Evidence Based Library and Information Practice

Research Article

Embracing the Generalized Propensity Score Method: Measuring the Effect of Library Usage on First-Time-In-College Student Academic Success

Jingying Mao
Department of Statistics
Florida State University
Tallahassee, Florida, United States of America
Email: mjy_jean@hotmail.com

Kirsten Kinsley
Assessment Librarian
Florida State University Libraries
Tallahassee, Florida, United States of America
Email: kkinsley@fsu.edu

Received: 2 Aug. 2017 **Accepted**: 9 Nov. 2017

Abstract

Objective – This research focuses on First-Time-in-College (FTIC) student library usage during the first academic year as number of visits (frequency) and length of stay (duration) and how that might affect first-term grade point average (GPA) and first-year retention using the generalized propensity score (GPS). We also want to demonstrate that GPS is a proper tool that researchers in libraries can use to make causal inferences about the effects of library usage on student academic success outcomes in observation studies.

Methods – The sample for this study includes 6,380 FTIC students who matriculated in the fall 2014 and fall 2015 semesters at a large southeastern university. Students' library usage (frequency and duration), background characteristics, and academic records were collected. The Generalized Propensity Score method was used to estimate the effects of frequency and duration of FTIC library visits. This method minimizes self-selection bias and allows researchers to control for demographic, pre-college, and collegiate variables. Four dose-response functions were estimated for each treatment (frequency and duration) and outcome variable (GPA and retention).

Results – The estimated dose-response function plots for first-term GPA and first-year retention rate have similar shapes, which initially decrease to the minimum values then gradually increase as the treatment level increases. Specifically, the estimated average first-term GPA is minimized when the FTIC student only visits the library three times or spends one hour in the library during his/her first semester. The threshold for first-year retention occurs when students visit the library 15 times or spend 21 hours in the library during their first semester. After those thresholds, an increase in students' library usage is related to an increase in their academic success.

Conclusions – The generalized propensity score method gives the library researcher a scientifically rigorous methodological means to make causal inferences in an observational study (Imai & van Dyk, 2004). Using this methodological approach demonstrates that increasing library usage is likely to increase FTIC students' first-term GPA and first-year retention rates past a certain threshold of frequency and duration.

Introduction

The collegiate experience often includes a diversity of opportunities and experiences to foster student development and engagement affecting the retention and academic success of the first-time-in-college (FTIC) student. According to Astin's Input-Environment-Output (I-E-O) Model of Student Involvement, student inputs—such as high school grade point average (GPA), ACT scores, and gender—are often associated predictors of first-year student success outputs (or outcomes), such as grades and retention (Strauss, 2014; Astin, 1997). The collegiate environment, including a student's major, enrolled credit hours, involvement in athletics, living in learning communities, and employment is also an important influence on student outputs. Another potential environmental factor that may affect student success outputs is time spent in the library.

The research study presented in this article attempts to isolate the treatment variables of number of library visits (frequency) and total hours of stay (duration) during the first year of college while controlling for other potential predictors of college success, such as student input and other collegiate environmental variables, by measuring the effects of frequency and duration of library visits on retention and GPA. Since randomizing a control group of students who do not use the library and those who do is ethically impossible, how do we measure FTIC students' success and the effects of library usage while also controlling for student inputs and other non-library environmental impacts?

We decided to apply the generalized propensity score (GPS) method for a number of reasons. Using GPS in addition to the I-E-O design gives a more rigorous approach to measuring library impact on student academic success because we attempt to control for as many inputs and other environmental collegiate variables as possible. In addition, it allows us to "make causal inferences from correlational data" and to "minimize the chances that our inferences are wrong" (Astin & Antonio, 2012, p. 31). As Astin & Antonio (2012) emphatically state, "Although we can never be sure that we have controlled all such variables, the more we control, the greater confidence we can have in our causal inferences" (p. 31). Furthermore, using the GPS method reduces the effects of self-selection bias (Astin & Antonio, 2012, p. 31). The bias may be caused because students who have certain characteristics, such as higher ACT scores and higher high school GPA, may self-select to use the library frequently and for long durations. This may cause an overestimation of the treatment effect of library usage. GPS also allows us to measure the effect of continuous library usage variables over time by frequency and duration. Moreover, we can predict that with each treatment or dose of library time, retention and GPA for FTIC students will increase. If more library visits and duration of stay are related to increasing retention rates and higher grades, we will have more confidence to say that as library visits increase so do the student success variables of first-year retention and GPA.

Literature Review

According to Astin's Input-Environment-Output (I-E-O) Model of Student Involvement (1970, 1990, 1993), both student inputs and the college environment influence student outputs (arrows B and C on Figure 1). (Please note: The terms output and outcomes will be used interchangeably throughout this paper as they relate to Astin's theory, even though outputs are typically defined differently than outcomes.) At the same time, student inputs (arrow A on Figure 1) affect how students experience the college environment.

According to the model, input variables such as pre-college high school grades and college entrance exam scores (e.g., SAT scores) collectively impact whether a student succeeds in college. Higher education research has been exploring the environmental and engagement variables that contribute to student academic success or outputs. These variables may includes student engagement, investment in "educationally purposeful activities" (Kuh, 2001, p. 12), involvement in student organizations, social interactions, and engagement with faculty (Braxton, Hirschy, & McClendon, 2004; Kuh, Cruce, Shoup, Kinzie, & Gonyea, 2008; Roksa & Whitley, 2017). "Without knowing how students spend their time, it's almost impossible to link student learning outcomes to the educational activities and processes associated with them" (Kuh, 2001, p. 15).

Librarians who research what factors the library contributes to student success would benefit from applying Astin's Model since it offers a practical, holistic theoretical approach to looking at the interaction between student attributes and their environment and can easily incorporate library activities as part of the environmental variables. It acknowledges what academic librarians already know—that "many other factors besides the library contribute to students' academic success . . ." (Jantii & Cox, 2012, p. 4). Even so, libraries provide many services and resources that help to engage students in "educationally purposeful activities" that contribute to student success. "Students engage in a wider variety of interactions with their libraries and it is important to examine the differences those interactions can have on student outcomes" (Soria, Fransen, & Nackerud, 2013, p. 149).

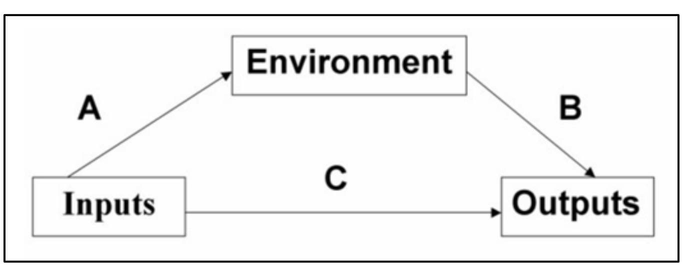

Figure 1
Astin's Input-Environment-Output Model.

In 2003, Kuh and Gonyea stated that “relatively little is known about what and how students’ academic library experiences contribute to desired outcomes of college . . .” (p. 258). Over 15 years later, Soria et al. (2017a, 2017b) report a similar dearth of research in this area, though more and more research is rapidly being published on this topic. Almost 50 years ago, Kramer and Kramer (1968) looked at the retention rates of freshman who used the library and found that borrowing library books was associated with retention. Mezick (2007) found a significant positive association between library expenditures and student persistence for all Carnegie Classifications and between retention and the “number of library professional staff . . . at doctoral granting institutions” (p. 564).

Although other studies have looked at student outcomes and library use, it was not until the Value of Academic Libraries’ initiative of the Association of College & Research Libraries (ACRL) that a collective, concentrated effort was made to create a body of research demonstrating academic library value and impact related to student success measures (Oakleaf, 2010). Following the commencement of the Value of Academic Libraries initiative, current library research demonstrates connections between FTIC student library usage and its impact on GPA and retention outcomes. Emmons & Wilkinson (2011) found that library input variables (e.g., wages, library volumes, and expenditures) had an effect on student retention. Using a linear regression model while controlling for socioeconomic status, race, and ethnicity, they discovered that an increase in the ratio of professional library staff to students had a positive effect on both student retention (measured by students returning for their second year) and six-year graduation rates. Interestingly, Stemmer and Mahan (2016) found that the ways that freshman used the library (outputs) were associated with GPA and retention. Using the library for academic purposes like checking out books or using online resources were associated with GPA and retention, but using the library computers for personal use and the late-night study rooms for cramming sessions was negatively associated with success outcomes.

Nine recent studies examined by the authors found that a combination of library space, instruction, and resource usage by FTIC students was positively associated with retention, GPA, or both (Kot & Jones, 2015; Soria et al., 2013, 2014, 2017a, 2017b; Haddow, 2013; Murray, Ireland, & Hackathorn, 2016; Stemmer & Mahan, 2016; Stone & Ramsden, 2012). Note that of the studies examined, most focused on library space and resource usage effects on student outcomes which included workstation logins, study room usage, e-resources and print books usage, interactions with library personnel, use of ILL and reference, and other similar resources. Kot & Jones (2015), Soria et al. (2017b), and Murray et al. (2016) also included library instruction in their list of environmental variables. Some of the studies controlled for other input and environmental variables that may impact student success (Kot & Jones, 2015; Soria et al., 2013, 2014, 2017a, 2017b). Some used the propensity score matching methodology (Kot & Jones, 2015; Soria et al. (2017b) and some studies applied Astin’s I-E-O model as their conceptual framework (Kot & Jones, 2015; Soria et al., 2014, 2017a, 2017b; Stemmer & Mahan, 2016).

Another study, conducted by masters of economics students at Florida State University using our local library turnstile data, found that students who had low GPAs showed “larger academic gains from additional library usage than their high-GPA library user counterparts” (Holcombe, Lukashevich, & Alvarez (2016, p. 14). Note that though this study examined undergraduate student library usage and GPA, it was not limited to the FTIC population. The use of the GPS methodology is unique to this library study since we were predicting outcomes based on continuous variables of library usage over time from actual turnstile data. It is interesting to note that the two outcomes measured in this study, GPA and retention, have been correlated: higher individual GPAs "may well be the single best predictors of student persistence . . ." (Pascarella & Terenzini 2005, p. 396). In addition, scholarship that focuses exclusively on the critical role of library instruction and its effect on first-year retention and GPA is not reviewed here.

Aims

This study aims to evaluate the effect of library usage (frequency of visits and duration of stay) over the course of a semester on FTIC student academic success measured in first-term GPA and first-year retention rate. In our study, student outputs or dependent variables are first-term GPA and first-year retention rate. The independent variables include the environmental variables of library usage (library visit frequency and duration) while controlling for other non-library related college environment variables. Other controlled variables include student inputs, such as demographic characteristics and other pre-college academic variables. By studying first-year students we by default control for the effects "of later collegiate experiences that may also influence students' outcomes . . ." (Soria et al., 2017a, p. 10).

This is an observational study where we could not randomly assign students to different amounts of library visit treatment during their first year. As a result, students have self-selected themselves into different levels of treatment because of their different input variables, such as gender, class, major etc. So we also tried to find a statistical method to minimize the self-selection bias in our sample.

Specifically, the research questions for this study are:

1) Does library usage measured in frequency (visits per semester) and duration (length of stay per semester) impact student academic success in terms of first-term GPA and first-year retention rate?
2) Are these impacts still observed after controlling for other input and environmental variables? and
3) Does embracing generalized propensity scoring give librarians more rigorous research results?

Methods

Data

The sample for this study includes 6,380 FTIC students who matriculated in the fall 2014 and fall 2015 semesters at a large southeastern university. Here FTIC refers to an entering freshman or a first-year student attending college for the first time at the undergraduate level. This includes students who attended college for the first time in the prior summer term and are also enrolled in the fall term. Also included are students who entered with advanced standing (having earned college credits before graduation from high school). For the purposes of this paper, retention is measured for FTIC students by their "persistence between the first and second year at college" (Kuh, et al., 2008, p. 555).

Data in the study comes from two sources: the C-Cure System (card swipe system) and the Office of Institutional Research. The campus has two major libraries and these were chosen sites for the study because they have turnstiles that could provide primary data for our study. Each library has six turnstiles, including two entrances, two exits, and a handicap entrance and exit. Both libraries require students to swipe student IDs at the turnstiles to enter or exit libraries. The C-Cure System collects card-swipe data that includes student identification information, time that students enter or exit the library, direction (in or out), and which turnstile they use. By matching swipe-in and swipe-out records, we extracted frequency and duration of individual library usage for each semester.

At our request, the Office of Institutional Research provided all other student background characteristics and academic records for all FTIC students. By merging card-swipe data and student information data, the final data set was ready for analysis. This data was coded to keep student information anonymous. The output (dependent) variables of interest were first-term GPA and first-year retention rate.

The environment (treatment) variables of interest were library usage measures, defined as first-term library visit frequency and duration (measured in hours). Other environment variables that we controlled for include major (college), class (freshman, sophomore, junior, senior or non-degree), military status, participation in athletics or sports, current load (credit hours enrolled in the first term), matriculation year (2014 or 2015), housing status (whether living on or off campus), and participation in the Center for Academic Retention and Enhancement program (provides transition support for minority students).

The input variables for the study included students' demographic characteristics and pre-college academic variables. Demographic characteristics included the student's gender, race, citizenship, age at matriculation, parent income level, and education levels of students' mothers and fathers. Pre-college academic variables included the student's high school GPA, ACT scores, and transfer credits. Some of students were admitted with SAT or ACT scores only. To compare those two measures, we transferred SAT scores into corresponding ACT scores using an SAT/ACT concordance/comparison chart. For those students who had both test scores, only the ACT scores were used. Table A1 in the Appendix presents summary statistics for all variables.

Generalized Propensity Score Method

To adjust for self-selection bias and control for the inputs and other environmental variables in a scientifically rigorous way, we use the GPS method developed by Hirano and Imbens (2004). This method is a generalization of the binary treatment propensity score matching method (Rosenbaum & Rubin, 1983) and is used to make causal inference in the observational studies (Imai & Dyk, 2004).

In this study, the treatment variables (library visit frequency and duration per student) are continuous measurements that can take the value of all positive integers. So, we decided to use the GPS method instead of the binary propensity score matching method to estimate the effects of continuous treatments—that is, the number of library visits and the number of hours spent in the library over time on student grades and retention.

Following Hirano and Imbens (2004), we have random samples of FTIC students indexed by $i = 1, \dots, N$. For each sample i, there is a set of potential outcomes, $Y_i(t)$ (i.e. first-term GPA, first-year retention rate) with a given level of treatment $t \epsilon \Gamma$, referred to as the unit-level dose-response function. In our study, treatment t is the first-term library visit frequency and duration and Γ is an interval $[t_0, t_1]$. For each sample i, we observed a vector of covariates, X_i, its actual treatment received, $T_i \epsilon [t_0, t_1]$, and actual outcome corresponding to the actual treatment received, $Y_i(T_i)$. Our goal was to estimate the average dose-response function: $\mu(t) = E[Y_i(t)]$. Hereafter, we will omit i to simplify the notation.

The key assumption for the GPS method is weak unconfoundedness introduced by Hirano and Imbens (2004):

$$Y(t) \perp T |\, X \; for \; all \; t \; \in \Gamma.$$

We assumed that the level of treatment received is independent of the potential outcome given observed covariates. This assumption requires us to get a rich set of covariates including all possible variables that may influence selection into different levels of treatment.

Based on this assumption, we were able to estimate the GPS. If we write the conditional density of the treatment given the covariates as $r(t,x) = f_{T|X}(t|x)$, then the GPS is defined as:

$$R = r(T, X).$$

If the GPS is correctly estimated, then it has a balance property as the binary propensity score:

$$X \perp 1\{T = t\} \mid r(t, X).$$

Hirano and Imbens (2004) mentioned that this property does not require unconfoundedness. In combination with weak unconfoundedness, it implies that the level of treatment received is unconfounded given the GPS as well.

Given this result, GPS can be used to remove bias caused by difference in covariates in the following two steps. First, we estimated the conditional expectation of potential outcome as a function of the treatment level and estimated GPS:

$$\beta(t, r) = E[Y|T = t, R = r].$$

Second, we estimated the dose-response function at each treatment level by taking the average of this conditional expectation over the GPS evaluated at that particular treatment level:

$$\mu(t) = E[\beta(t, r(t, X))].$$

Implementation

The first step is to estimate the GPS. Since our treatment variables (frequency and duration) are counts and highly skewed with a large amount of zero values, a negative binomial generalized linear model with log link function is used to model the conditional distribution:

$$T_i|X_i \sim NB(\exp(\beta_0 + \beta_1' X_i), k).$$

Then the GPS is estimated via the following:

$$\widehat{R_\iota} = \frac{\Gamma(T_i + \hat{k})}{\Gamma(T_i + 1)\Gamma(\hat{k})} p^{\hat{k}} (1-p)^{T_i}, where\ p = \frac{\hat{k}}{\exp\left(\widehat{\beta_0} + \widehat{\beta_1'} X_i\right) + \hat{k}}.$$

There are many other ways to specify the distribution and estimate the GPS. As long as the balance of covariates is achieved after adjusting for the GPS, the model specification is not the key point here.

The second step is to specify the conditional expectation of potential outcome given the treatment level and estimated GPS using OLS. In our study, a quadratic approximation including the interaction term was used when the outcome variable is first-year GPA:

$$E[Y_i|T_i, R_i] = \alpha_0 + \alpha_1 T_i + \alpha_2 {T_i}^2 + \alpha_3 R_i + \alpha_4 {R_i}^2 + \alpha_5 T_i R_i.$$

When the outcome is first-year retention rate, we used a logistic regression model to estimate the conditional expectation of potential outcome because retention is a binary outcome with value 0 as not being retained and 1 as being retained:

$$E[Y_i|T_i, R_i] = g(\alpha_0 + \alpha_1 T_i + \alpha_2 {T_i}^2 + \alpha_3 R_i + \alpha_4 {R_i}^2 + \alpha_5 T_i R_i), where\ g(x) = \frac{1}{1+e^{-x}}.$$

However, there is no direct causal interpretation of those estimated coefficients (Hirano & Imbens, 2004).

The final step was to estimate the average dose-response function at treatment levels of interest given the estimated parameters in the last step. In the case of first-term GPA, the dose-response function was estimated as the following:

$$\hat{E}[Y(t)] = \frac{1}{N} \sum_{i=1}^{N} (\widehat{\alpha_0} + \widehat{\alpha_1} t + \widehat{\alpha_2} t^2 + \widehat{\alpha_3} \hat{r}(t, x_i) + \widehat{\alpha_4} \hat{r}(t, x_i)^2 + \widehat{\alpha_5} \cdot t \cdot \hat{r}(t, x_i)).$$

And in the case of first-year retention, the dose-response function is estimated as the following:

$$\hat{E}[Y(t)] = \frac{1}{N}\sum_{i=1}^{N} g\big(\widehat{\alpha_0} + \widehat{\alpha_1}t + \widehat{\alpha_2}t^2 + \widehat{\alpha_3}\hat{r}(t,x_i) + \widehat{\alpha_4}\hat{r}(t,x_i)^2 + \widehat{\alpha_5}\cdot t\cdot \hat{r}(t,x_i)\big),$$
$$where\ g(x) = \frac{1}{1+e^{-x}}.$$

We also computed the 95% confidence bands for the dose-response function based on 1,000 bootstrap replications, considering all estimation steps including GPS and α-parameters.

Common Support Condition and Balancing of Covariates

As in the standard propensity score matching method, we needed to check the common support condition. We adapted the approach from Kluve, Schneider, Uhlendorff, & Zhao (2012). First, we divided the sample into three groups by the 30th and 70th quartiles of the treatment. For each group, we evaluated the GPS for the whole sample at the group mean of the treatment. Then we plotted the distribution of the evaluated GPS for that group against the distribution of the evaluated GPS for the rest of the sample. The overlap of those two distributions is the common support. We repeated the above procedures for all three groups. Finally, we restricted our final sample to individuals who are comparable across all three groups simultaneously. In other words, we deleted individuals whose GPS fell out of any common support of the three groups.

Besides assessing the common support condition, balancing of covariates is also very important to the GPS method. We regressed each covariate on the treatment with and without conditioning on the predicted level of treatment E[T|x_i] (Imai & van Dyk, 2004). If there was no correlation between treatment and any covariate after conditioning on the predicted treatment, then we concluded that the covariate balance is achieved after adjusting for the GPS.

Results

First-Term GPA

All tables and figures regarding the process of implementing the GPS method are included in the Appendix. As previously noted, Table A1 provides summary statistics. Table A2 provides the estimated coefficients from the negative binomial generalized linear models using the first-term GPA as the outcome variable. Both models showed that age, participation in athletics, ACT scores, college attended, current academic load, matriculation year, and race had influence on student library usage.

We assessed the common support condition using the method we described in the methodology section. Figures A1 and A2 in the Appendix illustrate the distribution of the evaluated GPS before and after deleting the non-overlap for the treatment variables of frequency and duration, respectively. After imposition of common support for the frequency treatment, we deleted only 0.4% of our original sample. For the duration treatment, we deleted 0.3% of our original sample.

Then we checked the balancing properties of the GPS using the method proposed by Imai & van Dyk (2004). Table A3 presents the coefficient and its standard error for each covariate with and without conditioning on $E[T|x_i]$. Table A3 clearly demonstrates that before we conditioned on $E[T|x_i]$ multiple covariates were significant. After we conditioned on $E[T|x_i]$, no significant covariate was observed. For example, participation in athletics had a high positive correlation with both treatments (frequency and duration). However, once we conditioned on the predicted level of treatment, athletic participation was not significant in either case. So, we concluded that the balancing properties of the GPS were achieved in both treatment cases.

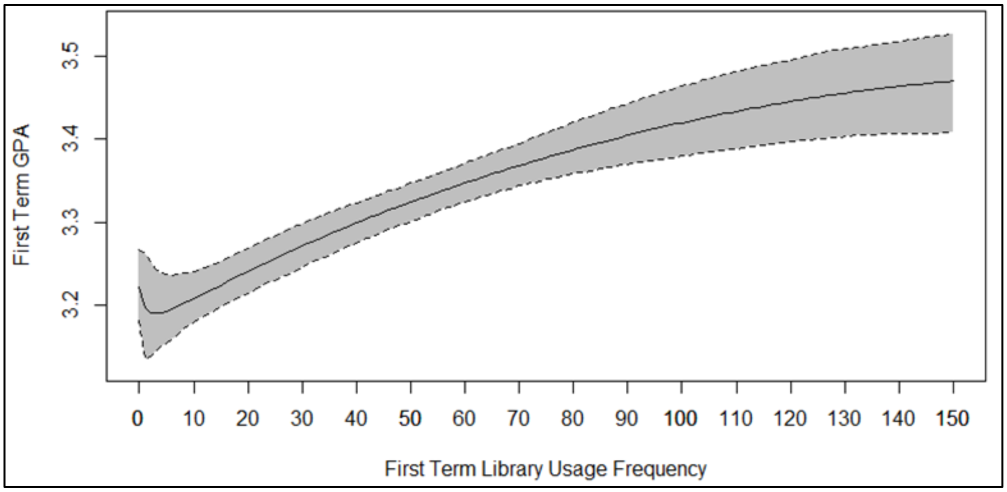

Figure 2
The dose-response function of first-term library usage frequency vs. first-term GPA.

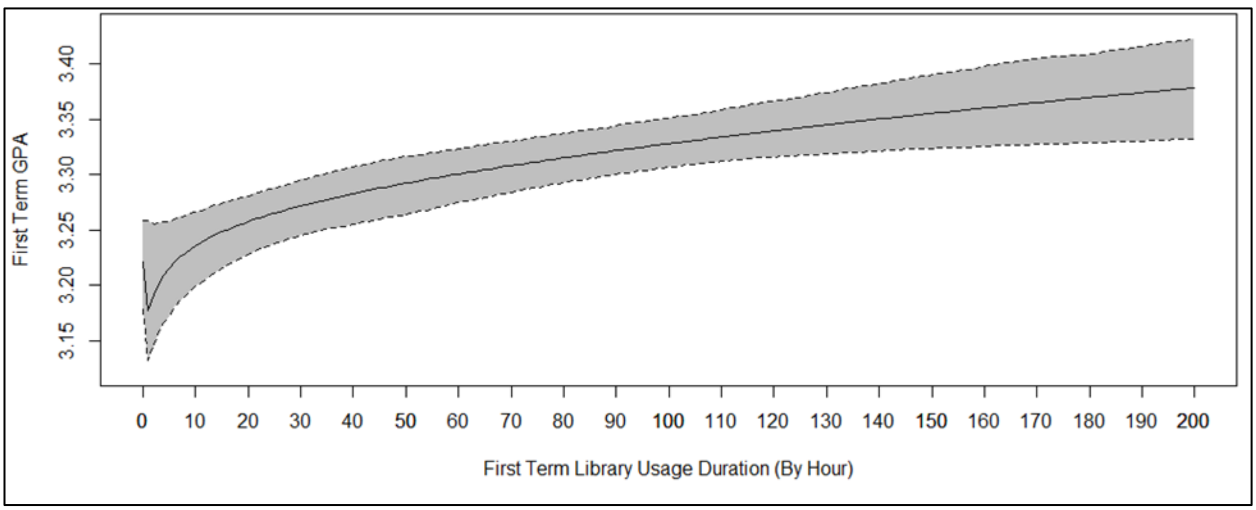

Figure 3
The dose-response function of first-term library usage duration vs. first-term GPA.

The final step of our study was to estimate the dose-response function. We regressed the outcome: first-term GPA on the treatment variable and the GPS. The estimated coefficients are listed in Table A4. As was mentioned before, the estimated coefficients did not have any direct causal interpretation.

The dose-response function was estimated for each treatment level of interest by averaging the estimated regression function over the GPS evaluated at the desired treatment level. Figures 2 and 3 present the dose-response function of first-term GPA for the treatment variables of frequency and duration, respectively. The dotted lines were 95% confidence bands based on 1,000 bootstrap replications that accounted for all estimation steps.

Figures 2 and 3 show the dose-response functions for frequency and duration have similar shapes. First-term GPA first decreased and reached its minimum value, then gradually increased when the library usage frequency and duration increased.

For frequency, first-term GPA was minimized at 3.19066 when the FTIC student only visited the library three times in their first semester. Once the student visited the library over three times, library usage had a continued positive relationship with their first-term GPA.

Similarly, for duration, first-term GPA was minimized at 3.177407 when the FTIC student only spent one hour in the library during their first semester. When the student spent an hour or longer in the library there were gains in first-term GPA. The longer the time spent in the library, the larger the increase in first-term GPA.

First-Year Retention Rate

Analysis procedures for first-year retention rate were almost the same as the procedures for first-term GPA, except that we included first-term GPA as a covariate when the outcome variable was retention rate. We then used a logistic regression model in order to estimate the conditional expectation of outcome.

In the Appendix, Table A5 presents the estimated coefficients from the GPS estimation step. Figures A3 and A4 and Table A6 (see the Appendix) verified the common support condition and the balancing properties. The estimated coefficients from the logistic regression model are presented in Table A7.

The dose-response functions were finally estimated at each treatment level of interest. Figures 4 and 5 present the dose-response function of first-year retention rate for the treatment variables of frequency and duration, respectively. The dotted lines are 95% confidence bands based on 1,000 bootstrap replications that accounted for all estimation steps.

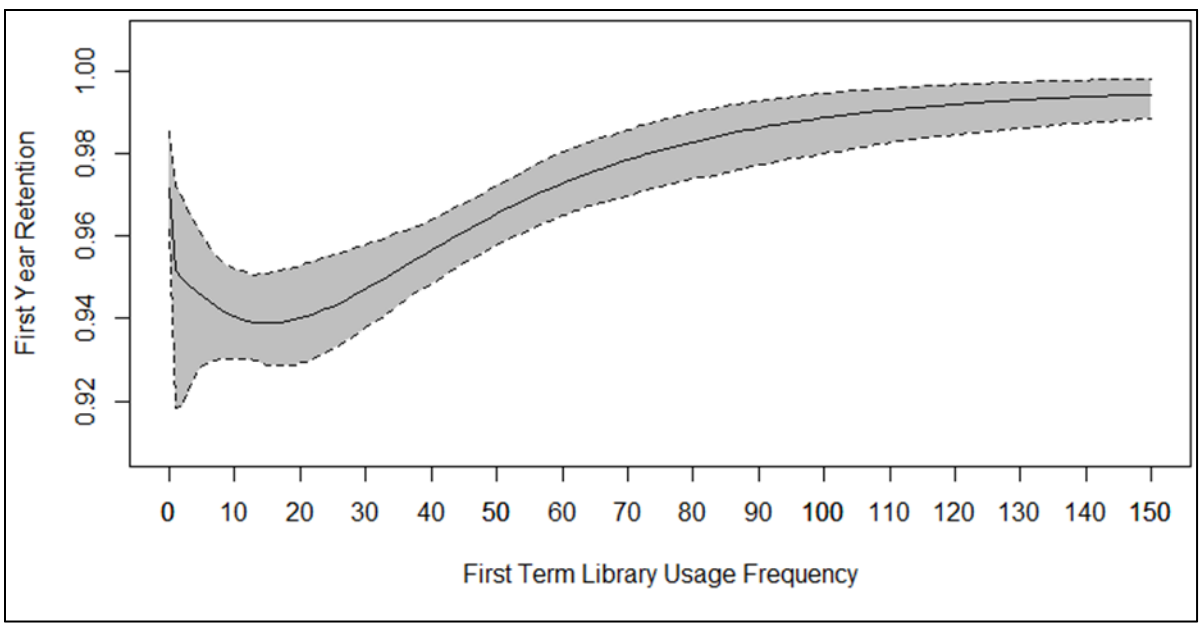

Figure 4
The dose-response function of first-term library usage frequency vs. first-year retention.

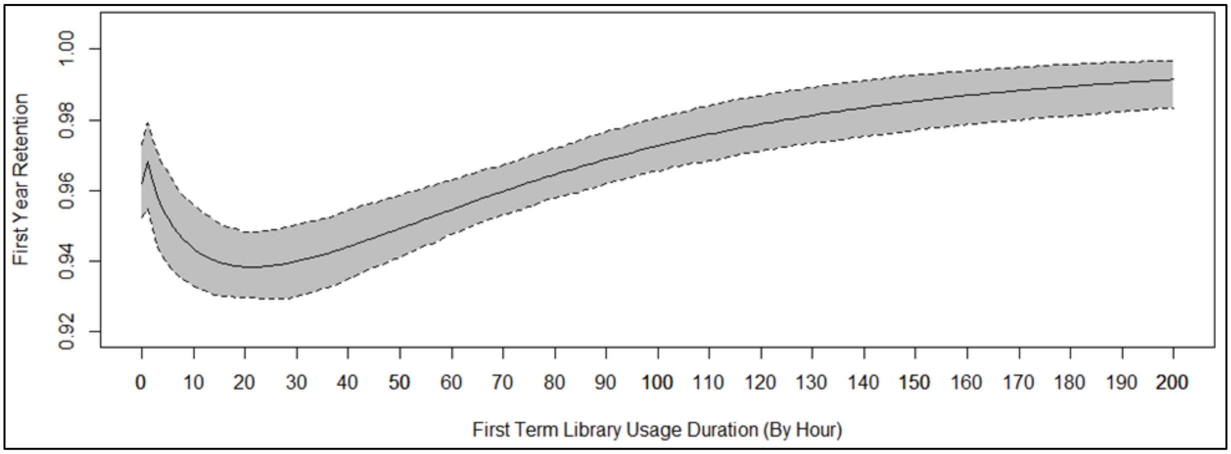

Figure 5
The dose-response function of first-term library usage duration vs. first-year retention.

Both dose-response functions have a shape similar to Figures 2 and 3. Both plots indicate that first-year retention rate first declined to its minimum value within the lower value of the treatment and then gradually increased as the treatment increased.

For frequency, when students visited the library only fifteen times in their first semester, they had the lowest first-term retention rate at 93.89%. For duration, the minimum retention rate was achieved at 93.84% when FTIC students spent only twenty-one hours in the library during their first semester. After that, further increases in first-term library usage frequency and duration both resulted in higher first-year retention rate.

The estimated dose-response function plots for first-term GPA and first-year retention rate have similar shapes, which initially decrease to minimum values and then gradually increase as the treatment levels increase. In other words, there was a threshold of frequency and duration of library visits where an increase of students' library usage had a negative effect on their first-term GPA and retention rates. Specifically, the estimated average first-term GPA was minimized when FTIC students visited the library only three times or spent only one hour in the library during their first semester. The threshold for measurable increases in first-year retention occurred when students visited the library fifteen times or spent twenty-one hours in the library during their first semester.

As the estimated dose-response functions reveal, increasing library usage was likely to increase FTIC students' first-term GPA and first-year retention rates past a certain threshold of frequency and duration. When FTIC students visited more than three times or spent more than two hours in the library during their first semester, library usage positively affected students' first-term GPAs. After FTIC students crossed the threshold of visiting the library more than fifteen times or spending more than twenty-one hours there in their first semester, students with higher library usage had higher first-year retention rates.

Discussion

The small drop of both first-term GPA and retention rate before reaching the thresholds for frequency and duration may be explained in several possible ways. First, we did not account for those FTIC students who may go to other libraries on campus other than the two major libraries included in this study. For example, engineering majors may not choose to come to the two on-campus libraries because their department and library are located off-campus. Some students may only come to the libraries at the beginning of the semester or during finals. Holcombe et al. (2016), using the same cohort and data set, found that those students who come to the library only to cram during finals week do not seem to benefit from low frequency, high duration library usage per semester.

The study has several limitations. The definition of library usage used here (total frequency and duration in one semester) may be too broad. We consider only when and how long the students entered the building, ignoring what they might be doing while in the building such as using other library services, collections, and spaces (such use of study rooms) (Soria et al. 2017a; 2017b). Furthermore, we cannot presume that students are studying when they visit the library. We can only assume they are doing some form of "educationally purposeful activities" that include using databases to conduct research and studying (Kuh, 2001, p. 12; Kuh & Gonyea, 2003). In one recent survey by Cengage, results showed that student library users spend their time studying alone, using the databases and reference materials, and meeting study groups (Strang, 2015). In a fall 2016 survey, the activities our students reported coming to the library for were to 1) work on a paper, project, or homework; 2) study for an exam; 3) print something; or 4) wait between classes (Dawson, 2016). Another limitation of this study is that it is not possible to control or account for all possible covariates that may influence the student success outcomes of GPA and first-year retention rates. Especially difficult to measure are intangible, intrinsic, and individual student inputs. For example, one study found that a student's "grit" or "mindset," which is the "willingness to work hard for an extended period in search of a long-term goal," was a key factor in college student success (Barton, 2015, para. 9).

Conclusion

Our results indicate that increasing library usage contributes to higher FTIC students' first-term GPAs and first-year retention rates past a certain threshold of frequency and duration. In addition, GPS is a valid methodology to use because it minimizes self-selection bias and estimates the potential outcome, GPA and retention rate, at every possible value of library usage (frequency and duration).

Using the GPS method, future studies could build on the findings of this study by looking at library usage and the relative impact on student four-to-six-year graduation rates, library usage across different academic disciplines, and other populations of library users, such as faculty and graduate students. Furthermore, future analyses could triangulate these results by analyzing the effects of library e-resource and equipment usage, instruction, and participation in library outreach and engagement activities to gain a more comprehensive understanding of how the academic library services, spaces, and resources collectively impact student success.

References

Astin, A. W. (1970). The methodology of research on college impact, part one. *Sociology of Education*, *43*(3), 223–254. https://dx.doi.org/10.2307/2112065

Astin, A. W. (1990). *Assessment for excellence: The philosophy and practice of assessment and evaluation in higher education*. New York: Maxwell Macmillan International.

Astin, A. W. (1993). *What matters in college?: Four critical years revisited* (1st ed.). San Francisco: Jossey-Bass.

Astin, A. W. (1997). How "good" is your institution's retention rate? *Research in Higher Education*, *38*(6), pp. 647-658. https://dx.doi.org/10.1023/A:1024903702810

Astin, A. W., & Antonio, A. L. (2012). *Assessment for excellence: The philosophy and practice of assessment and evaluation in higher education*. Lanham, MD: Rowman & Littlefield Publishers.

Barton, D. (2015, September 16). The most important factor in a college student's success [Blog post]. Retrieved from https://blogs.wsj.com/experts/2015/09/16/the-most-important-factor-in-a-college-students-success/

Braxton, J. M., Hirschy, A. S., & McClendon, S. A. (2004). *Understanding and reducing college student departure. ASHE-ERIC higher education report, volume 30, issue 3*. Indianapolis: Jossey-Bass, An Imprint of Wiley.

Cox, B. L., & Jantti, M. (2012, July 17). Discovering the impact of library use and student performance. *EDUCAUSE Review*. Retrieved from http://er.educause.edu/articles/2012/7/discovering-the-impact-of-library-use-and-student-performance

Dawson, A. (2016). *Strozier daytime visit feedback fall 2016 results*. Retrieved from https://docs.google.com/document/d/1y8RJdKgnVUvvwmS6dTNHwSOFkqM1IUonq2qvb-enRgo/edit?usp=drive_web&usp=embed_facebook

Donnelly, P. J. (2010). *Examining pre-college academic variables: Investigating future college success*. Retrieved from ProQuest Dissertations & Theses Global. (3398089).

Haddow, G. (2013). Academic library use and student retention: A qualitative analysis. *Library & Information Science Research, 35*(2), 127-136. https://dx.doi.org/10.1016/j.lisr.2012.12.002

Hirano, K., & Imbens, G. W. (2004). The propensity score with continuous treatments. In A. Gelman & X. L. Meng (Eds.), *Applied Bayesian modeling and causal inference from incomplete-data perspectives* (pp. 73–84). John Wiley & Sons, Ltd.

Holcombe, C., Lukashevich, I., & Alvarez, J. (2016, July 29). Measuring the effects of increased library use on GPA outcomes of FSU undergraduates. S*ymposium on Applied Economics 2016*: *The* Final Presentations *for the M.S. in Applied Economics.* Florida State University. Retrieved from https://www.lib.fsu.edu/sites/default/files/sites/default/files/upload/executive_summary.pdf

Imai, K., & van Dyk, D. A. (2004). Causal inference with general treatment regimes. *Journal of the American Statistical Association*, *99*(467), 854–866. https://dx.doi.org/10.1198/016214504000001187

Kot, F. C., & Jones, J. L. (2014). The impact of library resource utilization on undergraduate students' academic performance: A propensity score matching design. *College & Research Libraries*, *76*(5), 566-586. https://dx.doi.org/10.5860/crl.76.5.566

Kramer, L. A., & Kramer, M. B. (1968). The college library and the drop-out. *College & Research Libraries*, *29*(4), 310–312.

Kuh, G. D. (2001). Assessing what really matters to student learning: Inside the national survey of student engagement. *Change: The Magazine of Higher Learning*, *33*(3), 10–17. https://dx.doi.org/10.1080/00091380109601795

Kuh, G. D., & Gonyea, R. M. (2003). The role of the academic library in promoting student engagement in learning. *College & Research Libraries*, *64*(4), 256–282. https://dx.doi.org/10.5860/crl.64.4.256

Kuh, G. D., Cruce, T. M., Shoup, R., Kinzie, J., & Gonyea, R. M. (2008). Unmasking the effects of student engagement on first-year college grades and persistence. *The Journal of Higher Education*, *79*(5), 540–563. https://doi.org/10.1080/00221546.2008.11772116

Kluve, J., Schneider, H., Uhlendorff, A., & Zhao, Z. (2012). Evaluating continuous training programmes by using the generalized propensity score. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *175*(2), 587–617. https://dx.doi.org/10.1111/j.1467-985X.2011.01000.x

Mezick, E. M. (2007). Return on investment: Libraries and student retention. *The Journal of Academic Librarianship*, *33*(5), 561–566. https://dx.doi.org/10.1016/j.acalib.2007.05.002

Murray, A., Ireland, A., & Hackathorn, J. (2016). The value of academic libraries: Library services as a predictor of student retention. *College & Research Libraries*, *77*(5), 631–642. https://dx.doi.org/10.5860/crl.77.5.631

Oakleaf, M. (2010). *The value of academic libraries: A comprehensive research review and report*. Chicago: Association of College and Research Libraries. http://www.ala.org/acrl/sites/ala.org.acrl/files/content/issues/value/val_report.pdf

Pascarella, E. T., & Terenzini, P. T. (1991). *How college affects students: Findings and insights from twenty years of research*. San Francisco: Jossey-Bass Publishers.

Roksa, J., & Whitley, S. E. (2017). Fostering academic success of first-year students: Exploring the roles of motivation, race, and faculty. *Journal of College Student Development*, *58*(3), 333–348. https://dx.doi.org/10.1353/csd.2017.0026

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41–55. https://dx.doi.org/10.2307/2335942

Soria, K. M., Fransen, J., & Nackerud, S. (2013). Library use and undergraduate student outcomes: New evidence for students' retention and academic success. *Portal: Libraries and the Academy*, *13*(2), 147–164. https://dx.doi.org/10.1353/pla.2013.0010

Soria, K. M., Fransen, J., & Nackerud, S. (2014). Stacks, serials, search engines, and students' success: First-year undergraduate students' library use, academic achievement, and retention. *The Journal of Academic Librarianship*, *40*(1), 84–91. https://dx.doi.org/10.1016/j.acalib.2013.12.002

Soria, K. M., Fransen, J., & Nackerud, S. (2017a). Beyond books: The extended academic benefits of library use for first-year college students. *College & Research Libraries*, *78*(1), 8–22. https://dx.doi.org/10.5860/crl.v78i1.16564

Soria, K. M., Fransen, J, & Nackerud, S. (2017b). The impact of academic library resources on undergraduates' degree completion. *College & Research Libraries*, *78*(6), 812-823. https://dx.doi.org/10.5860/crl.78.6.812

Stemmer, J. K., & Mahan, D. M. (2016). Investigating the relationship of library usage to student outcomes. *College & Research Libraries*, *77*(3), 359-375. https://dx.doi.org/10.5860/crl.77.3.359

Stone, G., & Ramsden, B. (2013). Library impact data project: Looking for the link between library usage and student attainment. *College and Research Libraries*, *74*(6), 546-559. https://dx.doi.org/10.5860/crl12-406

Strang, T. (2015, July 2). Top four reasons students use their college library [Blog post]. Retrieved from https://blog.cengage.com/top-four-reasons-students-use-their-college-library

Appendix

Table A1
Summary Statistics

	Variables	Mean	Standard deviation
Output Variables	GPA	3.278	0.690
	Retention	0.957	0.204
Environment (treatment) Variables	Frequency	35.066	39.705
	Duration	56.019	74.300
Other Environment Variables	Military	0.026	0.160
	Athlete	0.018	0.134
	Housing	0.821	0.384
	CARE	0.000	0.022
	Current Load	12.869	1.842
	Class		
	Freshman	0.711	0.453
	Sophomore	0.253	0.435
	Junior	0.036	0.186
	Senior	0.001	0.025
	Non-Degree	0.000	0.013
	College		
	Applied Studies	0.000	0.018
	Arts & Sciences	0.301	0.459
	Business	0.150	0.357
	Communication & Information	0.046	0.210
	Criminology	0.029	0.167
	Education	0.021	0.143
	Engineering	0.070	0.255
	Film School	0.005	0.071
	Fine Arts	0.006	0.075
	Human Sciences	0.072	0.259
	Music	0.027	0.163
	Nursing	0.025	0.157
	Registrar	0.000	0.013
	Social Sciences	0.071	0.257
	Social Work	0.006	0.078
	Undergraduate Studies	0.146	0.353
	Visual Arts, Theatre, & Dance	0.024	0.153
	Matriculation Year		
	2014	0.453	0.498
	2015	0.547	0.498
Input Variables	Age	20.749	0.776
	US Citizen	0.978	0.146
	HS GPA	4.045	0.340

	ACT	27.145	2.740
	Transfer or Exam Credit	21.679	16.793
	Race		
	White	0.683	0.465
	Hispanic/Latino	0.177	0.382
	Black/African American	0.046	0.210
	Asian	0.031	0.174
	American Indian/Alaska Native	0.002	0.041
	Native Hawaiian/Other Pacific Islands	0.002	0.040
	Two or More Races	0.041	0.199
	Not Specified	0.018	0.131
	Gender		
	Female	0.593	0.491
	Male	0.407	0.491
	Father's Education Level		
	College	0.057	0.231
	High School	0.028	0.165
	Middle School	0.001	0.028
	Unknown	0.914	0.280
	Mother's Education Level		
	College	0.058	0.235
	High School	0.024	0.153
	Middle School	0.002	0.040
	Unknown	0.916	0.277
	Parent Income Level		
	< $1000	0.008	0.091
	$1000-$40000	0.018	0.132
	$40000-$75000	0.017	0.130
	$75000-$100000	0.013	0.114
	$100000+	0.036	0.187
	Unknown	0.907	0.290

Table A2
Estimated Coefficients from the GPS Estimation

	Treatment: Frequency		**Treatment: Duration**	
Covariates	Estimate	Std. Error	Estimate	Std. Error
military	-0.0713	0.1049	-0.0987	0.1201
athlete	-0.5749[a]	0.1277	-0.6429[a]	0.1459
housing	0.0723	0.0444	0.1100[c]	0.0509
CARE	0.2593	0.7719	-0.2987	0.8878
current load	0.0319[a]	0.0096	0.0239[c]	0.0110
class.Freshman	2.3445	1.5296	1.6594	1.6231
class.Sophomore	2.3328	1.5314	1.6293	1.6253
class.Junior	2.3246	1.5368	1.7034	1.6319
class.Senior	2.5368	1.6819	1.5132	1.8105
college.Applied.Studies	-2.1336[c]	1.0327	-0.9900	1.1066

college.Arts & Sciences	0.2616[c]	0.1132	0.5256[a]	0.1298
college.Business	0.0681	0.1180	0.3541[b]	0.1352
college.Communication & Information	0.0556	0.1338	0.3242[c]	0.1533
college.Criminology	0.0034	0.1471	0.1712	0.1686
college.Education	-0.1176	0.1593	-0.0022	0.1824
college.Engineering	0.3619[b]	0.1272	0.6368[a]	0.1459
college.Film.School	-0.0923	0.2603	-0.2208	0.2986
college.Fine.Arts	-0.1341	0.2564	-0.1448	0.2934
college.Human.Sciences	0.2856[c]	0.1257	0.6087[a]	0.1440
college.Music	-0.2808[d]	0.1488	-0.5593[b]	0.1707
college.Nursing	0.2225	0.1511	0.5199[b]	0.1731
college.Social.Sciences	0.2755[c]	0.1260	0.5308[a]	0.1444
college.Social.Work	0.2448	0.2405	0.3673	0.2756
college.Undergraduate.Studies	0.0885	0.1178	0.3144[c]	0.1350
MatriculationYearTer.20149	-0.1387[b]	0.0427	-0.1155[c]	0.0489
age	0.0755[b]	0.0276	0.0652[c]	0.0317
US citizen	-0.1027	0.1189	-0.0344	0.1363
HS GPA	0.0655	0.0591	0.0191	0.0677
ACT	-0.0139[c]	0.0070	-0.0236[b]	0.0080
Transfer Or Exam Credit	-0.0009	0.0019	-0.0014	0.0022
Race.White	-0.1113	0.1281	-0.0075	0.1468
Race.Hispanic.Latino	-0.0377	0.1327	0.0865	0.1522
Race.Black.African.American	0.0161	0.1490	0.0765	0.1709
Race.Asian	0.2804[d]	0.1585	0.3924[c]	0.1817
Race.American.Indian.Alaska	0.1095	0.4228	0.1406	0.4849
Race.Native.Hawaiian.Oth.Pa	0.2246	0.4402	0.0388	0.5055
Race.Two.or.More.Races	-0.0897	0.1509	0.0016	0.1730
Gender.Male	0.1047[b]	0.0368	-0.0265	0.0422
EducationFather.College	-0.2234	0.2676	-0.3814	0.3063
EducationFather.High.School	-0.1018	0.2706	-0.3427	0.3098
EducationFather.Middle.School	-0.6790	0.5771	-1.3476[c]	0.6611
EducationMother.College	0.1792	0.2459	0.1591	0.2815
EducationMother.High.School	0.0914	0.2560	0.0494	0.2930
EducationMother.Middle.School	-0.0591	0.4932	-0.2111	0.5648
ParentIncome....1000	0.0774	0.2275	0.2417	0.2605
ParentIncome..1000..40000	-0.2691	0.2604	-0.1351	0.2981
ParentIncome..40000..75000	-0.0937	0.2729	0.0781	0.3124
ParentIncome..75000.100000	-0.3024	0.2875	-0.0555	0.3290
ParentIncome..100000	-0.2199	0.2579	-0.0599	0.2952

[a]Significant at the 0.1% level
[b]Significant at the 1% level
[c]Significant at the 5% level
[d]Significant at the 10% level

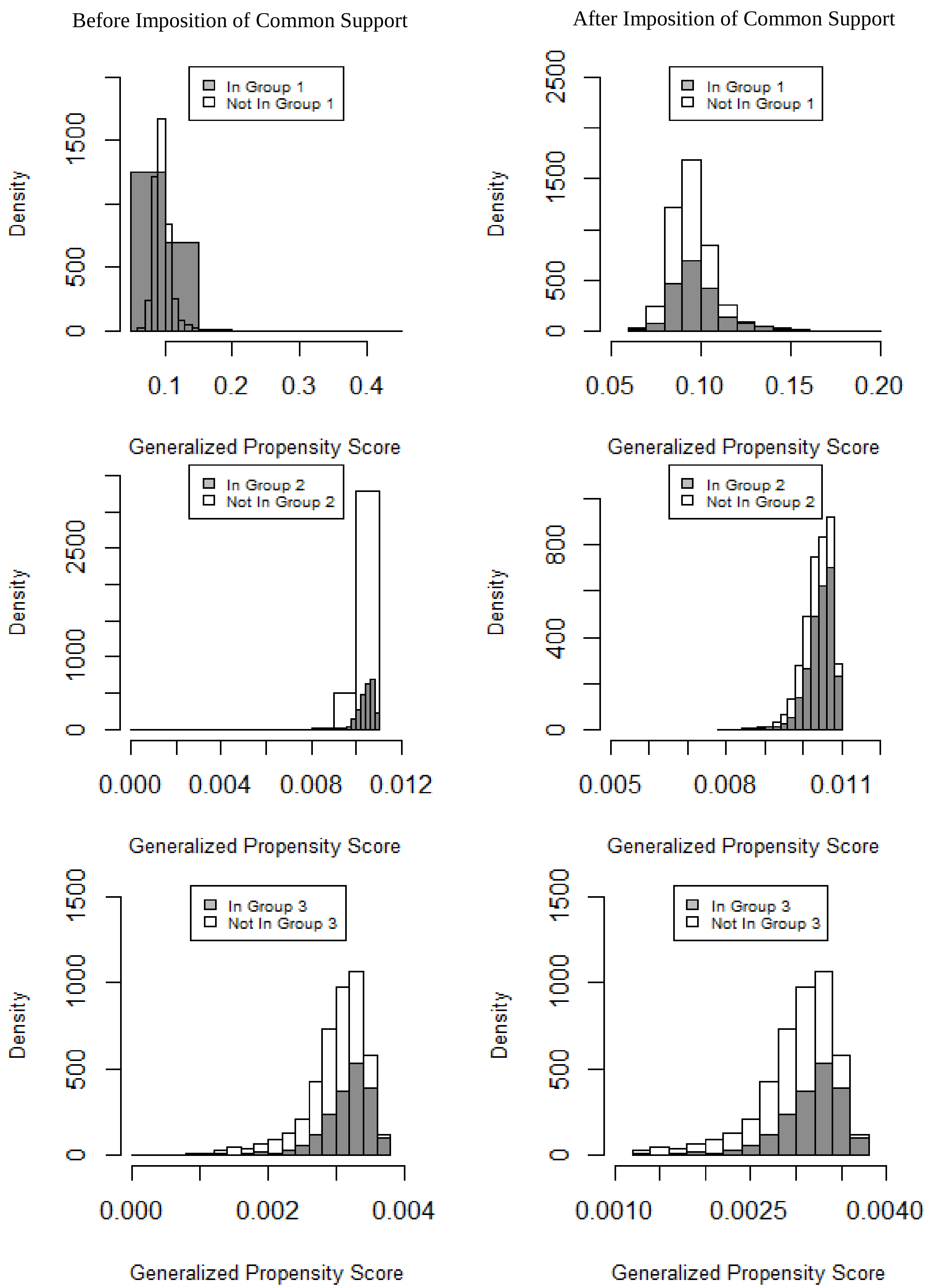
Before Imposition of Common Support
After Imposition of Common Support
In Group 1
Not In Group 1
In Group 2
Not In Group 2
In Group 3
Not In Group 3
Density
Generalized Propensity Score

Figure A1

Common support condition for frequency.

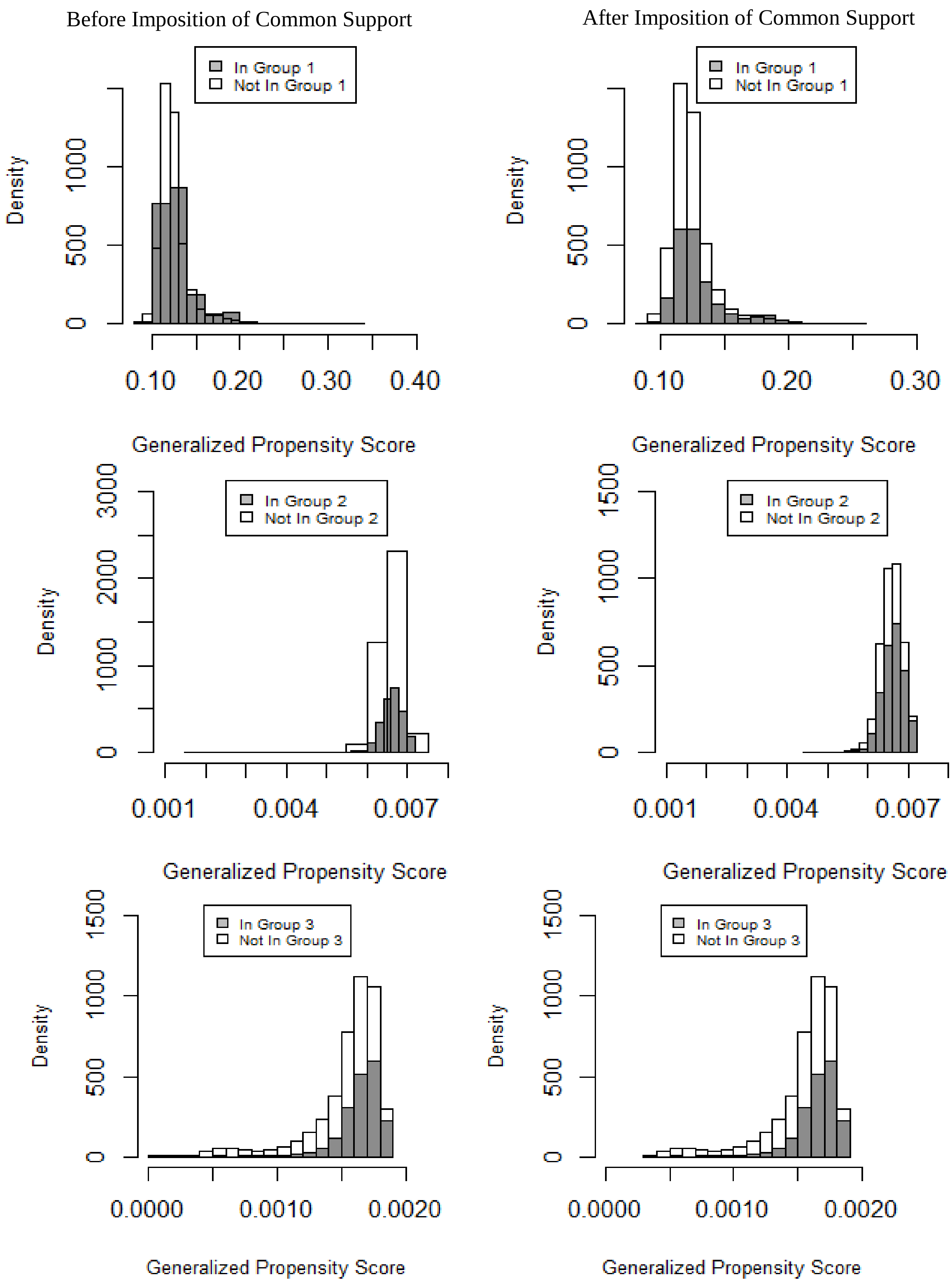

Figure A2

Common support condition for duration.
Table A3
Covariate Balance With and Without Conditioning on $E[T|x_i]$

	Treatment: Frequency				**Treatment: Duration**			
	Without Condition		Condition		Without Condition		Condition	
Covariates	Est	Std. Error	Est	Std. Error	Est	Std. Error	Est	Std. Error
military	-1.936	3.108	0.526	3.057	-2.772	5.784	1.440	5.688
athlete	-14.716[a]	3.801	-0.301	3.864	-25.067[a]	6.985	-0.703	7.060
housing	1.317	1.301	-0.655	1.285	4.120[d]	2.422	-0.504	2.399
CARE	11.519	22.951	-2.977	22.564	-17.749	42.721	-1.992	41.973
currentload	1.118[a]	0.270	0.075	0.275	0.892[d]	0.503	0.028	0.498
class.Freshman	-0.359	1.100	-0.267	1.080	1.943	2.046	-0.724	2.017
class.Sophomore	0.657	1.147	0.267	1.127	-1.968	2.134	0.912	2.105
class.Junior	-1.365	2.692	0.260	2.646	-0.424	5.000	-0.542	4.911
class.Senior	-5.406	19.878	-7.218	19.525	-20.587	37.000	-7.299	36.352
college.Arts & Sciences	4.786[a]	1.085	0.087	1.115	8.660[a]	2.018	0.145	2.068
college.Business	-3.644[b]	1.394	-0.120	1.390	-4.658[d]	2.594	-0.519	2.563
college.Communication & Infor	-4.302[d]	2.369	0.145	2.346	-4.382	4.410	-0.331	4.340
college.Criminology	-6.015[c]	2.996	-0.233	2.969	-11.474[c]	5.562	0.612	5.523
college.Education	-9.548[b]	3.481	0.706	3.489	-19.332[b]	6.455	0.973	6.487
college.Engineering	8.641[a]	1.951	-0.073	2.010	11.458[b]	3.637	-0.691	3.666
college.Film.School	-6.655	7.043	-0.487	6.930	-25.044[d]	13.107	-0.126	12.981
college.Fine.Arts	-15.940[c]	7.153	0.055	7.108	-33.430[b]	12.358	-1.315	12.331
college.Human.Sciences	3.163	1.926	-0.034	1.903	13.329[a]	3.585	1.253	3.617
college.Music	-11.205[a]	3.087	0.574	3.137	-33.874[a]	5.820	1.200	6.247
college.Nursing	0.914	3.163	-0.293	3.108	6.410	5.887	-1.413	5.806
college.Social.Sciences	3.658[d]	1.939	0.037	1.920	5.109	3.606	-0.348	3.560
college.Social.Work	-1.366	6.384	-0.835	6.270	-6.215	11.882	-0.654	11.676
college.Undergraduate.Studies	-3.875[b]	1.410	0.001	1.409	-6.168[c]	2.622	0.457	2.613

MatriculationYearTer.20149	-1.728[d]	1.002	0.089	0.991	-2.460	1.863	-0.307	1.836
age	1.165 [d]	0.649	0.013	0.643	1.267	1.200	-0.483	1.184
UScitizen	-6.396 [d]	3.444	0.910	3.418	-9.033	6.389	-1.147	6.297
HSGPA	1.525	1.468	-0.031	1.445	-1.398	2.734	-0.209	2.686
ACT	-0.168	0.182	-0.045	0.179	-1.129[a]	0.339	-0.029	0.341
Transfer Or Exam Credit	0.005	0.030	0.006	0.029	-0.054	0.055	0.016	0.054
Race.White	-5.577[a]	1.069	-0.653	1.107	-9.178[a]	1.990	-0.937	2.038
Race.Hispanic.Latino	2.554[d]	1.305	0.497	1.289	5.730[c]	2.427	0.340	2.412
Race.Black.African.American	4.788[c]	2.377	0.488	2.352	7.144	4.417	1.146	4.357
Race.Asian	16.637[a]	2.869	0.482	3.049	26.383[a]	5.344	0.283	5.561
Race.American.Indian.Alaska	8.863	11.993	0.214	11.794	7.120	22.325	-0.085	21.932
Race.Native.Hawaiian.Oth.Pa	8.661	12.578	-2.597	12.377	-6.284	23.412	-3.421	22.996
Race.Two.or.More.Races	0.594	2.503	0.275	2.459	0.310	4.651	0.560	4.568
Gender.M	3.301[b]	1.01	-0.371	1.027	-1.505	1.888	-0.548	1.856
EducationFather.College	-9.825[a]	2.176	-0.668	2.231	-16.136[a]	4.041	-1.312	4.099
EducationFather.High.School	-4.732	3.063	1.153	3.034	-11.430[c]	5.653	1.782	5.622
EducationFather.Middle.School	-18.915	19.877	-5.248	19.546	-31.344	36.999	3.270	36.412
EducationMother.College	-8.686[a]	2.148	-0.640	2.183	-14.549[a]	3.989	-1.151	4.025
EducationMother.High.School	-7.704[c]	3.304	0.271	3.290	-14.884[c]	6.090	0.268	6.068
EducationMother.Middle.Scho	-7.497	13.257	1.780	13.036	-11.964	26.172	7.415	25.736
ParentIncome....1000	-0.193	5.534	-2.504	5.438	5.859	10.301	-0.247	10.125
ParentIncome..1000..40000	-8.768[c]	3.821	-0.093	3.799	-14.877[c]	7.113	1.502	7.072
ParentIncome..40000..75000	-4.059	3.822	0.459	3.766	-7.888	7.147	0.072	7.039
ParentIncome..75000.100000	-10.535	4.470[c]	0.485	4.453	-17.606[c]	8.220	-1.511	8.146
ParentIncome..100000.	-9.337[a]	2.719	-0.525	2.738	-16.642[a]	5.028	-1.055	5.052

[a]Significant at the 0.1% level
[b]Significant at the 1% level
[c]Significant at the 5% level
[d]Significant at the 10% level

Table A4
Estimated Coefficients of Conditional Distribution of GPA Given Treatment and GPS

Treatment: Frequency			**Treatment: Duration**		
	Estimate	Std. Error		Estimate	Std. Error
Intercept	3.0990[a]	0.1311	**Intercept**	3.2390[a]	0.0880
Frequency	0.0039[a]	0.0010	**Duration**	0.0008[c]	0.0003
Frequency^2	0.0000[b]	0.0000	**Duration^2**	0.0000	0.0000
GPS	1.9740	3.2350	**GPS**	-2.1390	1.7650
GPS^2	-7.1340	20.2600	**GPS^2**	15.7100[d]	9.0180
Frequency*GPS	0.1875	0.3512	**Duration*GPS**	0.1173	0.3676

[a]Significant at the 0.1% level
[b]Significant at the 1% level
[c]Significant at the 5% level
[d]Significant at the 10% level

Table A5
Estimated Coefficients from the GPS Estimation

	Treatment: Frequency		**Treatment: Duration**	
Covariates	Estimate	Std. Error	Estimate	Std. Error
GPA	0.2140[a]	0.0283	0.2084[a]	0.0324
military	-0.0586	0.1045	-0.0911	0.1199
athlete	-0.6102[a]	0.1273	-0.6777[a]	0.1457
housing	0.0482	0.0442	0.0838	0.0507
CARE	0.2962	0.7687	-0.2671	0.8852
current load	0.0069	0.0099	-0.0008	0.0113
class.Freshman	2.3856	1.5245	1.6851	1.6187
class.Sophomore	2.3646	1.5263	1.6456	1.6209
class.Junior	2.3548	1.5316	1.7060	1.6276
class.Senior	2.7508	1.6760	1.6585	1.8056
college.Applied.Studies	-2.1790[c]	1.0298	-1.0332	1.1037
college.Arts & Sciences	0.3227[b]	0.1131	0.5905[a]	0.1298
college.Business	0.1013	0.1176	0.3939[b]	0.1350
college.Communication & Information	0.0601	0.1333	0.3383[c]	0.1529
college.Criminology	0.0301	0.1466	0.2083	0.1682
college.Education	-0.1111	0.1586	0.0170	0.1819
college.Engineering	0.4516[a]	0.1274	0.7308[a]	0.1463
college.Film.School	-0.0267	0.2593	-0.1574	0.2978
college.Fine.Arts	-0.2152	0.2556	-0.2062	0.2927
college.Human.Sciences	0.3389[b]	0.1254	0.6642[a]	0.1439
college.Music	-0.2335	0.1483	-0.4992[b]	0.1703

college.Nursing	0.2451	0.1506	0.5535[b]	0.1727
college.Social.Sciences	0.2956	0.1255	0.5550[a]	0.1440
college.Social.Work	0.3005	0.2394[c]	0.4239	0.2748
college.Undergraduate.Studies	0.1287	0.1175	0.3610[b]	0.1348
MatriculationYearTer.20149	-0.1213	0.0425	-0.1020[c]	0.0487
age	0.0595[c]	0.0276	0.0515	0.0316
US citizen	-0.0978	0.1184	-0.0327	0.1359
HS GPA	-0.0619	0.0616[b]	-0.1012	0.0707
ACT	-0.0163[c]	0.0070	-0.0264[a]	0.0080
Transfer Or Exam Credit	-0.0003	0.0019	-0.0007	0.0022
Race.White	-0.1151	0.1275	-0.0031	0.1464
Race.Hispanic.Latino	-0.0488	0.1322	0.0879[d]	0.1517
Race.Black.African.American	0.0074[d]	0.1484	0.0770	0.1704
Race.Asian	0.2748	0.1578	0.3960[c]	0.1812
Race.American.Indian.Alaska	0.1277	0.4212	0.1675	0.4837
Race.Native.Hawaiian.Oth.Pa	0.2161	0.4384	0.0228	0.5042
Race.Two.or.More.Races	-0.0783	0.1503	0.0170	0.1725
Gender.Male	0.1198	0.0368	-0.0140	0.0422
EducationFather.College	-0.2083	0.2665	-0.3705	0.3054
EducationFather.High.School	-0.0887	0.2695	-0.3393	0.3089
EducationFather.Middle.School	-0.5736	0.5743	-1.2376[d]	0.6588
EducationMother.College	0.1774	0.2449	0.1567	0.2807
EducationMother.High.School	0.0653	0.2549	0.0233	0.2922
EducationMother.Middle.School	-0.0353	0.4912	-0.1828	0.5631
ParentIncome....1000	0.1116	0.2267	0.2785	0.2598
ParentIncome..1000..40000	-0.2009	0.2596[b]	-0.0745	0.2975
ParentIncome..40000..75000	-0.0625	0.2719	0.1074	0.3116
ParentIncome..75000.100000	-0.3075	0.2864	-0.0456	0.3281
ParentIncome..100000.	-0.1718	0.2570	-0.0019	0.2945

[a]Significant at the 0.1% level
[b]Significant at the 1% level
[c]Significant at the 5% level
[d]Significant at the 10% level

Before Imposition of Common Support

After Imposition of Common Support

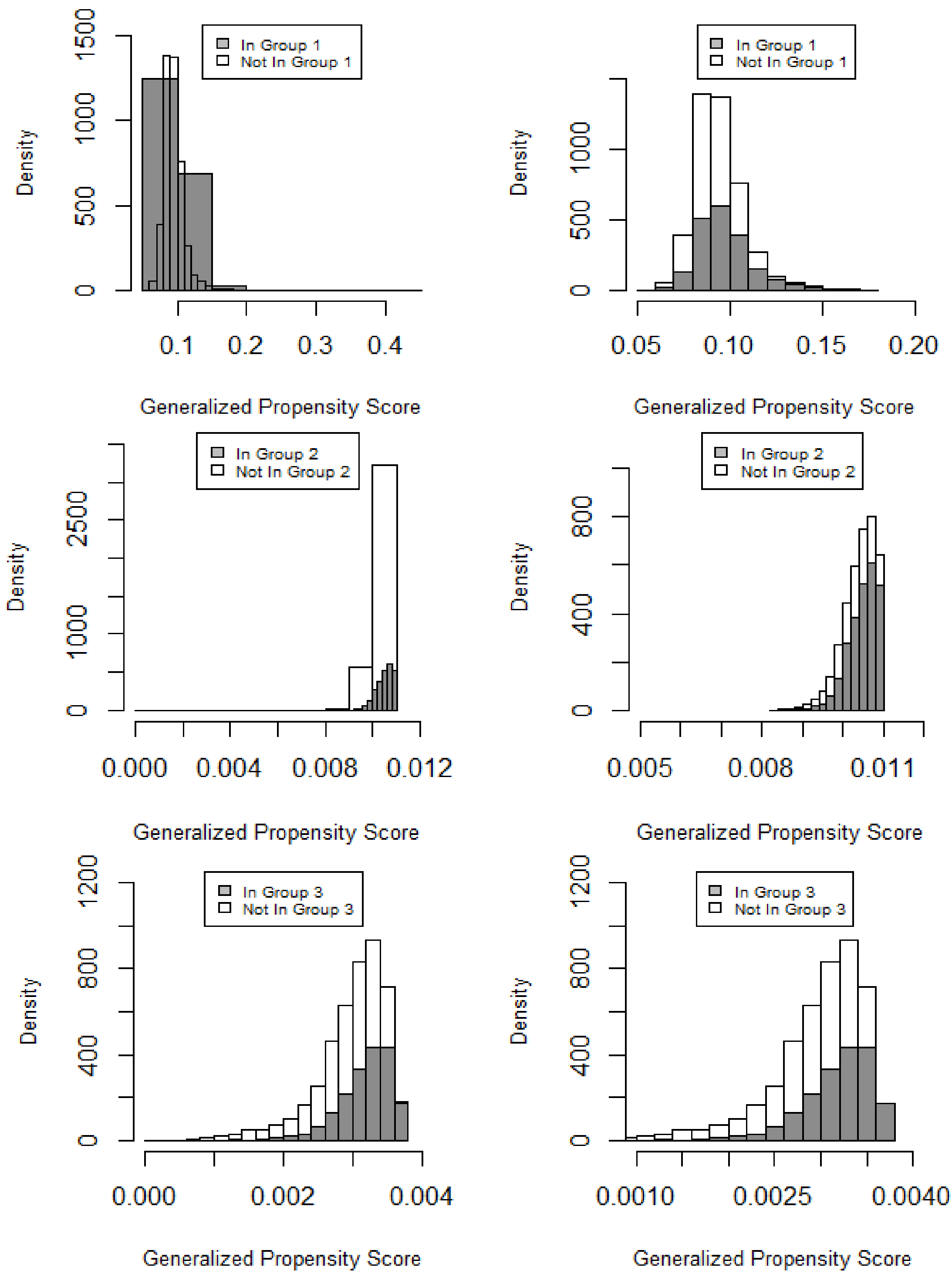

Figure A3
Common support condition for frequency.

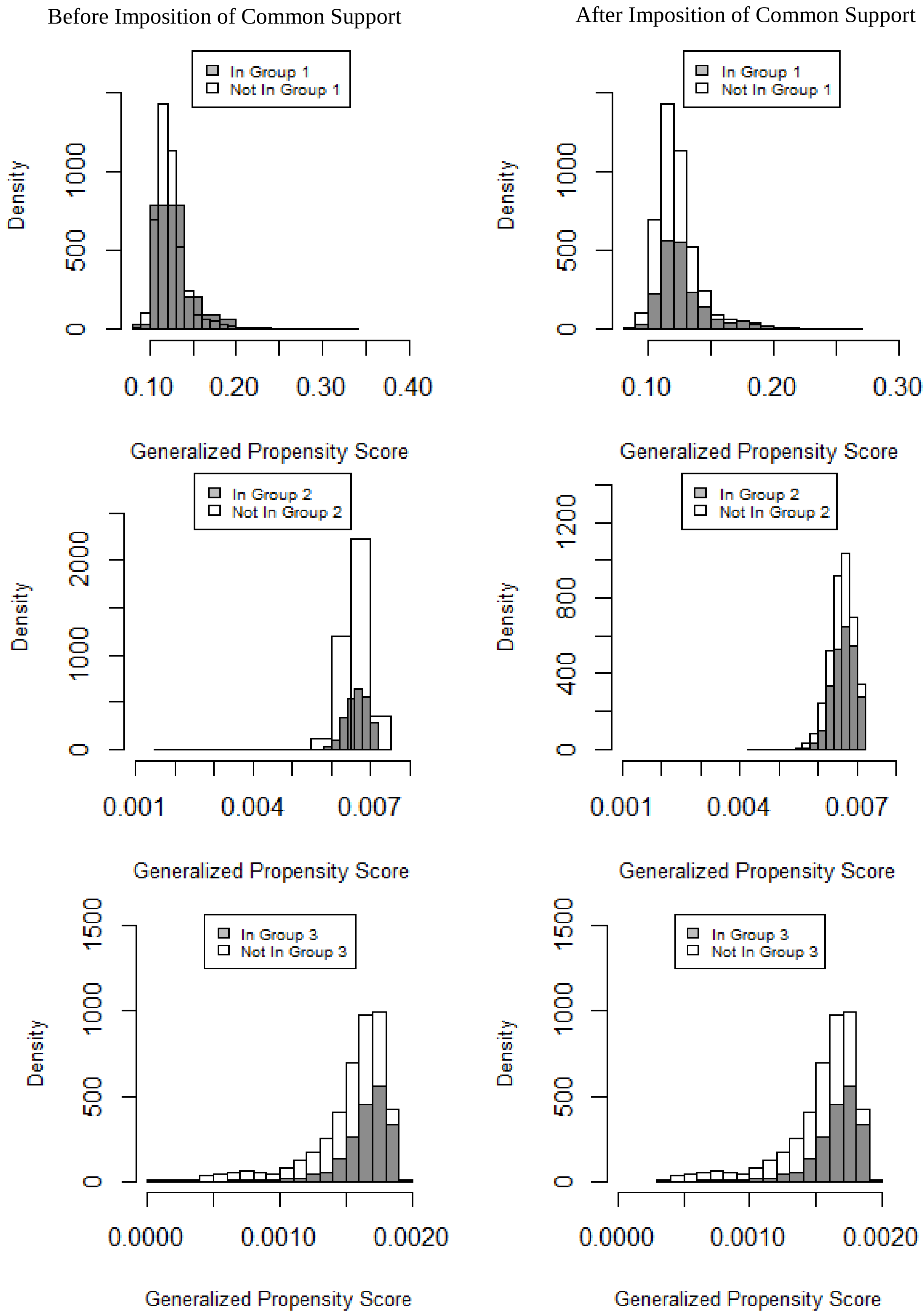

Figure A4
Common support condition for duration.

Table A6
Covariate Balance With and Without Conditioning on $E[T|x_i]$

	Treatment: Frequency				**Treatment: Duration**			
	Without Condition		Condition		Without Condition		Condition	
Covariates	Est	Std. Error	Est	Std. Error	Est	Std. Error	Est	Std. Error
GPA	5.674[a]	0.727	0.327	0.781	7.768[a]	1.350	0.429	1.395
military	-1.898	3.102	0.923	3.026	-2.804	5.793	2.214	5.666
athlete	-15.467[a]	3.713	-0.152	3.721	-25.607[a]	6.935	-0.445	6.940
housing	1.262	1.299	-0.087	1.268	4.324[d]	2.423	0.579	2.378
CARE	11.556	22.913	-3.566	22.338	-17.780	42.785	-0.885	41.806
currentload	1.053[a]	0.275	0.284	0.271	0.887[d]	0.506	0.443	0.495
class.Freshman	-0.397	1.098	-0.143	1.069	1.966	2.050	-0.482	2.007
class.Sophomore	0.649	1.144	0.075	1.115	-1.988	2.138	0.522	2.094
class.Junior	-1.110	2.699	0.708	2.631	-0.456	5.008	0.236	4.892
class.Senior	-5.369	19.845	-14.297	19.339	-20.618	37.056	-12.298	36.201
college.Arts... Sciences	4.909[a]	1.082	-0.303	1.096	8.608[a]	2.022	-0.461	2.049
college.Business	-3.680[b]	1.391	0.252	1.373	-4.695[d]	2.598	-0.191	2.552
college.Communication...Infor	-4.263[d]	2.365	0.465	2.319	-4.415	4.417	-0.438	4.321
college.Criminology	-5.976[c]	2.991	0.432	2.936	-11.501[c]	5.570	1.372	5.493
college.Education	-9.678[b]	3.462	1.356	3.429	-19.364[b]	6.464	1.681	6.436
college.Engineering	8.373[a]	1.952	-0.750	1.971	11.757[b]	3.647	-0.627	3.637
college.Film. School	-6.618	7.031	-0.666	6.858	-25.075[d]	13.127	0.707	12.912
college.Fine. Arts	-17.297[b]	6.628	0.784	6.536	-33.462[b]	12.376	0.447	12.255
college.Human.Sciences	3.219[d]	1.922	-0.502	1.884	12.929[a]	3.587	0.253	3.585
college.Music	-11.371[a]	3.064	0.921	3.064	-33.435[a]	5.918	2.781	6.196
college.Nursing	0.952	3.158	0.182	3.077	6.378	5.896	-1.268	5.777
college.Social .Sciences	3.795[c]	1.934	-0.128	1.897	5.076	3.612	-0.439	3.543
college.Social .Work	-1.329	6.373	-2.496	6.209	-6.246	11.900	-2.610	11.627

college.Undergraduate.Studies	-3.782[b]	1.409	0.352	1.392	-6.205[c]	2.626	0.820	2.598
college.Visual.Arts..Theatre.	-5.690[d]	3.246	-0.013	3.178	-20.066[a]	6.058	-0.168	6.035
MatriculationYearTer.20149	-1.807[d]	0.999	0.134	0.979	-1.994	1.867	0.121	1.828
Age	1.308[c]	0.644	0.053	0.631	1.649	1.201	-0.155	1.178
UScitizen	-6.704[c]	3.414	2.121	3.361	-8.449	6.398	0.951	6.274
HSGPA	1.396	1.465	-0.311	1.430	-1.224	2.737	-0.355	2.674
ACT	-0.183	0.182	-0.015	0.177	-1.161[a]	0.339	0.058	0.339
TransferOrExamCredit	0.004	0.030	-0.002	0.029	-0.057	0.055	0.002	0.054
Race.White	-5.593[a]	1.067	-0.339	1.083	-9.155[a]	1.994	-0.598	2.016
Race.Hispanic.Latino	2.671[c]	1.303	0.303	1.276	5.693[c]	2.431	-0.392	2.402
Race.Black.African.American	4.739[c]	2.369	0.602	2.319	6.910	4.417	1.316	4.327
Race.Asian	16.431[a]	2.871	-0.979	2.975	27.114[a]	5.392	0.059	5.520
Race.American.Indian.Alaska	8.900	11.973	1.262	11.673	7.089	22.358	1.818	21.843
Race.Native.Hawaiian.Oth.Pa	8.698	12.556	-3.485	12.251	-6.315	23.448	-2.985	22.905
Race.Two.or.More.Races	0.508	2.494	0.468	2.430	0.277	4.658	1.287	4.550
Gender.M	3.468[a]	1.012	-0.257	1.008	-1.556	1.892	0.040	1.851
EducationFather.College	-9.672[a]	2.170	-0.011	2.185	-16.042[a]	4.053	-0.649	4.066
EducationFather.High.School	-5.033[d]	3.032	1.256	2.975	-11.238[c]	5.678	2.428	5.603
EducationFather.Middle.School	-18.878	19.843	-5.654	19.347	-31.375	37.055	3.601	36.254
EducationMother.College	-8.656[a]	2.136	-0.218	2.136	-14.566[a]	3.995	-0.715	3.990
EducationMother.High.School	-7.534[c]	3.299	0.959	3.248	-14.423[c]	6.139	1.349	6.069
EducationMother.Middle.Scho	-7.460	13.235	1.873	12.904	-11.995	26.211	7.913	25.629

ParentIncome 1000	0.682	5.473	-2.517	5.335	4.650	10.220	-2.945	9.992
ParentIncome ..1000..40000	-8.851[c]	3.815	0.328	3.752	-14.909[c]	7.124	2.560	7.033
ParentIncome ..40000..75000	-4.022	3.816	0.834	3.727	-7.920	7.157	0.953	7.011
ParentIncome ..75000.100000	-10.584[c]	4.435	1.780	4.375	-17.638[c]	8.232	-0.373	8.106
ParentIncome ..100000.	-9.479[a]	2.702	-0.412	2.682	-16.324[b]	5.058	-1.122	5.023

[a]Significant at the 0.1% level
[b]Significant at the 1% level
[c]Significant at the 5% level
[d]Significant at the 10% level

Table A7
Estimated Coefficients of Conditional Distribution of GPA Given Treatment and GPS

Treatment: Frequency			**Treatment: Duration**		
	Estimate	Std. Error		Estimate	Std. Error
Intercept	5.2350[a]	0.9633	**Intercept**	3.0600[a]	0.6626
Frequency	0.0127	0.0083	**Duration**	0.0148[a]	0.0028
Frequency^2	0.0000	0.0000	**Duration^2**	0.0000[b]	0.0000
GPS	-53.1700[c]	24.3100	**GPS**	17.2900	12.1200
GPS^2	366.7000[c]	161.7000	**GPS^2**	-123.1000[c]	55.9100
Frequency*GPS	-8.7860[a]	2.6010	**Duration*GPS**	-4.1490	2.9280

[a]Significant at the 0.1% level
[b]Significant at the 1% level
[c]Significant at the 5% level
[d]Significant at the 10% level