NEW APPROACHES TO THE ANALYSIS OF ACADEMIC OUTCOMES: MODELING STUDENT PERFORMANCE AT A COMMUNITY COLLEGE

Karl Boughan
Supervisor of Institutional Research
Office of Institutional Research and Analysis
Prince George's Community College
Largo, Maryland

Methodological Introduction. Since the Fall of 1990, the Office of Institutional Research and Analysis at Prince George's Community College has been tracking the academic careers of a cohort of first-time entrants (N=2,643).[1] In an earlier conference paper,[2] we presented a community college-oriented approach to measuring academic achievement and illustrated its utility in an exploratory regression analysis of the predictors of Cohort 1990 four-year outcomes. In this paper, we present an analysis of Cohort 1990 six-year outcomes, one which moves beyond exploratory research to a more fully-realized causal understanding of the forces impinging on student academic progress at PGCC. While regression has much to recommend it as a data-exploratory technique in the early stages of research, its linear-additive structure implies a causal structure inherently unrealistic, given the complexity of the academic process. This is illustrated in Figure 1, below. The reality envisioned by regression analysis is of the Model A type — a single "dependent" variable (DEP) is influenced by a series of predictor variables (IND1-IND3), each impacting directly upon the dependent variable and none of them intercorrelating with any others (independent effects, hence "independent" variables). The B Model, on the other hand, rests upon a whole series of recursive linear equations permitting the representation of mediated effects, joint effects, local interactions and chains of causality.

Path Analysis. This approach, called *causal path analysis*, can much better capture the more convoluted reality of the academic process. For example, suppose VAR4 represents a measure of student goal attainment, and VARs 1-3 respectively measure student age, study load and grade point average. In this case, Model B would suggest that AGE affects GOAL not only directly (the single negative VAR1-VAR4 arrow) but also indirectly by impacting positively on GPA (directly and positively

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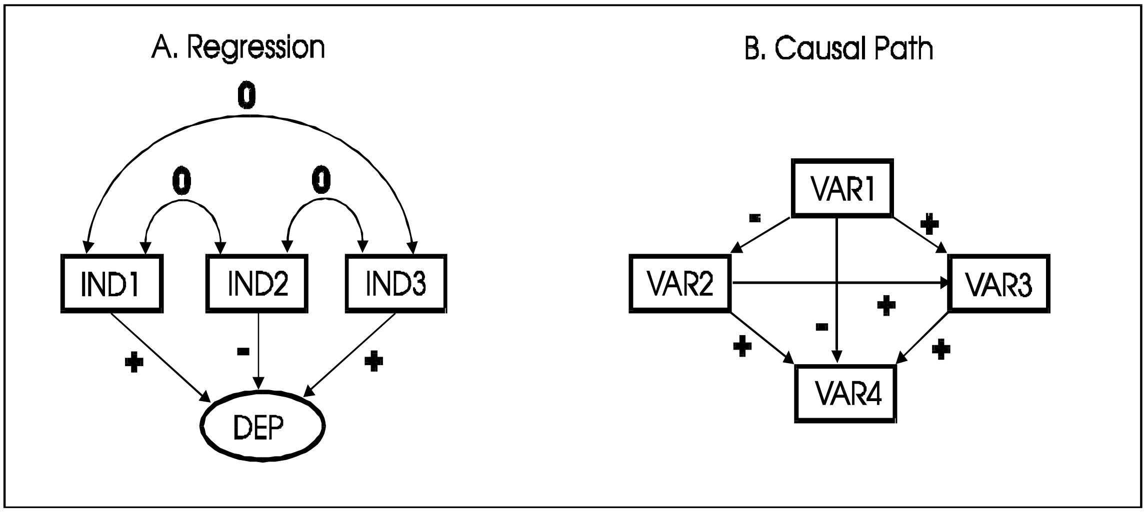
[1]The Cohort 1990 data set was drawn from PGCC student record databases, augmented with material supplied by the Maryland Higher Education Commission's Transfer Student System to enable us to identify cohort members who ceased community college attendance due to transfer to a Maryland four-year public post-secondary institution. Attendance, study progress and related data were all organized on a term-by-term basis so that we might assess student academic status and level of achievement at any term point in the cohort's effective six-year life span, connect patterns of attendance with outcomes, and summarize any part of the process in terms of time to outcome.

[2]Boughan and Clagett (1995). See also Clagett (1995), and Boughan and Clagett (1996).

correlated with GOAL) and negatively on LOAD (directly and positively correlated with GOAL). Additionally, the model would make explicit a second LOAD>GOAL path, one detouring through GPA.

Figure 1. Two Types of Analytical Models



If the B Model represents the true state of affairs, running a straight regression of these same three academic process variables upon GOAL would result in serious underestimates of their predictive power: only their *direct* effects would be gauged individually, while their *indirect* impacts on the behavior of GOAL would be absorbed into the opaque residue of explained variance represented by the difference between R^2 and the sum of all squared part-correlations. (The explanatory force of AGE, with *two indirect links* with GOAL obscured in the analysis, would be particularly under-assessed.) Furthermore, all that is most interesting from both a theoretical and educational policy perspective — just how the components of the academic process work together in complex interaction patterns to produce academic outcomes — would be lost.

In this paper, we present the results of a causal path analysis of the academic process at Prince George's Community College, based on data used in a six-year tracking of the college careers of Fall 1990 first-time entering students. The components of the model cover all major process domains: student socio-economic and cultural background, secondary educational experience and performance, student attitude and motivation, student academic and occupational objectives, institutional financial and academic support, college preparedness level and remediation history, critical early term experience, study load and academic effort, attendance pattern and study persistence, and course performance and program progress.

The web of causality uncovered is graphically embodied in an academic process *map* which makes explicit all critical variable links (single-headed arrows) found by the path analysis, along with their associated *path coefficients* (measures of the causal interaction between pairs of variables joined by a path when the effects of all preceding linked variables have been statistically eliminated). The discussion will focus on identifying the key model components (process variables strategically located at the juncture of many paths) and principle "trails" (chains of paths characterized by high path coefficient totals) leading to the summary academic achievement measure.

Cluster Analysis. As a supplement and complement to the path analysis just described, we also present the results of a K-Means *cluster analysis* of essentially the same academic process data. Our path analysis produced a well-defined and theoretically intelligible model of the academic process, but also one highly abstract and difficult to relate to practical educational policy concerns. Its model provides a clear theoretical picture of how the academic process works *on average*, but often more helpful to educational policy makers would be a concrete modeling of the *varieties* of academic processing taking place. Cluster analysis involves sorting cases into "clusters" which are maximally within-group homogeneous and without-group heterogeneous, according to the patterns found in an all-case distance matrix based on multiple dimension scores. When applied to our Cohort 1990 tracking data, its product is a typology of stable student career patterns defined by the main variety of treks actually made through the academic process. While path analysis models the academic process itself, cluster analysis, in effect, models the *student body* with respect to the workings of the academic process.

Past literature on community college academic outcomes has tended to focus on simple divisions of students into achievers and non-achievers; persisters and non-persisters; full-timers and part-timers; adult learners and immediate-from-high school entrants; the transfer-bound and the occupationally-oriented; the college-prepared and those "at-risk"; the community participants and the isolates. In this paper, the presentation of our cluster-analytic results will focus on how the emerging ten-fold classification scheme collates these and other such process categories into a single, well-realized set of recognizable student types, in the process revealing that, at PGCC at least, there are several different roads both to academic success and to academic frustration.

Modeling Components. In all of the results to follow, the variable of prime focus was Academic Achievement (ACHIEVER). The ACHIEVER classifier was developed by the Office of Institutional Research and Analysis as a simple summary measure of positive academic outcome for college internal assessment reporting, and takes the dichotomous form 0=Non-Achiever/1=Achiever. Classified as Achievers are all members of a cohort who earned an academic award (associate degree, occupational certificate or occupational letter-of-recognition); successfully transferred to a four-year post-secondary institution; or who accumulated 30 or more credit hours in good academic standing (sophomore status).

Selection of the predictor variables was more difficult. Our earlier regression research, involving over 90 separate independent variables, quickly alerted us to the need for a radical data reduction program. Not only was this very large data set extremely awkward to manipulate and interpret, regression statistics implied a truly confounding level of multicollinearity. Reduction to a manageable list of predictors was mainly achieved by means of factor analysis,[3] which transformed the original vast array of variables into just 11 factor scales. These are summarized in Table 1 above, which provides the name used to identify each factor scale in all data displays, a capsule review of the original variables loading most highly on each and defining each's underlying sense, and a descriptive title.

TABLE 1. MODEL COMPONENT FACTOR SCALE NAMES AND DESCRIPTIONS

TRADSTU	***Traditional Student***: Under 20 Yrs Old/Unmarried/Immediate from High School
ADVANTGD	***Socially/Educationally Advantaged Background***: White/High Income, Job Status, College-Educated Home Neighborhood*/Prestige County H.S. Graduate**
REGOBJ	***Regular College Objectives***: Transfer Program/A&S Program/Stated 4-Yr Transfer Motive/Stated Degree PGCC Goal/No Stated Enrichment or Occupational Motive
ATTITUDE	***Implied Study Motivation & Success Commitment***: Combined Day-Evening or Campus-Extension Center Attendance/Summer Attendance/Study Major Shift/No "Stopping Out"/Enrolled All 3 Earliest Major Terms
SUPPORT	***Institutional Financial & Academic Support***: Pell Grants Received/Minority Retention Program /Student Services/ Job Planning or Study Technique Courses
PREPARED	***College Preparedness and Remediation Progress***: High Basic Skills Placement Test Scores/# Dev. Requirements (-)/Completed Dev. Program/No Dev. Math Requirement
LAUNCH	***Early Term Survival and Progress***: Enrolled 3 Earliest Major Terms/Yr-1 Good Standing/ 10+ Credits Yr-1/Post-Fall-1 Enrollment/Any Yr-1 Credits/Yr-1 GPA
EFFORT	***Term Study Load***: Mean Yr-1 Course Hour Attempts/Mean Major Term Course Hour Load/Fall-1 Course Hour Load 15+
PERFORM	***Course Performance and Academic Status***: Yr-1 Cum GPA/Final Cum GPA/ Earned-to-Attempted Hours Ratio/Always in Good Standing/# Good Standing Terms
PERSIST	***Attendance Persistence and Continuity***: Attendance Span/# Major Terms/Post-Yr-1 Enrollment/Post-Fall1 Enrollment/10+ Credits Earned/No "Stopping Out"
PROBLEMS	***Patterns of Remediation Difficulties and Stalled Academic Progress***: # Dev. Areas/Yr-1 Dev. Course-Taking/Dev. Course Repeating/Academic Restriction or Probation /No Credit Courses/No Credit Course Passing/Dev. Math Incomplete

* Derived from student 1990 Census Tract data **From a prestige ranking of area high schools by a panel of PGCC staff

[3]SPSS factor module: principle components extraction method, .1 minimum Eigenvalue extraction criterion, oblique rotation to conserve dimensional intercorrelation, regression-based case scores.

As the table makes clear, for the most part our factor analysis of academic background and process variables rounded up the usual suspects, but the unexpected emergence of three factors deserves special comment:[4] First, variables measuring non-normative course scheduling (taking both day and evening classes, taking both main campus and extension center classes, and attending both major and summer terms), midstream change in program curriculum, and strict sequential term enrollment (no "stopping-out") combined to define a separate factor (ATTITUDE). We interpreted the resulting scale as a gauge of student commitment to academic success, because each of the defining variables, in its own way, seemed to imply extra effort, determination or attention to study goals. As we shall see, this turned out to be a key component of the overall causal matrix.

Second, a group of attendance and performance variables specific to the three earliest major semesters, instead of factoring in with other attendance and performance variables, coalesced into a separate factor measuring initial study survival and success (LAUNCH). This suggests that the first year of study has its own dynamic which may be critical to ultimate success or failure.

Lastly, the factor analysis detected a substantive interaction among certain developmental- and credit course-related variables (PROBLEMS). It would seem that some combination of the number and types of remediation required, absence of remedial progress, and subsequent difficulties in entering credit courses and accumulating credit hours is a common enough pattern in the working out of the academic process at PGCC to constitute an independent phenomenon.

[4]For a complete treatment of the original predictors and the derivation of the factor scales, see Boughan (1997).

Findings from Path Analysis. Our final path analytic model, developed after much trial and error, is graphically depicted in Figure 2, below, as a mapping of the causal network making up PGCC's academic process.[5] It shows the 11 predictor variables distributed in rough terms of temporal, logical and structural distance from the achievement classifier and from one another. The causal flow works downwards towards the bottom of the diagram, with many lateral links in between. The diagram indicates by means of arrows the existence and direction of causal paths linking variable pairs. Each arrow is shown with its associated path coefficient (p), a probability weight measuring the impact of the first on the second variable, controlling for all causally preceding variables. Thick arrows indicate a moderate to strong link ($p \geq .10$) while fine arrows show marginal relationships (.05 - .09). Since path coefficients are *discrete* probability weights, absolute p-values for a sequence of paths can be summed, and their total (P_t) can be used in a rough and ready way as a measure of the probability weight of the entire "trail."

Our path model result in a wealth of insights concerning local areas of academic process function (e.g., the high positive impact of institutional support on study load: p=.25), but space permits only an overview of the major features of the model:

■ The total path model explained almost half of the achievement variance (R^2=.47). This suggests that the model's ability to portray just how process vectors impact on this final key component is reasonably good. Technically, however, this coefficient of determination statistic only estimates the model's predictiveness at a single, albeit very important, node; it does not measure overall model performance or *goodness-of-fit*. For path analysis, this involves tests of numerous aspects of model operation, not all of which our model passed; in general, however, our model performed acceptably within key diagnostic parameters.[6]

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[5] For model development we used AMOS v. 3.6 software. All AMOS models are fully saturated; latent variables and covariance estimates were calculated but are not shown in Figure 2 to preserve clarity.

[6] E.g., one measure judged our model just outside technical acceptability (CMIN/DF=8.319, 5=cut-off), but another implied excellent fit (GFI=.988, 1=perfect), and a third very favorably compared path results with straight regression results (perfect CMIN=0, path CMIN=175, regression CMIN=7369), a good practical test.

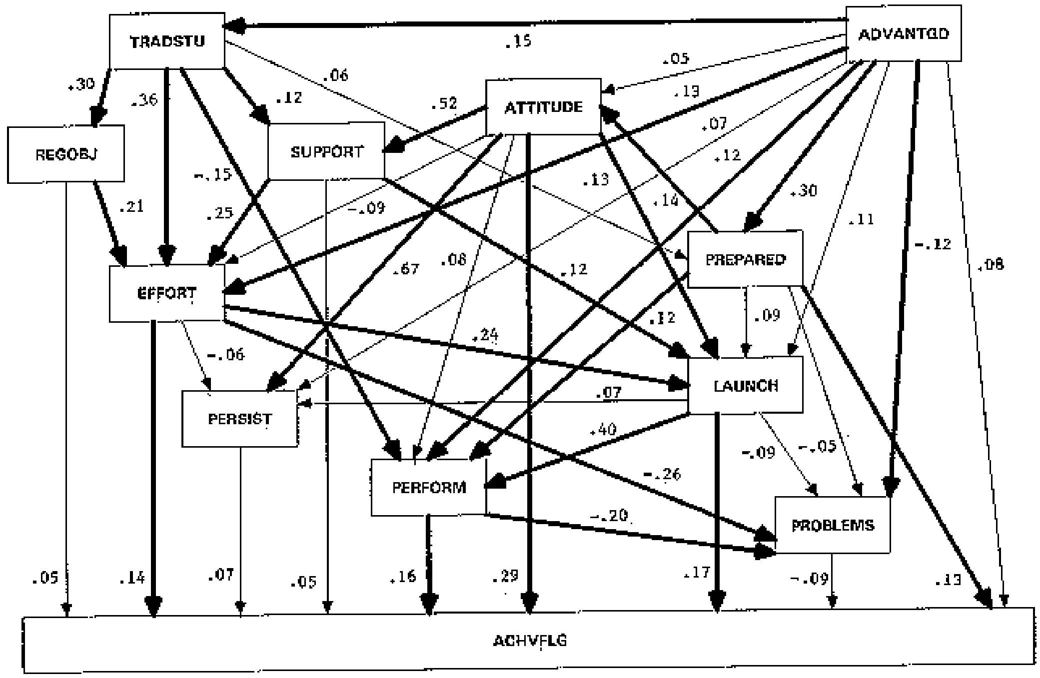

Figure 2. The Academic Achievement Causal Network

■ A central feature of the path diagram turned out to be the existence of two semi-independent "trails" (sequences of paths), of almost equal probability weight, leading to Achiever Classification. The first was the "*Effort Trail*" which linked the following in rough causal sequence: "traditional student" attributes (young, single, immediate from high school), transfer program orientation, level of institutional support, typical term study load, and attendance persistence (P_t=1.56). The second was a broad "*Performance Trail*" of student socio-educational attributes (race, social class, quality of high school experience), college preparation level and remedial need, early term survival and progress, course performance, and academic problem syndromes (P_t=1.58). These may be compared with the whole model path sum (7.06).

■ Another prominent feature of the path model was a busy junction of paths with study motivation level (ATTITUDE) at its center. Moderate-to-strong paths ran from it to Achiever Classification and to virtually all nodes along the Effort and Performance trails. The centrality of study motivation in student achievement, as represented by its strategic positioning in the model and its very high total probability weight (P_t=1.83), was perhaps the single most important finding of this study.[1]

[1]The central role played by personal attitude factors in academic performance was also the finding of another academic process path analysis, although method (survey research), and model elements (GPA as performance measure; multiple motivation variables) and base (four-year university students) differed significantly from ours.

■ Other key findings were the importance of early term survival and progress (LAUNCH), a prime node of the Performance Trail, and the significant role student services (SUPPORT) was shown playing in conditioning both Launch Period outcomes and study load (EFFORT). These two findings have major implications for academic policy.

■ Finally, in this brief review, we should mention how the model depicted the specific way student background variables operated in the overall causal network conditioning student outcomes. Past research on the correlates of academic achievement often found student background factors like race and socio-economic status as having little impact on college success. The path analysis model, however, suggests that these low achievement correlations may have been a methodological artifact—the restriction of the analysis to *direct effects*. Situated at the "head" of the Performance Trail, the factor scale summarizing various forms of socio-educational advantage (ADVANTGD) showed strongly *local* predictive power (P_t=1.13 with all impacted variables), especially affecting level of college preparation; and the measure of "traditional student" attributes (TRADSTU), beginning the Effort Trail, proved to have a good deal to do with program orientation, level of institutional support, and study load (P_t=.99).

Findings from Cluster Analysis. As already discussed, the last part of our research involved using cluster analysis to capture the actual study career patterns resulting from the academic process at PGCC. To assure that only student behavior would define career types, socio-educational background variables ADVANTGD and TRADSTU were dropped and data elements restricted to the 9 pure academic process factor scales. To these data we applied the *k-means* form of cluster analysis, which calculates the mathematically optimum case sort for a specified number of group breaks, and examined cluster solutions 5 through 15. The 10-fold solution was found best in satisfying our two key evaluation criteria—high realism of emergent student career types and high articulation of types with achievement level. The student career types were easy to interpret through an examination of the pattern of each cluster's defining mean factor scores, and to tag with summary characterizations in the form of cluster "nicknames."

Furthermore, the Eta^2 correlation[8] between student career type and achiever classification with the former as the predictor came in at a robust .381. Table 2, below, embodies the model. The table displays the 10 student career clusters, labeled by nickname, in percent Achiever order. The data columns display cluster means for the original 9 process variables used in the sort, indexed to the overall cohort averages to make cross-scale and cluster comparisons easier. Also shown are indexed cluster achievement tendencies by main classifier and achievement sub-types, plus indexed scores for TRADSTU and ADVANTGD to identify the socio-educational backgrounds predominating within each career type. The cluster model is rich in detail,[9] but again, space limitation permits only a general review:

[8]Eta^2 is the appropriate statistic for gauging how much of the variance of a two-category variable can be explained by placement within a typology; it is highly analogous to the R^2 statistic used in linear models like regression and causal path analysis.

[9]See Boughan (1997), for a full report of the cluster model.

Table 2. Student Career Clusters within Cohort 1990 (Achievement *Eta*^{2}=.381)

Factors	(Raw) COHORT	Student Career Clusters (Index Values) EXTRA EFFORT	SUPPORTED SCHOLARS	COLLEGIATES	TRUE GRIT	PRAGMA-TISTS	FULL-TIME STRUGGLE	PART-TIME STRUGGLE	VANISHERS	UNPREPARED	CASUALS
Cluster %	100.0	9.8	6.6	14.3	9.9	4.4	5.6	10.6	7.0	15.5	16.2
Cluster (N)	(2,386)	(233)	(158)	(342)	(236)	(106)	(134)	(254)	(168)	(369)	(386)
REGOBJ	*50.0*	110	113	126	109	63	100	58	115	98	92
PREPARED	*50.0*	120	119	129	114	79	91	90	105	30	127
LAUNCH	*50.0*	126	137	155	80	117	102	116	54	74	62
	50.0	174	132	87	154	83	109	106	68	68	63
ATTITUDE	*50.0*	93	222	86	91	88	210	81	82	81	75
SUPPORT	*50.0*	127	144	150	84	105	117	49	138	107	66
	50.0	162	117	92	159	99	107	125	64	73	50
EFFORT	*50.0*	126	131	130	94	131	87	126	125	61	61
PERSIST	*50.0*	58	71	67	137	57	170	120	61	140	97
PERFORM											
PROBLEMS											
ACHIEVER	31.2	242	219	212	139	97	79	56	36	3	2
Transfers	13.4	202	208	325	89	63	44	21	36	2	4
Awards	8.6	340	253	122	172	121	43	55	14	0	0
Trs. or Awds.	18.9	244	217	254	123	89	47	35	28	2	3
Soph Status	12.3	237	221	145	163	107	128	85	49	4	0
Continuing	9.8	118	52	54	264	67	132	177	55	66	29
Dropout	63.7	36	48	51	67	107	103	114	135	146	152
ADVANTD	*50.0*	126	90	121	94	108	64	102	106	75	102
TRADSTU	*50.0*	114	107	123	97	81	109	63	109	107	86

NOTE: In the Student Career columns, all figures are indexed group means (Index=100*(raw group mean/raw whole population mean)). In the Whole Cohort column, unitalicized figures are percentages of all cohort students in the variable criterion category; figures in italics (e.g. *50.0*) are transformed factor scale score means. In their original format, factor score whole population means are always 0, with scores below the mean indicated by negative numbers. This format does not permit indexing because indexing requires division by the population mean and mathematics forbids zero division. The transformation formula (Index=50+(20*cluster score mean)) resets the population factor mean to 50, with a constant multiplier (20) which has the effect of creating a factor score case range of between 0 and 100.

■ *High Achievement Clusters (60 % or more)*. Three student clusters registered high achievement levels. All had in common elevated group preparedness, academic goal, launch period success, course performance and study load scores, and low cumulative problem scores, but each distinguished itself in some salient fashion. The **Collegiate** cluster was special for its below-average PERSIST and ATTITUDE scores; it contained the highest concentration of full-time "traditional students" (the youngest and most straight-from-high-school group), most strongly favored transfer programs, especially in the Arts & Sciences, and had the highest transfer rate (especially early and without a degree). In contrast, **Extra Effort** students registered extreme PERSIST and ATTITUDE scores and exhibited strong *degree*-seeking behavior. While also inclined to be "traditional students," nevertheless many were a bit older, entered PGCC on a somewhat delayed basis, often took evening and extension center classes, and tended more to favor technical programs like computer programming and allied health. The PERSIST and ATTITUDE scores of the **Supported Scholars** fell somewhere between those of the first two. These were mostly strongly motivated African American "traditional students" from the middle socio-educational ranks, while Collegiates and Extra Effort students were mostly white and upper-middle class. Most notably, students with this academic career pattern were the likeliest of any to bolster their study success chances by participating in institutional support programs.

■ *High Medium Achievement Clusters (40-59%)*. At this level of achievement we found only one study career pattern—**True Grit**. Many in this essentially African American middle class cluster of older students, often part-timers taking evening classes, experienced significant problems with remedial programs and credit courses, but over two-fifths eventually became achievers through drive (second highest ATTITUDE score) and pluck (second highest PERSIST score).

■ *Average Achievement Clusters (20-39 %).* Two unlike clusters occupied this niche. The somewhat more successful **Pragmatists**, like True Grit students, tended to be middle class adult learners, but were predominantly white, much older, more part-time (fourth lowest EFFORT score), and more oriented to occupational courses and job-related goals (second lowest REGOBJ score). Most arrived at PGCC poorly prepared, but nevertheless did well academically as a group (tied for highest PERFORM score). Their only moderate group PERSIST score and 30 percent achievement rate may be related to a prevalence of short-term occupational objectives for attendance. In contrast, **Full-Time Strugglers** were mostly young working class African American full-time students straight from lower prestige high schools. These entered PGCC somewhat unprepared, exhibited only moderate drive and persistence, and then typically bogged down in the remediation process (highest group PROBLEMS score). Despite a strong tendency to avail themselves of support programs (second highest SUPPORT score), only around a quarter became Achievers by their last term.

■ *Low Achievement Clusters (Under 20%)*. Four disparate study career types were found in this category. **Part-Time Strugglers**, mostly African American, were fully-employed, delayed-entry, part-time students (lowest TRADSTU score) with clear job-related attendance objectives (lowest REGOBJ score). Below average college preparation, low study loads and high "stop-out" tendencies prevented any more than one in five becoming Achievers, despite high PERSIST scores (third best mean). **Vanishers**, on the other hand, were predominantly white, degree- and transfer-oriented full-time students with excellent initial course performance records. Nevertheless, most of them dropped out within a few terms (second lowest PERSIST score)—as if study had been cut short by some personal emergency like ill-health or financial collapse. Hardly more than one in ten made it into the Achiever category. Much less mysterious were the **Unpreparedss**, who arrived at PGCC with the greatest remediation needs of any cluster; most of the students in this working class African American group did not survive the first year of study (57 percent never earned a single credit hour), and less than 1 percent became Achievers. Lastly in this bottom achievement tier were the **Casuals**, mostly well-prepared, part-time students from middle and upper-middle class neighborhoods, many explicitly giving job and personal enrichment reasons for attending, who took very few courses and exerted little effort to get good grades in those they did take. Again, less than 1 percent became Achievers.

The cluster model taught three main lessons. First, our top performing students were *not* necessarily socially and educationally advantaged transfer-bound "traditional students" (the equivalent of the Collegiate cluster). Two other high success clusters emerged, one consisting mainly of evening students and the another of lower-middle class African Americans, both more oriented toward degree-seeking than transferring. Second, a goodly proportion of our cohort member actually fell outside the regular parameters of college study. Around 7 percent "vanished" in the midst of successful study careers, probably due to personal emergencies, and fully 16 percent proved to be "casual" course-takers, not serious about pursuing a degree or transfer. Third, another 16 percent (Unpreparedss) proved so unready for college work that they were beyond the best efforts of our developmental teachers and counselors to help in any real way. And fourth, among clusters with high concentrations of the socio-educationally disadvantaged, adult learners, part-time and job-oriented students, those who accomplished the most academically had in their study career profiles high scores on either level of personal motivation or level of financial/academic support receipt or both. Sheer attendance persistence, often present, did not seem to be enough.

Conclusions. Although works-in-progress, even in unfinished form our path and cluster analyses managed to yield many important if tentative findings. Path analysis revealed the critical importance of personal motivation and the Launch Period in conditioning achievement probabilities. And cluster analysis highlighted the inherent diversity of motives, needs and academic experiences within community college student bodies and the importance of taking student career differences seriously. Particularly gratifying to us is how these core findings validated the wisdom of recent steps taken by

Prince George's Community College to establish academic support programs which reach students early in their careers at PGCC, were designed to build confidence and esprit as well as develop academic skills, and which could be customized to reflect individual educational needs and objectives. On the research side, however, much work still needs to be done. In our future efforts, we intend to fill large gaps in the social and educational background data by carrying out entrant surveys of newly formed tracking cohorts, and to increase the richness and accuracy of our academic outcomes measure by means of exiter surveys.

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