College students' time use and labor market plans

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Abstract

I examine the patterns of association between college students' time use and their senior-year labor market expectations. Using data from the National Longitudinal Survey of Freshmen, I investigate the relationship between reported time use and students' plans after graduation. Specifically, I consider three labor market outcomes: whether students intend to work full-time work after graduating (regardless of field), whether they intend to start working in a job (full- or part-time) that is a step in a desired career, and whether they apply to at least one graduate school. The problem reduces to determining which time use components are associated with each outcome, and then quantifying the relative strengths of those associations. Using elastic-net penalized regression for variable selection, I find that the activity most negatively associated with full-time job plans is time spent in class, while socially-oriented activities are the strongest positive predictors. This result can be explained by the inverse relationship between full-time job plans and applying to graduate school.

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1 Introduction

The sources of heterogeneity in college students' labor market outcomes have been studied extensively but are not fully understood. It is well known that students' choice of college is an important determinant of their future success on the labor market, but this could be due as much to students' individual traits as to the traits of the schools they attend (Dale & Krueger, 1999). It is also known that the time cost of college has fallen over the last several decades (Babcock & Marks, 2010). If college students do not need to spend as much time doing school work as before, they must be using that time some other way. This could lead to increasing differentiation among students, and therefore increasing differentiation in the quality, quantity, and type of labor they supply once they enter the job market.

In this paper, I ask whether college students' time use is associated with their plans for the labor market shortly after graduation, and if so what the nature of that relationship might be. To answer this question, I use data from the National Longitudinal Survey of Freshmen ("NLSF," n.d.), a four-year panel survey of nearly 4,000 thousand students at high-ranked colleges that includes stylized time use data for freshman, sophomore, and junior year. To capture some of the diversity in post-graduate labor market trajectories, I identify three binary survey outcomes to represent students' intentions. The first is whether the student plans to work full time in the fall after graduation (regardless of industry). The second is, among students who plan to have either a full- or part-time job after graduating, whether that job is a step in a desired career. The third is whether the student applied to any graduate schools. The problem reduces to one of determining which time use components are associated with each outcome, and then quantifying the relative strengths of those associations.

If time use is indeed associated with these outcomes, it can point to new causal pathways toward variables that are associated with time use. For instance, time use could be an input to students' human and social capital production while in college, and heterogeneity in human capital investment is a possible determinant of occupation choice (Altonji, Blom, & Meghir, 2012). Furthermore, Rudel and Yurk (2013) have shown that time use is dependent on pre-college family background. Family background, in turn, is known to be related to heterogeneity in labor outcomes for college graduates (Brand & Xie, 2010). If a relationship is found between time use and college outcomes, then time use is a link in a chain of dependence connecting socioeconomic characteristics before college to labor market outcomes after college.

The main finding is that full-time job plans are positively associated with socially-oriented time use and negatively associated with academic time use. This result might be explainable by the fact that a student is very unlikely to have full-time job plans and also have applied to graduate school, but further research is needed to determine the validity of that explanation. More broadly, this study helps map some of the heterogeneity in labor outcomes to heterogeneity in the college experience. This mapping could inform future work by suggesting chains of association that could be tested as chains of causality.

This paper is organized as follows. 2 is a selective review of previous work related to college students' time use. 3 is a detailed description of the relevant parts of the National Longitudinal Survey of Freshmen (NLSF). In 4 I lay out the principled multiple hypothesis testing procedure that I use to look for prominent correlations in students' time use, and a penalized regression estimator for selecting important time use components. The results are presented in 5 and discussed in 6.

2 Literature review

Brint and Cantwell (2010) examine in detail the relationship between time use and academic outcomes recorded in the University of California Undergraduate Experience Survey. They identify three "dimensions" of time use along by which an activity can be categorized: scholarly/non-scholarly, active/passive, and connecting/separating (with respect to campus life), and through this lens review a large number of older studies of time use. They emphasize that their study improves on previous work because it considers time use taken together, rather than one variable at a time. They then identify five patterns in time use and find that pattern membership is related to academic conscientiousness, college grades, major, and background characteristics such as high school GPA.

Rudel and Yurk (2013) use the second wave of the NLSF (data from spring of Freshman year) to investigate whether a student's financial aid status predicts college time use. They too dichotomize time use by splitting it at the mean, and use that dichotomization to assign labels to different time use patterns, but they go a step further by binning students into types. Using a latent class model, they derive three classes of use patterns that they identify as corresponding to "Serious Student," "Play Hard," and "Disengaged" types. They find that students with greater academic loan burdens were more likely to be "Serious" and less likely to "Play Hard." Taken together with the study by Brint and Cantwell (2010), these results suggest a chain of dependence between students' personal backgrounds and academic outcomes.

A different approach is taken by R. Stinebrickner and T. R. Stinebrickner (2004) and T. R. Stinebrickner and R. Stinebrickner (2007). Instead of analyzing time use as a whole, this pair of studies looks very carefully at the effect of time spent studying on academic outcomes. Both, however, consider a sample of students from a community college in rural Kentucky, in contrast to the high-ranked (and in most cases high-cost) schools of national renown covered by the NLSF. The first study reports confidently that students who study more get better grades. The second study is a causal analysis, using grades as a proxy for human capital accumulation, and finds that students' effort and time spent studying is a causal input to their human capital growth while in college. A similar approach is taken by R. Stinebrickner and T. R. Stinebrickner (2003) for investigating the effect of working during school on academic performance.

3 Data

The National Longitudinal Survey of Freshmen (NLSF) is a panel study that follows a cohort of college students over four years in five survey waves. The sample was drawn from the incoming freshman classes at twenty-eight four-year colleges in the Fall of 1999. The sample was limited to students who were U.S. citizens or resident aliens, and had not previously been to college. The survey was designed "to provide comprehensive data to test different theoretical explanations for minority underachievement in higher education" ("NLSF," n.d.).

The first survey wave was a lengthy in-person interview administered in Fall 1999, covering detailed background and personal information. The second through fifth waves were shorter phone interviews administered in the Springs of 2000, 2001, and 2003. A sixth "wave" of data was also collected to determine if and when students had graduated, within the first six years after starting college, or by the Spring of 2006. This data was derived from the National Student Clearinghouse and schools' own offices of the registrar.

Colleges were classified as one of "private research," "public research," "liberal arts," and "historically black." The sample of schools was chosen to "mirror" the sample used by Bowen, Bok, and Loury (2000), with the addition of the historically black category and one public research university (UC Berkeley). Thirty-five schools were asked to participate and twenty-eight agreed. The number of students sampled at each college was proportional to the number of black undergraduates at that school. Within colleges, white, black, Latino, and Asian students were sampled in roughly equal numbers.

All together, $4{,}573$ students were selected to participate and $3{,}924$ students completed the Wave 1 survey. The data is provided in separate files for each wave, along with additional files containing indices used in Massey, Charles, Lundy, and Fischer (2006), institution-level characteristics from the 1998-1999 and 2001-2002 school years, and a detailed household roster. Respondents were given unique case ID numbers and these were used to merge the data files.

In this paper, the sample is further restricted to only students who do not transfer and graduate in no more and no less than four years. This is because the scope of the research question is limited to students who follow more or less traditional paths through college. To enforce this restriction, students are dropped if they do not meet the following criteria:

1. In Wave 3, they report that they were enrolled in college
2. In Wave 4, they report that they are enrolled in the same college as in Wave 3
3. In Wave 5, they report that they are enrolled in the same college as in Wave 4
4. They were determined to have graduated from their original school with a bachelor's degree

in Spring 2003 and not before

5. They completed all five survey waves.

As it appears in the documentation, criterion 4 should be sufficient to include only students who graduated in four years and did not transfer. However, cross-tabulations reveal that the first three criteria are not entirely consistent with the fourth, and so the redundant criteria are included to ensure that the sample is restricted appropriately. $1{,}474$ students remain after these exclusions are made. Finally, 42 students in the remaining sample have at least one missing response to a time use question. Of these, 14 are missing the entire Wave 4 time use data. One is missing only the weekday time use data from Wave 4. The rest are missing one or a few scattered activities. This can still be considered a "large" sample for the statistical techniques used here.

3.1 Labor outcomes

The outcomes considered in this study are:

FULLTIME

Description: The student planned to have a full time job in Fall 2003 (the fall after graduation).

Original question: In the fall of 2003 do you plan to be working full time, part time, or not at all?

Answer coding:

$$\begin{array}{rcl} \text{full-time} & \mapsto & 1 \\ \left.\begin{array}{r} \text{part-time} \\ \text{not at all} \\ \text{don't know} \end{array}\right\} & & 0 \\ \text{refused} & \mapsto & \text{missing} \end{array}$$

CAREER

Description: If the student planned to have a job (full-time or otherwise) in Fall 2003, that job is a step in a desired career.

Original question: Do you view this job as a step towards a career you wish to have?

$$
\text{Answer coding:}\quad
\begin{array}{rcl}
\text{full-time} & \mapsto & 1 \\
\left.\begin{array}{r}\text{no}\\ \text{don't know}\end{array}\right\} & & 0 \\
\text{refused} & \mapsto & \text{missing}
\end{array}
$$

GRADAPP

Description: The student applied to at least one graduate school.

Original question: To how many graduate or professional schools (did you apply/have you applied)?

$$
\text{Answer coding:}\quad
\begin{array}{rcl}
0 & \mapsto & 0 \\
1\text{–}20 & \mapsto & 1 \\
\left.\begin{array}{r}\text{no}\\ \text{don't know}\end{array}\right\} & & \text{missing}
\end{array}
$$

These are all based on questions asked in Wave 5. Each was recoded to be a ternary variable, taking values "yes" (mapped to 1), "no" (mapped to 0), and "missing". The "missing" response was used to flag students for listwise deletion before modeling, leaving binary responses for analysis. The handling of the "don't know" responses is deliberately inconsistent here. In the case of CAREERSTEP, there are in fact zero "don't know" responses in the data. In the case of GRADAPP, students ought to know whether whether or not they have already *applied*, even if they don't know whether they've been accepted. And indeed only 5 students are flagged for deletion on these grounds.

For FULLTIME, the "don't know" is much more likely to be valid because students do not necessarily know their plans. But in this case the "don't know" is substantive, rather than an issue of data quality. The question of how to code these responses is difficult in principle because coding them as "missing" would throw away information, while coding them as "no" would impose a somewhat arbitrary assumption. However only 9 students—0.6 % of the sample—responded "don't know" to the FULLTIME question, so the issue of how to properly code their responses is unlikely to seriously affect the results. If the proportion were much larger, uncertainty itself would have to be considered a valid labor market expectation, and a multinomial model would have been necessary.

3.2 Time use

In Waves 2, 3, and 4, students were asked twice to estimate the "total number of hours" spent on each of several activities. First they were asked about their activities during the "last full week of classes, from Monday through Friday." Then they were asked about activities during the "most recent weekend between two weeks when classes were being held and you were on campus . . . beginning on Saturday morning and continuing through Sunday night". I will refer to the first such block of questions (and their respective variables) as "weekday" questions, to the second block as "weekend" questions, and to each block as a "day" block. That is, the "day type" of a question can be "weekday" or "weekend." "Weekday" activities in junior year constitute a "wave-day" block.

Students were asked about a pre-determined list of specific activities, one at a time. Valid responses were integers 0–120 for the "weekday" questions and 0–48 for "weekend" questions. Therefore students were required to round their estimates to the nearest hour, and were primed on the maximum number of hours they could give for any one activity. They were not, however, required to ensure that their *total* time use did not exceed the correct number of hours, nor were they required to account fully for the 120-hour work week and 48-hour weekend. Juster and Stafford (1991) notes that respondents in "stylized" time use surveys are more likely than respondents in hour-by-hour "diary" surveys to overestimate their time spent in nearly every category. This is because if an activity was prominent on one day but not on other days, the prominent day will stick in the respondent's mind and the respondent will treat it as average.

Even if students did report their complete time use with perfect accuracy, the data would not be inherently compositional. This is because activities could easily overlap. For instance, in the author's experience many college students find it perfectly reasonable to be both watching television and studying simultaneously. Therefore an analysis of *total* time reported, while outside the scope of this paper, could be interesting in its own right. On the other hand, watching television and attending class are more likely to be mutually exclusive. Therefore a student's possible total is at least as large as the number of hours in the time period, but probably much smaller than the number of hours times the number of activities. This total will also depend on the level of each activity as well as (potentially unobservable) student characteristics. I call this "quasi-compositional" data: each unit's total is itself a (possibly unobserved) unit-level variable.

Each question block also asked for hours spent on "something else," and included a follow-up question asking what that activity was. The follow-up question took single answers from another pre-determined list that also included at least one generic "other" option. Only one response to this question is recorded, meaning that a student could only specify one "else" activity per block. Furthermore, the majority of students who answered the "something else" question did not give an answer to "what else" question (30 to 65 percent, depending on the wave-day block). I do not examine the "else"–"what else" meta-activity here, in the interest of simplicity and clarity.[1]

Table 1 lists the activity variables used in this study, and the waves in which they appear. The biggest change between waves is that a few of the "what else" activities from Waves 2 and 3 were turned into regular-question activities in Wave 4. The answers "don't know" and "refused" were also allowed in each question. Here they are simply recoded as "missing" to flag these students for listwise deletion. The activities whose identifiers begin with ELSE are derived from the "what else" question.

It is somewhat alarming to note that the original survey instrument does not ask about time spent completing assignments, only about "studying" (and, in Wave 4, "studying and doing research"), which is wide open to interpretation. Biology students might spend much more time in class or lab than history majors, who might spend more time completing reading assignments and writing papers. But in this data set such a distinction could swallowed by students having to guess at whether they should include their homework time in their "studying" time. The problem is exacerbated further for art and music students. There is no obvious way to improve the resolution of the data without external validation data. Somewhat optimistically, I interpret STUDYING as a coarse and noisy stylization of "school work outside of class."

[1]In preliminary analyses, I found that including these variables did not change any point estimates but notably reduced precision. Moreover, the extreme rarity of some "else" categories such as "babysitting" suggests that their importance is limited.

Table 1: Activity identifiers and their appearance by wave

Identifier in this paper	Wave 2	Wave 3	Wave 4
CLASS	✓	✓	✓
COMPUTER			✓
EATING			✓
ERRANDS			✓
EXTRACURRICULAR	✓	✓	✓
LIBERAL			✓
MUSIC	✓	✓	✓
PARTYING	✓	✓	✓
PROFESSORS			✓
SLEEPING	✓	✓	✓
SOCIALIZING	✓	✓	✓
SPORT_EVENT	✓	✓	✓
SPORTS	✓	✓	✓
STUDYING_ALONE			✓
STUDYING	✓	✓	
STUDYING_STUDENTS			✓
TELEVISION	✓	✓	✓
VOLUNTEERING	✓	✓	✓
WORKING	✓	✓	✓

3.2.1 Time use sampling

This data is implicitly sampled from two populations. The first is a population of students (stratified by college and college type), and the second is a population of time periods. This leads to two types of sampling—one type from each population—that occur simultaneously to produce the observed data. I will refer to the first type of sampling as "student sampling" and the second type as "time sampling." The phrase "student-sampling variation" will refer to random variation in actual time use because only a fraction of the student population is included. The phrase "time-sampling variation" will refer to variation in time use reports because 1) students' time use can be different from one week to the next and 2) students were not all surveyed on the same day.

I also define "reporting variation" to mean variation in reported time use specifically due to reporting error; in other words, to variation of reported time use around actual time use.

Herein I will always refer to the time use reported by students in the NLSF as "reported time use" and to students' (unobserved) actual time use as "actual time use." With these definitions in place, it is possible to refer to "true reported time use," meaning the hypothetical distribution of reported time use across *all* students in the student population, even if in reality only a fraction of those students are sampled (so that only a fraction of those reports are observed). The phrase "observed reported time use" is therefore not redundant, and both qualifications are necessary. These definitions will be helpful in 4.

The interview date is not available in the public data set, so it is impossible to estimate how much variation in time use can be attributed to the first kind of time sampling. In the worst case, this variation could be substantial. Moreover, student activities can vary significantly over the course of a semester. For example, students study more before exams, and probably increase leisure activity after midterms. These patterns will be different between schools, majors, and students themselves.

4 Methods

4.1 Pairwise correlations

Correlations are a straightforward way to study the pattern of bivariate associations in the time use and outcome data. Since the time use data is quasi-compositional, some amount of the dependence exhibited in the correlation matrix will be due to students' personal maximum time constraints (see 3.2). This is in fact desirable in the context of the research question, because it implicitly conditions each pairwise correlation on the student's overall time use pattern.

Regardless of the correlation structure in students' actual time use, it is plausible that the correlation matrix of students' *reported* time use is relatively sparse. This is because the combined effect of time-sampling variation and reporting variation is probably large (see 3.2). Moreover, there is a lower limit to how small a correlation can be in actual time use before that correlation is effectively zero. Even if the true underlying correlation matrix of actual time use had no zero-valued elements, it would be practical and reasonable to treat many of those elements as if they were zero.

Observed reported time use is sampled from the population of reported time use, and a correlation matrix computed from the NLSF data is an estimate of a population-level quantity. Note that the rounding heuristic applies only to the population-level quantity, and I take that rounding for granted in this analysis. Therefore the ground-truth correlation matrix is sparse, and one of the goals of estimating the correlation matrix is to determine which correlations are nonzero.

The Neyman-Pearson hypothesis testing framework is well-suited to this purpose, because most classical hypothesis testing techniques require a point null, which in this case is zero. For each pair of variables X_1 and X_2, the testing framework is as follows:

$$H_0 : \rho_{12} = 0$$

$$H_A : \rho_{12} \neq 0$$

$$\alpha = 0.0125$$

where α is the significance level of each test. The test statistic is the standard asymptotic t statistic for correlations.

For illustration of this choice, suppose that the only true nonzero correlations are within time use activities that are not specific to Wave 4. These would be correlations within CATEGORY: blocks, excluding Wave-4-only activities like PROFESSORS, and aggregating STUDYING_ALONE + STUDYING_STUDENTS to STUDYING. There are 14 such activities, and each block contains 15 unique correlations, so there would be 210 true nonzero correlations, out of the $14{,}706$ total, leaving 14496 true zeros. Therefore $\alpha = 0.05$ would produce about 725 false rejections of the null hypothesis in expectation. The testing procedure would then detect more than three false correlations for every true one. Bringing this ratio below 1 would require $\alpha \leq\sim 0.014$. Note that this is also a best-case ratio because it assumes that all the true correlations are detected.

This free conversion between probabilities and long-run proportions depends on the false-rejection rate for each test being the same as for the combined "family" of $14{,}706$ tests. This is well known to be untrue. In order to control the familywise error rate (FWER), I apply the Holm correction (Holm, 1979) to the list of p values corresponding to unique tests. This ensures that the probability of rejecting any one test for which the null hypothesis is true (i.e. for which $\rho_{12} = 0$) is less than or equal to 0.0125. In the back-of-the-envelope calculations above, we can expect between 210 and $210 + 181 = 391$ rejections of the zero-correlation null hypothesis, of which between 0 and 181 are erroneous.

These calculations are predicated on the assumption that the power of each test (the probability of correctly rejecting the null hypothesis when it is false) is 1. This is completely unrealistic, especially if the nonzero correlations are not large in absolute value. If some of the true rejections are missed, then the ratio of false rejections to true rejections could be even higher. To investigate this possibility, I computed the power of the t test described above in a sample of 1400 observations and with a significance level of $\alpha = 0.0125$, for hypothetical correlations between -1 and 1 in increments of 0.001. Plotting hypothetical power against hypothetical correlation reveals that correlations with absolute value less than 0.2 have power appreciably lower than 1. The plot is an "upside-down bell curve," approaching 1 at the limits and decreasing sigmoidally from 0.2 (and -0.2) to zero. The power for a correlation of 0.1 is 0.560. These calculations will allow for a post-hoc check on the results.

Note, of course, that these calculations apply to the case when the 210 non-zero correlations could be *any* non-zero correlations. The probability under the null hypothesis of one specific arrangement of these correlations, such as the one proposed above, is 0.014. Therefore it would be overly cynical to take these approximations to mean that the correlation results cannot be trusted unless the true correlations are all greater than 0.2. On the contrary, it simply suggests that the individual correlations are less relevant than the overall pattern of correlations. If that pattern is obviously not random, there is little reason to doubt its legitimacy.

4.2 Effect of time use on outcomes

Among the myriad modeling techniques available for binary responses, linear and generalized linear regression models are the most intuitive and interpretable. Regression coefficients are immediately interpretable as measures of conditional association, and when the inputs are appropriately standardized the conditional associations can be directly compared. Therefore it is the natural choice here for modeling the effect of each time use component, conditional on every other time use component, simultaneously. Here I use logistic regression, because it is an easily interpretable model that is designed for modeling binary responses.

4.2.1 Interpretation

There are three important caveats to logistic regression that are not specific to this application but are important to emphasize. The first is that the log-odds of the response occurring is assumed to be a linear function of the inputs. Therefore if the underlying data generating process is not linear, this model will necessarily "average over" the nonlinearities.[2] The second is that the model will also "average over" any factors that affect the response and are correlated with the inputs, but are not themselves included as inputs.[3] This averaging effect remains true when using the elastic net estimator.

In logistic regression these kinds of averaging have an *additional* attenuating effect on the estimated coefficients regardless of whether the omitted variables are correlated with the inputs. In any regression model, omitted variables amount to additional variation in the response that the model does not explain. In logistic regression specifically, this additional variation has an

[2]A classic example of this problem is that of fitting a line to a parabola: the fitted line suggests that there is no relationship, when in fact the relationship is strong but nonlinear.

[3]This is the mechanism behind the phenomenon known as Simpson's Paradox.

attenuating effect on the regression coefficients themselves (Mood, 2010). The third caveat is that the regression coefficients — the estimated weights of the inputs with respect to the log odds of the outcome — are log odds ratios and are therefore multiplicative. Therefore the "effect" of a particular input (the change in the probability of the response that is attributable to a unit change in that input) depends on the baseline probability of the response, which in turn depends on the baseline level of *every* input in the model.

To account for the difficulty in interpreting individual regression coefficients, I identify four representative students whose predicted outcomes I will use to assess the fitted model. These students are selected based on their time use and sex (that is, not including their outcomes), using the partitioning around medoids algorithm (Reynolds, Richards, de la Iglesia, & Rayward-Smith, 2006). The four-student solution was a good compromise between obtaining a diverse group and not having so many different types that they cannot be easily compared. In addition, the four-student solution contained the three-student solution, which in turn contains the two-student solution. The five-student solution, however, was not a superset of the four-student solution.

4.2.2 Specification, estimation, and inference

The logistic regression model for a binary outcome Y and vector of inputs X takes the form

$$
\begin{aligned}
Y \mid X &\sim \text{Bernoulli}(\mu) \\
\log\left(\frac{\mu}{1-\mu}\right) &= \beta_0 + X\beta
\end{aligned}
$$

where β_0 is a parameter to be estimated and β is a vector of parameters. It is assumed that the observed data for every student follows this data-generating process identically and independently.

Here, X is a vector of time use data and one covariate, a binary indicator for whether the student is female denoted FEMALE. Denote with A^t the vector of all weekday and weekend activities in Wave t. For each outcome — FULLTIME, CAREER, and GRADAPP — I fit two versions of this model: a junior-year model in which

$$X = \begin{bmatrix} A^4 & \textsc{female} \end{bmatrix}$$

and a three-year model in which

$$X = \begin{bmatrix} A^2 & A^3 & A^4 & \textsc{female} \end{bmatrix}$$

This model is fitted using the standard iteratively reweighted least squares algorithm. I standardize all of the time use variables by centering at the mean and scaling by two standard deviations to ensure that their coefficients are comparable to the coefficient on FEMALE (Gelman, 2008). Denote the centered X by

$$Z = \frac{\widehat{\text{mean}\, X}}{2 \times \widehat{\text{standard deviation}\, X}}$$

where $\widehat{\cdot}$ denotes the sample estimate of a population quantity. Therefore the jth coefficient β_j is the change in $\log\left(\frac{\mu}{1-\mu}\right)$ associated with Z_j increasing by one unit, or with X_j increasing by two standard deviations. $\frac{\mu}{1-\mu}$ is the odds of $Y = 1$ given some level of X, so β_j is a difference in logarithms of odds, or equivalently the logarithm of a ratio of odds.

The task at the heart of this study is to determine which student activities, if any, are associated with each outcome, and to determine the relative importance of those activities. The junior-year-only model is a straightforward comparison of activities that avoids any intertemporal complications in the data. While severe multicollinearity is unlikely in this setting, it could be that modeling multiple waves at once would introduce higher-order relationships that the linear model cannot capture. The correlation results 5.1 also show that time use is moderately correlated over time, so capturing junior year time use alone could be a useful simplification that does not throw out too much data. It is also possible that junior year time use has a stronger effect on outcomes than freshman and sophomore year time use, in which case it would the most important subset to model.

However the full trajectory of student time use is the independent variable of interest in this study. The question of which components of time use matter most amounts to a best-subset selection problem, for which exact solutions are combinatorially intractable. Instead, I fit each model a second time using a shrinkage estimator called the elastic net (Zou & Hastie, 2005). The elastic net is a penalized likelihood estimator, in that it shrinks the coefficients toward zero (not including the intercept) by adding a penalty term to the likelihood.[4] The strength of the penalty term is controlled by a user-determined parameter; this parameter is optimized in ten-fold cross-validation with the objective of minimizing the deviance of the model. The elastic net penalty is also controlled by a mixing parameter in $[0, 1]$. With large values of this parameter, the estimator will tend to select arbitrarily among correlated predictors, leaving one coefficient large and shrinking the rest to zero. Smaller values of this parameter tends to shrink coefficients on correlated inputs towards the same value, but tends to induce less sparsity overall. I select a value of 0.2 for this parameter.

The effect of this shrinkage is to reduce some of the coefficients to zero exactly. Inputs that have nonzero coefficients, after the shrinkage is applied, are considered "important." The remaining coefficients are heavily attenuated, so their actual values are not meaningful in terms of the original variables, but they remain valid as estimates of sign and relative importance.Feature selection by shrinkage is known to produce models with very good out-of-sample predictive accuracy. This suggests that it is apt for selecting subsets that are resistant to sampling variation—an important trait in light of the discussion in 3.2. Finally, the elastic net is better-suited to this analysis than the pure LASSO because it is known to the coefficients of correlated inputs towards the same value. The LASSO is known to select arbitrarily among correlated inputs, leaving one coefficient relatively unaffected while shrinking the others entirely to zero.

The NLSF includes many other possible covariates that could be of substantive interest, such as students' grades, majors, and personal backgrounds, as well as high-school-level and college-level data. They are not studied here in the interest of focusing the analysis. Moreover, many of them (especially GPA and major) vary between waves and would require a richer analysis to incorporate in a principled way. As discussed in the previous section, this means that these covariates are

[4] The details are technical rather than substantive, so I omit them here.

implicitly "averaged out" of the model, imposing both the well-known omitted-variable bias and an additional attenuation bias due to whatever heterogeneity these covariates contribute to the outcome. I include the indicator for sex, FEMALE, because it is easy to construct and interpret, and there is no risk of introducing additional complexity by including it. It will also help serve to benchmark the relative strength of the attenuation effect.

4.3 Other approaches

Most previous studies of college students' time use rely on standard regression models. In this section I highlight two atypical and distinctive approaches. They are intended to answer slightly different questions than the one posed here, but the methods they demonstrate should be considered in future studies on this subject.

4.3.1 Accounting for weekly variation

I have been careful to qualify students' "time use" as "*reported* time use" in this paper. That is partly because self-reported time use data is likely to be contaminated by reporting error and recall biases. But it is also because it is important to distinguish between the quantity measured–time use in a particular week—and the quantity of interest—the average weekly time use in a school year. Indeed, one fundamental problem with time use data collected in retrospective surveys is that the time period covered by the survey is typically very small compared to the time period of interest. In this case, that time period is a full school year, which is typically between 24 and 32 weeks of classes.

The issue is complicated even further by the fact that the school year is usually divided into sessions such as semesters, trimesters, or quarters, and that activities usually change between sessions. Course loads can vary widely, for instance, or a sport can become more demanding in the competitive season. Therefore, even if weekly time use can be reasonably modeled as a trend-stationary process within each session, it is very likely that the trend is different from one session to the next.

R. Stinebrickner and T. R. Stinebrickner (2004) regress freshman students' GPAs against the average number of hours spent studying each day. Their data, from the Berea Panel Study (BPS) consists of six time use reports from the same year. Denote the ith study time in period t with s_i^t, and denote that student's average study time over T periods with $S_i = \frac{1}{T}\sum_{t=1}^{T} s_i^t$. They begin by noting that S_i can be estimated with $\hat{S}_i = \frac{1}{N_i}\sum_{t=1}^{N_i} s_i^t$, where s_i^t is student i's time use on day t, and $1 \leq N_i \leq 6$ is the number of time use reports completed by student i. Then they propose that s_i^t takes the form:

$$s_i^t = c_t + \mu_i + v_i^t$$

where μ_i is different between students but constant over time, c_t is deterministic over time, and v_i^t is random each day with mean 0, constant variance σ_v^2, and no autocorrelation. They also include student-level covariates, but I omit them here because they are not essential to the model. Then

$$S_i - \hat{S}_i = \frac{1}{T}\sum_{t=1}^{T} s_i^t - \frac{1}{N_i}\sum_{t=1}^{N_i} s_i^t$$

They proceed by assuming that $\forall\ t > 6\ c_t \in C = \{c_1, \ldots, c_6\}$ and that each element of C occurs exactly $\frac{T-6}{6}$ times in the sequence $\{c_7, \ldots, c_T\}$. They use this assumption to build a maximum likelihood estimator. This assumption amounts to the idea that the mean of each s_i^t s.t. $t > 6$ is similar to the mean of one of the observed s_i^t s.t. $t \leq 6$. In practical terms, this assumption implies that 1) the distribution of time use varies over time only in its average, 2) time units can be grouped into a small number representative types, so that there are only a few distinct average study times and that these average study times rotate over the course of the period of interest (in this case a school year), and 3) each observed time use report corresponds to one such type.

Each survey in the BPS includes a 7-day time use report (1 period $=$ 1week) and a 24-hour weekday time use report (1 period $=$ 1 day). To fix the value of T, (R. Stinebrickner & T. R. Stinebrickner, 2004) assume that a school year consists of 120 weekdays and 24 weeks. They obtain similar results for both the weekly and daily data, suggesting that their method can perform well even when N_i is much smaller than T. In this case the burden of approximating $\{c_{N+1}, \ldots\ c_t\}$ falls to relatively few time period types. The BPS reports also benefit from being spread predictably across the school year with "strict completion deadlines," and this strongly supports the assumption of representativeness.

4.3.2 Aggregation and latent classes

(Rudel & Yurk, 2013) take a very different approach to solving a different but not unrelated problem, using Wave 2 of the NLSF. In their study, freshman-year time use is the *dependent* variable, and they look to model it as a coherent whole. To make sense of their high-dimensional dependent variable, they first aggregate the raw time use components described in 3.2 into broader time use categories. Then they dichotomize each category by labeling category totals above the mean as "high" and below the mean as "low." Their final step is to estimate a latent class model for three classes or types. These classes are then easily modeled with a standard multinomial regression.

Heavy compression does not necessarily constitute a loss of information if the data is very noisy, and could in fact help reduce noise while preserving essential structure. In particular, aggregating individual time use components to broader categories on heuristic grounds could help smooth out some of the extreme variance in the NLSF data (see 5) if it is done judiciously. And while feature selection as such is impossible with this technique, the need to select individual features is reduced or even supplanted by the compression from several manifest variables to a few latent ones. Latent variable modeling is also readily extended to continuous latent variables (as in factor analysis) and can also be used to describe "trajectories" over time (as across NLSF Waves 2, 3, and 4).

4.4 Computation

All computation and data manipulation was conducted in R version 3.2.0 (R Core Team, 2015b), using the following packages:

- `foreign` (R Core Team, 2015a)

- `memisc` (Elff, 2015)
- `yaml` (Stephens, 2014)
- `cluster` (Maechler, Rousseeuw, Struyf, Hubert, & Hornik, 2015)
- `caret` (Kuhn, 2015)
- `glmnet` (Friedman, Hastie, & Tibshirani, 2010)
- `pwr` (Champely, 2015)
- `psych` (Revelle, 2015)
- `robustbase` (Rousseeuw et al., 2015)
- `reshape2` (Wickham, 2007)
- `magrittr` (Bache & Wickham, 2014)
- `dplyr` (Wickham & Francois, 2015)
- `tidyr` (Wickham, 2014)
- `ggplot2` (Wickham, 2009)

5 Results

Univariate summary statistics for the time use data are plotted in Figure 1 and reported in A. The "fences" of the boxplot are computed using the "adjusted boxplot" method of Hubert and Vandervieren (2008) in order to account for the highly skewed distributions. Blocks of activity variables are sorted according to the average across the entire block. That is, across all waves and between weekdays and weekends, sleeping had the highest average reported value, and meeting with professors had the lowest. Note the strong "clumping" exhibited at round numbers: this is a good indication that students' personal time use reports are coarse and therefore noisy estimates.

Weekday sleep also happens to stand out as being remarkably consistent across waves. This is in contrast to weekend sleep, in which the first quartile falls slightly over time. There is also a dense knot of outliers who reported 20 hours of weekend sleep (10 hours a night) in sophomore year. Class time also seems to decrease over time, which is logical if only because recitation and lab sections can be less common in advanced courses. The addition of time use categories in Wave 4 does not seem to have had an attenuating effect on the existing categories. Since these new categories had previously been "what else" answers (see 3.2), students were probably already accounting for them in previous waves, even if their levels were going unreported.

For some activities, sophomore year seems different from freshman and junior years. Socializing, for instance, drops notably in sophomore year and increases again in junior year. Television watching follows the opposite pattern. Weekday working and weekday partying also decrease in sophomore year and rise in junior year. Music listening and weekday partying increase overall in sophomore year and fall again in junior year. It is impossible to determine from this data alone what, if any, mechanism is responsible for these shifts in the "bulk" of each distribution.

5.1 Pairwise correlations

The correlation matrix is plotted as a heat map (also called a false-color plot, a checkerboard plot, or a corrgram) in Figure 2. For visual clarity, the main diagonal (which consists of only 1s) has been replaced with 0s. The salient feature of these results is that most of the correlation is clustered around the main diagonal; that is, by wave and day. This result is similar to the prediction made in 4.1, and the back-of-the-envelope calculations in that section should be kept in mind when assessing these results. A secondary feature is that, within these blocks, activities are correlated in off-diagonal "stripes" that are parallel to the main diagonal. This represents correlation between weekday and weekend activity.

The results are marked by a lack of negative correlation. On the same graph without filtering by Holm-corrected p value (not shown), much of the white (zero-correlation) space is filled with very weak negative correlation. This suggests that students are not making strong pairwise trade-offs in time use, and that any compositional dependence between activities is of a higher order.[5] The only negative correlations in time use are between studying and television-watching, and studying

[5] A compositional K-dimensional data vector $C = (C_1, \ldots, C_K)$ is one for which $\sum_{k=1}^{K} C_K = 1$ and $C_k > 0 \; \forall \, k$. For such a vector, it is always true that $\mathrm{Cov}\,(C_1, C_2 + \cdots + C_K) = 0$, so $\mathrm{Cov}\,(C_1, C_2) + \cdots + \mathrm{Cov}\,(C_1, C_K) = -\mathrm{Var}\,(C_1)$ (Aitchison, 2003). It is easily confirmed that this identity does not hold in the NLSF data.

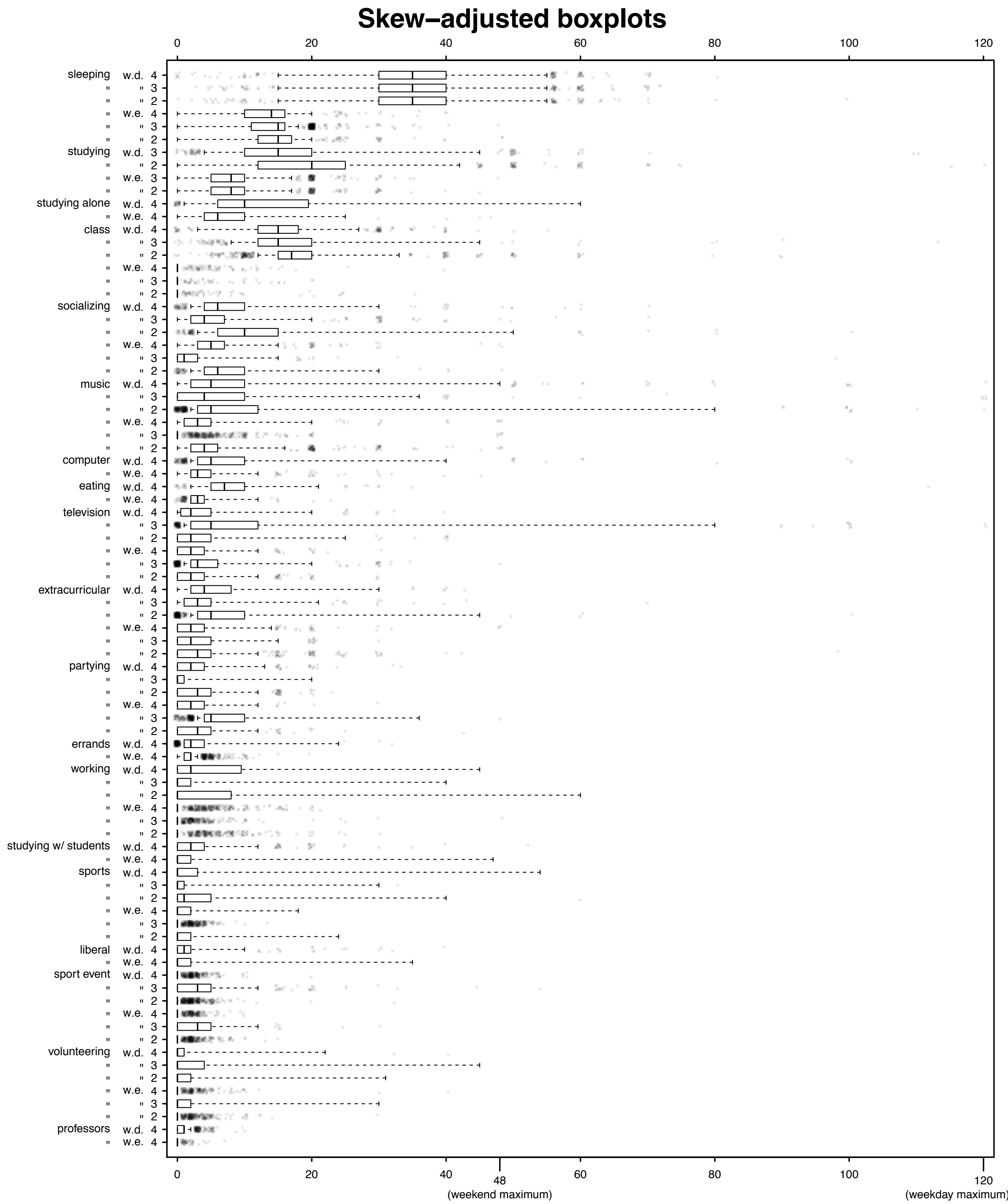

Figure 1: Skew-adjusted boxplots for time use data in the NLSF. The central line is the median, and the ends of the box are the first and third quartiles. The outer fences are computed according to the method of Hubert and Vandervieren (2008) that takes into account the skew of the distribution. The individual points represent outliers. The outlier points are heavily jittered in order to convey relative density.

and partying. Since the effect of budgeting is invisible everywhere else, it is possible that this negative correlation is due to negative correlation in preferences and not simply time constraints by students who study more. But these correlations are not strong and do not “fill” their respective blocks, so they should be treated as merely suggestive.

The major off-diagonal associations are between socializing and several “non-academic” activities: partying, extracurriculars, television, and music, and to a lesser extent eating and errands. This is should not be surprising because all of those activities are inherently social or can easily occur simultaneously with socializing. Other positive correlations are between playing sports and attending sport events, between sports and volunteering, between attending sport events and partying, and between volunteering and weekday working. The parallel striping seen in these blocks indicates correlation between an activity in one particular wave and an activity across all waves, as in the correlation between attending sport events in sophomore year and partying in all waves.

Interestingly, *all* of the obvious parallel striping occurs for activities in sophomore year. Moreover, the blocks along the main diagonal (the within-activity correlations) almost all exhibit an anti-diagonal stripe that cuts perpendicularly across the main diagonal. This striping pattern indicates a correlation between freshman year and junior-year time use, and a lack of correlation between sophomore year and these years. It is possible that this is an artifact of undocumented inconsistencies between waves. But it is also possible that sophomore year is somehow different from freshman and junior years, although it is not clear what that difference might be. This anomaly could be related to the univariate results in the previous section, in which junior year time use followed a different correlation pattern than in freshman and junior year.

A binary-by-continuous correlation coefficient is equal to $\frac{t^2}{t^2+\nu}$, where t is the T statistic corresponding to an unpaired t-test of a difference in means between groups of equal variance with ν degrees of freedom, and the t statistic for this correlation coefficient is itself t. Interestingly but not surprisingly, most of these binary-by-continuous correlations are effectively zero. This means that no one time use component stands out, after averaging over all other time use components, as important for any outcome.

The binary-by-binary correlations are equivalent to Pearson's ϕ coefficient of association in 2-by-2 contingency tables. Among the outcomes themselves, FULLTIME has a strong negative association with GRADAPP, and FULLTIME has a weak positive association with CAREER. Also, FEMALE has a very strong negative association with GRADAPP, with one of the strongest correlations observed here. FEMALE is not associated with any one time use category except sports participation and volunteering, but only sparsely in both cases.

5.2 Outcome models

The maximum-likelihood (ML) regression estimates, their standard errors, their corresponding penalized estimates, and the standard deviation of the associated variables are reported in Table 2, 3, 4, for the junior-year model, and B for the three-year model. The standard deviations are included because the non-binary inputs (that is, all inputs other than FEMALE) were scaled down by two standard deviations. Therefore each coefficient represents the change in log odds of the outcome that is associated with a two-standard-deviation increase in each input.

Hours of junior-year sports participation is the most important positive predictor whether students plan to work full time after graduation. Also represented in the top five are hours spent listening to music in sophomore year, hours spent on extracurricular activities in junior year, and partying in junior year. The most important negative predictors are freshman year class time, junior-year *weekend* class time, hours attending sport events on weekdays freshman year, and hours studying alone on weekdays in junior year. The most important positive and negative predictors of whether students' first jobs after college are career steps are broadly similar. The main exceptions are computer time on weekdays in junior year and time spent on reading, writing, or drawing for pleasure. Surprisingly, junior-year sport event attendance is among the most important positive predictors, but sophomore year sport attendance is among the most important negative predictors.

The most important positive predictors of whether students applied to at least one graduate school overlap somewhat with the most important negative predictors of the other two outcomes. This can be at least partially attributed to the strong negative association between full time job

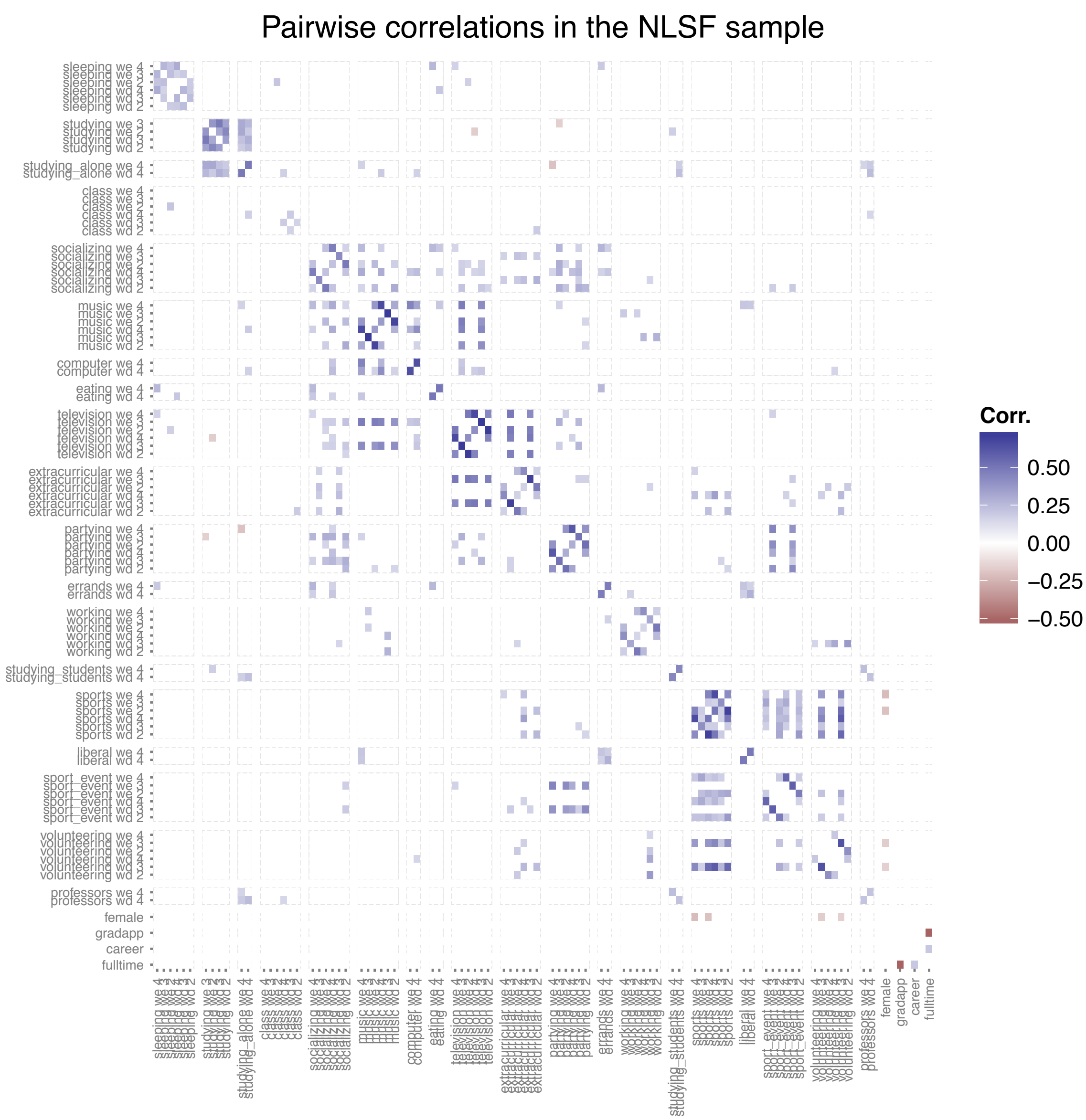

Figure 2: Pairwise correlations in the NLSF sample. Darker blue indicates stronger positive correlation, and darker red indicates stronger negative correlation. The main diagonal, which normally contains only 1s, is here set to 0 for readability

plans and applying to graduate school. The overall sense from these results is that the activities that predict full time job plans and immediate career plans are fundamentally social, while the activities that predict graduate school application are fundamentally academic. Social and academic activities are not necessarily mutually exclusive and there is no evidence that students are forced to trade off between them in the pairwise analysis (although a higher-order relationship is possible). The exception to this characterization is SPORT_EVENT, which is presumably a very social event but is among the most strongly negative predictors of FULLTIME and CAREER.

The three-year results are surprisingly concordant with the junior-year results. The top activities in each junior-year regression are broadly similar to the top activities in the corresponding three-year regressions, and most of the large coefficients in the three-year regressions are in fact coefficients on junior-year activities. Freshman year time use is particularly underrepresented. This is good evidence that junior-year time use is more closely related to labor outcomes than sophomore and especially freshman year time use.

The largest positive predictors of FULLTIME are weekday sports participation, weekday extracurricular participation, and weekend partying. The other positive predictors are smaller by an order of magnitude or more. The strongest negative predictors are studying alone on weekdays and weekends, and attending class on weekends. This last coefficient is particularly interesting because the vast majority of students do not attend class on weekends in junior year, and a contingency table (not shown) reveals that the *marginal* effect of weekend class attendance in junior year is negligible.

Many more activities are selected as important for CAREER, and their coefficients decrease more steadily in magnitude. The largest five, with coefficients above 0.1, are weekday studying with students, weekend and weekday sport event attendance, and weekday and weekend sports participation. The large number of nonzero coefficients is a sign that the elastic net mixing parameter of 0.2 is perhaps too low, and more aggressive shrinkage might have produced a more interpretable result. The largest negative predictor is weekday studying alone. The next two strongest negative predictors are "reading, writing, and drawing for pleasure" (denoted LIBERAL, as in "liberal arts") on weekends, and playing music on weekdays.

The GRADAPP results also include a large number of non-zero coefficients, and so might also have benefited from stronger penalization. The largest positive coefficient in this model corresponds to weekend class time—the most negative coefficient in the FULLTIME model. Television, studying alone on weekends, volunteering on weekends, weekday class time, weekday sleeping. Weekday professor meetings are also positive. The strongest negative predictor is in fact FEMALE, which does not appear in the other two models. Of time use activities, weekday socializing, weekend arts, and weekday extracurriculars are the most strongly negative.

As a digest of the three-year results, the five largest and five smallest penalized predictors for each outcome is shown in Table 5, 6, 7. Recall that these regression coefficients are deliberately biased towards zero, so they correspond to negligible changes in log odds. It is more appropriate to interpret them a measures of relative importance than as literal odds ratios.

Table 2: Estimated penalized coefficients in the junior-year FULLTIME model.

	ML coef.	ML std. error	Penalized coef.	S.d. of predictor
(Intercept)	0.740	0.058	0.706	NA
$\text{PROFESSORS}^4_{\text{WD}}$	-0.080	0.062	.	1.123
$\text{PROFESSORS}^4_{\text{WE}}$	0.033	0.061	.	0.367
$\text{VOLUNTEERING}^4_{\text{WD}}$	-0.061	0.060	.	2.764
$\text{VOLUNTEERING}^4_{\text{WE}}$	-0.063	0.060	-0.008	1.814
$\text{SPORT\_EVENT}^4_{\text{WD}}$	-0.052	0.069	.	1.341
$\text{SPORT\_EVENT}^4_{\text{WE}}$	0.003	0.068	.	1.011
$\text{LIBERAL}^4_{\text{WD}}$	0.064	0.073	.	3.213
$\text{LIBERAL}^4_{\text{WE}}$	-0.032	0.072	.	1.983
$\text{SPORTS}^4_{\text{WD}}$	0.262	0.097	0.053	4.287
$\text{SPORTS}^4_{\text{WE}}$	-0.098	0.077	.	1.885
$\text{STUDYING\_STUDENTS}^4_{\text{WD}}$	0.013	0.066	.	3.961

	ML coef.	ML std. error	Penalized coef.	S.d. of predictor
$\text{STUDYING\_STUDENTS}^4_{\text{WE}}$	0.086	0.070	.	2.679
$\text{WORKING}^4_{\text{WD}}$	0.043	0.067	.	6.463
$\text{WORKING}^4_{\text{WE}}$	0.033	0.066	.	2.820
$\text{ERRANDS}^4_{\text{WD}}$	0.015	0.069	.	3.076
$\text{ERRANDS}^4_{\text{WE}}$	-0.014	0.069	.	1.851
$\text{PARTYING}^4_{\text{WD}}$	-0.029	0.076	.	3.463
$\text{PARTYING}^4_{\text{WE}}$	0.146	0.078	0.046	2.872
$\text{EXTRACURRICULAR}^4_{\text{WD}}$	0.177	0.074	0.050	6.307
$\text{EXTRACURRICULAR}^4_{\text{WE}}$	-0.064	0.067	.	4.256
$\text{TELEVISION}^4_{\text{WD}}$	-0.039	0.079	.	4.513
$\text{TELEVISION}^4_{\text{WE}}$	-0.031	0.080	.	3.230
$\text{EATING}^4_{\text{WD}}$	-0.079	0.073	.	5.051
$\text{EATING}^4_{\text{WE}}$	0.011	0.071	.	1.884
$\text{COMPUTER}^4_{\text{WD}}$	0.082	0.085	0.001	8.507
$\text{COMPUTER}^4_{\text{WE}}$	0.027	0.085	.	3.714
$\text{MUSIC}^4_{\text{WD}}$	-0.081	0.086	.	11.318
$\text{MUSIC}^4_{\text{WE}}$	0.123	0.092	0.004	5.185
$\text{SOCIALIZING}^4_{\text{WD}}$	0.025	0.074	.	6.879
$\text{SOCIALIZING}^4_{\text{WE}}$	0.033	0.073	0.010	4.342
$\text{CLASS}^4_{\text{WD}}$	0.050	0.060	.	5.865
$\text{CLASS}^4_{\text{WE}}$	-0.152	0.067	-0.071	1.958
$\text{STUDYING\_ALONE}^4_{\text{WD}}$	-0.110	0.069	-0.068	9.030
$\text{STUDYING\_ALONE}^4_{\text{WE}}$	-0.117	0.072	-0.014	4.742
$\text{SLEEPING}^4_{\text{WD}}$	-0.078	0.062	.	10.094
$\text{SLEEPING}^4_{\text{WE}}$	0.120	0.066	0.009	4.566

	ML coef.	ML std. error	Penalized coef.	S.d. of predictor
female	0.332	0.125	.	0.487

Table 3: Estimated penalized coefficients in the junior-year CAREER model.

	ML coef.	ML std. error	Penalized coef.	S.d. of predictor
(Intercept)	1.643	0.092	1.517	NA
$\text{PROFESSORS}^4_{\text{WD}}$	-0.102	0.087	-0.009	1.129
$\text{PROFESSORS}^4_{\text{WE}}$	-0.019	0.074	.	0.390
$\text{VOLUNTEERING}^4_{\text{WD}}$	0.022	0.097	.	2.551
$\text{VOLUNTEERING}^4_{\text{WE}}$	0.099	0.109	0.013	1.853
$\text{SPORT\_EVENT}^4_{\text{WD}}$	0.181	0.141	0.116	1.284
$\text{SPORT\_EVENT}^4_{\text{WE}}$	0.309	0.163	0.176	1.005
$\text{LIBERAL}^4_{\text{WD}}$	0.120	0.103	.	3.280
$\text{LIBERAL}^4_{\text{WE}}$	-0.168	0.089	-0.084	2.076
$\text{SPORTS}^4_{\text{WD}}$	0.245	0.170	0.136	4.382
$\text{SPORTS}^4_{\text{WE}}$	0.178	0.148	0.130	1.831
$\text{STUDYING\_STUDENTS}^4_{\text{WD}}$	0.355	0.116	0.203	3.776
$\text{STUDYING\_STUDENTS}^4_{\text{WE}}$	-0.021	0.088	.	2.521
$\text{WORKING}^4_{\text{WD}}$	0.015	0.093	.	6.590
$\text{WORKING}^4_{\text{WE}}$	0.111	0.095	0.037	2.925
$\text{ERRANDS}^4_{\text{WD}}$	0.019	0.092	.	3.197
$\text{ERRANDS}^4_{\text{WE}}$	-0.028	0.092	.	1.902
$\text{PARTYING}^4_{\text{WD}}$	0.057	0.111	.	3.443
$\text{PARTYING}^4_{\text{WE}}$	-0.112	0.101	-0.014	2.831

	ML coef.	ML std. error	Penalized coef.	S.d. of predictor
$\text{EXTRACURRICULAR}^4_{\text{WD}}$	0.031	0.101	0.002	6.407
$\text{EXTRACURRICULAR}^4_{\text{WE}}$	0.132	0.109	0.077	4.153
$\text{TELEVISION}^4_{\text{WD}}$	0.026	0.110	.	4.566
$\text{TELEVISION}^4_{\text{WE}}$	0.085	0.108	0.041	3.236
$\text{EATING}^4_{\text{WD}}$	-0.101	0.101	.	4.235
$\text{EATING}^4_{\text{WE}}$	0.093	0.109	.	1.796
$\text{COMPUTER}^4_{\text{WD}}$	-0.058	0.105	-0.022	8.904
$\text{COMPUTER}^4_{\text{WE}}$	-0.032	0.107	.	3.772
$\text{MUSIC}^4_{\text{WD}}$	-0.078	0.109	-0.065	11.375
$\text{MUSIC}^4_{\text{WE}}$	-0.068	0.117	-0.008	5.130
$\text{SOCIALIZING}^4_{\text{WD}}$	0.046	0.100	.	7.007
$\text{SOCIALIZING}^4_{\text{WE}}$	0.056	0.100	.	4.240
$\text{CLASS}^4_{\text{WD}}$	0.147	0.084	0.070	5.825
$\text{CLASS}^4_{\text{WE}}$	-0.081	0.080	-0.008	1.336
$\text{STUDYING\_ALONE}^4_{\text{WD}}$	-0.259	0.090	-0.143	8.759
$\text{STUDYING\_ALONE}^4_{\text{WE}}$	0.176	0.099	0.044	4.342
$\text{SLEEPING}^4_{\text{WD}}$	0.070	0.087	0.015	10.030
$\text{SLEEPING}^4_{\text{WE}}$	0.036	0.090	.	4.535
female	0.066	0.176	.	0.484

Table 4: Estimated penalized coefficients in the junior-year GRADAPP model.

	ML coef.	ML std. error	Penalized coef.	S.d. of predictor
(Intercept)	-0.654	0.061	-0.631	NA

	ML coef.	ML std. error	Penalized coef.	S.d. of predictor
$\text{PROFESSORS}^4_{\text{WD}}$	0.088	0.065	0.039	1.137
$\text{PROFESSORS}^4_{\text{WE}}$	-0.011	0.063	.	0.356
$\text{VOLUNTEERING}^4_{\text{WD}}$	0.025	0.064	.	2.875
$\text{VOLUNTEERING}^4_{\text{WE}}$	0.079	0.064	0.056	1.897
$\text{SPORT\_EVENT}^4_{\text{WD}}$	0.002	0.072	.	1.304
$\text{SPORT\_EVENT}^4_{\text{WE}}$	0.051	0.069	.	1.022
$\text{LIBERAL}^4_{\text{WD}}$	-0.058	0.083	-0.019	3.039
$\text{LIBERAL}^4_{\text{WE}}$	-0.102	0.092	-0.080	1.973
$\text{SPORTS}^4_{\text{WD}}$	-0.080	0.090	-0.022	4.006
$\text{SPORTS}^4_{\text{WE}}$	-0.001	0.081	.	1.834
$\text{STUDYING\_STUDENTS}^4_{\text{WD}}$	-0.038	0.070	-0.012	4.024
$\text{STUDYING\_STUDENTS}^4_{\text{WE}}$	-0.061	0.070	-0.008	2.724
$\text{WORKING}^4_{\text{WD}}$	-0.039	0.070	.	6.227
$\text{WORKING}^4_{\text{WE}}$	-0.003	0.068	.	2.824
$\text{ERRANDS}^4_{\text{WD}}$	-0.047	0.077	-0.026	3.127
$\text{ERRANDS}^4_{\text{WE}}$	-0.011	0.077	-0.015	1.801
$\text{PARTYING}^4_{\text{WD}}$	-0.048	0.082	-0.018	3.463
$\text{PARTYING}^4_{\text{WE}}$	-0.040	0.080	-0.019	2.881
$\text{EXTRACURRICULAR}^4_{\text{WD}}$	-0.133	0.076	-0.074	6.144
$\text{EXTRACURRICULAR}^4_{\text{WE}}$	0.048	0.068	.	4.076
$\text{TELEVISION}^4_{\text{WD}}$	0.198	0.088	0.094	4.400
$\text{TELEVISION}^4_{\text{WE}}$	-0.064	0.090	.	3.213
$\text{EATING}^4_{\text{WD}}$	-0.038	0.072	.	5.187
$\text{EATING}^4_{\text{WE}}$	0.028	0.074	.	1.895
$\text{COMPUTER}^4_{\text{WD}}$	-0.110	0.094	.	8.689

	ML coef.	ML std. error	Penalized coef.	S.d. of predictor
$\text{COMPUTER}^4_{\text{WE}}$	0.100	0.090	.	3.837
$\text{MUSIC}^4_{\text{WD}}$	0.081	0.090	.	11.006
$\text{MUSIC}^4_{\text{WE}}$	-0.046	0.095	.	4.952
$\text{SOCIALIZING}^4_{\text{WD}}$	-0.187	0.085	-0.134	6.710
$\text{SOCIALIZING}^4_{\text{WE}}$	.	0.077	.	4.221
$\text{CLASS}^4_{\text{WD}}$	0.101	0.064	0.055	5.886
$\text{CLASS}^4_{\text{WE}}$	0.199	0.079	0.141	1.965
$\text{STUDYING\_ALONE}^4_{\text{WD}}$	-0.017	0.074	.	9.256
$\text{STUDYING\_ALONE}^4_{\text{WE}}$	0.155	0.077	0.084	4.881
$\text{SLEEPING}^4_{\text{WD}}$	0.125	0.067	0.052	10.072
$\text{SLEEPING}^4_{\text{WE}}$	-0.103	0.070	-0.021	4.601
female	-0.396	0.132	-0.168	0.484

Table 5: FULLTIME

Activity	Log o.r., s.d. scale	Log o.r., original scale
$\text{SPORTS}^4_{\text{WD}}$	0.074	0.0172
$\text{MUSIC}^3_{\text{WE}}$	0.068	0.0166
$\text{EXTRACURRICULAR}^4_{\text{WD}}$	0.064	0.0102
$\text{PARTYING}^4_{\text{WE}}$	0.054	0.0187
$\text{MUSIC}^3_{\text{WD}}$	0.038	0.0041
$\text{SPORTS}^3_{\text{WD}}$	0.027	0.0111
...	...	...
$\text{CLASS}^2_{\text{WE}}$	-0.038	-0.0191
$\text{CLASS}^2_{\text{WD}}$	-0.041	-0.0051

Activity	Log o.r., s.d. scale	Log o.r., original scale
SPORT_EVENT$^{2}_{WD}$	-0.044	-0.0265
STUDYING_ALONE$^{4}_{WD}$	-0.067	-0.0074
CLASS$^{4}_{WE}$	-0.073	-0.0375

Table 6: CAREER

Activity	Log o.r., s.d. scale	Log o.r., original scale
STUDYING_STUDENTS$^{4}_{WD}$	0.16	0.043
PARTYING$^{3}_{WE}$	0.16	0.033
SPORT_EVENT$^{4}_{WE}$	0.15	0.145
SPORTS$^{4}_{WD}$	0.14	0.032
SOCIALIZING$^{3}_{WD}$	0.13	0.020
WORKING$^{3}_{WD}$	0.12	0.038
...	...	...
STUDYING$^{2}_{WD}$	-0.051	-0.0044
COMPUTER$^{4}_{WD}$	-0.056	-0.0062
LIBERAL$^{4}_{WE}$	-0.073	-0.0349
SPORT_EVENT$^{3}_{WE}$	-0.079	-0.0260
STUDYING_ALONE$^{4}_{WD}$	-0.105	-0.0119

Table 7: GRADAPP

Activity	Log o.r., s.d. scale	Log o.r., original scale
CLASS$^{4}_{WE}$	0.095	0.0483
STUDYING$^{3}_{WE}$	0.086	0.0159

Activity	Log o.r., s.d. scale	Log o.r., original scale
$\text{CLASS}^2_{\text{WD}}$	0.070	0.0086
$\text{SLEEPING}^3_{\text{WE}}$	0.066	0.0140
$\text{VOLUNTEERING}^2_{\text{WE}}$	0.055	0.0376
$\text{TELEVISION}^4_{\text{WD}}$	0.054	0.0125
...	...	...
$\text{MUSIC}^3_{\text{WE}}$	-0.044	-0.0107
$\text{LIBERAL}^4_{\text{WE}}$	-0.050	-0.0253
$\text{EXTRACURRICULAR}^4_{\text{WD}}$	-0.051	-0.0084
$\text{SOCIALIZING}^4_{\text{WD}}$	-0.066	-0.0098
$\text{TELEVISION}^3_{\text{WD}}$	-0.069	-0.0047

5.2.1 Illustration with representative students

The time use patterns of the four representative students are plotted in Figure 3. Students 2 and 4 are female. A detailed analysis of clustering, typing, and representative observations in the time use data is outside the scope of this analysis, so I do not attempt to fully characterize each student here. However it is clear that each one represents a different trajectory of time use over his (or her) first four years of college, within loose bounds that correspond to normal behavior.

The variation in the predicted probabilities of their outcomes can provide a rough sense of how informative the models are, by demonstrating the range of possible predictions across different time use patterns. The actual and predicted outcomes for each representative student are shown in Table 8, 9, 10. Without any variable selection (that is, without penalization), time use and sex alone can predict substantially different probabilities. With penalization, the range of predicted probabilities is much smaller. These amount to more conservative estimates that are more robust to noise in the data. That is, they are deliberately underfitted, but in a principled way that could improve generalizability to other students that are similar to those sampled in the NLSF.

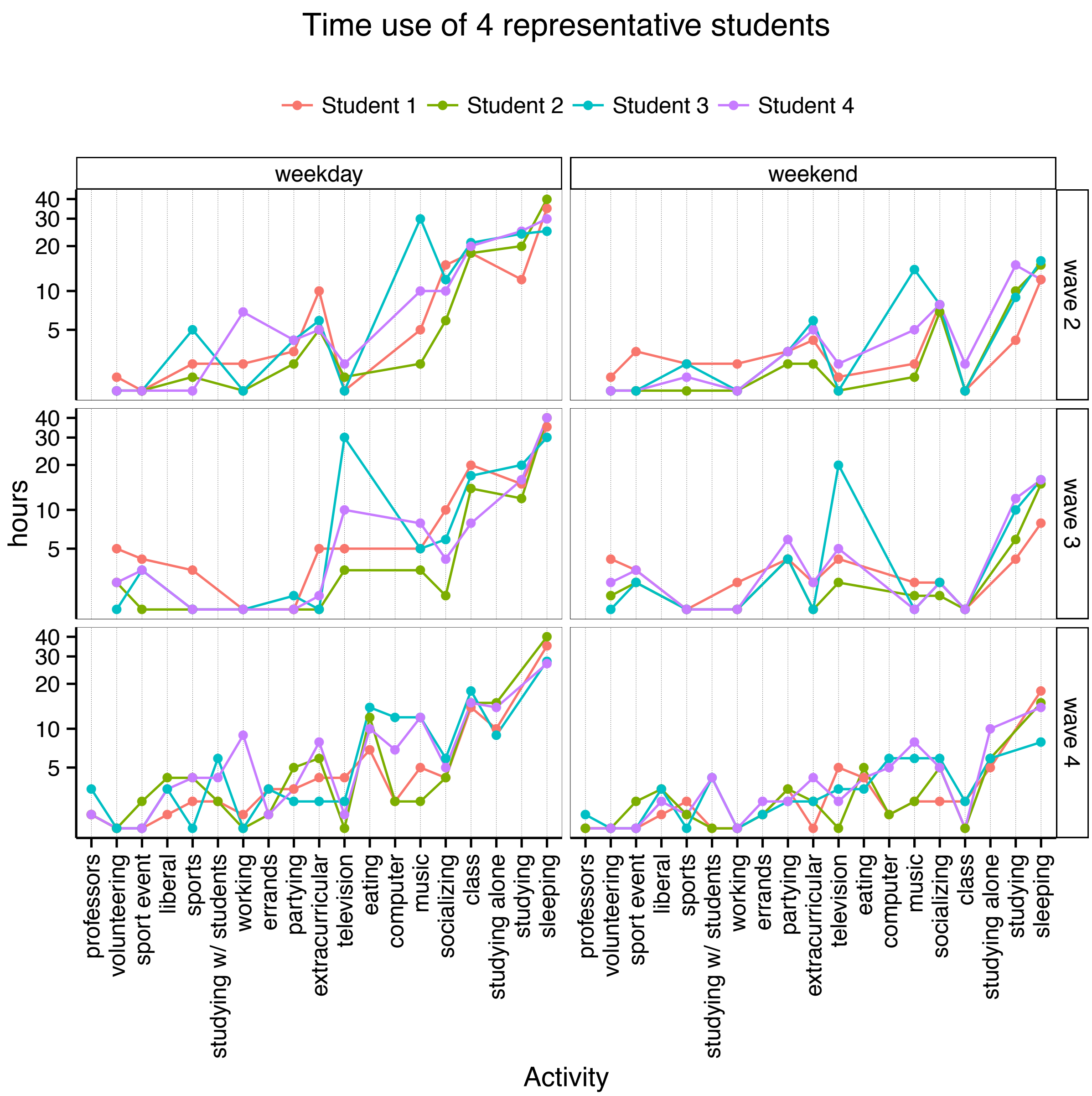

Figure 3: Time use of four students that are representative of the sample analyzed in this paper, as selected by the partitioning around medoids algorithm. The vertical axis has been transformed by the inverse hyperbolic sine function, producing the irregular spacing.

Table 8: Actual and fitted FULLTIME outcomes for representative students

	FULLTIME	ML, W4	E-net, W4	ML, all	E-net, all
Student 1	0	0.58	0.56	0.66	0.65
Student 2	1	0.69	0.71	0.68	0.68
Student 3	1	0.56	0.57	0.65	0.62
Student 4	1	0.77	0.76	0.68	0.68

Table 9: Actual and fitted CAREER outcomes for representative students

	CAREER	ML, W4	E-net, W4	ML, all	E-net, all
Student 1	1	0.79	0.83	0.81	0.82
Student 2	1	0.90	0.90	0.86	0.84
Student 3	1	0.68	0.66	0.80	0.74
Student 4	1	0.83	0.84	0.82	0.79

Table 10: Actual and fitted GRADAPP outcomes for representative students

	GRADAPP	ML, W4	E-net, W4	ML, all	E-net, all
Student 1	1	0.44	0.46	0.41	0.36
Student 2	0	0.29	0.27	0.31	0.32
Student 3	0	0.46	0.41	0.41	0.37
Student 4	0	0.26	0.31	0.31	0.36

6 Discussion

In this paper, I model each of three labor-related outcomes for graduates of high-ranked colleges as a function of their reported time use while in college. These outcomes are whether they plan to work full time after graduating, whether their planned job (either full or part time) is a step in a career, and whether they applied to at least one graduate school. I find that the probability of applying to graduate school is most positively associated with higher reported hours spent on academic activity, primarily time spent in class but also studying alone. Meanwhile, I find that the probability of planning full time work is most positively associated with social and extracurricular activity, and negatively associated with reported hours spent in class. This result can be explained by the strong negative association between planning full time work and applying to graduate school.

The results imply that the students at high ranked colleges who spend less time in class—and more time on extracurricular activities—are the ones who are more likely to enter the labor market immediately upon graduating. This pattern of association is not trivial. If, for instance, spending time in class directly contributes to human capital development in college, this suggests that the students who developed the greatest amount of human capital are either selecting or being selected into graduate school. Similarly, the graduate student population could consist of students who obtained the least *social* capital while in school.

Studying alone is negatively associated with immediate career plans, while studying with students is positively associated with career plans. This suggests that a student's decision to enter the labor market immediately after graduating depends on heterogeneous personality traits, incentives, and preferences that may supersede the desire to find a job right away. Alternatively, it could be the case that students make their post-graduate plans early in their college careers, and that graduate school requires students to spend more time in class. Therefore the students who do not plan to go to graduate school do not need intensive course schedules and therefore fill that time with socializing and other activities. This explanation is particularly viable for students at high-ranked schools like those in the NLSF, where students might have been specifically selected for being motivated and goal-oriented.

One limitation of this study is that it does not take into account students' majors, and major is known to be an important determinant of labor outcomes (see, for instance Rumberger and Thomas (1993), Freeman and Hirsch (2007), Robst (2007), and Arcidiacono (2004)). If time use patterns differ by major, it could be the case that the relationship between time use and outcomes is mediated by the relationship between major and outcomes. If, for example, mechanical engineers are more likely to study with other students than history majors, and if mechanical engineers are more likely to find career-oriented jobs right after graduating, the relationship between social-vs-solitary time use and career plans would be mediated by the relationship between major and outcomes.

Another possibility is that the effect of time use is magnified within some majors and not others. That is, a "loner" mechanical engineer (by way of exampel) might be at a career-starting disadvantage compared to a "social" one, but where "loner" and "social" history majors have similar career-starting prospects. If, for example, history majors are more likely to plan to go to graduate school eventually, the ones who do start working after college might just be filling time until they are ready to start working on their next degree. Including major as a covariate would not be able to distinguish among all these scenarios, but it would be a significant improvement over speculation. And because major is known to be a significant source of heterogeneity in outcomes, its inclusion would help limit the attenuation bias in the estimated regression coefficients, even if there is no association between major and time use at all.

The similarity between the junior-year and three-year models, and the underrepresentation of freshman year activities in the three-year models, suggests that differences in time use might be more informative or meaningful as students become increasingly differentiated. Interestingly, there is no evidence that the actual dispersion of time use in any category increases year to year. This hypothesis, therefore, depends on the testable assumption that the amount of between-student variation stays the same over time and that students' time use becomes more coherent every year. One simple way to test this hypothesis would be to fit a common factor model to time use in each wave, and then see if the loadings are stronger in later years. Alternatively, if students make post-graduate goals first and choose their time use to obtain those goals, the increased importance of junior-year time use could also reflect that students' goals become increasingly clear over time.

This study extends the current understanding of college students' time use by providing an account of the pairwise relationships between time use activities, and relates those activities directly to students' plans for work after graduation. Future research could build on these results by examining the association of time use with other aspects of the college experience. In addition, it would be instructive to map these "raw" results back to the taxonomy of Brint and Cantwell (2010) and the latent classes identified by Rudel and Yurk (2013). Such a mapping could be a powerful validation tool, and also begin to form the basis of a more causally-oriented investigation. This data is also over a decade old; if comparable data from a more recent cohort becomes available, it would be instructive to repeat this analysis and compare the results over time.

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A Summary statistics

Table 11: Univariate summary statistics for time use data

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
$\text{PROFESSORS}^{4}_{\text{WD}}$	0	0	1	0.93	1.0	10	16
$\text{PROFESSORS}^{4}_{\text{WE}}$	0	0	0	0.06	0.0	7	14
$\text{VOLUNTEERING}^{2}_{\text{WD}}$	0	0	0	1.30	2.0	31	0
$\text{VOLUNTEERING}^{3}_{\text{WD}}$	0	0	0	2.80	4.0	45	0
$\text{VOLUNTEERING}^{4}_{\text{WD}}$	0	0	0	1.12	1.5	40	15
$\text{VOLUNTEERING}^{2}_{\text{WE}}$	0	0	0	0.55	0.0	30	0
$\text{VOLUNTEERING}^{3}_{\text{WE}}$	0	0	0	1.18	2.0	30	0
$\text{VOLUNTEERING}^{4}_{\text{WE}}$	0	0	0	0.44	0.0	40	14
$\text{SPORT\_EVENT}^{2}_{\text{WD}}$	0	0	0	0.63	0.0	32	0
$\text{SPORT\_EVENT}^{3}_{\text{WD}}$	0	0	3	3.44	5.0	54	0
$\text{SPORT\_EVENT}^{4}_{\text{WD}}$	0	0	0	0.50	0.0	20	15
$\text{SPORT\_EVENT}^{2}_{\text{WE}}$	0	0	0	0.51	0.0	15	0
$\text{SPORT\_EVENT}^{3}_{\text{WE}}$	0	0	3	3.12	5.0	30	0
$\text{SPORT\_EVENT}^{4}_{\text{WE}}$	0	0	0	0.33	0.0	10	14
$\text{LIBERAL}^{4}_{\text{WD}}$	0	0	1	1.77	2.0	40	15
$\text{LIBERAL}^{4}_{\text{WE}}$	0	0	0	1.10	2.0	35	14
$\text{SPORTS}^{2}_{\text{WD}}$	0	0	1	3.36	5.0	60	0
$\text{SPORTS}^{3}_{\text{WD}}$	0	0	0	0.82	1.0	33	0
$\text{SPORTS}^{4}_{\text{WD}}$	0	0	0	2.00	2.0	54	15
$\text{SPORTS}^{2}_{\text{WE}}$	0	0	0	1.45	2.0	24	0
$\text{SPORTS}^{3}_{\text{WE}}$	0	0	0	0.48	0.0	13	0
$\text{SPORTS}^{4}_{\text{WE}}$	0	0	0	0.95	2.0	18	14
$\text{STUDYING\_STUDENTS}^{4}_{\text{WD}}$	0	0	2	2.84	4.0	52	16
$\text{STUDYING\_STUDENTS}^{4}_{\text{WE}}$	0	0	0	1.40	2.0	47	14
$\text{WORKING}^{2}_{\text{WD}}$	0	0	0	4.14	8.0	60	1
$\text{WORKING}^{3}_{\text{WD}}$	0	0	0	1.58	2.0	40	1
$\text{WORKING}^{4}_{\text{WD}}$	0	0	2	5.05	9.0	45	16
$\text{WORKING}^{2}_{\text{WE}}$	0	0	0	1.08	0.0	98	0

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
$\text{WORKING}^3_{\text{WE}}$	0	0	0	0.60	0.0	48	0
$\text{WORKING}^4_{\text{WE}}$	0	0	0	1.11	0.0	21	14
$\text{ERRANDS}^4_{\text{WD}}$	0	1	2	3.12	4.0	32	16
$\text{ERRANDS}^4_{\text{WE}}$	0	1	2	1.88	2.0	20	15
$\text{PARTYING}^2_{\text{WD}}$	0	0	3	3.45	5.0	23	0
$\text{PARTYING}^3_{\text{WD}}$	0	0	0	0.80	1.0	99	0
$\text{PARTYING}^4_{\text{WD}}$	0	0	2	2.79	4.0	33	15
$\text{PARTYING}^2_{\text{WE}}$	0	0	3	3.44	5.0	43	0
$\text{PARTYING}^3_{\text{WE}}$	0	4	5	6.76	10.0	48	0
$\text{PARTYING}^4_{\text{WE}}$	0	0	2	2.69	4.0	30	14
$\text{EXTRACURRICULAR}^2_{\text{WD}}$	0	3	5	8.06	10.0	100	2
$\text{EXTRACURRICULAR}^3_{\text{WD}}$	0	1	3	4.37	5.0	70	1
$\text{EXTRACURRICULAR}^4_{\text{WD}}$	0	2	4	6.13	8.0	43	16
$\text{EXTRACURRICULAR}^2_{\text{WE}}$	0	0	3	4.02	5.0	98	0
$\text{EXTRACURRICULAR}^3_{\text{WE}}$	0	0	2	3.02	5.0	30	0
$\text{EXTRACURRICULAR}^4_{\text{WE}}$	0	0	2	2.90	4.0	48	14
$\text{TELEVISION}^2_{\text{WD}}$	0	0	2	3.72	5.0	40	1
$\text{TELEVISION}^3_{\text{WD}}$	0	2	5	10.61	12.0	120	1
$\text{TELEVISION}^4_{\text{WD}}$	0	0	2	3.68	5.0	40	15
$\text{TELEVISION}^2_{\text{WE}}$	0	0	2	2.80	4.0	98	0
$\text{TELEVISION}^3_{\text{WE}}$	0	2	4	4.93	6.0	48	0
$\text{TELEVISION}^4_{\text{WE}}$	0	0	2	2.80	4.0	30	14
$\text{EATING}^4_{\text{WD}}$	0	5	7	8.04	10.0	112	15
$\text{EATING}^4_{\text{WE}}$	0	2	3	3.54	4.0	23	14
$\text{COMPUTER}^4_{\text{WD}}$	0	3	5	7.98	10.0	100	15
$\text{COMPUTER}^4_{\text{WE}}$	0	2	3	3.84	5.0	45	13
$\text{MUSIC}^2_{\text{WD}}$	0	3	5	10.66	12.0	120	4
$\text{MUSIC}^3_{\text{WD}}$	0	0	4	6.03	10.0	120	0
$\text{MUSIC}^4_{\text{WD}}$	0	2	5	8.02	10.0	120	18
$\text{MUSIC}^2_{\text{WE}}$	0	2	4	5.76	6.0	98	0
$\text{MUSIC}^3_{\text{WE}}$	0	0	0	1.45	0.0	48	0
$\text{MUSIC}^4_{\text{WE}}$	0	1	3	4.18	5.0	48	17
$\text{SOCIALIZING}^2_{\text{WD}}$	0	6	10	12.65	15.0	120	4
$\text{SOCIALIZING}^3_{\text{WD}}$	0	2	4	5.47	7.0	70	1
$\text{SOCIALIZING}^4_{\text{WD}}$	0	4	6	7.88	10.0	70	16
$\text{SOCIALIZING}^2_{\text{WE}}$	0	4	6	7.75	10.0	98	0
$\text{SOCIALIZING}^3_{\text{WE}}$	0	0	1	2.18	3.0	98	0
$\text{SOCIALIZING}^4_{\text{WE}}$	0	3	5	5.63	7.0	48	14
$\text{CLASS}^2_{\text{WD}}$	0	15	17	18.44	20.0	90	1
$\text{CLASS}^3_{\text{WD}}$	0	12	15	16.68	20.0	113	1
$\text{CLASS}^4_{\text{WD}}$	0	12	15	14.94	17.0	60	15
$\text{CLASS}^2_{\text{WE}}$	0	0	0	0.32	0.0	98	0
$\text{CLASS}^3_{\text{WE}}$	0	0	0	0.19	0.0	20	0

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
$\text{CLASS}^4_{\text{WE}}$	0	0	0	0.34	0.0	40	14
$\text{STUDYING\_ALONE}^4_{\text{WD}}$	0	6	10	13.16	19.0	60	18
$\text{STUDYING\_ALONE}^4_{\text{WE}}$	0	4	6	6.54	10.0	47	15
$\text{STUDYING}^2_{\text{WD}}$	0	12	20	19.78	25.0	120	4
$\text{STUDYING}^3_{\text{WD}}$	0	10	15	17.48	20.0	110	1
$\text{STUDYING}^2_{\text{WE}}$	0	5	8	8.60	10.0	98	0
$\text{STUDYING}^3_{\text{WE}}$	0	5	8	8.43	10.0	48	0
$\text{SLEEPING}^2_{\text{WD}}$	0	30	35	33.94	40.0	100	2
$\text{SLEEPING}^3_{\text{WD}}$	3	30	35	34.58	40.0	72	1
$\text{SLEEPING}^4_{\text{WD}}$	0	30	35	34.66	40.0	100	15
$\text{SLEEPING}^2_{\text{WE}}$	0	12	15	14.52	17.0	98	0
$\text{SLEEPING}^3_{\text{WE}}$	0	10	15	14.21	16.0	98	0
$\text{SLEEPING}^4_{\text{WE}}$	0	10	14	13.72	16.0	40	15

Table 12: Cross-tabulation of career plans and graduate school application, where FULLTIME $= 0$.

	career plan: no	career plan: yes	N/A	Sum
0 grad apps	25	29	40	94
1 or more grad apps	32	61	281	374
N/A	5	10	5	20
Sum	62	100	326	488

Table 13: Cross-tabulation of career plans and graduate school application, where FULLTIME $= 1$.

	career plan: no	career plan: yes	N/A	Sum
0 grad apps	120	630	0	750
1 or more grad apps	11	66	0	77
N/A	23	136	0	159
Sum	154	832	0	986

Table 14: Count of males and females

M	F
568	906

B Regression coefficients, all waves

Table 15: FULLTIME

	ML coef.	ML std. error	Penalized coef.	S.d. of predictor
(Intercept)	0.782	0.061	0.717	NA
$\text{PROFESSORS}^4_{\text{WD}}$	-0.078	0.064	-0.014	1.125
$\text{PROFESSORS}^4_{\text{WE}}$	0.027	0.065	.	0.369
$\text{VOLUNTEERING}^2_{\text{WD}}$	-0.066	0.067	-0.016	2.620
$\text{VOLUNTEERING}^3_{\text{WD}}$	0.153	0.098	0.017	4.900
$\text{VOLUNTEERING}^4_{\text{WD}}$	-0.007	0.066	.	2.771
$\text{VOLUNTEERING}^2_{\text{WE}}$	-0.034	0.065	.	1.663
$\text{VOLUNTEERING}^3_{\text{WE}}$	-0.098	0.081	.	2.386
$\text{VOLUNTEERING}^4_{\text{WE}}$	-0.038	0.061	-0.019	1.822
$\text{SPORT\_EVENT}^2_{\text{WD}}$	-0.155	0.073	-0.061	1.664
$\text{SPORT\_EVENT}^3_{\text{WD}}$	-0.002	0.078	.	4.071
$\text{SPORT\_EVENT}^4_{\text{WD}}$	-0.071	0.071	.	1.345
$\text{SPORT\_EVENT}^2_{\text{WE}}$	-0.123	0.072	-0.038	1.379
$\text{SPORT\_EVENT}^3_{\text{WE}}$	0.004	0.085	.	3.001
$\text{SPORT\_EVENT}^4_{\text{WE}}$	0.006	0.074	.	1.015
$\text{LIBERAL}^4_{\text{WD}}$	0.083	0.076	.	3.223
$\text{LIBERAL}^4_{\text{WE}}$	-0.046	0.074	.	1.990
$\text{SPORTS}^2_{\text{WD}}$	-0.007	0.094	.	5.444
$\text{SPORTS}^3_{\text{WD}}$	0.127	0.100	0.040	2.451
$\text{SPORTS}^4_{\text{WD}}$	0.253	0.110	0.092	4.298
$\text{SPORTS}^2_{\text{WE}}$	0.042	0.097	.	2.587
$\text{SPORTS}^3_{\text{WE}}$	0.071	0.075	0.008	1.197
$\text{SPORTS}^4_{\text{WE}}$	-0.079	0.086	.	1.855
$\text{STUDYING\_STUDENTS}^4_{\text{WD}}$	0.016	0.069	.	3.974
$\text{STUDYING\_STUDENTS}^4_{\text{WE}}$	0.096	0.073	0.019	2.688
$\text{WORKING}^2_{\text{WD}}$	-0.015	0.079	.	6.316
$\text{WORKING}^3_{\text{WD}}$	-0.051	0.071	-0.026	3.414
$\text{WORKING}^4_{\text{WD}}$	.	0.074	.	6.481
$\text{WORKING}^2_{\text{WE}}$	-0.032	0.072	.	2.807
$\text{WORKING}^3_{\text{WE}}$	-0.055	0.064	-0.013	2.313
$\text{WORKING}^4_{\text{WE}}$	0.012	0.071	.	2.812
$\text{ERRANDS}^4_{\text{WD}}$	0.026	0.071	.	3.082
$\text{ERRANDS}^4_{\text{WE}}$	-0.015	0.072	.	1.850
$\text{PARTYING}^2_{\text{WD}}$	-0.034	0.082	.	3.580
$\text{PARTYING}^3_{\text{WD}}$	-0.094	0.069	.	1.080
$\text{PARTYING}^4_{\text{WD}}$	-0.042	0.080	.	3.473
$\text{PARTYING}^2_{\text{WE}}$	0.048	0.078	.	3.355
$\text{PARTYING}^3_{\text{WE}}$	0.111	0.077	0.030	4.775
$\text{PARTYING}^4_{\text{WE}}$	0.163	0.088	0.066	2.879

	ML coef.	ML std. error	Penalized coef.	S.d. of predictor
$\text{EXTRACURRICULAR}^2_{\text{WD}}$	-0.083	0.071	-0.011	8.090
$\text{EXTRACURRICULAR}^3_{\text{WD}}$	-0.005	0.089	.	5.516
$\text{EXTRACURRICULAR}^4_{\text{WD}}$	0.225	0.078	0.085	6.303
$\text{EXTRACURRICULAR}^2_{\text{WE}}$	-0.052	0.065	-0.025	5.456
$\text{EXTRACURRICULAR}^3_{\text{WE}}$	0.031	0.091	.	3.458
$\text{EXTRACURRICULAR}^4_{\text{WE}}$	-0.052	0.071	.	4.243
$\text{TELEVISION}^2_{\text{WD}}$	0.067	0.092	.	5.180
$\text{TELEVISION}^3_{\text{WD}}$	0.072	0.096	0.012	14.550
$\text{TELEVISION}^4_{\text{WD}}$	-0.053	0.090	.	4.465
$\text{TELEVISION}^2_{\text{WE}}$	-0.089	0.088	.	3.529
$\text{TELEVISION}^3_{\text{WE}}$	0.007	0.100	0.004	5.251
$\text{TELEVISION}^4_{\text{WE}}$	-0.044	0.088	.	3.207
$\text{EATING}^4_{\text{WD}}$	-0.100	0.076	-0.013	5.064
$\text{EATING}^4_{\text{WE}}$	0.030	0.074	.	1.886
$\text{COMPUTER}^4_{\text{WD}}$	0.078	0.091	0.017	8.527
$\text{COMPUTER}^4_{\text{WE}}$	0.038	0.090	0.006	3.708
$\text{MUSIC}^2_{\text{WD}}$	0.045	0.088	0.015	14.064
$\text{MUSIC}^3_{\text{WD}}$	0.125	0.105	0.050	9.377
$\text{MUSIC}^4_{\text{WD}}$	-0.098	0.091	.	11.331
$\text{MUSIC}^2_{\text{WE}}$	-0.022	0.090	.	6.256
$\text{MUSIC}^3_{\text{WE}}$	0.170	0.100	0.084	4.092
$\text{MUSIC}^4_{\text{WE}}$	0.089	0.098	0.005	5.184
$\text{SOCIALIZING}^2_{\text{WD}}$	0.060	0.079	0.001	9.650
$\text{SOCIALIZING}^3_{\text{WD}}$	0.024	0.069	.	6.423
$\text{SOCIALIZING}^4_{\text{WD}}$	-0.008	0.078	.	6.889
$\text{SOCIALIZING}^2_{\text{WE}}$	-0.024	0.075	.	5.248
$\text{SOCIALIZING}^3_{\text{WE}}$	-0.034	0.063	.	3.988
$\text{SOCIALIZING}^4_{\text{WE}}$	0.061	0.077	0.024	4.319
$\text{CLASS}^2_{\text{WD}}$	-0.102	0.063	-0.052	8.029
$\text{CLASS}^3_{\text{WD}}$	-0.064	0.061	-0.016	7.507
$\text{CLASS}^4_{\text{WD}}$	0.078	0.065	.	5.879
$\text{CLASS}^2_{\text{WE}}$	-0.106	0.061	-0.049	1.976
$\text{CLASS}^3_{\text{WE}}$	0.047	0.067	.	1.401
$\text{CLASS}^4_{\text{WE}}$	-0.162	0.070	-0.086	1.954
$\text{STUDYING\_ALONE}^4_{\text{WD}}$	-0.141	0.074	-0.077	9.045
$\text{STUDYING\_ALONE}^4_{\text{WE}}$	-0.102	0.078	-0.028	4.749
$\text{STUDYING}^2_{\text{WD}}$	0.119	0.073	0.003	11.725
$\text{STUDYING}^3_{\text{WD}}$	0.016	0.074	.	11.150
$\text{STUDYING}^2_{\text{WE}}$	-0.014	0.073	.	5.358
$\text{STUDYING}^3_{\text{WE}}$	-0.030	0.075	-0.002	5.396
$\text{SLEEPING}^2_{\text{WD}}$	0.009	0.066	.	9.612
$\text{SLEEPING}^3_{\text{WD}}$	-0.013	0.067	.	9.770
$\text{SLEEPING}^4_{\text{WD}}$	-0.085	0.069	-0.012	9.941

	ML coef.	ML std. error	Penalized coef.	S.d. of predictor
$\text{SLEEPING}^2_{\text{WE}}$	0.056	0.068	.	4.680
$\text{SLEEPING}^3_{\text{WE}}$	-0.107	0.066	-0.024	4.647
$\text{SLEEPING}^4_{\text{WE}}$	0.116	0.070	0.034	4.559
female	0.350	0.134	0.050	0.487

Table 16: CAREER

	ML coef.	ML std. error	Penalized coef.	S.d. of predictor
(Intercept)	1.821	0.105	1.537	NA
$\text{PROFESSORS}^4_{\text{WD}}$	-0.111	0.095	-0.012	1.131
$\text{PROFESSORS}^4_{\text{WE}}$	0.016	0.083	.	0.391
$\text{VOLUNTEERING}^2_{\text{WD}}$	.	0.101	.	2.607
$\text{VOLUNTEERING}^3_{\text{WD}}$	0.050	0.151	0.026	5.039
$\text{VOLUNTEERING}^4_{\text{WD}}$	-0.006	0.108	.	2.559
$\text{VOLUNTEERING}^2_{\text{WE}}$	0.162	0.115	0.053	1.653
$\text{VOLUNTEERING}^3_{\text{WE}}$	0.010	0.133	.	2.382
$\text{VOLUNTEERING}^4_{\text{WE}}$	0.118	0.105	0.012	1.861
$\text{SPORT\_EVENT}^2_{\text{WD}}$	0.037	0.128	.	1.738
$\text{SPORT\_EVENT}^3_{\text{WD}}$	0.187	0.122	0.001	3.710
$\text{SPORT\_EVENT}^4_{\text{WD}}$	0.190	0.153	0.102	1.289
$\text{SPORT\_EVENT}^2_{\text{WE}}$	-0.061	0.107	.	1.351
$\text{SPORT\_EVENT}^3_{\text{WE}}$	-0.316	0.118	-0.079	3.025
$\text{SPORT\_EVENT}^4_{\text{WE}}$	0.356	0.173	0.146	1.009
$\text{LIBERAL}^4_{\text{WD}}$	0.102	0.112	.	3.290
$\text{LIBERAL}^4_{\text{WE}}$	-0.141	0.095	-0.073	2.083
$\text{SPORTS}^2_{\text{WD}}$	-0.017	0.142	.	5.644
$\text{SPORTS}^3_{\text{WD}}$	0.257	0.179	0.051	2.672
$\text{SPORTS}^4_{\text{WD}}$	0.386	0.203	0.140	4.399
$\text{SPORTS}^2_{\text{WE}}$	0.038	0.151	.	2.587
$\text{SPORTS}^3_{\text{WE}}$	-0.138	0.114	.	1.234
$\text{SPORTS}^4_{\text{WE}}$	0.116	0.153	0.109	1.838
$\text{STUDYING\_STUDENTS}^4_{\text{WD}}$	0.310	0.120	0.162	3.787
$\text{STUDYING\_STUDENTS}^4_{\text{WE}}$	0.040	0.095	.	2.528
$\text{WORKING}^2_{\text{WD}}$	-0.045	0.107	.	6.278
$\text{WORKING}^3_{\text{WD}}$	0.229	0.133	0.116	3.077
$\text{WORKING}^4_{\text{WD}}$	-0.040	0.108	.	6.610
$\text{WORKING}^2_{\text{WE}}$	0.148	0.114	0.050	2.815
$\text{WORKING}^3_{\text{WE}}$	0.040	0.090	.	2.287
$\text{WORKING}^4_{\text{WE}}$	0.128	0.105	0.022	2.915
$\text{ERRANDS}^4_{\text{WD}}$	-0.049	0.098	.	3.203
$\text{ERRANDS}^4_{\text{WE}}$	-0.031	0.100	.	1.900
$\text{PARTYING}^2_{\text{WD}}$	0.149	0.118	0.002	3.538

	ML coef.	ML std. error	Penalized coef.	S.d. of predictor
$\text{PARTYING}^3_{\text{WD}}$	0.040	0.115	0.007	0.951
$\text{PARTYING}^4_{\text{WD}}$	0.114	0.122	.	3.452
$\text{PARTYING}^2_{\text{WE}}$	-0.198	0.111	-0.033	3.360
$\text{PARTYING}^3_{\text{WE}}$	0.273	0.130	0.158	4.817
$\text{PARTYING}^4_{\text{WE}}$	-0.117	0.118	.	2.835
$\text{EXTRACURRICULAR}^2_{\text{WD}}$	-0.076	0.111	.	7.630
$\text{EXTRACURRICULAR}^3_{\text{WD}}$	-0.237	0.123	-0.034	5.719
$\text{EXTRACURRICULAR}^4_{\text{WD}}$	-0.047	0.111	.	6.416
$\text{EXTRACURRICULAR}^2_{\text{WE}}$	-0.145	0.102	-0.015	4.626
$\text{EXTRACURRICULAR}^3_{\text{WE}}$	0.056	0.135	.	3.542
$\text{EXTRACURRICULAR}^4_{\text{WE}}$	0.165	0.116	0.055	4.161
$\text{TELEVISION}^2_{\text{WD}}$	0.228	0.148	0.078	5.149
$\text{TELEVISION}^3_{\text{WD}}$	-0.154	0.121	-0.046	15.080
$\text{TELEVISION}^4_{\text{WD}}$	-0.004	0.129	.	4.510
$\text{TELEVISION}^2_{\text{WE}}$	-0.008	0.139	0.008	3.454
$\text{TELEVISION}^3_{\text{WE}}$	0.056	0.135	.	5.108
$\text{TELEVISION}^4_{\text{WE}}$	0.167	0.123	0.039	3.204
$\text{EATING}^4_{\text{WD}}$	-0.085	0.110	.	4.242
$\text{EATING}^4_{\text{WE}}$	0.126	0.118	0.001	1.798
$\text{COMPUTER}^4_{\text{WD}}$	-0.114	0.121	-0.056	8.923
$\text{COMPUTER}^4_{\text{WE}}$	-0.062	0.115	-0.008	3.762
$\text{MUSIC}^2_{\text{WD}}$	-0.022	0.119	-0.001	14.555
$\text{MUSIC}^3_{\text{WD}}$	0.082	0.127	.	9.892
$\text{MUSIC}^4_{\text{WD}}$	0.029	0.125	-0.032	11.382
$\text{MUSIC}^2_{\text{WE}}$	-0.079	0.127	-0.023	6.267
$\text{MUSIC}^3_{\text{WE}}$	-0.023	0.117	.	4.435
$\text{MUSIC}^4_{\text{WE}}$	-0.123	0.136	-0.022	5.123
$\text{SOCIALIZING}^2_{\text{WD}}$	0.056	0.117	.	9.902
$\text{SOCIALIZING}^3_{\text{WD}}$	0.334	0.130	0.130	6.574
$\text{SOCIALIZING}^4_{\text{WD}}$	-0.043	0.108	.	7.016
$\text{SOCIALIZING}^2_{\text{WE}}$	0.147	0.115	0.047	5.114
$\text{SOCIALIZING}^3_{\text{WE}}$	-0.028	0.100	.	3.106
$\text{SOCIALIZING}^4_{\text{WE}}$	0.042	0.110	.	4.206
$\text{CLASS}^2_{\text{WD}}$	-0.033	0.093	.	8.098
$\text{CLASS}^3_{\text{WD}}$	0.033	0.088	.	7.828
$\text{CLASS}^4_{\text{WD}}$	0.122	0.092	0.052	5.841
$\text{CLASS}^2_{\text{WE}}$	0.176	0.204	0.030	1.695
$\text{CLASS}^3_{\text{WE}}$	-0.010	0.085	.	1.504
$\text{CLASS}^4_{\text{WE}}$	-0.079	0.084	-0.009	1.316
$\text{STUDYING\_ALONE}^4_{\text{WD}}$	-0.225	0.101	-0.105	8.767
$\text{STUDYING\_ALONE}^4_{\text{WE}}$	0.175	0.111	0.039	4.346
$\text{STUDYING}^2_{\text{WD}}$	-0.078	0.093	-0.051	11.704
$\text{STUDYING}^3_{\text{WD}}$	0.013	0.099	.	10.986

	ML coef.	ML std. error	Penalized coef.	S.d. of predictor
$\text{STUDYING}^2_{\text{WE}}$	0.014	0.107	.	5.119
$\text{STUDYING}^3_{\text{WE}}$	-0.024	0.102	.	5.169
$\text{SLEEPING}^2_{\text{WD}}$	.	0.094	.	9.489
$\text{SLEEPING}^3_{\text{WD}}$	-0.079	0.092	.	9.835
$\text{SLEEPING}^4_{\text{WD}}$	0.132	0.101	0.039	9.823
$\text{SLEEPING}^2_{\text{WE}}$	0.012	0.096	.	4.544
$\text{SLEEPING}^3_{\text{WE}}$	0.122	0.093	0.037	4.609
$\text{SLEEPING}^4_{\text{WE}}$	-0.028	0.099	.	4.521
female	0.144	0.191	.	0.484

Table 17: GRADAPP

	ML coef.	ML std. error	Penalized coef.	S.d. of predictor
(Intercept)	-0.701	0.065	-0.630	NA
$\text{PROFESSORS}^4_{\text{WD}}$	0.088	0.069	0.009	1.140
$\text{PROFESSORS}^4_{\text{WE}}$	0.003	0.066	.	0.357
$\text{VOLUNTEERING}^2_{\text{WD}}$	0.111	0.074	0.031	2.676
$\text{VOLUNTEERING}^3_{\text{WD}}$	-0.082	0.100	.	4.629
$\text{VOLUNTEERING}^4_{\text{WD}}$	-0.048	0.072	.	2.881
$\text{VOLUNTEERING}^2_{\text{WE}}$	0.106	0.072	0.055	1.465
$\text{VOLUNTEERING}^3_{\text{WE}}$	0.118	0.084	.	2.332
$\text{VOLUNTEERING}^4_{\text{WE}}$	0.033	0.067	0.007	1.904
$\text{SPORT\_EVENT}^2_{\text{WD}}$	0.025	0.082	.	1.727
$\text{SPORT\_EVENT}^3_{\text{WD}}$	-0.014	0.081	.	4.138
$\text{SPORT\_EVENT}^4_{\text{WD}}$	0.027	0.074	.	1.307
$\text{SPORT\_EVENT}^2_{\text{WE}}$	0.105	0.077	.	1.365
$\text{SPORT\_EVENT}^3_{\text{WE}}$	0.043	0.088	.	2.987
$\text{SPORT\_EVENT}^4_{\text{WE}}$	0.064	0.075	.	1.026
$\text{LIBERAL}^4_{\text{WD}}$	-0.063	0.086	-0.012	3.047
$\text{LIBERAL}^4_{\text{WE}}$	-0.091	0.094	-0.050	1.979
$\text{SPORTS}^2_{\text{WD}}$	-0.091	0.099	-0.021	5.374
$\text{SPORTS}^3_{\text{WD}}$	-0.055	0.093	-0.012	2.565
$\text{SPORTS}^4_{\text{WD}}$	-0.013	0.103	.	4.014
$\text{SPORTS}^2_{\text{WE}}$	-0.080	0.098	.	2.415
$\text{SPORTS}^3_{\text{WE}}$	-0.051	0.079	.	1.209
$\text{SPORTS}^4_{\text{WE}}$	-0.047	0.092	.	1.797
$\text{STUDYING\_STUDENTS}^4_{\text{WD}}$	-0.037	0.073	.	4.036
$\text{STUDYING\_STUDENTS}^4_{\text{WE}}$	-0.083	0.072	.	2.731
$\text{WORKING}^2_{\text{WD}}$	0.007	0.081	.	6.025
$\text{WORKING}^3_{\text{WD}}$	-0.028	0.077	.	3.516
$\text{WORKING}^4_{\text{WD}}$	0.016	0.078	.	6.240
$\text{WORKING}^2_{\text{WE}}$	0.042	0.076	.	2.711

	ML coef.	ML std. error	Penalized coef.	S.d. of predictor
$\text{WORKING}^{3}_{\text{WE}}$	0.130	0.075	0.042	2.278
$\text{WORKING}^{4}_{\text{WE}}$	0.004	0.075	.	2.823
$\text{ERRANDS}^{4}_{\text{WD}}$	-0.086	0.081	-0.019	3.135
$\text{ERRANDS}^{4}_{\text{WE}}$	-0.011	0.082	-0.018	1.801
$\text{PARTYING}^{2}_{\text{WD}}$	-0.060	0.089	.	3.558
$\text{PARTYING}^{3}_{\text{WD}}$	0.068	0.075	.	1.091
$\text{PARTYING}^{4}_{\text{WD}}$	-0.044	0.087	.	3.472
$\text{PARTYING}^{2}_{\text{WE}}$	0.087	0.081	.	3.394
$\text{PARTYING}^{3}_{\text{WE}}$	-0.042	0.084	-0.010	4.706
$\text{PARTYING}^{4}_{\text{WE}}$	-0.067	0.090	-0.001	2.887
$\text{EXTRACURRICULAR}^{2}_{\text{WD}}$	0.068	0.075	.	8.119
$\text{EXTRACURRICULAR}^{3}_{\text{WD}}$	0.108	0.093	.	5.192
$\text{EXTRACURRICULAR}^{4}_{\text{WD}}$	-0.159	0.082	-0.051	6.139
$\text{EXTRACURRICULAR}^{2}_{\text{WE}}$	0.090	0.075	0.032	5.537
$\text{EXTRACURRICULAR}^{3}_{\text{WE}}$	-0.096	0.097	.	3.462
$\text{EXTRACURRICULAR}^{4}_{\text{WE}}$	0.036	0.074	.	4.059
$\text{TELEVISION}^{2}_{\text{WD}}$	0.030	0.095	.	5.072
$\text{TELEVISION}^{3}_{\text{WD}}$	-0.169	0.111	-0.069	14.687
$\text{TELEVISION}^{4}_{\text{WD}}$	0.165	0.099	0.054	4.338
$\text{TELEVISION}^{2}_{\text{WE}}$	-0.027	0.094	.	3.544
$\text{TELEVISION}^{3}_{\text{WE}}$	-0.029	0.107	.	5.226
$\text{TELEVISION}^{4}_{\text{WE}}$	-0.023	0.098	.	3.183
$\text{EATING}^{4}_{\text{WD}}$	-0.045	0.077	.	5.199
$\text{EATING}^{4}_{\text{WE}}$	0.031	0.079	.	1.896
$\text{COMPUTER}^{4}_{\text{WD}}$	-0.123	0.100	.	8.705
$\text{COMPUTER}^{4}_{\text{WE}}$	0.112	0.095	.	3.829
$\text{MUSIC}^{2}_{\text{WD}}$	-0.015	0.094	.	14.118
$\text{MUSIC}^{3}_{\text{WD}}$	-0.147	0.114	-0.032	9.510
$\text{MUSIC}^{4}_{\text{WD}}$	0.149	0.098	.	11.023
$\text{MUSIC}^{2}_{\text{WE}}$	0.011	0.094	.	6.172
$\text{MUSIC}^{3}_{\text{WE}}$	-0.125	0.108	-0.044	4.162
$\text{MUSIC}^{4}_{\text{WE}}$	-0.019	0.102	.	4.946
$\text{SOCIALIZING}^{2}_{\text{WD}}$	-0.082	0.086	-0.021	9.846
$\text{SOCIALIZING}^{3}_{\text{WD}}$	-0.022	0.075	.	6.003
$\text{SOCIALIZING}^{4}_{\text{WD}}$	-0.127	0.088	-0.066	6.717
$\text{SOCIALIZING}^{2}_{\text{WE}}$	-0.009	0.081	.	5.143
$\text{SOCIALIZING}^{3}_{\text{WE}}$	-0.102	0.094	-0.005	4.069
$\text{SOCIALIZING}^{4}_{\text{WE}}$	-0.046	0.083	.	4.211
$\text{CLASS}^{2}_{\text{WD}}$	0.155	0.067	0.070	8.160
$\text{CLASS}^{3}_{\text{WD}}$	-0.039	0.068	.	7.728
$\text{CLASS}^{4}_{\text{WD}}$	0.071	0.069	0.019	5.902
$\text{CLASS}^{2}_{\text{WE}}$	0.117	0.066	0.037	2.032
$\text{CLASS}^{3}_{\text{WE}}$	-0.082	0.074	.	1.266

	ML coef.	ML std. error	Penalized coef.	S.d. of predictor
$\text{CLASS}^4_{\text{WE}}$	0.207	0.080	0.095	1.973
$\text{STUDYING\_ALONE}^4_{\text{WD}}$	-0.043	0.080	.	9.268
$\text{STUDYING\_ALONE}^4_{\text{WE}}$	0.114	0.084	0.020	4.886
$\text{STUDYING}^2_{\text{WD}}$	-0.027	0.075	.	11.380
$\text{STUDYING}^3_{\text{WD}}$	0.071	0.077	0.030	11.376
$\text{STUDYING}^2_{\text{WE}}$	-0.011	0.078	.	5.396
$\text{STUDYING}^3_{\text{WE}}$	0.137	0.081	0.086	5.421
$\text{SLEEPING}^2_{\text{WD}}$	-0.070	0.072	-0.001	9.678
$\text{SLEEPING}^3_{\text{WD}}$	-0.080	0.073	.	9.808
$\text{SLEEPING}^4_{\text{WD}}$	0.170	0.075	0.009	9.913
$\text{SLEEPING}^2_{\text{WE}}$	-0.085	0.073	.	4.694
$\text{SLEEPING}^3_{\text{WE}}$	0.190	0.071	0.066	4.705
$\text{SLEEPING}^4_{\text{WE}}$	-0.105	0.076	.	4.603
female	-0.440	0.144	-0.046	0.483