Influence of self-regulated learning and parental education on post-secondary remediation

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ABSTRACT

This study examines the relationship between self-regulated learning (SRL), parent education, and the need to enroll in postsecondary remedial education courses, using first year college student data from the National Center for Education Statistics (NCES) Education Longitudinal Study of 2002 (ELS: 2002). This observational study was conducted using 6149 sample elements for first year college students, including 2296 sample elements for students who enrolled in at least one remedial course during their first year in college. Observable covariates for high school grade point average (GPA) and standardized test scores were used in a cluster analysis to assign sample elements to either the treatment or control group. Propensity score matching was used to address selection bias and imbalances in the sample data, with stratification on the estimated propensity scores to create equal-sized strata composed of treatment and control group elements with equivalent pretreatment characteristics. Logistic regression was used to predict the odds that a first year college student will need to enroll in at least one postsecondary remedial education course, based on observable covariates that represent self-regulatory behaviors, control of personal time, parental education, and demographic factors. After controlling for selection bias, self-regulatory behaviors were found to be highly correlated with enrollment in postsecondary remedial courses. The results indicate that self-regulatory behaviors, such as study habits and proactive control over use of personal time, and parent education are significant mediating factors between high school preparation and the need for postsecondary remediation.

Keywords: self-regulated learning, postsecondary remedial education, cluster analysis, propensity score analysis, logistic regression

INTRODUCTION

Postsecondary remedial education is a topic of national importance and concern that is being addressed by government officials, college administrators and academic researchers who are trying to develop strategies to reduce the negative effects of postsecondary remediation on degree completion rates, time to degree, and the overall cost of enrollment (Bailey, 2009; Bailey, Jeong and Cho, 2009; Howell, 2011; Melguizo, Hagedorn and Cypers, 2008; Tierney and Garcia, 2008). The annual cost to provide remedial courses at public postsecondary institutions was estimated to be a staggering $900 million to $1 billion in 1993-94, with approximately 29% of first year students in at least one remedial course (Breneman, 1998). By 2007-08, approximately 36% of first year students had taken at least one remedial course (US Dept. Education: NCES, 2010). The National Governors Association (NGA) Center for Best Practices released an issue brief in 2010 stating, “It is clear that more work needs to be done to [prepare high school graduates] for success in postsecondary education and training”.

Efforts to address postsecondary remediation mostly occur at the state level. State government entities, high schools, postsecondary institutions, and private foundations and have made efforts to respond to the remediation problem by working together to implement state level avoidance model intervention programs that are designed to reduce current levels of enrollment in remedial courses (Rutschow and Schneider, 2011). Avoidance model interventions are designed to reduce remediation by addressing deficiencies in targeted subject areas, but they are not intended to address deficiencies in basic study skills that impact academic performance in all subject areas (Bahr, 2010; Bailey, 2009). Students with severe deficiencies in basic study skills pose the greatest challenge to the success of postsecondary remediation programs (Bahr).Academics have expressed concerns about inconsistencies and structural flaws in the assessment models that are being used at the state level for institutional decisions on remediation, primarily due to a lack of consensus on the definition of college readiness (Bailey, 2009). Students who score close to the margins or cutoff scores on placement tests can alter the likelihood of being placed in remediation by simply choosing to attend a different institution, due to the previously noted inconsistencies in institutional guidelines on remediation (Bettinger and Long, 2009; Deli-Amen, 2011).

The NGA, the Council of Chief State School Officers (CCSSO) and the American Council on Education (ACE) jointly acknowledged the need for a defined set of Common Core State Standards (CCSS) for education, which will ensure that U.S. high school graduates are ready to succeed in entry-level college courses, without the need for postsecondary remediation (King, 2011). The CCSSO recommended the development of a system of interventions to assess college readiness earlier to allow sufficient time to help students reach basic levels of literacy, before they fail. The NGA, however, noted that efforts to address postsecondary remediation on a national basis have been hampered due to the lack of sufficient consistency across comparable institutions to reveal appropriately, and common points of intervention.

Academic studies have found mixed results from avoidance model interventions that have been implemented in different states (Karp, Calcagno, Hughes, Jeong and Bailey, 2007; Spence and Barnett, 2007). City University of New York and California State University have implemented early assessment programs that are strategically designed to reduce the need for remediation with assessment testing in the high school sophomore or junior years, for early identification of college readiness and time for early efforts at remediation before students apply for college (Hillard, 2011; Howell, Kurlaender and Grodsky, 2010).

Several states have initiated “Early College” programs that provide opportunities for dual enrollment in high school and college courses, with private support from organizations such as the Gates Foundation (Kim and Barnett, 2008). Texas implemented a summer bridge program of intensive remedial instruction at selected postsecondary institutions, to address identified deficiencies during the summer before high school graduates enroll in regular college courses (Wathington, Barnett and Pretlow, 2011).

Student success courses address and self-regulated learning deficiencies in basic study skills

Self-regulated learning (SRL) theory provides a research-based model with the potential to influence the design of student success programs in a way that will help students to improve their own basic study skills by encouraging them to strive toward self-defined academic goals. SRL is based on the premise that students can be taught to proactively set academic goals and self-monitor their progress toward meeting defined goals in a holistic manner (Zimmerman, 2002). Some institutions have implemented student success courses to address basic study skill deficiencies by including offerings such as note-taking, test-taking strategies and time management. The results of academic studies on student success courses in several states indicate that participants in student success courses are more likely to have positive academic outcomes, than similarly prepared students who do not participate in the courses (Zeidenberg, Jenkins and Calcagno, 2008; Cho, 2010). However, the studies also reveal inconsistencies in the content and outcome expectations of student success programs across institutions. The national focus on college readiness offers an opportunity to define a consistent model for basic study skills training in high school and postsecondary student success programs.

The results of numerous educational research studies have found positive relationships between SRL behavior and academic performance (Pintrich and De Groot, 1990; Orange, 1999; Bail, Zhang and Tachiyama, 2008; Bembenutty, 2008). The results from Pintrich and De Groot’s (1990) study indicates that students who are encouraged to become self-regulated learners will generally increase their cognitive engagement in the classroom and strive for higher academic performance. The theoretical grounding for this study is based on Pintrich and Zusho’s (2007) model for student motivation and SRL. Pintrich and Zusho’s model is focused on motivational strategies that encourage students to make behavioral choices which will result in positive outcomes. The model displayed in Table 1 in the appendix is based on four phases of self-regulated learning.

This study focuses on the effect on academic outcomes that result from the practice of SRL behaviors. This analysis is limited to “Phase Two-Acting” activities represented by SRL behaviors such as homework hours per week and “Phase Three-Control” activities which include self-directed efforts to control distractions in the learning environment, such as limiting the time spent on activities such as watching TV, playing video games or working for pay.

Purpose of the study and research questions

The purpose of this study is to determine whether the demonstrated level of SRL behaviors has an influence on the rate of postsecondary remediation. The following hypotheses form the research questions that guide this study:

1. Students who demonstrate higher than average levels of academic performance will have significantly lower than average rates of postsecondary remediation

2. Students who demonstrate higher than average levels of SRL behaviors will have significantly lower than average rates of postsecondary remediation
3. Parental education level will have a positive relationship with demonstrated levels of SRL behavior for high school students

METHOD

Study design

This study uses observational data from the National Center for Education Statistics (NCES) Educational Longitudinal Study of 2002 (ELS: 2002) in a quasi-experimental design (Shadish, Cook and Campbell, 2002) to examine the impact of self-regulated learning behaviors on the need for postsecondary remediation. The data are from a nationally representative sample of students who entered the 10th grade in 2002, with follow up interviews in 2004 and 2006. The analysis for this study is limited to data from students with English as their first language and active participation in the study during each of the survey waves. The unweighted sample size is 6149; 2296 are students who enrolled in at least one remedial course during their first year in a postsecondary institution.

Observable covariates for high school grade point average (GPA) and standardized test scores were used in a cluster analysis to assign sample elements to either the treatment or control group. Selection bias in the sample is addressed by using propensity score analysis (Rosenbaum and Rubin, 1983) where propensity score quintile break points were used to create five approximately equal strata, composed of treatment and control group elements with approximately equivalent pretreatment characteristics (Cochran, 1968; Rosenbaum and Rubin, 1984).

Propensity score matching was used to address selection bias and imbalances in the sample data, with stratification on the estimated propensity scores to create equal sized strata composed of treatment and control group elements with equivalent pretreatment characteristics. Logistic regression was used to predict the odds that a first year college student will need to enroll in at least one postsecondary remedial education course, based on observable covariates that represent self-regulatory behaviors, control of personal time, parental education, and demographic factors.

Treatment and control group assignment

For the purposes of this study, sample elements are assigned to treatment and control groups based on two observable covariates that represent high school GPA and standardized test scores. These covariates, high school grades and standardized test scores, are used in the scoring process for college admissions at most US four year postsecondary institutions and are recognized as reliable predictors of collegiate academic success (Camara and Echternacht, 2000; Korbin, Camara and Milewski, 2002; Cohn, Cohn, Balch & Bradley, 2004).

The treatment variable for this study is used as a proxy for high school preparation or college readiness. The high school preparation variable was created by using k-means cluster analysis, with transformed variables that represent the ELS: 2002 variables for high school GPA (F1RGPP2), standardized reading test scores (BYTXRSTD) and standardized math test scores (F1TXMSTD) as indicated in table 2 in the appendix.

It was necessary to create transformations of the original high school GPA and test score variables because the original variables are measured on different numeric scales. The natural disparity in the size of these numeric variables would compromise the reliability of the cluster analysis (Stoddard, 1979; Everitt, Landau and Leese, 2001). The problem of numeric disparity was addressed by using mean standardization (equation 1) to rescale each of the variables. Traditionally, z-score standardization is often used to reduce the influence from differences in numeric scales. However, z-score standardization reduces the variability within rescaled variables. Rescaling by mean standardization reduces the influence of scale differences due to numeric disparity, but retains the significant variability within each variable (Moisl, 2010).

$$v_{MEANstd} = \frac{v}{\mu_v} \qquad (1)$$

The k-means clustering algorithm, that was used to assign students to the treatment and control groups, determines group membership by minimizing the sum of the squared Euclidean distances between individuals and their group means (Hartigan, 1975; Everitt, et al., 2001). Equation (2), is the Euclidean distance formula used in the clustering algorithm, where g =2 for the number of groups, n is the number of individuals, and $d_{ml,mv}$ is the Euclidean distance between the lth and vth individual in the mth group.

$$E = \sum_{m=1}^{g} \frac{1}{2n_m} \sum_{l=1}^{n_m} \sum_{v=1, v \neq l}^{n_m} d_{ml,mv}^2 \qquad (2)$$

The results of the cluster analysis assigned 3634 students to the treatment group and 2515 students to the control group. Table 3 in the appendix, shows descriptive statistics for the standardized variables that were used to determine group assignment and descriptive statistics for the original variables. Students with the highest academic performance measures were assigned to the treatment group.

Selection bias due to non-random assignment to treatment and control groups

The non-random assignment of observational sample elements to the treatment and control groups can result in biased estimates of treatment effects (Salzberg, 1999; Schneider, Carnoy, Kilpatrick, Schmidt, and Shavelson, 2007). The presence of selection bias in this sample was determined based on an analysis of the balance between treatment and control groups on selected covariates. The covariate selection was based on a review of the literature related to associations between SRL behaviors, demographics, and college readiness for first year college students (Pintrich et al. 1990; Orange, 1999; Bail et al. 2008; Bembenutty, 2008).

Table 4 in the appendix, displays the results of chi-square based Cramer's *V* measures of the associations between treatment assignment and the observed covariates. The null hypothesis of independence between treatment assignment and observed covariates can be rejected, based on the *p* values for each of the selected covariates. The lack of independence indicates imbalances on the selected covariates, which indicates the presence of selection bias in the observational data sample.

Propensity score matching and stratification to address selection bias

Propensity score matching was the method used to address the problem of selection bias in the sample. Logistic regression was used to estimate the propensity score as indicated in table 5 the appendix, for each individual student i (i=1, …, N), as the conditional probability of assignment to the treatment group ($Z_i = 1$), based on the selected covariates, x_i :

$e(x_i) = pr(Z_i = 1 | X_i = x_i)$ (Rosenbaum and Rubin, 1983). As mentioned above, the covariates used in the regression model were selected based on a review of the literature on previously identified associations between SRL behaviors, demographics, and college readiness for first year college students.

The sample population was divided into five strata of approximately equal size, using quintile break points on the estimated propensity scores as indicated in table 6 in the appendix. Prior studies on propensity score stratification have found that five strata are generally sufficient to remove over 90% of the bias from covariates used in an observational study (Cochran, 1968; Rosenbaum and Rubin, 1984). Table 6 displays descriptive statistics for the propensity score estimates within each of the five stratum.

A loglinear main effects model was developed for each covariate to examine the relationship between the covariate and the treatment assignment, based on an analysis of standardized residuals. The difference between the standardized residuals (SR) for the treatment (T) and control (C) groups was used to estimate the sample bias (SB) for each covariate, where $n_{ij} =$ observed frequencies and $\hat{m}_{ij} =$ expected values.

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$$SB = SR^T - SR^C \;;\; SR_{ij} = \frac{n_{ij} - \hat{m}_{ij}}{\sqrt{\hat{m}_{ij}}} \qquad (3)$$

The sample bias estimate for each stratum (SB_s) was calculated based on the difference between standardized residuals for the within strata treatment and control groups. The SB_s where *s= 1 ,…, 5*), were used to produce an estimated average sample bias (ASB) for the five strata, weighted by the percentage of the total sample (*N*) represented by the sample elements in each stratum (n_s).

$$ASB = \sum_{s=1}^{5} \frac{n_s}{N} SB_s \qquad (4)$$

Table 7, as indicated in the appendix, displays bias estimates for the total sample, average bias for the five strata and the estimated bias reduction after stratification. The results indicate that a five strata subclassification on the propensity score was sufficient to reduce over 90% of the bias for the observed covariates in this sample.

Estimation of average treatment effect on outcome

Students who attended at least one postsecondary remedial course are identified in the sample by using the ELS: 2002 variable F2PS1REM, as the binary outcome variable. Let Y represent the outcome variable, which identifies whether or not a student enrolled in a postsecondary remedial course. The analysis is designed to predict the odds that a student will not need remediation. Let Y_{ti} represent the outcome for an individual student in the treatment group and Y_{ci} represent the outcome for a student in the control group. In theory, the causal effect of the treatment on the outcome for an individual student would be: $\delta_i = Y_{ti} - Y_{ci}$. However, it is not possible to estimate individual causal effects because it is not possible to simultaneously observe both treatment and control states for individual sample elements in a cross-sectional dataset, but the average treatment effect (ATE) on the outcome for the sample population can be estimated: $\overline{\delta} = \overline{Y}_t - \overline{Y}_c$.

The Assumptions for unbiased estimation of the average treatment effect was stratified as follows:

a. The stable unit treatment value assumption (SUTVA), which requires that the treatment status of one sample element does not affect the potential outcome of other sample elements (Rubin, 1986), was satisfied because the treatment assignment for each individual sample element has no influence on the status of other sample elements.
b. The assumption that every sample element has a non-zero probability of assignment to the treatment or control group was satisfied by estimating a propensity score, with a value greater than zero and less than one, for each element in the sample (Rosenbaum and Rubin, 1983).
c. The assumption that the treatment must be manipulable was satisfied by allowing each sample element to be assigned to either the treatment or control group, based on pre-treatment characteristics (Holland, 1986).
d. The assumption of strongly ignorable treatment assignment was satisfied, based on the conditional independence of the treatment assignment and the response (Steiner, Cook, Shadish, and Clark, 2010).

RESULTS

The average treatment effect was calculated by estimating the difference between the effects of the treatment and control groups on the outcome, which is the percentage of students who did not enroll in postsecondary remedial courses. Table 8, as indicated in the appendix, shows the estimates ATE is for each stratum and the stratification adjusted ATE for the total sample. The total sample ATE is calculated using the weighted average of the differences between treatment ($\bar{Y}_{ts}$) and control ($\bar{Y}_{cs}$) groups on the probability of postsecondary remedial course enrollment. The total sample percentages of students who did not enroll in postsecondary remedial courses are $\bar{Y}_t$ = .668 for the treatment group and $\bar{Y}_c$ = .479 for the control group. The estimated total sample ATE is .016 with standard error of the estimate $\hat{s}(\hat{\delta}) = 0.002$, where s_{ts}^2 and s_{cs}^2 are the sample variance estimates for the treatment and control groups, respectively.

$$\hat{\delta} = \sum_{s=1}^{5} \frac{n_s}{N}(\bar{Y}_{ts} - \bar{Y}_{cs}) \tag{5}$$

$$\hat{s}(\hat{\delta}) = \sqrt{\sum_{s=1}^{5} \frac{n_s^2}{N^2}\left(\frac{s_{ts}^2}{n_{ts}} + \frac{s_{cs}^2}{n_{cs}}\right)} \tag{6}$$

Significance test for the effect of high school preparation on the need for remediation

In order to test the significance of the treatment effect (high school preparation for college) on the need for remediation, a logit loglinear model was developed for each stratum, using remedial course enrollment as the dependent variable and the treatment variable as the independent variable. A similar logit loglinear model was developed for the stratification adjusted total sample using remedial course enrollment as the dependent variable, with the treatment variable as the first independent variable and propensity score stratification (*S*) as the second independent variable. The predicted log odds of a student who received the treatment and did not enroll in a remedial course is $\lambda^{Treatment-NoRemediation}$ = 0.788, with *p value* = 0.000. This translates to an odds ratio of 2.198, which is interpreted as a student who received the treatment (high school preparation for college work) is 2.2 times more likely to not need remediation, than a student in the control group. Table 9, in the appendix, shows the stratum level mean propensity scores, parameter estimates and odds ratios for students in each stratum treatment group. The model results provide evidence to support hypothesis 1, which states that students who demonstrate higher than average levels of academic performance will have significantly lower than average rates of post-secondary remediation.

Effect size and power estimates for differences between proportions

An arcsine transformation (equation 7) was applied to provide a scale to detect differences between proportions when calculating the effect size (*h*) for the stratification adjusted difference in outcomes between the treatment and control group (Cohen, 1988). The estimated effect size is *h* = 0.385, where $\phi_1 = 1.914$ and $\phi_2 = 1.529$.

$$h = |\phi_1 - \phi_2| \text{ , where } \phi = 2\arcsin\sqrt{P} \qquad (7)$$

Power estimates (equation 8) for the difference between proportions of unequal size are calculated using a harmonic mean adjusted sample size (Cohen, 1988). The adjusted sample size for power estimation is $n' = 2972.7$, using proportion sample sizes of $n_1 = 3634$ and $n_2 = 2515$. The power of the test, with effect size $h = 0.3852$ and adjusted sample size $n' = 2972.7$, exceeds 0.995 at $\alpha = .01$.

$$n' = \frac{2n_1n_2}{n_1 + n_2} \qquad (8)$$

Examining the influence of SRL behavioral factors on academic performance

The results from the logistic regression model displayed in Table 5, in the appendix, are consistent with the literature on the influence on academic performance from factors that represent SRL behaviors and distractions. The influence of homework on academic performance has been clearly established in previous studies of self-regulated learning practices (Kitsantas and Zimmerman, 2009; Bembenutty, 2011; Ramdass and Zimmerman, 2011). Increases in homework hours result in positive contributions to academic performance. Increases in time spent on distractions from study, such as television and videos, can result in negative contributions to academic performance (Cool, Yarbrough, Patton and Runde, 1994). Time spent on video games has less influence on academic performance than time spent viewing television or recorded videos. Previous studies have found positive outcomes for high school students from part-time employment, but excessive hours of work for pay have been found to result in negative contributions to academic performance (Oettinger, 1999; Roisman, 2002; Singh, Chang and Dika, 2007).

Chart 1, in the appendix, shows the relationship between postsecondary remediation and SRL behaviors within the structure of the propensity score stratification. The propensity score stratification provides a framework that clearly displays the influence of SRL factors on the need for postsecondary remediation measured by the propensity score, within levels of academic performance. The chart shows an ordered progression from high to low on the rate of postsecondary remediation and low to high on demonstrated SRL behaviors. Stratum 1 has the highest rate of postsecondary remediation and the lowest levels of demonstrated SRL behaviors. Stratum 5 has the lowest rate of postsecondary remediation and the highest levels of demonstrated SRL behaviors.

Association of SRL behavior with need for remediation

The independent samples t-test results as indicated in Table 10 in the appendix show that SRL behaviors for students who enrolled in postsecondary remedial courses differ significantly from students who did not enroll in remedial courses.

Predicted odds of needing postsecondary remediation based on SRL behaviors

Demonstrated hours per week for selected SRL behaviors were used as predictor variables in a logistic regression model to estimate the odds of a student needing postsecondary remediation. The model results displayed in Table 11 indicate that students who indulged excessively in entertainment distractions or worked excessive hours are more likely to increase their odds of needing postsecondary remediation, while students who spend more time on homework are less likely to need remediation. Students spending 4 to 12 hours per week on homework were over 35% less likely to need postsecondary remediation. Students spending more than 12 hours per week on homework were over 50% less likely to need postsecondary remediation. Students spending over 3 hours per day watching TV or recorded videos were over 35% more likely to need postsecondary remediation. Students spending 16 hours or more per week working for pay were over 20% more likely to need postsecondary remediation. The results for hours spent playing video games were inconclusive. The logistic regression results provide evidence to support hypothesis 2 as dictated in table 11 appendix, which states that students who demonstrate higher than average levels of SRL behaviors will have significantly lower than average rates of postsecondary remediation.

The descriptive statistics shown in Table 12 in the appendix indicate that high school academic performance and SRL behaviors rise with increasing levels of parental education, while the rate of postsecondary remediation decreases with increasing levels of parental education. The rate of postsecondary remediation is significantly lower for households with educated parents when compared to households with some college experience or less. Table 13, in the appendix, displays t-test results which indicate that demonstrated levels of SRL behaviors of students differ significantly between households based on the education level of parents in the households.

DISCUSSION

The results of this study provide evidence to support all three hypotheses: 1. Students who demonstrate higher than average levels of academic performance will have significantly lower than average rates of postsecondary remediation. The results of the propensity score stratification provided evidence that the lowest stratum of representing low academic performance had the highest rate of postsecondary remediation whereas the higher stratum representing higher academic performance had a lower rate of postsecondary remediation. This result is very logical; students employing self-regulatory behaviors such as, effective study skills, good attitude, high motivation and high self-efficacy understandably enjoy the benefits of better academic performance.

T-test results support hypothesis 2 that students who demonstrate higher than average levels of self-regulatory behaviors will have significantly lower than average rates of postsecondary remediation. In comparison, students who enrolled in postsecondary remedial courses spent fewer hours per week on homework, more hours per week watching TV, or other video media, and more hours per week working for pay than students who did not enroll in postsecondary remedial courses. There were no significant differences between comparison groups on hours playing video games.

The independent samples t-test results also provide evidence to support hypothesis 3, that Parental education level will have a positive relationship with demonstrated levels of SRL behavior for high school student. The level of demonstrated SRL behaviors can be predictive of college readiness. Parental education has been described as a primary determinant of parental involvement in academic preparation and goal setting for high school students (Crosnoe, 2001). Parental involvement provides opportunities for parents to instruct students in the use of self-regulatory behaviors (Zimmerman, 2002). The quality of parental assistance to students is directly related to family background variables, such as parental education level (Dumont, H, Trautwein, U., Ludtke, O., Neumann, M., Niggli, A. & Schnyder, I., 2012). Previous studies have found that students from college educated households are more likely to be prepared for the academic challenges of college work, than first generation college students (Hahs-Vaughn, 2004).

Transitioning from secondary to college requires a different set of skills. The answers to why parent education is such a mediating factor in acquiring the necessary skills perhaps lies in the social capital provided by degreed parents. A definition of social capital might be to provide a support network that is moral, educational, and financial such as income support that parents with degrees are more likely to be in a position to provide. Parent education can influence college student aspirations and successful outcomes. Their encouragement and involvement can enhance college-related outcomes.

According to Wells & Lynch (2012), delayed college entry decreases the likelihood of staying in college to complete a degree. Wartman & Savage (2008) proposes that parents' educational level has significant influence on first-generation college students. A form of social capital is when parents take time to filter their children's friends and associates, encouraging them to keep friends that have similar values. Culture and peers also impact the student's decision to go to college.

College-educated parents can help students choose appropriate courses in high school, learn self-regulatory behaviors such as: to manage their time, to obtain appropriate study skills, and to learn how to organize themselves. As students are encouraged to take college preparatory courses, this enhances their social and cultural capital by increasing their access to students who have college pursuits and their knowledge of the college planning process (Gregory & Huang, 2013). College-educated parents offer encouragement that enhances student self-efficacy. They also help mediate stressful high school and college situations; they communicate the importance of having a degree. Parents that have a college education are more likely to help their children to understand that the bachelor's degree is the first step toward social acceptance, upward mobility and professional status.

Degreed parents note that getting a degree also provides an income that can sustain the student for life. Understandably, they push their students to attain a bachelor's degree at minimum. College-educated parents are likely to research schools that have the best retention and graduation rates, which will minimize the need for remediation. They are more likely to pay for preparation courses for standardized tests, such as the SAT and the ACT, to assure their students an opportunity to go to the college of their choice. These parents are also likely to do a better job of helping their students with their college applications and to explore colleges. Degreed parents often push the importance of GPA and rank throughout high school to prepare the student for college. These parents are vigilant about student college selection to avoid the consequences of poor choices, and undermatching. Hurwitz, Howell, Smith & Pender (2012) stressed the importance of finding a college that is academically aligned with the student's abilities and ambitions.

The presence of college educated parents is an influential factor in determining study habits and college readiness of high school students, but every student will not have this advantage. Bailey & Dynaski (2011) argue that inequities in competition may be a result of ineffective or an adequate social capital. Inadequate capital may include self-regulatory behaviors and skills. In the absence of college-educated parents and the social capital they provide, formal training in self-regulated learning can produce similar outcomes by serving as a source of guidance to improve study habits and college readiness.

Universities can help parents understand the resources available on campus to enhance the parental support process. All parents, with or without college degrees, should encourage their children to utilize support services, especially career counseling on campus. A study of 151 undergraduate nursing students highlighted that parental support and career counseling, during the first year of college, enhanced persistence for eighteen months beyond the middle of the first year (Restubog, Florentino, & Garcia, 2010).

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APPENDIX

Table 1. Four phases of self-regulated learning

Phase One	Phase Two	Phase Three	Phase Four
Forethought	Monitoring	Control	Reaction
Planning	Acting	Acting	Reflection
Activation			

Table 2: High school academic performance variables

	Original sample variables		Mean standardized	
ELS: 2002 Variables	**Mean**	**SD**	**Mean**	**SD**
High school GPA (F1RGPP2)	3.019	0.651	1.000	0.216
Reading test score (BYTXRSTD)	54.432	8.818	1.000	0.162
Math test score (F1TXMSTD)	53.704	8.953	1.000	0.167

Table 3: Standardized and original variables by group assignment

	Treatment Group		Control Group	
	Mean	**SD**	**Mean**	**SD**
Standardized variables				
High School GPA	1.131	0.118	0.810	0.181
Reading test score	1.083	0.124	0.881	0.133
Math test score	1.093	0.121	0.865	0.127
Original variables				
High School GPA	3.415	0.356	2.447	0.545
Reading test score	58.93	6.753	47.93	7.256
Math test score	58.72	6.499	46.46	6.800
n =	3634		2515	

Table 4: Associations between treatment assignment and observed covariates

ELS:2002 Variables		**Cramer's *V***	***p* value**
F1S31	Homework hours per week	0.262	0.000
F1S34A	TV/Video/DVD hours per day on weekdays	0.196	0.000
F1S35A	Video game hours per day on week-days	0.119	0.000
F1S60	Work hours per week during school year	0.203	0.000
F1PARED	Parent's highest level of education	0.246	0.000
F1RACE	Race/Ethnicity	0.291	0.000
F1SEX	Gender	0.030	0.017

Note: Treatment group: n = 3634; Control group: n = 2515

Table 5: Logistic regression model results for propensity score estimates

		N	**B**	**S. E.**	**Exp(β)**	***p-value***
	Constant		.324	.132	1.382	.000
Homework hrs per week	Over 12 hrs week	813	1.309	.105	3.702	.000
	4 to 12 hrs week	3216	.744	.062	2.104	.000
	Less than 4 hrs week	2120				
TV/Video hrs per day (weekdays)	Over 3 hrs day	1421	-.631	.087	.532	.000
	1 to 3 hrs day	3174	-.293	.073	.746	.000
	Less than 1 hr day	1554				
Gaming hrs per day (weekdays)	Over 2 hrs day	597	-.217	.109	.805	.047
	1 to 2 hrs day	2157	-.041	.069	.960	.554
	None	3395				
Work hrs per week	Over 20 hrs	1647	-.703	.099	.495	.000
	16 to 20 hrs	1158	-.521	.105	.594	.000
	11 to 15 hrs	1012	-.260	.109	.771	.017
	1 to 10 hrs	1481	.032	.103	.968	.756
	None	851				
Parental Education	Advanced Degree	1491	1.061	.097	2.392	.000
	College Graduate	1696	.563	.089	1.474	.000
	2yr-4yr College Experience	1994	.261	.085	1.098	.002
	High School Grad or Less	968				
Race/ Ethnicity	American Indian/Alaskan Native	35	-1.264	.384	.283	.001

	Asian, Hawaii/Pacific Islander	218	-.103	.161	.902	.522
	African American	680	-1.667	.103	.189	.000
	Hispanic	376	-.885	.117	.413	.000
	More than one race	250	-.463	.140	.629	.001
	White	4590				
Gender	Male	2800	-.037	.066	.963	.573
	Female	3349				

Table 6: Descriptive statistics for propensity score estimates within strata

	N	Minimum	Maximum	Mean	SD
Observational Sample	6149	0.0524	0.9367	0.5910	0.2145
Stratum 1	1229	0.0524	0.3926	0.2571	0.0959
Stratum 2	1260	0.3926	0.5631	0.4856	0.0493
Stratum 3	1209	0.5632	0.6800	0.6248	0.0356
Stratum 4	1234	0.6800	0.7883	0.7379	0.0329
Stratum 5	1217	0.7884	0.9367	0.8547	0.0395

Table 7: Bias reduction after stratification on propensity scores

	SB	ASB	Bias reduction
Homework hrs per week	15.113	0.392	0.974
TV/Video hrs per day	-7.167	-0.176	0.975
Gaming hrs per day	-5.490	-0.080	0.985
Work hrs per week	-3.545	-0.130	0.963
Parental education	16.060	0.415	0.974
Race/Ethnicity	-25.541	-1.150	0.955
Gender	-2.478	-0.168	0.932

Table 8: Estimated mean values and ATE on outcome

	Treatment Group			Control Group			Estimated ATE		
	μ	SE	N	μ	SE	N	ATE	SE	N
Stratum 1	.292	0.004	326	.245	0.003	903	.048	0.010	1229
Stratum 2	.490	0.002	612	.481	0.002	648	.009	0.002	1260
Stratum 3	.627	0.001	740	.621	0.002	469	.006	0.001	1209
Stratum 4	.738	0.001	900	.737	0.002	334	.002	0.000	1234
Stratum 5	.857	0.001	1056	.839	0.003	161	.019	0.004	1217
Strata Average	.668	0.001	3634	.479	0.001	2515	.016	0.002	6149

Table 9: Treatment group odds on need for postsecondary remediation

	Propensity Score (μ)	Parameter Estimate (λ)	SE	p-value	Odds Ratio
Stratum 1	0.2571	1.067	0.142	0.000	2.907
Stratum 2	0.4856	0.676	0.116	0.000	1.966
Stratum 3	0.6248	0.727	0.122	0.000	2.069
Stratum 4	0.7379	0.673	0.132	0.000	1.960
Stratum 5	0.8547	0.912	0.172	0.000	2.489
Strata Average	0.5910	0.788	0.059	0.000	2.198

Chart 1: Postsecondary remediation within propensity score stratification levels

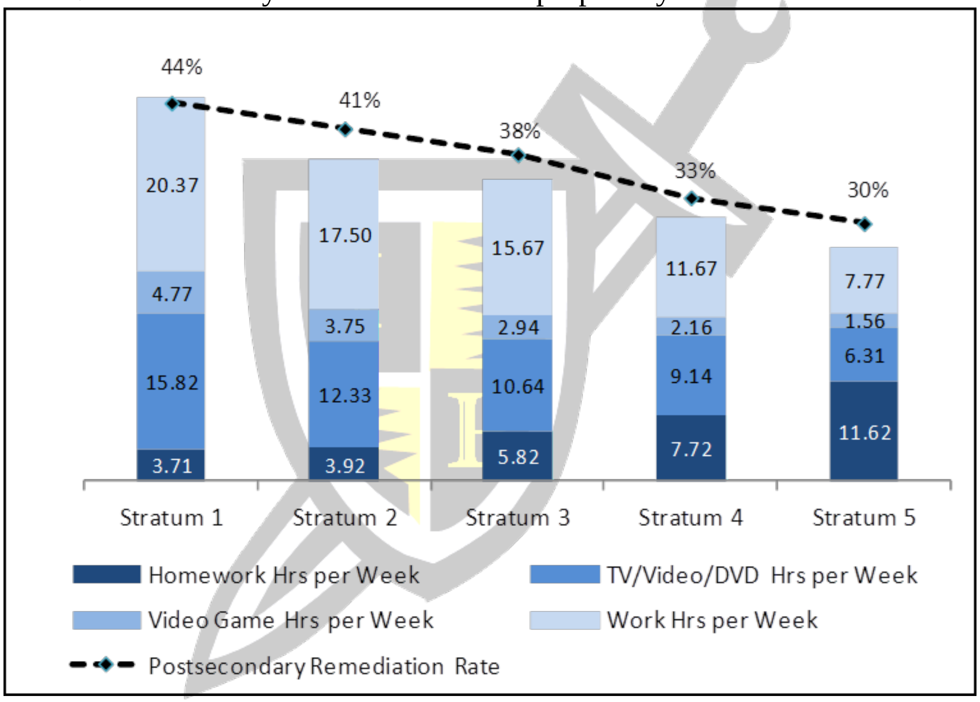

Table 10: Demonstrated SRL behavior grouped by postsecondary remediation

	Postsecondary Remediation		**No Postsecondary Remediation**				
	μ	**SE**	**μ**	**SE**	**t value**	**df**	**Sig.**
Homework hrs per week	5.990	0.109	6.865	0.089	6.228	5033	0.000
TV/Video/DVD hrs per Week	11.493	0.165	10.490	0.122	4.89	4648	0.000
Video Game Hrs per week\	3.190	0.117	2.954	0.084	1.637	4553	0.102

Work hrs per week	15.066	0.223	0.144	0.173	2.532	4841	0.011
n=	*2296*		*3853*				

Table 11: Logistic regression model results for odds of postsecondary remediation

		N	B	S. E.	Exp(β)	*p-value*
	Constant		.576	.100	1.780	.000
Homework hrs per week	Over 12 hrs week	813	.437	.089	1.548	.000
	4 to 12 hrs week	3216	.314	.058	1.369	.000
	Less than 4 hrs week	2120				
TV/Video hrs per day (weekdays)	Over 3 hrs day	1421	-.313	.078	.731	.000
	1 to 3 hrs day	3174	-.106	.066	.899	.108
	Less than 1 hr day	1554				
Gaming hrs per day (weekdays)	Over 2 hrs day	597	.095	.095	1.099	.317
	1 to 2 hrs day	2157	.008	.058	1.008	.887
	None	3395				
Work hrs per week	Over 20 hrs	1647	-.215	.090	.806	.016
	16 to 20 hrs	1158	-.197	.095	.821	.039
	11 to 15 hrs	1012	-.141	.099	.869	.154
	1 to 10 hrs	1481	.172	.091	.842	.059
	None	851				

Table 12: Academic performance, SRL behavior and postsecondary remediation

	Parental Education							
	High School or Less		**College Experience**		**4 Yr College Graduate**		**Advanced Degree**	
	μ	**SE**	**μ**	**SE**	**μ**	**SE**	**μ**	**SE**
High school GPA	2.87	.02	2.91	.02	3.07	.01	3.20	.02
Reading test scores	50.83	.27	52.97	.19	55.24	.21	57.80	.22
Math test scores	49.65	.27	51.89	.19	54.73	.21	57.60	.22
Homework hrs per week	5.36	.15	5.86	.11	6.73	.13	8.00	.15
TV/Video/DVD hrs per week	12.10	.26	11.50	.18	10.53	.18	9.59	.19
Video game hrs per week	3.45	.19	3.29	.13	2.97	.13	2.52	.12
Work hrs per week	17.08	.35	16.07	.24	13.73	.25	12.09	.27

Postsecondary remediation	44 %	40%	35%	32%
n=	*968*	*1994*	*1696*	*1491*

Table13: Demonstrated SRL behaviors grouped by parental education

	Non-College Graduate		**College Graduate**				
	µ	**SE**	**µ**	**SE**	**t value**	**df**	**Sig.**
Homework hrs per week	5.694	0.092	7.324	0.101	11.982	6126	0.000
TV/Video/DVD hrs per week	11.697	0.146	10.091	0.131	8.190	6030	0.000
Video Game hrs per week	3.345	0.104	2.760	0.090	4.238	5949	0.000
Work hrs per week	16.399	0.197	12.962	0.186	12.697	6094	0.000
n=	*2962*		*3187*				

Table 14. Frequency and percentage values of the sample

Department	**N**	**%**
Psychological Counseling and Guidance	26	11,4
Geography	38	16,6
Turkish Language and Literature	40	17,5
Mathematics	41	17,9
History	42	18,3
Philosophy	42	18,3
Total	229	100,0