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 taxonomy of how first-year students spend their time using a large multi-institution sample. We 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. Holding a range of student and institutional factors constant, members of the involved group, on average, reported higher levels of engagement than the Balanced group, while Partiers reported lower levels of engagement. Implications for policy and practice are discussed.

Keywords  Higher education · Time use · Student engagement · First-year students · Latent profile analysis

Introduction

Recent popular accounts of the undergraduate experience suggest that students learn little and spend considerable time on partying and other leisure activities (e.g., Armstrong and Hamilton 2013; Arum and Roksa 2011; Babcock and Marks 2011). While these accounts have captured media and public attention, it is not clear that these portrayals reflect reality for all undergraduates, and others have put forward alternate explanations (McCormick 2011). Time usage is a critical component of student learning and development (Pace

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1980); consequently, it is imperative to better understand how students utilize their time and what relationship time use has on 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 classified students into discrete groups (e.g., Armstrong and Hamilton 2013; Brint and Cantwell 2010; Hu and McCormick 2012; Quadlin and Rudel 2015; Rau and Durand 2000), these efforts have used data from a single, or particular type, of college or they have used older, non-probabilistic classification methods. In this paper, we seek to overcome these limitations by using latent profile analysis with data from a variety of institution types to classify students based on their time-use patterns. Furthermore, we investigate the predictors of the time use categories and how the categories correlate with various dimensions of student engagement, perceived gains, and GPA.

**Undergraduates’ Time Use**

Students make varying choices in how they allocate their time to a range of activities like 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. How students use their time has implications for their level of engagement, learning, and development. As Kuh et al. (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 suggest that students’ time use patterns have changed over time (Babcock and Marks 2011). It was estimated that full-time students spent 40 h per week studying and attending class in 1961, but only 27 h 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 recent time-use data, it is estimated that undergraduates expend approximately 14% of their time or roughly 3.2 h 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 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 h 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 and Cantwell 2010; Ehrenberg and Sherman 1987; Stinebrickner and Stinebrickner 2003). Two studies found that receiving a scholarship alters students’ time use and activities (DesJardins et al. 2010; Harris and Goldrick-Rab 2012). Additionally, student loan debt has been correlated with time use (Quadlin and Rudel 2015). Thus, it appears that undergraduate time use is 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—that is, the joint allocations of time to various activities—relate to outcomes.

**Student Typologies and Taxonomies**

Compared to studying time use, more effort has been devoted to developing classifications of students, using either typological or taxonomic techniques. (Although the terms typology and taxonomy are often used interchangeably, Bailey [1994] distinguishes typology as conceptually driven while taxonomy results from quantitative analysis.) 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 and 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 taxonomy using factor analysis with Cooperative Institutional Research Program data that identified seven student subcultures: hedonists, status strivers, scholars, leaders, social activists, artists, and uncommitted. These categories were associated with a variety of college outcomes. An important implication of Astin’s taxonomy 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 and taxonomies of students to help improve and guide practice (see Hu et al. 2011 for a comprehensive literature review). While the resulting classifications 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 taxonomy using measures of student effort in educationally beneficial activities. They identified ten distinct types of students: disengaged, recreator, socializer, collegiate, scientist, individualist, artist, grind, intellectual, and conventional. Zhao et al. (2013) found eight types of students by using NSSE data: unconventionals, collegiate, vocationals, conventions, 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 student types, which substantially overlapped with Zhao and colleagues’ (2013) work. However, Hu and McCormick’s study is distinguished by its focus on how their student types were related with directly assessed learning gains, self-reported gains, GPA, and persistence. They found that compared to the grinds group, unconventionals, maximizers, and conventions 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 conventions 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 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. Males tended to cluster in the passive groups, while females were predominant in the scholars and workers groups. Asian Americans were over-represented in the scholars and passive groups. African Americans tended to be in the workers group. Scholars tended to major in the arts, humanities, biological sciences, physical sciences, and engineering. Scholar actives were clustered in the arts, biological sciences, and engineering. However, actives were less represented in the physical sciences, and engineering. Additionally, scholars and scholar actives had higher than average GPAs and levels of academic conscientiousness. In contrast, actives, workers, and passives generally had lower than average GPAs and levels of academic conscientiousness.

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. Additionally, they note that student debt appears to stratify students as debt-free students engaged in social activities at high rates, while students with debt were uninvolved in campus life or spent substantial time working for pay and involved in academics.

Most of the existing research classifies students according to their psychological profiles or participation in specific activities, rather than their general patterns of time use. Additionally, this research typically uses older, more descriptive techniques that may not properly describe the latent distribution (Magidson and Vermunt 2002). The exception, Quadlin and Rudel (2015) used a latent class analysis, but utilized a sample from 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 using a 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. This approach improves upon the methods employed by most previous taxonomy researchers studying baccalaureate degree-seeking undergraduates.

**Theoretical Framework**

Student engagement theory and the economic notion of utility 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 by students, and Astin’s (1984) student involvement theory, in which student involvement in academic and co-curricular activities promotes retention. Additionally, 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 et al. (1991) and combines these concepts as well as considers how institutions can promote learning outside of the classroom (McCormick et al. 2013). Consequently, we do not view student learning and development as solely occurring in a classroom environment.
We 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 external community.

In economics, utility is the personal satisfaction derived from a good or service. We extended the definition to encompass the satisfaction that results from spending time on different activities. Individuals place different values on goods, services, and activities, and these preferences subsequently influence how they allocate resources, including time. Individuals are viewed as seeking to maximize their utility through the optimal consumption of a basket of goods, services, and activities. Therefore, students are viewed as making different decisions based on the varying utility they placed on the different options. An important related concept is the notion of marginal utility, which is the change in utility due to an increase or decrease in the consumption of a good or service. For example, an individual may place a large value on the first slice of pizza, but place less and less value on subsequent slices since the first slice fulfilled their caloric needs. In the case of time usage, students may not receive any additional benefit or satisfaction from an additional hour of studying as they could have achieved mastery of course material in the previous hour. Consequently, their time could be better used in other ways, as previously demonstrated by Stinebrickner and Stinebrickner (2004).

Not all time use is discretionary. Students have some obligations (e.g., paid employment) that constrain the amount of time available for other activities. Indeed, certain categories of students—such as low-income and nontraditional-aged students—may face more constraints in discretionary time due to work and family commitments. However, nondiscretionary activities such as paid employment and family have associated utilities. In combination, the theories led us to view students’ time allocation as an input into their learning and development, which can later be used in the labor market for greater pay (immediately or over time). Students allocate their time based on their individual preferences and constraints. Consequently, student time expenditures are assumed to be heterogeneous as some students may derive much satisfaction from playing video games, while others may prefer to volunteer for a community group. Additionally, time expenditures are presumed to have a declining marginal utility as the time spent in a particular activity increases, although the diminishing rate of satisfaction is presumed to vary by activity. Furthermore, preferences for time usages are believed to be shaped by both individual and institutional (environmental) factors. According to student engagement theory, institutions are believed to play an important role in how students decide to spend their time through their 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 student time use as a function of both students’ decisions, their personal circumstances, and the environment they experience.

**Research Questions**

Guided by the aforementioned theoretical framework, we sought to investigate and identify patterns in first-year students’ time use, how these patterns are related to student and institutional characteristics, and how they influence engagement in educationally beneficial activities and learning outcomes. Consequently, we investigated the following research questions:
1. How do first-year students allocate their time across a range of distinct activities?
2. What homogenous time usage patterns exist among first-year students?
3. How do time usage patterns correlate with student and institutional characteristics?
4. How are the time usage patterns correlated with engagement in educationally beneficial activities, perceived gains, and GPA?

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 administered annually in the winter and spring to first-year and senior students attending bachelor’s degree-granting institutions in the US and Canada. Institutions elect to participate in NSSE, so it is not a nationally representative sample. However, the distribution of participating institutions resembles the U.S. distribution with regard to Carnegie type, size, control, region, and urbanicity (see National Survey of Student Engagement 2014, 2015). Public institutions tend to be somewhat overrepresented, while very small institutions (fewer than 1000 undergraduates) are underrepresented.

Our initial sample included 233,164 first-year students attending 958 bachelor’s degree-granting U.S. institutions. The response rate for the initial sample was 22%. Previous research indicates that NSSE data produces accurate group means at this response rate (Fosnacht et al. 2017). Due to the computational intensity of our analyses, we extracted an analytic sample of 3000 students from this larger sample. Students were chosen for 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/associate’s degree, 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 doctorate-granting 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.

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 categories were 0, 1–5, 6–10, 11–15, 16–20, 21–25, 26–30, and more than 30 h per week. 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.

We also utilized data on various student and institutional characteristics previously correlated with student engagement (National Survey of Student Engagement 2016b). 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 (first major if two were reported). These variables were primarily reported by respondents, except for sex, race/ethnicity, part-time status, and standardized test score which were institution-reported. While our analyses were largely exploratory, we selected these variables for two primary reasons. First, we wanted to account for student constraints that may lead to differential constraints on students’ time-use. For instance, living off-campus would be expected to be correlated with more commuting due to the distance students must travel from their home to campus, and certain majors may require greater

| Table 1 | Profile of First-Year Students in the Analytic Sample (N = 3000) |
|---------|---------------------------------------------------------------|
| 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 |
| Associate’s/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 |
levels of time commitment to achieve mastery of course material (McCormick et al. 2013; National Survey of Student Engagement 2012). Second, students’ background characteristics are expected to influence their preferences. Students from higher socio-economic backgrounds may devote more time to leisure activities as they have a financial safety net from their parents (Armstrong and Hamilton 2013) and students aspiring to a graduate degree may devote more time to academics to improve their chance of admission for graduate school (Khattab 2015). 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 2011), and Barron’s Educational Series (2012). We included a variety of institutional characteristics in our analyses as we expect that different types of students will be drawn to different institutional types based on their preferences. For example, students who work full-time will typically be attracted to institutions that prioritize flexibility in scheduling and offer support services for non-traditional students. In contrast, students who hope to spend substantial amounts of time engaged in volunteering or co-curricular activities will desire to attend a more traditional, residential campus with a vibrant social life.

Additionally, we used data on student engagement in educationally beneficial activities, perceived gains, and GPA. The engagement data was represented by NSSE’s 10 Engagement Indicators. Information on the validity and reliability of the Engagement Indicators is available from NSSE’s Psychometric Portfolio (2016c). The perceived gains variable was an index created from ten items asking students how much their experience at their institution contributed to their knowledge, skills, and personal development in a variety of areas. The Cronbach’s $\alpha$ of the index was 0.91. All of the Engagement Indicators and the Perceived Gains scales were created by recoding their component items to a 0–60 scale and then averaging the items per NSSE’s standard practice (see NSSE 2016a). Our GPA variable was a recode of an item asking students about their typical letter grades, recoded to the conventional 4-point scale. We utilized these variables to examine the relationship between students’ time use patterns and their learning and development. The descriptive statistics of the Engagement Indicators, perceived gains index, and GPA can be found in Table 6 of Appendix A.

**Analytic Methods**

We began our analyses by examining descriptive statistics for 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 and Henry 1968). LPA is closely linked to the more common latent class analysis; however, unlike latent class analysis, LPA uses 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 and 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 et al. 2013). This process entailed fitting a series of latent profile models starting with two classes. We estimated models with up to six 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 model with $k$ classes fits better than the $k - 1$ class model. If the value is less than 0.05, 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 et al. 2007). However, the BLRT is not always the most reliable indicator in practice (Muthén 2009). As a robustness check, we drew an additional five random samples and repeated the LPA to ensure that the model was converging on the same number of classes.

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 mean 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. At this step, we also examined an important assumption for latent profile analysis: normality (Oberski 2016). For the overall sample, non-normality helps to identify discrete groups of individuals. However, LPA assumes that the distributions of the variables within a class are normal. A classic example of this concept is height, which is typically not normally distributed throughout the entire population. Rather, height is normally distributed with the distinct male and female populations. Therefore, for each of the variables used in the LPA, we examined a histogram plot by latent class to check this assumption. For most of the variables and classes, the distributions approximated a normal distribution. The main exception was for working for pay, which had excessive zeros. Additionally, the “parents” group (see the results section for a description of the latent class) had a spike in working for pay at around 40 hours per week (HPW).

Next, we developed a multinomial logistic regression model to examine how various student and institutional characteristics were related to membership in 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 20 imputed datasets were created as recommended by Wang et al. (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 based on the location of the random number in the posterior class distribution for that student. For example, a student with a 25, 45, and 30% estimated probability of membership in latent classes 1, 2, and 3, respectively, would be assigned to the first class if the random number was .15 (as it falls between 0 and 0.25) or the third class if the random number was .80 (as it falls between .70 [0.25 + 0.45] 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 et al. 2014) and the appropriate form of logistic regression for binary, ordinal, and nominal variables. The percent of missing data by variable ranged from 0 to 28%. However, only two variables exceeded 5%: Barron’s selectivity (6%) and SAT I/ACT score (28%). After creating the imputed datasets which contained a student ID, the class membership pseudo-class result, and the covariates, we estimated a multinomial logistic regression on class membership using each dataset. The coefficients were averaged across the models and the standard errors were calculated as recommended by Rubin (1987). Next, 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. For each of the 20 imputed datasets we calculated VIF statistics to check for multicollinearity. The largest VIF for a variable among any of the datasets was 2.51 indicating that our models met the assumptions for collinearity.

Finally, using the 20 imputed datasets described previously we examined the relationship between the time-use categories and our outcome variables: the Engagement Indicators, the perceived gains index, and GPA. We estimated the relationship between these variables by simply regressing the outcome variables on time-use category membership and the student and institutional characteristics described above. We converted the coefficients to standardized regression coefficients and adjusted the standard errors to account for the uncertainty of the imputation (Rubin 1987).

Limitations

Our sample was limited to first-year students attending four-year colleges and universities. Therefore, the generalizability of our results to other students is unknown and should be the focus of future research. Latent class and profile analyses are limited in their ability to detect rare groups. Consequently, our results may overlook some rare time usage patterns. Our time usage data was self-reported and captured on a survey instrument that did not include an exhaustive list of possible uses of time and omitted important categories like sleep and class attendance. Self-reported time-use data has been criticized as inaccurate due to recall error by respondents (Porter 2011). Consequently, it would be valuable to replicate the study using alternate methods, such as daily time diaries or experience-sampling methods. However, other research suggests that survey and time-diary estimates of time use produce similar results (McCormick 2011). Additionally, our time-use data did not capture the quality of the time use. For example, time spent studying with a tutor is probably substantially more impactful than a student reading for class in their room while their roommate is watching TV. Our time-use data was captured in ranges and recoded to point estimates, so our data should not be viewed as precise estimates of student time use. As noted in the analyses section, the LPA model assumes a normal distribution for each variable with the latent class. We observed two deviations from a normal distribution for the working for pay measure. It had excessive zeros for all classes and a spike at the tail end of the distribution around 40 HPW for one of the classes. Consequently, our latent class model includes some slight assumption violations for the working for pay variable. Our dataset did not include data on variables, like student loan debt, that have been previously been found to be related to time use (Quadlin and Rudel 2015). Therefore, our regression analyses maybe subject to omitted variable bias. Finally, one of our latent classes represented approximately five percent of the sample and had limited variation in some of the variables used in the multinomial logistic model as some of the cell counts were 1. Therefore, the power to predict this group in the multinomial logistic model is limited and some of the relationships maybe spurious.
Results

Descriptive Statistics

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 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. These activities accounted for a total weekly average of 45 HPW. However, the standard deviations indicate that there is considerable variation in how students allocate their time to these activities.

Latent Profile Analysis

Next, we conducted the latent profile analysis. We began by fitting models that identified between two and six latent classes. The information criteria summarized in Table 3 (AIC, BIC, and aBIC) all indicated that a 4-class model is most appropriate for the data; therefore, we did not estimate additional models. Next, we calculated the LMR and BLRT significance tests for the candidate models. The LMR test indicated that the 4-class model was

Table 2  Descriptive statistics of the time expenditure variables

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

Time expenditures were collected in discrete ranges and recoded to the midpoint except for the unbounded top category (More than 30) which was set to 32

Table 3  Factor mixture model fit statistics and significance tests

| Classes | AIC     | BIC     | aBIC    | LMR    | BLRT   | Entropy |
|---------|---------|---------|---------|--------|--------|---------|
| 2       | 118960  | 119074  | 119014  | –      | –      | 0.919   |
| 3       | 118535  | 118691  | 118609  | 0.000  | 0.000  | 0.854   |
| 4       | 115562  | 115760  | 115655  | 0.000  | 0.000  | 0.868   |
| 5       | 118953  | 119194  | 119067  | 0.572  | 0.000  | 0.919   |
| 6       | 119307  | 119589  | 119440  | 1.000  | 0.000  | 0.897   |

LMR & BLRT compare the k-class model to the (k −1)-class model (not conducted for k = 2)
AIC Akaike information criterion, BIC Bayesian information criterion, aBIC adjusted Bayesian information criterion, LMR Lo-Mendell-Rubin test, BLRT bootstrapped likelihood ratio test
superior to the 3-class model, but the 5-class model did not improve on the 4-class model. The BLRT did not indicate a preferred model. Because all of our indicators except for the BLRT favored the 4-class solution as the most appropriate fit for our data, we concluded that the 4-class solution was optimal. We ensured the robustness of this model by drawing an additional five random samples and analyzing their information criteria. The results from the replicated models can be found in Table 7 of Appendix B, and all five replications pointed to the 4-class models as being correct.

Figure 1 presents the item-profile plot from the 4-class model. This figure displays the mean number of hours per week spent in each activity by members of each class. The first class, Balanced, were typical first-year students and accounted for 69% of the sample. The second class, Involved, contained students who were primarily distinguished by the amount of time spent on co-curricular activities and volunteering, representing 12% of the sample. The Involveds averaged 23 HPW in co-curricular activities and volunteering, compared to an average of no more than 5 HPW for the other three classes. The third class, Partiers, were differentiated by a substantial amount of time devoted to relaxing and socializing and represented 14% of the sample. Partiers averaged 27 HPW relaxing and socializing, more than twice that of the next-highest average. The fourth class, Parents, spent substantial time caring for dependents and working for pay. Representing 5% of the sample, Parents averaged 28 HPW caring for dependents, compared with less than 3 HPW for the other groups. Parents also averaged 14 HPW working—about 7–10 h more than the other groups. All four classes averaged roughly comparable amounts of time preparing for class and commuting to campus, 13–15 HPW studying and 2–4 HPW commuting. The four classes differed notably with respect to the total number of HPW accounted for by these six activities, with Balanced and Partiers averaging the lowest time commitment (39 and 51 HPW, respectively) and Involved and Parents averaging the highest (62 and 73).
Predicting Class Membership

Next, we estimated a multinomial logistic regression that predicted students’ 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 significantly related to institutional characteristics. The following discussion therefore focuses on the student characteristics related to group membership net of all controls.

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 might be expected, being a student-athlete and having Greek membership were strongly related to being in the Involved rather than the 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.

Partiers After controlling for other factors, being male and residing on campus were 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. Notably, 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.

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.

Latent Class Relationship with Outcomes

Finally, we examined the relationship between the time use latent classes and students’ engagement in educationally beneficial activities, perceived gains, and GPA. Table 5 summarizes the results from these analyses. Holding other factors constant, students in the Involved group reported higher levels of engagement in higher-order learning, reflective and integrative learning, quantitative reasoning, learning strategies, collaborative learning, discussions with diverse others, and student-faculty interaction activities compared with the Balanced group. Additionally, the Involveds scored higher on the supportive campus environment indicator and perceived a stronger institutional contribution to their learning and development. In contrast, the Partier group reported less engagement in higher-order learning, quantitative reasoning, learning strategies, collaborative learning, and student-faculty interaction than the Balanced group. Furthermore, the Partier group perceived fewer gains in their learning and development than otherwise similar Balanced members. While the magnitude of these effects was generally modest, the greatest contrast between Involved and Partiers (relative to Balanced) was for Student-Faculty Interaction. No significant differences were observed between the Parents and Balanced groups on these outcomes after holding other factors constant. Consistent with the finding of small differences in study time across the four groups, the analysis did not find any GPA differences related to membership in the Involved, Partiers, and Parents groups relative to Balanced after controlling for student and institutional characteristics.
Table 4  Multinomial logistic regression predicting latent class membership (n = 3000)

|                          | Involved |          | Partiers |          | Parents |          |
|--------------------------|----------|----------|----------|----------|---------|----------|
|                          | RRR      | Sig.     | RRR      | Sig.     | RRR     | Sig.     |
| Male                     | 1.53     | **       | 1.48     | **       | 0.55    | *        |
| Race/Ethnicity (ref: White) |          |          |          |          |         |          |
| Asian/Pacific Islander   | 0.84     |          | 0.82     |          | 1.48    |          |
| Black                    | 0.45     | *        | 0.89     |          | 0.65    |          |
| Hispanic/Latino          | 0.88     |          | 0.82     |          | 0.47    |          |
| Multiracial              | 0.65     |          | 0.65     |          | 1.03    |          |
| Foreign                  | 0.93     |          | 0.84     |          | 1.11    |          |
| Other                    | 0.65     |          | 1.66     |          | 0.21    |          |
| Parental education (ref: bachelor’s) |          |          |          |          |         |          |
| HS or less               | 1.02     |          | 0.94     |          | 1.37    |          |
| Some college             | 1.05     |          | 0.90     |          | 1.40    |          |
| Graduate                 | 1.17     |          | 0.96     |          | 0.56    |          |
| Educational expectations (ref: bachelor’s) |          |          |          |          |         |          |
| Some college             | 1.16     |          | 0.53     |          | 0.76    |          |
| Master’s degree          | 0.94     |          | 0.77     |          | 0.92    |          |
| Doctoral/professional    | 1.27     |          | 0.76     |          | 0.88    |          |
| SAT (100s)               | 0.89     |          | 1.14     | *        | 0.97    |          |
| Part-time                | 1.06     |          | 0.79     |          | 1.97    | *        |
| Nontraditional age       | 0.66     |          | 0.72     |          | 12.92   | ***      |
| All courses online       | 0.01     |          | 0.83     |          | 1.02    |          |
| Greek-life member        | 3.95     | ***      | 0.83     |          | 0.81    |          |
| On-campus resident       | 1.36     |          | 1.58     | **       | 0.22    | ***      |
| Athlete                  | 6.17     | ***      | 0.51     | *        | 0.42    |          |
| Major field (ref: social sciences) |          |          |          |          |         |          |
| Arts & Humanities        | 0.95     |          | 0.66     |          | 0.30    |          |
| Bio. Sci., Agr., and Nat. Res. | 1.09    |          | 0.43     | **       | 0.39    |          |
| Phys. Sci., Math, and Comp. Sci. | 0.62    |          | 0.55     | *        | 0.41    |          |
| Business                 | 1.54     |          | 0.60     |          | 0.56    |          |
| Comm., Media, and Pub. Rel. | 1.67    |          | 0.76     |          | 0.53    |          |
| Education                | 1.46     |          | 0.72     |          | 0.71    |          |
| Engineering              | 1.00     |          | 0.57     |          | 0.42    |          |
| Health professions       | 1.46     |          | 0.67     |          | 0.46    |          |
| Social service professions | 0.94  |          | 0.68     |          | 0.88    |          |
| All other                | 1.14     |          | 1.11     |          | 0.50    |          |
| Undecided, undeclared    | 0.96     |          | 0.82     |          | 0.67    |          |
| Carnegie classification (ref: doctoral) |          |          |          |          |         |          |
| Master’s                 | 0.80     |          | 0.95     |          | 1.53    |          |
| Baccalaureate            | 1.01     |          | 1.05     |          | 0.96    |          |
| Other                    | 0.43     |          | 0.86     |          | 2.42    |          |
| Barron’s rating (ref: competitive) |          |          |          |          |         |          |
| Non/less competitive     | 1.12     |          | 1.14     |          | 0.63    |          |
| Very competitive         | 0.82     |          | 0.86     |          | 1.17    |          |
| Highly/most competitive  | 1.18     |          | 0.72     |          | 0.83    |          |
Discussion and Implications

Popular and media narratives about the college student experience both suggest that students learn little and party to excess. We subjected this narrative to empirical scrutiny by

Table 4 (continued)

| Urbanity (ref: city) | Involved | Partiers | Parents |
|----------------------|----------|----------|---------|
| Suburb               | 1.37     | 1.08     | 1.39    |
| Town                 | 1.38     | 0.97     | 1.48    |
| Rural                | 1.40     | 0.68     | 0.73    |
| % female             | 0.62     | 1.58     | 1.37    |
| % White              | 0.54     | 1.09     | 0.76    |
| UG enrollment (1000s)| 1.00     | 1.00     | 1.00    |
| Private institution  | 0.99     | 0.92     | 1.20    |
| Constant             | 0.40     | 0.05     | ** 0.14 |

*p < 0.05, **p < 0.01, ***p < 0.001

Base model is the Balanced Class; RRR relative risk ratio; Standard errors adjusted to account for the uncertainty of the imputation

Table 5 Relationship between time-use latent class membership and selected outcomes compared to the Balanced group (n = 3000)

| Outcome                      | Involved | Partiers | Parents | R² |
|------------------------------|----------|----------|---------|----|
|                              | Beta     | Sig.     | Beta    | Sig. | Beta | Sig. |    |
| Higher-order learning        | 0.06     | *        | -0.06   | **  | 0.01 |      | 0.05 |
| Reflective and integrative learning | 0.07     | **       | -0.04   |      | 0.03 |      | 0.06 |
| Quantitative reasoning       | 0.09     | ***      | -0.08   | *** | 0.03 |      | 0.09 |
| Learning strategies          | 0.05     | *        | -0.10   | *** | 0.04 |      | 0.07 |
| Collaborative learning       | 0.09     | ***      | -0.07   | **  | -0.01|      | 0.13 |
| Discussions w/diverse others | 0.05     | *        | -0.01   |      | 0.02 |      | 0.07 |
| Student-faculty interaction  | 0.14     | ***      | -0.09   | *** | -0.04|      | 0.10 |
| Effective teaching practices | 0.01     |          | -0.02   |      | 0.01 |      | 0.04 |
| Quality of interactions      | 0.03     |          | -0.01   | -    | 0.01 |      | 0.06 |
| Supportive environment       | 0.07     | **       | -0.03   |      | -    | 0.04 | 0.06 |
| Perceived gains              | 0.07     | ***      | -0.07   | **  | 0.02 |      | 0.07 |
| GPA                          | 0.01     |          | -0.02   |      | 0.00 |      | 0.15 |

Each row corresponds to a separate regression model. Coefficients are standardized regression coefficients. Controls include sex, race/ethnicity, parental education, educational expectations, SAT I/ACT score, part-time enrollment, age, distance learner status, Greek-life membership, on-campus residence, student-athlete status, major field, Basic 2010 Carnegie Classification, Barron’s rating, urbanicity, % female, % White, undergraduate enrollment, and institutional control. Standard errors were adjusted to account for the uncertainty of the imputation

*p < 0.05, **p < 0.01, ***p < 0.001
examining first-year students’ time-use patterns using a comprehensive multi-institutional sample. Using latent profile analysis, we identified four distinct time-use patterns that characterize first-year students, focusing specifically on the allocation of time to six activities: class preparation, co-curricular activities and volunteering, working for pay, relaxing and socializing, caring for dependents, and commuting to campus. The groups identified—Balanced, Involved, Partiers, and Parents—indicate the various patterns of student time use during the first year of college. 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 HPW 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 HPW relaxing and socializing, about 2–3 times as much as the other groups. On average, Partiers devoted about 51 HPW to the six activities examined. Involved students—about 12% of first-year students—averaged 23 HPW on co-curricular activities and volunteer work, about 4–6 times more than the other groups, with a total of 62 HPW accounted for by the six activities. Parents—about 5% of our sample—demonstrated higher levels of involvement in working (14 HPW on average, or 2–3 times more than the other groups) and caring for dependents (28 HPW), with a total of 73 HPW on average devoted to the six activities, nearly twice the average total 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 in similar proportions. 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.

Our results indicate that student time-use patterns correspond to educationally important aspects of the student experience. Members of the Involved class had higher levels of engagement in educationally beneficial activities across a variety of domains. In contrast, the Partier class demonstrated lower levels of engagement across several measures. The contrast between the Involved and Partiers was greatest for Student-Faculty Interaction, indicating important differences between the two groups in this important aspect of college-level learning. We also did not observe any significant differences in the engagement of Parents compared to the Balanced class after holding other characteristics constant. The lack of a difference suggests that non-traditional students are not less engaged than their more traditional counterparts, as some may believe that their parental responsibilities inhibit their engagement in effective educational activities.

The model of class membership found only one significant relationship for race/ethnicity: Black students were less likely than their otherwise similar White peers to be in the Involved group. This is a source of concern given the positive relationship between Involved membership and educationally beneficial activities and experiences. Colleges and universities should devote special effort to ensure that opportunities for involvement are available and attractive to underrepresented populations. Similarly, this finding underscores the urgency of understanding what may deter Black students from participating in co-curricular and volunteer activities.

Additionally, time-use patterns were related to students’ perceived gains in learning and development as the Involved class had higher levels of perceived gains than the Balanced
group, while Partiers had lower levels. However, we observed no significant GPA difference between the groups, a finding that comports with previous studies associating time use and GPA (Brint and Cantwell 2010; Lahmers and Zulauf 2000; Stinebrickner and Stinebrickner 2004).

In addition to class attendance, the normative first-year student devoted about 25 HPW to a combination of studying, working, participating in co-curricular activities, and volunteering, plus 10 HPW relaxing and socializing. While our results did identify a distinctive “Partier” time use pattern, they nonetheless refute the popular narrative that college students trade studying for partying: Only about two HPW separated the lowest and highest groups with regard to the amount of time spent preparing for class (Partiers and Involved, averaging 13 and 15 HPW respectively). Indeed, Partiers spent nearly as much time preparing for class as the Balanced group, and higher entrance examination scores were associated with an increased likelihood of Partier membership. While we observed significant differences in engagement between the Partier and Balanced groups, the magnitude of the differences was modest—at most one-tenth of a standard deviation—and we found no significant GPA differences related to group membership. We, therefore, conclude that there is little support for the “trading studying for partying” narrative.

The large differences in total time allocation across the four groups raise a number of important questions. What are the consequences for student learning for the different time commitments of the four groups? The considerable total time expenditure by Parents—73 versus 39–62 HPW for the other groups— rais es questions about the consequences for other aspects of these students’ lives, especially considering that our time-use categories exclude important activities such as sleep and work in the home other than dependent care. At the other extreme, the Balanced group—representing nearly seven in ten first-year students—averaged only 39 HPW in the six categories of time use. This begs the question—what else are they doing with their time? The two extremes in total time use indicate that this is a ripe area for further investigation.

Our results are partially contradictory in that they indicate no differences in GPA related to group membership, but differences in engagement and perceived gains. One possible explanation is that Partier membership was associated with higher SAT scores; Partiers may have to exert less academic effort than their peers during the first college year to achieve similar grades. Another possibility is different grading standards related to major or intended major, given that the model of class membership showed that prospective biological and physical science majors were less likely than social science majors to be Partiers. Whatever the explanation, further research should investigate whether the relationship between latent class membership and GPA changes as students progress through college.

As noted earlier, the NSSE data represent the diversity of U.S. bachelor’s-granting institutions, so the lack of relationship between institution type and the time-use categories suggests these patterns exist across a wide range of institutional contexts. (Students in for-profit institutions are present but somewhat underrepresented in our data—3.4% of our sample compared with about 8% of all undergraduates nationally in 2015 [U.S. Department of Education 2016]). It also leads us to ask: what can or should institutions do to influence students’ time allocation choices? Student engagement theory establishes an important role for institutions to create an environment that promotes student learning and development. Therefore, theory and our results suggest that institutions should take a greater interest in helping students manage their time and in facilitating engagement outside of the classroom. 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.

An important aspect of student engagement theory is the quality of students’ effort and time use (Pace 1980). Unfortunately, our data do not capture the quality of time spent engaged in activities. While we did not find meaningful differences in time spent preparing for class between the categories, we would expect that how students utilize this time is an important factor in their learning and development. Consequently, an important line of future inquiry into students’ time use would be to capture such qualitative features of how students spend their time.

Another important conclusion from this research is that the reality of student time use is far more complicated than the image of party animals who neglect their studies conjured by the popular media and even some scholarly research. Large between-group differences in the amount of time devoted to certain activities, such as co-curricular activities, volunteering, socializing, working for pay, and caring for dependents do not appear to come at the cost of study time. On the other hand, many would agree that an average of 13–15 HPW devoted to class preparation is insufficient, bringing us once again to the question of the role of the institution—and individual faculty—in setting expectations for how students should allocate their time.

Appendix A

See Table 6.

|                          | Mean | SD  |
|--------------------------|------|-----|
| Higher-order learning    | 39.3 | 13.7|
| Reflective and integrative learning | 35.9 | 12.4|
| Quantitative reasoning   | 27.7 | 16.4|
| Learning strategies      | 39.5 | 14.2|
| Collaborative learning   | 32.0 | 14.2|
| Discussions w/diverse others | 41.1 | 16.1|
| Student-faculty interaction | 20.0 | 14.7|
| Effective teaching practices | 40.2 | 13.1|
| Quality of interactions  | 41.5 | 12.3|
| Supportive environment   | 37.2 | 13.9|
| Perceived gains          | 34.7 | 14.2|
| GPA                      | 3.4  | 0.6 |

Appendix B

See Table 7.
Table 7  Factor mixture model fit statistics for the primary model and 5 replications

| Classes | Primary model | Replication | 1 | 2 | 3 |
|---------|---------------|-------------|---|---|---|
|         | AIC  | BIC   | aBIC | AIC  | BIC   | aBIC | AIC  | BIC   | aBIC | AIC  | BIC   | aBIC |
| 2       | 118960 | 119074 | 119014 | 120018 | 120132 | 120072 | 119654 | 119768 | 119708 | 120134 | 120248 | 120188 |
| 3       | 118535 | 118691 | 118609 | 119539 | 119695 | 119613 | 119121 | 119277 | 119195 | 119674 | 119830 | 119748 |
| 4       | **115562** | **115760** | **115655** | **117139** | **117337** | **117232** | **116375** | **116573** | **116468** | **116968** | **117167** | **117062** |
| 5       | 118953 | 119194 | 119067 | 120419 | 120659 | 120532 | 120047 | 120287 | 120160 | 120104 | 120344 | 120217 |
| 6       | 119307 | 119589 | 119440 | 120433 | 120715 | 120566 | 120061 | 120343 | 120194 | 120633 | 120915 | 120766 |

| Classes | Replication | 4 | 5 |
|---------|-------------|---|---|
|         | AIC  | BIC   | aBIC | AIC  | BIC   | aBIC |
| 2       | 119010 | 119125 | 119064 | 119840 | 119954 | 119893 |
| 3       | 118634 | 118790 | 118707 | 119433 | 119589 | 119507 |
| 4       | **117925** | **118124** | **118019** | **116661** | **116859** | **116754** |
| 5       | 119413 | 119654 | 119527 | 120268 | 120508 | 120381 |
| 6       | 119403 | 119685 | 119536 | 120282 | 120564 | 120415 |

Lowest value in bold. Each replication used a unique randomly selected sample of 3000 students.

*AIC* Akaike information criterion, *BIC* Bayesian information criterion, *aBIC* adjusted Bayesian information criterion
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