Cooling Out in the Community College: What is the Effect of Academic Advising on Students' Chances of Success?

by

Peter Riley Bahr
Department of Sociology
Wayne State University

13,531 words
4 tables
2 figures
2 appendices

Key Words:
Cooling Out, Advising, Counseling, Transfer, Remediation, Remedial Education, Developmental Education, Mathematics, Race, Inequality, Community College

*All correspondence should be directed to the author at the Department of Sociology, Wayne State University, Detroit, Michigan, 48202. Email: peter.bahr@wayne.edu. Phone: 313-577-3285. Fax: 313-577-2735. I am indebted to Tim Brown, Willard Hom, Myrna Huffman, Tom Nobert, Mary Kay Patton, and Patrick Perry of the Chancellor's Office of California Community Colleges for their assistance with the data employed in this study. I thank Elisabeth Ashmore for her assistance with the editing of this manuscript. This study was made possible by a grant from the Association for Institutional Research and the National Postsecondary Education Cooperative. An earlier version of this paper was presented at the 2007 Annual Forum of the Association for Institutional Research.

Cooling Out in the Community College: What is the Effect of Academic Advising on Students' Chances of Success?

ABSTRACT

Burton Clark's proposition concerning the *cooling out* of underprepared students in community colleges has a controversial history and remains a point of contention. Central to Clark's description of the *cooling out* process is the academic counselor, whose job it is to dissuade underprepared students from goals perceived to be overambitious, and ease these students into lesser, presumably better fitting, academic trajectories. In this research, I test a number of hypotheses concerning the effect of academic advising on students' chances of academic success. I seek to determine what effect advising has on students' attainment and whether this effect of advising is dependent upon students' academic preparation, students' race/ethnicity, the racial/ethnic composition of the college, and the representation of underprepared students in the college. I use discrete-time event history analysis to analyze data addressing two subsets (N_1 = 30,118; N_2 = 68,241) of the Fall 1995 cohort of first-time freshmen who enrolled in any of California's 107 semester-based community colleges. Students' academic progress was tracked for a total of six years, through the Spring semester of 2001.

Cooling Out in the Community College: What is the Effect of Academic Advising on Students' Chances of Success?

BACKGROUND

Cooling Out

The idea, proposed by Burton Clark (1960, 1980), that one of the functions of the community college, and specifically the community college counselor/advisor, is to *cool out* students whose academic ambitions exceed their abilities has a long and contentious history in educational research, and it continues as a point of debate (e.g., Adelman 2005; Bahr 2004; Deil-Amen & Rosenbaum 2002). The concept of *cooling out* is drawn from Goffman's (1952) description of the process whereby an individual who has been the victim of a con game is eased out of his/her recently held identity as a "sure winner" by the *cooler* (the agent of *cooling out*) into a some other identity *other than* "victim." Extending this perspective to the community college, Clark (1960) described *cooling out* as a "gradual disengagement" of a student from his/her professed academic goal, accomplished primarily through the substitution of lesser avenues of achievement perceived to be more appropriate to a given student's preparation, skills, and abilities.

Central to the *cooling out* process described by Clark (1960) is the academic counselor – the most active *cooler* within the institutional structure of the community college. In Goffman's description, "the cooler has the job of handling persons who have been caught out on a limb – persons whose expectations and self-conceptions have been built up and then shattered" (p. 452). Clark explains that, as the agent of *cooling out,* the academic counselor works closely with the student, discussing the academic and professional implications of the student's placement exam scores, assisting with course selection, informing the student about the requirements and hurdles associated with his/her academic goals, and later advising the student based on his/her accumulating academic record. For students who do not perform well in their coursework, even the academic probationary process returns them to the academic counselor. Through these interactions with the student, the academic counselor is charged with easing from the student's grasp academic goals that are perceived to be overambitious, and substituting in their place goals befitting the perceived abilities of the student.

While Clark's work focused on the *cooling out* of academically underprepared students without regard to ascribed characteristics of the students, recent evidence suggests a possible racial twist on *cooling out*. In particular, Bahr (2004) found significant variation across racial groups in the effect of advising on the likelihood of successful remediation in math among mathematically underprepared community college students. More specifically, Bahr found that, on average, White and Asian remedial math students in community colleges experienced a small, but significant, increase in the likelihood of successful remediation associated with receiving academic advising. Among Hispanics, this beneficial effect of advising was significantly less than that for Whites and Asians, but remained positive. However, Black students who received advising actually were slightly less likely to remediate successfully than were Black students who did *not* receive advising. In other words, while White and Asian remedial math students benefited equally from advising, and while Hispanics also benefited from advising albeit to a lesser degree, the chance of success for Black remedial math students was diminished slightly by advising. One interpretation of this finding is that some aspect of the advising process itself tends, on average, to discourage underprepared Black students from the pursuit of college-level math skills, perhaps in a fashion akin to the *cooling out* processes described by Clark.

While the connection between *cooling out* and larger issues of social conflict, particularly the reproduction of class structure, is not new (Alba & Lavin 1981; Dougherty 1987; Karabel

1972; McClelland 1990; Rosenbaum 2001), the proposition that *cooling out* may tend to be moderated by the race of the student is both novel and controversial. Such a proposition, however, is not without contextual support. Recent research indicates that racism is alive and well on college campuses (Rankin & Reason 2005; Suarez-Balcazar, et al. 2003; Swim, et al. 2003), and that Blacks in particular are likely to be subjected to negative stereotypes as being less academically able (Davis, et al. 2004). Thus, in light of Bahr's findings, one might envision race-specific *cooling out* processes whereby academically underprepared Black students tend, on average, to be discouraged from ambitious academic goals in favor of lesser goals perceived to be more suitable for historically disadvantaged students of color, particularly students whose basic skills are deficient (Weissman, Bluakowski & Jumisko 1998). This is not to suggest overt or intentional racism but, rather, the tendency for racial biases and stereotypes to emerge in the course of everyday behavior (Bobo & Fox 2003; Brezina & Winder 2003; Devine 2001).

Yet, this interpretation of Bahr's findings disagrees with several recent studies concerning *cooling out* in community colleges. Specifically, Deil-Amen and Rosenbaum (2002) observed a shift toward "stigma-free" remediation in community colleges that tends to hide from underprepared students their remedial status. This finding implies that the direct and active *cooling out* by academic counselors, described by Clark (1960), occurs less frequently than in the past. In fact, Deil-Amen and Rosenbaum suggest that the "stigma-free" remedial environment is actively encouraging to underprepared students, although the authors further surmise that allowing students to discover their remedial status (and associated low chances of attaining their academic goals) on their own forestalls only temporarily high rates of attrition.

In another recent study, Adelman (2005) found a reasonably high level of stability in long-term educational objectives of community college students and little variation (in this stability) across racial/ethnic groups. This finding suggests that neither community college students generally nor students of historically disadvantaged racial/ethnic groups specifically are being discouraged from ambitious educational goals. In fact, Pascarella, Wolniak, and Pierson (2003) found that nonwhite community college students experienced a *greater* increase in end-of-first-year educational plans than did white students.

These findings are supported by a few small-scale studies, documented by Pascarella and Terenzini (2005), that suggest that advising is actively beneficial to students' academic attainment (e.g., Metzner 1989; Young, Backer & Rogers 1989). In one particularly noteworthy study, Seidman (1991), using a design that involved random assignment, observed that academic advising increased significantly community college students' persistence into a second year of attendance.

However, Deil-Amen and Rosenbaum's study drew on data from just two community colleges, so the external validity of this study is weak. It also did not address the possibility of race-specific biases in academic advising. Neither Adelman's study nor the study conducted by Pascarella and his colleagues addressed underprepared students specifically (the population that, according to Clark's thesis, is most likely to experience *cooling out*), nor did either study address the role of academic advising in students' outcomes. Seidman's study employed a very small sample drawn from one community college and a short observation period, and it explored neither the effect of underpreparation nor the effect of race on the effect of advising. In contrast, Bahr's study focused specifically on underprepared students, drew on data that addressed a population of students enrolled in over one hundred colleges, observed students for a period of six years, and examined the race-specific effect of advising. Thus, Bahr's findings are derived from a different analytical perspective on *cooling out* than that of other recent studies.

Nevertheless, considerable caution must be exercised in interpreting Bahr's findings because the analysis employed in his study effectively forces a cross-sectional design on longitudinal data, so the order of events with respect to advising is not clear. It may be that, on average, advising discourages underprepared Black students from pursuing college-level math competency. Alternatively, it may be that Black students tend, on average, to seek advising at different points in their academic careers than do Whites and Asians, thereby possibly receiving lesser benefits and contributing to the appearance of a race-specific advising effect. Such a differential in the timing of advising also might explain the lesser average benefit of advising noted for Hispanic students.

Bahr also does not examine the influence of racial context on the race-specific effects of academic advising. In recent decades, the role of campus racial climate in the educational outcomes of historically disadvantaged racial groups has received increasing empirical attention (e.g., Cabrera, et al. 1999; Hurtado 1992; Hurtado, et al. 1999; McClelland & Auster 1990). Although findings regarding the impact of institutional racial composition on the academic achievement of historically disadvantaged racial groups are mixed (e.g., Pascarella, Smart & Stoecker 1989; Wassmer, Moore & Shulock 2004), the evidence appears to suggest that institutions with high minority enrollments tend to exhibit more supportive academic environments for historically disadvantaged racial groups than do institutions with low minority enrollments (e.g., Fries-Britt & Turner 2002; Hagedorn, et al. 2007). Thus, one reasonably could hypothesize that, if the *cooling out* of historically disadvantaged racial groups occurs at all, it occurs less frequently, or to a lesser degree, in institutions with high minority enrollments compared to institutions with low minority enrollments.

Unanswered Questions

Clearly, important questions concerning *cooling out* processes in the community college remain to be explored, and further study of the relationship between academic advising and attainment is required to explain fully the findings of prior research. Perhaps most important, it is not clear if the direct and active *cooling out* by academic counselors, described by Clark (1960), is occurring at all. With the exception of Bahr's (2004) study, no prior large-scale, quantitative studies that purport to address the *cooling out* proposition have included advising as a predictor variable, which seems a rather important oversight in light of the centrality of academic counselors in Clark's thesis. It follows that one might ask, what effect does academic advising in the community college have on students' attainment of their academic goals?

Second, while Clarks' original proposition concerning *cooling out* focused primarily on underprepared students, some subsequent explorations of the *cooling out* proposition have thrown a wider net, so to speak, and foregone a specific focus on underprepared community college students (e.g., Adelman 2005). Thus, one might ask whether the effect of advising on students' chances of achieving their academic goals differs according to students' level of preparation for college coursework.

Third, Bahr's work raises the question of whether the effect of advising varies according to the race of the student receiving the advising, and his study is the first and only study to date to address the possibility of a race-specific effect of advising. However, his study failed to take into account the timing of advising within students' academic careers, and, thus, the internal validity of the identified race-specific effects is suspect. What is needed to confirm or disconfirm Bahr's findings is a test of the race-specific effect of advising that is sensitive to the longitudinal nature of the academic record. Thus, one might ask whether the effect of advising on students' chances of success varies according to students' race, net of the timing of academic advising within students' academic careers.

Finally, although, as noted earlier, prior research on the effect of racial composition of postsecondary institutions on students' achievement has produced mixed findings, the existing literature does beg the question of whether any race-specific effect of advising on students' chances of success varies according to the racial composition of the college. For example, does the effect of advising on Black students' chances of attaining their academic goals vary according to the percentage of Black students in the college?

Going a step further, one might also ask a similar question about underprepared students and the percentage of students requiring remediation. Namely, does advising in colleges that serve a greater percentage of underprepared students have a different average effect on underprepared students' chances of success as compared with advising in colleges that serve relatively few underprepared students? More specifically, are underprepared students in colleges that serve relatively few underprepared students more likely, on average, to be *cooled out*?

This Study

In this study, I seek to extend prior research on the *cooling out* proposition with particular attention to academic advising as a predictor and with sensitivity to the timing of advising within students' academic careers. I test the effect of advising on attainment of two different outcomes in two cohorts of first-time freshmen community college students. First, I use a cohort of remedial math students to test the effect of advising on the likelihood of successful remediation in math. A cohort of remedial students is utilized because underprepared students are at the heart of Clark's original thesis. Remedial math was selected because more students require remedial assistance with math than with any other subject (Adelman 2004; Boylan & Saxon 1999a;

Parsad, Lewis & Greene 2003).

Second, I test the effect of advising on the likelihood of transfer for a transfer-seeking cohort. Transfer is of particular interest here because it was the implied primary outcome of interest in Clark's original discussion of *cooling out*.

For both of these analyses, I test the direct effect of advising on attainment of the outcome of interest, the race-specific effect of advising (i.e., the effect of advising conditional on the race of the student), and the deficiency-specific effect of advising (i.e., the effect of advising conditional on the remedial status of the student at college entry). In addition, in both of these analyses I test the effect of college racial composition on the race-specific effect advising, and the effect of college skill composition (i.e., percentage of underprepared students) on the deficiency specific-effect of advising.

Methodological Complications

Measuring (for the purpose of analysis) the timing of academic advising within a given student's academic career appears to be a straightforward task. At first glance, one might think that it would be as simple as generating a single, nominal variable with some predetermined set of mutually exclusive categories, such as: did not receive advising at any point in time; received advising during first year of attendance; received advising during second year of attendance, but not during first year attendance; received advising during third year of attendance, but not during first or second year of attendance; and so on. Given such a variable, it would seem that one would need only a set of multiplicative interactions of race and the timing of advising to test the race-specific effect of advising on the outcome of interest for some designated cohort of students, and a similar set of interaction terms to test the deficiency-specific effect of advising.

Unfortunately, such a model can represent the data accurately only when all students are retained in the system for the same duration, an assumption that cannot be met with most longitudinal data that address college students, particularly community college students. More specifically, in order for this hypothetical "timing of advising" variable to be useful, all of the students included in the analytical cohort must remain in attendance for all periods addressed by the variable. For example, if the "timing of advising" variable includes a category for receiving first advising experience in the third year of attendance or later, then all students in the analytical cohort must be retained in the system for at least three years. Otherwise, the "effect" of timing of advising is confounded by the "effect" of retention, because only those students who were retained for at least three years could have received their first advising experience in the third year of attendance.

Because persistence (or retention) varies widely, particularly in community colleges (e.g., Bahr 2007), a solution to this problem must take into account both the timing of advising and variation in the duration of enrollment. Such a solution can be found in the discrete-time event history model (Allison 1982, 1984, 1995; Powers & Xie 2000; Yamaguchi 1991). Event history analysis, as a class of models, generally is used to model the *hazard* of an event of interest, defined loosely as the instantaneous probability of occurrence of the event or the average probability of the occurrence of the event per unit of time.[1] Event history analysis allows for variation in the timing of predictor variables, in the timing of an outcome variable, and in students' entry and exit from the analytical pool. As it pertains to this particular analytical problem, the model allows for variation in the timing of advising, persistence, and the outcomes

[1] While the hazard of an event often is defined in terms of a probability, technically speaking it is *not* a probability because the hazard of an event may exceed one while the probability of an event may not (Allison 1995:17). However, if, as a function of operationalization, the event of interest may occur no more than once per unit of time for any given individual, then the hazard of the event may not exceed one; hence the usefulness of the "instantaneous probability" definition.

of interest.

HYPOTHESES

Hypothesis #1: *Cooling Out* as a General Phenomenon of Underprepared Students

Clark's original proposition placed academically underprepared students at the heart of the *cooling out* phenomenon. Thus, one could hypothesize that, if active, counselor-driven *cooling out* is occurring, then advising is detrimental to the likelihood of successful remediation among students in the remedial math cohort, all else being equal. More specifically, the experience of advising reduces, on average, the hazard of successful remediation among remedial math students.

A similar hypothesis could be offered for the transfer-seeking cohort. However, despite Clark's focus on underprepared students, some subsequent work has expanded the scope of the *cooling out* concept to suggest that it is a general phenomenon of the community college. Given that any transfer-seeking cohort would *not* be composed exclusively of underprepared students, a test can be executed to determine if the effect of advising differs between underprepared and college-prepared students. Thus, I hypothesize, first, that the effect of advising on the hazard of transfer for underprepared, transfer-seeking students differs significantly and negatively from that of college-prepared, transfer-seeking students, and, second, that the net effect of advising for underprepared, transfer-seeking students is negative.

Hypothesis #2: *Cooling Out* as a Specific Phenomenon of the Poorest Skilled Students

Alternatively, it is worthwhile to consider the possibility that only those students who have the poorest academic skills are *cooled out*. In other words, if advising generally is beneficial to remedial math students (in opposition to Hypothesis #1), perhaps it is detrimental only to the subset of remedial math students who have the poorest math skills at college entry.

With this possibility in mind, I offer a conditional hypothesis that, if the average effect of advising on the hazard of successful remediation in math for the remedial math cohort is positive, then the net effect of advising for those remedial math students who have the poorest math skills at college entry is negative.

Hypothesis #3: *Cooling Out* as Institutional Racism

One prior study suggests that advising may be slightly detrimental to Black remedial math students, in contrast to the beneficial effect of advising for White and Asian remedial math students and the lesser beneficial effect for Hispanic students. This finding is supported indirectly by research indicating that racist stereotypes persist on college campuses, and that Black students in particular are likely to be subjected to negative stereotypes. In light of these findings, one would anticipate that, if race-specific *cooling out* is occurring, the effect of advising on Black students' goal attainment would differ negatively from that of Whites, and, furthermore, that the net effect of advising for Blacks is negative. Thus, I hypothesize that the effect of advising on the hazard of successful remediation in math for Black students in the remedial math cohort differs significantly and negatively from that of White remedial math students, and that the net effect of advising on the hazard of successful remediation for Black remedial math students is negative (in keeping with Hypothesis #1). Moreover, extending this proposition to transfer-seeking students, I hypothesize that the effect of advising on the hazard of transfer for Black transfer-seeking students differs significantly and negatively from that of White transfer-seeking students, and that the net effect of advising for Black transfer-seeking students is negative.

Hypothesis #4: *Cooling Out* as a Contextual Phenomenon

Finally, some prior research suggests that colleges with high minority enrollments tend to offer more supportive environments for minority students. It follows that, if race-specific *cooling out* is occurring, it may be moderated by racial context, such that, on average, advising is less detrimental (or may be beneficial) to a student of a given minority group in a college that enrolls a disproportionately large percentage of students of the same race. Thus, I hypothesize that any race-specific effect of advising on the hazard of successful remediation varies positively with the percentage representation in the student body of a given racial group. For example, the effect of advising on the hazard of successful remediation in math for Blacks increases (moves in the positive direction) as the percentage of Black students increases. Likewise, I hypothesize that any race-specific effect of advising on the hazard of transfer for the transfer-seeking cohort varies positively with the percentage representation in the student body of a given racial group.

In addition, it is intuitively reasonable that colleges that serve a greater percentage of underprepared students will be more focused on, and will offer more support to, underprepared students. Following from this supposition, I further hypothesize that any deficiency-specific effect of advising on the hazard of successful remediation for the remedial math cohort varies positively with the percentage representation of remedial math students in the student body. Likewise, I extend this same hypothesis to the transfer-seeking cohort: I hypothesize that any remedial math-specific or remedial English-specific effect of advising on the hazard of transfer varies positively with the percentage representation of remedial math and remedial English students in the student body, respectively.

DATA & MEASURES

Data

To test these hypotheses, I draw upon data collected by the Chancellor's Office of California Community Colleges. The Chancellor's Office collects data each term via electronic submission from the 112 community colleges and affiliated adult education centers in California. The data maintained by the Chancellor's Office represent a census of community college students in California and include transcripts, demographics, financial aid awards, matriculation records, degree/certificate awards, etc. In addition, the database is cross-referenced periodically against the enrollment records of all California public four-year postsecondary institutions and the National Student Clearinghouse database (Boughan 2001) in order to identify students who transferred to public and private four-year institutions, both in-state and out-of-state (Bahr, Hom & Perry 2005).

I selected for this research the Fall 1995 cohort of first-time college freshmen who enrolled in any of California's 107 semester-based community colleges (N = 202,484). Valid course enrollment records were available for 93.9% of these students (N = 190,177). I observed the academic histories of these students across all semester-based colleges for six years, through the Spring semester of 2001, and then selected two subsets of students from this larger cohort based upon particular, pre-determined characteristics and behaviors of the students.[2]

Remedial Math Cohort

The first subset of students is defined by race and remedial math status.[3] From the larger body of the Fall 1995 first-time freshmen cohort, I retained those students whose first math enrollment was remedial in nature and who enrolled in this first math course in their first term of

[2] It is possible that students will begin at one community college and then transfer to another community college, or simultaneously complete courses at two or more community colleges. To account for these possibilities, students were observed across all semester-based community colleges without regard to the first institution of attendance.

[3] For the purpose of this analysis, I use the commonly accepted definition of remedial math as any nonvocational math course presenting material that is lower in skill than college algebra (Hagedorn, et al. 1999).

attendance (*N* = 37,577).[4] From this smaller remedial math cohort, I retained the students of the four most numerous racial groups – White, Black, Hispanic, and Asian – comprising 91.1% of the cohort (*N* = 34,217). I then dropped 614 students (1.8%) who were missing data on sex, age, or the ID variable used to track student records across colleges, and 3,485 additional students (10.2%) who did not return to college for at least one semester at some point (during the six-year observation window) subsequent to their first term of attendance. The resulting cohort is composed of 30,118 students. Frequency distributions for various characteristics of the remedial math cohort are provided in Table 1.

[insert Table 1 about here]

Transfer-Seeking Cohort

The second subset of students is defined by race and academic goal. From the larger body of the Fall 1995 first-time freshmen cohort, I retained only those students who indicated that their primary academic objective was transfer to a four-year institution exclusively or transfer to a four-year institution with an allied objective of a nonvocational Associate's degree (*N* = 76,826). From this smaller transfer-seeking cohort, I again retained the students of the four most numerous racial groups, comprising 91.8% of the cohort (*N* = 70,540). I then dropped 1,400 students (2.0%) who were missing data on sex, age, or the ID variable used to track student records across colleges, and 899 students (4.0%) who appeared on the enrollment records of a four-year college in their first term of attendance at the community college (suggesting simultaneous, or parallel, enrollment in a four-year college and a community college). The resulting cohort is composed of 68,241 students. Frequency distributions for various characteristics of the transfer-seeking cohort are provided in Table 2.

[4] Slightly more than half (52.9%) of all students whose first math course was remedial in nature enrolled in their first math course in the first term of attendance.

[insert Table 2 about here]

Outcome Variables

Two outcomes are analyzed in this study, corresponding to the two analytical cohorts. The outcome of interest for the remedial math cohort is successful remediation in math, operationalized as a passing grade (A, B, C, D, or Credit) in a college-level math course.[5] The outcome of interest for the transfer-seeking cohort is transfer to a four-year postsecondary institution at any point during the six-year observation window.

Data Format

Data for standard regression models generally include only a single record per unit of analysis (e.g., one row of data per student). In contrast, data for discrete-time event history models consist of intervals of time for which a particular event is observed to either occur or not occur for a given individual (Scott & Kennedy 2005). In this case, the intervals of time are semester terms. The event of interest is a passing grade in a college-level math course (for the remedial math cohort) or transfer (for the transfer-seeking cohort). In order to execute a discrete-time event history analysis using these data, the data must be reformatted from student records to student-term records.

In reformatting the data for the remedial math cohort, I retained all terms in which a given member of the cohort enrolled in any coursework *after* the term of first math enrollment (Fall 1995), up to and including the earlier of [a] the term in which a given student achieved college-level math skill, [b] the last term in which the student was observed in the system, or [c] the last term of observation (Spring 2001). The resulting data define the "risk period" in which a

[5] This outcome – one of several possible operationalizations of successful remediation – is the most widely accepted because, as Boylan and Saxon (1999b, p. 6) argue, "[t]he most essential purpose of remedial courses is to prepare students to be successful in the college curriculum."

given student is "at risk" of remediating successfully. In total, the reformatted data include 142,145 student-terms, with a mean number of "at risk" terms per student of 4.72 (s = 3.27).

The data for the transfer-seeking cohort were reformatted similarly, although with some important differences. For the transfer-seeking cohort, I retained all terms *after* the term of first term of attendance (Fall 1995), up to and including the earlier of [a] the term in which transfer occurred or [b] the last term of the observation window (Spring 2001). Unlike the data for the remedial math cohort, I did *not* drop terms in which a given student was *not* enrolled in a community college prior to the transfer event because technically the student is still "at risk" of transfer even when not in attendance at the community college. Thus, all students who did not transfer within the six-year window of observation have sixteen "at risk" terms (i.e., seventeen observed terms minus one for the first term of attendance). In total, the reformatted data for the transfer-seeking cohort include 968,584 student-terms, with a mean number of "at risk" terms per student of 15.06 (s = 2.45).

Explanatory Variables for the Remedial Math Model

In analyzing the hazard of successful remediation in math for the remedial math cohort, I consider three *levels* of explanatory variables: a *term-level* indicator of receipt of academic advising, *student-level* indicators of race/ethnicity and math skill deficiency, and *college-level* indicators of racial composition and math skill composition. The term-level indicator of receipt of advising is coded *0* for all terms prior to the receipt of advising, coded *1* for the term in which a given student received advising, and coded *1* for all terms subsequent to the term in which advising was received. This variable is set to *0* in all terms for students who did not receive advising at any point during their attendance. In effect, the indicator of receipt of advising is treated as an "on/off switch" that is "switched on" (with respect to a given student's academic record) in the term in which advising occurs.

The student-level indicator of race/ethnicity is self-reported, nominal measure of a student's primary racial/ethnic identification: White, Black, Hispanic, or Asian. It is treated as a set of three dummy variables, with "White" excluded.

The student-level indicator of math skill deficiency is set to the skill-level of a given student's first remedial math course. Remedial math is structured to provide a "ladder" of coursework leading up to the minimum expected math competency of entering college freshmen. To categorize math courses, I used course catalogs and course characteristics in the data to determine the skill-level of each math course in which any member of the first-time freshmen cohort enrolled at any time during the observation period. In total, I collapsed 3,110 substantive math course listings into six categories: basic arithmetic, pre-algebra, beginning algebra, intermediate algebra/geometry, college-level math, and vocational math. Basic arithmetic represents the lowest level of math skill, followed in order by pre-algebra, beginning algebra, and intermediate algebra and geometry (the latter two are parallel courses in the institutionalized math progression). The category of college-level math encompasses all math courses of a skill equal to, or greater than, college algebra. For the purposes of the analysis of the remedial math cohort, I ignored nonsubstantive math courses (e.g., math labs, math tutoring) and vocational math. Math skill deficiency, like race/ethnic identification, is treated as a set of three dummy variables, with "Intermediate Algebra/Geometry" excluded.

Four college-level variables are included in the analysis of the remedial math cohort. Three of these address the percentage (logged) of the Fall 1995 first-time freshmen cohort at a given college who are Black, Hispanic, or Asian, respectively. Collectively, these variables serve as indicators of racial context. The fourth variable measures the percentage (squared) of the Fall 1995 first-time freshmen cohort at a given college whose first nonvocational math course was remedial in nature (regardless of whether this first math course was taken in the first semester of attendance or not). This variable serves as an indicator of math skill context (i.e., some colleges serve many students whose math skills are deficient, while other colleges serve few such students). All four of these variables are treated as continuous.[6]

Control Variables for the Remedial Math Model

I include as controls a number of term- and student-level variables found in prior research to be predictors of academic outcomes among remedial students (Bahr n.d.; Bahr 2007; Burley, Butner & Cejda 2001; Hagedorn, et al. 1999; Hoyt 1999). At the level of the term, I control for age (measured in years and treated as a continuous variable) and three proxies of socioeconomic status (SES): a dichotomous indicator of receipt of a fee waiver (1 = received; 0 = not received), a dichotomous indicator of receipt of any grants (1 = received; 0 = not received), and a continuous indicator of the total monetary value of any grants received (measured in thousands of dollars). All four of these term-level variables are time variant.

At the level of the student, I control for sex (female = 1; male = 0), grade in first math course, English competency at college entry, and academic goal. Grade in first math course includes ten nominal attributes: A, B, C, D, F, Withdrawal, Credit, No Credit, Ungraded, and missing/unreported. It is treated as a set of dummy variables, with "A" excluded.

English competency, like math deficiency, is set to the skill-level of a student's first English course. Through a process similar to that used to categorize math, I collapsed 6,625 substantive English courses into four categories: remedial reading, remedial writing, English-as-a-Second-Language (ESL), and college-level English. To these four categories, I added a fifth to

[6] The college-level variables were transformed (e.g., logged, squared) to approximate normality.

account for students who did not enroll in any English coursework. English competency is treated as a set of dummy variables, with “college-level English” excluded.

Academic goal is a self-reported measure of a student's primary objective, collected at the time of application, which I collapsed into ten nominal categories: transfer to a four-year institution as an exclusive objective; transfer to a four-year institution with an allied objective of a nonvocational Associate's degree; nonvocational Associate's degree as an exclusive objective; vocational Associate's degree as an exclusive objective; vocational certificate as an exclusive objective; other job-related goals (e.g., acquiring or advancing job skills, maintenance of a professional license); abstract educational goals (e.g., discovering educational interests, personal development); remediation in fundamental academic subjects (including seeking credit for a high school diploma or GED); undecided; and unreported. Academic goal is treated as a set of dummy variables, with "transfer to a four-year institution as an exclusive objective" excluded.

Explanatory Variables for the Transfer Model

The explanatory variables for the transfer model are similar to those of the remedial math model, but with several noteworthy differences. The term-level indicator of receipt of advising is treated in the same manner in which it is treated in the remedial math model. At the student-level, I consider three indicators: race, math track, and English track. Race again is treated as a set of three dummy variables, with “White” excluded. Math track is a four-category nominal variable defined by a given student’s first nonvocational math course, if any. Each student was placed into one of four mutually exclusive categories: college-level math, remedial math, vocational math only (i.e., student enrolled only vocational math, and never in remedial or college-level math), and no math. The category of “college-level math” was excluded. Similarly, English track is defined by a given student’s first English course: college-level

English, remedial English (i.e., remedial reading or remedial writing), ESL, or no English. Like math track, the category of "college-level English" was excluded.

At the college-level, I include five variables. As with the remedial math model, three of these address the percentage (logged) of the Fall 1995 first-time freshmen cohort at a given college who are Black, Hispanic, or Asian, respectively. Likewise, the fourth variable measures the percentage (squared) of the first-time freshmen cohort at a given college whose first math course was remedial in nature. The fifth variable measures the percentage of the first-time freshmen cohort at a given college whose first English course was remedial in nature. Like the indicator of math skill context, this latter variable serves as an indicator of English skill context. All five of these variables are treated as continuous.

Control Variables for the Transfer Model

I include fewer control variables in the transfer model than in the remedial math model, in part because some of the controls in the remedial math model are explanatory variables in the transfer model. At the level of the term, I again control age and the three proxies of SES. All are treated in the same fashion in the transfer model as in the remedial math model. At the student-level, I control for sex and academic goal, although academic goal takes on only two values, one of which (transfer as an exclusive objective) is excluded as the comparison category.

Strengths and Weaknesses of the Data

The data I assembled for this study have a number of strengths and weaknesses. Among the strengths are access to a population (rather than a sample), a population that is larger than any used in prior studies of this topic, the length of time over which academic careers are observed, the capacity to distinguish between temporary breaks in enrollment and long-term exit from the postsecondary system, and the capacity to observe students' records despite movement from one college to another. However, three weaknesses of the data also must be noted.

First, the data do not address two control variables found to be important in prior studies of educational outcomes, namely employment intensity (e.g., hours worked per week) and credit course load (e.g., part-time versus full-time enrollment). Employment intensity has been found to be moderately negatively correlated with degree expectations, persistence, and other desirable outcomes (American Council on Education, 2003; Carter, 1999; Hoyt, 1999; Toutkoushian & Smart, 2001), although this finding is not entirely consistent across studies (Titus, 2004). The findings concerning the effects of course load on academic outcomes are clearer and generally indicate that part-time students are somewhat less likely to experience desirable outcomes than are full-time students (Hoyt, 1999; O'Toole, Stratton & Wetzel, 2003; Stratton, O'Toole & Wetzel, 2007; Szafran, 2001). While a variable measuring course load could be constructed from the transcript data, it would face the same problems and complications described by Adelman (2004, p. 96).

Second, in terms of the outcome for the remedial math cohort (completing a college-level math course), the data do not account for academic progress accomplished outside of California's semester-based community colleges. More specifically, students who enter one of the 107 colleges included in this analysis, enroll in a remedial math course in their first term of attendance, and subsequently transfer to one of the five quarter-system community colleges, to a private two-year college, or to a community college outside of California, effectively are treated as unsuccessful in these data because academic progress that occurs outside of the 107 colleges is unobserved. Although such unobserved progress is expected to represent only a small fraction of the total progress, due consideration should be given to the possible impact on the findings.

The third weakness of the data concerns the external validity of the findings. While the use of a population has substantial advantages over the use of a sample, the population addressed here was drawn exclusively from California's community colleges. Although California's community college system, which has annual enrollment of 2.9 million students (Turnage, 2003), is the largest postsecondary system in the world, the external validity of the findings of this analysis to other states is uncertain. In addition, it should be noted that the population addressed in this study includes only first-time college freshmen, who constitute a segment of a larger population of first-time *and* returning students. Consequently, any inferences drawn from this study are limited to first-time students, an important, but not all encompassing, segment of the population served by community colleges.

METHOD

Remedial Math Model

I employ a three-level hierarchical logistic regression specification to execute the discrete-time event history analysis of successful remediation in math (Raudenbush & Bryk 2002). In total, three nested models of successful remediation were estimated, the most complex of which (the third of the three models) is detailed in Appendix A. Note that the left-hand side of the first equation represents the logged odds of the probability of student i, who is enrolled in college j, remediating successfully in term t, given that the student is in attendance in term t and has not completed successfully a college-level math course prior to term t. Furthermore, note that the term-level effect of advising (A_{1ij}) on this outcome is allowed to vary as a function of the race of the student (B_{11j}, B_{12j}, B_{13j}), the degree of math deficiency of the student at college entry (B_{14j}, B_{15j}, B_{16j}), and a random student-level error term (ε_{1ij}). In turn, the race-specific effects of advising (B_{11j}, B_{12j}, B_{13j}) are allowed to vary as a function of the racial composition of the college (C_{111}, C_{121}, C_{131}; grand mean-centered) and a set of random college-level error terms (u_{11j}, u_{12j},

u_{13j}). Likewise, the math deficiency-specific effects of advising are allowed to vary as a function of the math skill composition (context) of the college (C_{141}, C_{151}, C_{161}; grand mean-centered) and a set of random college-level error terms (u_{14j}, u_{15j}, u_{16j}). In sum, the remedial math model tests whether the effect of advising on the hazard of remediating successfully varies as a function of race and math deficiency, and, in turn, whether the effects of race and math deficiency on the effect of advising vary as a function of racial context and math context, respectively.

In addition, note that effects of student's race and math deficiency appear twice in the model; these student-level variables also are used to condition variation in the term-level constant (A_{0ij}). This is an important aspect of the model, as it is impossible to determine what effects race and math deficiency have on the effect of advising without distinguishing the effects of these variables on students' baseline hazard of remediating successfully (e.g., Black students may have a lower average hazard of remediating successfully, yet the effect of advising may be equally beneficial for White students and Black students).

Transfer Model

The discrete-time event history analysis of transfer for the transfer-seeking cohort is treated in a similar fashion, and, again, three nested models are estimated, the most complex of which is detailed in Appendix B. The term-level effect of advising (A_{1ij}) on the hazard of transfer is allowed to vary as a function of the race of the student (B_{11j}, B_{12j}, B_{13j}), the math track of the student (B_{14j}, B_{15j}, B_{16j}), the English track of the student (B_{17j}, B_{18j}, B_{19j}) and a random student-level error term (ε_{1ij}). In turn, the race-specific effects of advising (B_{11j}, B_{12j}, B_{13j}) are allowed to vary as a function of the racial composition of the college (C_{111}, C_{121}, C_{131}; grand mean-centered) and a set of random college-level error terms (u_{11j}, u_{12j}, u_{13j}). However, concerning the deficiency-specific effects of advising, only the effect of the remedial math and remedial English tracks vary conditionally, in this case as a function of math and English deficiency contexts (C_{141}, C_{171}; grand mean-centered), respectively, and a set of random college-level error terms (u_{14j}, u_{17j}). The remaining math track and English track dummy variables are allowed to vary randomly and unconditionally (u_{15j}, u_{16j}, u_{18j}, u_{19j}). Taken as a whole, the transfer model tests whether the effect of advising on the hazard of transfer varies as a function of race, math track, and English track, and, in turn, whether the effects of race, the remedial math track, and the remedial English track vary as a function of racial context, math deficiency context, and English deficiency context, respectively.

Potential Source of Bias

At least one possible source of bias in the remedial math models should be mentioned. With regard to the hazard of successful remediation, students who remain in the system for a longer time prior to remediating successfully may exhibit an artificially depressed hazard rate relative to students who advance quickly through the remedial math sequence. For example, consider hypothetical *Student A* who enrolled in her first math class in her first term of attendance, passed this math class, enrolled in a college-level math course in the next term, passed this college-level math class, and then continued to attend college for two additional semesters. Although *Student A* continued to attend college after passing a college-level math course, any semesters in which *Student A* returned to college after remediating successfully are not "counted against," or observed, in the calculation of her hazard rate.

In contrast, consider hypothetical *Student B* who enrolled in his first math class in his first term of attendance, passed this math class, and then worked on completing other, non-mathematical classes for two subsequent semesters. In his fourth semester of attendance, *Student B* completed successfully a college-level math course and then departed from the system.

Although *Student A* and *Student B* both achieved the same end with regard to math, and both enrolled in college for a total of four semesters, *Student B* has two additional terms of attendance included in the calculation of his hazard rate, resulting in a lower hazard of successful remediation relative to *Student A*.

A problem could arise in the remedial math models if this pattern of delayed remediation varies systematically with the experience of, or the timing of, academic advising. I have no *a priori* reason to believe that such a systematic relationship exists, but some consideration should be given to this possibility as the findings of this study are contemplated. Note, however, that this possible source of bias does not apply to the transfer models because nonenrolled terms prior to transfer were not removed from the analytical pool.

ANALYSIS

In Table 3, I present the results of the three nested event history models of successful remediation in math for the remedial math cohort. Model 3-1 (the baseline model) estimates a baseline effect of advising on the hazard of remediating successfully by excluding the following effects from the model presented in Appendix A: $B_{11j} – B_{16j}$ and $C_{111} – C_{161}$. Model 3-2 (the intermediate model) tests the effects of student's race and student's math skill deficiency on the effect of advising by adding to Model 3-1 the previously excluded student-level effects, $B_{11j} – B_{16j}$. Finally, Model 3-3 (the complete model) adds to Model 3-2 the previously excluded contextual effects, $C_{111} – C_{161}$. This last model jointly tests the effect of student's race on the effect of advising, the effect of racial context on the race-specific effects of advising, the effect of student's math skill deficiency on the effect of advising, and the effect of math skill context on the math deficiency-specific effects of advising.

[insert Table 3 about here]

Similarly, in Table 4, I present the results of the three nested event history models of transfer. In Model 4-1 (the baseline model), I exclude the student-level effects $B_{11j} – B_{19j}$ and the college-level effects $C_{111} – C_{141}$ and C_{171}. In Model 4-2 (the intermediate model), I add to Model 4-1 the student-level effects $B_{11j} – B_{19j}$. In Model 4-3 (the complete model), I add to Model 4-2 the college-level effects $C_{111} – C_{141}$ and C_{171}.

[insert Table 4 about here]

Hypothesis #1: *Cooling Out* as a General Phenomenon of Underprepared Students

As discussed previously, if *cooling out* of underprepared students is occurring as an active, counselor-driven process in community colleges, one would anticipate that the experience of advising would reduce, on average, the hazard of remediating successfully among remedial math students. None of the three nested models presented in Table 3 support this conclusion. Across all three models, the effect of advising is positive and statistically significant, indicating that the receipt of advising increases the hazard of remediating successfully, net of controls.

Turning to the transfer models (Table 4), if *cooling out* of underprepared students were occurring, one would anticipate that the *net* effect of advising on the hazard of transfer would be negative for students on the remedial math and remedial English tracks. However, again there is no evidence to support this supposition. In fact, for students on the remedial math and remedial English tracks, advising has a significantly greater positive effect on the hazard of transfer than it does for students on the college-level math and college-level English tracks, respectively. In other words, in terms of the hazard of transfer, students on the remedial math and remedial English tracks appear to benefit *more* from advising than do students on the college-level math and college-level English tracks. Taken together, the findings presented in Tables 3 and 4 suggest that active, counselor-driven *cooling out* is not a general phenomenon of *underprepared* community college students. In addition, the net effect of advising for transfer-seeking students on the *college-level* math and English tracks is statistically significant and positive, suggesting that active, counselor-driven *cooling out* is not a general phenomenon of the community college either (i.e., applicable even to college-prepared students), as might be implied by some subsequent work on *cooling out* that has not distinguished between underprepared and college-prepared students.

Hypothesis #2: *Cooling Out* as a Specific Phenomenon of the Poorest Skilled Students

Alternatively, as discussed earlier, one might reason that only those remedial math students who have the poorest math skills (i.e., the bottom rungs of the remedial math ladder) are actively *cooled out*. The models presented in Table 3 do not provide evidence to support this conclusion. To the contrary, in both Model 3-2 and Model 3-3 the positive effect of advising on the hazard of successful remediation is significantly *greater* among students who entered college at any of the bottom three rungs of the remedial math hierarchy relative to those who enter at the top rung. Thus, this analysis does not support a conclusion that active, counselor-driven *cooling out* is occurring among mathematically deficient community college students generally, nor among those remedial math students who have the poorest skills, nor among underprepared transfer-seeking students. To the contrary, in all of these cases advising is more beneficial for those students who face greater disadvantages with respect to academic preparation than it is for better-prepared students.

Hypothesis #3: *Cooling Out* as Institutional Racism

Another possibility considered here is that the *cooling out* phenomenon is race-specific in nature. In other words, *cooling out* may be predominantly a phenomenon of students of historically disadvantaged racial groups, particularly Black students. The analysis presented in

Table 3 does not support this conclusion. Instead, among White, Black, and Hispanic remedial math students, I find no significant differences in the effect of advising on the hazard of successful remediation in math. In other words, across historically advantaged and historically disadvantaged racial groups, advising is equally beneficial in terms of increasing the hazard of remediating successfully in math.

However, the effect of advising for Asian remedial math students is less clear. In the intermediate model (Model 3-2) the *net* effect of advising on the hazard of successful remediation in math for Asians effectively is zero, which differs significantly from the positive *net* effect of advising for Whites, Blacks, and Hispanics. Yet, this race-specific effect for Asians "drops out" (becomes statistically insignificant) once racial context is introduced as a variable in Model 3-3, suggesting that Whites, Blacks, Hispanics, and Asians do *not* differ in terms of the effect of advising on the hazard of successful remediation. Thus, it appears that advising may or may not be beneficial, but is not detrimental, for Asian remedial math students in terms of the likelihood of successful remediation in math.

This finding concerning the effect of advising for Asian remedial math students is ambiguous for several reasons. First, none of the variables added in Model 3-3 are statistically significant, which is contrary to what one would anticipate given that the race-specific effect of advising for Asian remedial math students becomes statistically insignificant in Model 3-3. In other words, one would anticipate that the change in (loss of) statistical significance for this race-specific effect is due to the moderating effect of context, but none of the contextual variables proves to be statistically significant, indicating that context does not play a role in the race- or deficiency-specific effects of advising on the hazard of successful remediation. Second, the literature does not lead one to anticipate that the effect of advising for Asian remedial math students would differ significantly from that of White students. Thus, this finding is somewhat of a mystery.

Concerning the hazard of transfer for the transfer-seeking cohort (Table 4), one race-specific effect of advising emerges as statistically significant in both Models 4-2 and 4-3. Specifically, Black students appear to be benefit significantly less from advising than do White students, on average, which is consistent, in part, with the hypothesis offered here. However, the *net* effect of advising on the hazard of transfer for Black students remains positive, so Black transfer-seeking students *do* benefit from advising, but to a lesser degree than do White students.

Hypothesis #4: *Cooling Out* as a Contextual Phenomenon

I hypothesized that any race-specific effect of advising on the hazard of successful remediation in math varies as a function of the context in which it occurs. More specifically, it may be that any race-specific effect of advising is conditioned on, and varies positively with, the representation of a given racial group within a college. The analysis presented in Table 3 does not support this conclusion. The race-specific effects of advising on the hazard of successful remediation in math do not vary significantly as a function of college racial composition.

The transfer model (Table 4) tells a different story, but a story that is not consistent with the hypothesis offered here. The race-specific effect of advising on the hazard of transfer for Hispanic students varies significantly and *negatively* with the percentage (logged) of Hispanics in the first-time freshmen cohort. This indicates that, on average, advising is *less* beneficial for Hispanic students as the percentage of Hispanics in the college *increases*.

The absolute size of this effect, however, is somewhat difficult to interpret due to the transformed (logged) nature of the variable and the centering of the variable around its grand mean. To aid in interpretation, I illustrate in Figure 1 the additive effect of this variable on the hazard of transfer. As it pertains to this analysis, the most important point to draw from Figure 1 is that the *additive* effect of this variable never drops so far below zero that the *net* effect of advising for Hispanic students is less than zero. Put succinctly, an increasing percentage of Hispanic students *is* associated with a reduction in the benefits of advising for Hispanic transfer-seeking students, but advising is *not* detrimental for Hispanic students even in colleges that serve a disproportionately large number of Hispanics. Thus, it does not appear that colleges that serve a disproportionate percentage of Hispanic students exhibit active, counselor-driven *cooling out* of Hispanic transfer-seeking students.

[insert Figure 1 about here]

Lastly, I hypothesized that any deficiency-specific effect of advising varies positively with the percentage of students in a college who require remedial assistance. The findings presented in Table 3 do not support this conclusion. None of the three deficiency-specific effects of advising on the hazard of successful remediation in math varies significantly by math skill context.

Yet, the transfer model (Table 4) again tells a somewhat different story. The effect of advising on the hazard of transfer increases (grows more beneficial) for students on the remedial math track as the percentage (squared) of remedial math students in the first-time freshmen cohort grows larger. This finding is consistent with my hypothesis in that it suggests that colleges that serve a greater percentage of remedial math students may offer more support or encouragement (with respect to advising) to mathematically underprepared, transfer-seeking students.

Once more, the absolute size of this contextual effect is difficult to interpret, so I illustrate in Figure 2 the additive effect of this variable on the hazard of transfer. Of note, Figure

2 demonstrates that the beneficial effect of advising for transfer-seeking students on the remedial math track grows substantially as the percentage of mathematically underprepared students increases above the mean of the squared values for the 107 colleges. More importantly, however, the additive effect of this variable never drops so far below zero (as the percentage of mathematically underprepared students declines) that the *net* effect of advising would be less than zero for students on the remedial math track. Thus, a declining percentage of mathematically underprepared students *is* associated with a reduction in the benefits of advising for students on the remedial math track, but advising is *not* detrimental for students on the remedial math track even in colleges that serve relatively few mathematically underprepared students. As with the effect of Hispanic concentration, it does not appear that colleges that serve relatively few remedial math students exhibit active, counselor-driven *cooling out* of mathematically underprepared, transfer-seeking students.

[insert Figure 2 about here]

DISCUSSION

As discussed out the outset of this paper, Clark's (1960) proposition concerning the *cooling out* of underprepared community college students by academic counselors has a controversial history and continues as a point of contention. In this study, I sought to answer several fundamentally important questions concerning the role of academic advising in students' attainment. In particular, what is the effect of advising on students' attainment, and does this effect depend upon students' level of academic preparation or, alternatively, students' race/ethnicity? Moreover, does the effect of advising on the attainment of academically underprepared students depend upon the representation of underprepared students in the college, and, similarly, does the effect of advising on the attainment of minority students depend upon the representation of a given minority group in the college? To answer these questions, I utilized data from 107 of California's 112 community colleges and analyzed two separate outcomes (successful remediation in math and transfer to a four-year institution) using two cohorts of first-time college freshmen (a remedial math cohort and a transfer-seeking cohort), each of which was observed for six years.

Based upon the findings presented here, I conclude that the active, counselor-driven *cooling out* process described by Clark (1960) is no longer occurring. This analysis provides no evidence to support *cooling out* as a general phenomenon of transfer-seeking community college students, nor as phenomenon that is specific to the academically underprepared segment of the larger transfer-seeking group. It also provides no evidence to support *cooling out* as a phenomenon that is specific to mathematically underprepared students, nor even as a phenomenon specific to those students who exhibit extremely poor academic skills at college entry. To the contrary, in all cases underprepared students appear to benefit more from advising than do college-prepared students.

The concentration of underprepared students in a college's first-time freshmen cohort appears to have little effect on the deficiency-specific effect of advising, with just one exception. With regard to the hazard of transfer, an increasing concentration of mathematically underprepared first-time freshmen is associated with increasing benefits of advising for mathematically underprepared students. This is consistent with my hypothesis and suggests that colleges that serve a great percentage of mathematically underprepared students offer a counseling environment that is more supportive to academically underprepared students than do colleges that serve relatively few such students. However, the findings presented here clearly indicate that advising is not detrimental to the attainment of mathematically underprepared students even in colleges that serve relatively few such students. Thus, this analysis does not support a conclusion favoring *cooling out* as a phenomenon that is dependent upon skill context.

Students' race appears to have comparatively little influence on the effect of advising on either the hazard of successful remediation in math or the hazard of transfer, although two exceptions regarding this generality must be noted. First, although the findings in this regard are somewhat ambiguous, Asian remedial math students may not benefit as much from advising as do White, Black, and Hispanic students in terms of the hazard of successful remediation in math. Second, Black transfer-seeking students do not benefit as much from advising as do White, Hispanic, and Asian students in terms of the hazard of transfer. The latter of these two exceptions somewhat parallels Bahr's (2004) finding concerning the differential effect of advising for Black remedial math students. However, in neither of these two exceptions do I find that advising is detrimental to students' chances of success, as one would anticipate if race-specific *cooling out* is occurring. Thus, this analysis does not a support a conclusion favoring *cooling out* as a race-specific phenomenon, which is consistent with Adelman's (2005) finding regarding the stability of students' long-term educational objectives across racial groups.

College racial composition also appears to have little effect on the race-specific effect of advising, with just one exception. With regard to the hazard of transfer, an increasing concentration of Hispanics in the first-time freshmen cohort of a college is associated with a reduced benefit of advising for Hispanic students. Nevertheless, even in colleges that serve relatively few Hispanic students, the effect of advising for Hispanic transfer-seeking students remains positive. Thus, this analysis does not support a conclusion favoring *cooling out* as a phenomenon that is dependent upon racial context.

Of note, this finding concerning the effect of Hispanic concentration on the effect of advising for Hispanic transfer-seeking students appears contrary to recent work presented by Hagedorn, et al. (2007), which suggests that Hispanic students benefit academically from a "critical mass" of Hispanics. On the other hand, it parallels work presented by Wassmer, Moore and Shulock (2004) concerning the effect of Hispanic composition on institutional transfer rates. Yet, some caution must be exercised in comparing the findings presented here with those of the aforementioned studies because the focus of this analysis is the effect of racial context on the effect of advising on the hazard of transfer, rather than the direct effect of context on the academic outcomes of Hispanic students or the effect of context on institutional outcomes. Therefore, the findings presented here do not contradict directly the study of Hagedorn and her colleagues nor do they corroborate directly the findings of Wassmer and his colleagues, and the seeming discrepancy between the findings of these various studies deserves further empirical attention.

Considered holistically, the findings presented here generally fail to support Clark's original proposition concerning the active role of counselors in the *cooling out* process. If *cooling out* is occurring, it does not appear to be associated directly with students' participation in academic advising. Instead, academic advising appears to be beneficial to students' chances of academic success, at least in terms of the outcomes considered here, and all the more so for students who face academic deficiencies. This finding should put to rest much of the debate surrounding the Clark's controversial thesis. Furthermore, this study provides indirect support for Deil-Amen and Rosenbaum's (2001) argument concerning the encouraging environment implicit to today's "stigma-free" approach to remediation.

However, the fact remains that, in the community college, comparatively few remedial math students remediate successfully and comparatively few transfer-seeking students actually transfer. In fact, in these data less than one-third of students achieved the end goal indicated indirectly by their course taking decisions (in the case of remediation in math) or directly by students' self-reports (in the case of transfer). Why this is the case is the subject of longstanding debate and much research that, no doubt, will continue for decades. Nevertheless, one finding is exceedingly clear in this analysis: academic advising is *not* hurting students' chances of attaining their goals.

CONCLUSION

The idea that academic counseling may be detrimental to students' chances of attaining their goals has haunted community colleges for decades, and heretofore, no large-scale, longitudinally sensitive tests of the effect of advising on community college students' chances of success have been conducted. In this study, I used event history analysis to test a number of hypotheses concerning the effect of advising on the academic attainment of students in two large first-time freshmen cohorts enrolled in 107 community colleges. Specifically, I tested the effect of advising across variation in students' underpreparation for college coursework, students' race (focusing on the four largest racial groups represented in California's community college system), minority representation in the college, and representation of skill-deficient students in the college, while controlling for a set of confounding variables. In all cases, I found no evidence of the active, counselor-driven *cooling out* process described by Burton Clark. In fact, in nearly all cases, advising appears to be actively beneficial to students' attainment.

REFERENCES

Adelman, Clifford. 2004. *Principal Indicators of Student Academic Histories in Postsecondary Education, 1972-2000*. Washington, D.C.: Institute of Education Sciences.

Adelman, Clifford. 2005. "Educational 'Anticipations' of Traditional Age Community College Students: A Prolegomena to Any Future Accountability Indicators." *Journal of Applied Research in the Community College* 12:93-107.

Alba, Richard D., and David E. Lavin. 1981. "Community Colleges and Tracking in Higher Education." *Sociology of Education* 54:223-237.

Allison, Paul D. 1982. "Discrete-Time Methods for the Analysis of Event Histories." *Sociological Methodology* 13:61-98.

Allison, Paul D. 1984. *Event History Analysis: Regression for Longitudinal Event Data*. Thousand Oaks, California: Sage.

Allison, Paul D. 1995. *Survival Analysis Using the SAS System: A Practical Guide*. Cary, North Carolina: SAS Institute, Inc.

American Council on Education. 2003. *Issue Brief: Student Success: Understanding Graduation and Persistence Rates.* Washington, D.C.: American Council on Education.

Bahr, Peter Riley, Willard Hom, and Patrick Perry. 2005. "College Transfer Performance: A Methodology for Equitable Measurement and Comparison." *Journal of Applied Research in the Community College* 13:73-87.

Bahr, Peter Riley. 2004. *The Rough and Rocky Road of Remediation: Racial Inequalities in Postsecondary Remedial Mathematics*. Unpublished doctoral dissertation, Department of Sociology, University of California – Davis.

Bahr, Peter Riley. 2007. "Double Jeopardy: Testing the Effects of Multiple Basic Skill

Deficiencies on Successful Remediation." *Research in Higher Education* 48:695-725.

Bahr, Peter Riley. n.d. "Preparing the Underprepared: An Analysis of Racial Disparities in Postsecondary Mathematics Remediation." Manuscript under review, Wayne State University, Department of Sociology.

Bobo, Lawrence D., and Cybelle Fox. 2003. "Race, Racism, and Discrimination: Bridging Problems, Methods, and Theory in Social Psychological Research." *Social Psychology Quarterly* 66:319-332.

Boughan, Karl. 2001. Closing the Transfer Data Gap: Using National Student Clearinghouse Data in Community College Outcomes Research. *Journal of Applied Research in the Community College* 8:107-116.

Boylan, Hunter R., and D. Patrick Saxon. 1999a. *Remedial Courses: Estimates of Student Participation and the Volume of Remediation in U.S. Community Colleges*. Boone, North Carolina: National Center for Developmental Education.

Boylan, Hunter R., and D. Patrick Saxon. 1999b. *Outcomes of Remediation*. Boone, North Carolina: National Center for Developmental Education.

Brezina, Timothy, and Kenisha Winder. 2003. "Economic Disadvantage, Status Generalization, and Negative Racial Stereotyping by White Americans." *Social Psychology Quarterly* 66:402-418.

Burley, Hansel, Bonita Butner, and Brent Cejda. 2001. "Dropout and Stopout Patterns among Developmental Education Students in Texas Community Colleges." *Community College Journal of Research and Practice* 25:767-782.

Cabrera, Alberto F., Amaury Nora, Patrick T. Terenzini, Ernest Pascarella, and Linda Serra Hagedorn. 1999. “Campus Racial Climate and the Adjustment of Students to College.” *Journal of Higher Education* 70:134-160.

Carter, Deborah Faye. 1999. "The Impact of Institutional Choice and Environments on African-American and White Students' Degree Expectations." *Research in Higher Education* 41:17-41.

Clark, Burton R. 1960. “The 'Cooling-Out' Function in Higher Education.” *American Journal of Sociology* 65:569-576.

Clark, Burton R. 1980. “The 'Cooling Out' Function Revisited.” *New Directions for Community Colleges* 32:15-31.

Davis, Mitzi, Yvonne Dias-Bowie, Katherine Greenberg, Gary Klukken, Howard R. Pollio, Sandra P. Thomas, and Charles L. Thompson. 2004. “'A Fly in the Buttermilk': Descriptions of University Life by Successful Black Undergraduate Students at a Predominantly White Southeastern University.” *Journal of Higher Education* 75:420-445.

Deil-Amen, Regina, and James E. Rosenbaum. 2002. “The Unintended Consequences of Stigma-Free Remediation.” *Sociology of Education* 75:249-268.

Devine, Patricia G. 2001. “Implicit Prejudice and Stereotyping: How Automatic are They?” *Journal of Personality and Social Psychology* 81:757-759.

Doughery, Kevin. 1987. “The Effects of Community Colleges: Aid or Hindrance to Socioeconomic Attainment?” *Sociology of Education* 60:86-103.

Fries-Britt, Sharon, and Bridget Turner. 2002. “Uneven Stories: Successful Black Collegians at a Black and a White Campus.” *Review of Higher Education* 25:315-330.

Goffman, Erving. 1952. "On Cooling the Mark Out: Some Aspects of Adaptation to Failure." *Psychiatry* 15:451-463.

Hagedora, Linda Serra, Winny (Yan Fang) Chi, Rita M. Cepeda, and Melissa McLain. 2007. "An Investigation of Critical Mass: The Role of Latino Representation in the Success of Urban Community College Students." *Research in Higher Education* 48:73-91.

Hagedorn, Linda Serra, M. Vali Siadat, Shereen F. Fogel, Amaury Nora, and Ernest T. Pascarella. 1999. "Success in College Mathematics: Comparisons between Remedial and Nonremedial First-Year College Students." *Research in Higher Education* 40:261-284.

Hoyt, Jeff E. 1999. "Remedial Education and Student Attrition." *Community College Review* 27:51-73.

Hurtado, Sylvia. 1992. "The Campus Racial Climate: Contexts of Conflict." *Journal of Higher Education* 63:539-569.

Hurtado, Sylvia, Jeffrey Milem, Alma Clayton-Pedersen, and Walter Allen. 1999. *Enacting Diverse Learning Environments: Improving the Climate for Racial/Ethnic Diversity in Higher Education*. ASHE-ERIC Higher Education Reports, Volume 26, Number 8. Washington, D.C.: The George Washington University.

Karabel, Jerome. 1972. "Community Colleges and Social Stratification." *Harvard Educational Review* 42:521-562.

McClelland, Katherine E. 1990. "The Social Management of Ambition." *The Sociological Quarterly* 31:225-251.

McClelland, Katherine E., and Carol J. Auster. 1990. "Public Platitudes and Hidden Tensions: Racial Climates at Predominantly White Liberal Arts Colleges." *Journal of Higher Education* 61:607-642.

Metzner, Barbara S. 1989. “Perceived Quality of Academic Advising: The Effect on Freshmen Attrition.” *American Educational Research Journal* 26:422-442.

O'Toole, Dennis M., Leslie S. Stratton, and James N. Wetzel. 2003. "A Longitudinal Analysis of the Frequency of Part-Time Enrollment and the Persistence of Students Who Enroll Part-Time." *Research in Higher Education* 44:519-537.

Parsad, Basmat, Laurie Lewis and Bernard Greene. 2003. *Remedial Education at Degree-Granting Postsecondary Institutions in Fall 2000 (NCES 2004-010)*. Washington, D.C.: National Center for Education Statistics.

Pascarella, Ernest T., John C. Smart, and Judith Stoecker. 1989. “College Race and the Early Status Attainment of Blacks.” *Journal of Higher Education* 60:82-107.

Pascarella, Ernest T., and Patrick T. Terenzini. 2005. *How College Affects Students, Volume 2: A Third Decade of Research*. San Francisco, California: Jossey-Bass.

Pascarella, Ernest T., Gregory C. Wolniak, and Christopher T. Pierson. 2003. “Influences on Community College Students’ Educational Plans.” *Research in Higher Education* 44:301-314.

Powers, Daniel A., and Yu Xie. 2000. *Statistical Methods for Categorical Data Analysis*. San Diego, California: Academic Press.

Rankin, Susan R., and Robert D. Reason. 2005. “Differing Perceptions: How Students of Color and White Students Perceive Campus Climate for Underrepresented Groups.” *Journal of College Student Development* 46:43-61.

Raudenbush, Stephen W., and Anthony S. Bryk. 2002. *Hierarchical Linear Models: Applications and Data Analysis and Methods*. Thousand Oaks, California: Sage.

Rosenbaum, James E. 2001. *Beyond College for All: Career Paths for the Forgotten Half*. New

York: Russell Sage Foundation.

Scott, Marc A., and Benjamin B. Kennedy. 2005. “Pitfalls in Pathways: Some Perspectives on Competing Risks Event History Analysis in Education Research.” *Journal of Educational and Behavioral Statistics* 30:413-442.

Seidman, Alan. 1991. “The Evaluation of Pre/Post Admissions/Counseling Process at a Suburban Community College: Impact on Student Satisfaction with the Faculty and the Institution, Retention, and Academic Performance.” *College and University* 66:223-232.

Stratton, Leslie S., Dennis M.O'Toole, and James N. Wetzel. 2007. "Are the Factors Affecting Dropout Behavior Related to Initial Enrollment Intensity for College Undergraduates?” *Research in Higher Education* 48:453-485.

Suarez-Balcazar, Yolanda, Lucia Orellana-Damacela, Nelson Portillo, Jean M. Rowan, and Chelsea Andrews-Guillen. 2003. “Experiences of Differential Treatment among College Students of Color.” *Journal of Higher Education* 74:428-444.

Swim, Janet K., Lauri L. Hyers, Laurie L. Cohen, Davita C. Fitzgerald, and Wayne H. Bylsma. 2003. “African American College Students' Experiences with Everyday Racism: Characteristics of and Responses to these Incidents.” *Journal of Black Psychology* 29:38-67.

Szafran, Robert F. 2001. "The Effect of Academic Loan on Success for New College Students: Is Lighter Better?" *Research in Higher Education* 42:27-50.

Titus, Marvin A. 2004. "An Examination of the Influence of Institutional Context on Student Persistence at 4-Year Colleges and Universities: A Multilevel Approach." *Research in Higher Education* 45:673-699.

Toutkoushian, Robert K., and John C. Smart. 2001. "Do Institutional Characteristics Affect

Student Gains from College?" *Review of Higher Education* 25:39-61.

Turnage, Robert. 2003. "2004-05 Comprehensive Five-Year Capital Outlay Plan." Presentation to the Board of Governors of California Community Colleges, July 14-15, Sacramento.

Wassmer, Robert, Colleen Moore, and Nancy Shulock. 2004. “Effect of Racial/Ethnic Composition on Transfer Rates in Community Colleges: Implications for Policy and Practice.” *Research in Higher Education* 45:651-672.

Weissman, Julie, Carole Bluakowski, and Marci Jumisko. 1998. “A Study of White, Black, and Hispanic Students' Transition to a Community College.” *Community College Review* 26:19-32.

Yamaguchi, Kazuo. 1991. *Event History Analysis*. Thousand Oaks, California: Sage.

Young, Robert B., Richard Backer, and Gregory Rogers. 1989. “The Impact of Early Advising and Scheduling on Freshmen Success.” *Journal of College Student Development* 30:309-312.

Table 1: Frequency distributions of selected variables for the remedial math cohort ($N_{students}$ = 30,118)

VARIABLE	VALUES	*N*	%
Remediation in Math	remediated successfully	8,984	29.83
	did not remediate successfully	21,134	70.17
Term of First Advising	Fall 1995 – Spring 1996	19,328	64.17
	Summer 1996 – Spring 1997	1,833	6.09
	Summer 1997 – Spring 1998	853	2.83
	Summer 1998 – Spring 1999	356	1.18
	Summer 1999 – Spring 2000	218	0.72
	Summer 2000 – Spring 2001	146	0.48
	did not receive advising at any point	7,384	24.52
Race	White	14,303	47.49
	Black	2,991	9.93
	Hispanic	9,669	32.10
	Asian	3,155	10.48
Math Deficiency	intermediate algebra / geometry	7,559	25.10
	beginning algebra	11,391	37.82
	pre-algebra	4,491	14.91
	arithmetic	6,677	22.17
English Competency	college-level	8,141	27.03
	remedial writing	15,383	51.08
	remedial reading	2,056	6.83
	ESL	2,248	7.46
	none	2,290	7.60
Academic Goal	transfer	6,286	20.87
	transfer with AS/AA	13,547	44.98
	AS/AA	1,883	6.25
	vocational degree	820	2.72
	vocational certificate	513	1.70
	other job-related goal	2,086	6.93
	abstract	1,198	3.98
	remediation	567	1.88
	undecided	2,976	9.88
	unreported	242	0.80
First Math Grade	A	3,898	12.94
	B	4,821	16.01
	C	5,430	18.03
	D	2,588	8.59
	F	3,773	12.53
	withdrawal	6,401	21.25
	credit	1,490	4.95
	no credit	803	2.67
	ungraded	240	0.80
	missing/unreported	674	2.24
Sex	male	13,552	45.00
	female	16,566	55.00

Fee Waiver	received fee waiver at some point	14,879	49.40
	did not receive fee waiver at any point	15,239	50.60
Grant	received grant(s) at some point	10,190	33.83
	did not receive grant(s) at any point	19,928	66.17
Age at Start (years)	< 18	2,632	8.74
	18-20	22,398	74.37
	21-25	2,247	7.46
	26-30	1,021	3.39
	31-35	753	2.50
	36-40	506	1.68
	41-50	436	1.45
	> 50	125	0.42
Total Number of Enrolled Terms	2-3	6,810	22.61
	4-5	5,655	18.78
	6-7	5,448	18.09
	8-9	4,794	15.92
	10-11	3,792	12.59
	12-14	3,014	10.01
	15-17	605	2.01

Table 2: Frequency distributions of selected variables for the transfer-seeking cohort ($N_{students}$ = 68,241)

VARIABLE	VALUES	*N*	%
Transfer	transferred	18,557	27.19
	did not transfer	49,684	72.81
Term of First Advising	Fall 1995 – Spring 1996	39,955	58.55
	Summer 1996 – Spring 1997	4,725	6.92
	Summer 1997 – Spring 1998	2,392	3.51
	Summer 1998 – Spring 1999	1,137	1.67
	Summer 1999 – Spring 2000	712	1.04
	Summer 2000 – Spring 2001	551	0.81
	did not receive advising at any point	18,769	27.50
Race	White	33,591	49.22
	Black	7,067	10.36
	Hispanic	19,027	27.88
	Asian	8,556	12.54
First Math Course	college-level math	11,740	17.20
	intermediate algebra / geometry	10,335	15.14
	beginning algebra	16,176	23.70
	pre-algebra	6,211	9.10
	arithmetic	6,975	10.22
	vocational math only	552	0.81
	no math	16,252	23.82
First English Course	college-level	22,159	32.47
	remedial writing	25,285	37.05
	remedial reading	3,461	5.07
	ESL	5,220	7.65
	none	12,116	17.75
Academic Goal	transfer	22,520	33.00
	transfer with AS/AA	45,721	67.00
Sex	male	33,243	48.71
	female	34,998	51.29
Fee Waiver	received fee waiver at some point	29,752	43.60
	did not receive fee waiver at any point	38,489	56.40
Grant	received grant(s) at some point	18,602	27.26
	did not receive grant(s) at any point	49,639	72.74
Age at Start (years)	< 18	6,507	9.53
	18-20	48,684	71.34
	21-25	6,005	8.80
	26-30	2,786	4.08
	31-35	1,776	2.60
	36-40	1,174	1.72
	41-50	1,018	1.49
	> 50	291	0.43

Total Number of Enrolled Terms	1-2	13,001	19.05
	3-4	11,625	17.04
	5-6	12,107	17.74
	7-8	11,576	16.96
	9-11	12,858	18.84
	12-14	5,938	8.70
	15-17	1,136	1.66

Table 3: Estimated coefficients and standard errors for the discrete-time event history analysis of <u>successful mathematics remediation</u> on selected variables (N_{terms} = 142,145; $N_{students}$ = 30,118; $N_{colleges}$ = 107; control variables not shown)

		Model 3-1	Model 3-2	Model 3-3
Effect of Advising		0.357***	0.225***	0.229***
		(0.050)	(0.059)	(0.059)
Effect of Race on the Effect of Advising	Black (vs. White)	-----	-0.076	-0.078
			(0.118)	(0.127)
	Hispanic (vs. White)	-----	-0.023	-0.009
			(0.068)	(0.070)
	Asian (vs. White)	-----	-0.240*	-0.207
			(0.096)	(0.107)
Effect of Math Deficiency on the Effect of Advising	Beginning Algebra (vs. Inter Alg/Geom)	-----	0.261***	0.265***
			(0.076)	(0.078)
	Pre-Algebra (vs. Inter Alg/Geom)	-----	0.695***	0.711***
			(0.127)	(0.129)
	Basic Arithmetic (vs. Inter Alg/Geom)	-----	0.313*	0.316*
			(0.150)	(0.150)
Effect of Racial Composition on the Race-Specific Effect of Advising				
	Effect of % Black (logged) on Advising for Blacks	-----	-----	0.007
				(0.066)
	Effect of % Hispanic (logged) on Advising for Hispanics	-----	-----	-0.067
				(0.059)
	Effect of % Asian (logged) on Advising for Asians	-----	-----	-0.053
				(0.058)
Effect of Math Composition on the Deficiency-Specific Effect of Advising				
	Effect of % Math Deficient (squared) on Advising for Beginning Algebra Students	-----	-----	-0.00002
				(0.00003)
	Effect of % Math Deficient (squared) on Advising for Pre-Algebra Students	-----	-----	-0.00004
				(0.00004)
	Effect of % Math Deficient (squared) on Advising for Basic Arithmetic Students	-----	-----	0.00002
				(0.00009)

Notes: *$p \le 0.05$; **$p \le 0.01$; ***$p \le 0.001$; results presented here are based on the unit-specific model, rather than the population-average model.

Table 4: Estimated coefficients and standard errors for the discrete-time event history analysis of transfer on selected variables (N_{terms} = 968,584; $N_{students}$ = 68,241; $N_{colleges}$ = 107; control variables not shown)

		Model 4-1	Model 4-2	Model 4-3
Effect of Advising		0.556***	0.492***	0.503***
		(0.042)	(0.051)	(0.051)
Effect of Race on the Effect of Advising	Black (vs. White)	-----	-0.182*	-0.173*
			(0.087)	(0.088)
	Hispanic (vs. White)	-----	0.077	0.085
			(0.060)	(0.060)
	Asian (vs. White)	-----	-0.057	-0.095
			(0.057)	(0.059)
Effect of Math Track on the Effect of Advising	Remedial Math (vs. College-Level)	-----	0.228***	0.204***
			(0.037)	(0.038)
	Vocational Math Only (vs. College-Level)	-----	-0.373	-0.410
			(0.347)	(0.346)
	No Math (vs. College-Level)	-----	-0.383***	-0.384***
			(0.066)	(0.066)
Effect of English Track on the Effect of Advising	Remedial English (vs. College-Level)	-----	0.234***	0.221***
			(0.052)	(0.052)
	English-as-a-Second-Language (vs. College-Level)	-----	0.529***	0.529***
			(0.099)	(0.099)
	No English (vs. College-Level)	-----	-0.251**	-0.254**
			(0.084)	(0.084)
Effect of Racial Composition on the Race-Specific Effect of Advising				
	Effect of % Black (logged) on Advising for Blacks	-----	-----	-0.014
				(0.046)
	Effect of % Hispanic (logged) on Advising for Hispanics	-----	-----	-0.091*
				(0.044)
	Effect of % Asian (logged) on Advising for Asians	-----	-----	0.055
				(0.031)
Effect of Math/English Composition on the Track-Specific Effect of Advising				
	Effect of % Math Deficient (squared) on Advising for Remedial Math Students	-----	-----	0.00008***
				(0.00002)
	Effect of % English Deficient (identity) on Advising for Remedial English Students	-----	-----	0.002
				(0.002)

Notes: *$p \leq 0.05$; **$p \leq 0.01$; ***$p \leq 0.001$; results presented here are based on the unit-specific model, rather than the population-average model.

Figure 1: Additive Effect of the College-Level Percentage of Hispanic First-Time Freshmen on the Effect of Advising on the Hazard of Transfer for Hispanic Transfer-Seeking Students

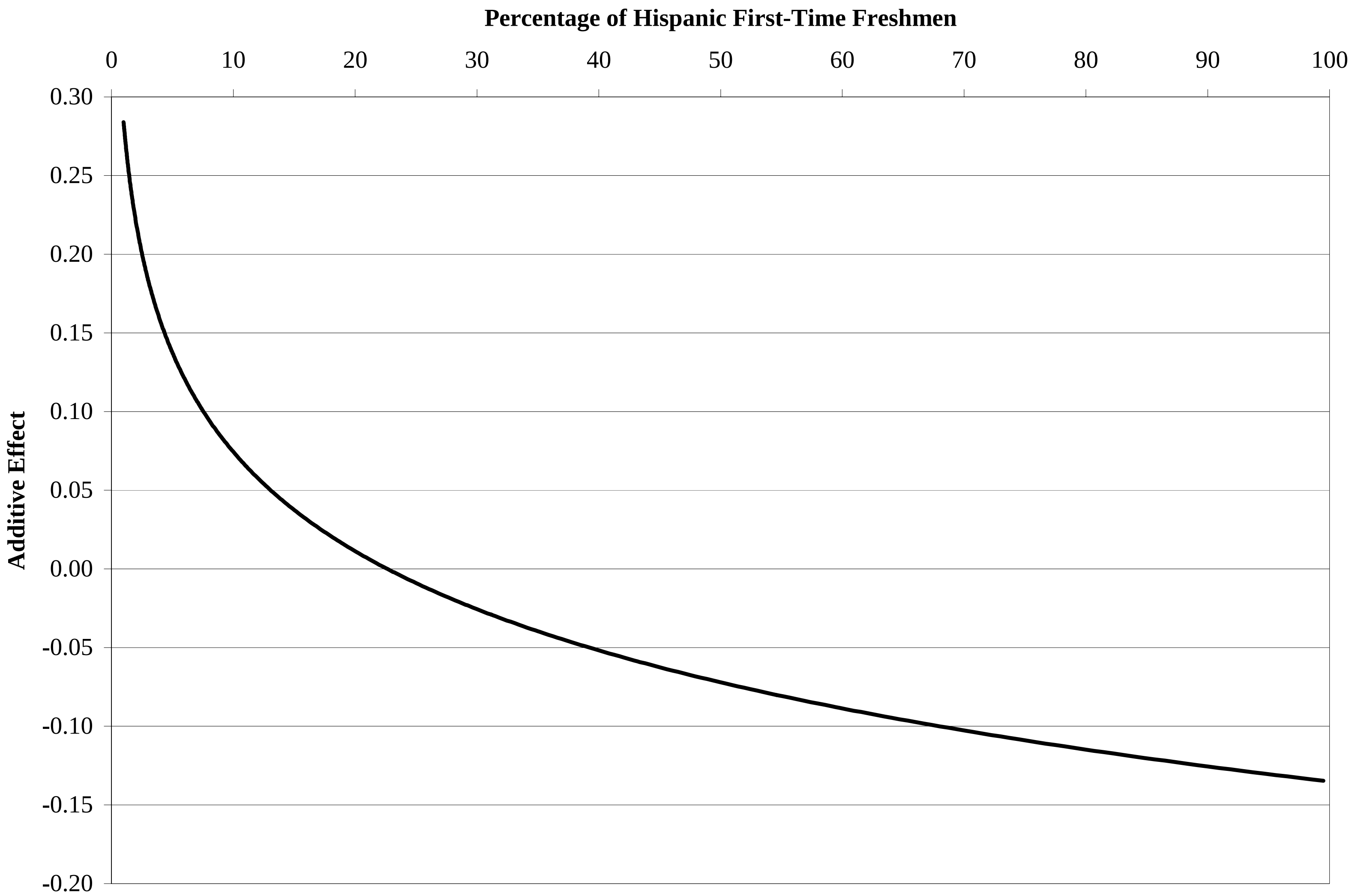
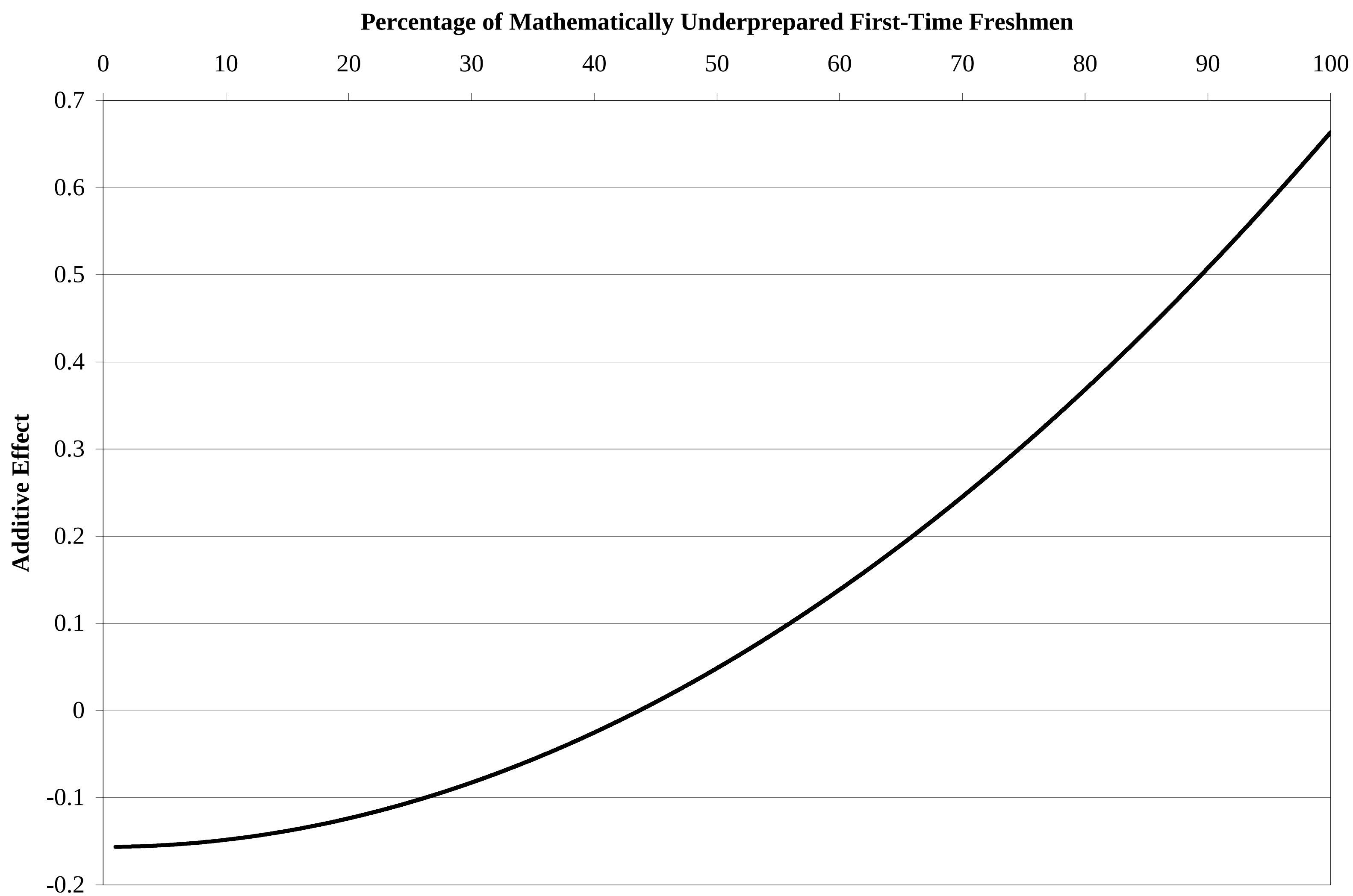


Figure 2: Additive Effect of the College-Level Percentage of Mathematically Underprepared First-Time Freshmen on the Effect of Advising on the Hazard of Transfer for Transfer-Seeking Students on the Remedial Math Track



APPENDIX A

$$\log\left(\frac{P(y_{tij}=1)}{1-P(y_{tij}=1)}\right) = A_{0ij} + A_{1ij}(ADVISING)_{tij} + A_{kij}(TERM\ LEVEL\ CONTROLS)_{tij}$$

$$A_{0ij} = B_{00j} + B_{01j}(BLACK)_{ij} + B_{02j}(HISPANIC)_{ij} + B_{03j}(ASIAN)_{ij} + B_{04j}(BEG\ ALG)_{ij} +$$

$$B_{05j}(PRE\ ALG)_{ij} + B_{06j}(BASIC\ ARITH)_{ij} + B_{0mj}(STUDENT\ LEVEL\ CONTROLS)_{ij} + \varepsilon_{0ij}$$

$$A_{1ij} = B_{10j} + B_{11j}(BLACK)_{ij} + B_{12j}(HISPANIC)_{ij} + B_{13j}(ASIAN)_{ij} + B_{14j}(BEG\ ALG)_{ij} +$$

$$B_{15j}(PRE\ ALG)_{ij} + B_{16j}(BASIC\ ARITH)_{ij} + \varepsilon_{1ij}$$

$$A_{kij} = B_{k0j} + \varepsilon_{kij}$$

$$B_{00j} = C_{000} + u_{00j}$$

$$B_{01j} = C_{010} + u_{01j}$$

$$B_{02j} = C_{020} + u_{02j}$$

$$B_{03j} = C_{030} + u_{03j}$$

$$B_{04j} = C_{040} + u_{04j}$$

$$B_{05j} = C_{050} + u_{05j}$$

$$B_{06j} = C_{060} + u_{06j}$$

$$B_{0mj} = C_{0m0}$$

$$B_{10j} = C_{100} + u_{10j}$$

$$B_{11j} = C_{110} + C_{111}(\%\ BLACK)_j + u_{11j}$$

$$B_{12j} = C_{120} + C_{121}(\%\ HISPANIC)_j + u_{12j}$$

$$B_{13j} = C_{130} + C_{131}(\%\ ASIAN)_j + u_{13j}$$

$$B_{14j} = C_{140} + C_{141}(\%\ MATH\ DEFICIENT)_j + u_{14j}$$

$$B_{15j} = C_{150} + C_{151}(\%\ MATH\ DEFICIENT)_j + u_{15j}$$

$$B_{16j} = C_{160} + C_{161}(\%\ MATH\ DEFICIENT)_j + u_{16j}$$

$$B_{k0j} = C_{k00}$$

APPENDIX B

$$\log\left(\frac{P(y_{tij}=1)}{1-P(y_{tij}=1)}\right) = A_{0ij} + A_{1ij}(ADVISING)_{tij} + A_{kij}(TERM\ LEVEL\ CONTROLS)_{tij}$$

$$A_{0ij} = B_{00j} + B_{01j}(BLACK)_{ij} + B_{02j}(HISPANIC)_{ij} + B_{03j}(ASIAN)_{ij} + B_{04j}(INT\ ALG\ or\ GEOM)_{ij} +$$
$$B_{05j}(BEG\ ALG)_{ij} + B_{06j}(PRE\ ALG)_{ij} + B_{07j}(BASIC\ ARITH)_{ij} + B_{08j}(VOC\ MATH\ ONLY)_{ij} +$$
$$B_{09j}(NO\ MATH)_{ij} + B_{010j}(REM\ WRIT)_{ij} + B_{011j}(REM\ READ)_{ij} + B_{012j}(ESL\ ENGL)_{ij} +$$
$$B_{013j}(NO\ ENGL)_{ij} + B_{0mj}(STUDENT\ LEVEL\ CONTROLS)_{ij} + \varepsilon_{0ij}$$
$$A_{1ij} = B_{10j} + B_{11j}(BLACK)_{ij} + B_{12j}(HISPANIC)_{ij} + B_{13j}(ASIAN)_{ij} + B_{14j}(REM\ MATH)_{ij} +$$
$$B_{15j}(VOC\ MATH\ ONLY)_{ij} + B_{16j}(NO\ MATH)_{ij} + B_{17j}(REM\ ENGL)_{ij} + B_{18j}(ESL\ ENGL)_{ij} +$$
$$B_{19j}(NO\ ENGL)_{ij} + \varepsilon_{1ij}$$
$$A_{kij} = B_{k0j} + \varepsilon_{kij}$$
$$B_{00j} = C_{000} + u_{00j}$$
$$B_{01j} = C_{010} + u_{01j}$$
$$B_{02j} = C_{020} + u_{02j}$$
$$B_{03j} = C_{030} + u_{03j}$$
$$B_{04j} = C_{040} + u_{04j}$$
$$B_{05j} = C_{050} + u_{05j}$$
$$B_{06j} = C_{060} + u_{06j}$$
$$B_{07j} = C_{070} + u_{07j}$$
$$B_{08j} = C_{080} + u_{08j}$$
$$B_{09j} = C_{090} + u_{09j}$$
$$B_{010j} = C_{0100} + u_{010j}$$
$$B_{011j} = C_{0110} + u_{011j}$$
$$B_{012j} = C_{0120} + u_{012j}$$
$$B_{013j} = C_{0130} + u_{013j}$$
$$B_{0mj} = C_{0m0}$$
$$B_{10j} = C_{100} + u_{10j}$$
$$B_{11j} = C_{110} + C_{111}(\%\ BLACK)_j + u_{11j}$$
$$B_{12j} = C_{120} + C_{121}(\%\ HISPANIC)_j + u_{12j}$$
$$B_{13j} = C_{130} + C_{131}(\%\ ASIAN)_j + u_{13j}$$
$$B_{14j} = C_{140} + C_{141}(\%\ MATH\ DEFICIENT)_j + u_{14j}$$
$$B_{15j} = C_{150} + u_{15j}$$
$$B_{16j} = C_{160} + u_{16j}$$
$$B_{17j} = C_{170} + C_{171}(\%\ ENGL\ DEFICIENT)_j + u_{17j}$$
$$B_{18j} = C_{180} + u_{18j}$$
$$B_{19j} = C_{190} + u_{19j}$$
$$B_{k0j} = C_{k00}$$