First-year students' time use in college:

A latent profile analysis

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Abstract

Students' time expenditures influence their learning and development. This study used latent profile analysis to identify a typology of how first-year students spend their time using a large, comprehensive sample. It identified four time usage patterns by first-year students titled balanced, involved, partiers, and parents. Sex, expected major field, on-campus residency, age, Greek-life membership, and standardized test scores were predictive of students' time use patterns. Implications for policy and practice are discussed.

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Recent popular accounts of the undergraduate experience suggest that students learn little and spend considerable time partying and on other leisure activities (e.g., Armstrong & Hamilton, 2013; Arum & Roksa, 2011; Babcock & Marks, 2011). While these accounts have captured the media's and public's attention, it is not clear that these portrayals reflect reality for all undergraduates and other explanations have been put forward (McCormick, 2011). Time usage is a critical component of student learning and development (Pace, 1980); consequently, it is imperative to better understand how students utilize their time and its relationship to student learning and development. In this study, we analyzed first-year students' time-use patterns to subject these narratives to careful scrutiny. While others have previously attempted to classify students into discrete groups (e.g., Armstrong & Hamilton, 2013; Brint & Cantwell, 2010; Hu & McCormick, 2012; Quadlin & Rudel, 2015; Rau & Donald, 2000), these efforts have used data from a single or particular type of college or use older, non-probabilistic frameworks. In this paper we seek to overcome these limitations by classifying students based on their time-use patterns using data from a variety of institution types using latent profile analysis.

Undergraduates' Time Use

Students make varying choices in how they allocate their time to a range of activities, such as class attendance, studying, working, leisure and recreation, personal care, and so on. This variation in time use can have important implications for the student experience. The way students use their time has implications for their level of engagement, learning and development. As Kuh and colleagues (2005) have argued, "what students do during college counts more in terms of desired outcomes than who they are or where they go to college" (p. 8).

Time use among college students is a surprisingly underexplored concept. The available data suggests that students' time use patterns have changed over time (Babcock & Marks, 2011). It is estimated that full-time students spent 40 hours per week studying and attending class in 1961, but only 27 hours per week in 2003. In their analysis, Babcock and Marks (2011) challenge the suggestion that the decline is attributable to changes in technology, student demographics, or the extent of work for pay. Using more recent time use data, it is estimated that undergraduates expend approximately 14% of their time or roughly 3.2 hours per day, on average, attending class and studying (Pell Institute, 2015). However, there is some suggestive evidence that low-income students, specifically those receiving Pell grants, spend more time studying than the average student (Goldrick-Rab, 2016; Pell Institute, 2015);

While Babcock and Marks (2011) speculate that the declining amount of time spent studying has resulted in less learning and development, the existing literature is mixed on how study time allocations relates to formal academic performance. Lahmers and Zulauf (2000) estimate that meaningful GPA increases would require substantial changes in the time allocated to studying, a finding replicated by Brint and Cantwell (2010). In contrast, Stinebrickner and Stinebrickner (2004) found substantial effects on GPA when the amount of study time increased from 1 to 2 hours per day, but diminishing returns for additional hours.

There is some evidence to suggest that working during college, particularly off campus, negatively impacts students' academic performance (Brint & Cantwell, 2010; Ehrenberg & Sherman, 1987; Stinebrickner & Stinebrickner, 2003). Two studies found that receiving a scholarship alters students' time use and activities (DesJardins, McCall, Ott, & Kim, 2010; Harris & Goldrick-Rab, 2012). Additionally, student loan debt has been correlated with time use (Quadlin & Rudel, 2015). Thus, it appears that undergraduate time use is malleable and a function of the students' personal circumstances. However, much of the available research has focused on students attending a single institution or type of institution. Consequently, it is difficult to generalize these relationships to the broader student population. Furthermore, there has been little investigation of how various combinations of time use relate to outcomes.

Student Typologies

Compared to the study of time use, more effort has been devoted to identifying student typologies. An early example is Cowley and Waller's (1935) work. They examined college life, from student traditions to lifestyles, in order to analyze the cultural complexities, processes, and defined patterns of human behavior to explain student life in America. A more prominent example is Clark and Trow's (1966) two-dimensional model of college student subcultures that classified students by their identification with the institution and involvement with ideas. This model was partially validated quantitatively by Terenzini and Pascarella (1977), but they noted that the involvement with ideas dimension was problematic in distinguishing between students.

Astin (1993) developed an empirical student typology using factor analysis with Cooperative Institutional Research Program data that identified 7 student subcultures: Hedonists, Status Strivers, Scholars, Leaders, Social Activists, Artists, and Uncommitted. Not surprisingly, these typologies were associated with a variety of college outcomes. However, an important implication of Astin's typology is the finding that the student-type composition of a student's peer group was the most important environmental influence on students during college.

Since Astin's (1993) work, postsecondary researchers have continued to develop typologies to help improve and guide practice (see Hu, Katherine, & Kuh, 2011 for a comprehensive literature review). While the typologies use different labels, many substantially overlap with Astin's (1993) subcultures and have been derived from student engagement data.

Kuh and colleagues (2000) used factor and cluster analysis to develop a typology using measures of student effort in educationally beneficial activities. They identified 10 distinct types of students: disengaged, recreator, socializer, collegiate, scientist, individualist, artist, grind, intellectual, and conventional. Zhao, Gonyea, and Kuh (2003) found eight types of students using NSSE data: unconventionals, collegiate, vocationals, conventionals, grinds, academics, maximizers, and disengaged. A notable finding by Zhao and colleagues (2003) is the emergence of the unconventional group which included students with lower levels of engagement in social and academic activities, but who frequently engaged with individuals from diverse backgrounds. They partially attribute the unconventional group to the increasing number of part-time and non-traditional students.

Hu and McCormick (2012) used NSSE data to identify seven types of students, which substantially overlapped with Zhao and colleagues' (2003) work. However, Hu and McCormick's study is distinguished by its focus on how their student types correlated with directly assessed learning gains, self-reported gains, GPA, and persistence. They found that compared to grinds, unconventionals, maximizers, and conventionals had higher scores on a direct assessment of student learning gains, while disengaged students scored lower, after controlling for other factors. Additionally, academics, unconventionals, collegiates, maximizers and conventionals were more likely to persist than grinds, holding other variables constant.

Using data from students attending the University of California, Brint and Cantwell (2010) classified students into the following five categories based upon their time-use patterns: scholars, scholar actives, actives, workers, and passives. They found a variety of student characteristics were correlated with membership in the five time-use categories. In particular, major field, race/ethnicity, first-generation status, SAT I score, and academic conscientiousness were predictive of category membership. Quadlin and Rudel (2015) also classified students by their time usage using latent class analysis, based on data from the National Longitudinal Survey of Freshmen. Roughly 40% of their sample was classified as serious students, 25% as inactives, and a third were labeled socially engaged. They found that sex, race/ethnicity, parental financial contributions, student loan debt, major choice, and institution type were predictive of group membership.

Most of the existing research classifies students according to their psychological profiles or participation in specific activities, not based on their general patterns of time use. Additionally, this research typically uses older, more descriptive techniques that may not properly describe the latent distribution (Magidson & Vermunt, 2002). The exception, Quadlin and Rudel (2015), utilized a sample from students attending highly selective institutions, therefore, it is unclear how their findings generalize to the broader population of undergraduate students. Consequently, we sought to fill in these literature gaps by examining how students use their time using a diverse sample of first-year students attending a variety of institution types. Additionally, we employed latent profile analysis which allowed us to describe the latent distribution of how students spent their time, which improves upon the methods employed by most previous typology researchers studying bachelor's-seeking undergraduates.

Theoretical Framework

Student engagement theory guided this inquiry. The current understanding of student engagement theory has been informed by previous work including Pace's (1980) "quality of effort" concept, wherein student learning is related to the quality and quantity of effort, and Astin's (1984) student involvement theory, in which student involvement in academic and co-curricular activities promotes retention. Additionally, the work of Chickering and Gamson

(1987) highlighted a range of effective educational practices that institutions can use to promote students' learning and development. The current understanding of student engagement theory was conceptualized by Kuh and colleagues (1991) and combines these concepts, but also considers how institutions can promote learning outside of the classroom (McCormick, Kinzie, & Gonyea, 2013). Consequently, we do not view student learning and development as solely occurring in a classroom environment, but take a more holistic approach and view student learning as taking place in the classroom, through formal and informal co-curricular activities, and via interactions with students, faculty, peers, and the surrounding community.

In the student engagement paradigm, students' time allocation is viewed as an input into their learning and development. However, institutions are believed to play an important role in how students decide to spend their time. Institutions can influence students' time allocations through curriculum structure (e.g., courses offered, timing of courses, modes of delivery), pedagogical practices, physical space (e.g., residence halls, study spaces), support services, expectations for students, co-curricular activities, and institutional culture (interactions with faculty, staff, and peers). Consequently, we regard students' time usage to be influenced by both students' decisions and the environment experienced by students.

Research Questions

Guided by student engagement theory, we sought to investigate and identify patterns in first-year students' time use and how these patterns are related to student and institutional characteristics. We investigated the following research questions:

1. How do first-year students allocate their time?
2. What homogenous time usage patterns exist among first-year students?
3. How do time usage patterns correlate with student and institutional characteristics?

Data and Methods

Data

Our data come from the 2014 and 2015 administrations of the National Survey of Student Engagement (NSSE). NSSE is a large multi-institutional survey that assesses students' engagement in educationally beneficial activities, time use, perceptions of the campus environment, perceived institutional contribution to their educational gains, and academic and demographic characteristics. NSSE is annually administered in the winter and spring to first-year and senior students attending bachelor's-granting institutions in the US and Canada. Our initial sample included 233,164 first-year students attending 958 bachelor's-granting U.S. institutions. The response rate for the initial sample was 22%. Due to the computational intensity of our analyses, we extracted an analytic sample of 3,000 students from this larger sample. Students were selected into the analytic sample through a weighted random selection approach that accounted for differential rates of non-response by sex, enrollment status (full/part-time) and institution size.

Table 1 presents the characteristics of the analytic sample. About three out of five students were White. Asian/Pacific Islander, Black, and Hispanic/Latino students accounted for 6%, 9% and 13% of the sample, respectively. About three-fifths (56%) of the sample was female. The sample was roughly evenly divided between students with a parental education of high school or less, some college, bachelor's degree, and graduate degree. About 7 in 10 students were enrolled at a public institution. Half of the sample attended an institution with a Barron's selectivity rating of competitive, with another 42% attending more selective institutions. About 40% of the sample attended doctoral universities, 42% master's colleges and universities, 13%

baccalaureate colleges, and 5% special focus institutions, tribal colleges, or institutions that were not classified in the 2010 Basic Carnegie Classifications.

Table 1: Profile of First-Year Students in the Analytic Sample (N=3,000)

	%
Race/ethnicity	
Asian/Pacific Islander	6
Black	9
Hispanic/Latino	13
White	60
Multiracial	4
International	5
Other	<1
Sex	
Female	56
Male	44
Parental Education	
High school or less	22
Some college	22
Bachelor's degree	28
Graduate degree	28
Institutional Control	
Public	69
Private	31
Barron's Rating (aggregated)	
Non-/Less competitive	11
Competitive	48
Very competitive	27
Highly/Most competitive	15
Carnegie Classification (aggregated)	
Doctoral	40
Master's	42
Baccalaureate	13
Other	5

The primary variables utilized in the study represent the number of hours students reported spending in a typical week on the following activities: preparing for class, participating in co-curricular activities, working on campus, working off campus, doing community service or volunteer work, relaxing and socializing, providing care for dependents, and commuting to campus. Students reported time use in discrete ranges on the NSSE instrument which were recoded to their midpoints for this analysis. (The unbounded upper choice was assigned a fixed value slightly above the cut point.) We combined the two work variables into a single variable, and did the same with co-curricular activities and volunteering/community service.

The other variables used in the analyses were various student and institutional characteristics previously correlated with student engagement (National Survey of Student Engagement, 2016). Student characteristics included sex, race/ethnicity, parental education, educational expectations, SAT I or ACT equivalent, part-time status, nontraditional age (24 or older), distance education status, Greek-life member, on-campus resident, student athlete status, and expected major field. These variables were primarily reported by respondents, except for sex, race/ethnicity, part-time status, and standardized test score which were institution-reported. Institutional characteristics included 2010 Basic Carnegie Classification (aggregated), Barron's rating, urbanicity, proportion of women students, proportion of white students, total undergraduate enrollment, and institutional control. These data were assembled from IPEDS (National Center for Educational Statistics, n.d.), the Carnegie Classifications (Carnegie Foundation for the Advancement of Teaching, 2010), and Barron's Educational Series (2012).

Analytic Methods

We began our analyses by examining the descriptive statistics of the time expenditure data. Next, we analyzed the time expenditure data using latent profile analysis (LPA), a type of finite mixture model. LPA identifies unobserved groups of individuals from observed data through a probabilistic framework (Lazarsfeld & Henry, 1968). LPA is closely linked to the more common latent class analysis; however unlike latent class analysis, LPA permits the use of continuous variables. LPA has methodological advantages over other approaches such as cluster and discriminant analysis as it uses a probabilistic framework that describes the latent distribution, rather than simply analyzing the distance between individuals (Magidson & Vermunt, 2002).

As the correct number of classes or groups was not known *a priori,* we used an iterative process to identify the best fitting LPA model and thereby the appropriate number of latent classes (Clark, Muthén, Kapri, D'Onofrio, Viken, & Rose, 2013). This process entailed fitting a series of latent profile models starting with 2 classes. We estimated models with up to 6 classes, and would have fit additional models, if needed. To identify the best candidate models, we examined the Akaike information criterion (AIC), Bayesian information criterion (BIC), and adjusted Bayesian information criterion (aBIC) for each model. Next, we performed the Lo–Mendell–Rubin (LMR) test and the parametric bootstrapped likelihood ratio test (BLRT) to compare the candidate models. These tests provide significance tests on the probability that a k versus k-1 class model fits better. If the p value is less than .05, the k model is preferable, otherwise the k-1 model is a better fit for the data. Simulation studies have shown that the BIC is the best predictor of the information criterion tests, but that the BLRT is the best overall indicator of the correct number of classes (Nylund, Asparouhov, & Muthén, 2007). However, the BLRT is not always the most reliable indicator in practice (Muthén, 2009).

After identifying the model with the best characteristics, we examined that model's results. We used the parameter estimates to create an item-profile plot, which visually displays the average amount of time spent in each activity by members of the identified latent classes. Additionally, we examined the proportion of the sample in each latent class identified.

Next, we developed a multinomial logistic regression model to examine how various student and institutional characteristics were related to the latent classes identified. As LPA provides probability estimates of latent class membership, we estimated a multinomial logistic regression model via a multiple imputation framework. This allowed us to use multiple pseudo-class draws to account for the uncertainty of latent class membership. A total of twenty imputed datasets were created as recommended by Wang, Hendricks Brown, and Bandeen-Roche (2005). For each imputed dataset, we first generated a random number for each student ranging from 0 to 1. Next, we assigned the student to the class where the random number fell in the posterior class distribution for that student. For example, a student with a 25%, 50%, and 25% estimated probability of being a member of latent classes 1, 2, and 3, would be assigned to the first class if the random number was .15 (as it falls between 0 and .25) or the third class if the random number was .80 (as it falls between .75 [.25+.50] and 1). Additionally, we took the opportunity to impute other covariates using predictive mean matching for continuous variables (from a pool of 10 nearest neighbors; Morris, White, & Royston, 2014) and the appropriate form of logistic regression for binary, ordinal, and nominal variables. After creating the imputed datasets which contained a student ID, the class membership pseudo-class draw, and the imputed covariates, we estimated a multinomial logistic regression using the covariates described above using each dataset. The coefficients were averaged across the models and the standard errors were calculated as recommended by Rubin (1987). Finally, we converted the coefficient estimates to relative risk ratios (RRR) by exponentiating the coefficients. The RRRs represent the change in relative risk of being a member of a given group relative to the comparison group for a unit change in the independent variable, holding other factors constant.

Results

We began our analyses by examining how first-year students spent their time, on average. Table 2 summarizes the results of this analysis. On average, students spent about 14 hours per week (HPW) preparing for class, 6 HPW working for pay, 12 HPW relaxing and socializing, 7 HPW participating in co-curricular activities and community service, 2 HPW caring for dependents, and 3 HPW commuting to campus. On average, these activities accounted for a total of 45 HPW. However, the standard deviations indicate that there is considerable variation in how students allocate their time to these activities.

Table 2: Descriptive statistics of the time expenditure variables

	Hours per week	
Activity	Mean	SD
Preparing for class	13.8	8.1
Working for pay	6.3	9.6
Relaxing & socializing	12.3	8.4
Co-curricular activities & community service	7.0	7.7
Dependent care	2.4	6.7
Commuting to campus	3.1	4.4

Next, we conducted the latent profile analysis. We began by fitting models that identified between 2 and 6 latent classes. The information criteria summarized in Table 3 all indicated that a 4-class model is most appropriate for the data; therefore, we did not estimate additional models with more latent classes. Next, we calculated the LMR and BLRT significance tests for the candidate models. The LMR test suggested that the 5 class model did not was not superior to the 4 class model. However, the BLRT did not point to a specific model. As all of our indicators, except for the BLRT, point to the four class solution as being most appropriate fit for our data, we concluded that the four-class solution was optimal.

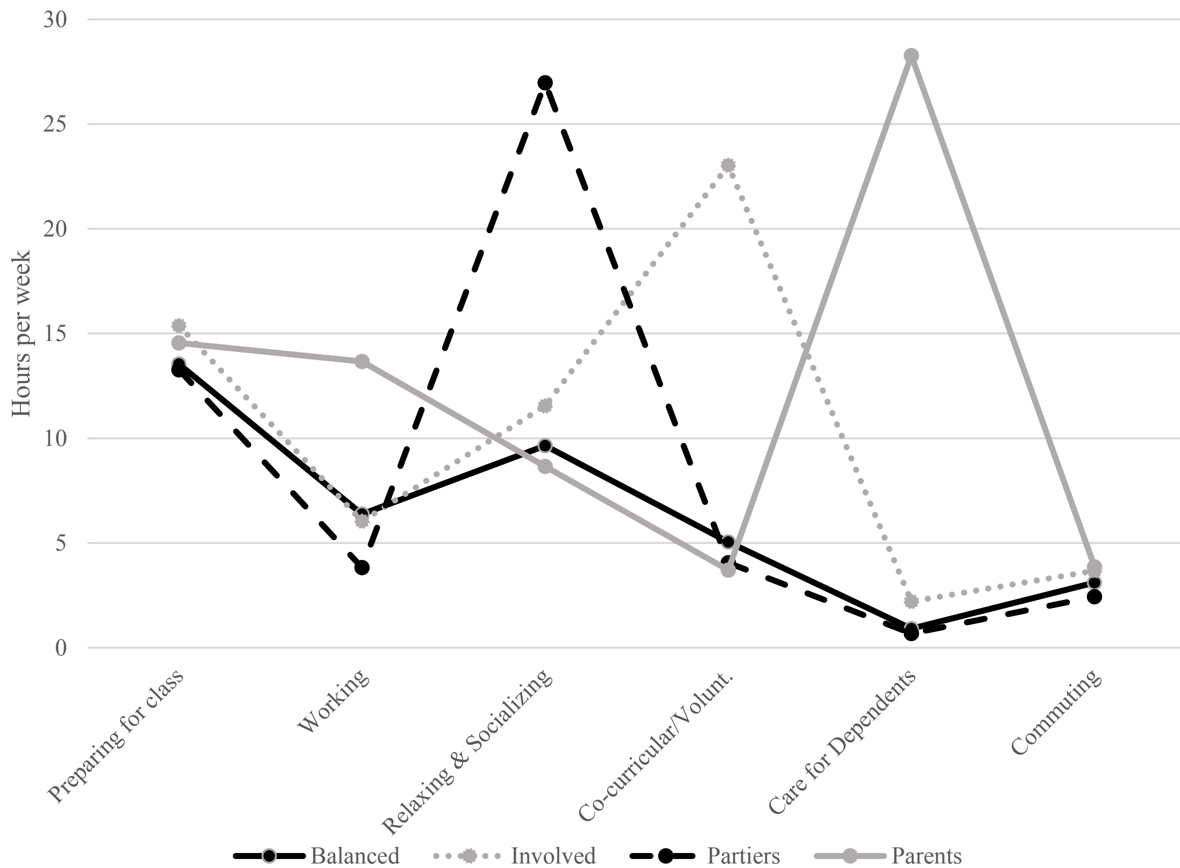
Table 3: Factor mixture model fit statistics and significance tests

Classes	AIC	BIC	aBIC	LMR	BLRT	Entropy
2	118960	119074	119014	--	--	.919
3	118535	118691	118609	.000	.000	.854
4	115562	115760	115655	.000	.000	.868
5	118953	119194	119067	.572	.000	.919
6	119307	119589	119440	1.000	.000	.897

Notes: AIC= Akaike information criterion, BIC=Bayesian information criterion, aBIC=adjusted Bayesian information criterion, LMR= Lo-Mendell-Rubin test, BLRT= bootstrapped likelihood ratio test, -- indicates that the test was not conducted. LMR & BLRT compare *k* class model to *k*-1 class model.

Figure 1 presents the item-profile plot from the 4-class model. This figure displays the average number of hours per week spent in each activity by members of each class. The first class, which we named Balanced, appears to contain the typical first-year student as it contains 69% of the sample. The second group, Involved, accounts for 12% of the sample—students who were primarily distinguished by the amount of time spent on co-curricular activities and volunteering. The Involveds averaged 23 hours per week on co-curricular activities and volunteering, compared to no more than 5 hours for the other three groups. The third class, Partiers, represents 14% of the sample and contained students differentiated by a substantial amount of time devoted to relaxing and socializing. This group averaged 27 hours per week relaxing and socializing. The fourth group, Parents, contained students who spent substantial amounts of time caring for dependents and working for pay. Representing 5% of the sample, Parents averaged 28 hours per week caring for dependents and 14 hours per week working—about 7–10 hours more than the other groups. All four groups averaged roughly comparable amounts of time preparing for class and commuting to campus (13–15 hours per week studying and 2–4 hours per week commuting). However, the four groups differed notably with respect to the total number of hours per week accounted for by these six activities, with Balanced and Partiers averaging the lowest time commitment (39 and 51 hours per week, respectively) and Involved and Parents averaging the highest (62 and 73).

Figure 1: Item Profile Plot



Share of sample:	69%	12%	14%	5%

Table 4: Multinomial logistic regression predicting latent class membership (n=3,000)

	Parents		Partiers		Involved	
	RRR	Sig.	RRR	Sig.	RRR	Sig.
Male	.55	*	1.48	**	1.53	**
Race/Ethnicity (ref: White)						
Asian/Pacific Islander	1.48		.82		.84	
Black	.65		.89		.45	*
Hispanic/Latino	.47		.82		.88	
Multiracial	1.03		.65		.65	
Foreign	1.11		.84		.93	
Other	.21		1.66		.65	
Parental education (ref: Bachelor's)						
HS or less	1.37		.94		1.02	
Some college	1.40		.90		1.05	
Graduate	.56		.96		1.17	
Educational expectations (ref: Bachelor's)						
Some college	.76		.53		1.16	
Master's degree	.92		.77		.94	
Doctoral/professional	.88		.76		1.27	
SAT (100s)	.97		1.14	*	.89	
Part-time	1.97	*	.79		1.06	
Nontraditional age	12.92	***	.72		.66	
All courses online	1.02		.83		.01	
Greek-life member	.81		.83		3.95	***
On campus resident	.22	***	1.58	**	1.36	
Athlete	.42		.51	*	6.17	***
Major field (ref: Social Sciences)						
Arts & Humanities	.30		.66		.95	
Bio. Sci., Agr., & Nat. Res.	.39		.43	**	1.09	
Phys. Sci., Math, & Comp. Sci.	.41		.55	*	.62	
Business	.56		.60		1.54	
Comm., Media, & Pub. Rel.	.53		.76		1.67	
Education	.71		.72		1.46	
Engineering	.42		.57		1.00	
Health Professions	.46		.67		1.46	
Social Service Professions	.88		.68		.94	
All Other	.50		1.11		1.14	
Undecided, undeclared	.67		.82		.96	
Carnegie Classification (ref: Doctoral)						
Master's	1.53		.95		.80	
Baccalaureate	.96		1.05		1.01	
Other	2.42		.86		.43	
Barron's rating (ref: Competitive)						
Non/less competitive	.63		1.14		1.12	
Very competitive	1.17		.86		.82	
Highly/most competitive	.83		.72		1.18	
Urbanity (ref: City)						
Suburb	1.39		1.08		1.37	
Town	1.48		.97		1.38	
Rural	.73		.68		1.40	
% female	1.37		1.58		.62	
% White	.76		1.09		.54	
UG enrollment (1000s)	1.00		1.00		1.00	
Private institution	1.20		.92		.99	
Constant	.14		.05	**	.40	

*$p < .05$, **$p < .01$, ***$p < .001$

Notes: Base model is the Balanced Class; RRR=Relative Risk Ratios; Standard errors adjusted to account for the uncertainty of the imputation.

Next, we estimated a multinomial logistic regression that predicted students' time use class membership (Table 4). The results of this analysis are presented for membership in the Parents, Partiers, and Involved groups compared to the Balanced group. The model results indicate that with all controls entered, membership in these three groups relative to Balanced group membership is not signficantly related to institutional characteristics. The following discussion therefore focuses on the student characteristics related to group membership net of all controls.

Parents. Part-time and nontraditional-aged students were more likely to be in the Parents rather than the Balanced group, controlling for other factors (the age effect being quite large). Male and campus-resident students were less likely to belong to the Parents group compared to the Balanced group, net of other factors.

Partiers. After controlling for other factors, being male students and residing on campus was positively related to membership in Partiers relative to the Balanced group. Standardized test scores were also positively related to being a member of the Partier rather than the Balanced group. However, student-athletes were less likely to be Partiers relative to the Balanced group. Furthermore, majors in various physical and life science fields as well as mathematics and computer science were less likely than social science majors to be Partiers rather than members of the Balanced group, net of other factors.

Involved. Male students were more likely than female students to be members of the Involved group relative to the Balanced group, after controlling for other factors. As would be expected, being a student-athlete and Greek membership were strongly related to being in the Involved rather than Balanced group, net of other characteristics. Black students were less likely than White students to be in the Involved group relative to the Balanced group.

Discussion and Implications

The popular and media narrative on the college student experience suggests that students learn little and party to excess. We subjected this narrative to empirical scrutiny by examining first-year students' time-use patterns using a comprehensive multi-institutional sample. Using a latent profile analysis, we identified four quite distinct time-use patterns that characterize first-year students, focusing specifically on the allocation of time to six activities: class preparation, co-curriculars and volunteering, working for pay, relaxing and socializing, caring for dependents, and commuting to campus. The groups identified—Balanced, Partiers, Involved, and Parents, indicate the various patterns of student time use during the first college year. The Balanced group contains about two out of three students and thus appears to represent the normative first-year college experience—one showing the lowest overall time commitment to the six activities (about 39 hours per week on average). The other three groups are characterized by distinctive forms of specialization with regard to time use that also correspond to increasing total time commitments. Partiers—about 14% of first-year students—averaged 27 hours per week relaxing and socializing, about 2–3 times as much as the other groups. On average, Partiers devoted about 51 hours per week to the six activities. Accounting for about 12% of first-year students, Involved students averaged 23 hours per week on co-curricular activities and volunteer work, about 4–6 times as many hours as the other groups, with a total of 62 hours per week on the six activities. The remaining 5% of first-year students were in the Parents group, and demonstrated higher levels of involvement to both working (14 hours per week on average, or 2–3 times more than the other groups) and caring for dependents (28 hours per week), with a total of 73 hours per week on average devoted to the six activities—nearly twice the time commitment of the Balanced group.

We found no evidence of a relationship between institutional characteristics and student types, suggesting that the four types exist across a wide range of institutional contexts. Several student characteristics were predictive of group membership. Sex, on-campus residence, and student-athlete status were predictive of membership in at least two groups relative to Balanced, while several other student characteristics were related to membership in one group relative to Balanced. Neither parental education nor educational expectations were predictive of group membership net of the other variables in the model.

Important next steps in this research will involve examining the relationship between group membership and a number of educational processes and outcomes, including engagement in other educationally purposeful activities, perceptions of the campus environment, college grades, perceived gains, and satisfaction with the college experience.

While our results did identify a distinctive "Partier" time-use pattern, they nonetheless refute the popular narrative that college students trade studying for partying. In addition to class attendance, the normative first-year student devoted about 25 hours per week to a combination of studying, working, participating in co-curricular activities, and volunteering, plus 10 hours per week relaxing and socializing. With regard to the amount of time spent preparing for class, only about two hours per week separated the lowest and highest groups (Partiers and Involved, averaging 13 and 15 hours per week respectively). Indeed, Partiers spent nearly as much time engaged in educationally beneficial activities as the Balanced students, and higher entrance examination scores were associated with an increased likelihood of Partier membership. We therefore conclude that there is little support for the "trading studying for partying" narrative.

However, the large differences in total time allocation across the four groups raise a number of important questions. What are the consequences for student engagement and student learning for the different overall time commitments of the four groups? If relationships exist, what can or should institutions do to influence students' time allocation choices? Are there other consequences of these differences, such as variation in the amount of time available for sleep? The categories of time use asked about on the NSSE survey exclude a number of other activities, such as class attendance, work in the home other than dependent care, personal care, and sleep. Future research should strive for a more complete accounting of student time use so we can more fully understand both the choices and consequences of how different students spend their time and the consequences for learning and development.

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