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Student Readiness for Postsecondary Coursework: Developing a College-Level Measure of Student Average Academic Preparation

Peter Riley Bahr
Wayne State University

Willard Hom and Patrick Perry
Chancellor's Office, California Community Colleges

California's community college accountability strategy, the Partnership for Excellence program, includes, as an aspect of the outcome assessment component of the program, a mechanism to "level the playing field" between colleges. This function is accomplished through adjustment models, statistically derived equations that "adjust" for observed relationships between exogenous variables and college-level outcomes of interest. The development of adjustment models for each of the several outcomes has relied upon an exploratory process to derive a parsimonious set of exogenous variables with nonzero (statistically significant) relationships to the outcome of interest. One previously unmeasured adjustment variable has received considerable interest in discussions of the adjustment model development process, namely the academic preparedness of entering students at each college. This article addresses the work of the authors to develop a measure of student average academic preparation for use in "leveling the playing field" in community college outcome measurement and accountability.

Introduction

The Board of Governors of California's Community College system, in executing California's Partnership for Excellence (PFE) program, has recognized formally that the colleges operate within remarkably disparate social and economic environments, and that these differences include variation in factors that are likely to affect the performance of colleges on the standard outcome measures. The attempt to account for such disparities in performance measurement has taken the form of an "adjustment modeling" process. Adjustment models are statistically derived equations that correct for observed relationships between factors that are beyond the control of the individual colleges/districts (called "exogenous variables") and each of the college-level outcome measures.

While the exploratory process undertaken by the Chancellor's Office of the California Community College system to select a parsimonious set of adjustment variables has drawn upon numerous data sources and examined a variety of possible adjustment factors, considerable attention has been focused on one important adjustment factor for which data previously were unavailable. This factor, dubbed Student Average Academic Preparation (SAAP), would represent the relative academic preparedness of entering students at each college, as indicated by prior academic achievement.

The use of prior student academic achievement is a broadly accepted and recommended variable for models of expected student achievement and institutional performance (Astin, 1975; Bryk & Hermanson, 1993; Stiefel, Schwartz, & Rubenstein, 1999). Research has indicated that prior student academic achievement, such as high school grades and test scores, correlates with at least one academic outcome for community college students, namely transfer to four-year institutions (Lee & Frank, 1990). Thus, the academic preparedness of the incoming student population was expected to be a principal factor affecting the performance of each college with regard to accountability measures derived from aggregate student outcomes.

The Chancellor's Office, in an effort to develop a measure that could be used to adjust for the effects of differences in the academic preparedness of incoming students on the performance of each college, forged a data sharing alliance with the California Department of Education (CDE). In 1998, CDE implemented statewide testing of public high school students using the Stanford 9 test battery as one component of California's Standardized Testing and Reporting (STAR) program. The Stanford 9 was used in aggregate form by CDE to assign an Academic Performance Index (API) score to each public high school in California. The use of this measure as a component of California's STAR program is discussed in detail on CDE's website, http://star.cde.ca.gov/star2002/help/AboutSTAR.html.

The Stanford 9 test represented a promising measure of academic preparation for postsecondary coursework. The test is nationally standardized and is widely used and recognized throughout the United States. The primary use of the test is measuring student achievement (Council on the Great City Schools & Harcourt Educational Measurement, 2001; Stecher, McCaffrey, & Bugliari, 2003), and, as such, it is an appropriate proxy of student preparedness for postsecondary academic coursework. Also, it includes a broad range of subject areas (e.g., mathematics, reading, language, history/social science, and science) and, at the time, was administered in a consistent manner to students across public high schools in California (recent changes, discussed in detail later in this paper, have led to the replacement of the Stanford 9 with an alternate standardized test).

The California Department of Education agreed to share with the Chancellor's Office the Stanford 9 test results for public high school juniors for the two terms for which data were available (spring semester 1998 and spring semester 1999) at the time of the initiation of the data sharing relationship. The intention of the Chancellor's Office was to cross reference the Stanford 9 test results with the Summer/Fall 2000 cohort of incoming first-time freshmen at each college, and, by calculating the mean of each cohort's Stanford 9 test results, develop an index of the average academic preparation of incoming freshmen at each college. Unfortunately, CDE was unable to provide social security numbers or other relevant unique identifiers for students' Stanford 9 test results, precluding a unique match against Chancellor's Office records. Thus, a simple match against college enrollment records was not possible.

Several solutions to this problem were considered. One solution was to calculate the mean of the API scores for all high schools contributing students to each college, based upon the high school of origin indicated by each student at first college enrollment. Since the API represents the aggregate academic performance of students at each high school, degree of academic preparedness for a given college could be represented by the average of the API's scores of all high schools from which students originated to attend that college. A second related solution that was somewhat less gross in measurement was to calculate the *weighted* mean of the API scores for all contributing high schools, based upon the percentage of college enrollees originating from each high school. In calculating an average academic preparedness score for a given college, this latter alternative would give more weight to the API scores of high schools that contribute a greater percentage of a given college's enrollees.

However, both of these methods involved the use of scores that were already in aggregate form and therefore represented very gross measures of student average academic preparation. These methods also introduced the assumption that students from each high school choose to attend a given community college at random, without regard to their own academic performance/preparation. In other words, the use of high school API to assign an average academic preparation score to a particular college presupposes that students at all levels of academic preparation are equally likely to elect to attend a local community college instead of an alternate institution or not to attend college at all. This assumption is almost certainly false, as student academic preparation was expected to be a strong predictor of individual postsecondary decisions. Moreover, if this error were consistent across high schools, and the colleges fed by them, it would be of less consequence. However, it was more reasonable to assume wide variation across high schools in the relationship between academic preparation and community college attendance due to the substantial variation in economic conditions across California. This meant that the API scores of some high schools would be more representative of the academic preparation of students who chose to attend a local community college than are the API scores of other high schools. Thus, the direct use of high school API was ruled out as a method of assigning an SAAP score to each college.

The third solution to the problem of not having unique identifiers in the CDE data, and the solution ultimately selected by the authors, was a "fuzzy match" process designed to unite college student records with the CDE Stanford 9 test results. A fuzzy match relies upon the combined uniqueness of multiple student-level descriptive variables to connect student records across two or more datasets. The fuzzy match process employed by the authors, which is the focus of the remainder of this paper, draws upon mathematical theory developed more than thirty years ago (Fellegi & Sunter, 1969) and represents an application of a general method of *record linkage* employed in many disciplines. Related methods include *statistical matching* (Rassler, 2002) and *data fusion* (Baker, 2000; Soong & Montigny, 2001; Van der Puttan, Kok, & Gupta, 2002).

Solution Methodology

A "Fuzzy Match" Process

The methodology of record linkage primarily has focused upon connecting individual-level data contained within disparate data sources via the names of individuals and other identifying characteristics, such as date of birth, gender, and race (Newcombe, Fair, & Lalonde, 1992; Newcombe, Kennedy, Axford, & James, 1959). Researchers in demographics (Jaro, 1989; Winkler, 1995, 1999), health (Bell & Sethi, 2001; Reardon, Ney, Scheuren, Cougle, Coleman & Strahan, 2002) and management information systems (Van der Puttan, et al., 2002) have used this method for merging data from multiple databases in order to expand the number of available variables given a particular unit of analysis. In this case, we selected four identifying characteristics upon which to base the fuzzy match: gender, date of birth, race/ethnicity, and high school of origin (high school of origin in the Chancellor's Office database and high school of enrollment at the time of test administration in the CDE database).

Adding further to the complexity of the fuzzy match process, the Chancellor's Office data include only a single racial/ethnic identification variable, while the high school Stanford 9 data include both a primary race/ethnicity variable and a secondary variable indicating one or more additional racial/ethnic identifications. A fuzzy match employing only the primary race/ethnicity variable in both datasets (in addition to gender, date of birth, and high school of origin) would have been a reasonable method of matching records. However, with the goal of using all available information to maximize the percentage of matched records across the two datasets, we expanded the matching process to capitalize on the information contained within this secondary race/ethnicity variable in the CDE data.

The matching process we employed included five stages. First, all first-time community college freshmen for the Summer/Fall semester/quarter of

2000 were identified in the Chancellor's Office database. Second, this first-time freshmen cohort was screened to eliminate all students who were younger than seventeen years of age at first enrollment, all students who were older than twenty-two years of age at first enrollment, and all students who did not specify a valid California high school as their high school of origin. The rationale for the age criteria was that the youngest student matches across the two data sets likely would be those who completed the Stanford 9 test in the Spring semester of their junior year in 1999 at age sixteen, and who subsequently enrolled in college in the Summer or Fall terms of 2000 immediately following graduation from high school in the Spring term of 2000. Likewise, the oldest student matches likely would be those students who had been "held back" one or more years during primary or secondary schooling, who then completed the Stanford 9 test in the Spring semester of their junior year in 1998, and who subsequently postponed college enrollment for one year following graduation from high school in the Spring term of 1999.

Third, the student records of the screened first-time freshmen cohort were matched against the Stanford 9 test data (1998 and 1999 spring semesters combined) using the combination of the four variables. Fourth, the matched records from the previous step were set aside, and the remaining unmatched first-time freshmen were matched against the Stanford 9 test data using the same four variables with the exception that the secondary race/ethnicity variable in the Stanford 9 data was used instead of the primary race/ethnicity variable. It should be noted that this fourth step of the matching process included only Stanford 9 records with a single racial/ethnic identification in the secondary race/ethnicity variable, as the Stanford 9 data collection process allowed for multiple secondary racial/ethnic identifications. In other words, Stanford 9 test takers had the option of coding multiple racial/ethnic identifications in the secondary race/ethnicity variable, and all students who did so were eliminated from the matching process accomplished in this step. As the fifth and final step of the matching process, the matched student records from the third and fourth steps were pooled into a single body of matched students.

Unduplicating Matched Records

Despite the relatively unique combination of birth date, high school, gender, and race/ethnicity, a number of duplicate observations were generated during the matching process. Duplicate observations occurred when a single college student matched with multiple Stanford 9 records. We expected that duplicate observations were most likely for colleges drawing students from few high schools which contain populations that are relatively homogenous with regard to race/ethnicity.

Because the Stanford 9 test data lacked a unique identifier, it was impossible to determine which of the several Stanford 9 records were matched correctly to a given freshmen college student. As a consequence, duplicate matches either had to be eliminated entirely (dropping all students for whom multiple matches occurred) or eliminated at random such that only a single test score match remained. In order to maximize the match rate for each college, we elected for the latter of the two options and eliminated all but the first occurrence of multi-matched student records. Because the CDE data were not sorted by test score prior to the matching process we considered them to be effectively random and unordered. Thus, the elimination of all but the first match of multiply matched student records should not result in any systematic bias. However, this assumption was not tested.

Calculating the College-Level Summary Measure of Academic Preparation

The Student Average Academic Preparation (SAAP) score for each college was calculated as a simple, unweighted mean of the average of each student's five normal curve equivalent test scores. Stated briefly, CDE provided the nationally standardized normal curve equivalent score (a percentile) for each of the five Stanford 9 components for each student. We calculated the mean of these normal curve equivalent scores for each student with equal weights given to each of the five components. We then calculated the mean of these student-level means for each college to generate a summary "mean of the means" of the five tests for matched students.

Analysis

Analysis of Match Representativeness

Prior to matching, we identified 103,929 unique student records in the college database that met the criteria of: 1) first-time freshmen enrolled in the Summer 2000 or Fall 2000, 2) originated from a California high school, and 3) aged 17 to 22 years. The fuzzy match process with the Stanford 9 test records resulted in 45,655 single matches and 12,910 duplicate matches. Following unduplication of the student records, Stanford 9 test scores were connected to 58,565 college students for an overall match rate of 56.35%. Of these, 53,939 students had valid scores on all five Stanford 9 tests, resulting in a practical match rate of 51.90%.

Match rates by gender and race/ethnicity are provided in Table 1. The findings presented in Table 1 suggest reasonably equal match rates by gender and across prevailing categories of race/ethnicity, although some numerically smaller racial/ethnic groups (e.g., Pacific Islander and Native American) are underrepresented in the match. While the reason for the low representation of the smaller racial groups is not entirely clear, it may be that the matching process was tended to act as a random sampling process. The representativeness of a random sample is increased by greater homogeneity in the population sampled, hence the value of stratified random samples. In this case, the high level of racial heterogeneity in the population may have contributed to the low match rates of the smaller racial groups.

While not equal across colleges, match rates appeared to be sufficiently large at most colleges to warrant a reasonable degree of confidence in the aggregate statistic derived from the match. Descriptive statistics for match rate by college are provided in Table 2, and a histogram representing the distribution of match rate is presented in Figure 1. The mean match rate was 48.64%, and the median was 49.49%. Half the colleges had match rates falling between 42.75% (the 25th percentile) and 56.83% (the 75th percentile), and fully 95% of the colleges (101 of 106) had match rates above 30%. However, two low match outliers were evident (rates of 6.57% and 13.17%, respectively).

Analysis of the SAAP Index

Descriptive statistics for the average of the five Stanford 9 test scores for all high school juniors (regardless of successful matching against college records) in the CDE database, for all high school juniors in the CDE database for whom matches were obtained, and for the college-level aggregate SAAP

Table 1: Percent of first-time college freshmen successfully matched against the Stanford 9 test database, by gender and race

		N	% Match
Gender	Male	50,417	51.53
	Female	53,010	52.74
	Nonreporting	502	0.00
Race	White	40,982	58.78
	Black	6,469	44.21
	Hispanic	33,194	55.83
	Asian	10,496	54.99
	Pacific Islander	781	26.67
	Filipino	3,974	50.05
	Native American	958	22.65
	Other	2,264	9.58
	Nonreporting	4,811	1.10
Total		103,929	51.90

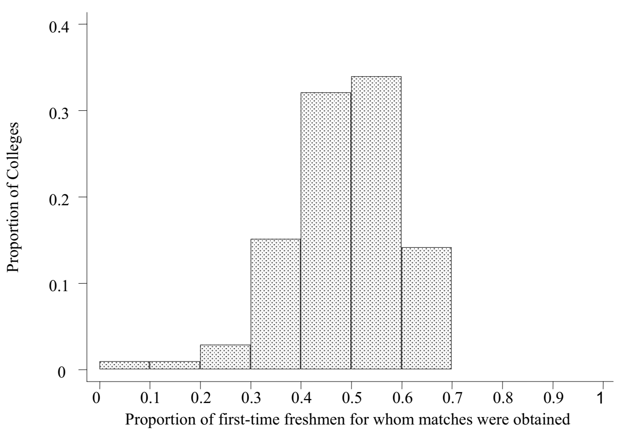
Table 2: Descriptive statistics for match rate when matched by college

	% Match
Mean	48.64
Standard Deviation	11.21
Median	49.49
25th Percentile	42.75
75th Percentile	56.83
Minimum	6.57
Maximum	67.85
Skewness	-0.87
Kurtosis	4.38
N	106

score derived from the student-level means are provided in Table 3. The distribution of the average of the five Stanford 9 test scores for all high school juniors and for all high school juniors for whom matches were obtained are provided in Figures 2 and 3, respectively. The distribution of the college-level SAAP scores is presented in Figure 4.

A review of Table 3 reveals means and medians that are similar both within and between the student-level and college-level measures. The mean of the five tests for all high school juniors in the CDE data is 48.16, while the mean for matched high schools juniors is 48.43. The mean aggregate college-level SAAP score is 47.77. This is an encouraging finding because it indicates that there was little or no gross bias generated in the matching process. Conversely, if the mean for matched high school juniors differed substantially from the mean for all high school juniors, it would have indicated that either higher- or lower-scoring juniors were more likely to be matched to the Chancellor's Office database.

Figure 1: Histogram of the distribution of match rate for all California two-year colleges (*N* = 106)



Moving across the columns of Table 3, progressively less variation is observed in average test scores. The standard deviation for the average of the five tests for all high school juniors is 18.32, and the standard deviation for matched high school juniors is 15.76. The standard deviation for the SAAP score is 5.18. This is not surprising in the case of the two student-level variables (columns 1 and 2) given the self-selection process implicit to college enrollment. In other words, students who elected to attend a community college were expected to be more similar to one another in terms of academic preparation/performance than they were to students who chose other postsecondary options or not to attend college. Likewise, as would be expected for a mean of means, the college-level aggregate SAAP score (column 3) has a fairly low degree of variation relative to the variation in the student-level scores (columns 1 and 2). For example, while the interquartile range (IQR) for matched high school juniors is 22.96, the IQR for the aggregate SAAP is only 7.80.

Concerning the overall distribution of the scores, Figures 2 and 3 reveal slightly skewed but largely bell-shaped distributions for the student-level data. The distribution of the aggregate SAAP score, dis-

Table 3: Descriptive statistics for the mean of the five Stanford 9 normal curve equivalent scores and for the SAAP score

	All High School Juniors (*N* = 575,985)	Matched High School Juniors (*N* = 53,939)	SAAP Score (*N* = 106)
Mean	48.16	48.43	47.77
Median	46.72	47.74	48.23
Standard Deviation	18.32	15.76	5.18
25th Percentile	33.82	36.64	43.90
75th Percentile	61.24	59.60	51.70
Minimum	0.40	0.80	30.87
Maximum	99.00	99.00	61.34
Skewness	0.31	0.22	-0.29
Kurtosis	2.41	2.55	3.24

played in Figure 4, exhibits the Gaussian distribution desired for variables employed in regression modeling.

Figure 2: Histogram of the distribution of the average of the Stanford 9 test scores for all California high school juniors in the Spring terms of 1998 and 1999, combined (*N* = 575,985)

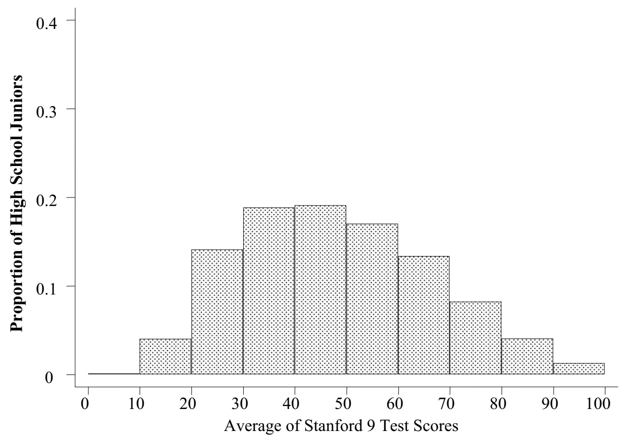
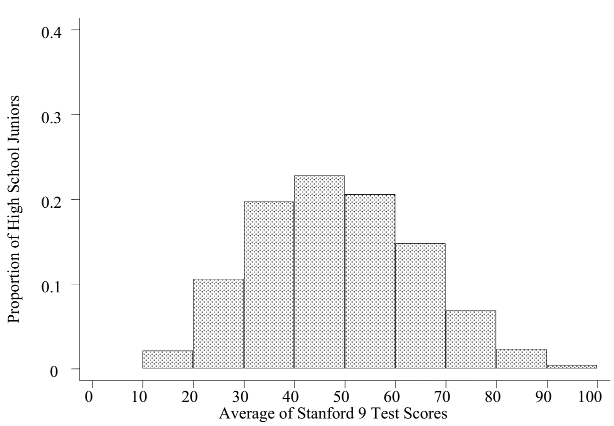


Figure 3: Histogram of the distribution of the average of the Stanford 9 test scores for all matched California high school juniors in the Spring terms of 1998 and 1999, combined (*N* = 53.939)

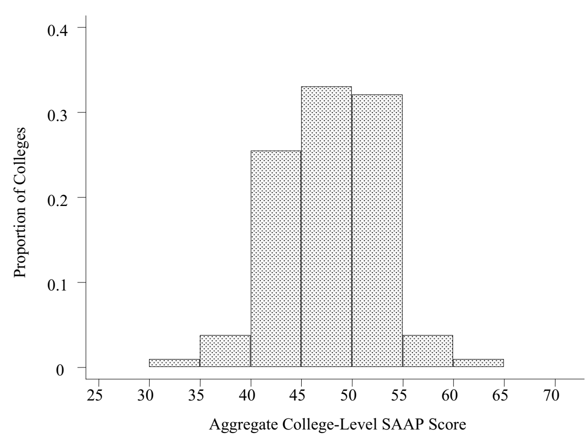


Practical Validation of the SAAP

As evidence for the value and validity of the SAAP index, the measure proved to be a statistically significant and positive adjustment factor in three of the five accountability adjustment models required by the PFE program, suggesting that the measure serves its intended purpose of measuring differences in average academic preparation of incoming students at each college. The measure was found to be a significant predictor of rates of remedial progress, rates of course completion, and rates of transfer to four-year universities, outcomes about which further information can be obtained from the Chancellors Office website, http://www.cccco.edu/divisions/tris/rp/pfe.htm. Likewise, the measure was found to be a statistically significant and positive adjustment factor in models developed by the Chancellor's Office to identify colleges with persistently low rates of transfer, as discussed by Bahr, Hom, and Perry (in press, 2005).

The measure was not found to be a statistically significant adjustment factor in models of degree/certificate completion and vocational course completion, after accounting for other adjustment factors. However, this lack of explanatory significance of the SAAP is likely a consequence of the manner in which the outcome variables were measured. Namely, in these

Figure 4: Histogram of the distribution of the college-level SAAP score for all California two-year colleges (*N* = 106)



Note: The *x*-axis scale in this figure is truncated relative to Figures 2 and 3 to account for the reduced level of variation in the SAAP measure.

latter two models the outcomes were counts rather than rates, and the primary adjustment factors in both cases were closely related count variables that dominated most of the variation in the dependent variables, in effect "swamping out" other adjustment factors.

The explanatory power of the SAAP measure was also corroborated in subsequent work by a separate team of researchers (Wassmer, Moore, & Shulock, 2003). In this later analysis, additional explanatory variables, differing variable definitions, and modified approaches to modeling were used in analyzing transfer rates. Despite these modifications to the model employed by the Chancellor's Office, Wassmer and his colleagues concluded that, "[t]he results of all three analyses indicate that academic preparedness exerted the greatest positive influence on transfer rates; higher levels of academic preparedness among a college's students lead to higher transfer rates" (p. 14).

Problems and Future Directions

A number of unresolved weaknesses in the SAAP measure are immediately evident. First, the measure addresses only the academic preparation of recent high school students, effectively ignoring the impact that the academic preparedness of nontraditional students may have on the performance of a college. Second, the measure addresses only students of California high schools, which is particularly problematic for the few community colleges near the borders of the state where the influx of nonresident students is comparatively high. Third, the measure addresses only public high school students, excluding students of private high schools and unconventional secondary schooling options. Fourth, at present the measure is calculated for only one year (Summer/Fall 2000), although this problem could be remedied using additional waves of data made available by CDE. Fifth, the year for which the SAAP measure is calculated is several years after the baseline years addressed by the PFE adjustment models, the consequence of which is the unverified assumption of relative temporal continuity in the academic preparation of incoming college freshmen at each college. Finally, the rules of administration under the STAR program preclude certain segments of the public high school population, most notably students who have been enrolled in a given school district for less than one year. This suggests that transient populations may be underrepresented in the Stanford 9 data and, as a consequence, the SAAP measure.

Future work on the SAAP measure is expected to include an expansion in the number of first-time freshmen cohorts addressed by the measure, cross-year validation of the assumption of continuity in relative student average academic preparedness, and college-by-college validation of the representativeness of the match. The expansion of the number of cohorts addressed by the SAAP is arguably the most important area of needed development, and will be necessary in order to capture any shifts in the average level of academic preparedness of students at each college. Such shifts in preparedness would be expected under a number of circumstances. For example, community colleges may experience increases or decreases in the proportion of first-time freshmen originating from source high schools. Likewise, shifts in average preparedness may arise as a consequence of significant changes in the academic achievement of students at a given source high school, even without any change in the proportion of students originating from that school. This latter condition would be particularly important to identify if the growth in achievement occurs among groups of students who tend to enroll in community colleges. Also, shifts may result from increases or decreases in the proportion of first-time freshmen who do not enter college directly from high school (i.e., a change in the proportion of nontraditional students), which would lead to an expected reduction in the utility of the fuzzy match and the predictive power of the SAAP measure.

Recent Developments

California's State Board of Education recently elected to replace the Stanford 9 test with the California Achievement Test, Sixth Edition (CAT-6) (Bell, 2002). Practically speaking, the consequence of this change is that future work on the SAAP will need to employ student scores on the CAT 6, rather than the Stanford 9. More importantly, this switch from the Stanford 9 to the CAT 6 may make comparing levels of average academic preparedness based upon the differing tests challenging. As it relates to shifts in aggregate academic preparedness of incoming college freshmen, this change in testing places some doubt upon the degree of confidence with which conclusions can be made regarding actual change over time in the academic preparedness of incoming students across colleges.

Conclusions and Implications

The SAAP measure discussed here represents a substantial step forward in system-wide efforts to account for the disparate exogenous conditions affecting college performance. While the measure is not without weaknesses, it still satisfies in part an essential and long-standing need voiced by numerous researchers and administrators for balanced and circumspect accountability. Moreover, although the measure was constructed to meet the immediate requirements of adjustment modeling for the purpose of accountability, it has the potential to contribute to the advancement of many future research efforts aimed at understanding the dynamics of education in community colleges. However, with due consideration given to the temporal and budgetary restrictions present at the time of development, it is recognized that the measure is in its infancy and that improvements and refinements on the measure should continue.

Given the concern about privacy associated with social security numbers and other unique identifiers, the "fuzzy match" method underlying the development of the SAAP holds promise for many state two-year college systems. As dependence upon social security numbers is reduced in these important record-linkage efforts, we can expect increased dependence upon other linking/matching variables such as date of birth and race/ethnicity. However, match rates using fuzzy match processes are unlikely to ever equal match rates employing unique student identifiers. Thus, the future of record linkage methodology is likely to hinge upon, and be driven by, necessity rather than ideology. That is to say that it is likely to be inaccessibility of unique identifiers that drives progress in identifying and executing proxy matching processes.

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Peter Riley Bahr is an Assistant Professor of Sociology specializing in quantitative methodology, social psychology, and the sociology of education at Wayne State University, Detroit, MI. He can be contacted at peter.bahr@wayne.edu, or Department of Sociology, Wayne State University, Detroit, MI 48202.

Willard Hom is Director of the Research & Planning Unit of the Chancellor's Office of California Community Colleges. **Patrick Perry** is Vice Chancellor of the Technology, Research, and Information Systems Division of the Chancellor's Office of California Community Colleges.

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