Significant at the 5% level

TABLE 4. Cross-Classified Conditional Models

	Grade "A"		Grade "B" or higher		Grade "C" or higher	
	Model 1.1	Model 1.2	Model 2.1	Model 2.2	Model 3.1	Model 3.2
Intercept	-13.60 (0.37)*	-9.49 (0.52)*	-11.80 (0.37)*	-8.53 (0.52)*	-9.61 (0.41)*	-7.65 (0.56)*
Level-1						
Course credit hours		-0.16 (0.03)*		-0.08 (0.03)*		-0.02 (0.03)
Level-2: Student characteristics						
Female	0.50 (0.06)*	0.51 (0.06)*	0.46 (0.06)*	0.46 (0.06)*	0.45 (0.07)*	0.45 (0.07)*
Non-Caucasian	0.07 (0.09)	0.07 (0.09)	-0.06 (0.09)	-0.06 (0.09)	-0.13 (0.09)	-0.13 (0.10)
State resident	0.07 (0.06)	0.07 (0.06)	0.06 (0.06)	0.06 (0.06)	0.01 (0.06)	0.01 (0.06)
High School GPA	1.70 (0.07)*	1.72 (0.07)*	1.82 (0.07)*	1.83 (0.07)*	1.74 (0.08)*	1.75 (0.08)*
ACT or SAT Equivalent	0.20 (0.01)*	0.20 (0.01)*	0.19 (0.01)*	0.19 (0.01)*	0.14 (0.01)*	0.14 (0.01)*
Member of a fraternity or sorority	0.03 (0.06)	0.03 (0.06)	0.15 (0.06)*	0.15 (0.06)*	0.28 (0.07)*	0.27 (0.07)*
Number of classes took	0.14 (0.02)*	0.14 (0.02)*	0.18 (0.02)*	0.18 (0.02)*	0.24 (0.02)*	0.24 (0.02)*
Level-2: Faculty characteristics						
Tenure-track	-0.61 (0.12)*	-0.44 (0.12)*	-0.72 (0.12)*	-0.54 (0.11)*	-0.65 (0.12)*	-0.52 (0.11)*
Hard-pure-life		-3.14 (0.38)*		-2.87 (0.37)*		-2.23 (0.38)*
Hard-pure-non-life		-2.88 (0.26)*		-2.77 (0.26)*		-2.33 (0.28)*
Hard-applied-life		-1.81 (0.41)*		-1.06 (0.40)*		-0.52 (0.43)
Hard-applied-non-life		-2.18 (0.32)*		-1.47 (0.32)*		-1.08 (0.34)*
Soft-pure-life		-2.43 (0.30)*		-1.70 (0.31)*		-1.10 (0.32)*
Soft-pure-non-life		-2.69 (0.24)*		-1.70 (0.25)*		-1.05 (0.27)*
Soft-applied-non-life		-2.76 (0.29)*		-1.78 (0.30)*		-1.05 (0.32)*
ln(CS)		-0.37 (0.08)*		-0.37 (0.08)*		-0.19 (0.08)*
Random parameters						
Student $\left(\delta_u^2\right)$	1.74	1.77	1.81	1.83	1.81	1.84
Faculty $\left(\delta_v^2\right)$	1.81	1.30	1.59	1.08	1.26	0.84

*Significant at the 5% level

TABLE 5. Expected Probabilities of Getting an “A”, a “B” or Higher, and a “C” or Higher by Class Size, Discipline Area, High School GPA, and ACT Scores

	Grade "A" (Model 1.2 in Table 4)	Grade "B" or higher (Model 2.2 in Table 4)	Grade "C" or higher (Model 3.2 in Table 4)
Expected probabilities by class size			
Class of 10	0.45	0.87	0.95
Class of 20	0.38	0.84	0.95
Class of 50	0.31	0.79	0.94
Class of 100	0.26	0.75	0.93
Expected probabilities by discipline			
Hard-pure-life	0.21	0.61	0.86
Hard-pure-non-life	0.25	0.63	0.85
Hard-applied-life	0.50	0.90	0.97
Hard-applied-non-life	0.41	0.86	0.95
Soft-pure-life	0.35	0.83	0.95
Soft-pure-non-life	0.29	0.83	0.95
Soft-applied-life	0.86	0.96	0.98
Soft-applied-non-life	0.28	0.82	0.95
Expected probabilities by high school GPA			
High school GPA 2.50	0.06	0.34	0.67
High school GPA 3.00	0.14	0.56	0.83
High school GPA 3.50	0.27	0.76	0.92
High school GPA 4.00	0.47	0.89	0.97
Expected probabilities by ACT or SAT Equivalent			
ACT 20	0.14	0.60	0.88
ACT 25	0.30	0.79	0.94
ACT 30	0.55	0.91	0.97
ACT 35	0.77	0.96	0.98

TABLE 6. Multiple Membership Unconditional Models

	Single-level	Proportional weights	Equal weights
Outcome: Spring 1 Cumulative GPA			
Intercept $\beta_0(SE(\beta_0))$	2.80 (0.01)*	2.99 (0.07)*	2.96 (0.06)*
Student-level $\delta_{e0}^2\left(SE\left(\delta_{e0}^2\right)\right)$	0.72 (0.02)*	0.54 (0.01)*	0.53 (0.01)*
Faculty-level $\delta_{u0}^2\left(SE\left(\delta_{u0}^2\right)\right)$		1.66 (0.17)*	1.72 (0.17)*
Deviance (MCMC)	9827.29	8663.78	8613.45
Deviance Information Criterion (DIC)	9829.29	8972.23	8945.35
Outcome: Retention to the second year			
Intercept $\beta_0(SE(\beta_0))$	1.89 (0.05)*	1.90 (0.05)*	1.89 (0.05)*
Faculty-level $\delta_{u0}^2\left(SE\left(\delta_{u0}^2\right)\right)$		0.02 (0.02)	0.00 (0.00)
Deviance (MCMC)	3040.59	3037.61	3040.50
Deviance Information Criterion (DIC)	3041.53	3039.66	3041.52

TABLE 7. Multiple Membership Equal Weights Models of Spring 1 Cumulative GPA with and without Control for High School Academic Performance

	Model 1.1	Model 1.2	Model 2.1	Model 2.2
Outcome: Spring 1 Cumulative GPA				
Intercept $\beta_0(SE(\beta_0))$	1.67 (0.15)*	1.33 (0.12)*	-2.40 (0.19)*	-2.35 (0.16)*
Number of classes/Number of classes taught by tenure-track faculty $\beta_1(SE(\beta_1))$	0.16 (0.01)*	0.20 (0.01)*	0.14 (0.01)*	0.15 (0.01)*
Share of classes/Number of classes taught by contingent instructors $\beta_2(SE(\beta_2))$	-0.47 (0.15)*	0.14 (0.01)*	0.06 (0.12)	0.14 (0.01)*
High School GPA $\beta_3(SE(\beta_3))$			0.71 (0.03)*	0.71 (0.03)*
ACT $\beta_4(SE(\beta_4))$			0.05 (0.00)*	0.05 (0.00)*
Student-level $\delta^2_{e0}\left(SE\left(\delta^2_{e0}\right)\right)$	0.50 (0.01)*	0.49 (0.01)*	0.42 (0.01)*	0.42 (0.01)*
Faculty-level $\delta^2_{u0}\left(SE\left(\delta^2_{u0}\right)\right)$	1.66 (0.17)*	1.64 (0.16)*	0.75 (0.10)*	0.75 (0.09)*
Chi-square (df=1), $H_0 : \beta_1 - \beta_2 = 0$		18.60*		0.17
Deviance (MCMC)	8347.58	8343.02	7733.16	7732.12
Deviance Information Criterion (DIC)	8684.17	8678.70	7992.75	7992.28

*Significant at the 5% alpha level.

Model 1.1: Number of classes taken by a student and index of exposure to contingent instructors as predictors, no control for high school academic performance

Model 1.2: Number of classes taught by tenure-track instructors and number of classes taught by contingent instructors, no control for high school academic performance

Model 2.1: Number of classes taken by a student and index of exposure to contingent instructors as predictors with control for high school academic performance

Model 2.2: Number of classes taught by tenure-track instructors and number of classes taught by contingent instructors with control for high school academic performance

TABLE 8. Single-Level Retention Model and Multiple Membership Cumulative GPA Model

	Single-Level Retention Model 1	Single-Level Retention Model 2	Multiple Membership Equal Weights Cumulative GPA Model 1	Multiple Membership Equal Weights Cumulative GPA Model 2
Intercept $\beta_0(SE(\beta_0))$	-7.85 (0.57)*	-7.51 (0.51)*	-2.53 (0.12)*	-2.33 (0.16)*
Number of classes taught by tenure-track faculty $\beta_1(SE(\beta_1))$	0.57 (0.05)*		0.15 (0.01)*	
Number of classes taught by contingent instructors $\beta_2(SE(\beta_2))$	0.58 (0.04)*		0.15 (0.01)*	
Number of classes a student took		0.58 (0.04)*		0.14 (0.01)*
Female $\beta_3(SE(\beta_3))$	-0.05 (0.11)	-0.04 (0.11)	0.17 (0.03)*	0.17 (0.03)*
Non-Caucasian $\beta_4(SE(\beta_4))$	-0.08 (0.16)	-0.08 (0.16)	-0.05 (0.04)	-0.06 (0.04)
State resident $\beta_5(SE(\beta_5))$	0.75 (0.11)*	0.75 (0.11)*	-0.00 (0.02)	-0.00 (0.02)
High School GPA $\beta_6(SE(\beta_6))$	0.76 (0.13)*	0.67 (0.13)*	0.69 (0.02)*	0.67 (0.03)*
ACT $\beta_7(SE(\beta_7))$	0.04 (0.02)*	0.04 (0.01)*	0.05 (0.00)*	0.05 (0.00)*
Member of a fraternity or sorority $\beta_8(SE(\beta_8))$	0.97 (0.13)*	0.97 (0.13)*	0.08 (0.03)*	0.08 (0.03)*
Student-level $\delta_{e0}^2\left(SE\left(\delta_{e0}^2\right)\right)$			0.42 (0.01)*	0.42 (0.01)*
Faculty-level $\delta_{u0}^2\left(SE\left(\delta_{u0}^2\right)\right)$			0.66 (0.09)*	0.66 (0.09)*
Chi-square (df=1), $H_0 : \beta_1 - \beta_2 = 0$	0.10		0.14	
Deviance (MCMC)	2541.81	2540.70	7704.66	7703.61
Deviance Information Criterion (DIC)	2550.93	2548.40	7953.40	7952.14

*Significant at the 5% alpha level

FIG. 1. Student-faculty level versus student level relations between instructor type and grade performance

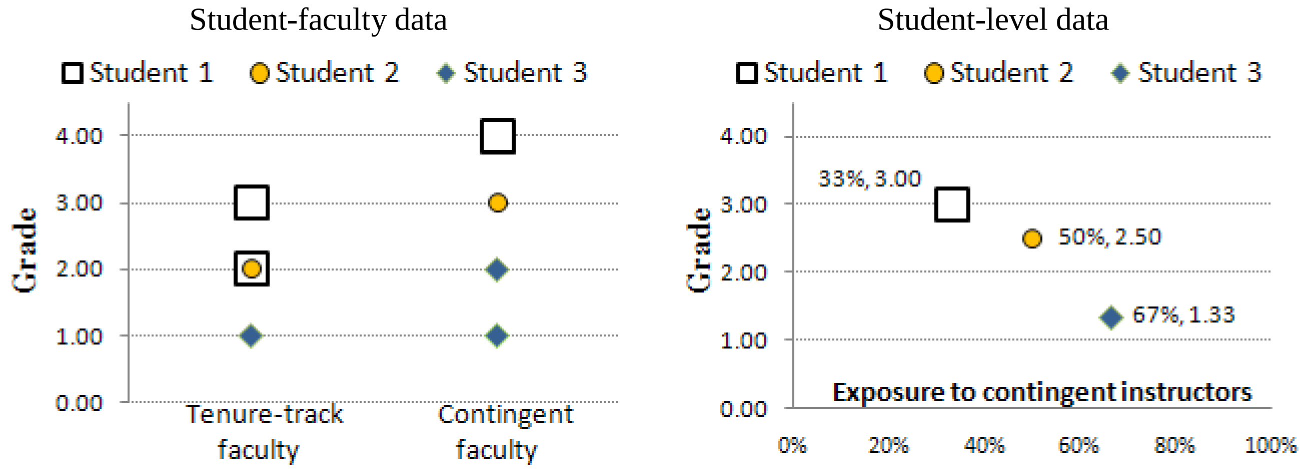


FIG. 2. Grades nested within students and instructors: A cross-classified data structure.

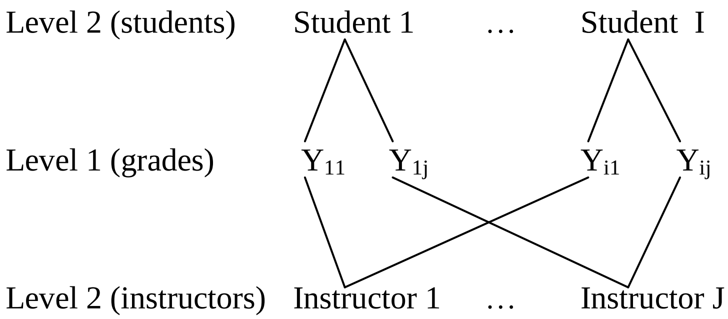
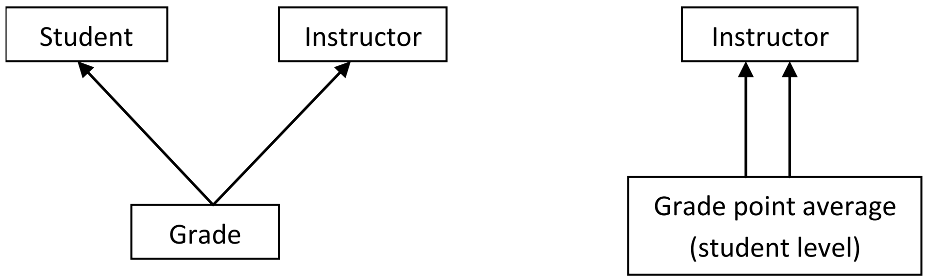


FIG. 3. Classification diagrams for cross-classified and multiple membership models.



Cross-classified model

Multiple membership model

FIG. 4. Expected probabilities of getting an "A", a "B" or higher, and a "C" or higher for a typical student taught by a typical faculty with one standard deviation whiskers by faculty and by students.

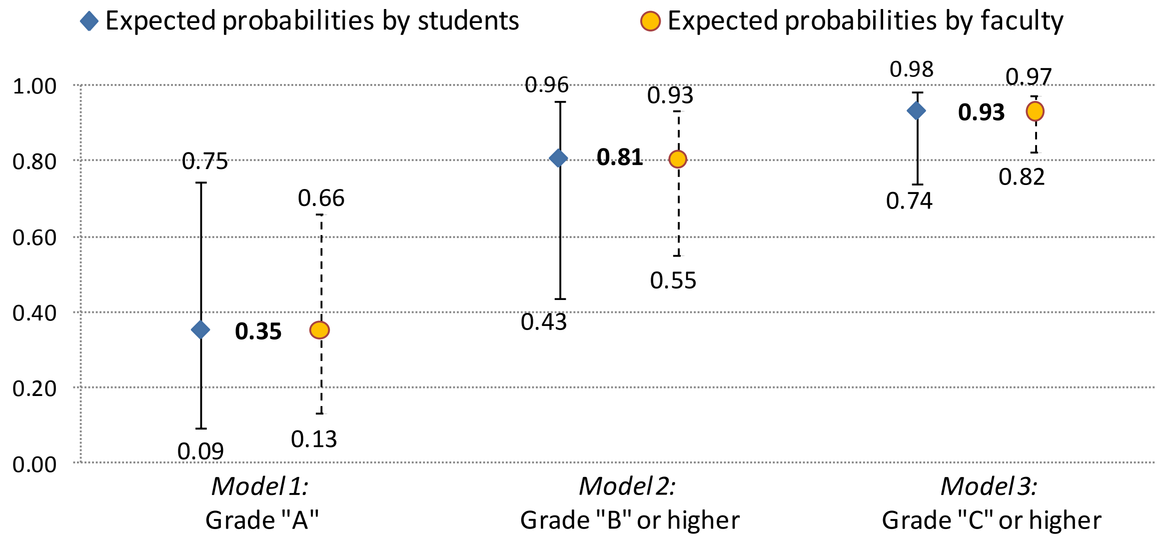
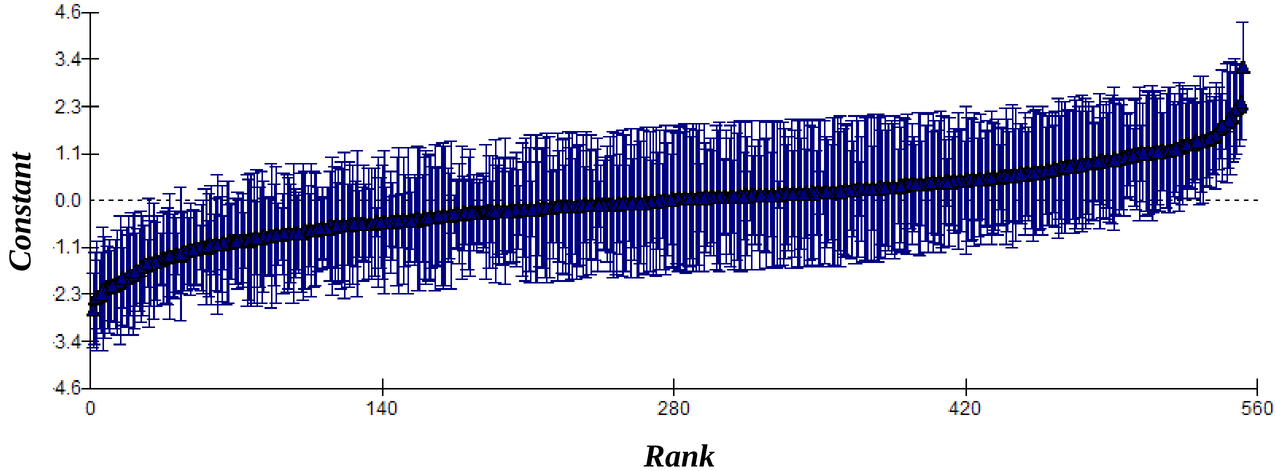


FIG. 5. Residuals for 553 faculty members*



*Based on equal weights unconditional model